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Bistatic and Multistatic Synthetic Aperture Radar Interferometric
Phenomenology and Change Detection

School of Defence and Security
Centre for Electronic Warfare, Information and Cyber

PhD
Academic Year: 2021 - 2024

Supervisor: Doctor Daniel Andre
Associate Supervisor: Professor Alessio Balleri
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This thesis is submitted in partial fulfilment of the requirements for
the degree of Doctor of Philosophy

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Alexander Eric Hagelberg

Abstract

Synthetic Aperture Radar (SAR) is an active remote sensing technique which allows for the collection of high-resolution imagery in any weather and in the day or night.

SAR Coherent Change Detection (CCD) allows for the detection of very small scene changes. This is particularly useful for Intelligence, Surveillance and Reconnaissance (ISR) as small changes such as vehicle tracks can be identified. Rapidly collecting repeat pass SAR imagery is important in these applications.

For space borne platforms, such repeat passes may however have significant baselines. CCD products are reliant on high coherence for good interpretability.

This thesis investigates two main areas:

The first is the sources and levels of incoherence associated with bistatic SAR imagery for a variety of baselines which maintained a high spatial frequency domain overlap. This investigation using simulations and measured laboratory data. This investigation showed the significant impact of the scattering parameter (added to the equations of coherence in this thesis) on the coherence of Rayleigh rough ground exhibiting speckle.

Secondly the impact of different combinations of change detection images for multistatic and multi-polarimetric change detection is investigated. It is shown that combining multiple images can reduce the number of false detections and give improved performance (shown with performance metrics). This performance improvement is dependent on the processing which is chosen.

Keywords:

Coherent Change Detection (CCD), fully polarimetric radar, ground based (laboratory) radar, ultra-wideband radar, speckle.

Acknowledgements & Thanks

This PhD was sponsored by the Defence Science and Technology Laboratory (DSTL) as a part of the “LabSAR: Experimental Multi-static and Low Frequency SAR Phenomenology” project.

Thanks, must be given to Doctor Daniel Andre for his excellent supervision and guidance, and to Professor Alessio Balleri for his support as associate supervisor. Additional thanks must be given to Dr Mark Finnis for his work on the GBSAR system.

I also wish to thank all the research students and members of staff who frequented building 70 and made this experience so much more enjoyable.

Finally, thanks go to my family for their ever steadfast support and encouragement.

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List of Symbols

Greek Alphabet symbols

β	Bistatic angle.
$\Gamma(x)$	Gamma function of x.
Γ_m, Γ_t	Two complex CCD images. Referred to as master and test respectively.
$ \Gamma_m , \Gamma_t $	The magnitude (estimated coherence) of CCD images. Referred to as master and test respectively.
$ \overline{\Gamma_m} , \overline{\Gamma_t} $	Mean magnitude ($\hat{\gamma}$ or estimated coherence) of two CCD images. Referred to as master and test respectively.
γ	Coherence.
$\hat{\gamma}$	Estimated coherence.
$\gamma_{baseline}$	Decorrelation due to a mismatch in the spatial frequency domain overlap.
γ_{Ber}	Coherence calculated using alternate complex cross correlation (Berger 1972).
$\gamma_{Curvefit}$	Coherence calculated by a polynomial fitted to the $\hat{\gamma}_{Meas}$ values.
γ_{geom}	Decorrelation due to the imaging geometry.
$\hat{\gamma}_{Meas}$	Estimated coherence from measured data.
γ_{proc}	Decorrelation due to processing.
$\gamma_{registration}$	Decorrelation due to misregistration.
γ_{scat}	Decorrelation due to the differences in scattering as a function of geometry.
$\hat{\gamma}_{Scat-baseline}$	Estimated value of γ_{scat} , calculated using $\gamma_{baseline}$.
$\hat{\gamma}_{Scat-isotropic-sim}$	Estimated value of γ_{scat} , calculated using $\hat{\gamma}_{Sim-isotropic}$.
$\hat{\gamma}_{Scat-Trimmed}$	Estimated value of γ_{scat} , calculated using $\hat{\gamma}_{Trimmed}$.
$\hat{\gamma}_{Sim-decorrelation}$	Estimated coherence from simulated data (non-isotropic scatterers).
$\hat{\gamma}_{Sim-isotropic}$	Estimated coherence from simulated data (isotropic scatterers).
γ_{SNR}	Decorrelation due to the SNR.
γ_{temp}	Decorrelation due to changes in the scene.
$\hat{\gamma}_{Trimmed}$	Estimated coherence from trimmed measured data.
γ_{true}	True coherence.
Δf	Frequency step size.
Δh	Surface height variation.

Δr	Distance between the antenna and the target/scatterer.
ΔR	Differential range.
Δr_{SC}	Distance between the antenna and the scene centre.
θ	Incidence angle.
λ	Wavelength.
λ_c	Wavelength for the centre frequency.
ρ	Change detection output (use for the CI-CCD two stage detector).
ρ_{MLE}	Output of the Maximum Likelihood Estimator.
ρ_{NCCD}	Output of the Non-Coherent Change Detection.
ρ_{res}	Resolution cell size.
ρ_{SVR}	Output of the Sample Variance Ratio.
σ_f^2, σ_g^2	Variance for reference and mission images.
$\widehat{\sigma_f^2}, \widehat{\sigma_g^2}$	Sample variance for reference and mission images.
σ_{fg}	Co-variance between reference and mission images.
τ	Generalised interval in time.
τ_n	Interval in time/ radar position index n .
$\Phi(\Delta R(m, \tau_n))$	Phase function.
ϕ	Phase term of the complex cross correlation.
ϕ_{Ber}	Alternate phase term of the complex cross correlation (Berger 1972).
ϕ_k	Phase term for k^{th} scatterer.
ϕ_{noise}	Phase term due to the noise.
ϕ_{scat}	Phase term due to scatterers.
ϕ_{stp}	Azimuth angle step size (radians).
ϕ_w	Azimuth angle swept through (radians).
ψ	Grazing angle.

Latin Alphabet symbols

A	Amplitude
$A(f_k, \tau_n)$	Scaling factor related to the RCS.
A_c	Area of overlap in the k-space.
A_k	Scaling factor related to the RCS for k^{th} scatterer.
A_m	Area of non-overlap in the k-space for the mission image.
A_{mt}	Full area in the k-space in the mission image.
A_r	Area of non-overlap in the k-space for the reference image.
A_{rt}	Full area in the k-space in the reference image.
B_x	Along track baseline (m).
B_z	Across track baseline (m).
b_f, b_g	De-correlated components of images I_f and I_g not due to noise.
BW	Bandwidth.
c	Speed of light.
c_{fg}	Correlated component of images I_f and I_g .
d	Distance from antennas to the scene.
d_{fraun}	Fraunhofer distance
${}_pF_q \left[\begin{smallmatrix} a \\ b \end{smallmatrix}; x \right]$	Gauss hypergeometric function (Touzi et al. 1996 & 1999, Gradshteyn et al. 1980).
f_1	Lowest frequency in the chirp.
f_c	Centre frequency.
f_k	Frequency at index k .
f_{max}	Maximum frequency.
f_{min}	Minimum frequency.
Δf	Frequency step size.
H_0	Hypothesis of no change in a SAR image.
H_1	Hypothesis of change in a SAR image.
h_s	Height (Z co-ordinate) of scatterer.
I	SAR image/ transduced reflectivity.
$ I $	SAR image Intensity.
I_f, I_g	Two complex SAR images, referred to as the reference and mission images in change detection.
K	Number of frequency samples.

$\pm L$	Extent of the illumination patch, size is $2L$.
L_{base}	Length (baseline).
L_{cr}	Monostatic unambiguous cross-range.
L_{cr_g}	Ground plane monostatic unambiguous cross-range.
$L_{cr_g Bi}$	Ground plane monostatic unambiguous cross-range.
L_r	Monostatic unambiguous range.
L_{r_g}	Ground plane monostatic unambiguous range.
$L_{r_g Bi}$	Ground plane monostatic unambiguous range.
m	A discrete range bin.
N	Number of point scatterers.
N_p	Number of pulses.
n_f, n_g	De-correlated components of images I_f and I_g due to noise.
$P(I)$	Intensity distribution function for SAR speckle.
P_{ant}	Co-ordinates of the antenna phase centre.
P_{trg}	Co-ordinates of a target/scatterer.
Q	UIQI performance metrics (Wang et al. 2002 & 2009, Novak 2013).
R_{cr}	Monostatic resolution, cross-range direction.
R_{cr_g}	Ground plane resolution, range direction.
$R_{cr_g Bi}$	Bistatic ground plane resolution, range direction.
R_f, R_g	Range in images f and g .
R_r	Monostatic resolution, range direction.
R_{rx}	Range to receiver.
R_{r_g}	Ground plane resolution, cross-range direction.
$R_{r_g Bi}$	Bistatic ground plane resolution, cross-range direction.
R_{tx}	Range to transmitter.
R_x or R_x	Receiver (number instead of x if applicable).
$R_{x_{pos}}$	Co-ordinate of receiver.
ΔR	Differential range.
Δr	Distance between the antenna and the target/scatterer.
Δr_{SC}	Distance between the antenna and the scene centre.
$S(f_k, \tau_n)$	Complex phase history data.

$s(m, \tau_n)$	Range profiles.
SC	Scene centre.
$s_{pix}(C, \tau_n)$	Complex value per pixel and per pulse.
T	Threshold.
t	Tolerance for classification bin size.
TR_{BEM}	Bistatic Equivalent Monostatic (BEM) transceiver location.
TR_{mid}	Transceiver midpoints.
T_x or T_x	Transmitter (number instead of x if applicable).
Tx_{pos}	Co-ordinates of transmitter.
T_{CCD}	Threshold for detecting a change from the CCD.
T_{NCCD}	Threshold for detecting a change from the NCCD.
u	Difference between range to the top of a scatterer and scene centre.
X_{ant}	X co-ordinate of the antenna phase centre.
X_{trg}	X co-ordinate of a target/scatterer.
x_0	X co-ordinate of scene centre.
x_r	X co-ordinate of receiver.
x_s	X co-ordinate of scatterer.
x_t	X co-ordinate of transmitter.
Y_{ant}	Y co-ordinate of the antenna phase centre.
Y_{trg}	Y co-ordinate of a target/scatterer.
y	Ground range of the scatterer/target to the scene centre.
y_0	Y co-ordinate of scene centre.
y_r	Y co-ordinate of receiver.
y_s	Y co-ordinate of scatterer.
y_t	Y co-ordinate of transmitter.
Z_{ant}	Z co-ordinate of the antenna phase centre.
Z_{trg}	Z co-ordinate of a target/scatterer.
z_0	Z co-ordinate of scene centre.
z_r	Z co-ordinate of receiver.
z_t	Z co-ordinate of transmitter.

Vectors symbols

$\hat{\mathbf{b}}$	Unit vector for direction of the true BEM.
$\hat{\mathbf{i}}$	Unit vector for the incident wave.
$\vec{\mathbf{K}}$	Vector in k-space. Defines the location of datapoints within the spatial frequency domain.
$\vec{\mathbf{K}}_{Bi}$	Vector in k-space for a bistatic SAR. Defines the location of datapoints within the spatial frequency domain.
$\vec{\mathbf{K}}_{mono}$	Vector in k-space for a monostatic SAR. Defines the location of datapoints within the spatial frequency domain.
$\vec{\mathbf{k}}$	Generalised unit vector in K-space.
$\vec{\mathbf{k}}_i$	Unit vector in the K-space, direction is defined by the incident wave ($\hat{\mathbf{i}}$), and the length is dependent on frequency.
$\vec{\mathbf{k}}_s$	Unit vector in the K-space, direction is defined by the scattered wave ($\hat{\mathbf{s}}$), and the length is dependent on frequency.
$\hat{\mathbf{s}}$	Unit vector for the scattered wave.

List of Acronyms

AI	Artificial Intelligence
ARM	Anti-Radiation Missile
ASAT	Anti-Satellite (missile)
ATR	Automatic Target Recognition
BEM	Bistatic Equivalent Monostatic
BPA	Back Projection Algorithm
BSA	Backscatter Alignment
BW	Bandwidth
CBP	Convolutional Back Projection algorithm
CCD	Coherent Change Detection
CI-CCD	Combined Intensity and Coherent Change Detection
CSI	Critical Success Index
CW	Continuous Wave
DARPA	Defense Advanced Research Projects Agency
DEM	Digital Elevation Model/Map
DIU	Defence Intelligence of Ukraine
DLR	Deutsches Zentrum für Luft- und Raumfahrt
DSS	Defence Space Strategy
DSTL	Defence Science and Technology Laboratory
EO	Electro Optical
ESA	European Space Agency
EW	Electromagnetic Warfare
EW	Electronic/Electro-magnetic Warfare
FAR	False Alarm Ratio/Rate
FM	Frequency Modulated
FN	False Negative
FOI	Totalförsvarets Forskningsinstitut
FP	False Positive
FSOC	Free-Space Optical Communications
GBSAR	Ground Based Synthetic Aperture
GMTI	Ground Moving Target Indication

GNSS	Global Navigation Satellite Systems
HSS	Heidke Skill Score
IEEE	Institute of Electrical and Electronics Engineers
IET	the Institution of Engineering and Technology
InSAR	Interferometric Synthetic Aperture Radar
IOA	Institute of Acoustics
ISAR	Inverse Synthetic Aperture Radar
ISR	Intelligence, Surveillance and Reconnaissance
ISW	Institute for the Study of War
KARI	Korea Aerospace Research Institute
KOMPSAT	KOrea Multi Purpose SATellite
MCC	Matthews Correlation Coefficient
MFA	Matched Filter Algorithms
MIMO	Multiple Input Multiple Output
MLE	Maximum Likelihood Estimate
MOD	Ministry of Defence
NCCD	Non-Coherent Change Detection
PC	Proportion Correct
PDF	Probability Density Function
PFA	Polar Format Algorithm
PFS	Projected Fourier Supports
PO	Physical Optics
POD	Probability Of Detection
PolInSAR	Polarimetric Interferometric Synthetic Aperture Radar
RAeS	Royal Aeronautical Society
RCS	Radar Cross Section
RSO	Resident Space Object
RF	Radio Frequency
RGB	Red Green Blue
RMSE	Root Mean Squared Error
ROI	Region of Interest
RSN	Radar, Sonar and Navigation (IET journal)
RUSI	Royal United Services Institute

Rx	Receiver antenna
SAM	Surface to Air Missile
SAR	Synthetic Aperture Radar
SAS	Synthetic Aperture Sonar
SCR	Signal to Clutter Ratio
SAD	Space Domain Awareness
SIGINT	Signals intelligence
SIMO	Single Input Multiple Output
SNR	Signal to Noise Ratio
SR	Success Rate
SRTM	Shuttle Radar Topography Mission
SSO	Sun-Synchronous Orbit
SVIT	Spatially Variant Incoherence Trimming
SVR	Sample Variance Ratio
TN	True Negative
TP	True Positive
Tx	Transmitter antenna
UAS	Uncrewed Air Systems
UIQI	Universal Image Quality Index
UK	United Kingdom
UKSA	United Kingdom Space Agency
UWB	Ultra-wideband
VNA	Vector Network Analyser

1 Introduction

Synthetic Aperture Radar (SAR) allows for the generation of high-resolution radar images, having applications both civilian and military. SAR uses a moving radar to generate a synthetically large aperture, this allows an airborne system to generate high resolution images with a practical sized antenna (a few meters).

In a monostatic geometry the transmitter and receiver are co-located. Multistatic and bistatic refer to geometries where the transmitter(s) and receiver(s) are not co-located. These geometries (which are explained in more detail in section 2.2.2) are becoming an increasingly viable proposition for space based remote sensing as the cost of launching payloads has decreased [1], [2]. This makes the possibility of large SAR satellite constellations [3], or a powerful SAR satellite and ground-based aircraft receivers, a more feasible possibility. Additional use cases for multistatic/bistatic SAR systems include drone swarms, aircraft and ground-based sensors (for applications such as mine detection).

Multistatic SAR can provide several advantages, such as providing improved cross-range resolution [4], [5], and Signal to Noise Ratio (SNR) [6], although the specific geometries have a strong influence on these [7]. Polarimetric SAR CCD has also been shown to improve CCD images [8], [9], [10].

1.1 Context and motivation

1.1.1 An increasingly transparent battlefield

Warfare has evolved significantly in the twentieth and twenty first centuries. In this time period many different terms have been used to describe the various conflicts. These include Industrial warfare, full scale interstate warfare, counterinsurgency, intrastate (civil war) conflicts, asymmetric-warfare, hybrid-warfare and peacekeeping operations [11]. In this myriad of different conflicts, information has always been vital [12], [13]. This was recognised as far back as the writings of Sun Tzu [11], [14] (first published over 2000 years ago).

The battlefield today is often referred to as *transparent* or as increasingly transparent. This refers to the vast array of sensors monitoring the battlefield and the battlefield networks that pass along the targeting information and close the *kill chains*. On the modern battlefield the movement of men and material can be observed by anything from satellites, aircraft, drones or static surveillance sensors.

Intelligence Surveillance and Reconnaissance (ISR) is a fundamental component of modern warfare [15], [16]. The battlefield has only grown more transparent, with improved tactical and operational situational awareness. This transparency has made fighting difficult and costly in recent conflicts [17], [18], [19].

In a modern conflict ISR assets can be anything from satellites in orbit, manned or uncrewed fixed and rotary wing aviation, ground vehicles and small Uncrewed Aerial Systems (UAS or drones) all the way down to an individual soldier. Organisations such as the Defense Advanced Research Projects Agency (DARPA) are looking at integrating all these different sensors and improving speed using concepts such as Mosaic Warfare [20].

Satellite imaging has been used militarily since the first reconnaissance satellites were launched in the 1960s. A modern day example of SAR images used in conflict, with images published in the public domain, is ICEYE satellites used to provide images to Ukraine. SAR satellites from ICEYE have played a role in the Russo-Ukrainian war since 2022 [21], [22]. In an article written by the Defence Intelligence of Ukraine (DIU) in

2024 it was stated that in two years specialists had analysed over 4000 images of 900 different targets [21]. These images were taken using the ICEYE constellation. The DIU described the satellite as being very important in collecting imagery of Russian military assets and allowing strikes to be planned [21].

An example SAR image is shown below in Figure 1.1 [23]. In this image of a Russian airfield several transport and bomber aircraft are identified.

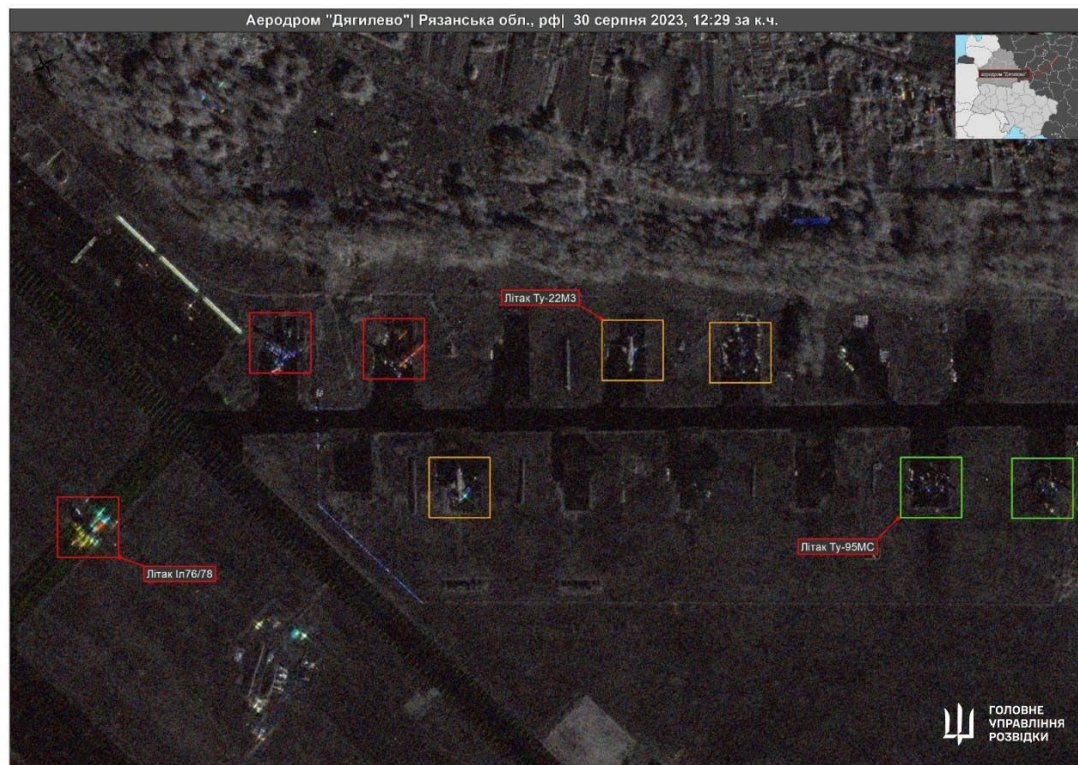


Figure 1.1 SAR image collected by an ICEYE satellite. Image was released by the Ukrainian DIU [23]. The SAR image shows the Dyagilevo airbase in Ryazan Oblast, Russia. In the image Il-76/78 transport aircraft are identified in red, TU-22 bombers in orange and TU-95 bombers in green.

It is not just satellites which have proved vital in providing ISR capabilities. Uncrewed Aerial System (UAS) are heavily used. For example, a report by the Institute for the Study of War (ISW) reported that as many as 100 Ukrainian and Russian drones could be operating within a 10 Km radius [24].

This thesis is applicable to multistatic and bistatic systems (see section 2.2.2). These systems can take many forms from aircraft, spacecraft, surface- and ground-based vehicles. Particular emphasis was placed on spacecraft (1.1.2) and UAS (1.1.3) borne systems, although the results remain applicable to the wide array of aforementioned SAR systems. This was done due to the interests of the sponsor; DSTL. Space based SAR systems can cover large areas with high powered systems. Small drones can be considered more expendable and would be useful in identifying mines in a minefield.

1.1.2 Increasing accessibility of space

Whilst SAR has been used for decades, Multistatic and Bistatic geometries are becoming an increasingly viable proposition for covering large areas of land. The cost of launching payloads to orbit has reduced to below 2000 \$/Kg for small launch systems [1]. A cost of around 2700 \$/Kg for the SpaceX Falcon 9 and 1400 \$/Kg for the Falcon Heavy [2]. This makes the possibility of large SAR satellite constellations [3], [5], or other multistatic geometries [25] a more viable proposition. A report by London Economics for the United Kingdom Space Agency (UKSA) showed that the value of satellites in constellations overtook the number of satellites not in constellations in 2024 [26]. And in 2025 the values would be approximately £5 billion in constellations compared to £3.5 billion. The report also estimates that the value of satellite constellations had will continue to rise and increase this gap [26]. This reflects a growth in the number of constellations and the size of existing constellations. Constellations of small monostatic satellites such as those operated by ICEYE [27], [28] can provide 24-hour revisit times. This is unlikely to be possible for a multistatic constellation of larger and more powerful satellites without significant costs. The revisit times for a single SAR satellite, or close cluster is in the order of days, this depends on the orbit parameters such as inclination, altitude and eccentricity. For example, the SENTINEL satellites operated by the European Space Agency (ESA) have a revisit time of 12 days [29].

A report by the Swedish Totalförsvarets Forskningsinstitut (FOI) in 2024 discussed investment by western militaries (such as France, Germany, Denmark, Norway, Sweden and the United States) in reconnaissance and surveillance satellites [30]. Other nations

such as China are also investing heavily in their space based ISR capability [31], [32], [33].

The improved density and cost of high-performance computer components make processing large volumes of data possible in a reasonable timeframe, this opens up new avenues for the generation and processing (including in orbit) of SAR imagery [34], [35].

1.1.2.1 ISTARI and OBERON

The United Kingdom's (UK) Defence Space Strategy (DSS) [36] published in 2022 and aimed at improving the UK's sovereign space capability [37]. A summary can be found by the Royal Aeronautical Society (RAeS) on their website [38]. The DSS [36] covers many areas relating to space such as new satellites, but also upskilling of personnel, space domain awareness, Electromagnetic Warfare (EW) and improved interoperability with allied nations. The DSS [36] allocates £1.4 billion for the next 10 years to fund new research and development programmes and new capabilities.

The majority of the funds allocated towards research and development (£970 million of £1.4 billion) are allocated towards enhancing the UK's ISR capabilities. This improved ISR capability has been given the name ISTARI (named in reference to the wizards in Tolkien's Lord of the rings) [36].

The ISTARI programme aims to provide the UK with a multi-satellite system that is compatible with allied nations and which can provide hyperspectral imagery.

Underpinning ISTARI¹ is the MINERVA programme which encompasses several concept demonstrators. The constellation is expected to be launched by 2026 [39] and to be fully operational in the early 2030s [35]. These satellites feature onboard processing for imagery and data [40], [41], [42].

¹ Information on the ISTARI AND MINERVA programmes in the public domain is limited. This section uses Janes, the Royal Aeronautical Society and the satellite manufacturers as sources and aims to provide as correct an overview as possible.

Within the MINERVA² programme:

- TYCHE – Concept demonstrator for Electro-Optical (EO) imaging satellites for earth observation [43] with a mass of 150 Kg. The satellite was successfully launched on the 16th of August 2024, becoming the first fully MOD owned satellite in orbit [44].
- JUNO - Concept demonstrator for Electro-Optical (EO) imaging satellites for space domain awareness. The satellite would be able to provide intelligence on other Resident Space Objects (RSOs) [40].
- TITANIA – Concept demonstrator for optical communications technique referred to as direct-to-earth free-space optical communications (FSOC) [42], [45]. The spacecraft may have speeds as high as 10 Gb per second [42].
- PROMETHEUS-2 – The PROMETHEUS-2 mission consisted of 2 cubesats with a mass of just 8.5 Kg each. The first (CubeSAT1) carried a hyperspectral imager and GPS receiver. The second (CubeSat2) carried two optical imaging cameras and a GPS receiver [41], [46]. These satellites were to demonstrate and test earth imaging and signals intelligence (SIGINT). The two satellites were unfortunately lost when the Virgin Orbit second stage failed [41]. It is unclear what the future is following the launch failure [46].
- OBERON – Concept demonstration of at least three SAR satellites orbiting together [35], [37], [47], [48]. The satellites will be small (by SAR standards) with a mass of around 430 Kg. These satellites will provide high resolution SAR imagery [47], [49]. The concept will utilise a constellation of multistatic SAR satellites.

The Defence Science and Technology Laboratory (DSTL) is the sponsor of this PhD, which aims to aid in the de-risking phase of the project and investigating concepts.

A cluster called Azalea is scheduled for launch in 2025 from BAE systems [34], [35], and will form part of the ISTARI satellite system. This constellation utilises a single SAR

² The UK has a tradition of space projects and satellites after Shakespearian characters [45].

satellite (from ICEYE) along with three other satellites. This provides SIGINT (signals intelligence) information from RF (Radio Frequency) signals, as well as optical imagery. These satellites are unusual as they will process the data onboard before transmitting to the ground.

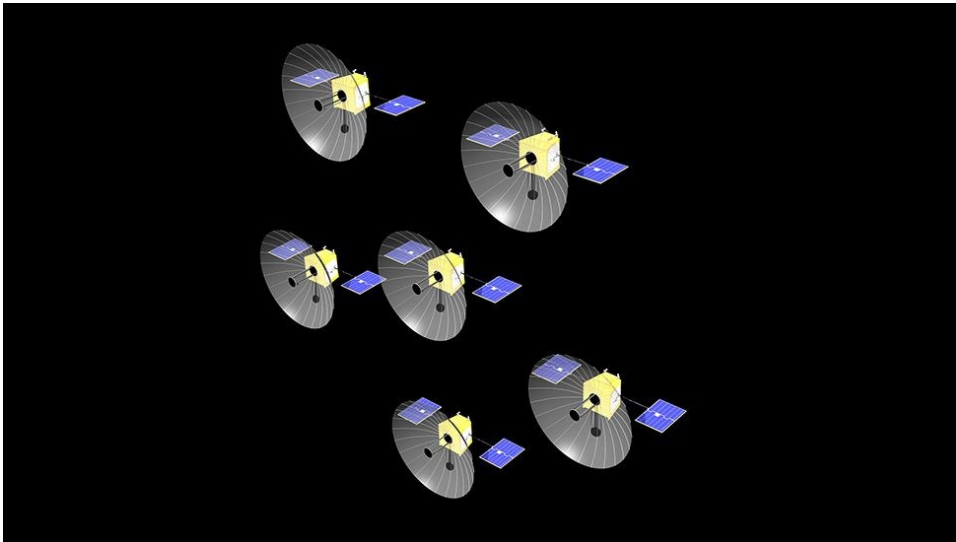


Figure 1.2 Concept art of the OBERON satellite constellation, released by Airbus (©Airbus)³.

Below are two figures⁴. These were created to visualise the MINERVA and ISTARI satellite systems. Figure 1.3 depicts the MINERVA satellites, and Figure 1.4 depicts the MINERVA satellites within the wider ISTARI system. These figures were created to help illustrate the paragraphs above. The style of these figures is partly inspired by a figure in the conclusion section of a post on the Royal Aeronautical Society website [50] which depicts the ISTARI system.

³ Project OBERON concept art. Released by Airbus:
<https://www.airbus.com/en/newsroom/press-releases/2019-09-airbus-to-develop-technology-for-ultra-high-resolution-satellites>
Permission granted for use after an email to Airbus Defence and Space media relations.

⁴ Sources for components in figures. Earth and space background [237]. Commercial Earth Observation (ICEYE satellite [238]), TYCHE [239], OBERON [47], TITANIA [240], PROMETHEUS-2 [241], SKYNET [242], JUNO (TYCHE used for visualisation [239]). Azalea cluster ([238], [243]). UK Space command logo [244].

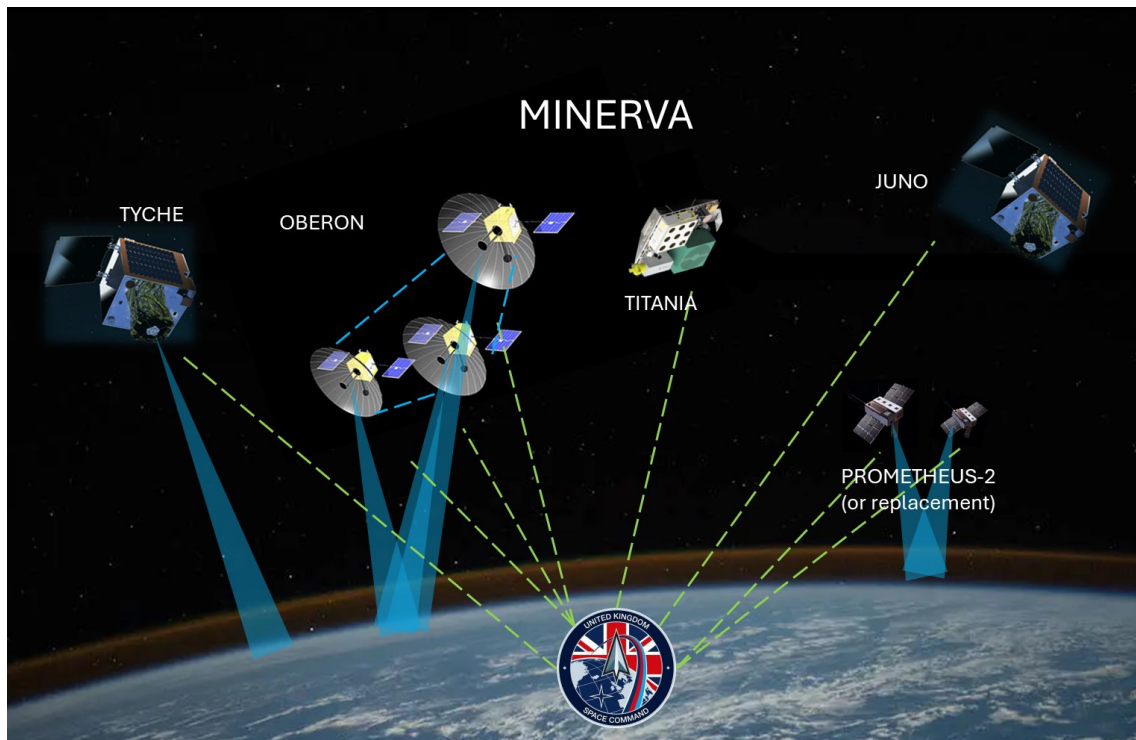


Figure 1.3 Image depicting the satellites in the MINERVA programme.

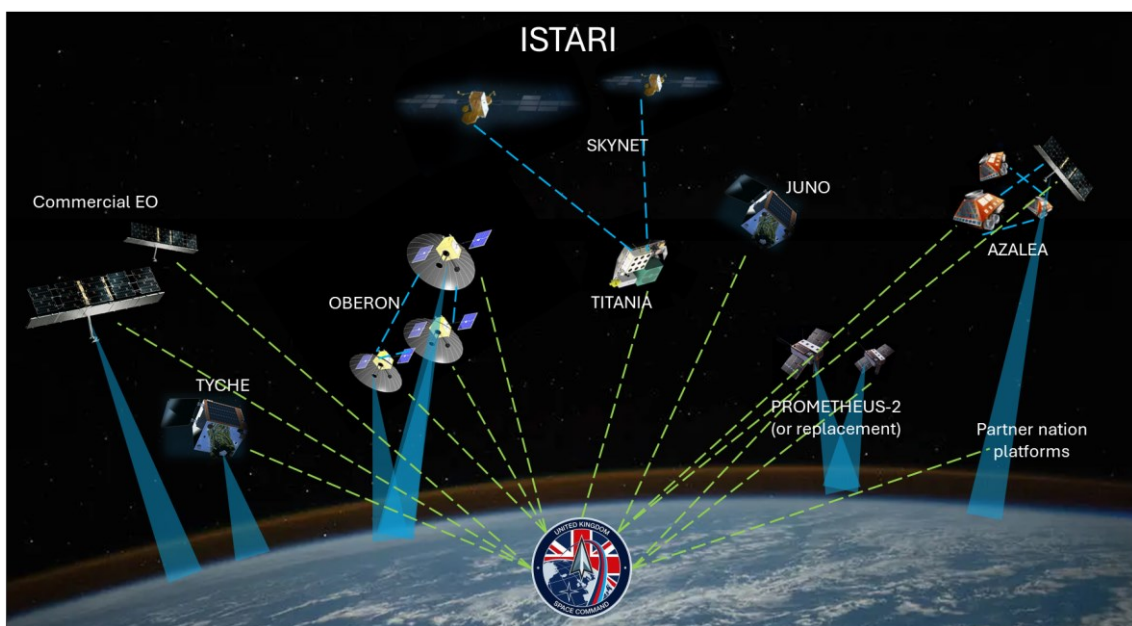


Figure 1.4 Image depicting the satellites in the ISTARI system.

1.1.3 Uncrewed Aerial Systems (UAS)

Uncrewed Aerial Systems, often called drones have a surprisingly long history. The first pilotless aircraft date as far back as the first world war[51]. These early uncrewed aircraft were used as aerial targets and developed by the British and Americans. Britain tested a small radio-controlled target in March 1917 [51]. An image of this drone can be found on the Imperial War Museum's website [52].

Pilotless aircraft continued to be developed, getting smaller and more capable. These aircraft began performing other roles such as reconnaissance imaging [51]. The use of drones for ISR on the modern battlefield is now well established [53], [54], [55], albeit mostly Electro Optical (EO) or thermal systems.

UAS equipped with radar has attracted more interest in recent years [56], [57]. Such systems offer some advantages over airborne and spaceborne systems in terms of cost and availability at a tactical level. Concepts such as the Phalanx platoon are investigating integrating drones on a section level [58]. As they are uncrewed, they are more expendable than a crewed aircraft [57], and are able to be rapidly deployed. However, they suffer from less payload capacity and stability. Such systems could be used to aid with mine clearing using ground penetrating radar [56], [59] allowing for large areas to be rapidly surveyed. [57], [60] UAS could be paired with illuminators on more larger platforms [56], [61]. Swarms of UAS are another application for multistatic (near field) SAR [56], [62], [63], [64]. UAS borne SAR would operate in the near field, and would likely find it difficult to conduct an exact repeated pass (due to factors such as turbulence and imprecise inertial navigation systems). These problems make UAS borne SAR another possible application are for the findings of this thesis.

1.2 Aims and Objectives

In chapter 1.1 (context and motivation) some key trends and problems were identified. As DSTL was the sponsor of this PhD a focus on space (and the OBERON constellation) has been chosen, however the results are applicable to SAR in general.

For a space based systems, one of the key limiting factors is the repeat pass time, which can be around 10 days and presents a challenge for enabling a responsive ISR system. Thus, this thesis investigates the impact of non-repeated trajectories on change detection images, and how a multistatic system may leverage the multidimensional nature of the data-collection to compensate.

Aim

To improve the understanding of bistatic and multistatic SAR change detection. In particular the effects on interferometric change detection and coherence, as a consequence of the bistatic/multistatic geometries and how the multidimensional nature of multistatic/polarimetric SAR images may compensate for decorrelations due to a baseline between the collections. The factors limiting the ability to perform change detection on speckle or near-speckle will also be investigated.

Objectives

Investigate bistatic CCD coherence

- Investigate the factors which impact CCD coherence using bistatic SAR images with a high frequency domain overlap.
 - These trajectories should allow for a variety of bistatic angles between the two SAR images used to form the CCD.
- The scattering decorrelation term (γ_{Scat}) should be investigated.
 - The behaviour of this term (particularly in relation to the bistatic angle and surface roughness) should be investigated and characterised.
 - The significance of this term and its impact on the interpretability of CCD images should be quantified.

Investigate multidimensional change detection algorithms

- Algorithms for multistatic change detection should be investigated.
- A multistatic change detection image can be formed in a variety of ways (coherent and incoherent), and it should be investigated which methods provide the best results.
- Master images and performance metrics should be used to provide quantitative metrics as to which method performed the best.

1.3 Novelty

Change detection phenomenology for bi- and multistatic geometries is an area of SAR that has received little attention in recent years, in particular investigation into the coherence of images.

The novelty of this thesis is derived from a few areas:

- **Bistatic and multistatic CCD**

This thesis investigates bistatic and multistatic CCD. This is an under researched area of SAR, particularly for bistatic coherence and multistatic CCD.

Two-stage change detection algorithms have previously been applied to a pair of monostatic images. These algorithms have been expanded to allow the processing of multistatic and multidimensional SAR data.

Additionally, the geometries chosen are novel. These trajectories contain a high baseline although maintain a high spatial frequency domain overlap. This is different from the majority of SAR collections which use very small baselines.

- **Measured laboratory data**

This thesis used new data measured in the Ground Based Synthetic Aperture Radar (GBSAR) laboratory. These measurements were conducted by the candidate/author.

- **Near field, curved wavefront**

The GBSAR laboratory operates in the near field. As such the wavefronts are curved. The majority of work published in the field of change detection is focussed on the far field scenario.

- **Ultrawideband**

The SAR images are classified as Ultra-Wideband (UWB) [65] Jo, the majority of published work utilises a much lower bandwidth. This high bandwidth was chosen to maximise the number of resolution cells within the region of interest.

- **Scattering term (γ_{Scat})**

The scattering component (γ_{Scat}) was added to the equations of coherence and quantified as an additional source of decorrelation. It had not previously been included, but as the results show it has a major impact on coherence for geometries with a significant baseline. Prior work mostly discussed the impacts of a baseline separation in terms of spatial frequency domain overlap.

Observations have been made as to how this term behaves with respect to bistatic angle and surfaces of different roughness.

1.4 A note on the structure of this thesis

This thesis is structured as the thesis by publication. An introduction and background section are provided in chapters 1 and 2 respectively. Chapter 3 covers the general methodology.

The publications produced during this PhD are listed in section 1.5. The contents of the three journal papers are contained in chapters 4 and 5. Chapter 4 covers Interferometric coherence for bistatic geometries in chapter 5 covers multistatic CCD processing.

As is the style of a thesis by publication an introduction and conclusion is provided for each of these chapters to tie them into the whole thesis. These papers have been modified to aid in their clarity and readability within a thesis. Where appropriate formulas and graphs have been reproduced to ensure consistent nomenclature throughout the thesis. To avoid repetition, elements of the background sections in these papers have been moved to the background and literature review (chapter 2).

Chapter 6 contains a discussion and conclusion section for the whole thesis.

Finally, appendices are provided. The letter of ethical approval provided under CURES (Cranfield University Research Ethics System) is included in Appendix A. The unedited Journal papers are found in Appendix B. Conference papers are contained in Appendix C.

1.5 Published works

The full papers can be found in the appendices.

Appendix B - Journal articles

Hagelberg, A., Andre, D. and Finnis, M.: '*Laboratory bistatic synthetic aperture radar coherent change detection investigation*'. In 'Electronics Letters' (IET), 59: e12913. <https://doi.org/10.1049/ell2.12913>, (2023).

Hagelberg, A., Andre, D., & Finnis, M.: '*Combined Intensity and Coherent Change Detection with four classes for Multistatic Polarimetric Synthetic Aperture Radar*'. In 'IET Radar Sonar & Navigation'. Special Issue: Synthetic Aperture in Sonar and Radar. 1–14. <https://doi.org/10.1049/rsn2.12588>, (2024).

A. Hagelberg, D. Andre, and M. Finnis, '*Bistatic Multi-polarimetric Synthetic Aperture Radar coherence investigation using Spatially Variant Incoherence Trimming*', In 'IET Radar, Sonar and Navigation', <https://doi.org/10.1049/rsn2.12659>, (2024).

Appendix C - Conference proceedings

Hagelberg, A., Andre, D., Finnis, M.: '*Polarimetric bistatic SAR image coherence*', in '14th European Conference on Synthetic Aperture Radar' (VDE) pp. 80–85. (2022)

Hagelberg, A., Andre, D., Finnis, M.: '*Non-overlapping trajectory Multistatic SAR Coherent Change Detection*', in 'IET International Conference on Radar Systems' (2022)

Hagelberg, A., Andre, D., & Finnis, M.: '*Laboratory multistatic and multipolar SAR CCD investigation*', in '5th International Conference on Synthetic Aperture in Sonar and Radar' (2023).

Hagelberg, A., Andre, D., & Finnis, M.: '*Polarimetrically augmented Coherent Change Detection three stage detector for laboratory multistatic Synthetic Aperture Radar*', in '2023 Defence and Security Doctoral Symposium (DSDS23)' (2024).

2 Background and literature review

2.1 Synthetic Aperture Radar

2.1.1 A brief history

Synthetic Aperture Radar (SAR) is a form of remote sensing, first being demonstrated in the 1950s. Any discussion of the early days of SAR would be remiss to leave out Carl Wiley, considered the inventor of SAR [66]. In 1954 he submitted a patent request to the United States patent office titled '*Pulsed doppler radar methods and apparatus*' [67], receiving acceptance in 1965. In 1955 the first SAR images (referred to as Simultaneous Build-up Doppler) were taken using a Goodyear system called DOUSER [66] deployed on a C-47 aircraft.

At first photographic film was used to record the radar data then a series of optical elements to enact the Fourier transforms. Some of these analogue systems were in use as late as the 1990s [66], [68]. Digital processing was however demonstrated early on in the 1960s on aircraft such as B-58, SR-71 and RF-4C [66]. This was possible at the time despite the limited processing power because there exist fast SAR processing algorithms [69], [70]. Since then airborne SAR systems have continued to advance and improve, offering better resolution, accuracy and speed.

By the 1960s spaceborne SAR systems had also begun to be launched. Some of the earliest systems were designed for the military such as Project Quill [68], [71] in the early 1960s. In these early systems and experiments the utility of all weather and change detection imagery were noted [68]. These early SAR systems such as SEASAT [71], [72], or the Space Shuttle SAR system [71], [73] were quite large in size. This contrasts with some of the modern SAR satellites such as those operated by ICEYE [27], [28] or COSMO-SkyMed [74] which are more numerous and substantially smaller.

As stated in the introduction (chapter 1) this thesis is applied to multistatic constellation consisting of more than two satellites, such as the Chinese Hongtu-1 [75] which is currently operational. Additionally several other SAR satellite constellations of interest. These take several forms. Existing systems, whether bistatic or multistatic, typically utilise very low baselines.

Monostatic – SAR only

The largest constellation of monostatic SAR satellites is the ICEYE constellation [27], [28], [76], [77]. The ICEYE constellation currently consists of over 30 satellites, although additional launches are planned to expand the constellation [76]. Another example is the COSMO-SkyMed constellation [74].

Monostatic – multispectral

Military organisations have paired monostatic SAR satellite(s) with Electro Optical (EO), multispectral/hyperspectral or SIGINT reconnaissance satellites in constellations. An example is the KOMPSAT (Korea Multi Purpose SATellite) constellation. These are operated by the Korea Aerospace Research Institute (KARI) [78]. Another example is the Azalea™ satellite cluster as a part of the ISTARI constellation which also includes the OBERON multistatic SAR satellites. These satellites are scheduled for launch in 2024 from BAE systems [34], [35].

Bistatic and multistatic

A bistatic SAR system is also operational. TerraSAR-X and TanDEM-X are twin satellites operated by the Deutsches Zentrum für Luft- und Raumfahrt (DLR) [79], [80], and allow for bistatic images to be collected. TerraSAR-X and TanDEM-X can operate in an alternating transmit-receive mode. This is referred to as a bistatic mode in [81]. This mode however can be considered to be a form of multistatic SAR imaging [25], [82], [83], [84] as a single transmitted signal is received by two receivers. This mode has been demonstrated to produce Digital Elevation Models (DEMs) [85], [86], [87].

2.1.2 Uses and features

SAR is primarily used in remote sensing, in both on airborne and spaceborne platforms [88], [89]. And even sees use in ground-based applications such as observing hillsides to identify subsidence and landslides, or to observe moving objects such as ships. In the last case the radar does not need to be moving and instead the movement of the ship provides the diversity in viewing angles. This is called Inverse SAR (ISAR) [90].

Targets can be detected when they contrast a surrounding homogenous environment. Such targets may include increased foliage density, different crop types, or the presence of vehicles and buildings [91], [92].

One of the major differences between SAR imagery and electro-optical imagery is that SAR imagery also records the phase information. This provides information on the dielectric properties and aids in classification of the ground, this is used to support the agriculture industry. Classification is also done on objects on the ground such as aircraft or vehicles. A lot of research is occurring in this area to use neural networks and machine learning for Automatic Target Recognition (ATR) [93]. The phase allows for interferometry (InSAR) [94] and thus the formation of a digital elevation map (DEM) to a high resolution [95], [96]. The Earth was imaged in this way by the space shuttle *Endeavor* in February 2000 (STS-99). This was known as the Shuttle Radar Topography Mission (SRTM) [73]. Other missions have mapped other planets and the moon using unmanned spacecraft. On a small-scale interferometry can be used to compare two coherent images using a process called Coherent Change Detection (CCD). This method allows us to identify small changes in a scene, these could be vehicle tracks or objects added/removed [95]. For a system with sufficient resolution, very small disturbances such as the tracks made by sheep (and the sheep themselves) can be seen. This was demonstrated by DSTL in an experiment using the Bright Spark SAR system operated by Thales [97]. SAR can also be used to identify buildings damaged in natural disasters such as earthquakes [98].

One distinct advantage over electro-optical systems is its “all weather” capability. This refers to SAR’s ability to take images even with cloud cover, however significant rain fall will impact the images taken.

SAR is not without its downsides however, one major disadvantage being its very high processing requirements for high quality images and another is the difficulty in interoperating SAR imagery. Other disadvantages relate to the transmitter power, and a low resolution compared to EO. Some SAR imaging systems result in a lower resolution than optical, this is particularly the case for shorter range systems, however this can be somewhat made up for by the additional information and processing possibilities SAR

provides. It should not be thought of as a replacement for electro-optical systems but rather as in a category all of its own.

2.1.3 Synthetic Aperture Sonar (SAS)

Synthetic Aperture Sonar (SAS) is an imaging technique that shares many similarities to SAR. Both imaging methods utilise a side mounted transmitter and receiver [99], [100]. Like SAR, SAS allows for interferometry for change detection and elevation mapping (bathymetric mapping) [100], [101], [102]. SAS is always considered to be in the near field and curved wavefront processing must be used [103].

The similarities between SAS and SAR have led to a cross-pollination of ideas, seen through conferences such as *Synthetic Aperture in Sonar and Radar* which is organised by the Institute of Acoustics (IOA). Whilst SAS is not discussed further in this thesis, it may still be of interest to readers. Some problems in the radar community may have solutions in the sonar community and vice-versa.

2.2 Collection geometries

SAR systems have a variety of geometries. At the most basic level they can be described by the number and relative position of transmitters and receivers [25], [94], [104], [105].

Monostatic

These systems use a single transmitter and receiver positioned together at the same location in space (co-located) [94]. A transceiver may be used; however, it is also common to use two different antennae positioned next to each other. For remote sensing (far field) this has very little impact, but for near field imagery the distance is sufficiently significant as to need to be accounted for. In this case the term pseudo-monostatic or near monostatic is more appropriate. Pseudo-monostatic data sets should be processed using bistatic algorithms that account for the difference in antenna position. Monostatic is the most common system and is widely used in both airborne and spaceborne systems.

Bistatic

In this case there is a single transmitter and receiver as with the monostatic, but they are now located in two different locations, and can be moving with different trajectories. In fact, only one needs to move to allow for SAR imaging. Bistatic imaging has some advantages over monostatic imaging as it is possible to view the target over a greater range of angles, which is particularly advantageous in detecting stealth aircraft [106] which are generally optimised for a narrow range of viewing angles. However, the implementation is more complex. A bistatic trajectory can result in lower resolution.

Multistatic

Multistatic geometries are similar to Bistatic geometries, but the number of transmitters and receivers combined is greater than two [25], [84].

Hitchhiker/passive

This is a specific case of the Multistatic system. Where several *transmitters of opportunity* are used. These typically take the form of radio, mobile phone, TV transmitters or Global Navigation Satellite Systems (GNSS) satellites and one or more receivers [105], [107]. The signal used to form the images is not always known beforehand and can be constantly

changing. These systems are complex to implement but offer advantages in regard to stealth. As the receiver is not transmitting it is harder to detect, particularly with anti-radiation weapon systems which are commonly used to counter radar systems.

2.2.1 SAR modes

SAR images can be collected in several different ways [108], [109]. These are shown visually in Figure 2.1.

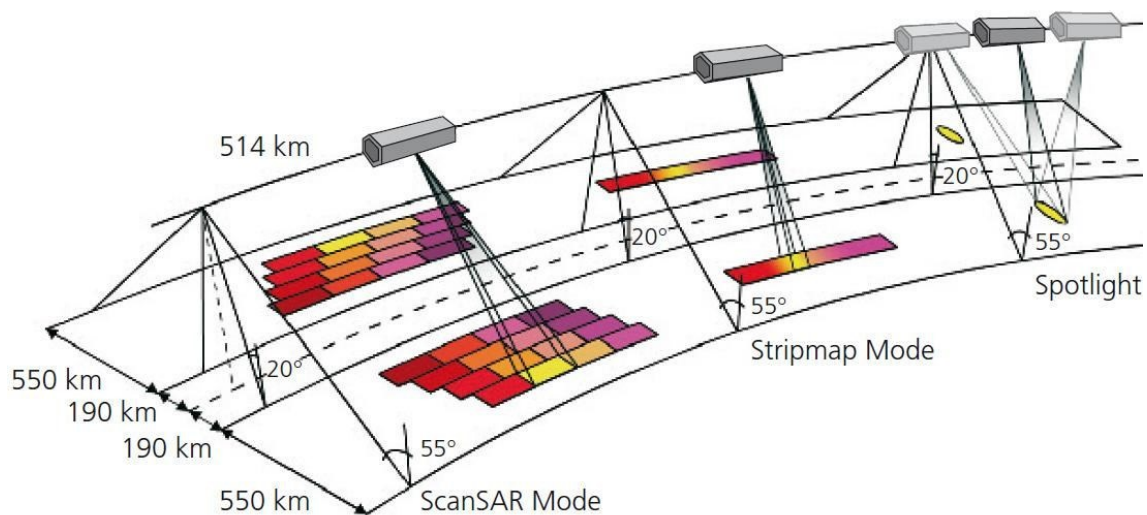


Figure 2.1 Image of the SAR imaging modes of the DLR TerraSAR-X. The image shows three SAR modes: Spotlight, Stripmap and ScanSAR. Source: DLR [108].

Spotlight

In spotlight mode SAR the radar is angled towards a point on the ground ahead or behind the path of the satellite (squinted). This provides illumination over a small area for an extended time period. A spotlight mode SAR will provide high resolution images although for a small area.

Stripmap

The radar platform moves in a straight line with a fixed side looking radar. The angle the radar makes with the line perpendicular to the flightpath is called the squint angle. If this angle is zero, then the SAR mode is called stripmap. This generates a lower resolution image compared to the spotlight mode, however the area is increased.

ScanSAR

In scanSAR the transmitter beam is squinted to cover additional area of the ground in a zig-zag pattern. This reduces dwell time and results in low resolution but large area coverage.

2.2.2 Bistatic and Multistatic SAR

2.2.2.1 Overview

Bistatic and Multistatic SAR systems, and radar systems in general, are significantly more complex and harder to implement than a monostatic system. There are however significant advantages that make this added complexity worthwhile in some cases.

Detection of low observable targets

First is the detection of stealthy targets such as modern aircraft or ships. Many low observable or stealthy radar target reflect the radar energy away from the transmitter direction. Thus reducing the amount of energy reaching a receiver which is co-located with the transmitter. Bistatic or multistatic systems however have the transmitter(s) and receiver(s) at different locations, which reduces the efficacy of the stealth [104], [110]. Additionally, bistatic radar images will have two shadows, these may aid in the identification of targets, as some classification methods use the shadow of an object [111], [112]. Multistatic SAR images would have more shadows. This increased spatial diversity of a multistatic image enhances the information space, this includes multiple shadows, but also more echoes. These echoes can come from imaging the target at an angle where it is 'less stealthy' or from capturing scattered energy. Stealthy targets aim to reflect

energy away from the boresight direction, so a multistatic system may pick up a stronger return.

Resilience

Bistatic and multistatic systems are more resilient than a monostatic system. A radar platform which actively emits can be targeted by Anti-Radiation Missiles (ARMs) [113]. Such platforms are also more easily targeted by Electromagnetic Warfare (EW) [110]. A bistatic or multistatic system which was distributed would be harder to target and require systems such as Surface to Air Missiles (SAMs), Anti-Satellite (ASAT) weapons or higher power EW. This is also true for passive radar. Passive, transmitter of opportunity or hitchhiker radar is a special case of bistatic or multistatic systems. Here there is no controlled transmitter but instead the receivers use the signals from transmitters such as TV/radio masts or other radar transmitters.

A large number of platforms, such as a drone swarm or large satellite constellation would be more resilient to the loss of individual platforms [114].

Single pass Interferometry

Bistatic SAR satellites pairs such as TanDEM-X [80] have demonstrated bistatic SAR in space, which allows for a larger baseline and improved resolution compared to splitting one antenna into sub-apertures. A bistatic SAR system can perform single pass interferometry such as the TanDem-X [80] or the Shuttle Radar Topography Mission (SRTM) [73]. SAR satellite constellations are also used. Some proposals use a set of different existing satellites [115]. Other commercial companies such as ICEYE aim to have a constellation of over 30 monostatic SAR micro satellites (under 100Kg) [28]. This is however quite different to the OBERON concept which aims at a constellation of multistatic SAR satellites. Multistatic constellations may use a set of identical transceiver satellites operating coherently, or a transmitter (master) satellite and several receiver (slave) satellites [116]. It has also been shown that multistatic SAR constellations may provide improved cross-range resolution with respect to a single bistatic trajectory [4], [5], and Signal to Noise Ratio (SNR) [6].

Multistatic or multiple passes can also be used to improve identification and interpretation of the scene and targets [117]. A multistatic system may also reduce the power requirements for remote sensing [118].

A multistatic system could contain antenna centres with some variation in the vertical direction, this would provide information on the vertical scene structure [63], [96].

2.2.2.2 Geometry

In a Bistatic radar system, the transmitter and receiver are in two different locations leading to a significant angle between the antennas and the target. This angle is called the bistatic angle, β . A bistatic or multistatic system may consist of multiple satellites of a similar design such as the TanDEM-X [80], or two antennas separated by a baseline on a spacecraft (SRTM)[73]. Other systems might utilise an illuminator and receiver consisting of two rather different systems. This may be a static transmitter of opportunity (such as a transmitter of opportunity) and then a moving receiver on an aircraft [119]. Other suggestions have included space-based illuminators and ground based or airborne receivers [25], [61], [107]. Fully space-based constellations are also under consideration [25], [84]. The OBERON satellite constellation is one such system.

In the case of the laboratory environment used for this thesis (see section 3.1) the monostatic antenna configuration results in a small offset of 255 mm. These images are still referred to as monostatic, although it is more accurate to describe them as near- or pseudo-monostatic. For improved image formation accuracy these images are produced using code developed for bistatic imaging.

Figure 2.2 shows an archetypical bistatic geometry with a single transmitter and receiver. Here the transmitter (Tx) and receiver (Rx) are separated by a baseline. The angle made between them is called the bistatic angle. The distance between the transmit antenna and the target is R_{tx} and the distance between the receiver and the target is R_{rx} . The bistatic angle is represented by β and the baseline by L_{base} .

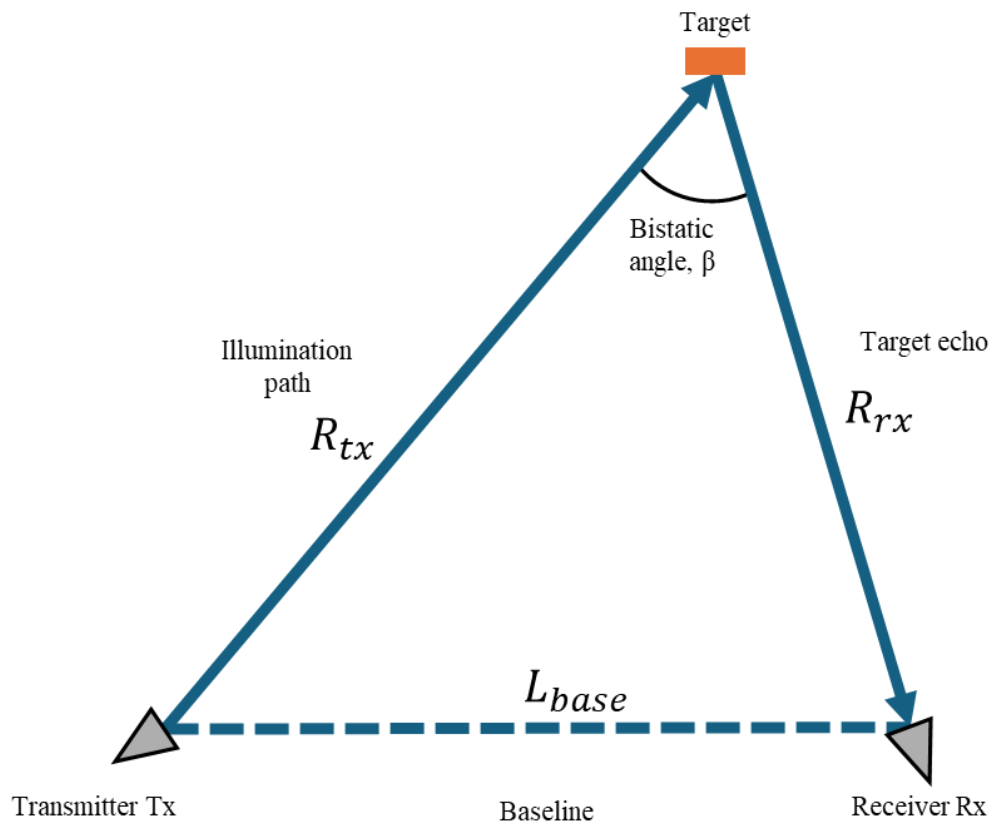


Figure 2.2 Diagram showing a typical bistatic geometry.

2.2.2.3 Bistatic Equivalent Monostatic (BEM)

The Bistatic Equivalent Monostatic (BEM) is a useful way of visualising SAR geometries. The BEM, sometimes called the *true BEM*, results in different co-ordinates to the transceiver midpoints. Thus using a BEM a much more accurate estimate of the bistatic resolution and incidence angle is possible. Using the incorrect geometry can lead to image distortions or incorrect resolution estimates [120], [121]. This is shown below in Figure 2.3.

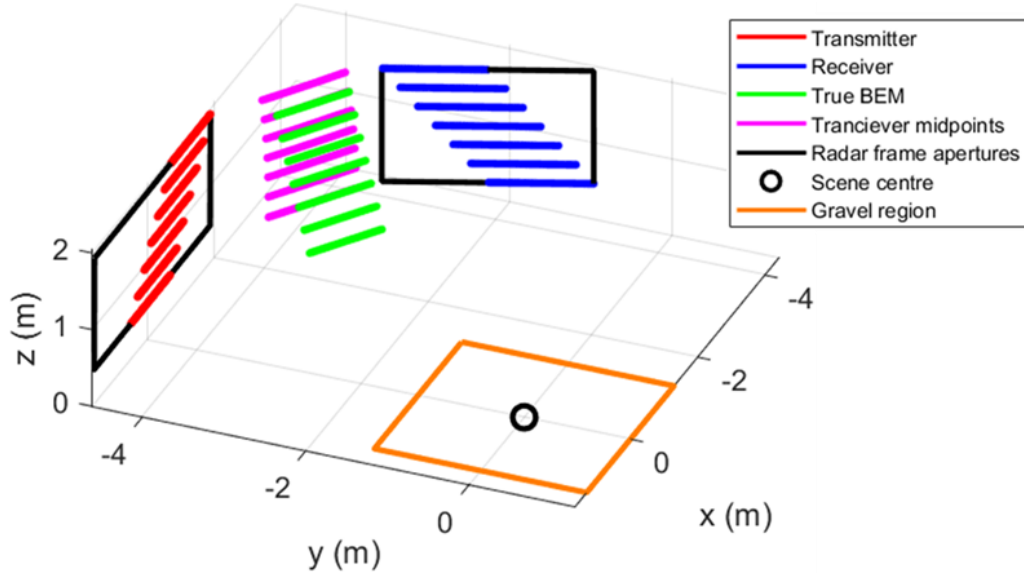


Figure 2.3 Diagram of radar trajectories showing the difference between the true BEM and transceiver midpoints.

Let us define two co-ordinates for the transmitter and receiver.

$$Tx_{pos} = \begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix}; \quad Rx_{pos} = \begin{bmatrix} x_r \\ y_r \\ z_r \end{bmatrix} \quad (2.1)$$

For the transceiver midpoints the co-ordinates would be as follows:

$$TR_{mid} = \begin{bmatrix} (x_t + x_r)/2 \\ (y_t + y_r)/2 \\ (z_t + z_r)/2 \end{bmatrix} \quad (2.2)$$

In order to calculate the true BEM, scene centre is defined as:

$$SC = \begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} \quad (2.3)$$

Then let us define several unit vectors. $\hat{\mathbf{i}}$ is the unit vector describing the direction of a wave moving from the transmitter to the scatterer. $\hat{\mathbf{s}}$ is the unit vector for the scattered wave towards the receiver. $\hat{\mathbf{b}}$ is the unit vector for direction of the true BEM from the scene centre [120].

$$\hat{\mathbf{t}} = \frac{(SC - Tx_{pos})}{\sqrt{\sum (SC - Tx_{pos})^2}} \quad (2.4)$$

$$\hat{\mathbf{s}} = \frac{-(SC - Rx_{pos})}{\sqrt{\sum (SC - Rx_{pos})^2}} \quad (2.5)$$

$$\hat{\mathbf{b}} = \frac{\hat{\mathbf{t}} - \hat{\mathbf{s}}}{\sqrt{\sum (\hat{\mathbf{t}} - \hat{\mathbf{s}})^2}} \quad (2.6)$$

Thus, the co-ordinate of the true BEM can be calculated:

$$TR_{BEM} = (SC - \hat{\mathbf{b}}) \cdot \left(\frac{\sqrt{\sum (SC - Tx_{pos})^2} + \sqrt{\sum (SC - Rx_{pos})^2}}{2} \right) \quad (2.7)$$

2.3 SAR image formation

SAR algorithms can be seen as having an inverse relationship between the number of assumptions and the computational load [122], [123].

For example, the *Back Projection Algorithm* (BPA) [122], [124], [125] is perhaps one of the simplest to understand and produce a script for [124]. It is however very computationally intensive. Alternatively other algorithms such as a *Matched Filter Algorithm* (MFA), such as the *Polar Format Algorithm* (PFA) are less computationally intensive. However, such algorithms require assumption and hypothesis about the target object/scene [69], [123], [124]. As long as these assumptions are the final image will be of the same quality.

Rapid algorithms which produce poorer quality results can have a useful role, whilst they may not produce the images needed for ISR, they are suitable for the terminal guidance of some weapon systems [70].

2.3.1 Back Projection Algorithm

The algorithm used by this thesis is the Back Projection Algorithm (BPA), sometimes referred to as the *Convolutional Back Projection* (CBP) algorithm [123], [124]. There are many versions, however this thesis used a modification of one shown in the paper [124] as a base for some of the SAR images. However, modifications were made to allow for bistatic and multistatic data sets, as well as pre- and post-processing steps.

For the benefit of the reader the derivation for the BPA in MATLAB shown in the Gorham et al. 2010 paper [124] is summarised here, however for the full background it is recommended to read the aforementioned paper, [124] which provides an excellent overview of both the BPA and PFA algorithms and how they may be applied in MATLAB.

SAR image processing relies on an accurate dataset and radar trajectory combination. It is important that these line up as accurately as possible with what occurred during the data collection in order to produce a sharp and clear image. [122], [123], [124]

2.3.1.1 Derivation

As the Gorham et al. 2010 paper [124] assumes a monostatic configuration, thus the co-ordinates of the transmitter and receiver are assumed to be the same. The transmitter and receiver are assumed to be co-located. This assumption will not hold for monostatic data collected for this thesis, as the space between the two antennae (255mm) is significant in the near field regime. As such the code used for the image formation in this thesis was generalised to the bistatic case. This resulted in ellipses of equal range rather than circles. The derivation provided below assumes the monostatic case.

The antenna *phase centre* (P_{ant}) will be assigned the following co-ordinates:

$$P_{ant}(\tau) = [X_{ant}(\tau), Y_{ant}(\tau), Z_{ant}(\tau)] \quad (2.8)$$

Here τ refers to the *slow-time* or synthetic aperture time domain. The radar is moving, thus its co-ordinates are a function of time. The *fast-time* refers to the frequency domain. These terms may be potentially confusing but are standard within SAR.

The antenna co-ordinates are defined with respect to a constant origin. This origin's location varies as to the preferences of the individual programmer. In some cases, it may be the starting point of the radar, in others the centre of the imaged area (particularly for spotlight mode). Wherever it is it is important that it is constant.

The distance between the antenna phase centre and scene centre (SC) can be defined. The scene centre is defined as the origin, $[0, 0, 0]$. Thus:

$$\Delta r_{SC}(\tau) = \sqrt{(X_{ant}(\tau))^2 + (Y_{ant}(\tau))^2 + (Z_{ant}(\tau))^2} \quad (2.9)$$

Again, note the dependence on τ as the radar is moving so this distance varies for each pulse.

Then consider a target within this scene, it can be assigned the co-ordinates with respect to the same origin:

$$P_{trg} = [X_{trg}, Y_{trg}, Z_{trg}] \quad (2.10)$$

The distance between the antenna and the target (Δr), is defined as the following [124]:

$$\Delta r(\tau) = \sqrt{(X_{ant}(\tau) - X_{trg})^2 + (Y_{ant}(\tau) - Y_{trg})^2 + (Z_{ant}(\tau) - Z_{trg})^2} \quad (2.11)$$

For a generalisation to bistatic, ranges from the target to both the transmitter and receiver would need to be calculated.

The majority of SAR algorithms use the differential range (ΔR) in their processing. It is the range from the origin to the target. Δr_{SC} is the distance between the antenna and the scene centre [124].

$$\Delta R(\tau) = \Delta r(\tau) - \Delta r_{SC}(\tau) \quad (2.12)$$

The range between the antenna and origin is already known, as it is simply the recorded flightpath. The range between the antenna and target however needs to be found. This is done with the use of radar pulses. A wide variety of waveforms are used in SAR, a common waveform, and indeed the one used in the GBSAR lab is the Linear Frequency Modulated (FM) Chirp waveform. A chirp waveform has a constant amplitude but varies in frequency. This contrasts to other waveforms such as the Continuous Wave (CW) which varies in amplitude (amplitude modulated). A chirp waveform has a set bandwidth, BW , which is split into K frequency samples. These frequencies can be denoted by the vector $\{f_k | k = 1, 2, 3, \dots, K\}$.

A SAR system transmits multiple pulses as it moves along its trajectory. The transmission time of each pulse is denoted by the vector $\{\tau_n | n = 1, 2, 3, \dots, N_p\}$. Each one of these times corresponds to a known location of the radar, this allows for motion compensation. The term means compensating for the antenna's motion; however, it is more accurate to think of it as compensating for its change in position. A small distinction but pointed out here as the radar system used in the GBSAR laboratory, and indeed many simulations where the start stop approximation is used, move in discrete steps, stop and then send out a pulse. In these systems the time is less relevant and instead move a set distance each time before transmitting. This tends to lead to very consistent spacing between pulses. So, the velocity that defines the motion is irrelevant for this particular case, but the change in position, and therefore viewing angle, is important.

The transmitted pulse then reflects off objects (scatterers) in the scene and return to the receiver. The complex output of the receiver after mixing is a delayed and scaled version of the original signal [124].

$$S(f_k, \tau_n) = A(f_k, \tau_n) \exp\left(\frac{-j4\pi f_k \cdot \Delta R(\tau_n)}{c}\right) \quad (2.13)$$

The term $A(f_k, \tau_n)$ is a scaling factor and is related to the Radar Cross Section (RCS) of the target, and as will be shown later this is related to the frequency of the incident waveform. The phase is dependent on ΔR , the differential range and the frequency. As the phase depends on the number of complete revolutions.

This information is presented as a complex number, containing the magnitude and phase. There is a value for each of the K frequency samples and N_p pulses. These matrices are therefore K by N_p in size, which very quickly leads to very large volumes of data.

The above equation can be rewritten to reflect the range of frequency samples [124].

$$s(m, \tau_n) = \sum_{k=1}^K S(f_k, \tau_n) \exp\left(\frac{-j4\pi f_k \cdot \Delta R(m, \tau_n)}{c}\right) \quad (2.14)$$

Here the target response at m , a discrete range bin is shown. Range bins arise from the resolution of the radar system being finite so for a bin, any returns from targets within that set of ranges cannot be resolved. The term (range) resolution cell may also be used. This response is for a phase history $S(f_k, \tau_n)$ from N_p transmitted over K frequencies. f_k can however be represented with respect to the starting frequency and size of the frequency steps, as $f_k = (k - 1)\Delta f + f_1$. Here Δf is the frequency step size, $\Delta f = BW/K$. f_1 represents the lowest frequency used in the chirp. By substituting this alternate form of f_k , and with some re-arranging a new equation can be obtained [124].

$$s(m, \tau_n) = \sum_{k=1}^K S(f_k, \tau_n) \cdot \exp[\Phi(\Delta R(m, \tau_n) \cdot (k - 1))] \cdot \exp\left[\frac{-j4\pi f_1 \cdot \Delta R(m, \tau_n)}{c}\right] \quad (2.15)$$

Where $\Phi(\Delta R(m, \tau_n)) = (+j4\pi\Delta f \cdot \Delta R(m, \tau_n))/c$, is the phase function.

This can then easily be rearranged into the form of an inverse Fourier transform, resulting in [124]:

$$s(m, \tau_n) = \sum_{k=1}^K S(f_k, \tau_n) \exp\left[\frac{+j2\pi(m-1)}{K} \cdot (k-1)\right] \cdot \exp\left[\frac{+j4\pi f_1 \cdot \Delta R(m, \tau_n)}{c}\right] \quad (2.16)$$

This results in the range profiles for the SAR data collection, these can now be used to plot the SAR image. The range profiles can also be expressed using the MATLAB command `ifft`, the inverse fast Fourier transform [124]. For the remainder of this derivation some MATLAB code is included in the formulae. This is done to demonstrate the practical implementation.

$$s(m, \tau_n) = K \cdot \text{ifft}(S(f_k, \tau_n)) \cdot \exp\left[\frac{+j4\pi f_1 \cdot \Delta R(m, \tau_n)}{c}\right] \quad (2.17)$$

Or alternatively, and more suited for MATLAB [124]:

$$s(m, \tau_n) = K \cdot \text{ifft}(S(f_k, \tau_n)) \cdot \exp\left[\frac{+j4\pi f_1 \cdot (m-1)}{K\Delta f}\right] \quad (2.18)$$

The factor K appears here because of the format of the Fourier transform in MATLAB. The manner in which MATLAB functions are coded must be considered. The function `ifft` calculates the values for m between 1 and K . To get the 1 at the centre the command `fftshift` is used. This means that m , the range index now has values $-\frac{K}{2} + 1 \leq m \leq \frac{K}{2}$. This is done to put the zero-frequency component in the centre, and correctly order the output of the Fourier transform [124].

$$s(m, \tau_n) = K \cdot \text{fftshift}\{\text{ifft}(S(f_k, \tau_n))\} \cdot \exp\left[\frac{+j4\pi f_1 \cdot (m-1)}{K\Delta f}\right] \quad (2.19)$$

The final aspect to consider is how the SAR image is formed from the above equation.

Recall the equation for the differential range $\Delta R(\tau)$ (2.12) which is the distance between the target/scatterer and the scene origin (0,0,0). For the processing this is done for each pixel resulting in a discrete set of ranges. This will not match the ranges for $\Delta R(m, \tau_n)$, so consequently the MATLAB linear interpolation command is used.

Zero-padding is another important step in SAR image processing. Zero-padding introduces additional zeros to the SAR data within the K-space (Fourier or spatial frequency domain, see section 2.5). Increasing the number of zeros does not change the content of the data, however when the data is transformed from the Fourier domain to the spatial domain the range profiles are more finely sampled. In MATLAB this involves making the length of the vector used in the Fourier transform (Nfft) significantly larger than the data, typically around 10 times. This results in the following equation [124]:

$$s(m, \tau_n) = Nfft \cdot \text{fftshift}\{\text{ifft}(S(f_k, \tau_n))\} \cdot \exp\left[\frac{+j4\pi f_1 \cdot (m - 1)}{Nfft\Delta f}\right] \quad (2.20)$$

The final image (I) is then the sum of all the pixel responses for every pulse. The response for each pulse, $s(m, \tau_n)$, is projected onto an imaging grid with co-ordinates (x,y). This results in a value for each pixel, labelled s_{pix} . Here s_{pix} contains the complex value for each pixel at range C and time index τ_n . The range C is a function of the x and y co-ordinates of the image [124].

The formula for the final image is shown in equation (2.21).

$$I = \sum_{n=1}^{N_p} s_{pix}(C(x, y), \tau_n) \quad (2.21)$$

A SAR image is shown below in Figure 2.4. This image shows a gravel scene with metal alignment spheres arranged around it. This image was formed from a total of 351 pulses. Figure 2.5 shows the increasing resolution and clarity of the SAR images as more of the aperture is processed. In the first image (a) the range profiles of a single pulse are projected onto the scene, resulting in circles of equal range. As additional pulses are included the azimuth (cross range resolution) increases and the shape of scatterers begins

to become clearer. Finally after all 351 pulses are processed the final SAR image clearly shows the gravel scene and metal spheres. These images are formed using the pseudo-monostatic setup within the GBSAR laboratory, as such circles of equal range are visible for the lower pulse numbers rather than ellipses as would be the case for bistatic geometries.

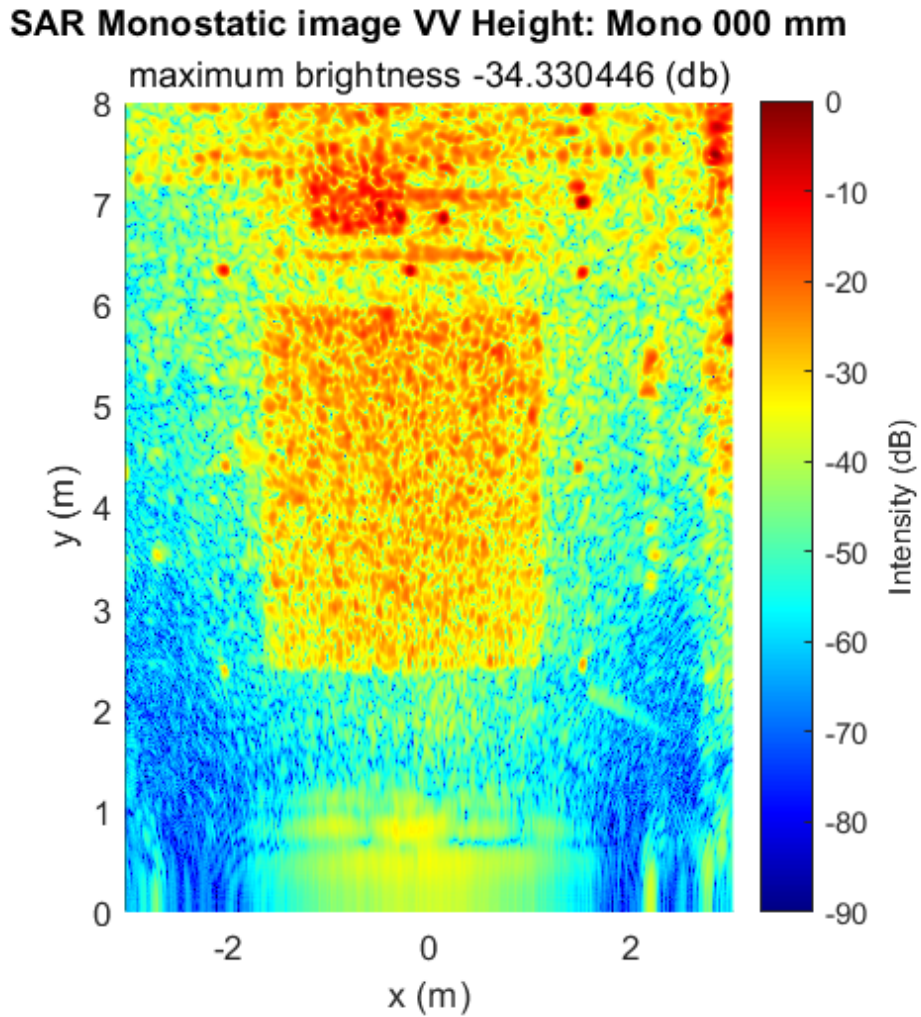


Figure 2.4 A normalised monostatic SAR image formed using the full aperture. It is an enlarged version of (f) in Figure 2.5.

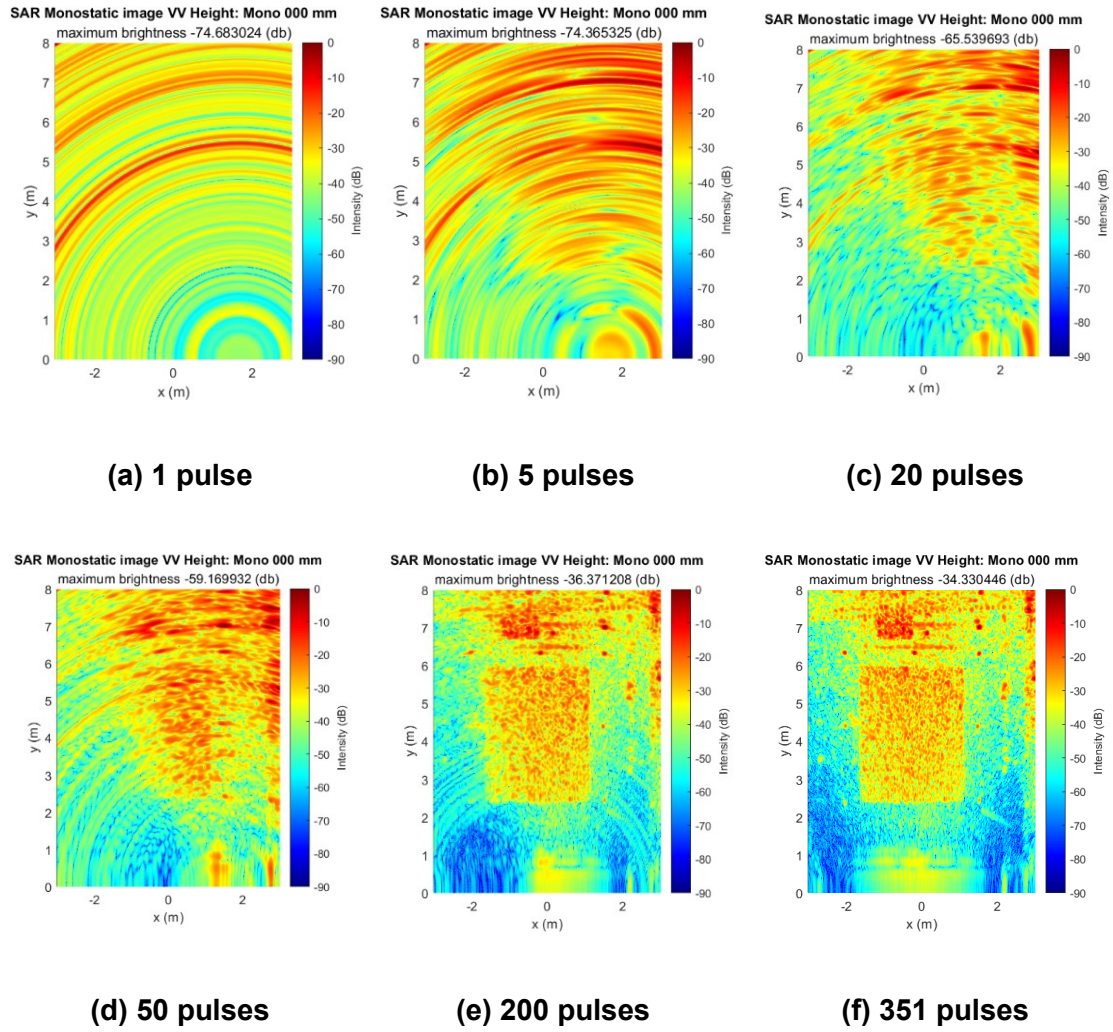


Figure 2.5 (a-f). A series of 6 SAR images formed using different pulse numbers. When only one pulse is used circles of equal range are visible as the collection was monostatic. As more pulses are added areas of constructive and destructive interference can be seen. Finally for the full SAR image the detail of the gravel area is clear.

2.4 SAR Near field

SAR images are typically classified by being in the near-field (curved wavefront) or far-field (plane wave) regimes. In this thesis the SAR near-field regime is defined as d_{fraun} , the Fraunhofer distance [126], [127], [128]:

$$d_{\text{fraun}} < \frac{2L_{\text{cr}}^2}{\lambda_c} \quad (2.22)$$

Here d_{fraun} is the distance from the radar antennas to the scene which is within the near field. The unambiguous cross-range is L_{cr} and a centre wavelength λ_c .

For the laboratory environment (see section 3.1, page 88), $d_{\text{fraun}} \approx 150$ m. The ranges in the laboratory are in the range of 4 – 10 m and are thus well within the near field (curved wavefront) regime.

2.4.1.1 Derivation

Consider the angular width of a scene (ϕ_w). Here L_{cr} represents the scene cross-range extent, which has been set to the unambiguous cross-range and d is the distance from the radar antennas to the scene.

$$\phi_w = \frac{L_{\text{cr}}}{d} \quad (2.23)$$

Now consider the Projected Fourier Supports (PFSs) corresponding to the extreme left and right sides of the scene. These will be explained in more detail in section 2.5, but for now they can be considered as representing the data contained within a SAR collection within a three dimensional space. The shape of the PFS is dependant on the imaging geometry and frequency. When these two PFSs deviate in angle corresponding to the Nyquist criterion then the collection can be considered to be in the near field regime.

So, the SAR far field can be defined as:

$$\phi_w < \frac{c}{2f_c L_{\text{cr}}} \quad (2.24)$$

Then rearranging.

$$\frac{L_{cr}}{d} < \frac{c}{2f_c L_{cr}} \quad (2.25)$$

The far field-distance is defined as:

$$d_{far} > \frac{2L_{cr}^2}{\lambda_c} \quad (2.26)$$

Thus near-field distance is defined as:

$$d_{near} < \frac{2L_{cr}^2}{\lambda_c} \quad (2.27)$$

2.5 Spatial frequency domain

2.5.1 Introduction to the spatial frequency domain

SAR data is often visualised within the spatial frequency domain, also called the K-space or Fourier domain. A Fourier transform of a SAR image would present the image data within the K-space.

To visualise the K-space consider a simple radar scene. A transmitter, scatterer and receiver. For now, only one instance in time will be considered.

The magnitude of a vector, $\vec{k}$ can be defined as:

$$|\vec{k}| = \frac{2\pi}{\lambda} = \frac{2\pi f}{c} \quad (2.28)$$

The direction however is defined in terms of two-unit vectors. The first $\hat{i}$, refers to the incident direction. That is from the transmitter to the scatterer. The second $\hat{s}$, refers to the scattered direction, and is the unit vector pointing from the scatterer position to the receiver antenna. These were defined in equations (2.4) and (2.5) (section 2.2.2.3).

$$\vec{k}_i = \hat{i} \frac{2\pi f}{c} \quad (2.29)$$

$$\vec{k}_s = \hat{s} \frac{2\pi f}{c} \quad (2.30)$$

It is then possible to begin plotting the K-space using the vector $\vec{K}$. This vector defines the location of datapoints within the spatial frequency domain for a given frequency and radar position. This is shown in Figure 2.6.

$$\vec{K} = \vec{k}_i - \vec{k}_s \quad (2.31)$$

Which can be simplified in the Monostatic case as:

$$\vec{K} = 2\vec{k}_i \propto f\hat{i} \quad (2.32)$$

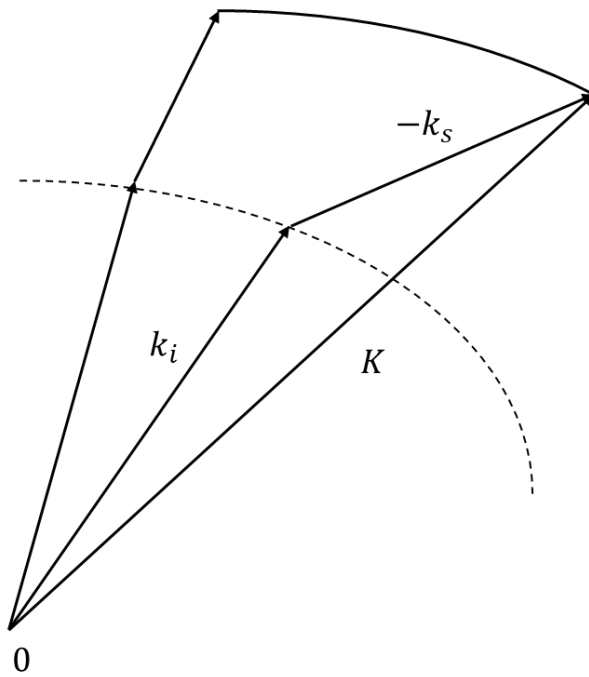


Figure 2.6 Diagram to show the vectors from equation (2.31).

This figure shows the vector $\vec{K}$ as it begins to trace out the K-space. As the radar positions change so will $\vec{k}_i$ and $\vec{k}_s$. This results in an arc. As the vector of frequencies that make up the radar pulse are considered, a three-dimensional shape emerges. This shape is often in the form of an annulus segment. An example is shown in Figure 2.7 projected onto the ground plane.

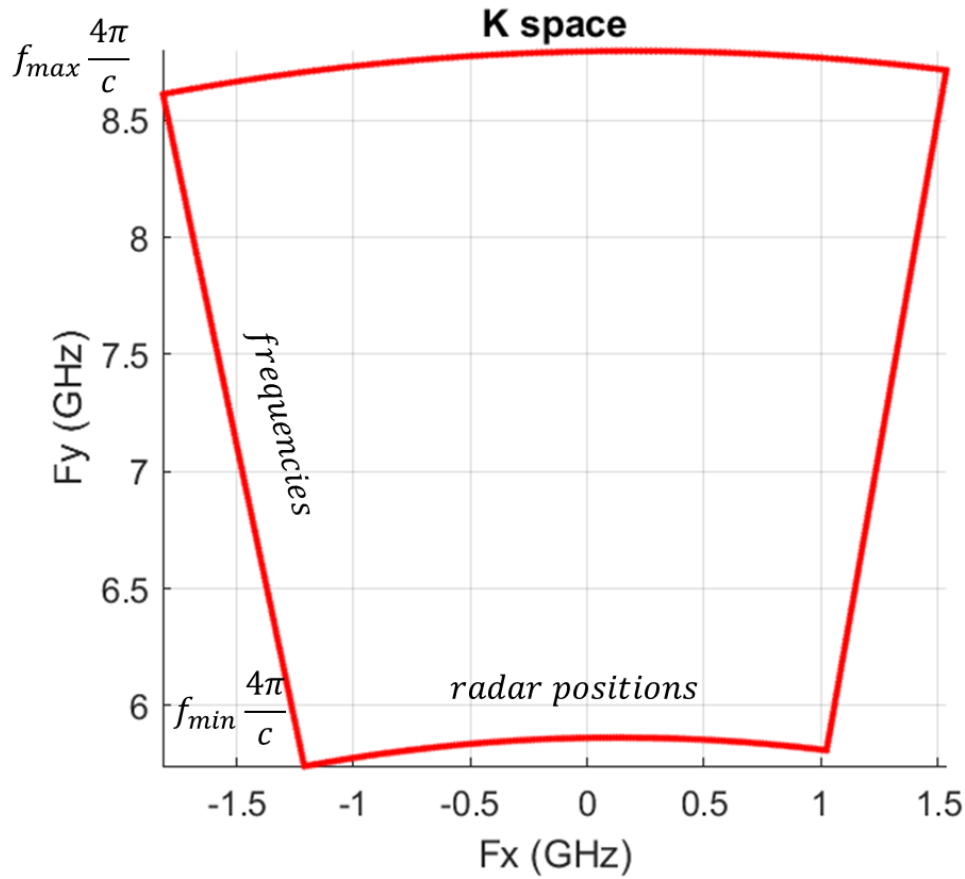


Figure 2.7 Diagram showing the full annulus segment for a scatterer.

In this image the frequencies are visible in the vertical extent of the annulus segment moving from the minimum to maximum frequency. Recall that a SAR antenna moves, and as such sweeps out a range of angles towards the scene centre. These are reflected in the annulus segment above. Sweeping through the radar positions projects the range of frequencies in an arc which then forms the characteristic annulus segment.

This is only for a single radar trajectory and scatterer co-ordinate. When two different trajectories are used there will be some areas of overlap and non-overlap. This is shown in Figure 2.8. Here the overlapping area A_c is defined as $A_c = A_{rt} \cap A_{mt}$. Where A_{rt} and A_{mt} are the frequency domain projected areas of the radar trajectories.

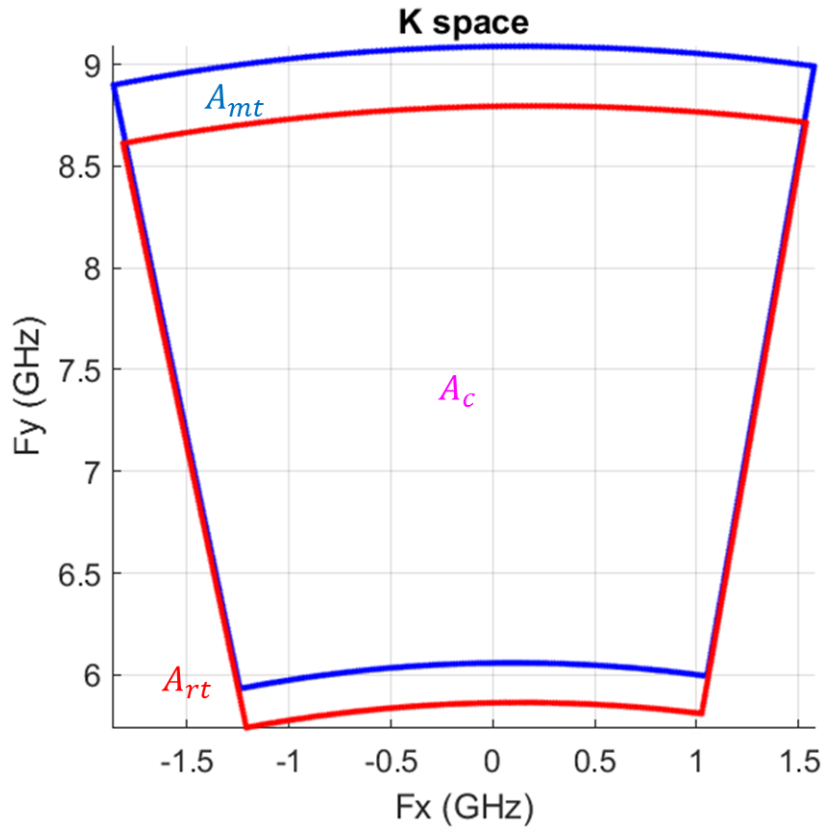


Figure 2.8 Diagram to give a visualisation of the overlap between two K-space segments.

The degree of overlap between two collections is an important consideration for CCD imagery as it has a large impact on the coherence (see section 2.5.2 and 2.7.4). This overlap is shown when two spatial frequency supports are projected onto the ground plane.

In the far field the incidence and azimuth angles from a SAR sensor to any position within a scene (if it is sufficiently small) does not meaningfully change. Thus a single annulus segment represents the far field data collection. In the near field there is a much greater variation in incidence and azimuth angle from the radar to the co-ordinates in the scene. As such the shape of the spatial frequency supports changes over a scene in the near field. An example is shown in Figure 2.9. In this image it is clear that the annulus segments closer to the radar experience a much wider range of azimuth angles than those further rearward. This results in a much wider annulus segment. Additionally the different

incidence angles can be seen, with the nearer co-ordinates having a greater incidence angle.

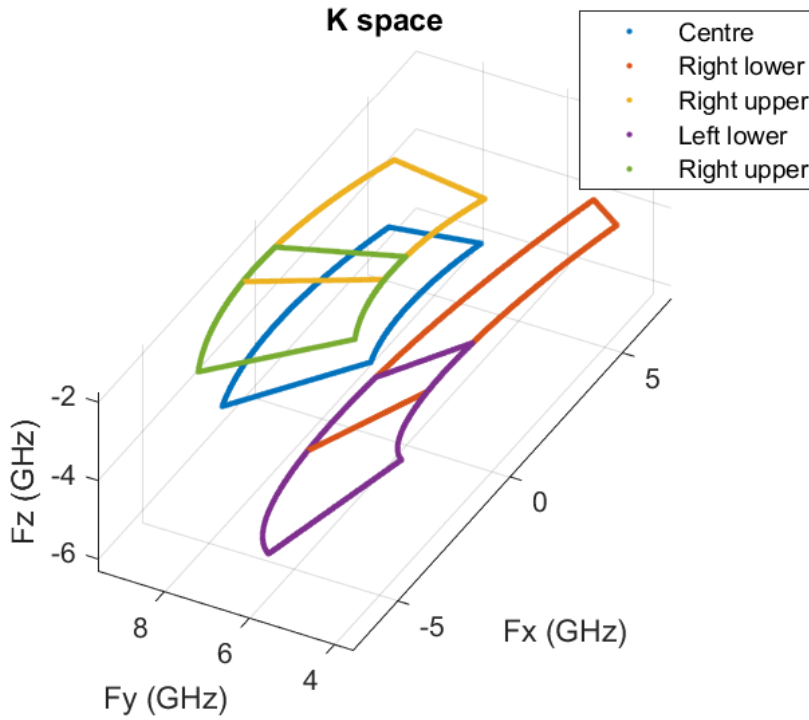


Figure 2.9 Diagram of K-space support outlines for a monostatic scan in the GBSAR laboratory. This scan used a rectangular gravel area. This diagram shows that the location and shape of the frequency support overlaps vary over a near-field scene.

The above figure shows the K-space for a monostatic collection. Five hoops are shown, with the one towards the scene centre often known as the slant plane. The supports nearer the transmitter are wider. This is related to the resolution (section 2.6).

2.5.2 Spatial frequency trimming

In a scenario where there is a proportion of non-overlap in the K-space, as shown in Figure 2.8, it may be beneficial to remove this area. This is referred to as incoherence trimming and can improve the coherence of change detection images [94], [97], [129], [130], [131],

[132], [133], [134]. A discussion of the implementation of near field trimming is provided in the methodology chapter in section 3.2.

For near field trajectories the Projected Fourier Supports (PFS) vary across the scene, as shown in Figure 2.9. As such the incoherence trimming must be spatially variant. It is referred to as Spatially Variant Incoherence Trimming (SVIT) and is a computationally expensive process [97], [131], [132], [133], [134]. The incoherent energy can also be removed before the image formation stage, in principle this resulting in SAR images with greater coherence [10], [132], [133], [134].

The SVIT algorithm calculates and then plots the for the centre of each pixel. The algorithm then determines which areas of the spatial frequency domain are overlapping and which are not. These areas can correspond to a component of the CCD image coherence. This is outlined in 2.7.4 on page 63.

The non-intersecting areas are removed for each pixel and new SAR images are formed.

Figure 2.10 and Figure 2.11 were produced by the SVIT algorithm. In these figures the PFS of a master and reference image are plotted in red and blue for a single pixel. The greyscale shows a running sum of the intersecting and non-intersecting regions. This shows the significant variation in the location within the k-space of overlapping and non-overlapping regions.

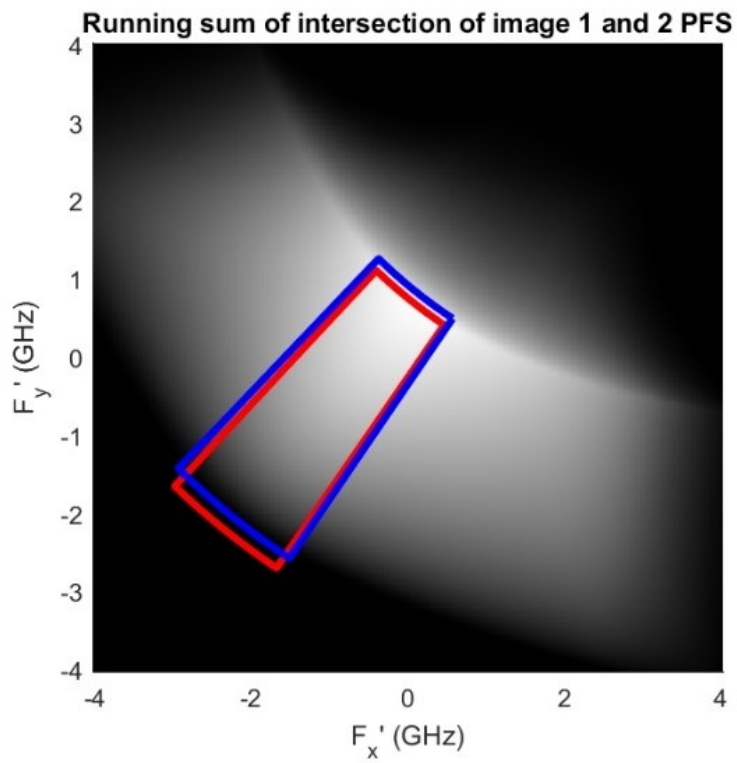


Figure 2.10 Figure produced by the SVIT algorithm. The red and blue lines represent the PFS for the reference and mission images for a single pixel. These are overlaid over the sum of all the intersecting regions. A bright pixel indicates many PFS overlap this region.

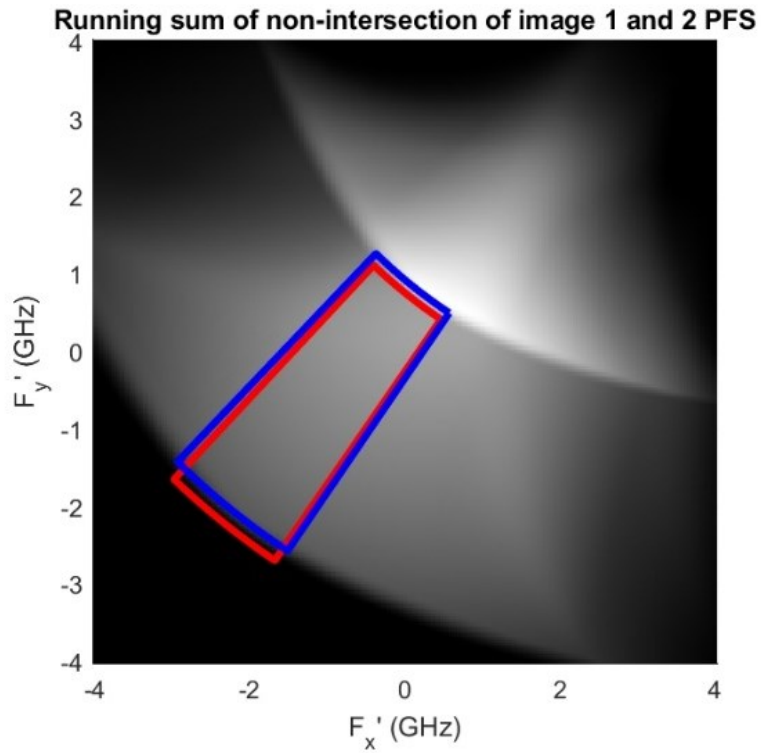


Figure 2.11 Figure produced by the SVIT algorithm. The red and blue lines represent the PFS for the reference and mission images for a single pixel. These are overlaid over the sum of all the non-intersecting regions. A bright pixel indicates many PFS overlap this region.[131], [135]

2.6 Resolution

2.6.1 Monostatic Resolution

The resolution of a SAR image is not constant and varies across the scene for near field SAR collections. Consider a typical radar trajectory (Figure 2.12).

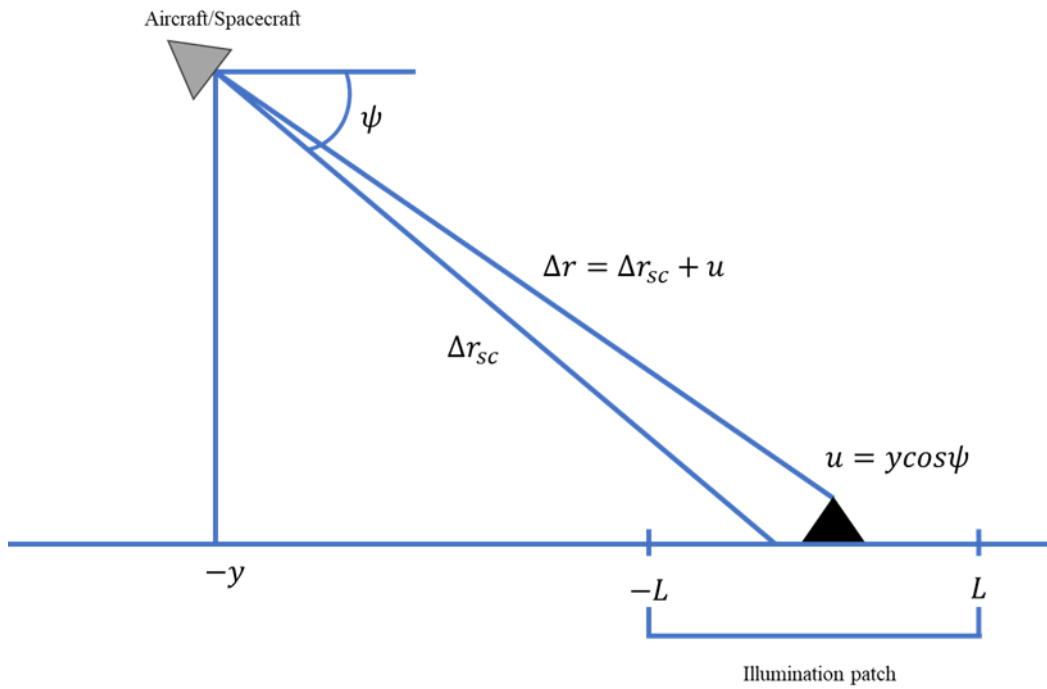


Figure 2.12 Collection geometry of a side looking SAR system.

Here ψ is the grazing angle (sometimes called depression angle). The incidence angle, $\theta = 90^\circ - \psi$. y represents the ground range. From the patch centre, and this is offset from the aircraft's position by distance y . It is important that the size of the illumination patch is small compared to the standoff distance y in order for far field imaging. In addition to the ground range, there is also the slant range, given by Δr for the top of the scatterer. The radar is at a distance $\Delta r = \Delta r_{sc} + u$ from the scatterer.

The equations for resolution (R) and the SAR unambiguous range (L) are shown below. The SAR unambiguous range is different to that of a surveillance radar, which is derived from the pulse repetition time. Here r is the range direction and cr is the cross-range

direction. ϕ_w is the total azimuth angle swept through (on the slant plane) in radians and ϕ_{stp} is the azimuth angle step size (in radians). Δf is the frequency step size.

For a monostatic SAR collection, the equations for resolution and unambiguous ranges are given by [94]:

$$R_r = \frac{c}{2BW} \quad (2.33)$$

$$R_{cr} = \frac{c}{2f_c \phi_w} \quad (2.34)$$

$$L_{cr} = \frac{c}{2f_c \phi_{stp}} \quad (2.35)$$

$$L_r = \frac{c}{2\Delta f} \quad (2.36)$$

The equations for resolution on a slant plane differ from those on a ground plane projection. For near-field imaging this results in spatially varying resolution. The resolution on the ground plane is dependant on the grazing angle, ψ . The ground plane resolutions and unambiguous ranges are denoted by the subscript g .

The ground plane resolution and unambiguous ranges are:

$$R_{r_g} = \frac{c}{2BW \cos(\psi)} \quad (2.37)$$

$$R_{cr_g} = \frac{c}{2f_c \phi_w \cos(\psi)} \quad (2.38)$$

$$L_{cr_g} = \frac{c}{2f_c \phi_{stp} \cos(\psi)} \quad (2.39)$$

$$L_{r_g} = \frac{c}{2\Delta f \cos(\psi)} \quad (2.40)$$

This results in a lower resolution, but higher unambiguous ranges than in the slant plane.

2.6.2 Resolution and the spatial frequency domain

The formulas for resolution presented in 2.6.1 are approximations and relate to the size of the spatial frequency domain. As the domain has been changed from the spatial to the frequency (Fourier) domain certain relationships are inverse. A large PFS will result in a high-resolution. A high-resolution image would have low range and cross-range resolution values.

This is shown below in Figure 2.13 where the Fourier domain frequency support is shown for the slant plane. In this figure a grey rectangle roughly corresponding to the resolution is shown, as well as the size of the rectangle.

Referring back to equations (2.37) and (2.34) in section 2.6.1, it can be seen that the size of the rectangle corresponds to the inverse of the resolution equations. The bandwidth is represented by BW and corresponds to $f_{max} - f_{min}$.

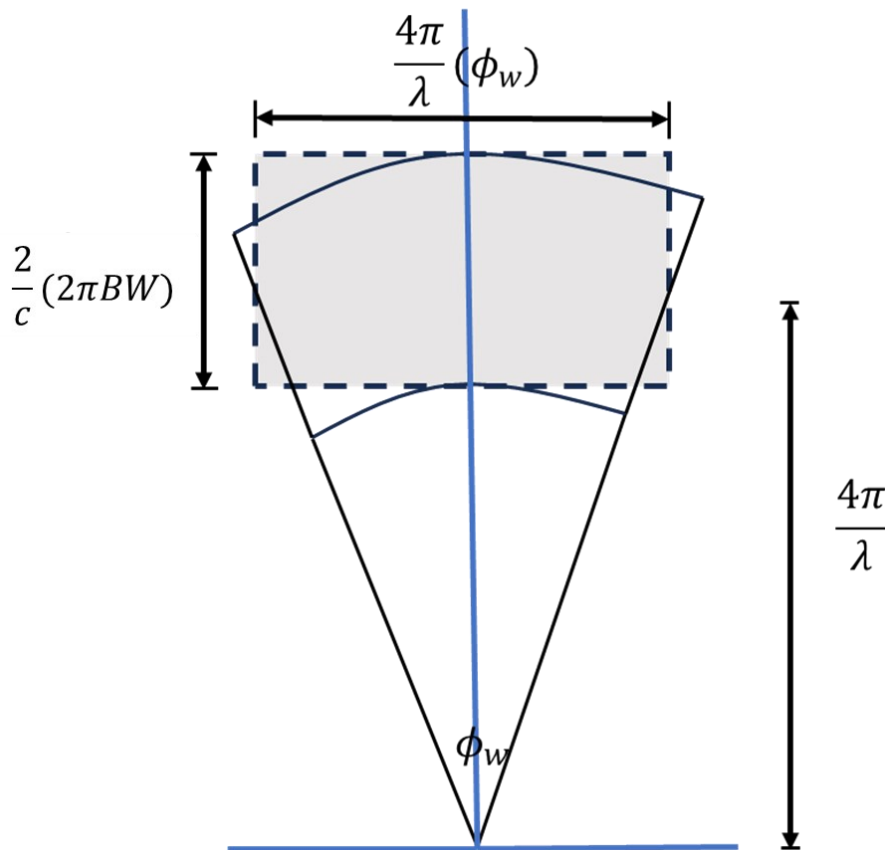


Figure 2.13 Image showing the Fourier domain frequency support in the slant plane. Key distances relating to the resolution are shown.

2.6.3 Bistatic resolution

The resolutions and unambiguous ranges of a bistatic collection is different than that of a monostatic collection. This can be related to the spatial frequency domain. Figure 2.14 shows the difference between the monostatic $\vec{K}$ vector ($\vec{K}_{mono}$) and the bistatic $\vec{K}$ vector ($\vec{K}_{Bi}$).

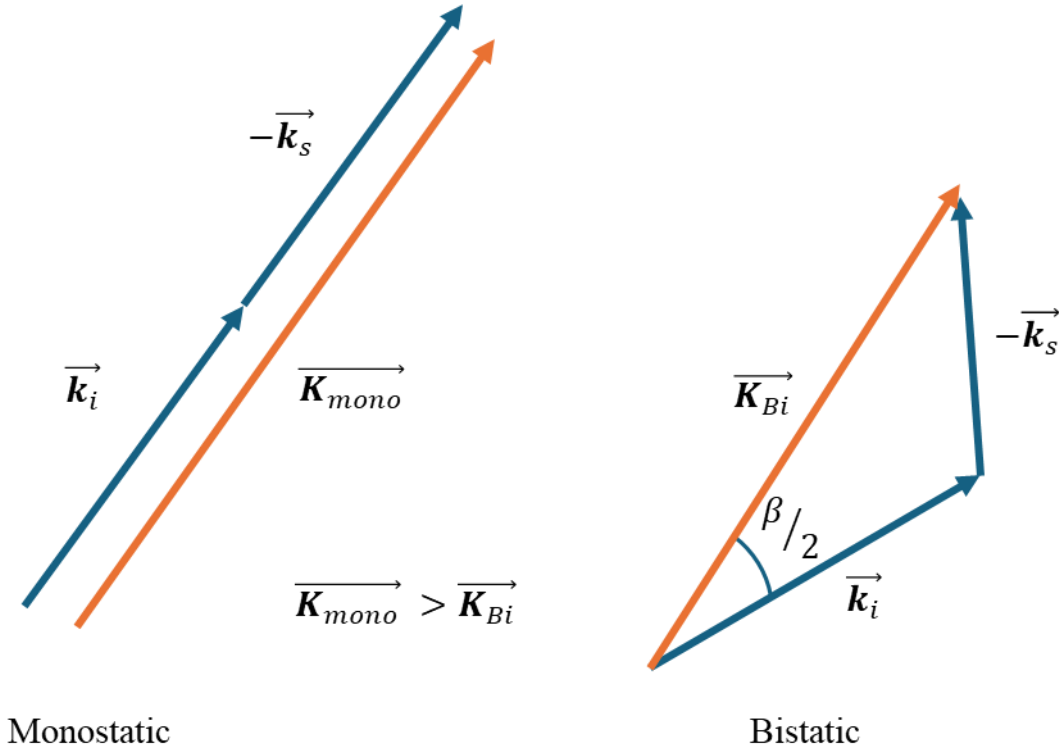


Figure 2.14 Diagram showing the impact of a bistatic trajectory on the size of the $\vec{K}$ vector.

This results in a smaller area for the PFS. This is reflected in the equations below where a $1/\cos(\beta/2)$ factor is applied.

Inspecting the equations it can be seen that a larger bistatic angle leads to poorer resolution, although the unambiguous ranges are improved.

$$R_{r_{gBi}} = \frac{c}{2BW \cos(\psi) \cos(\beta/2)} \quad (2.41)$$

$$R_{cr_{g\ Bi}} = \frac{c}{2f_c\phi_w\cos(\psi)\cos(\beta/2)} \quad (2.42)$$

$$L_{cr_{g\ Bi}} = \frac{c}{2f_c\phi_{stp}\cos(\psi)\cos(\beta/2)} \quad (2.43)$$

$$L_{r_{g\ Bi}} = \frac{c}{2\Delta f\cos(\psi)\cos(\beta/2)} \quad (2.44)$$

2.7 Interferometry

2.7.1 Introduction

SAR interferometry (InSAR), sometimes called Interferometric SAR is a branch of SAR image processing which use the phase information to detect changes or conduct processing. This is because phase is a much more sensitive indicator of change. Some of the key areas of interferometry are change detection, topographic mapping, and topographic change detection.

A series of SAR measurements can be used to map the heights of an area of land and generate a Digital Elevation Model (DEM). A good example of this is the space shuttle radar topography mission (STS-99) [73]. This mission flew aboard the space shuttle Endeavour in February 2000, and successfully mapped the topography of the Earth's surface. This is now done by the TanDEM-X [79], [81], [85], [87] satellite and others.

Changes in topography can also be measured, being able to detect changes in the order of mms. This is used to monitor unstable areas such as those liable to landslides or volcanic activity [95], [96].

Coherent Change Detection is used to identify changes between images [94], [95], [136]. These can be imperceptible to the naked eye. These might represent the tracks of vehicles and new or removed objects [8], [137], [138], [139]. This area of interferometry has applications both civilian and military. From the civilian perspective it is very useful in identifying changes such as destruction of areas due to natural disasters. From a military perspective it provides a great source of intelligence, having many advantages over optical imagery, primarily its sensitivity to small changes and all-weather capability.

2.7.2 Uses

SAR Interferometry uses at 2 different images. InSAR compares the phases and amplitudes. If the images are collected with a similar collection geometry CCD can be performed (see section 2.7.2.3 and 2.7.3.2). A difference in geometry is vital for

interferometry (except for CCD), as this can be exploited by InSAR to generate Digital Elevation Models (DEMs) or detect the change in height.

All applications of InSAR require at least two images, and some require a baseline between these images. The images may be formed using a single pass or multiple passes. Single pass InSAR is generally used for topographic mapping or ground moving target indication (GMTI). Whereas multipass collections can be used for topographic mapping, terrain motion and change detection. These require a spatial or temporal separation (baseline) [94], [95].

Sometimes it may not be necessary to collect repeat pass SAR imagery to detect a possible target. Depending on the sensitivity it may be possible to detect an increased foliage density, or the presence of vehicles and buildings in an otherwise homogenous environment [91], [92]. Such detectors however may be vulnerable to high false alarms and may not correctly detect changes between two SAR collections.

2.7.2.1 Topographic mapping, DEMs and landslides

When constructing DEMs a spatial baseline is needed. This separation needs to be sufficiently large so as to allow for interferometric change detection, but not too large as that would introduce a significant decorrelation. Consider two SAR images collected in two passes. There exists a baseline of two components B_x and B_z . These could be termed across and along track baselines respectively. For generating a DEM there across-track baselines are utilised [95].

An example DEM produced by the European Space Agency using images the ERS-2 spacecraft is presented in Figure 2.15.

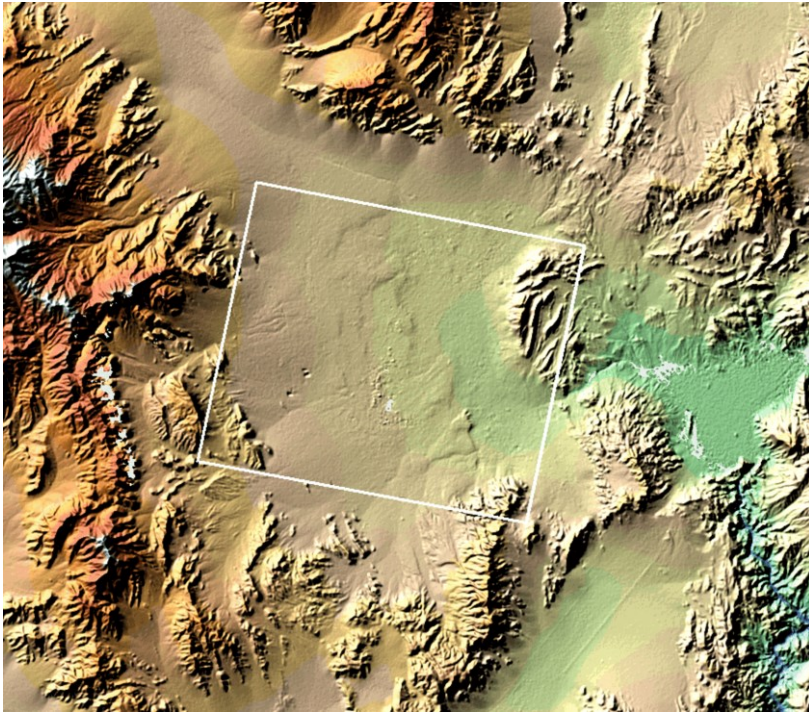


Figure 2.15 Digital Elevation Model (DEM) produced by the ESA. Image was formed using radar images from the ERS-2 spacecraft. Image is taken from the ESA website (©ESA)⁵.

2.7.2.2 Geoscience

In addition to forming a DEM, Interferometry can be used for geoscience applications. Because of the ability to penetrate forest canopies and from DEMs SAR can be used to monitor the biomass and susceptibility to ignition of forests [140], [141], [142].

Another application is the movement of regions of land, this may indicate areas at risk of landslides volcanoes at risk of an eruption. When used in this mode SAR interferometry can detect changes in height on the order of millimetres [143], [144], [145]. An example interferogram is shown in Figure 2.16.

⁵ Image from ESA website:

https://www.esa.int/ESA_Multimedia/Images/2003/04/Digital_elevation_model

Image is used in accordance with the “Terms and conditions of use of images and videos available on the ESA website”:

https://www.esa.int/ESA_Multimedia/Terms_and_conditions_of_use_of_images_and_videos_available_on_the_es_website

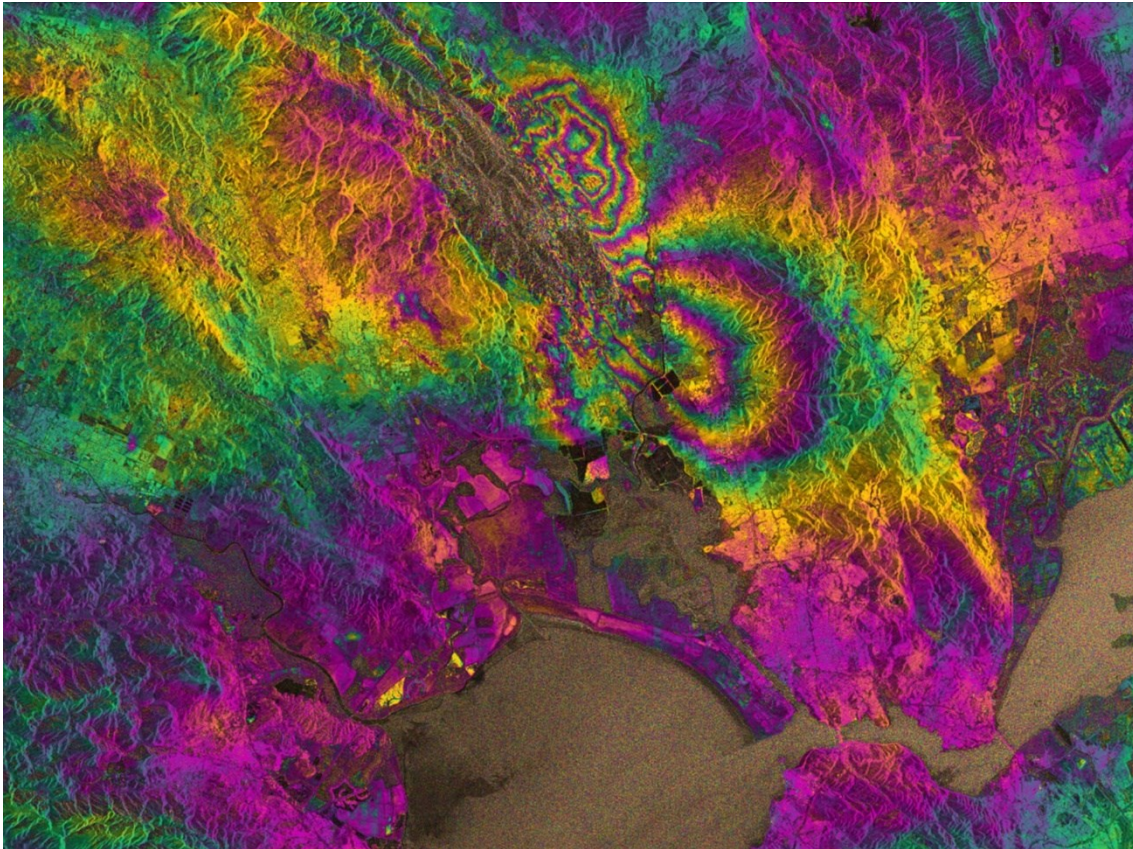


Figure 2.16 Interferogram showing the changes detected after an earthquake in California's Napa Valley on 24 August 2014. The two SAR images were collected by Copernicus Sentinel-1A. These images were collected on 7 August and 31 August 2014. Each fringe represents 2.8 cm of ground motion. This image shows the high sensitivity to height variation which SAR interferometry has. The crater is also clearly visible. Image is from the ESA website (©ESA)⁶

⁶ Image from ESA website:

https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Fogo_volcano_on_Sentinel_s_radar

Image is used for in accordance with the "Terms and conditions of use of images and videos available on the ESA website":

https://www.esa.int/ESA_Multimedia/Terms_and_conditions_of_use_of_images_and_videos_available_on_the_es_website

2.7.2.3 Change Detection

SAR change detection finds the differences and changes between two images. This can be changes in height as covered in the pervious section. SAR change detection can also be used to detect changes such as vehicle tracks or other scene changes which do not result in a difference in height.

Different methodologies exist to do this, but the most common is the Coherent Change Detection (CCD), typically displayed as a greyscale image. The Coherence takes values from 0 to 1 and these correspond to colours from black to white respectively. The result is an image that shows areas of no change in white and areas of change in black. Change is typically called decoherence (or a loss of coherence) as what is displayed as ‘change’ may also include areas of shadow or a change in the reflectivity of a target in response to a new collection geometry. An example CCD image is shown in Figure 2.17.

Coherent Change Detection, Coherence for gravel:

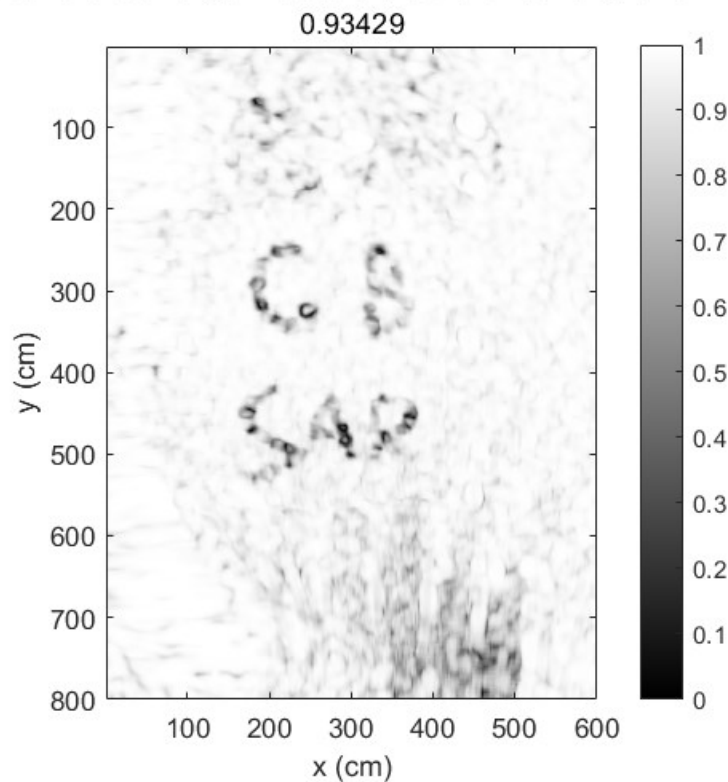


Figure 2.17 CCD image displaying the letters ‘GBSAR’ inscribed in gravel.

The above image (Figure 2.17) is a good example of a CCD image. The letters ‘GBSAR’ were traced in the gravel by a stick, and this was the only change made. This was imperceptible to the human eye when comparing two SAR images. A CCD algorithm is able to highlight this change however. However other areas still display change, particularly near the edges of the image. These areas correspond to the concrete floor and have a much lower signal to noise ratio (SNR). When decoherence occurs in areas with no change this is often referred to as a false alarm, and when producing CCD images, it is desirable to keep the False Alarm Ratio (FAR) as low as possible.

Other methods of change detection exist, and not all change detection images are presented with a range of values. Some may present a binary change or no change image. This may be formed using a threshold, probability or other methods.

2.7.3 Change Detection methodologies

Each individual pixel in a SAR image contains many individual scatterers. Each of these provides a contribution to the phase of the returning waveform. The transduced reflectivity I is the coherent sum of the contribution of all scatterers in a scene, in this case a pixel. It can be modelled as [146]:

$$I(x, y) = \sum_{k=1}^N A_k \exp(j\phi_k) \quad (2.45)$$

Here N is the number of point scatterers, A_k is the amplitude of the (k^{th}) point scatterer and ϕ_k is a phase term. The phase is dependent on the phase contribution of the scatterers and the distance travelled by the radar wave. This results in a random value for the phase ϕ_k .

This results in speckle, the seemingly random variation characteristic of SAR images (see section 2.8). However, it is not random noise as proved by this equation. Two images collected at the exact same geometry would have the same speckle pattern. So, whilst speckle is often considered gaussian, it would be incorrect to characterise it as mere random noise. Unfortunately, the terms in this equation are not determinable, but

components of them are. Since the speckle is the coherent sum of a large number of scatterers within a resolution cell, a change in radar geometry will lead to a change in relative position of the scatterers. As a result, the phase and amplitude of the response will be different. The change in phase is likely to be more significant however, and a small motion in the scene will cause the scatterers to move around but will not change their amplitudes (A_k). As a result, small changes might not be detected by non-coherent change detection methods.

The phase of two SAR images I_f and I_g can be described as [94], [95], [146], [147]:

$$\phi_f = \frac{4\pi}{\lambda} R_f + \phi_{scat,f} + \phi_{noise,f} \quad (2.46)$$

$$\phi_g = \frac{4\pi}{\lambda} R_g + \phi_{scat,g} + \phi_{noise,g} \quad (2.47)$$

Here there are 3 components. The first term refers to the change in phase due to the distance the wave has travelled, R . When using the Back-Projection Algorithm the scene centre corresponds to zero phase [124]. Multipath return will appear further away than the object is. The n refers to the noise. Finally, the term ϕ_{scat} refers to the phase contribution from the scatterer. This is affected where scatterers in the scene are moved or changed, and changes in the azimuth and elevation angle [94], [95], [146], [147].

2.7.3.1 Non-Coherent Change Detection algorithms

Non-Coherent Change Detection (NCCD) seeks to identify large changes in the scene by considering changes in the mean backscattered power (amplitude squared). Estimates of the average power are obtained for a sliding window. This method does not consider phase and is thus not a part of interferometry. Results from NCCD images are typically poorer than those from CCD images due to not utilising the phase information. In some cases the NCCD may outperform coherent methods as presented in the Novak 2013 paper [139]. In this paper a NCCD algorithm outperformed the CCD algorithm, achieving a higher Probability of Detection (POD) for a given False Alarm Rate (FAR). This was likely due to the particular scene/images chosen. A different scene may have resulted in different results favouring the CCD. Additionally the changes were quite large (vehicles)

whereas CCDs strength is the ability to detect very fine changes such as vehicle tracks. The NCCD formula is defined as:

$$\rho_{NCCD} = 1 - \frac{\left(\frac{1}{N} \sum_{k=1}^N |I_f(k)|^2\right) \left(\frac{1}{N} \sum_{k=1}^N |I_g(k)|^2\right)}{\left(\frac{1}{2} \left(\frac{1}{N} \sum_{k=1}^N |I_f(k)|^2 + \frac{1}{N} \sum_{k=1}^N |I_g(k)|^2\right)\right)} \quad (2.48)$$

Where I_f and I_g are the two complex images being compared and N is the number of pixels within a window which slides over the two images. ρ_{NCCD} is the value of the NCCD change detection. A higher value indicates a large change.

2.7.3.1.1 Sample Variance Ratio

The Sample Variance Ratio (SVR) is a simple NCCD algorithm for detecting large scale scene changes [146], [148], [149].

$$\rho_{SVR} = \frac{\widehat{\sigma_{I_f}^2}}{\widehat{\sigma_{I_g}^2}} = \frac{\sum_{k=1}^N |I_f(k)|^2}{\sum_{k=1}^N |I_g(k)|^2} \quad (2.49)$$

For this detector a value approaching 1 for ρ_{SVR} indicates no change and any other value indicates a change [148]. Here $\widehat{\sigma_{I_f}^2}$ and $\widehat{\sigma_{I_g}^2}$ represents the sample variance of the reference and mission images [148].

2.7.3.2 Coherent Change Detection algorithms

Coherent Change Detection (CCD) uses the magnitude of the sample complex cross correlation. This means both the amplitude and phase of the two repeat pass images are used (equation (2.46) and (2.47)). This offers a much greater sensitivity than the NCCD to changes between the images and allows the detection of very small or subtle changes such as vehicle tracks [139], [146].

As stated previously a CCD image shows the changes between two images on a scale of 0 to 1 for each pixel. The geometry should be as similar as possible, which is easier to

achieve with a ground-based system in a laboratory but with an aircraft or spacecraft it is significantly harder, the importance of this will be explained in the section on the K-space.

Coherent Change Detection between two SAR images, however, can highlight subtle changes between them [95]. These changes could be tracks made by people, animals, or vehicles, or even the appearances of new objects such as vehicles and structures. Images like this can be very useful for ISR, as it is quite simple to detect troop and vehicle movements from the tracks they leave, which would be very difficult to detect in optical imagery. Whilst CCD offers the potential for picking out small changes, it is reliant on a high degree of coherence between the two images. To achieve this the radar geometry needs to be as similar as possible. This is explained by the spatial frequency domain (Section 2.5), but also because the RCS of a scatterer is dependent on incidence angle [150]. It should be noted that in some cases only the large-scale changes are of interest, this might be in applications such as mapping natural disasters or deforestation.

2.7.3.2.1 Sample coherence/Normalised complex cross correlation

Consider a scenario where two complex images, I_f and I_g , are received by an antenna from a target area. These signals can be considered to have three components. Here c_{fg} represents the correlated parts of the signals and b_f and b_g represents the de-correlation from temporal and spatial baselines. Finally, n_f and n_g represent the thermal noise.

$$I_f = c_{fg} + b_f + n_f \quad (2.50)$$

$$I_g = c_{fg} + b_g + n_g \quad (2.51)$$

CCD algorithms, which utilise the phase in addition to the amplitude, can detect very small changes but are consequently susceptible to high false alarm ratios. This can be due to slight differences in acquisition geometry and thus differences in the scattering. The equation commonly used is the sample complex correlation which takes a value from 0 to 1 [94], [139], [146]. This formula is shown below in (2.52).

$$\gamma e^{i\phi} = \frac{\sum_{k=1}^N I_f(k) I_g^*(k)}{\sqrt{\sum_{k=1}^N |I_f(k)|^2 \sum_{k=1}^N |I_g(k)|^2}} \quad (2.52)$$

The coherence should be thought of as the proportion of the total energy backscattered that is coherent within a sliding window. These take various sizes but are typically an odd number such as 5x5 or 7x7.

This estimator is sometimes referred to as a Maximum Likelihood Estimator (MLE) for γ [94], [151], [152], although other papers utilise an alternate formula for the MLE [139] (see section 2.7.3.2.3). Where I_f and I_g are the two complex images being compared and N is the number of pixels within a window which slides over the two images. The magnitude and phase of the complex correlation are γ and ϕ . The coherence is presented on a pixel-by-pixel basis to produce a coherence or “CCD” image. The average can be taken for the desired image area.

The coherence magnitude represents the proportion of coherent energy that is backscattered, albeit only an estimate. The *true* coherence (the value of the coherence without any processing or estimation errors) will differ from the measured depending on the window size used [129], [146], [153] (see section 2.7.4). As such the term γ is more accurately referred to as the *estimated* coherence in this scenario and is shown with a circumflex as: $\hat{\gamma}$. As CCD algorithms work on a small neighbourhood (in a sliding window), its result is dependant on the size of the neighbourhood. A window should be sufficiently large to provide a statistical reliability for the coherence but not so large as to degrade the resolution to an unacceptable degree [94]. Smaller windows lead to an overestimate of the coherence, this is discussed in more detail in section 2.7.4.2.3. A small window will be much more susceptible to noise. However too large a neighbourhood would result in too great a loss of resolution in the final CCD image.

The effect of neighbourhood sizes can be demonstrated using data from the GBSAR laboratory. This is shown in Figure 2.18.

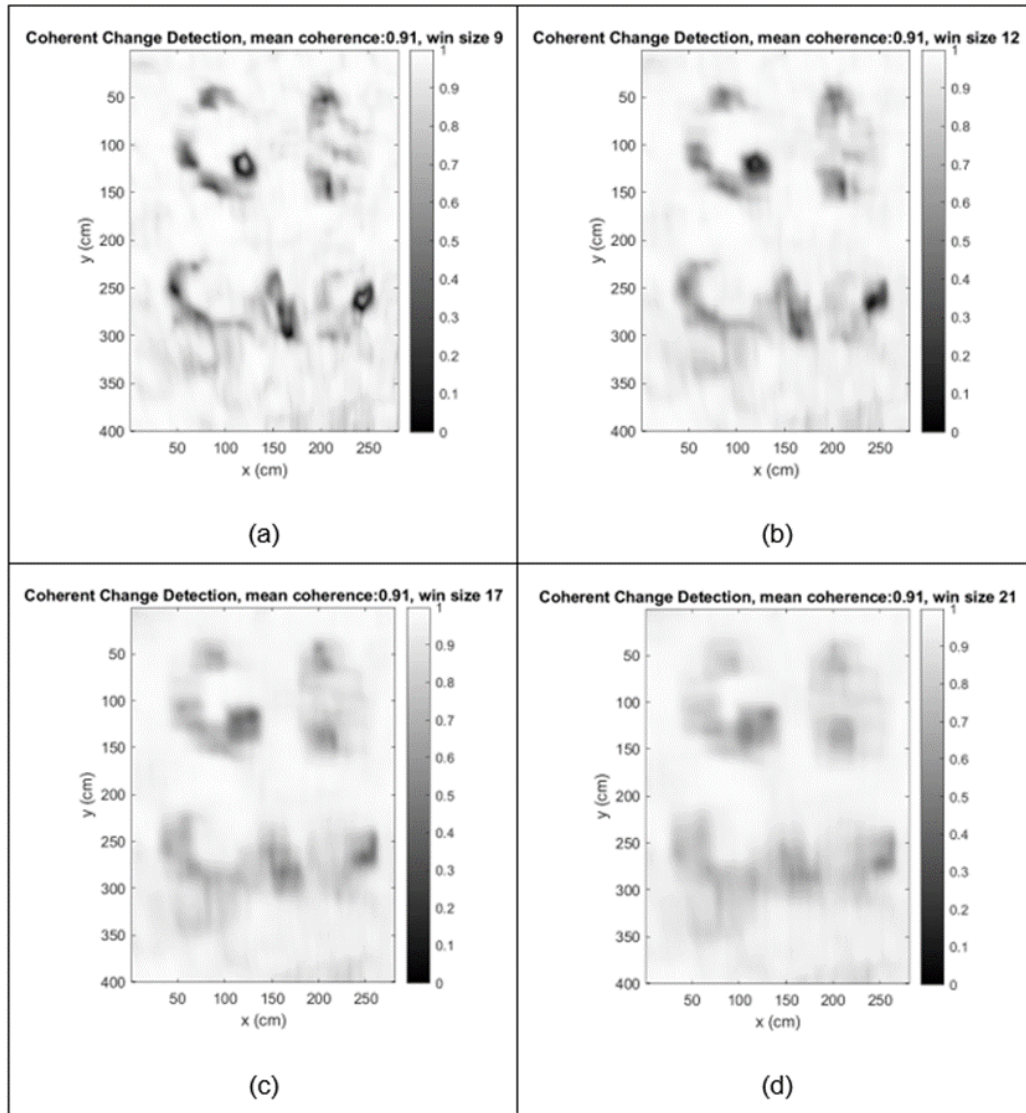


Figure 2.18. A set of four CCD images (a-d). These were produced using different window sizes of 9, 12, 17 & 21 respectively. These show the loss in resolution as the window size is increased. The mean coherence remains constant at 0.91 however.

Equation (2.52) can be re-written to show the sample complex correlation $\hat{\gamma}$ (estimated coherence) which is the magnitude of the previous equation. Values are in the range of 0 to 1.

$$\hat{\gamma} = \frac{|\sum_{k=1}^N I_f(k) I_g^*(k)|}{\sqrt{\sum_{k=1}^N |I_f(k)|^2 \sum_{k=1}^N |I_g(k)|^2}} \quad (2.53)$$

2.7.3.2.2 Alternate CCD formalism

The equation for an alternate CCD detector is shown below, where γ has been replaced by γ_{Ber} for clarity. This detector was from a 1972 paper [154]. The difference is the removal of the square root over the denominator, and the numerator being multiplied by two.

$$\gamma_{Ber} e^{i\phi_{Ber}} = \frac{2 * \sum_{k=1}^N I_f(k) I_g^*(k)}{\sum_{k=1}^N |I_f(k)|^2 \sum_{k=1}^N |I_g(k)|^2} \quad (2.54)$$

A scene was presented in [139] containing a racetrack and car park, where the proposed method showed promise. In the normal CCD methodology, the cars were not easily distinguishable from the false alarms. The images produced using the Combined Intensity and CCD method in several papers [148], [149], [155] were slightly clearer and with greater contrast. However, this efficacy was dependant on the images and disturbance as seen in the Figure 2.19. Here two monostatic images from the GBSAR lab were used. The alternate CCD does exhibit a slight improvement in clarity, although it was quite minor in for this particular data collection. It is also possible improve contrast by adjusting colour bars or thresholding, so small adjustments to the detector may not give much improvement over established methods.

For this thesis the normalised cross-correlation (2.7.3.2.1) is used as this is the standard change detector within SAR (and SAS). This allows for the best comparison to existing literature.

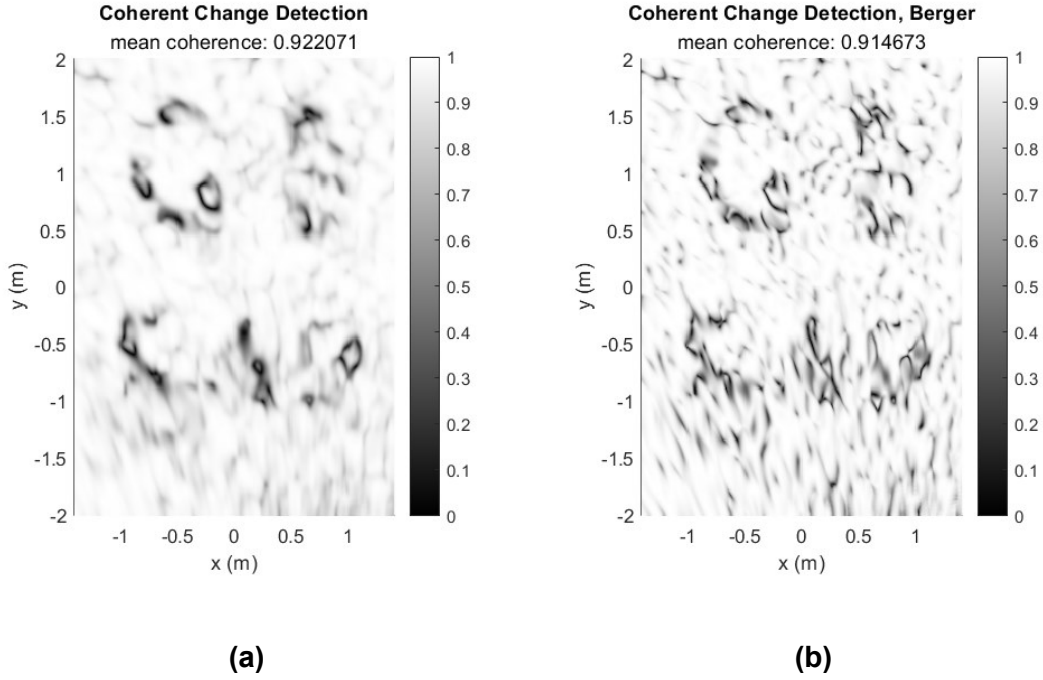


Figure 2.19 (a) shows a CCD image produced with the typical CCD equation (equation (2.52)) and (b) shows a CCD image formed using the alternate CCD equation form [155].

2.7.3.2.3 Maximum Likelihood Estimate

The Maximum Likelihood Estimate (MLE) is defined in [139] as:

$$\rho_{MLE} = \frac{|\sum_{k=1}^N I_f(k) I_g^*(k)|}{\frac{1}{2} (\sum_{k=1}^N |I_f(k)|^2 + \sum_{k=1}^N |I_g(k)|^2)} \quad (2.55)$$

It is suggested in [139], [156] that the MLE may have some favourable characteristics compared to the sample coherence, particularly with regards to an improved probability of detection and reducing the false alarm ratio.

2.7.3.2.4 Polarimetric change detectors

Some change detectors are designed to use polarimetric images [10], [146], [157], [158], [159], [160]. A polarimetric SAR collection is one where multiple polarisations are

collected at the same time. For these detectors to work they typically require reference and mission images to have all polarisations in order to use a covariance matrix. Each pixel can be thought of as having three (or four) channels, instead of considering three separate images [158]. A polarimetrically augmented detector was demonstrated in [159].

Polarimetry is discussed further in section 2.9 and 2.10.1. Polarimetric detectors are only introduced here as a part of the discussion around change detection methodologies.

2.7.3.2.5 Log Likelihood Change Statistic (LLCS)

The sample coherence is however susceptible to a high false alarm ratio. [146], [157] as it is not able to distinguish between decorrelations arising from human activity from those of natural processes or change in scattering. Manmade decorrelations are typically concentrated, whereas natural processes such as wind and rain are typically dispersed throughout the scene. The mean backscatter power may be less susceptible to change due to environmental effects however the manmade changes may result in a very low change as well. In the case of a vehicle track the disturbance would result in very little difference in backscatter power and is mainly detectable due to the change in phase. The FAR could be improved using averaging, although this would come at the cost of resolution, and potentially obscuring some small temporal changes.

2.7.4 Coherence and Incoherence

2.7.4.1 Sources of in-coherence

A pair of SAR images will never be identical. These differences can be detected by CCD algorithms and are called decorrelations. These de-correlations may be desirable to detect, as they reflect the changes in the scene such as vehicle tracks or new structures. Changes such as these provide information about what has been done in the scene. However, there will be decorrelations that are un-desirable, which makes it harder to identify and interoperate the changes within the scene.

Natural processes such as wind, rain, subsidence, flooding, plant growth and other environmental changes cause a lot of these effects. Weather such as rain or snow generally affects the whole or large areas of the scene. Another source of decorrelation due to nature

might be livestock moving in a field, or perhaps livestock creating tracks. These more localised changes will be clear and provides additional information about activity in the area.

Wind, rain and other natural effects have a far more significant effect on the overall coherence. The backscatter from a resolution cell is dependent on all the scatterers within that resolution cell [94]. If these scatterers were to change position (due to wind) or reflectivity (due to rainfall) then there will be a large loss of coherence. This necessitates that the two collection times be relatively close. The changes mentioned so far could all be considered as temporal, as they are due to the difference in the scene between the two collection times.

Errors in processing or assumptions made can result in decorrelations. These include errors in inertial measurement units, GPS and in navigation of the aircraft and spacecraft there will inevitably be a difference in geometry. This results in different incidence and scatter angles.

Geometric decorrelation is another area. In this case it is caused by a difference in the radar platform trajectory. An object's RCS is dependent on the imaging angle with some exceptions such as trihedral in monostatic and spheres in bistatic. This combined with a new path scattering of different sub-resolution cell scatterers leads to a different signal. Other effects such as shadowing are also affected by the radar geometry, and these will move throughout the scene.

Random noise is another, whilst having an effect over the whole scene, its effects are most strongly seen in areas of shadow where the Signal to Noise ratio (SNR) is lower.

2.7.4.2 Quantifying and forecasting coherence

Knowing that several factors affect the coherence, the coherence can be written as [146], [151], [153], [161]:

$$\gamma_{true} = \gamma_{SNR}\gamma_{temp}\gamma_{proc}\gamma_{geom} \quad (2.56)$$

In this equation γ_{true} represents the true coherence, rather than the measured coherence ($\hat{\gamma}$). The measured coherence is only an estimate, and as such has a bias [129], [146], [153]. This bias is explained in section 2.7.4.2.3. The measured coherence, $\hat{\gamma}$ is the sample cross correlation, seen in equation (2.53). It is distinguished from the true value with the use of a circumflex (hat).

This equation encompasses the effects mentioned in the previous section. The decorrelation due to noise is represented as γ_{SNR} . Temporal changes are represented by γ_{temp} , and γ_{proc} is the term for decorrelation due to processing. Each of these terms takes a value of 0 to 1. For example, for γ_{temp} . If there was no change in the scene (including environmental effects such as rain or wind) this would take a value of 1. If every scatterer in the scene changed then this would have a value of 0. γ_{geom} represents the terms which vary with the imaging geometry.

Additionally, there will also be some variation between polarisation [9], [162], [163].

2.7.4.2.1 Signal to Noise Ratio

As with all radar systems, noise is an important consideration. The Signal to Noise Ratio (SNR) is determined by the hardware making up the radar system.

For a one-way transmission the cross-correlation coefficient associated with the noise would be:

$$\gamma_{SNR1} = \frac{1}{\sqrt{1 + SNR_1^{-1}}} \quad (2.57)$$

There is of course a return path, but as the radar systems typically use the same antennas and hardware γ_{SNR} can be written as:

$$\gamma_{SNR} = \frac{1}{\sqrt{1 + SNR_1^{-1}} \sqrt{1 + SNR_2^{-1}}} \quad (2.58)$$

Using the above assumption SNR_1 is set equal to SNR_2 and then renamed SNR , this results in [146], [153]:

$$\gamma_{SNR} = \frac{1}{1 + SNR^{-1}} \quad (2.59)$$

2.7.4.2.2 Temporal

Temporal changes may be very subtle or major. Major changes might include objects being added or removed from the scene. These larger changes are detectable by comparing the amplitude images. There are some very subtle changes however that can be detected by the change in phase (from a changed path length). An example of this is tracks left by vehicles, humans, or animals along the ground. These tracks change the surface and disturb individual sub-resolution cell scatterers. There may be no change in the reflectivity of the surface, however a CCD algorithm will be able to detect the change in phase of the returned wave [139].

The temporal changes are due to activity in the scene and are thus not calculated in an equation. However, some models are used for the natural effects. The Zebker et al. 1992 paper [153] presents model that assumes gaussian motion, mostly applicable to remote sensing situations rather than a laboratory environment, where temporal changes will be very low.

Different scenes and different environments result in different changes in coherence. For example, in [164] the author presents decorrelations after 35 days. For large scale developments γ_{temp} was 0.7, however residential, high and low density, γ_{temp} was 0.4 and 0.3 respectively. Trees and countryside had a γ_{temp} of 0.3. Recent papers have shown similar differences [165], [166], [167]. Here ground types such as desert rocks and sand resulted in a higher coherence between passes than forests.

2.7.4.2.3 Processing

The processing term (γ_{proc}) refers to decorrelation arising from the SAR imaging algorithm approximations. This may include the wrong parameters during image

formation or incorrect trajectories. These errors should be small for well designed SAR systems.

The window size used in the CCD algorithm also has an impact on the measured coherence [129], [146], [153], however unlike the other factors mentioned, this increases the coherence, particularly for low coherence areas. The coherence that is measured and the true coherence should be equal, and when plotted against one and other. In reality the coherence is overestimated, which is more severe for smaller window sizes.

When the coherence for small window sizes is plotted the estimated coherence begins to flatten out at around $\gamma_{true} = 0.4$. A simple solution might be to increase the window size as this will lead to an improved accuracy, however this comes at the cost of reducing resolution. This loss in resolution is due to the averaging nature of the sliding window.

Figure 2.20 and Figure 2.21 show the expected value of coherence plotted against the true value. A function for the expected value of coherence is shown in (2.60) and was derived in [168]. This formula takes the form of a gauss hypergeometric function [146], [168], [169], [170]. This formula has been shown to match simulations of SAR imagery [171], [172].

The equation is as follows:

$$E\{\hat{\gamma}\} = \frac{\Gamma(N)\Gamma(1 + 1/2)}{\Gamma(N + 1/2)} \cdot {}_3F_2 \left[\begin{matrix} 1.5, N, N \\ N + 1, 1 \end{matrix}; \gamma_{true}^2 \right] \cdot (1 - \gamma_{true}^2)^N \quad (2.60)$$

Where N is the window size (number of pixels in the two dimensional window) and $\Gamma(z)$ is the gamma function of a variable, z . ${}_pF_q \left[\begin{matrix} a \\ b \end{matrix}; x \right]$ is the gauss hypergeometric function [168], [169], [170]. $E\{\hat{\gamma}\}$ is the expected value of the estimated (sample) coherence.

In cases where the number window size is insufficiently high, the sample coherence is biased towards higher values. This results in a reduction in the contrast of the CCD image [146].

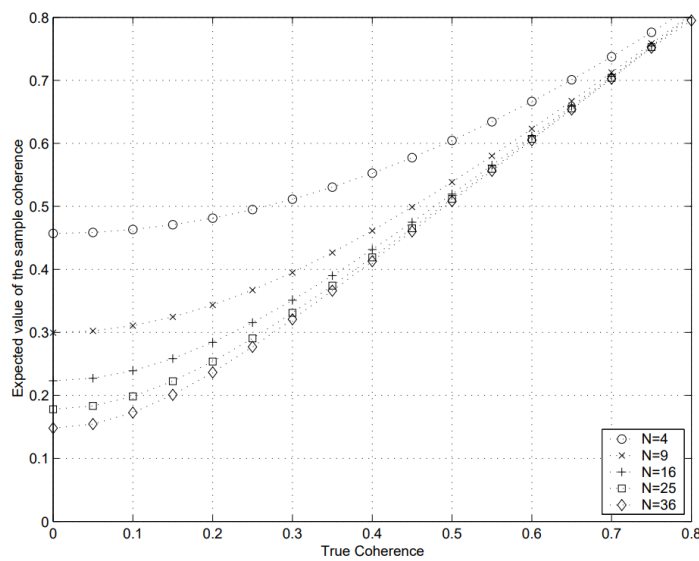


Figure 2.20 Graph showing the mean coherence of a CCD image (expected value) against the true coherence. Several curves are plotted for different window sizes. Graph is from [146]⁷.

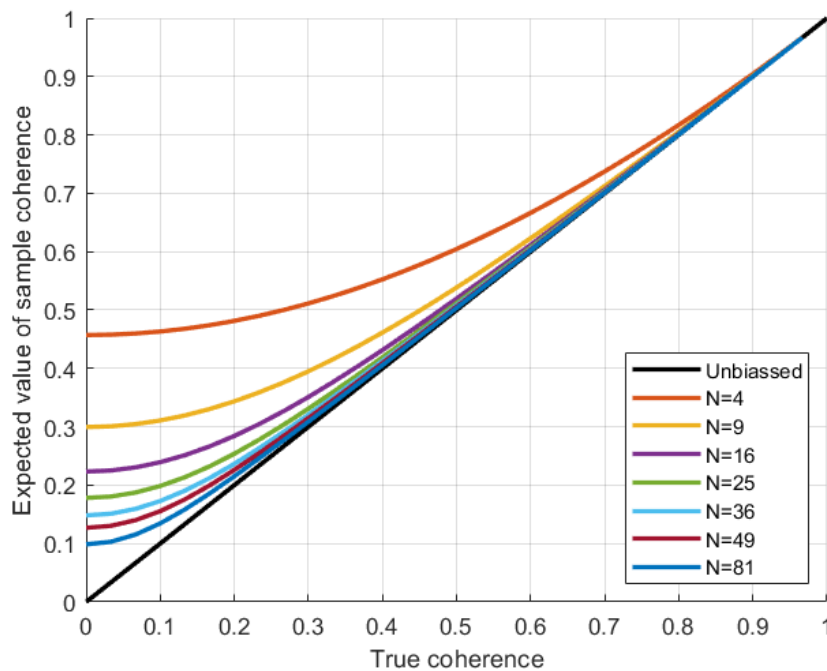


Figure 2.21 Graph showing the mean coherence of a CCD image (expected value) against the true coherence.

⁷ In [146] the figure is figure 22 on page 48.

Other causes of decorrelation that would be included in the processing term are incorrect assumptions used in the SAR processing and an incorrect ground truth.

2.7.4.2.4 Geometric

$$\gamma_{geom} = \gamma_{baseline}\gamma_{registration}\gamma_{Scat} \quad (2.61)$$

The geometry term has three components. The baseline effects, $\gamma_{baseline}$ arise from the mismatch in radar platform trajectories and in the resulting non-overlap in the spatial frequency domain [146], [151], [153]. The registration term, $\gamma_{registration}$ corresponds to decorrelations due to differential layover [146]. γ_{Scat} [10], [162] represents the decorrelation due to the change in scatterer RCS as a function of SAR geometry, polarisation [150], [173] the effects of multipath scattering between the different sub-resolution cell scatterers and complicated varying bistatic shadowing (bistatic SAR has double shadows).

2.7.4.2.4.1 Baseline & spatial

Due to turbulence or orbital mechanics there will always be a baseline between two SAR collections, this results in a decorrelation. The baseline factor $\gamma_{baseline}$ can be increased (brought closer to 1) through the process of removing radar data which is not part of the two image support overlap areas in K-space, when these are projected onto the ground surface plane. This is a process known as incoherent energy trimming [94], [134], [146], [150]

The baseline coherence can be represented in terms of ground-plane projected areas in K-space as follows for the monostatic case [146], and as is assumed to be valid for the bistatic case.

There are 3 regions in the K-space, these are shown in Figure 2.22. A_c or the common (overlapping) region, A_r the non-overlapping area of the reference image and A_m the non-overlapping area of the mission image. This overlap is dependent on the radar geometry, and there will be a set of geometries for which two collections overlap, but also a set of geometries where the overlap is zero. In order to perform interferometry, there must exist overlapping regions.

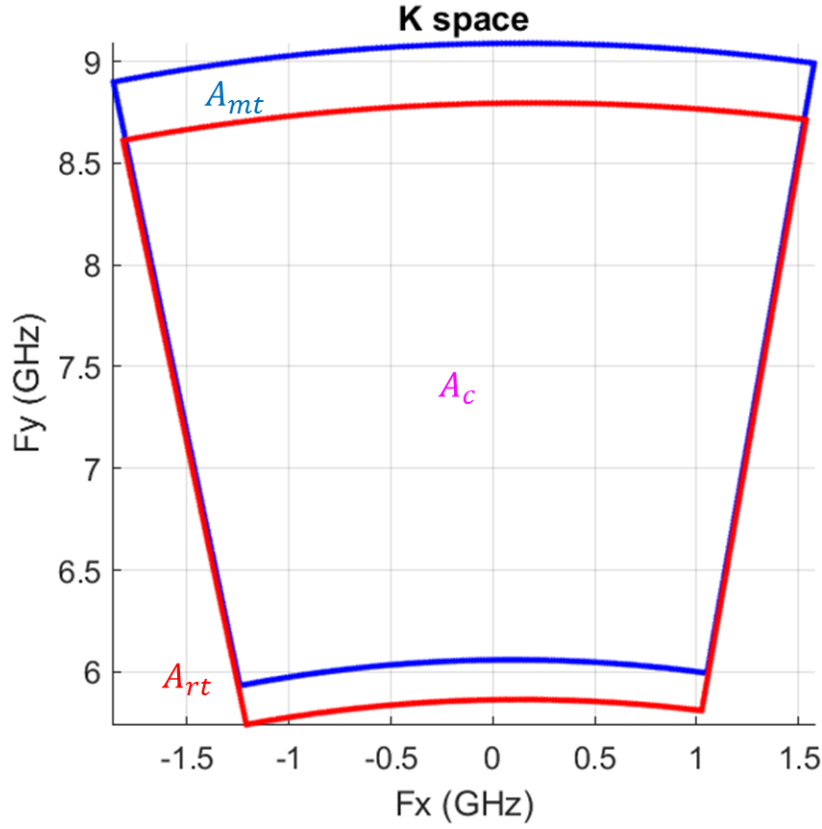


Figure 2.22 Diagram to give a visualisation of the overlap between two K-space segments.

$$\gamma_{baseline} = \frac{A_c}{\sqrt{(A_c + A_r)(A_c + A_m)}} \quad (2.62)$$

In situations where two images are produced with significant non-overlapping regions, the image processing is only performed on the regions that overlap. This does result in a loss of resolution. Additionally for near field scenarios, this will leave significant levels of incoherent energy in interferometric image pair as the overlap varies across the image.

Equation (2.62) can be rewritten to user terms representing the total mission and reference image support areas, which are shown in Figure 2.22.

$$\gamma_{baseline} = \frac{A_c}{\sqrt{A_{mT}A_{rT}}} \quad (2.63)$$

Where A_c is the common or overlapping region between the two projected image supports. A_{rT} and A_{mT} are the total K-space projected supports for the reference and mission images respectively [146], [151]. Another K-space projection is shown in Figure 2.23.

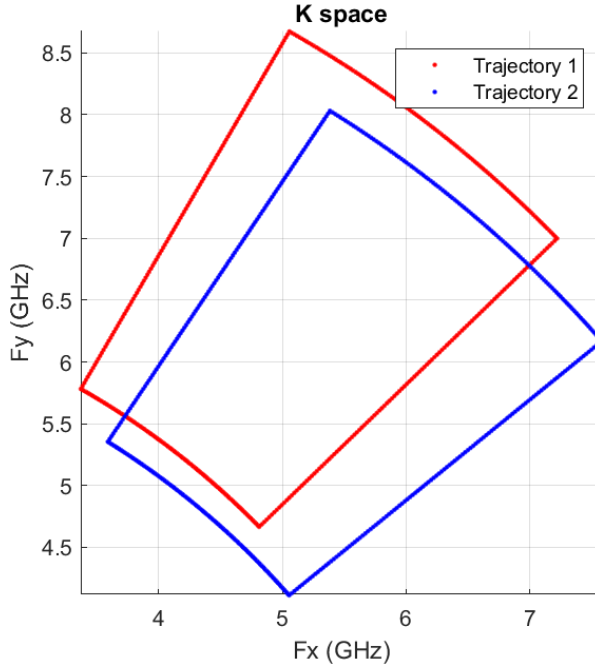


Figure 2.23 Figure showing the ground plane projection of two K-space annulus segments. The two trajectories were different, leading to a difference in location within the K-space. The frequency bands were kept the same. This results in areas of overlap and non-overlap.

If the target scene is non-flat then the baseline coherence needs to be calculated with respect to the normal of each resolution cell on the DEM [134], [135].

The Baseline factor can be split into two factors for an alternate method of calculation for the monostatic far field case. These are referred to as spatial and rotation parameters in the Zebker et al 1992 paper [153] and as along-track and across-track decorrelations in the Bickel 2014 paper [151]. These methods use the radar geometry and frequencies to calculate an estimate of the K-space overlap without plotting the K-space. These do need to be calculated for each pixel/resolution element for near field scenarios. However, as they are derived for the monostatic case they will not result in an accurate estimation of the baseline term.

2.7.4.2.4.2 Registration

In this thesis the $\gamma_{registration}$ term refers to decorrelations due to a difference in layover, the same definition as in [146]. This term is defined as being a function of the grazing angle and the height of the scatterers.

A difference in layover causes a scatterer to appear in a different location on the ground plane in the two images. In such a case it can have a major de-correlating effect, if the difference in layover is large (compared to the size of a resolution cell). For targets located on the ground plane there will be no layover effect [146]. Generally, an error less than 0.1 of the size of a resolution cell is deemed acceptable [146].

Estimating decorrelations due to errors in the ground truth is difficult however the Preiss et al. 2006 paper [146] shows a formula for the decorrelation due to different depression angles.

Consider a target is elevated with respect to the ground plane and lies at (x_s, y_s, h_s) that is imaged with a depression angle of ψ_1 . When projected onto the ground plane a layover effect occurs resulting in co-ordinates of $(x_s, y_s + h_s \tan \psi_1, 0)$. If the repeat pass images the scene with a different depression angle, then the ψ_2 elevated target appears at a different location on the ground plane. The resulting decorrelation can then be estimated [146] as:

$$\gamma_{registration} = \text{sinc} \left(\frac{h_s (\tan \psi_1 - \tan \psi_2)}{\rho_{res}} \right) \quad (2.64)$$

The resolution cell size is ρ_{res} . This means if the misregistration is equal to the resolution cell size, then the coherence for that pixel is zero. The result is that small changes in elevation leading to sub-resolution cell miss-registration will lead to a significant loss in coherence. This does reflect the sensitivity to change that CCD images demonstrate.

2.7.4.2.4.3 Scattering

The scattering term (γ_{scat}) is not seen in papers which cover coherence [95], [146], [153], [157], [174], [175], [176]. This is likely because the scattering term has a very minimal impact for monostatic collections with a good similarity or some bistatic collections [162]. These papers [95], [146], [153], [157], [174], [175], [176] do discuss incoherence

in terms of azimuth and elevation angles, however these equations include the range and cross-range resolutions. Thus, these are related to the spatial frequency overlap and are versions of the baseline factor shown in [146]. Additionally, these papers often approach coherence from a theoretical and mathematical (non-empirical) method. The laboratory environment, GBSAR, (see section 3.1) allowed the investigation of this term whilst eliminating many environmental and temporal effects found in outdoor datasets.

This term was the subject of several papers [162], [163], [177], and section 4 of this thesis.

Another element of the RCS is the polarisation. The four polarisations are scattered in different ways to each other [9], [178]. This means that the RCS term varies between polarisations [162], [163], [177].

For scenes with trees and other volumetric scatterers a component called *volumetric decorrelation* has been mentioned in Askne et al. 1997 [179]. This relates to the layover and misregistration, as volume scattering will cause an increased path length. The Askne et al. 1997 paper did use measured data, but as the authors noted, there would have been significant decorrelation from wind, rain and other natural processes. The SAR collections were also several days apart. Forested terrain is however exhibits different behaviour (volumetric decorrelation) to flat rough terrain [165], [166], [167].

2.8 SAR Speckle & Roughness

2.8.1 Roughness

A surface can be considered as behaving either smooth or rough to incident waves. In this simplistic behaviour model a smooth surface will reflect the wave based on the incidence angle, and a rough surface will reflect diffusely in all directions. A third case is also presented, which is a regime between a rough and smooth surface where there is a specular scattering component, but also diffuse scattering. These scattering types are shown in Figure 2.24.

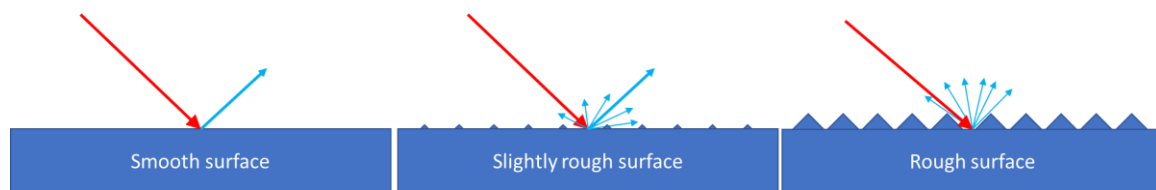


Figure 2.24. Diagram depicting scattering from a smooth and rough surface.

Understanding these scattering mechanisms helps explain what is seen in SAR images. The concrete floor of the GBSAR laboratory, or the ocean can typically be seen as smooth, or mostly smooth surfaces. As such these areas reflect very little energy towards the receivers (even in the bistatic case), and as such have a lower SNR. This scattering behaviour can have useful in some applications however such as the detection of oil slicks on the ocean [180], [181].

Whether a surface is considered ‘rough’ is dependent on its dimensions in relation to the incident wavelength [182].

2.8.1.1 Rayleigh roughness criterion

A rule of thumb that is often used is that a surface is considered smooth if the surface variation is around $\lambda/10$, where λ is the wavelength.

A more precise formula (the Rayleigh roughness criterion) can be used which accounts for the incidence angle (θ). This formula was derived from a book by Lord Rayleigh in 1877 [183], [184], [185].

Thus, a surface would be considered rough based on the following formula:

$$\Delta h > \frac{\lambda}{8 \cdot \cos \theta} \quad (2.65)$$

Where, Δh is the surface height variation, λ the wavelength and θ the incidence angle.

2.8.2 SAR Speckle

As was shown in section 2.7.3, each pixel in a SAR image contains many individual scatterers. Each of these provides a contribution to the phase of the returning waveform. [146]:

$$I(x, y) = \sum_{k=1}^N A_k \exp(j\phi_k) \quad (2.66)$$

With the phase of each pixel being a result of its total travel path.

The intensity distribution of speckle follows the negative exponential (section 2.8.2.1) if the surface is considered rough.

2.8.2.1 Statistics of SAR speckle

A surface which is rough will appear speckled. The idealised Probability Density Functions (PDFs) of Rayleigh SAR speckle amplitude and intensity can be described by formulae.

The intensity is equal to the amplitude squared $|I| = |A|^2$. The PDF of the amplitude conforms to the Rayleigh distribution [186]. This distribution can be described as:

$$P(|A|) = \begin{cases} \frac{|A|}{b^2} \exp\left(-\frac{|A|^2}{2b^2}\right) & |A| > 0 \\ 0 & \text{Otherwise} \end{cases} \quad (2.67)$$

Here b is a parameter of the distribution. The Rayleigh distribution is a special case of the Weibull distribution [187]. The parameters A and B (sometimes α and β) are specified as $A = \sqrt{2}b$ and $B = 2$.

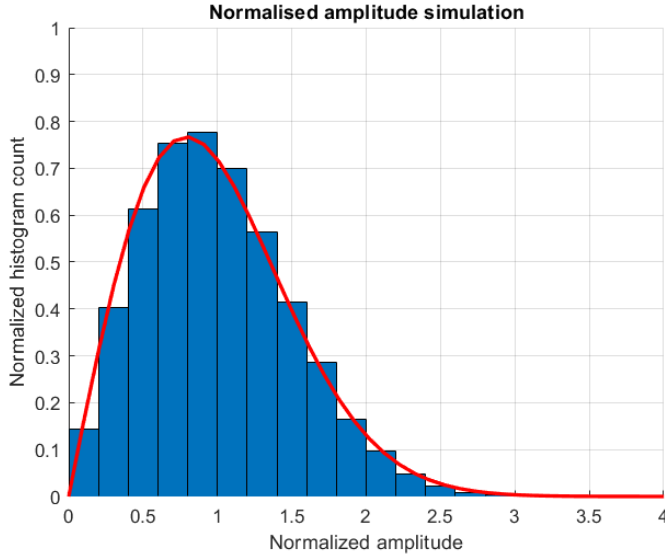


Figure 2.25 Normalised amplitude distribution (histogram) for an isotropic simulation and Rayleigh distribution (red).

The PDF of the intensity conforms to the negative exponential distribution. The equation for this distribution is shown below [94], [188], [189], [190].

$$P(|I|) = \begin{cases} \frac{1}{\langle |I| \rangle} \exp\left(-\frac{|I|}{\langle |I| \rangle}\right) & |I| > 0 \\ 0 & \text{Otherwise} \end{cases} \quad (2.68)$$

Here $|I|$ is the intensity only SAR image and $\langle |I| \rangle$ is the mean intensity [94], [188], [189], [190]. The distribution of an isotropic simulation is plotted in Figure 2.26 [163]. This simulation produced an intensity distribution which follows the negative exponential distribution (red line) closely.

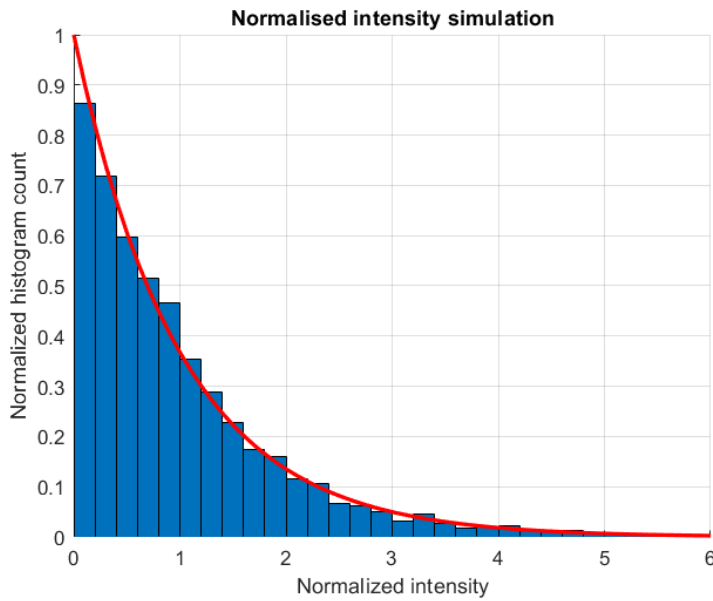


Figure 2.26 Normalised intensity distribution (histogram) for an isotropic simulation and negative exponential distribution (red).

2.8.3 Reflectivity and RCS

The response a SAR system receives is dependent on a number of factors. First is the beam shape of the antenna and the imaging geometry, which has a particularly profound effect for near-field imaging where there is not an even power distribution over the imaged scene.

Then the target characteristics such as Radar Cross Section. This is a function of the incident and azimuth angles, frequency and the polarisation.

Perhaps the most recognisable feature of radar images is the ‘speckle’. This is a grainy texture over images, which can make them seem less sharp. Whilst it may have the appearance of random noise it is deterministic. SAR speckle arises from constructive and destructive interference as the image is formed. As such it is not referred to as noise. A scene is made up of many small targets, these can be individual stones in gravel, twigs and leaves. What is important to note is that many of these scatterers are very small, smaller than the resolution of the radar. This means that within every resolution cell the number, type and arrangement of scatterers varies. Whatever signal that returns is the

coherent combination of the returns from all the scattering elements within that resolution cell. This means if an image were being taken of a field of grass, a fairly homogenous area to an optical system, the variation in the blades of grass would lead to a speckled appearance in radar.

The backscattered response of an incident signal is a function of:

- Imaging geometry [106], [191], [192], [193]
 - Near field or far field
 - target orientation
 - incidence and azimuth angles
- Target characteristics [192], [194]
 - Materials (absorption or reflectivity)
 - surface roughness
- Wave characteristics [192], [193], [194]
 - Frequency
 - Polarisation

Due to these factors two SAR images of the same scene taken from different imaging geometries, or with different polarisations or frequencies will look substantially different. Such images would have a reduced coherence.

2.8.4 Speckle pattern and k-space trimming

Whilst speckle is demonstrably not random noise, it can have some characteristics of random noise (such as a Rayleigh distribution), where a uniform surface will still exhibit variation in intensity. However, unlike noise it is reproduceable, with images produced with the same geometry having the same speckle. However since it is not possible to repeat a pass exactly outside a laboratory environment, methods of reducing speckle may be used. These might include multilooking (averaging over n pixels) or incoherent energy trimming. The result may improve the interpretability of the SAR image but will also result in a loss of resolution.

This is demonstrated below using simulated SAR images. In Figure 2.27 SAR images are presented for two SAR images with a significant along track baseline. The speckle pattern between these is significantly different. This can be seen in the CCD image presented in Figure 2.28, where the coherence is 0.72.

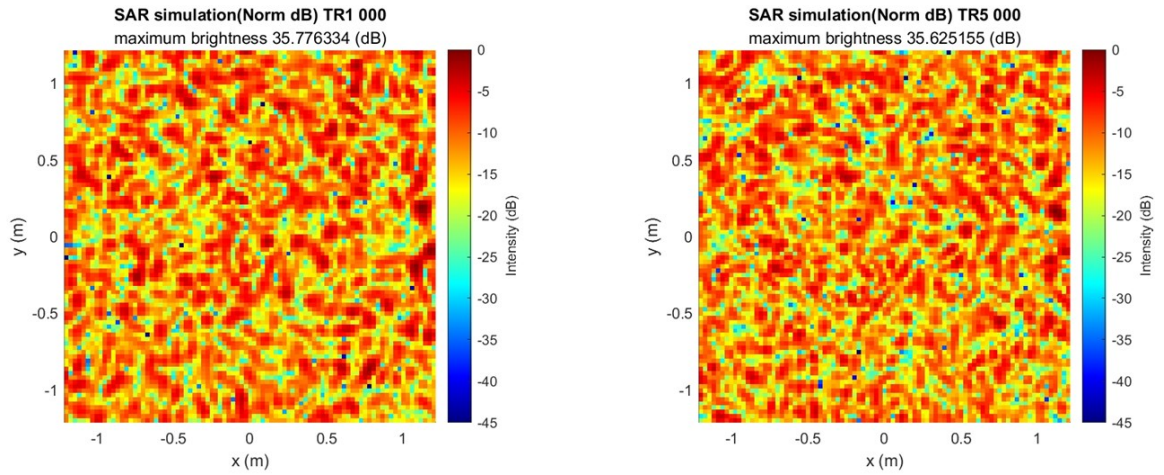


Figure 2.27 Simulated SAR images with an along track baseline. Images are normalised.

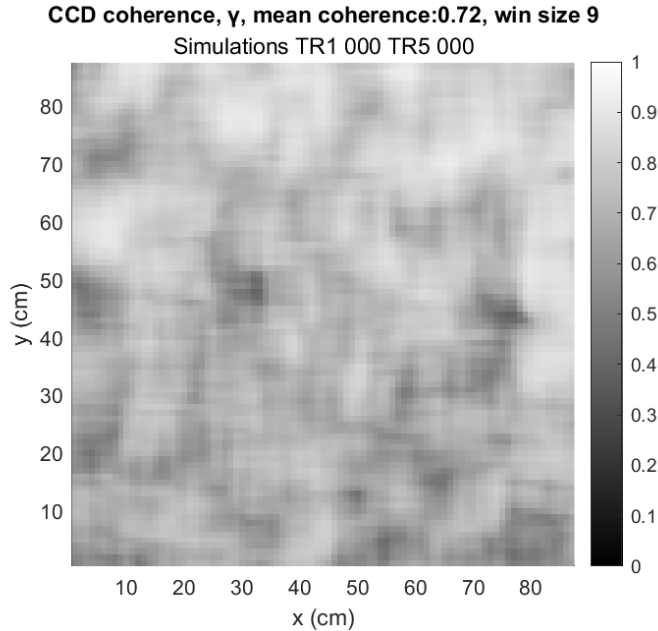


Figure 2.28 CCD image of the untrimmed SAR images (Figure 2.27).

The practical implementation of the SVIT process is explained in the methodology chapter, section 3.2. To show the effect of the SVIT process on coherence and speckle

the following figures are presented. The SVIT process was then applied to the two SAR images which resulted in Figure 2.29. Here the speckle pattern is visually much more similar, and this results in a much higher coherence of 0.96 shown in Figure 2.30. This value does not reach one due to the discrete, pixelized nature of the SVIT process.

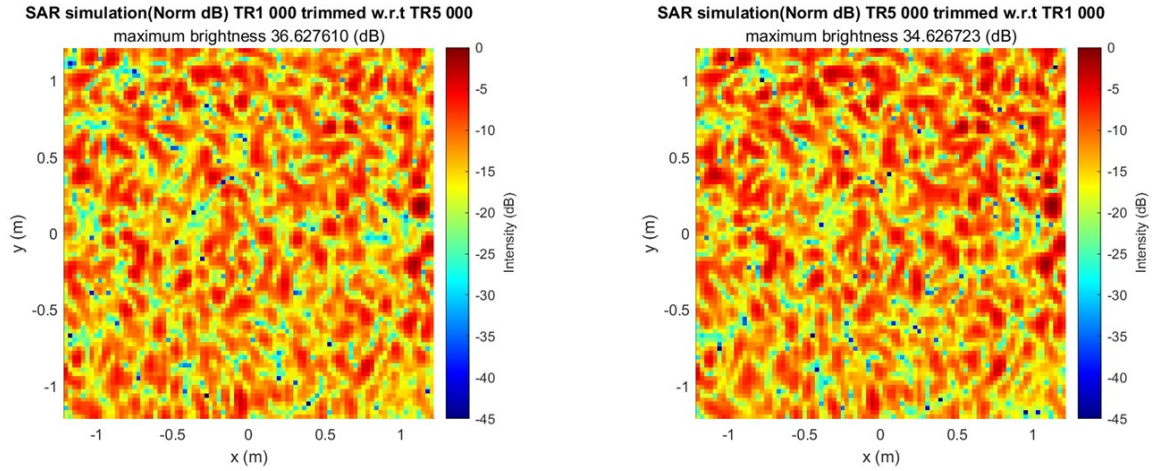


Figure 2.29 Simulated SAR images after the SVIT process. Trajectories have an along track baseline. Images are normalised.

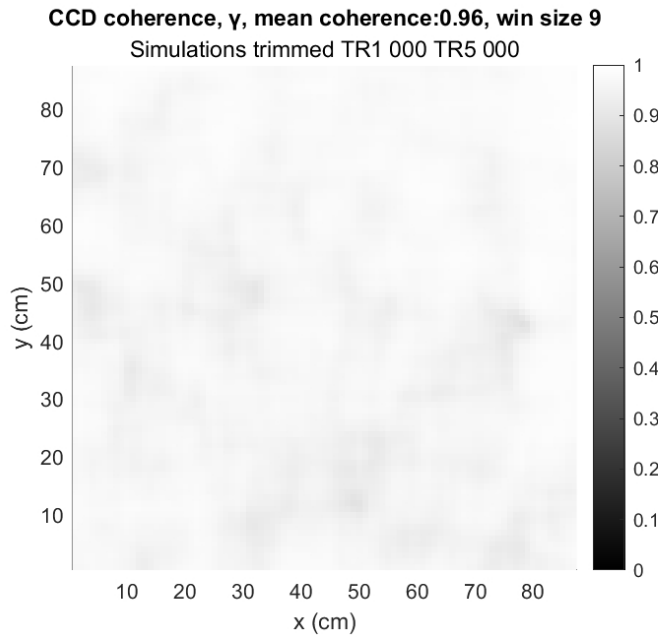


Figure 2.30 CCD image of the trimmed SAR images (Figure 2.29).

2.9 Polarimetry

Radar polarimetry uses the vector nature of electromagnetic waves to produce and analyse images. The main benefit of partial or fully polarimetric data collections is that the additional information provides a more detailed characterisation of the scatterer or target [8], [9], [195], [196], this is because the scattering of a target is dependent on the polarisation and imaging geometry [150], [197]. Multiple polarisations are sometimes referred to as polarimetric diversity. A multi or fully polarimetric SAR system is more complex and energy intensive.

According to the IEEE (Institute of Electrical and Electronics Engineers) definitions [198], the polarisation of a wave is defined as follows:

“Polarization of a wave (radiated by an antenna in a specified direction). In a specified direction from an antenna and at a point in its far field, the polarization of the (locally) plane wave which is used to represent the radiated wave at that point.”

This standard goes on to describe that the direction of polarisation is defined by the direction and magnitude of the polarisation vectors. These directions might be constant (as is the case with linear polarisations) or varying with time which leads to elliptical or circular polarisations.

Polarimetry is an important aspect of imaging radar because it provides additional information about the targets and how they interact with incident microwaves [8], [9], [178]. Polarimetric change detection is discussed in section 2.10.1.

2.9.1 Polarisations and wave theory

Electromagnetic waves can be decomposed into vertical “V” or horizontal “H” polarisations (for linearly polarised waves). These are orthogonal to one and other. There are four linear polarisations. VV, VH, HH and HV. These are termed co-polar (VV and HH) when the polarisations are the same and co-polar (VH and HV) when they are

different. The nomenclature is to write received-transmitted. So, a VH polarisation would be transmitted in horizontal and received in vertical.

There also exists elliptical and circular polarisations, however the GBSAR system only utilises the linear polarisations.

These polarisations are however not globally defined and are dependent on the local transmitter and receiver orientations, this makes polarimetry more difficult in bistatic and multistatic scenarios [150], [199], [200]. The horizontal and vertical components will however always be orthogonal to one and other.

2.10 Multichannel SAR Interferometry

A *multidimensional* SAR collection might be multistatic, multipass, multi-band or multi-polar. Multidimensional change detection describes a scenario where several change detection images are available for the same change and area. In this thesis, the dimensions for the multistatic data consist of multiple bistatic collections and four polarisations. In such scenarios the stack of change detection images may be combined in different ways, some of which are detailed below. Some multidimensional change detection images may be hyperspectral, using images from different frequency bands, such as radar, visible and Infrared.

2.10.1 Polarimetric Interferometry (Pol-InSAR)

Polarimetry was discussed in section 2.9. Polarimetric interferometry (Pol-InSAR) combines Interferometry with polarimetry (section 2.7.3.2.4). This may improve aid in their identification and/or classification of changes in the scene [8], [9], [201], [202].

Polarimetric interferometry might use SAR images created with polarimetric decompositions or that are of a single polarisation. If different polarisations are used in a CCD comparison (such as one image being VV and the other HH), then the coherence will be lower [9]. Such decompositions can indicate the type of target being imaged[203], [204], such as in [202], where false colour images clearly discriminated trihedral from the forest canopy. A well known example of this is the SAR images of the San Francisco bay area and golden gate bridge. Where areas of water, buildings and vegetation are clearly discriminated in false colour polarimetric imagery [205].

When performing change detection on SAR images formed using polarimetric decompositions the result is an image of changes for a scattering mechanism. This may aid in understanding what the change has been caused by.

If only single polarisations are considered, then multiple CCD images are created. This can allow for multidimensional CCD. These CCD images typically exhibit significant variation in coherence compared to one and other [9], [201]. This was discussed in section 2.7.3.2.4 and [162], [163], [177] where the coherence varied across polarisations. CCD

images produced with two collections of different polarisations offer very poor images with a high degree of decorrelation [206].

This variation is shown in Figure 2.31. This is an RGB (Red Green Blue) image formed using 4 four CCD images. The red channel uses the VV CCD image, the blue uses the HH CCD, and the green channel is an average of the cross polar channels, $(HV+VH)/2$. In the resulting image there are white areas, these represent areas of high coherence across all polarisations. Darker areas represent poor coherence across the polarisations. Then there are areas of magenta and light green, and some orange and yellow. These are areas where the coherence varies across polarisations.

CCD, Polarised, mean coherence: 0.93, win size 5

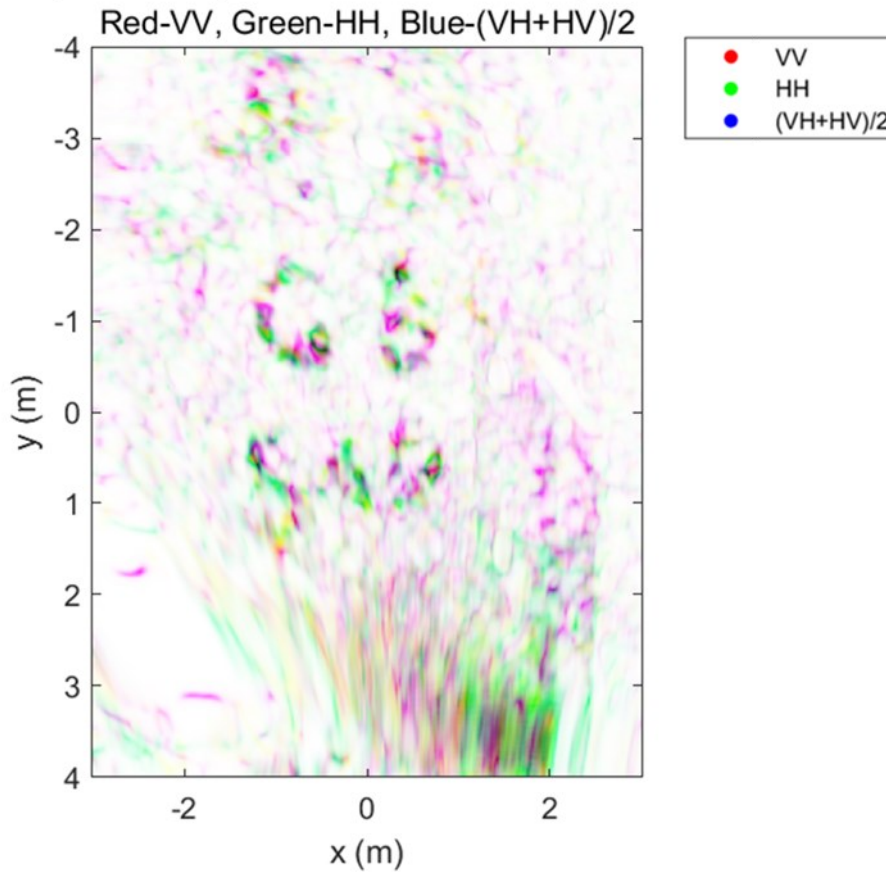


Figure 2.31 Multichannel CCD image formed using real data from polarised SAR images. The data used was bistatic, with both collections using receiver 1. This image illustrates the variation of coherence depending on polarisation. There is a large smear towards the lower edge of the screen, this is likely from antenna cross talk, and the low SNR of the concrete floor.

2.10.2 Multifrequency

As shown in [136] a CCD a composite CCD image can be formed using RGB values for the coherence values for different sub-bands. In this paper 3 sub-bands were used to form 3 sets of SAR images. CCD analysis was then carried out resulting in 3 CCD images. This could then be used to produce the composite RGB images.

2.10.3 Multistatic/ Multipass

Single Input Multiple Output (SIMO) and Multiple Input Multiple Output (MIMO) SAR are cases of multichannel SAR. SAR systems that utilise MIMO or SIMO tend to combine the channels into a single SAR image [207], [208], [209]. A multistatic SAR image would be formed in such a manner [210].

Multiple passes can also be combined after the CCD process has been carried out [211]. In this paper multiple change detection images had a threshold applied and then were combined. In the results of the paper this showed a decrease in the number of false alarms. The possibility of improved CCD performance and false alarms have been demonstrated in several papers investigating multistatic or multiangle SAR [118], [212]. Another paper [98] showed an improved change detection performance by using images from several passes (multi-temporal) to detect decorrelations after an earthquake. The SAR images in this paper were collected between February and October (2016) and as such exhibited low coherence. This resulted in individually poor change detection images. Forested, rural and agricultural areas in the scene had particularly poor coherence, however permeant scatterers such as buildings maintained a higher coherence, and damage to these could be identified.

Binary change detectors, which label the final change detection image pixels as either changed or unchanged can also be used for multidimensional SAR [213]. This paper aimed to improve the change map iteratively using the multichannel data.

Some papers have demonstrated multistatic change detection. A series of papers produced in the period 2012-2016 [214], [215], [216]. In these papers the authors performed a series

of experiments showing multistatic change detection. Unlike in SAR where the antennas are moving, the 4 antennas were in fixed positions. This meant that the results produced did not look like traditional CCD images. These papers did however show that it was possible to detect large scale changes within a scene, such as cylinders placed on the ground [215], [216] or a tree moving significantly and a person appearing [214]. These papers did not cover multistatic synthetic aperture CCD but do show the possibility of multistatic change detection.

Other papers form multistatic images using a stationary ground-based receiver and Global Navigation Satellite Systems (GNSS) satellites as moving transmitters. In [105] such images were formed. The SAR images exhibited very poor range resolution due to the low bandwidth of the GNSS signal. A change was introduced by moving the receive antenna, which would result in changes across the entire scene. This methodology was designed to demonstrate the feasibility of using a GNSS based passive SAR to monitor areas of ground for movement.

2.10.3.1 Probabilistic three pass model

Probabilistic models can be used in clutter suppression as seen in [217], [218]. This paper sought to use two CCD images, formed using three passes over a region of interest. The final product of the algorithm is a probability map that there is a change in the second CCD image, given the two CCD images [217]. It does however require the probability density functions in the two CCD images to be the same, which may not be valid when the two CCD images are formed using significantly different trajectories.

Other methods, in this case for Synthetic Aperture Sonar (SAS) uses a reference and mission change detection image (requiring three passes) [219]. Two passes are over the ‘unchanged scene’ (although there will be a significant number of changes due to natural processes) and a pass after the change has occurred. The two change detection images are then compared to produce a reduced clutter change detection image.

3 Methodology (general)

3.1 GBSAR laboratory

The Ground Based Synthetic Aperture Radar (GBSAR) laboratory is part of Cranfield University and located at the Defence Academy of the United Kingdom in Shrivenham. It allows for data collection within an 8 m by 8 m area. The controlled environment protects against unwanted scene changes, and the high repeatable precision allows for multistatic or repeated measurements. The GBSAR laboratory is shown in Figure 3.1



Figure 3.1 Image showing the GBSAR laboratory and scanning system with a gravel scene.

The GBSAR scanner system is a custom-built apparatus. It controls the position of two antennae within two dimensional rectangular apertures with finer than 1mm accuracy for positioning.

The hardware employed for the GBSAR laboratory measurements included:

- Two pairs of antenna horns:
 - A-Info UWB dual polarisation Antenna horns, 1–10 GHz, LB-SJ-10100, for the 6.6-10 GHz measurements
 - A-Info UWB dual polarisation Antenna horns 2-18 GHz, LB-SJ-20180, for the 8-12 GHz measurements.
- Vector Network Analyser (VNA)
 - Initially an Agilent (now Keysight) model N5230A VNA for the 6.6-10 GHz measurements.
 - This was upgraded to a Keysight model N5225B VNA for the 8-12 GHz measurements.
- Microwave cables with sufficient length for bistatic positioning,
- Hewlett Packard wide band microwave amplifier connected to the receive VNA port for the 6.6-10 GHz measurements, although not needed for the upgraded VNA which contained amplifiers.
- Two, Two-dimensional vertical plane positional scanner in system,
 - The first two-axis scanner, generally with just the transmitter, but also taking the receiver for monostatic scans, allowing positioning in a vertical rectangle 3500 mm in the horizontal and 1460 mm in the vertical;
 - The second two-axis scanner, generally with just the receiver, allowing positioning in a vertical rectangle 2400 mm in the horizontal and 1460 mm in the vertical.
- Two scanner controller boxes, each controlling one of the two-axis scanners.
- Control and data recording computer connected to the VNA and the two scanner controller boxes.

The antenna horns are shown in Figure 3.2 and Figure 3.3.

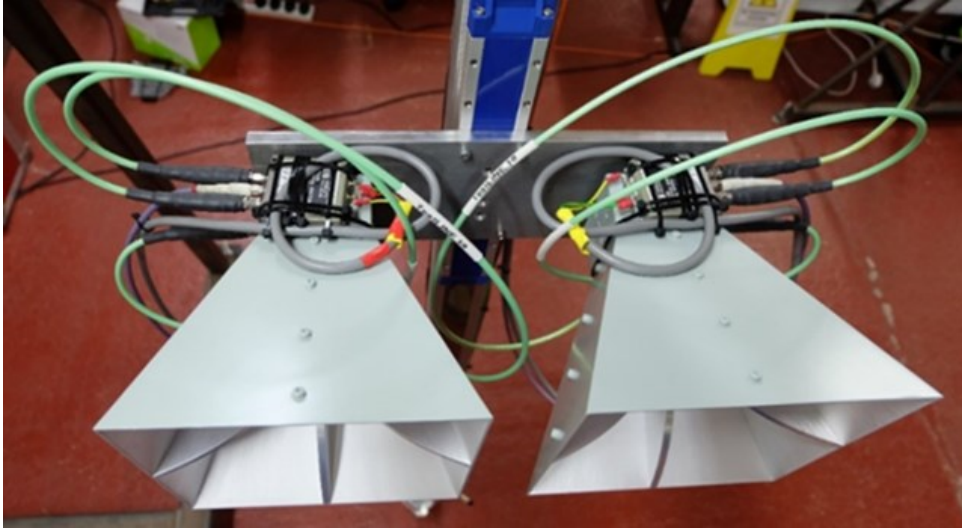


Figure 3.2 A-Info 1-10 GHz dual polarisation horn antennas setup in a monostatic configuration.



Figure 3.3 A-Info 2-18 GHz dual polarisation horn antennas setup in a monostatic configuration.

The measurements used in this thesis used data collections with frequency bands of 6.6 - 10 GHz and 8 - 12 GHz. The bandwidth (and resolution) chosen were higher than would be possible in a practical system, however this was done to ensure fully developed speckle

over the scenes. The Antennae can be mounted in a bistatic or a pseudo monostatic configuration. When in a bistatic configuration, each antenna is mounted on a different two-dimensional vertical SAR aperture scanner. One SAR aperture is 3.5 m wide by 1.46 m high, mounted on a brown frame, and the other is 2.4 m wide by 1.46 m high, mounted on a yellow frame.

Coherent summation is a process where multiple coherent images are added, in some cases they are divided by the number of images to result in an average value. Coherent means that the phases are added, not just the amplitude. This process allows a bistatic setup to be used to produce multistatic SAR images [220] and is shown in Figure 3.4.



Figure 3.4. This image was taken from behind the transmitter (labelled Tx) and shows a bistatic configuration (receiver is labelled Rx). Two steel frames can also be seen (one brown and one yellow), these hold two motorised rails which allow the antenna horns to move within their two-dimensional apertures. The scene in the image consisted of a gravel rectangle, with metal spheres around to aid in image alignment and quality assurance.

Many simulations use a ‘*start stop approximation*’, where the radar pulses are transmitted and received at discrete points along the trajectories. For simulations it was seen as a reasonable simplification, but in the case of the laboratory it was how the system was designed. The transmitter and receiver both move into position before pulses are transmitted. The SAR images generated are equivalent to those produced by a constantly moving SAR system, however it allows for precise knowledge of the radar positions in a controlled environment.

3.1.1 Time and position synchronisation

Because the GBSAR system operates in a discrete time manner, the location of each antenna during transmission and reception is very precisely known within the local antenna axis. This needed to be translated into a three-dimensional co-ordinate frame. Because of the flexing and warping of the rails as the antenna moves the ground truth is not fully accurate and does include some inaccuracies in the order of millimetres. This will lead to some very minor misregistration of the images.

The pulses however are discrete, and the antenna does not transmit continuously. This meant that the radar positions matrix could be precisely matched up with the phase history matrix. In an operational multistatic system this would be more complicated and require a highly accurate series of clocks and navigation systems.

3.1.2 Bistatic processing

The BPA was introduced in section 2.3.1. The BPA algorithm was generalised for bistatic radar trajectories. This was done by having a separate set of co-ordinates for the transmitter and receiver, which were then used to calculate ranges. This results in ellipses of equal range rather than circles.

3.1.3 Errors and Decorrelations

3.1.3.1 Multipath

The GBSAR laboratory provides a controlled environment for repeated measurements, where natural decorrelations such as wind and rain are not a factor. Multipath however is an issue. A gravel scene is shown in Figure 3.5, as well as a corresponding SAR image in Figure 3.6. Gravel was chosen as the scene because of its small size there would be many scatterers per resolution cell. The gravel scene is outlined in white, and the gravel multipath in cyan.

The gravel scene in Figure 3.5 was aligned with the transmitter rail. In Figure 3.6 the multipath overlapped a significant portion of the gravel leaving a 3 m x 1 m rectangular area of gravel which could be used for calculating coherence.



Figure 3.5 Photograph of large rectangular gravel region which was aligned with the transmitter (brown) rail. The receiver was mounted on the yellow rail.

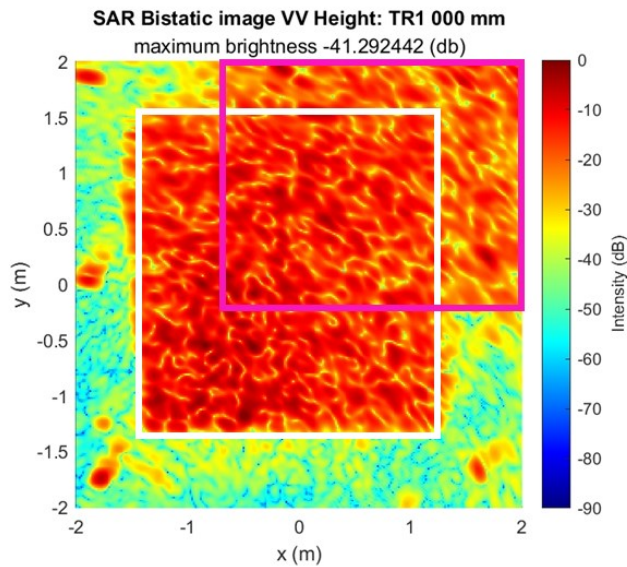


Figure 3.6 SAR image of the gravel region shown above. The gravel region is shown by the white outline, and the multipath is outlined in cyan.

The multipath was shifted back with respect to the BEM ‘boresight’ direction, as such subsequent experiments used rotated gravel, aligned with the BEM. This allowed for a larger ROI which was spatially separated from the multipath. This rotated gravel is shown in Figure 3.7. The resulting SAR image is shown in Figure 3.8.



Figure 3.7 Photograph of a rotated rectangular gravel region which was aligned with the BEM.

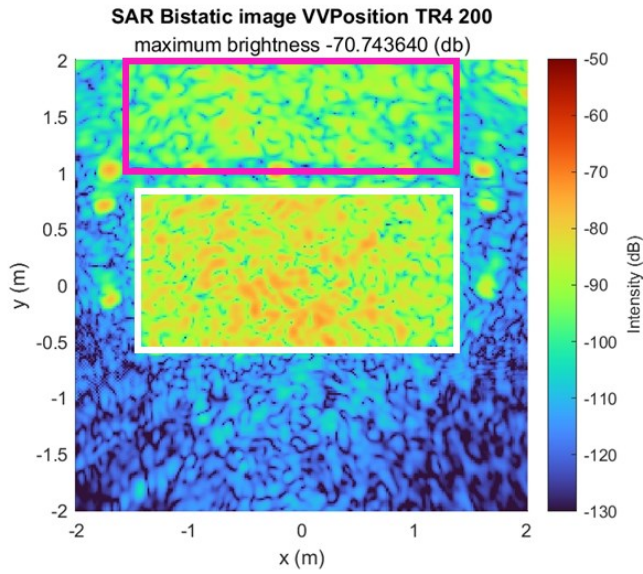


Figure 3.8 SAR image of the gravel region shown above. The gravel region is shown by the white outline, and the multipath is outlined in cyan.

3.1.3.2 SNR and background subtraction

Estimates for the SNR of the SAR images were carried out and used in a journal paper [163]. In this paper two scenes were used. Each was surrounded by spheres and top hat scatterers which were used to verify the alignment of the SAR images and ensure a correct ground truth.

The first scene was shown in Figure 3.9 and is a rectangle of gravel (2.7 m x 1.5 m). The gravel consisted of ≈ 1 cm sized pieces of gravel, significantly smaller than the resolution cell size. A rectangular area (1.5 m x 1.4 m) was used for the calculation of coherence and will be referred to as the Region Of Interest (ROI).



Figure 3.9 Image showing the gravel rectangle. The alignment spheres and top hat scatterers are shown.

The second scene was a rectangle (1.6 m x 1.5 m) of densely packed stones (Figure 3.10). This scene was less wide than the gravel scene, but encompassed the whole ROI used for this investigation.



Figure 3.10 Image showing the stone rectangle. The alignment spheres and top hat scatterers are not shown in this image but were located in the same positions as in the gravel scene.

In order to improve the Signal to Clutter Ratio (SCR) and estimate the Signal to Noise Ratio (SNR), background subtractions scans were carried out. A background subtraction was a scan of the laboratory without the gravel or stones in the scene. This was possible due to the high accuracy and repeatability of the GBSAR system.

From these images the SCR was estimated as 21 dB for the gravel and 25 dB for the stones. This clutter represents scattering from the laboratory floor and multipath. This clutter was however removed by the background subtraction. Some multipath remains visible, which is from the stones and gravel, and cannot be removed with a background subtraction. However, the geometry of the gravel and stones was such that the multipath appears behind the scene and away from the ROI.

The SNR was estimated as 30 dB for the gravel and 38 dB for the stones. SAR images for the gravel are presented in Figure 3.11 and Figure 3.12. The stone scene SAR images are presented in Figure 3.13 and Figure 3.14.

These high values of the SNR correspond to high values of γ_{SNR} (section 2.7.4). Using equation (2.59) γ_{SNR} was estimated at 0.967 and 0.974 for the gravel and stones respectively. This shows that for the GBSAR laboratory the SNR results in a very small decorrelation that is insufficient to significantly impact the coherence results.

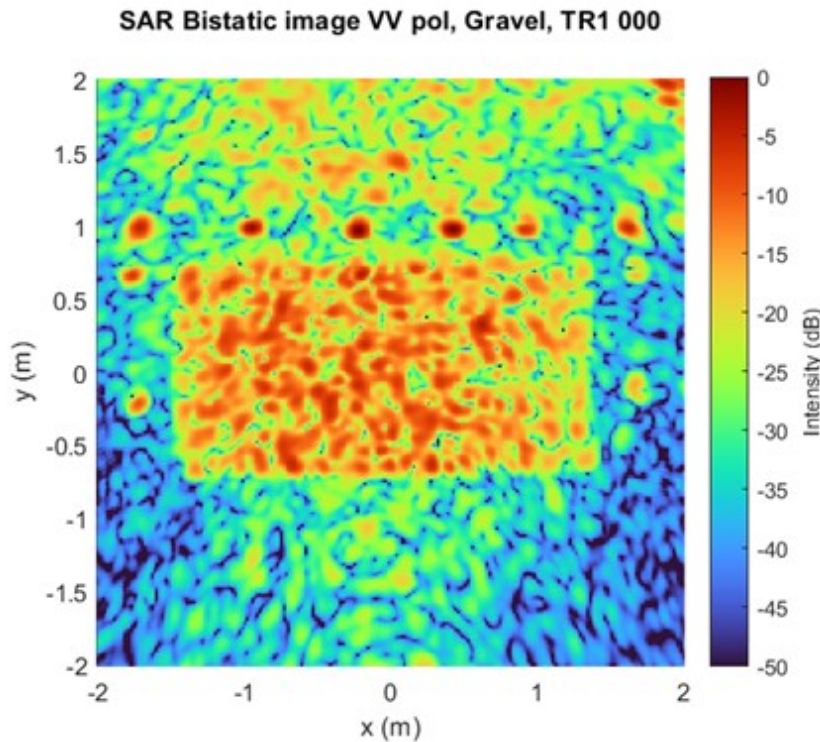


Figure 3.11 SAR image (formed using the VV polarisation and TR1 000) of the gravel scene (Figure 3.9) prior to the background subtraction. The SAR image is normalised.

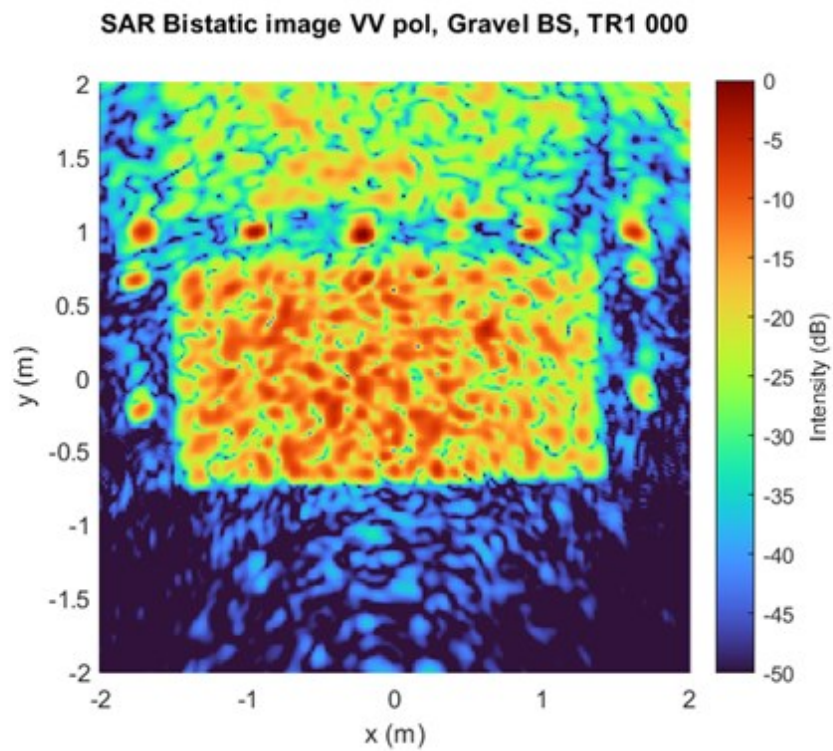


Figure 3.12 SAR image (formed using the VV polarisation and TR1 000) of the gravel scene (Figure 3.9) after to the background subtraction. The SAR image is normalised.

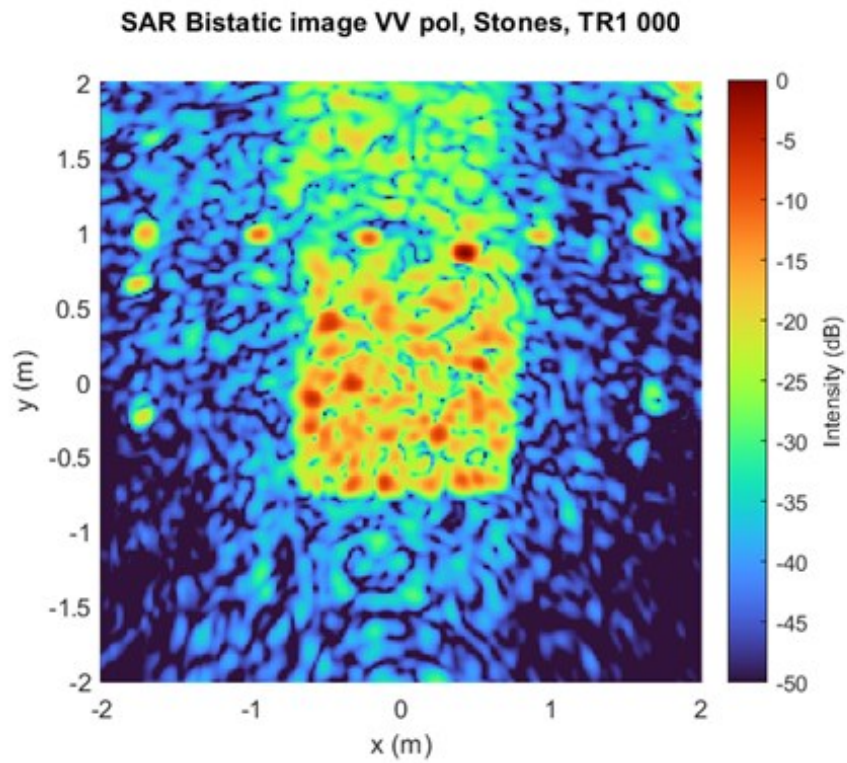


Figure 3.13 SAR image (formed using the VV polarisation and TR1 000) of the stone scene (Figure 3.10) prior to the background subtraction. The SAR image is normalised.

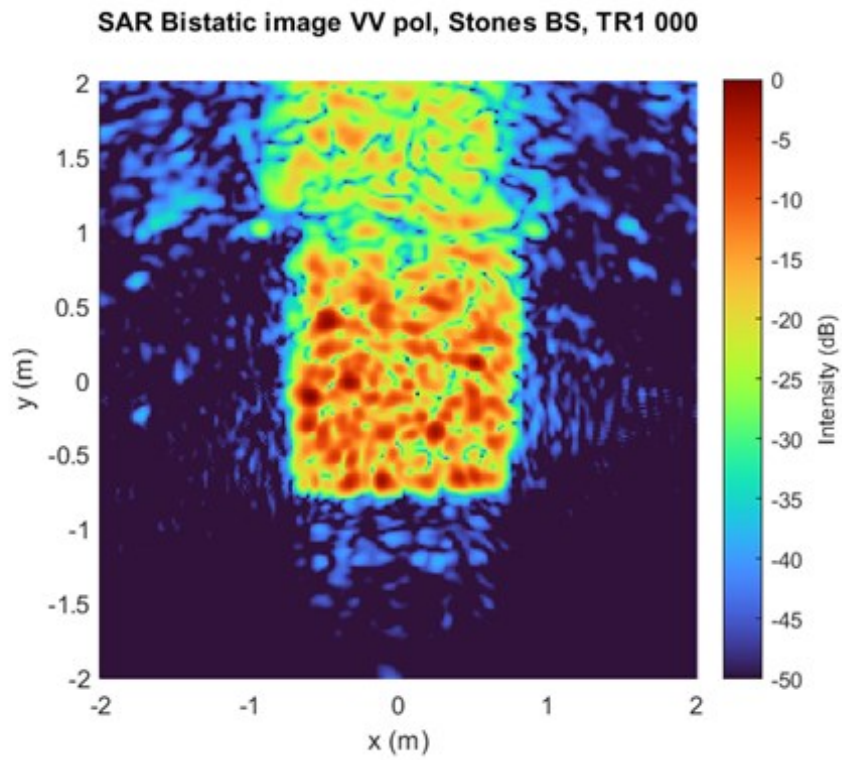


Figure 3.14 SAR image (formed using the VV polarisation and TR1 000) of the stone scene (Figure 3.10) after to the background subtraction. The SAR image is normalised.

3.2 SVIT

As discussed in section 2.5, spatial frequency domain projections of the radar collection data vary substantially across the scene when in the SAR near-field. Hence the calculation of $\gamma_{baseline}$ should be performed in a spatially variant manner. Additionally, Spatially Variant Incoherence Trimming (SVIT) can be implemented for increased coherence between images [10], [97], [131], [132], [133], [134]. The SVIT process was outlined in section 2.5.2. It was used in several papers to calculate the $\gamma_{baseline}$ values and to produce ‘*trimmed*’ images. In this manner the effects of $\gamma_{baseline}$ on coherence could be removed.

The SVIT process omits / removes incoherent energy from the non-overlapping PFS data for each SAR image pixel for both SAR collections, during the image formation stage, resulting in two SAR images with greater coherence between them. The PFS areas alone are used to calculate $\gamma_{baseline}$.

Figure 3.15 and Figure 3.16 are outputs from the SVIT algorithm corresponding to the laboratory measurements undertaken, showing the PFS outlines of a master and reference image for a single point in the scene, plotted in red and blue respectively. These images compare the K-space overlap of SAR geometries TR1 000 and TR4 000, which were used in paper [163] (see section 4.2.2.2, page 119). The greyscale figure backgrounds show a running sum of the intersecting PFS regions, in Figure 3.15, and non-intersecting, in Figure 3.16, where each PFS contributes values of one to the summation image (which is then normalized). The figures show significant variation in k-space of overlapping and non-overlapping regions as a function of scene position (or SAR pixel position).

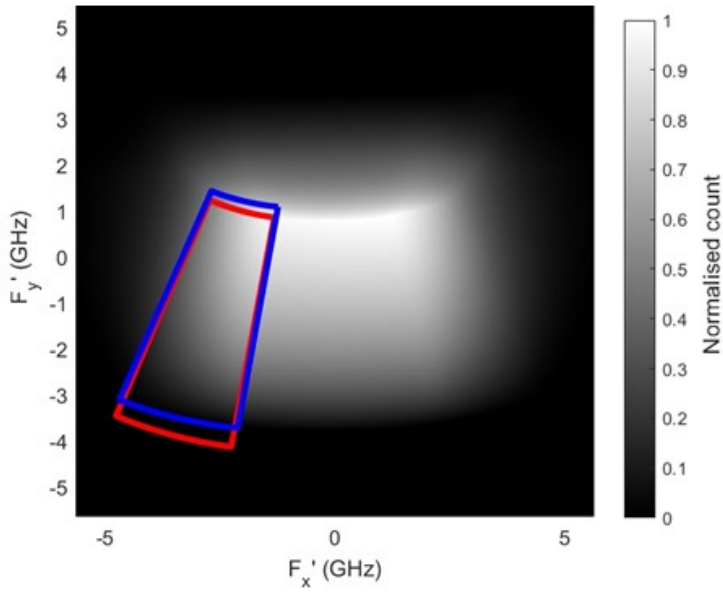


Figure 3.15 SVIT algorithm output for TR1 000 and TR4 000. The red and blue lines show the PFS for the reference and mission collections for a single scene position and collection pair. The grayscale background shows the sum over the scene of all intersecting regions, each given a value of 1.

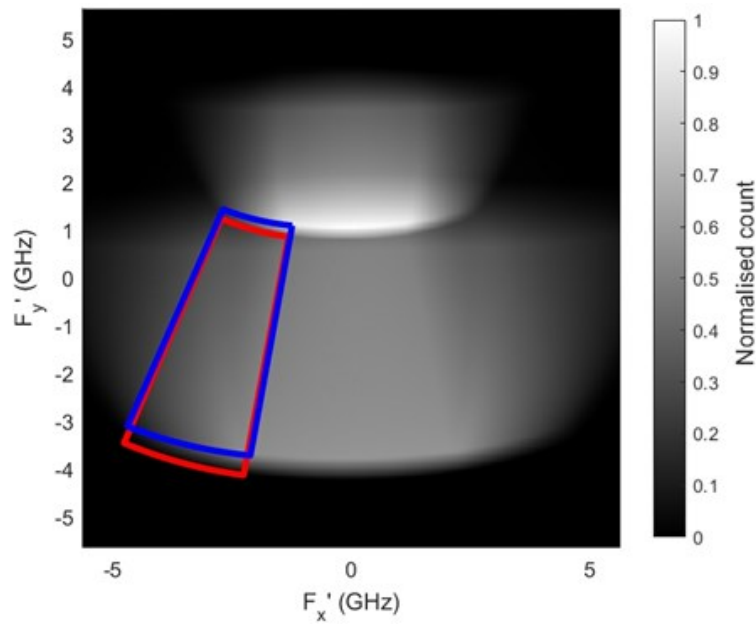


Figure 3.16 SVIT algorithm output for TR1 000 and TR4 000. The red and blue lines show the PFS for the reference and mission collections for a single scene position and collection pair. The grayscale background shows the sum over the non-intersecting regions, each given a value of 1.

3.3 Performance metrics

The performance metrics in this section have been applied to a wide variety of applications such as weather forecasting or neural network evaluation [221], [222], [223], [224].

3.3.1 Confusion matrix and master images

Many of the performance metrics are defined using a confusion matrix, sometimes called a contingency table. An event is defined, usually as exceeding a set threshold. Then two datasets are compared. A master which defines whether an event was observed/occurred or not, and a test dataset which is compared against the master. This matrix is shown below in Table 3-1. Here T and F mean true and false respectively, and P and N mean positive (change) and negative (no-change) in the CCD image [221], [223].

Table 3-1 Confusion matrix, showing the conditions that correspond to TP, TN, FP and FN.

Confusion Matrix		Event Observed	
		Yes	No
Event Forecast	Yes	TP	FP
	No	FN	TN

Using a confusion matrix (Table 3-1). Performance metrics such as the Probability of Detection (POD), Critical Success Index (CSI) and the False Alarm Ratio (FAR) can be calculated and used in the evaluation of CCD images [221], [223], [224], [225], [226], [227], [228].

A master image (or dataset when predicting storms) is used. As these have a range of values a threshold is set to determine if there has been an event or not. For this thesis the event is a change in the scene.

A master CCD image was used, this then had a threshold applied to form a binary master image. Thresholds would then be applied to the comparison images and these would then be compared with the confusion matrix (Table 3-1). Performance metrics can be calculated by comparing the detections in the master and comparison images. Example master images are shown in Figure 3.17.

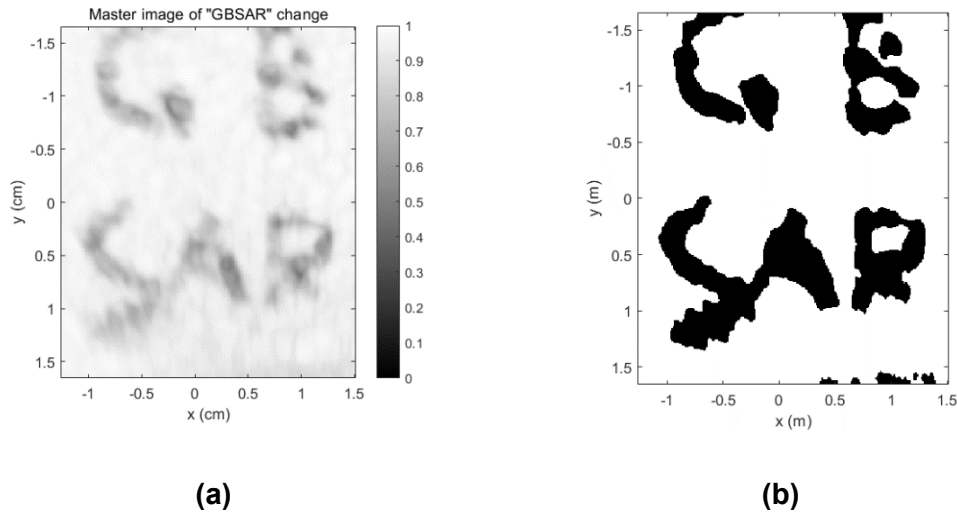


Figure 3.17 Fully polarimetric master images used for the performance metrics. Image (a) is a CCD image formed from the mean of fully polarised multistatic data collections. Image (b) is a binary image formed from applying a threshold to (a).

3.3.1.1 Four class confusion matrix

Conventionally for a two-class detection the confusion matrix in Table 3-1 was used. This leaves no room for ambiguous cases. In a paper [160] whose results are presented in section 5, page 154 a four class change detector was used. This was done in order to better take advantage of the multidimensional data available, and to reduce the impact of borderline cases. This necessitated a new confusion matrix, shown in Table 3-2. Here ρ is a measure of the change detection. $\rho = 1$ indicates no change and $\rho = -1$ indicates a change. A value of $\rho = -0.5$ or $\rho = 0.5$ indicates a probable change or no-change.

Table 3-2 Modified confusion matrix for the four class images.

Confusion Matrix		Master image			
		$\rho = -1$	$\rho = -0.5$	$\rho = 0.5$	$\rho = 1$
Test image	$\rho = -1$	TP = 1	TP=0.75	FP=0.75	FP=1
	$\rho = -0.5$	TP=0.75	TP=1	FP=0.5	FP=0.75
	$\rho = 0.5$	FN=0.75	FN=0.5	TN=1	TN=0.75
	$\rho = 1$	FN=1	FN=0.75	TN=0.75	TN=1

3.3.2 Performance metrics (Confusion matrix)

3.3.2.1 Probability Of Detection (POD)

The Probability Of Detection (POD) [223], [224]. This metric gives a value of [0,1] and is the proportion of true positive predictions compared to the number of events. A value approaching 1 indicates most events were detected, and a value approaching 0 indicates most events were missed.

$$POD = \frac{TP}{TP + FN}; \in [0,1] \quad (3.1)$$

3.3.2.2 Critical Success Index (CSI)

The Critical Success Index (CSI) was originally called the ratio of verification when it was introduced [221]. CSI shares some similarities with the POD. It compares the number of correct forecasts to the number of correct forecasts, false alarms and misses. It is not affected by the number of correct negative forecasts. A value approaching 1 indicates a perfect forecast. [223].

$$CSI = \frac{TP}{TP + FN + FP}; \in [0,1] \quad (3.2)$$

3.3.2.3 False Alarm Ratio (FAR)

The False Alarm Ratio (FAR) [223], [224] provides a measure of the number of false positives compared to the number forecast positives. Here a value of 1 indicates all forecast events were false. This is sometimes confused with the False Alarm Rate $FAR_{rate} = FP/(TN + FP)$ [229] .

$$FAR = \frac{FP}{TP + FP}; \in [0,1] \quad (3.3)$$

3.3.2.4 Proportion Correct (PC)

The Proportion Correct (PC) [223], [225] provides a measure of the number of correct forecasts of events compared to the total number. A value approaching 1 indicates most forecasts were true, a value approaching 0 indicates most were wrong.

$$PC = \frac{TP + TN}{TP + TN + FP + FN}; \in [0,1] \quad (3.4)$$

3.3.2.5 Heidke Skill Score (HSS)

The Heidke Skill Score (HSS) [223], [224], [225] shares some similarities with the Success Rate ($SR = 1 - FAR_{rate}$), however it also accounts for the random forecasts. The HSS outputs a value of $-\infty$ to 1. No incorrect forecasts would result in a value of +1. No correct forecasts would give a value of $-\infty$. A value of 0 would indicate ‘no skill’, and performance close to random guesses.

$$HSS = \frac{2 * (TP \cdot TN - FP \cdot FN)}{(TP + FN)(FT + TN) + (TP + FP)(FP + TN)} \quad (3.5)$$
$$HSS \in [-\infty, 1]$$

3.3.2.6 Matthew's Correlation Coefficient (MCC)

The Matthew's Correlation Coefficient (MCC) [226], [227] is an alternative to Pearson's Correlation Coefficient (R) but is less effected by unbalanced datasets. A value of 1 represents perfect classification, and -1 represents perfect miss-classification. Similarly to the HSS, a value of 0 represents a classification similar to the expected value (random or no skill).

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}} \quad (3.6)$$
$$MCC \in [-1, 1]$$

3.3.3 Performance metrics (statistics)

3.3.3.1 Root Mean Squared Error (RMSE)

The root mean squared error (RMSE) [223], [224], [225], [228] is a measure of the difference in values rather than the forecasting of events. In this case 0 indicates no error, and any other positive value indicates an error.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Predicted_i - Actual_i)^2} ; \in [0, \infty] \quad (3.7)$$

3.3.3.2 Universal Image Quality Index (UIQI)

The Universal Image Quality Index (UIQI) [139], [230], [231] can be used to assess the quality of SAR images used to form a CCD image, or the similarity between a master and test image. The equations are shown below numbering (3.8) to (3.14).

The two SAR images used in CCD analysis are termed the reference and mission. As for the estimated coherence (CCD) the master image is denoted by Γ_m and the test is denoted by Γ_t . For the UIQI the mean (3.8), variance (3.9), and co-variance (3.10) are first calculated.

$$\overline{|\Gamma_m|} = \frac{1}{N} \sum_{k=1}^N |\Gamma_m(k)|; \quad \overline{|\Gamma_t|} = \frac{1}{N} \sum_{k=1}^N |\Gamma_t(k)| \quad (3.8)$$

$$\sigma_{\Gamma_m}^2 = \frac{1}{N-1} \sum_{k=1}^N (\Gamma_m(k) - \overline{|\Gamma_m|})^2; \quad (3.9)$$

$$\sigma_{\Gamma_t}^2 = \frac{1}{N-1} \sum_{k=1}^N (\Gamma_t(k) - \overline{|\Gamma_t|})^2$$

$$\sigma_{\Gamma_m \Gamma_t} = \frac{1}{N-1} \sum_{k=1}^N (\Gamma_m(k) - \overline{|\Gamma_m|}) (\Gamma_t(k) - \overline{|\Gamma_t|}) \quad (3.10)$$

These values are then used to calculate the quality indices [139], [230], [231].

The first, Q_1 can be seen as a measure of the structural similarity of the images. Q_2 represents the similarity of the image mean. Q_3 denotes the similarity of the image constants [139], [230], [231].

$$Q_1 = \left[\frac{\sigma_{\Gamma_m \Gamma_t}}{\sigma_{\Gamma_m} + \sigma_{\Gamma_t}} \right] \in [0,1] \quad (3.11)$$

$$Q_2 = \left[\frac{2\overline{|\Gamma_m|}\overline{|\Gamma_t|}}{(\overline{|\Gamma_m|})^2 + (\overline{|\Gamma_t|})^2} \right] \in [0,1] \quad (3.12)$$

$$Q_3 = \left[\frac{2\sigma_{\Gamma_m}\sigma_{\Gamma_t}}{\sigma_{\Gamma_m}^2 + \sigma_{\Gamma_t}^2} \right] \in [0,1] \quad (3.13)$$

$$Q = Q_1 \cdot Q_2 \cdot Q_3 \in [0,1] \quad (3.14)$$

4 Interferometric coherence

Initial work focussed on Coherency of rough surfaces exhibiting speckle (gravel). This was used to produce a conference paper [162] presented at the 14th European Conference on Synthetic Aperture Radar (EUSAR 2022). In this paper the term γ_{RCS} was introduced. It was later renamed to γ_{Scat} .

A disparity between the expected coherence from standard equations and measured coherence was then further investigated in two journal papers [163], [177]. These papers investigated the change in coherence over Rayleigh rough ground exhibiting speckle for diverging sets of bistatic radar geometries.

This section contains content from two papers [177] and [163]. The first was a shorter paper published in the IET Electronics letters Journal [177]. The geometries chosen for this paper maximised the spatial frequency overlap between the trajectories ($0.83 \leq \gamma_{baseline} \leq 1$). The second paper [163] was longer used trajectories which allowed for very similar grazing angles. This paper also used non-isotropic simulations and two ground types.

These papers improved the definition of the scattering term (γ_{Scat}) from the conference paper and improved the characterisation of its behaviour.

4.1 Context & motivation

Typically for interferometry, the two radar platform trajectories are closely repeated, with a low baseline, for the best possible CCD results [94], [153], [176].

For satellites, this may necessitate long revisit times [29] which may for example lead to decorrelations due to natural processes such as wind and rain [153]. This would reduce CCD interpretability. Conducting rapid repeated passes is important for getting ISR images in a timely manner to facilitate battlefield effects.

For such constellations, the ability to utilize trajectories with greater baselines and differing bistatic geometries could help reduce revisit times. However, such image pairs may potentially have low SAR coherence. This paper investigates the impact of different trajectories on the coherence of SAR CCD images.[56], [57], [63][56], [61]

4.2 Methodology

This section outlines the methodology used in this chapter. The Cranfield GBSAR laboratory was used to collect the SAR images. This facility has been covered in section 3.1. The scene and radar geometries for the first paper [177] are covered in 4.2.1. The two scenes and radar geometries for the second paper are then covered in section 4.2.2.

The simulations used in both papers are then discussed in section 4.2.3. Finally, the estimation of the scattering component is outlined in section 4.2.4.

The SAR and CCD processing undertaken was the same for both simulated and measured data.

4.2.1 Paper 1

4.2.1.1 Scene

The scene used in the first paper is shown in Figure 4.1. This scene consisted of a gravel square 2.7 x 2.7 m. The measurements were conducted with a Vector Network Analyzer (VNA), with centre frequency of 10 GHz and bandwidth of 4 GHz.



Figure 4.1 Image showing the gravel square scene.

4.2.1.2 SAR geometries

The SAR geometries used were constrained by the available transmitter and receiver vertical and horizontal rails. These available extent is shown in black in Figure 4.2 (black), where the scene dimensions and SAR geometries measured are also shown.

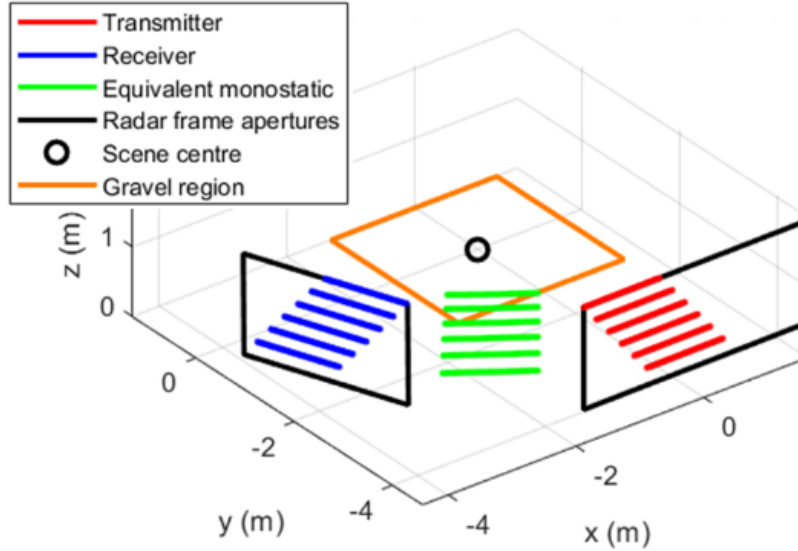


Figure 4.2 Diagram showing measured bistatic SAR geometries and scene dimensions. Each bistatic SAR geometry has transceivers at equal heights and the scene centre is denoted by “O”.

Due to the multipath (section 3.1.3.1) overlapping some of the gravel the ROI was restricted to the front third of the gravel. Thus, the ROI used was 1m x 2.5m to avoid multipath and low SNR regions (floor and gravel edges). This was accounted for in the methodology of the second paper in which the scene was aligned with the BEM. This prevented multipath echoes appearing on the gravel.

For each bistatic SAR geometry, transceiver heights were kept the same and a horizontal aperture of 1.2 m was scanned for both the receiver and transmitter antennas, which gave equivalent monostatic apertures of length 1.12 - 1.18 m. The six bistatic transceiver pairs were designated “TR1” to “TR6”, with the height progressively decreasing with increasing index (1 to 6) and bistatic angle progressively increasing – crucially, these geometries were chosen, to maintain a substantial K-space overlap between the SAR

geometries. It is noted that in previous measurements, variation in grazing angle between bistatic collections did not greatly influence coherence [162].

In order to improve the quality of the resulting images a background subtraction and normalisation across frequencies was performed.

4.2.1.2.1.1 Geometry tables and angles

Transceiver scan geometry parameters are listed in Table 4-1. The bistatic angle differences are shown in Figure 4.3. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the table are calculated to the centre of the scene and gravel region. For TR1 and TR6, there is only a 20 cm overlap (17% of the aperture). The K-space overlap between the six SAR geometries was high, with $\gamma_{baseline}$ (calculated using the areas of overlap and non-overlap in the K-space) ranging from 0.83 to 0.98 as seen in Figure 4.4.

Table 4-1 Scan geometry parameters for the six bistatic collections. Tx denotes the transmitter, Rx the receiver, and BEM the Bistatic Equivalent Monostatic values for the transceiver trajectories. Ranges are in the respective slant planes. Resolutions are in the ground plane and estimated at the scene centre.

		TR1	TR2	TR3	TR4	TR5	TR6
Bistatic angle, β ($^{\circ}$)		36.5	41.5	46.7	52.1	57.6	63.2
Grazing angle, ψ ($^{\circ}$)	Tx	22.1	19.7	17.2	14.6	11.8	8.9
	Rx	22.8	20.4	17.8	15.1	12.2	9.2
	BEM	23.7	21.5	19.2	16.6	13.8	10.7
Range (m)	Tx	5.16	5.02	4.91	4.81	4.73	4.67
	Rx	5.00	4.87	4.75	4.65	4.57	4.51
	BEM	5.08	4.95	4.83	4.73	4.65	4.59
BEM aperture length (m)		1.12	1.14	1.15	1.17	1.18	1.18
Transceiver height (m)		1.94	1.70	1.45	1.21	0.97	0.73
BEM resolution	Range (cm)	4.1	4.0	4.0	4.0	3.9	3.8
	Cross-range (cm)	6.8	6.5	6.3	6.1	6.0	5.9

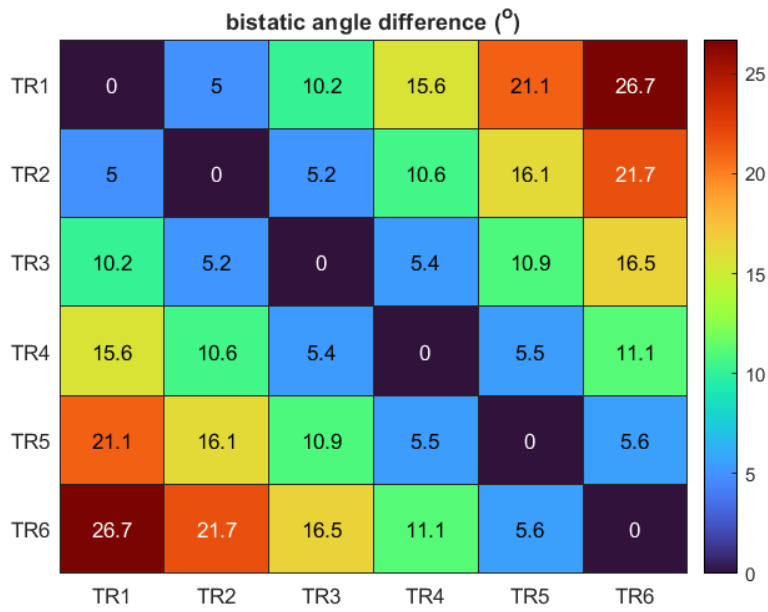


Figure 4.3 Heatmap showing the difference in bistatic angle for different transceiver pairs.

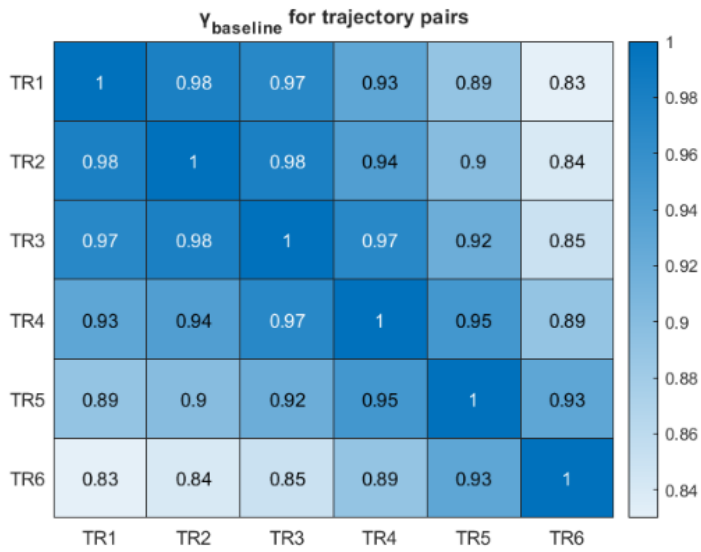


Figure 4.4 Heatmap showing the $\gamma_{baseline}$ values for the different trajectories.

4.2.2 Paper 2

4.2.2.1 Scenes

The scenes used in the second paper are shown below. Two scenes were used. Each was surrounded by spheres and top hat scatterers, used to verify the alignment of the SAR images.

4.2.2.1.1 Gravel Scene

The first measured scene is shown in Figure 4.5 and Figure 4.6 and was a rectangle of gravel (2.7 m x 1.5 m). The gravel consisted of approximately 1 cm sized pieces of gravel, significantly smaller than the resolution cell size. A smaller rectangular area (1.5 m x 1.4 m) was used for the calculation of coherence and will be referred to as the Region Of Interest (ROI).



Figure 4.5 Image showing the gravel rectangle, together with spheres and top hat scatterers used to ensure image alignment.

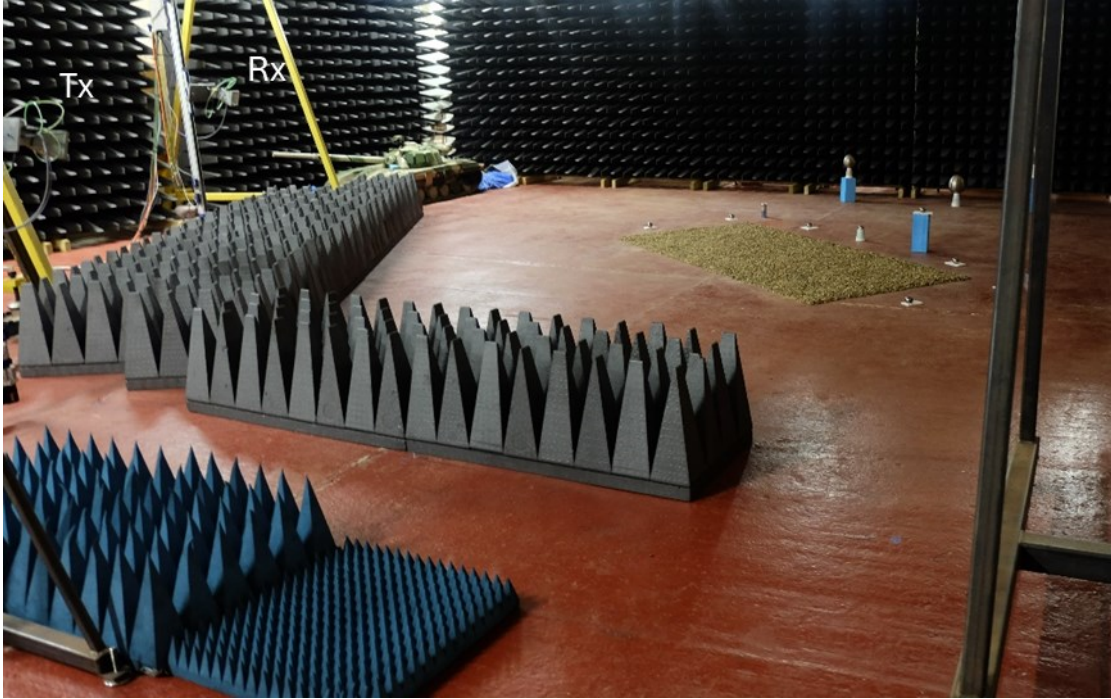


Figure 4.6 Image showing the gravel rectangle within the laboratory. The transmitter is labelled Tx and the receiver Rx.

4.2.2.1.2 Stone scene

The second scene was a rectangle (1.6m x 1.5m) of densely packed stones, seen in Figure 4.7 and Figure 4.8. This scene was less wide than the gravel scene, but encompassed the ROI used for this investigation.



Figure 4.7 Image showing the stone rectangle. The spheres and top hat scatterers shown in Figure 4.5 are also present.



Figure 4.8 Image showing the stone rectangle within the laboratory environment. The spheres and top hat scatterers shown in Figure 4.5 are in the same locations.

As outlined in section 3.1.3.1 the scenes were rotated to align with the BEM. This ensured that the multipath echo was projected behind the scenes in the SAR images.

The measurements were conducted with a Vector Network Analyzer (VNA), with centre frequency of 10 GHz and bandwidth of 4 GHz.

4.2.2.2 SAR geometries

The SAR geometries used were constrained by transmitter and receiver vertical rectangular scanning apertures 0.4 m high by 2.4 m wide, seen in the SAR geometry overview in Figure 4.9. The red lines correspond to the transmitter positions used, and the blue to receiver positions.

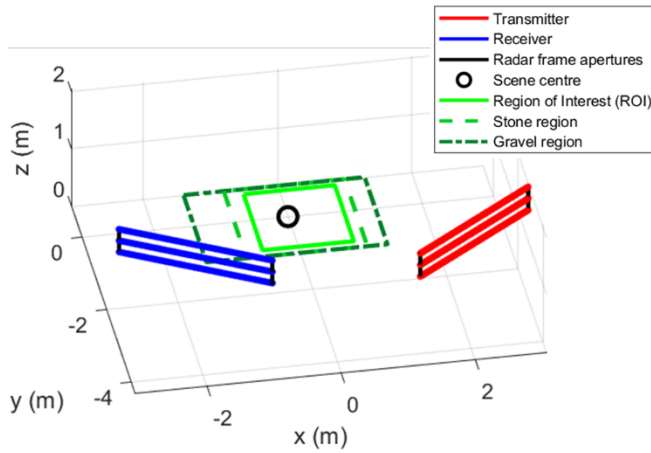


Figure 4.9 Diagram showing the radar geometries used. The transmitter and receiver geometries are shown in red and blue respectively. The scene centre is marked by the black circle. The stone and gravel regions are outlined with dashed green lines. The region of interest is outlined by the solid green line.

Fifteen bistatic SAR geometries were measured, and in each of them the transceiver heights were kept the same. For each of them, a 1.6 m horizontal aperture was scanned by both the transmitter and the receiver, and with five different horizontal positions labelled TR1 to TR5, and with three vertical positions, labelled 000, 200, 400, corresponding to vertical distances in millimetres to the scanner origin, with “000” corresponding to the highest trajectories and 400 corresponding to the lowest. The individual transmitter apertures are shown in Figure 4.10 and the corresponding receiver

apertures in Figure 4.11, with local scanner axis coordinates – in these, the “X” marker colours denote the scanned aperture extents for each geometry, where TR1 form the outer pair of transceiver positions and TR5 form the inner pair.

The chosen SAR geometries allow the bistatic angle to be progressively increased, whilst maintaining a substantial K-space overlap between them. The K-space overlap between the six SAR geometries was high, with $\gamma_{baseline}$ ranging from 0.7 to 0.96 for non-repeating trajectories.

Transceiver scan geometry parameters are listed in the appendices in section 4.2.2.2.1. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the tables are calculated to the centre of the scene and gravel region. The SAR resolutions were estimated using the Bistatic Equivalent Monostatic (BEM) antenna positions, calculated along the antenna bisecting direction to the scene centre [120], [121].

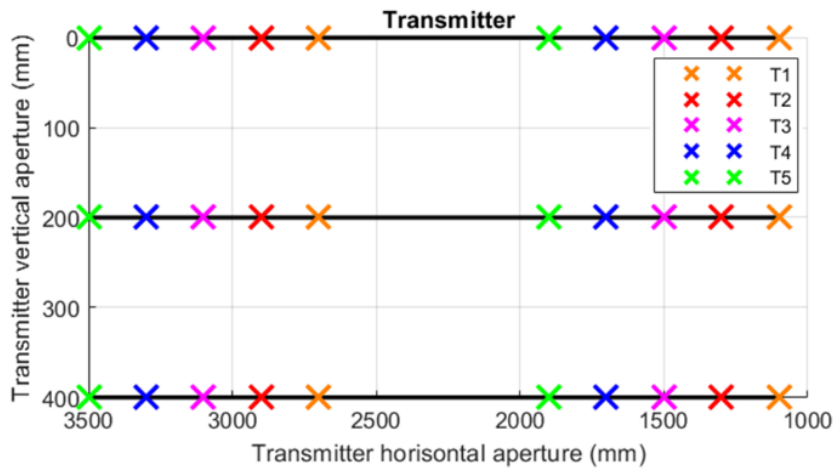


Figure 4.10 Diagram showing the horizontal extent of the *transmitter* apertures for each height, in the local axis coordinate system.

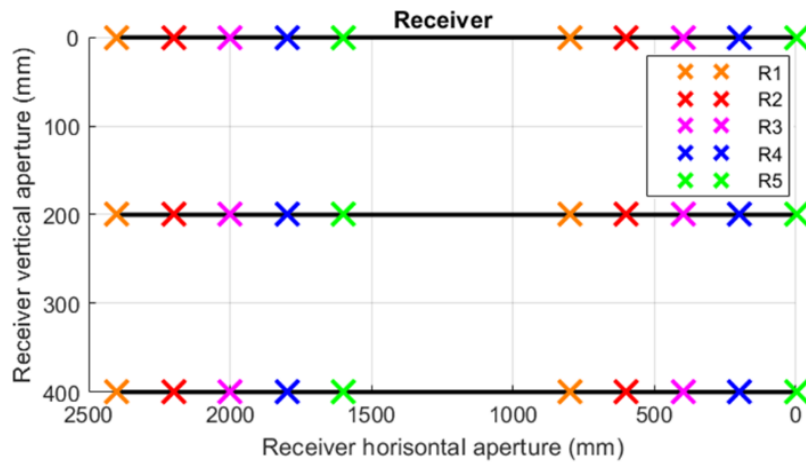


Figure 4.11 Diagram showing the horizontal extent of the *receiver* apertures for each height, in the local axis coordinate system.

4.2.2.2.1 Geometry tables and angles

In Table 4-2 several angles are presented. The first is the bistatic angle between the mean transmitter and receiver positions. Grazing angles for the mean transmitter, receiver and BEM positions are also presented. The BEM direction is the bisectrix of the vectors joining the antenna positions and the scene centre [120], [121]. The slant ranges to the scene centre, and heights for the mean transmitter, receiver and BEM positions are also presented in Table 4-2. The BEM range is given by the bistatic range.

The ground-range and cross-range resolutions are presented in Table 4-3.

Table 4-2 Table containing angles and heights for the different radar geometries. The table lists the bistatic and grazing angles and the heights and ranges for the transmitter (Tx), receiver (Rx) and the Bistatic Equivalent Monostatic (BEM).

Trajectory	Bistatic angle, β (°)	Grazing angle (°)		Range (m)				Height (m)		
		Tx	Rx	BEM	Tx	Rx	BEM	Tx	Rx	BEM
TR1 000	63.4	25.3	26.0	30.6	4.55	4.63	4.59	1.94	2.03	2.34
TR2 000	58.6	25.2	26.1	29.8	4.56	4.63	4.59	1.94	2.03	2.28
TR3 000	53.8	25.1	26.1	29.0	4.58	4.63	4.60	1.94	2.03	2.23
TR4 000	49.1	24.9	26.0	28.2	4.60	4.64	4.62	1.94	2.03	2.19
TR5 000	44.4	24.7	25.9	27.5	4.64	4.65	4.65	1.94	2.03	2.15
TR1 200	64.7	22.9	23.8	28.0	4.47	4.55	4.51	1.74	1.83	2.11
TR2 200	59.8	22.9	23.8	27.2	4.48	4.54	4.51	1.74	1.83	2.06
TR3 200	54.9	22.8	23.8	26.5	4.50	4.54	4.52	1.74	1.83	2.01
TR4 200	50.0	22.6	23.8	25.8	4.52	4.55	4.54	1.74	1.83	1.97
TR5 200	45.2	22.4	23.7	25.1	4.56	4.57	4.57	1.74	1.83	1.94
TR1 400	65.9	20.5	21.4	25.3	4.39	4.47	4.43	1.54	1.63	1.89
TR2 400	60.9	20.5	21.5	24.5	4.40	4.46	4.43	1.54	1.63	1.84
TR3 400	55.9	20.4	21.5	23.9	4.42	4.46	4.44	1.54	1.63	1.80
TR4 400	50.9	20.2	21.4	23.2	4.45	4.47	4.46	1.54	1.63	1.76
TR5 400	46.0	20.1	21.3	22.6	4.49	4.49	4.49	1.54	1.63	1.73

Table 4-3 The ground plane resolutions in the range and cross range directions for the different radar geometries.

Trajectory	Resolution (cm)	
	Ground range	Cross-range
TR1 000	5.11	5.34
TR2 000	4.95	5.19
TR3 000	4.80	5.09
TR4 000	4.67	5.02
TR5 000	4.57	4.99
TR1 200	5.02	5.24
TR2 200	4.86	5.10
TR3 200	4.72	4.99
TR4 200	4.59	4.92
TR5 200	4.48	4.88
TR1 400	4.93	5.16
TR2 400	4.78	5.01
TR3 400	4.64	4.91
TR4 400	4.52	4.84
TR5 400	4.41	4.79

The bistatic angle difference between the different trajectories and the grazing angle differences are shown in Figure 4.12 and Figure 4.13.

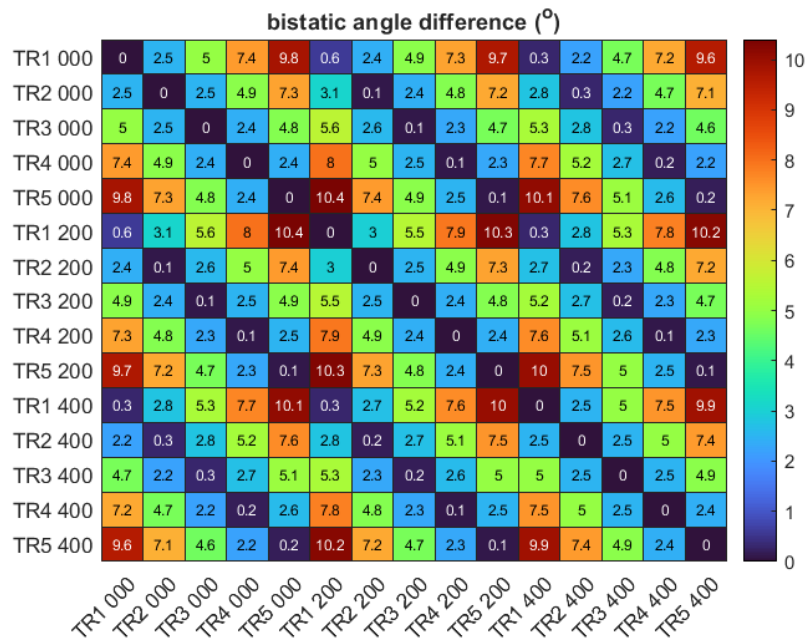


Figure 4.12 Heatmap and table showing the bistatic angle difference between the SAR geometries measured.

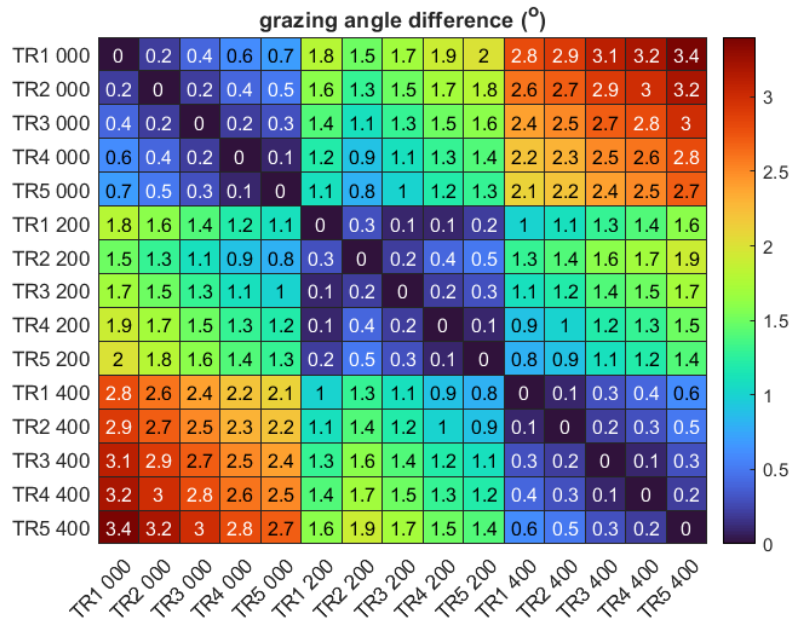


Figure 4.13 Heatmap and table showing the grazing angle difference between the SAR geometries measured.

4.2.3 Simulations & curve fitting

4.2.3.1 Isotropic simulations

In addition to the measurements, simulations were undertaken assuming isotropic point scatterers. This density was very high for the first paper at approximately 26 scatterers per resolution cell. The second paper used a larger ROI so consequently the scatterer density was reduced to 15 per resolution cell. The scatterers were randomly distributed using a seed, which ensured that scatterers were in the same locations when the simulation was repeated for a new set of radar geometries.

These densities were both relatively high and ensured convergence of results as well as providing fully developed SAR speckle. Although each individual point scatterer was isotropic, the interference between scatterers gave rise to the scintillation/SAR speckle.

This could be confirmed by investigating the scatterer intensity distribution. The intensity distribution for the 15 scatterers per resolution cell is shown below in Figure 4.14. The intensity distribution matches the red negative exponential distribution. This intensity distribution was calculated using the ROI across all 15 radar geometries.

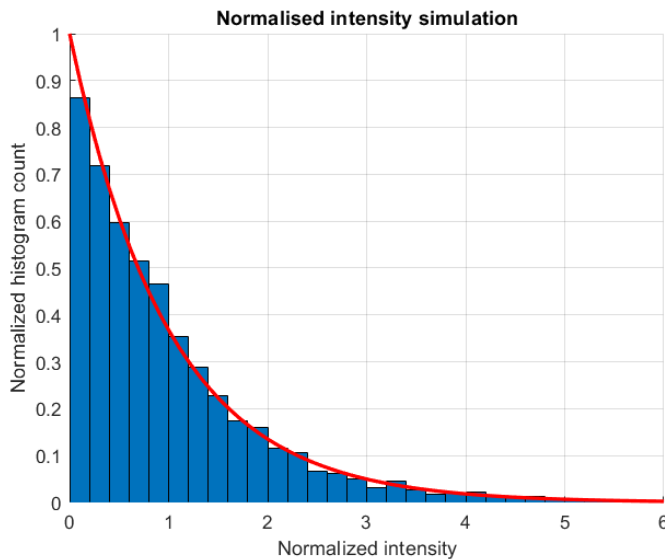


Figure 4.14 Normalised intensity distribution (histogram) for the isotropic simulations used in [163] and negative exponential distribution (red).

In the monostatic case, this simulation gave rise to the expected variation in coherence one would expect from given trajectory baselines [162]. In general, for the monostatic case, and for gravel, there is a close correspondence between the simulated results, and measured coherence results [162].

4.2.3.2 Non-isotropic simulations

Non-isotropic simulations were also conducted. The aim of these was to demonstrate the difference between images necessary to result in the decorrelation observed. The second set of simulations added a random phase contribution to each scatterer, which was scaled using the bistatic angle. This resulted in an additional decorrelation between SAR images, function of the difference between bistatic angles. The additional phase factor contribution to scatterer n took the following form,

$$\exp(i\pi C_{sim}\beta_n A_n) \quad (4.1)$$

where C_{sim} is a parameter to be determined empirically, β_n is the bistatic angle in radians at scatterer n , and A_n is a uniformly distributed random real number assigned to scatterer n such that $-1 \leq A_n < 1$. The values A_n were fixed across the simulations. The values of C_{sim} corresponded to a minimum Root Mean Squared Error (RMSE) between the simulation coherence and the measured data coherence. The values for the C_{sim} parameters used are presented in Table 4-4.

4.2.3.3 Curve fitting

A function of the difference in bistatic angle ($\Delta\beta$) was also used to fit coherence curves, as follows:

$$\gamma_{Curve\ fit} = (1 + C_{cf1}\Delta\beta + C_{cf2}\Delta\beta^2 + C_{cf3}\Delta\beta^3)\gamma_{baseline} \quad (4.2)$$

The coefficients C_{cf} were chosen so that they resulted in the lowest Root Mean Squared Error (RMSE) when compared with the measured data, with their chosen values for the two measured scenes presented in Table 4-4.

Table 4-4 Parameter values used to add a decorrelation factor to the simulation (section 4.2.3.2) , or to fit the overall coherence as a function of bistatic angle difference (equation (4.2)) for the two measured scenes.

	Bistatic decoherence simulation parameter	Coherence fitting coefficients		
	C_{sim}	C_{cf1}	C_{cf2}	C_{cf3}
Gravel	1.8	-0.72	-21.87	76.19
Stones	4.8	-8.23	16.62	50.85

4.2.4 Estimation of γ_{Scat}

Due to the nature of the laboratory environment, the equations for coherence (section 2.7.4.1) can be simplified to calculate the scattering component.

No scene changes were present, and the laboratory environment was well controlled, so $\gamma_{temp} \approx 1$. The measurement ground truth was accurately known due to the well-controlled antenna positioning and accurate curved wavefront bistatic back-projection image formation used, so $\gamma_{Proc} \approx 1$, assuming a sufficiently large window size is used.

From the background subtracted images, (section 3.1.3.2), the SNR was estimated by comparing the intensity of the signal with the intensity of the floor. As the images had been background subtracted the return from the floor should have been removed, leaving only noise. In reality some of the returns from the floor likely remains, however this value for the SNR represents the worst case scenario. The values for the SNR range from 30 to 38 dB depending on the ground type. Thus, using equation (2.59) γ_{SNR} was estimated. The SNR and γ_{SNR} values are shown in Table 4-5.

γ_{reg} was calculated using equation (2.64) and the geometries. These values are also shown in Table 4-5.

Table 4-5 Table showing the Signal to Noise Ratio (SNR) for the different scene types and experiments. Additionally, the decorrelation factors γ_{SNR} and γ_{reg} are shown.

	Paper 1	Paper 2	
	Gravel	Gravel	Stones
SNR (dB)	30	30	38
γ_{SNR}	0.967	0.967	0.974
γ_{reg}	1	0.997	0.997

Hence the following equation is used to give an *estimate* for γ_{Scat} :

$$\hat{\gamma}_{Scat-baseline} = \left\langle \frac{\hat{\gamma}_{Meas}(x, y)}{\gamma_{baseline}(x, y) \gamma_{SNR} \gamma_{reg}} \right\rangle \quad (4.3)$$

The angled brackets indicate an averaging of the quantities over the scene. It is noted that due to the SAR near-field nature of the measurements, both the $\gamma_{baseline}$ and $\hat{\gamma}_{meas}$ (evaluated within a square sliding window) vary spatially. Hence, they are functions of image coordinates (x, y) . Therefore $\hat{\gamma}_{Scat}$ is evaluated as a mean over the spatially varying fraction in. “*Meas*” denotes that the coherence value is from the measured data.

A method to predict $\hat{\gamma}_{Scat}$ is to use the simulated and measured CCD images directly, that is without the use of $\gamma_{baseline}$. This is shown in equation (4.4). Here “*Sim-isotropic*” denotes the simulated values (where $\hat{\gamma}_{Sim-isotropic} \approx \gamma_{baseline}$ [162] due to the isotropic scatterer assumption, see Figure 4.15 below). The γ_{Scat} for the isotropic simulations is = 1. Thus,

$$\hat{\gamma}_{Scat-Sim-isotropic} = \left\langle \frac{\hat{\gamma}_{Meas}(x, y)}{\hat{\gamma}_{Sim-isotropic}(x, y) \gamma_{SNR} \gamma_{reg}} \right\rangle \quad (4.4)$$

As in equation (4.3) an averaging over the spatially varying fraction is performed in (4.4) due to the SAR near-field nature of the measurements.

After the spatially variant incoherent trimming process, it is assumed that the resulting coherence between images $\hat{\gamma}_{Trimmed}(x, y) = \hat{\gamma}_{Meas}(x, y) / \gamma_{baseline}(x, y)$. This is because $\gamma_{Proc}, \gamma_{temp}, \gamma_{reg}, \gamma_{SNR} \approx 1$. Hence the following relation is assumed:

$$\hat{\gamma}_{Scat-Trimmed} = \left\langle \frac{\hat{\gamma}_{Trimmed}(x, y)}{\gamma_{SNR} \gamma_{reg}} \right\rangle \quad (4.5)$$

Three formulae are used to calculate γ_{Scat} in order to improve confidence in the results.

4.3 Bistatic coherence investigation – part 1

4.3.1 Results

The coherence of SAR image pairs (for the gravel ROI) was calculated as the mean over the CCD image. These mean coherence values were then plotted as a function of the bistatic angle (and by extension grazing angle) difference between the mission and reference trajectories. The measured coherence values are shown in Figure 4.15. As the separation (baseline) between bistatic trajectories increases, the coherence drops. The coherence also exhibits variation between the polarisations. Additionally, the coherence values of the measured results were then compared against the coherence of the simulated results and with the baseline correlation ($\gamma_{baseline}$). These are also shown in Figure 4.15. The simulated coherence, $\hat{\gamma}_{Sim}$, shows a close match to the $\gamma_{baseline}$ (validating the assumptions made in 4.2.4), however the measured results exhibit a coherence which becomes lower with increasing bistatic and grazing angle difference. This is attributed to γ_{Scat} .

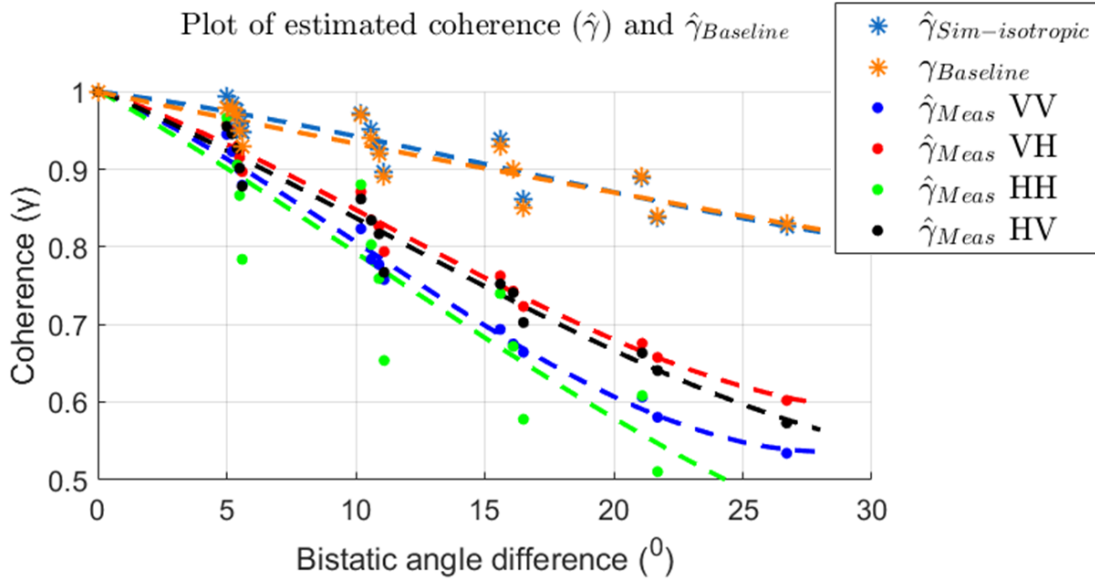


Figure 4.15 Graph of distribution of coherence and $\gamma_{baseline}$ as a function of the difference in the bistatic angle. The measured coherence values for all polarisations are shown in blue. Simulated coherences are shown in red and the baseline correlation in green. A curve of best fit was plotted for each.

As described in section 4.2.4 $\hat{\gamma}_{Scat}$ can be estimated in several ways. In Figure 4.16, $\hat{\gamma}_{Scat}$ is plotted for the different geometries and polarisations. $\hat{\gamma}_{Scat}$ can be seen to drop significantly, with increasing bistatic and elevation angular difference. The decorrelation may be so great that discriminating changes on the ground may not be possible for the greater bistatic angle differences. For bistatic angle differences greater than 10° , coherence is seen to be generally greater in the cross-polarisation channels. The HH channel has the least coherence and most variability, which may be due to ground-multipath effects.

The two $\hat{\gamma}_{Scat}$ estimates, $\hat{\gamma}_{Scat-baseline}$ and $\hat{\gamma}_{Scat-sim-isotropic}$ can also be compared with the estimated coherence of spatially variant incoherence trimmed (SVIT) images $\hat{\gamma}_{trimmed}$, which should have a similar value. The K-space incoherence-trimming excludes non-K-space overlap data from SAR images and is performed for each bistatic collection pair in a computationally intensive spatially variant manner [132], [133].

The comparison of the three approaches (see section 4.2.4) is shown in Figure 4.16 and shows good agreement. The difference between the results may be due to numerical errors in the calculation of $\gamma_{baseline}$ and in the spatially variant K-space trimming process. These are both computationally intensive processes requiring discretization choices.

Estimated Scattering component ($\hat{\gamma}_{Scat}$)

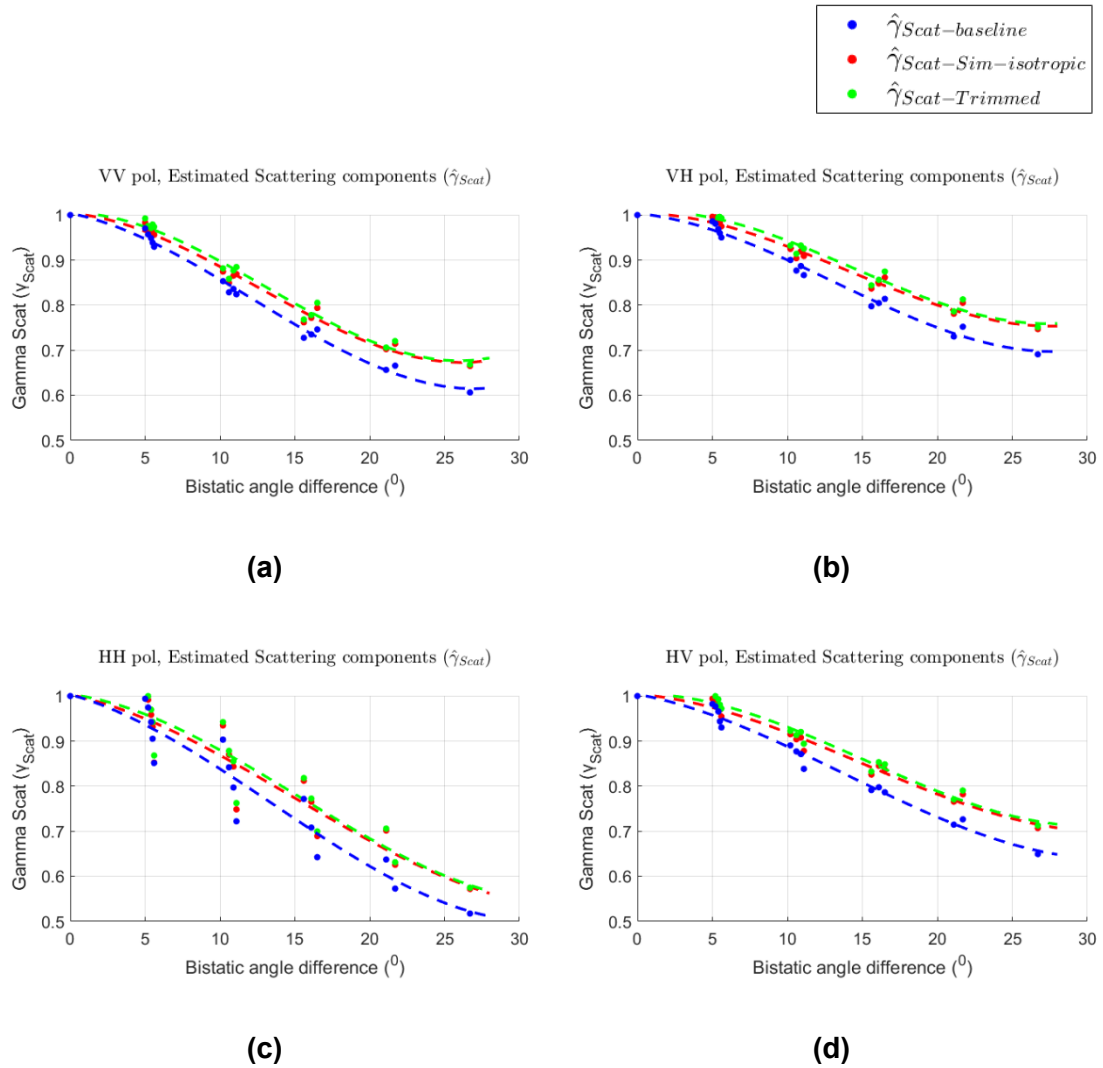


Figure 4.16 Graph showing $\hat{\gamma}_{Scat}$ estimated with three different methods, plotted against the difference in the bistatic angle. A point was plotted for each pair of radar positions and polarisation. A curve of best fit was plotted for each. All four polarisations are shown. VV in (a), VH in (b), HH in (c) and HV in (d).

4.3.2 Discussion

The results presented in this section show that SAR image speckle regions can suffer significant decorrelation due to differences in bistatic and elevation angles. It is hypothesised that the measured drop in coherence for the gravel is to do with variation in changes in scattering properties (RCS), multipath between stones, and possibly with complicated varying bistatic shadowing (bistatic SAR has double shadows). This occurred even in cases of high K-space overlap. It is hypothesized that other terrain types will give rise to different bistatic angle difference coherence variation, along with typical radar parameters such as frequency and resolution.

The effect is seen to be an important factor that should be considered when choosing bistatic SAR CCD geometries. For the bistatic geometries, frequencies and terrain considered, a difference in bistatic angle of 22° or greater led to a drop in coherence below 0.8, and in some cases below 0.7 (for some in HH polarisation). For these bistatic angle differences, there were regions of low coherence which could mistakenly be taken for regions of scene change. When combined with a loss in resolution from the SVIT process, discerning temporal changes with these geometries may become challenging.

Some differences in coherence were seen between the polarimetric channels, such that above a 10° difference in bistatic angle the cross-polarisations showed the highest coherence. This result follows preliminary predictions [150] and it is possible that there may be another polarimetric decomposition that increases coherence further for this type of terrain. Further investigation into the behaviour of the bistatic scattering factor is required, particularly with regard to different ground types and the impact of grazing angle differences, frequency band and polarimetric decomposition. Corresponding CCD performance analysis experiments would further aid in interpretation of results.

4.4 Bistatic coherence investigation – part 2

4.4.1 Intensity distribution and surface roughness

A surface is considered rough when the size of the scatterers is small in comparison to the wavelength, and there are a large number of scatterers per resolution cell [182]. Additionally, the following roughness criterion should be met [184], [185]:

$$\Delta h > \frac{\lambda}{8 \cdot \cos \theta} \quad (4.6)$$

where, Δh (cm) is the surface height variation, λ (cm) the wavelength and θ the electromagnetic wave incidence angle (it is expected that this formula extends to bistatic back-scattering geometries). This was discussed in section 2.8.1 on page 75.

The surface height variation (Δh) was around 1-2 cm for the gravel and 5-10 cm for the stones. These heights give values larger than the value of the criterion: $\frac{\lambda}{8 \cdot \cos \theta} = 0.41$ cm so that they are considered to be rough.

The intensity ($|I|$) Probability Density Function (PDF) of Rayleigh speckle takes the form of the negative exponential [94], [188], [189], [190].

$$P(|I|) = \frac{1}{\langle |I| \rangle} \exp \left(-\frac{|I|}{\langle |I| \rangle} \right) \quad (4.7)$$

where $|I|$ is the intensity and $\langle |I| \rangle$ is the mean intensity [94], [189], [190].

The pixel intensity distribution of the isotropic simulation is plotted in Figure 4.17 and closely follows the negative exponential distribution (red line), indicating that surface roughness has been well simulated.

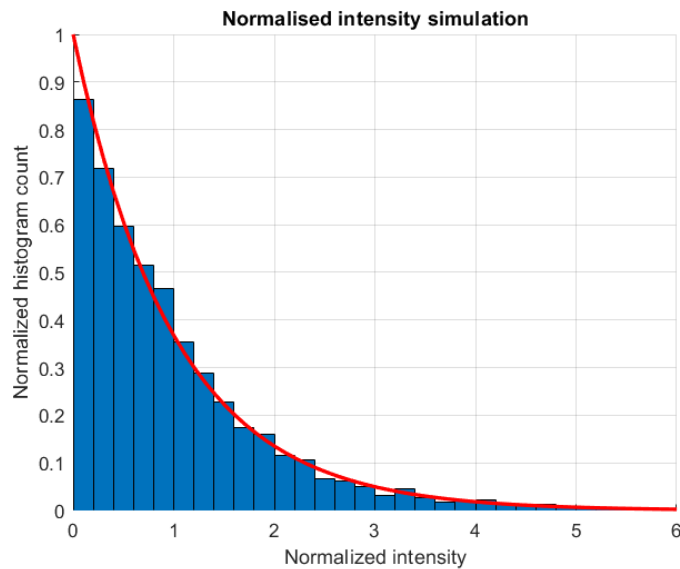


Figure 4.17 Normalised intensity distribution (histogram) for the isotropic simulations and negative exponential distribution (red).

Similar distributions can be plotted for the stone and gravel SAR images. The RMSE can be calculated between the measured intensity values and the negative exponential distribution. These are presented below in Table 4-6.

Table 4-6 RMSE calculated for the normalised intensity of the measured SAR images and the negative exponential distribution.

RMSE	Polarisation			
	VV	VH	HH	HV
Gravel	0.33	0.23	0.19	0.25
Stones	0.61	0.43	0.55	0.52

The gravel shows a closer alignment than the stones with the negative exponential distribution, as shown in Table 4-6. The 1 cm diameter gravel stones give rise to complex scattering, including multipath as well as direct scattering, however the radar wavelength is significantly larger than the scatterers themselves which may change the nature of the scattering away from the simpler and more intuitive Physical Optics (PO) regime.

The stones exhibit a greater deviation from the ideal rough (speckle) scattering response than for the gravel scene, which may be due to the presence of fewer scatterers per resolution cell, as the stones are larger. The stones are approximately 10 cm in size, larger than the centre wavelength of 3 cm.

4.4.2 Results

4.4.2.1 Overall coherence results

The coherence between SAR images is evaluated as the mean of the absolute value of $\hat{\gamma}$, over the ROI. For the measurements conducted, these are plotted in Figure 4.18, against the bistatic angle difference. Figure 4.12 and Figure 4.13 show that across the SAR geometries measured, the maximum bistatic angle difference is 10.3° , and the maximum grazing angle difference is 0.7° . All four polarisations are plotted, blue and cyan for the cross-polar and red and magenta for the co-polar. Crosses were used to represent the gravel scene data and circles the stone scene data, with curves of best fit added. The $\gamma_{baseline}$ values are plotted in green.

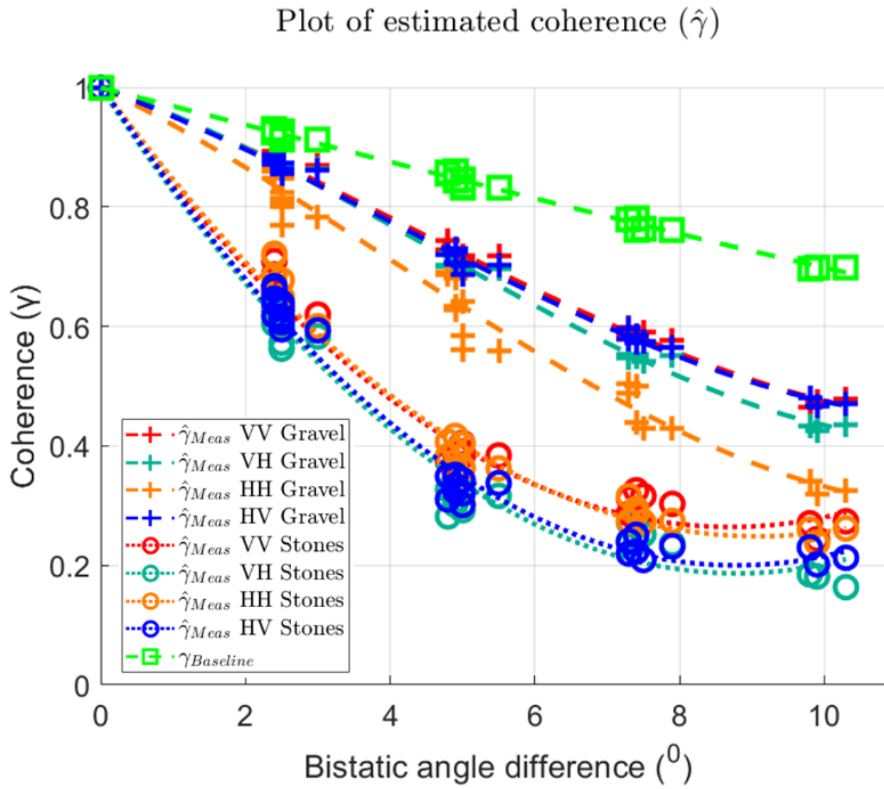


Figure 4.18 Coherence plotted against bistatic angle difference for the gravel and stone scene datasets, with $\gamma_{baseline}$.

For differing bistatic angles, the coherence for SAR images from both measured scenes was less than $\gamma_{baseline}$, with an increased difference as the bistatic angle difference increases. These results support previous findings [177] (4.3) and indicate that there is a geometry dependant decorrelation (γ_{scat}) other than that due to PFS overlap ($\gamma_{baseline}$).

The coherence for the stones is below that for the gravel scene, indicating that the decoherence is terrain type specific. Reasons for the difference may include a greater variability in bistatic RCS for the larger stones, due to their larger sizes compared to the radar wavelengths (approximately 10 cm compared to a centre wavelength of 3 cm). This would also affect the relative prominence and variability of multipath and shadowing effects. Additionally, the larger stones have a lower number of scatterers per SAR resolution cell, leading to the SAR speckle not being quite as fully developed (see 4.4.1).

The coherence for the stones plateaus at 8-10%, this behaviour is attributed to the biasing seen in CCD processing at low coherence levels [129], [146], which increases estimated coherence ($\hat{\gamma}$) above true coherence γ_{True} , dependant on the CCD window size [129], [146].

Figure 4.18 shows there is a variation in coherence between the different polarisations, which will be seen in greater detail in sections 4.4.2.2 and 4.4.2.3.

It is noted that a simulation using isotropic scatterers $\hat{\gamma}_{sim-isotropic}$ provides an overall good match for $\gamma_{baseline}$, seen in Figure 4.19, as was the case in prior publications [162], [177].

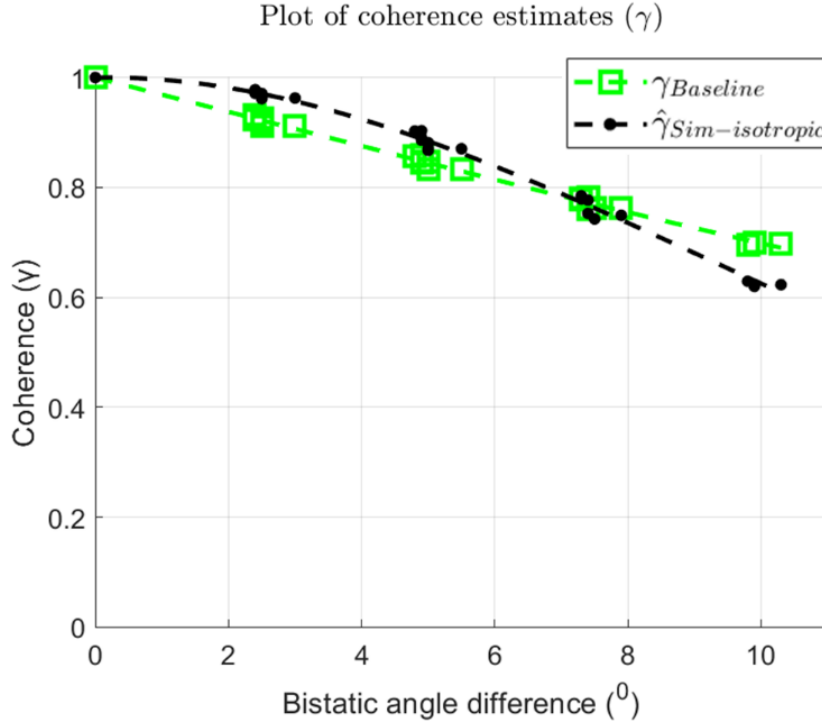


Figure 4.19 Graph showing the correspondence between $\gamma_{baseline}$ and $\hat{\gamma}_{Sim-isotropic}$.

Although there is a good match between the $\gamma_{baseline}$ and $\hat{\gamma}_{sim-isotropic}$ up to around 7° , there are however some differences. $\hat{\gamma}_{sim-isotropic}$ gives coherence values below $\gamma_{baseline}$ up to around 7° , after which it gives higher coherence values. This difference may be due to numerical errors and additionally the effects of CCD coherence estimation for the simulation [129], [146]. This results in slightly different corresponding values for $\hat{\gamma}_{Scat}$ in the following sections. The results are further described in section 4.4.2.2 for the gravel scene, and section 4.4.2.3 for the stones scene.

4.4.2.2 Gravel scene results

This section presents the coherence results for the gravel scene. The measured scene coherence is plotted in Figure 4.20. It includes measured and simulated coherence as well as $\gamma_{baseline}$ and a curve fitted to all of the measured data, $\gamma_{Curve\ fit}$. The simulated coherence incorporated the bistatic decoherence model phase factor in (4.1), (see section

4.2.3.2) and is referred to as $\hat{\gamma}_{sim-decorrelation}$. The parameters used for the fitted curve and for the decoherence simulation were provided in Table 4-4.

For differing bistatic angles, the $\gamma_{baseline}$ values are significantly higher than for the measured data for all polarisations. The bistatic decoherence simulation $\hat{\gamma}_{sim-decorrelation}$ matches the measured coherence better than the isotropic scatterer simulation $\hat{\gamma}_{sim-isotropic}$ (compare with Figure 4.19). The fit of $\hat{\gamma}_{sim-decorrelation}$ could be improved by replacing β with a polynomial function of β in equation (4.1), however the computationally intensive exercise of finding the optimal coefficient values was beyond the scope of this paper and thesis.

Of the four polarisations, HH shows the least coherence, for the gravel scene, and VV the most.

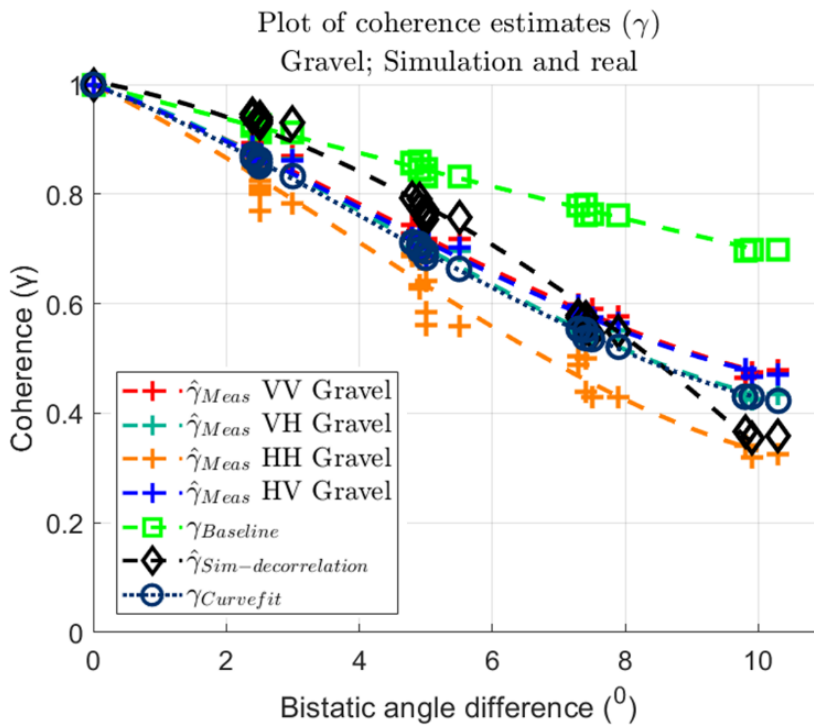


Figure 4.20 Coherence plots against bistatic angle difference for the gravel scene, including all four polarisations, $\gamma_{baseline}$, the bistatic decoherence simulation and the fitted curve, whose parameters are provided in Table 4-4.

Using equations (4.3)-(4.5) the coherence scattering component associated with a departure from bistatic isotropy, $\hat{\gamma}_{Scat}$, can be estimated with three approaches.

Figure 4.21 shows $\hat{\gamma}_{Scat}$ for each of the four polarisations. In the case of the gravel scene, polarisation HH exhibits the steepest decrease in $\hat{\gamma}_{Scat}$ as a function of the bistatic angle difference. The three different methodologies for estimating $\hat{\gamma}_{Scat}$ result in only slightly different coherence values.

The values for $\hat{\gamma}_{Scat-baseline}$ (4.3) and for $\hat{\gamma}_{Scat-Sim-isotropic}$ (4.4) are plotted in green and blue respectively. $\hat{\gamma}_{Scat-Trimmed}$ (4.5) is shown in red and represents the coherence of the incoherence trimmed image coherence $\hat{\gamma}_{Trimmed}$ (with compensations for the SNR and registration errors).

The three $\hat{\gamma}_{Scat}$ curves mostly show close alignment except for the increased coherence of $\hat{\gamma}_{Scat-Sim-isotropic}$ at the most extreme bistatic angle difference of 10° . This is due to the difference between $\hat{\gamma}_{sim-isotropic}$ simulated coherence and $\gamma_{baseline}$, seen in Figure 4.19.

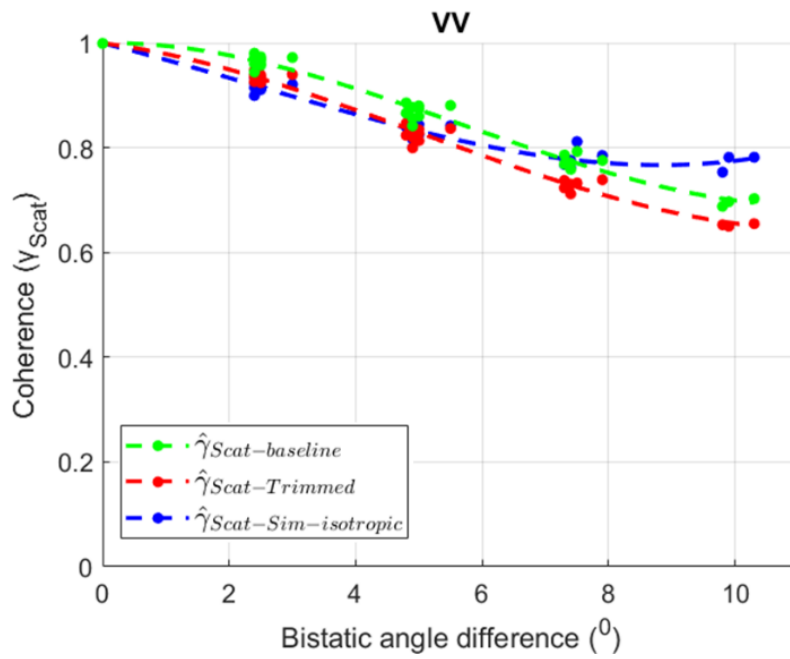


Figure 4.21 (a) VV polarisation. Gravel scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

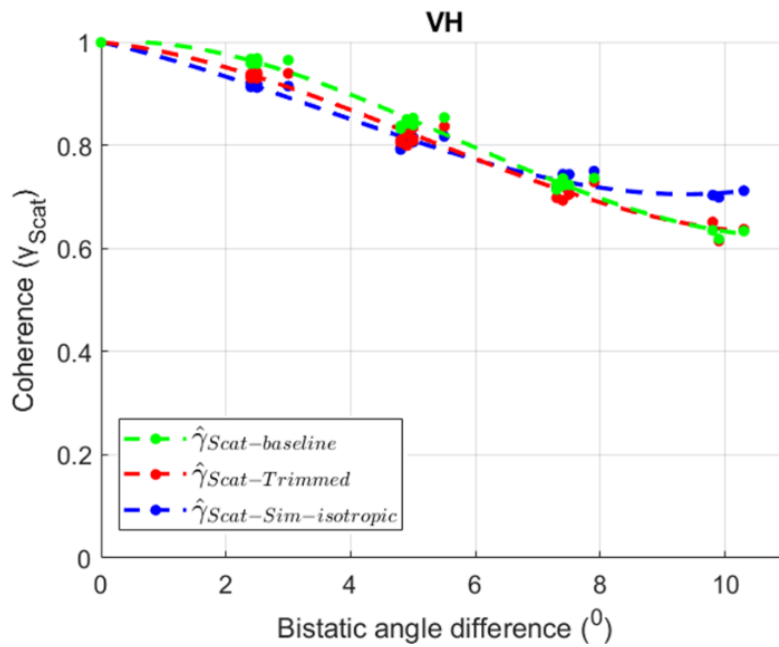


Figure 4.21 (b) VH polarisation. Gravel scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

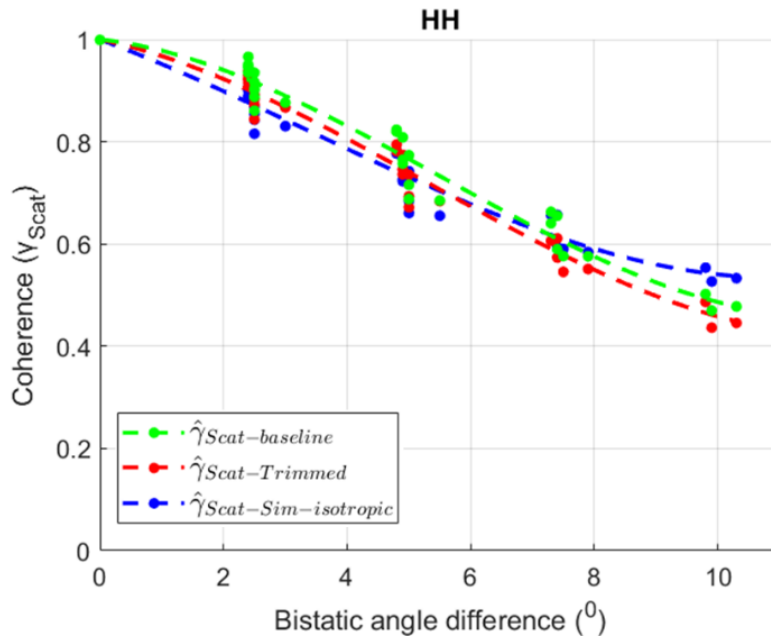


Figure 4.21 (c) HH polarisation. Gravel scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

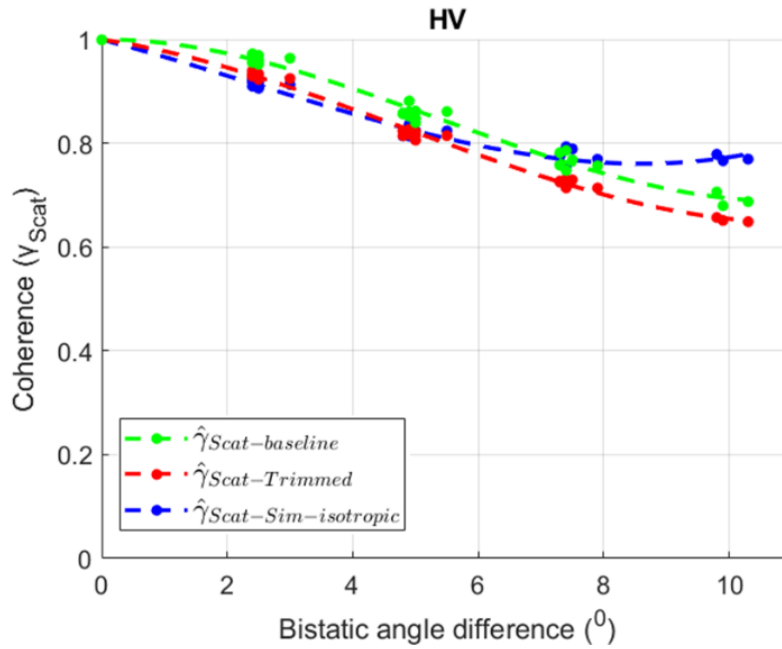


Figure 4.21 (d) HV polarisation. Gravel scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

In summarizing results, it has been found useful to divide the coherence into three performance bands [10]:

- *Good* CCD performance, occurs where changes are easily detected, and is associated with coherences above 0.8;
- *Moderate* CCD performance, occurs where useful detection information may still be available but is unreliable due to an elevated false alarm rate, and is associated with coherence below 0.8 and above 0.6;
- *Poor* CCD performance, occurs where changes are not discernible due to a very high false alarm rate, and is associated with coherence values below 0.6.

In the summarizing of results, the angular differences are rounded here to the nearest 1°.

For the gravel, “good” $\hat{\gamma}_{Scat}$ coherence is achieved for bistatic angle differences from 0° up to 4-6°, depending on polarisation. This corresponds to 0-6° for VV and HV, 0-5° for VH and 0-4° for HH.

“Moderate” CCD performance occurred at least for bistatic angle differences of 6-10° for VV and HV, 5-10° for VH and 4-7° for HH. The experimental setup did not allow for angular differences larger than 10°. “Poor” CCD performance occurred beyond these angular values.

The results are listed in the summary Table 4-7, and presented graphically in section 4.4.2.4.

Table 4-7 Summary of bistatic angular difference extents of coherence ($\hat{\gamma}_{Scat}$) performance bands for the gravel, where angles are rounded to the nearest 1°.

Scene	Pol	$\hat{\gamma}_{Scat} > 0.8$	$0.8 \geq \hat{\gamma}_{Scat} > 0.6$	$0.6 \geq \hat{\gamma}_{Scat}$
Gravel	VV	0-6°	6-10°	N/A
	VH	0-5°	5-10°	N/A
	HH	0-4°	4-7°	7-10°
	HV	0-6°	6-10°	N/A

4.4.2.3 Stone scene results

This section presents the coherence results for the stones scene. The coherence results are presented in Figure 4.22. The coherence for the stones is lower than for the gravel, and the difference increases as the bistatic angle difference increases, so that at 10° the difference is around 0.2. There is less variation with polarisation in the measured stones scene than with the gravel and HV is the polarisation in which coherence is least (whereas for the gravel, HH gave the least coherence).

The non-isotropic simulation $\hat{\gamma}_{sim-decorrelation}$ (see section 4.2.3.2) is plotted in black and the fitted coherence curve $\gamma_{Curve\ fit}$ is dark blue.

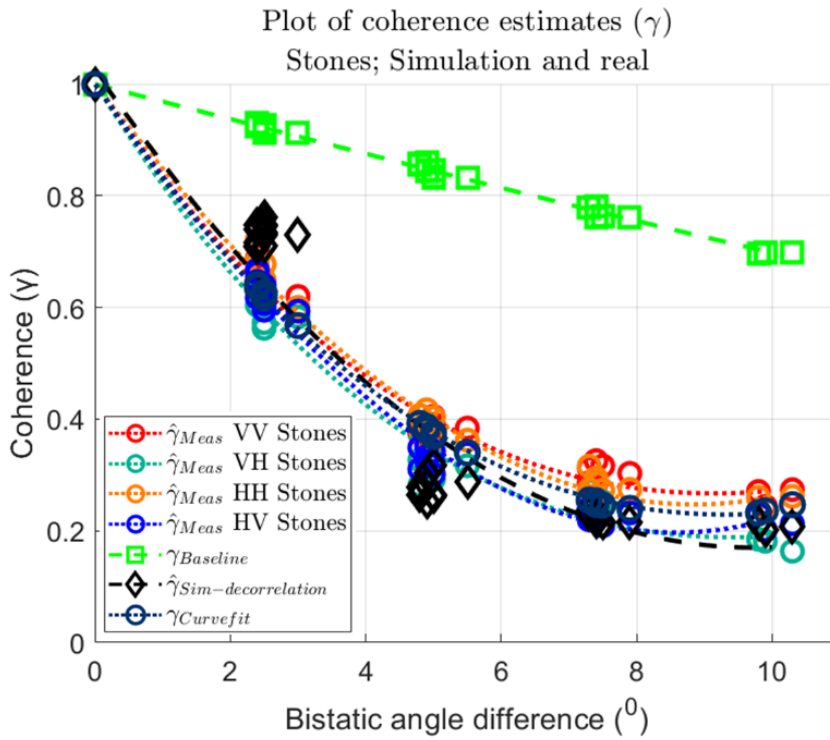


Figure 4.22 Coherence plots against bistatic angle difference for the stones scene, including all four polarisations, $\gamma_{baseline}$, the bistatic decoherence simulation and the fitted curve, whose parameters are provided in Table 4-4.

The estimates for $\hat{\gamma}_{Scat}$ (4.3)-(4.5) for the stones are plotted in Figure 4.23 for the four polarisations. The cross-polarization curves exhibit a steeper decrease in $\hat{\gamma}_{Scat}$ with respect to bistatic angle difference. The different methodologies result in only slightly different values.

The slight rise or plateauing of the $\hat{\gamma}_{Scat}$ values for the stones seen at 10° is attributed to the biasing seen in CCD processing at low coherence levels [129], [146] and the steeper decrease in coherence of the isotropic simulation ($\hat{\gamma}_{sim-isotropic}$) compared to the baseline ($\gamma_{baseline}$) (Figure 4.19).

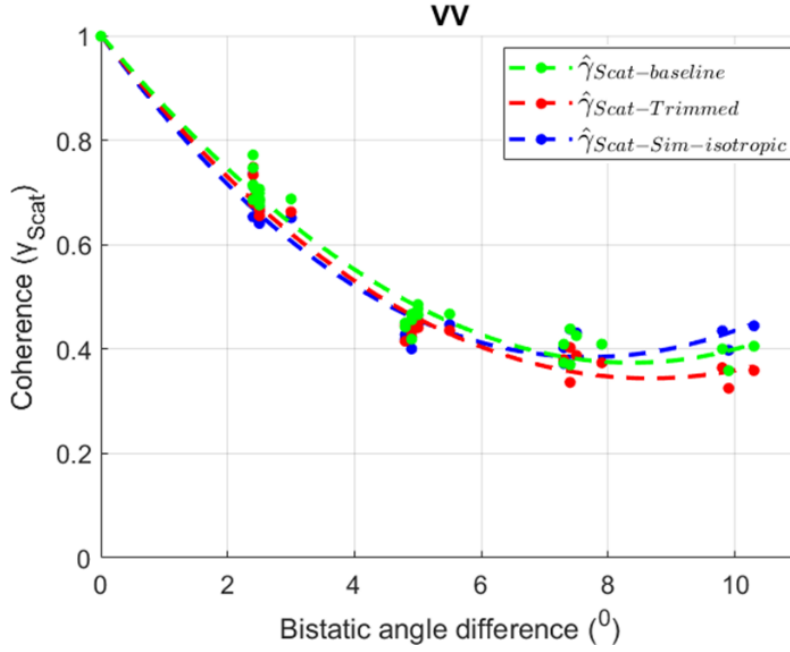


Figure 4.23 (a) VV polarisation. Stone scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

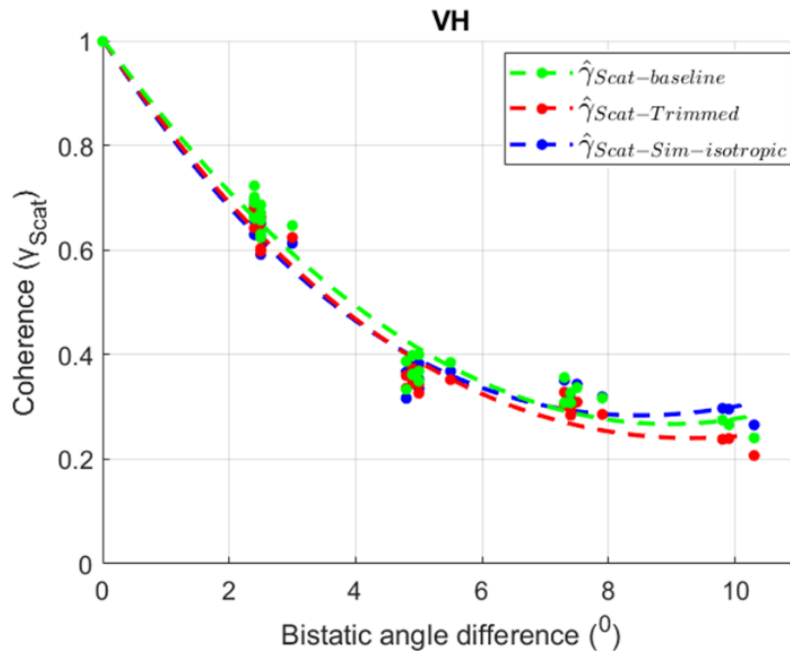


Figure 4.19 (b) VH polarisation. Stone scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

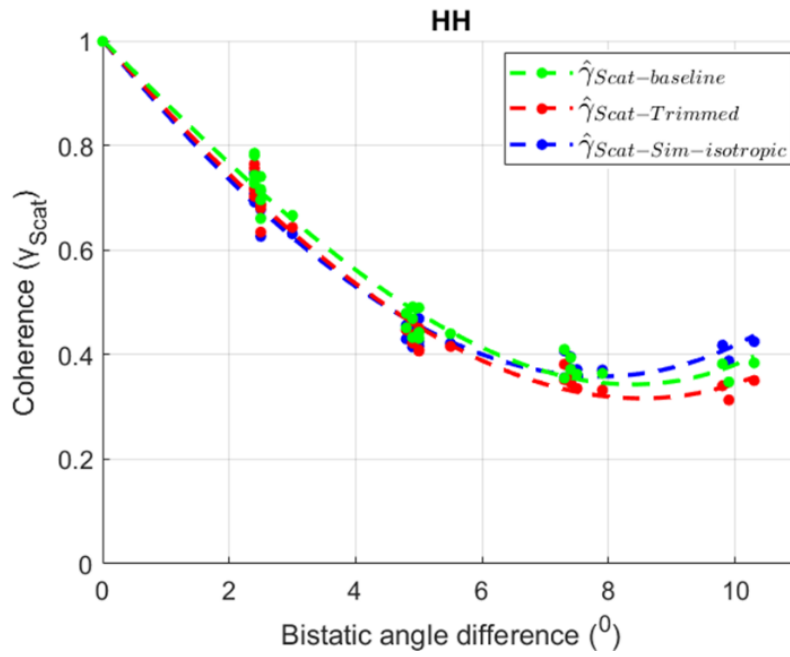


Figure 4.19 (c) HH polarisation. Stone scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

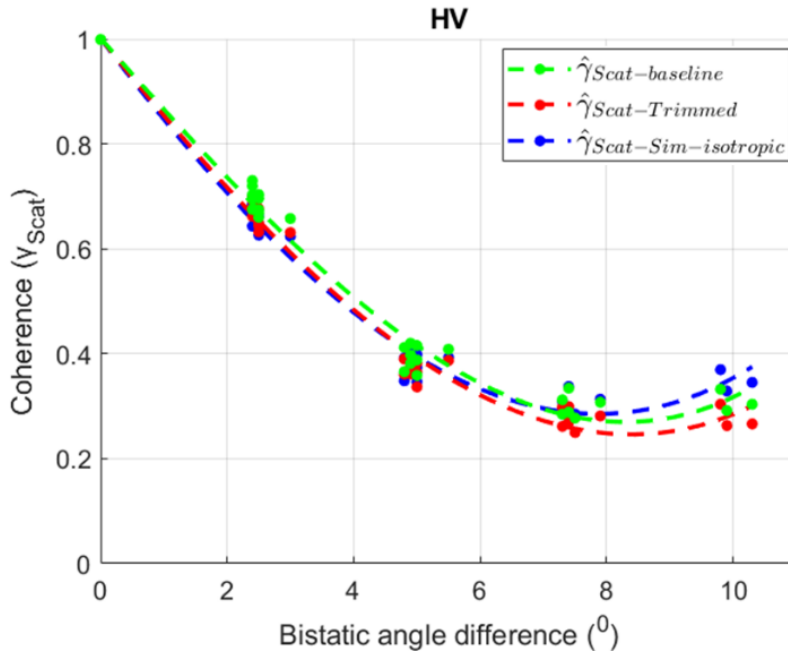


Figure 4.19 (d) HV polarisation. Stone scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (4.3)-(4.5).

In comparison to the gravel results in Figure 4.21, the values of $\hat{\gamma}_{Scat}$ for stones in Figure 4.23 reduce at a faster rate.

Using the three performance bands defined in section 4.4.2.2: “good” $\hat{\gamma}_{Scat}$ coherence is achieved for bistatic angle differences from 0-1° for VV, VH and HH, and 0-2° for HV; “Moderate” CCD performance occurred for bistatic angle differences in the range 1-3° or VV, VH and HH, and 2-4° for HV; “Poor” CCD performance occurred for angles greater than 3°.

The results are listed in the summary Table 4-8, and presented graphically in section 4.4.2.4.

Table 4-8 Summary of bistatic angular difference extents of coherence ($\hat{\gamma}_{Scat}$) performance bands for the stones, where angles are rounded to the nearest 1°.

Scene	Pol	$\hat{\gamma}_{Scat} > 0.8$	$0.8 \geq \hat{\gamma}_{Scat} > 0.6$	$0.6 \geq \hat{\gamma}_{Scat}$
Stones	VV	0-1°	1-3°	3-10°
	VH	0-1°	1-3°	3-10°
	HH	0-1°	1-3°	3-10°
	HV	0-2°	2-4°	4-10°

4.4.2.4 Graphical summary

The results presented in Table 4-7 and Table 4-8 are presented graphically in Figure 4.24. The curves of best fit in Figure 4.21 and Figure 4.23 were averaged across polarisations and plotted with a colourmap based on the three performance bands defined in section 4.4.2.2. “Good” CCD performance is represented by green, “Moderate” by yellow and “Poor” by red.

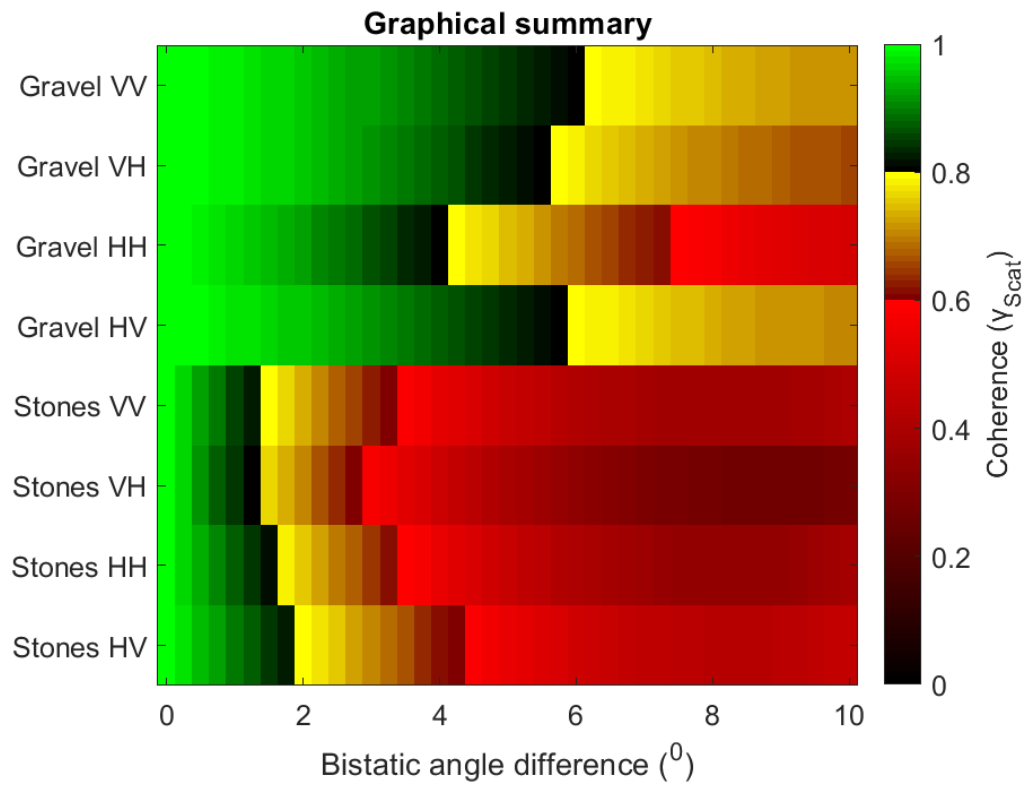


Figure 4.24 Graphical summary of results showing the bistatic angular difference extents of coherence ($\hat{Y}_{Scat}$) performance bands for the gravel and stone scenes. “Good” CCD performance is represented by green, “Moderate” by yellow and “Poor” by red.

4.4.3 Discussion

For two types of terrain, it has been shown that when the difference between bistatic angles is large enough for two bistatic collections, the coherence between the corresponding SAR images is less than would be expected from the degree of projected Fourier domain support overlap achieved.

It is hypothesised that the observed reduction in coherence is due to differences in the bistatic microwave scattering between the two SAR collections, which would include phenomena such as shadowing and multipath. These effects would be included within the proposed scattering coherence parameter γ_{Scat} .

The results presented build on those found in [162], [177] and provide improved characterisation of γ_{Scat} , now for two ground types. γ_{Scat} was calculated in three ways, which were in good agreement.

A CCD simulation was developed which modelled a decorrelation as a function of bistatic angle difference, implemented via a decorrelation phase factor controlled by one coefficient. Whilst matching to the experimental results was achieved, it is assumed that the match could be further improved by use of a polynomial function of the bistatic angle. The determination of the polynomial coefficients would be highly computationally intensive and a subject for future research. Additional further work could include the determination of improved curve fitting functions for γ_{Scat} .

It was shown that for bistatic SAR trajectories where there is a significant bistatic angle difference, the decorrelation due to γ_{Scat} dominates the coherence and can reduce it to a level where CCD interpretability becomes very poor. This shows that even when terrain has undergone little change, selection of bistatic SAR collections with high spatial frequency domain overlap may not be sufficient for forming good quality CCD images, and that the bistatic angle difference can have a major effect, which is terrain dependent. These considerations would affect the choice of useful interferometric imaging geometries obtained from a multistatic SAR system.

Table 4-7, Table 4-8 and Figure 4.24 summarise the $\hat{\gamma}_{Scat}$ coherence results and show that the CCD performance that can be expected depends upon the scene being imaged and the measured polarisation.

The two terrain surfaces investigated can be considered rough, with their surface height variations being above the Rayleigh Roughness Criterion height of 0.41 cm: the gravel with a surface height variation just above the criterion (1-2 cm), and the stones about an order of magnitude above it (5-10 cm).

Having investigated only two terrain types, it is difficult to extrapolate the results to general terrain, however the experiments conducted indicate that the bistatic angle difference extent for any particular CCD performance band broadly varies inversely with the terrain height variation (so long as it is above the Rayleigh Roughness Criterion). For example, for “Good” CCD performance, in the gravel case the angular extent reached 6°, whereas for the stones case it reached 2°.

Overall, however, it has been shown that the terrain surface has a significant impact on what different bistatic geometries can be used to form useful CCD images when an exact repeated pass is not possible, for example due to time or mission constraints.

An approach to simulating the decorrelation has been demonstrated, and matched to two types of terrain, controlled by one empirically determined parameter, however other ground types may respond differently. Future work could investigate additional ground types and how the combination of multistatic collections might be used to reduce the impacts of coherence loss [160]. To improve the understanding of the behaviour of the $\hat{\gamma}_{Scat}$ parameter, future experiments could utilise metal spheres or higher fidelity simulations using scene CAD model instead of point scatterers.

4.5 Conclusion – Interferometric Coherence

This chapter has investigated the coherence for bistatic geometries with a difference in bistatic angle. When this angle is sufficiently large the coherence between the corresponding SAR images is less than would be expected from the degree of projected Fourier domain support overlap achieved.

These investigations were the subject of two journal papers [163], [177]. In the first paper, a very high spatial frequency domain overlap was maintained for a single gravel scene. The second paper used a different set of trajectories which resulted in a more consistent grazing angle and used two scene types.

These trajectories are applicable to ISR satellites when an exact repeat pass is not possible due to time or mission constraints. These papers investigated to what degree the loss in coherence due to the scattering parameter, γ_{Scat} , might limit the possibility of forming useful CCD images.

It is hypothesised that the observed reduction in coherence is due to differences in the bistatic microwave scattering between the two SAR collections, which would include phenomena such as shadowing and multipath. These effects would be included within the proposed scattering coherence parameter γ_{Scat} .

It was shown that for bistatic SAR trajectories where there is a significant bistatic angle difference, the decorrelation due to γ_{Scat} dominates the coherence and can reduce it to a level where CCD interpretability becomes very poor. This shows that even when terrain has undergone little change, selection of bistatic SAR collections with high spatial frequency domain overlap may not be sufficient for forming good quality CCD images, and that the bistatic angle difference can have a major effect, which is terrain dependent. These considerations would affect the choice of useful interferometric imaging geometries obtained from a multistatic SAR system.

Having investigated only two terrain types, it is difficult to extrapolate the results to general terrain, however the experiments conducted indicate that the bistatic angle difference extent for any particular CCD performance band broadly varies inversely with the terrain height variation (so long as it is above the Rayleigh Roughness Criterion). For

example, for “Good” CCD performance, in the gravel case the angular extent reached 6° , whereas for the stones case it reached only 2° .

Overall, however, it has been shown that the terrain surface has a significant impact on what different bistatic geometries can be used to form useful CCD images when an exact repeated pass is not possible, for example due to time or mission constraints.

An approach to simulating the decorrelation has been demonstrated, and matched to two types of terrain, controlled by one empirically determined parameter, however other ground types may respond differently. Future work could investigate additional ground types and how the combination of multistatic collections might be used to reduce the impacts of coherence loss [160]. To improve the understanding of the behaviour of the $\hat{\gamma}_{scat}$ parameter, future experiments could utilise metal spheres or higher fidelity simulations using scene CAD model instead of point scatterers.

5 Multidimensional interferometric change detection

5.1 Introduction

Interferometry was introduced in section 2.7. As discussed in section 4, multistatic SAR may allow for the timely collection of repeat pass imagery [25], [116]. However, the CCD's may be subject to varying degrees of coherence due to differing baselines [162], [163], [177].

Multistatic SAR data is multidimensional and can be combined in different ways. For high coherence and an improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support overlap [94], [132], [176], yet it has been found that this alone is insufficient to guaranty high coherence and good CCD contrast [163], [177] (section 4).

CCD images are a product of two SAR images, a reference and a mission. However, for a multistatic SAR system there will be several bistatic image pairs. For n reference and m mission images, there will be up to $m \times n$ possible CCD images (assuming a good spatial frequency domain overlap between all). And if there are four polarisations then there will be four times that many CCD images ($m \times n \times 4$). Other detectors such as polarimetric parameter changes [8], [159] or incoherent change detectors [148], [149], [155], [160].

With a large number of possible combinations of these images it is important that the manner in which they are combined is considered.

This could be done during the initial SAR image formation phase. This would form a pair of multistatic SAR images to then form one change detection image. Alternatively, a combined change detection image could be formed from multiple bistatic change detection images. Polarimetry adds another dimension, as single pol change detection images can be formed, or combinations and decompositions.

In the context of defence applications, a human analyst might be required to examine the images. Such large volumes of data could quickly become overwhelming. Each of the

CCD images will however contain slightly different data, and what might be unclear in one image may become clear through the combination of several images.

This chapter investigates methodologies for utilising multidimensional SAR Interferograms and change detection images formed using multistatic and multipolarimetric collections.

This section formed using a paper [160] published in a special issue of the Institution of Engineering and Technology (IET) Radar Sonar and Navigation (RSN) journal on ‘*Synthetic Aperture in Sonar and Radar*’. This paper builds on previous work presented at conferences [10], [159].

This paper investigated the use of a two-stage change detector [148], [149], [155] extended to multistatic and fully polarimetric (near field) data [10], [159]. Several methods of forming the multistatic and fully polarimetric change detection images were used. These are presented in sections 5.2.3 and 5.2.4. These images are analysed using a variety of performance metrics, which were presented in section 3.3. This baseline leads to additional decorrelations [146], [177] which can be detected by the change detection algorithm. This can result in the actual change being obscured. This paper investigated how well different methods of forming multistatic change detection images are able to compensate for these decorrelations and produce a change detection image which is easy to interpret and captures the structure of the change.

5.2 Methodology

5.2.1 GBSAR Laboratory

Bistatic SAR measurements were conducted at the Cranfield University Ground Based SAR laboratory (GBSAR laboratory, section 3.1). The scene consisted of a gravel rectangle of 3.4×4 m, which is shown in Figure 5.1. The measurements were conducted with a Vector Network Analyzer (VNA), with a centre frequency of 8.3 GHz and bandwidth of 3.4 GHz. Due to the use of a single VNA, there were no signal synchronization issues associated with the bistatic measurements – often a significant issue for practical remote bistatic SAR sensing [25]. The SAR geometries used were constrained by the available transmitter and receiver rectangular apertures pictured in Figure 5.2, where the scene dimensions and SAR geometries measured are also shown.

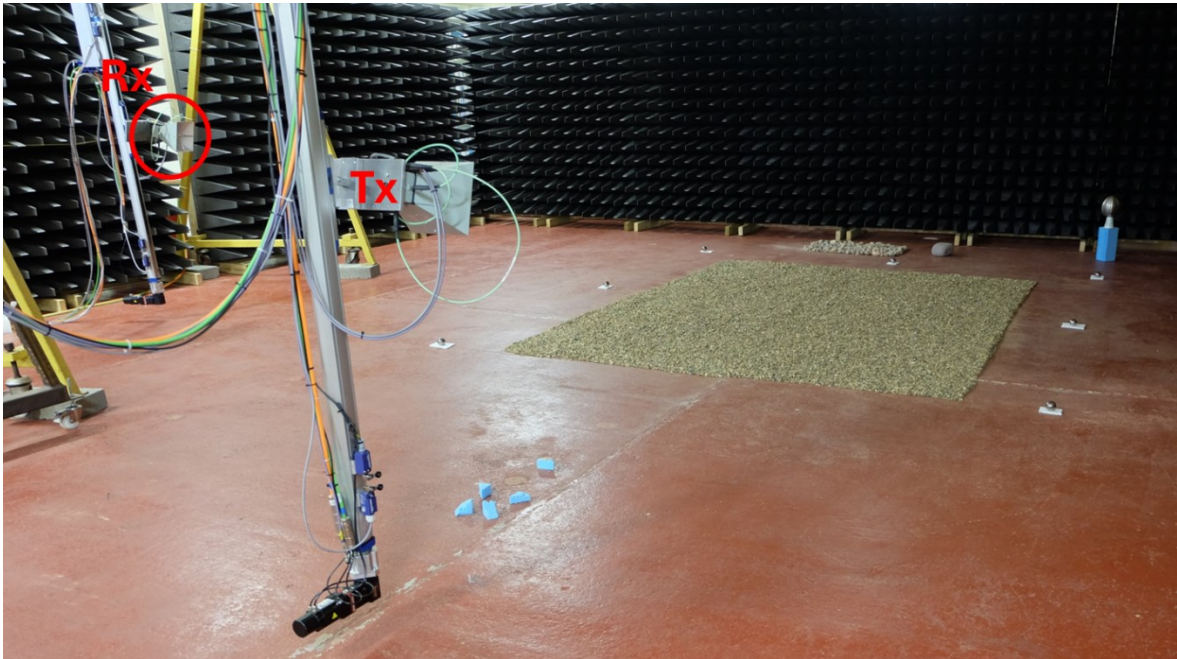


Figure 5.1 Image shows the GBSAR system in a bistatic configuration, with a gravel rectangle as the scene.

The multistatic data was collected for several geometries. In each case the transmitter moved along the red trajectory. The receivers were located in one of 6 positions. These are referred to as R1-6 (see Figure 5.2). The bistatic geometries are referred to as TR1-6.

The SAR data was collected for two collections. In the first, the reference, the scene was unchanged. In the second, called the mission, the letters ‘GBSAR’ were traced onto the

scene. This was done by gently disturbing the gravel for use in change detection performance evaluation.

For the reference collection TR1, TR2 and TR3 were used. For the mission collection TR4, TR5 and TR6 were used.

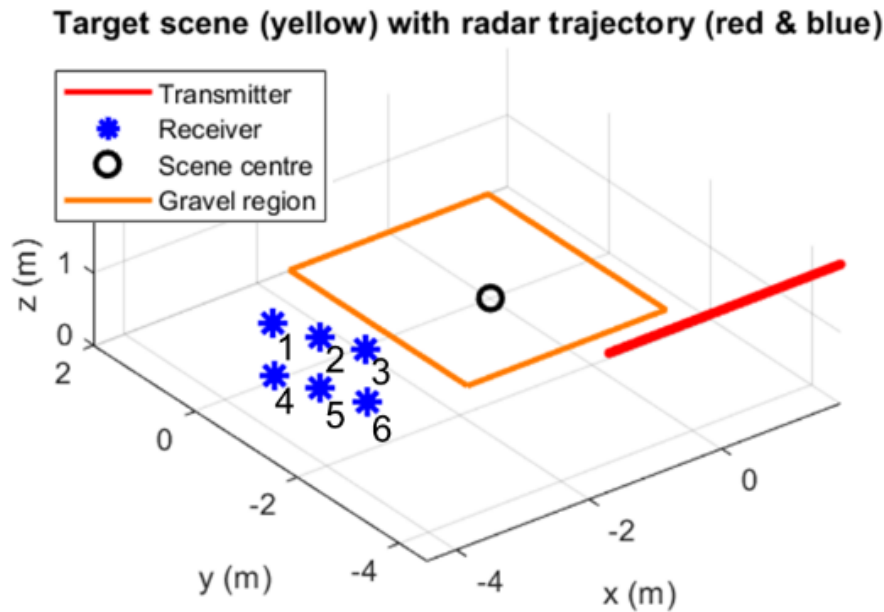


Figure 5.2 Diagram showing the radar trajectories used in the data collection. The transmitter trajectory is shown in red, the multiple fixed receiver positions in blue and the gravel region is shown in orange. The receivers are numbered 1 to 6 and are referred to as R1 through to R6.

Transceiver scan geometry parameters are listed Table 5-1. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the table are calculated to the centre of the scene and gravel region. The resolutions were calculated using the Bistatic Equivalent Monostatic (BEM) rather than the midpoints. This results in different co-ordinates to the transceiver midpoints. Using the incorrect geometry can lead to image distortions or incorrect resolution estimates [120], [121].

Table 5-1 Table showing the scan geometry parameters for the six bistatic trajectories. Tx denotes the transmitter, Rx the receiver, and BEM the Bistatic Equivalent Monostatic values for the transceiver trajectories. Ranges are in the respective slant planes. Resolutions are in the ground plane and estimated at the scene centre.

		TR1	TR2	TR3	TR4	TR5	TR6
Bistatic angle, β ($^{\circ}$)		64.2	57.4	50.8	66.6	59.6	52.8
Grazing angle, ψ ($^{\circ}$)	Tx	22.9	22.9	22.9	22.9	22.9	22.9
	Rx	22.1	22.1	22.8	14.5	14.5	14.2
Range (m)	Tx	4.95	4.95	4.95	4.95	4.95	4.95
	Rx	5.24	5.25	5.32	5.01	5.00	5.08
Transmitter height (m)		1.92	1.92	1.92	1.92	1.92	1.92
Receiver height (m)		1.97	1.97	1.97	1.50	1.50	1.50
BEM resolution	Range (cm)	4.21	4.17	4.13	4.06	4.03	4.01
	Cross-range (cm)	4.36	4.38	4.40	4.40	4.41	4.41

From the Reference and Mission multistatic collections, three pairs of bistatic geometries were used for CCD creation as follows: TR1 and TR4, TR2 and TR5, and TR3 and TR6 (effectively receiver columns). These allowed the formation of three bistatic CCD images

for each of the two collections. The three CCDs were combined to form multistatic CCD images in different ways.

5.2.2 Combined Intensity and CCD background

Change detection does not necessarily only have to use CCD images. Non-Coherent Change Detection (NCCD, section 2.7.3.1) can be used to complement CCD images as shown in [149], [155]. A two-stage detector was used. In his paper the NCCD products were used to detect large scale changes in the scene whereas the CCD was used to detect small scale changes.

The [149], [155] change detector is a two-stage detector. And in the paper, utilising both the NCCD (equation (2.50)) and CCD (equation (2.54)) results leads to an image with improved clarity. The block diagram of the detector is shown in Figure 5.3. The detector utilises the following hypothesis test:

$$\begin{aligned} H_0: \quad \rho_{SVR} &\approx 1 \text{ and } |\hat{\gamma}| \approx 1 \\ H_1: \quad \rho_{SVR} &\neq 1 \text{ or } |\hat{\gamma}| \lesssim 1 \end{aligned} \tag{5.1}$$

Here the hypothesis H_0 is for no change and H_1 is for a changed scene. $\hat{\gamma}$ is the sample complex correlation, and ρ_{SVR} is sample variance ratio. This type of detector only has two outputs (change or no change) and as such would be considered a binary detector.

The paper does however show that utilising multi-dimensional data can improve the detection performance.

A two-stage detector was presented in [149], [155], with [148] performing analysis on the theoretical performance. These detectors are described as ‘combined intensity and coherent change detection’ (shortened to CI-CCD in this thesis). For the Non-Coherent Change Detection (NCCD), changes are detected due to a difference in amplitude in the images. This typically indicates large scale scene changes. Smaller scene changes typically do not result in a change in intensity, but rather phase [94]. To detect these small-scale changes CCD is used.

The two-stage detector, introduced in [149], [155], is shown below in Figure 5.3 (replicated from [149]). Here I_f and I_g represent the reference and mission trajectories.

For the Intensity change detection, the difference in intensities ($|I|$) is calculated. This difference is then compared against a threshold T_{NCCD} . Differences exceeding this threshold are labelled as changes. The coherent change detection, as described in section 2.7.3.2.1 results in a coherence value, $\hat{\gamma}$. This value is also compared against a threshold T_{CCD} . In this case values exceeding the threshold (close to 1) are labelled as unchanged, whereas pixels with a value below the threshold are labelled as changes. The output of the detector is a binary value indicating a change or no change.

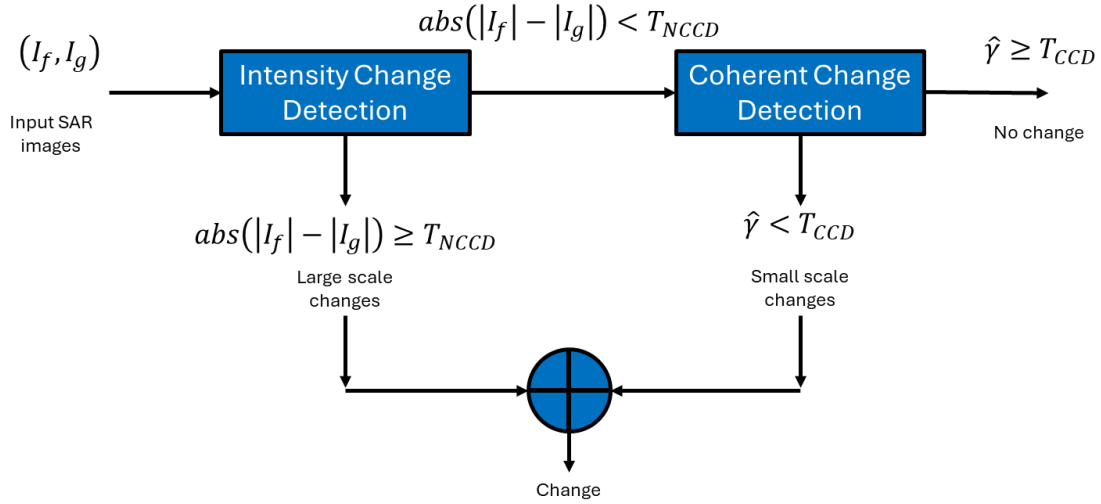
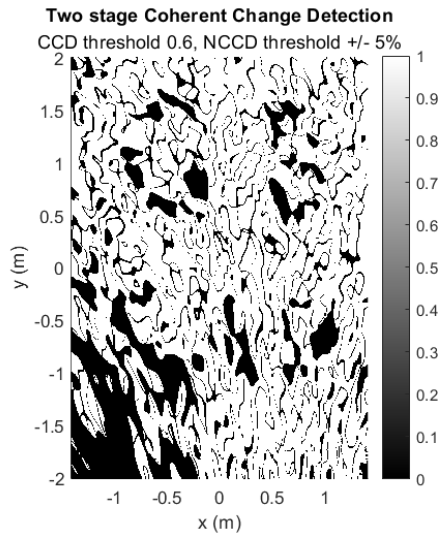
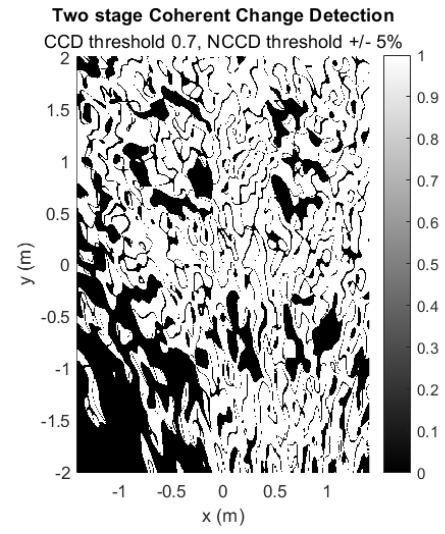


Figure 5.3 The block diagram of the two-stage detector introduced in [149], [155]. Image is reproduced from [149], where it is figure 3. Image shows the Intensity and Coherent change detection stages as well as how thresholding is used.

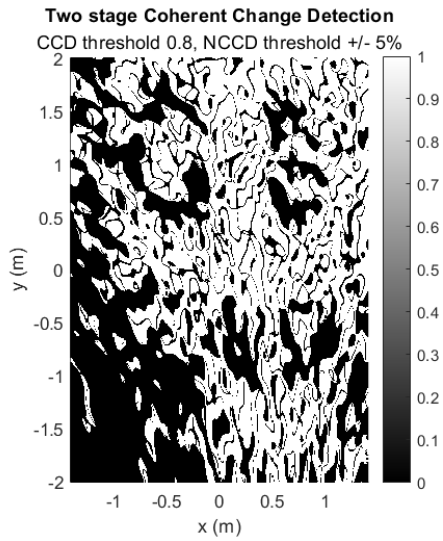
Figure 5.4 shows four different thresholds for the two-stage detector. As the threshold is increased from 0.6-0.9 the probability of detection increased, however so did the false alarm ratio. This reflects the results presented in [148], [149]. The results presented below do have a high false alarm ratio, however this is likely from clutter.



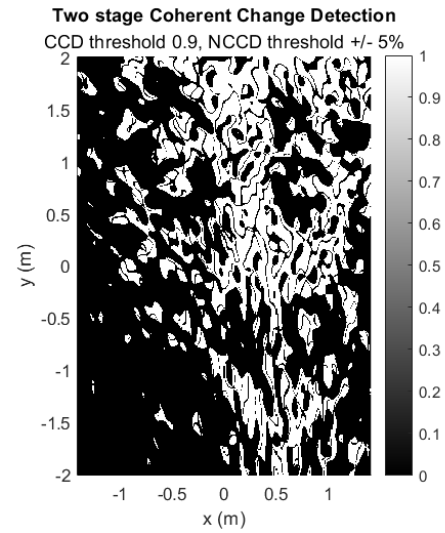
(a)



(b)



(c)



(d)

Figure 5.4 four change detection images (a-d) formed using various thresholds for the coomplex correlation, ranfing from 0.6 to 0.9.

5.2.3 Multistatic Image formation and nomenclature

A multistatic SAR image is formed using the coherent summation of bistatic SAR images. These SAR images were formed using a bistatic generalisation of the Back Projection Algorithm (BPA) [124]. In addition to multistatic SAR images, multistatic CCD and NCCD images are used in this paper. These may be either from multistatic SAR images or a combination of bistatic CCD/NCCD images from a multistatic SAR collection. A multistatic CCD or NCCD image formed from (coherent summation) multistatic SAR images is referred to as a ‘Coh sum’ image in the results plots. Multistatic CCD images formed using multiple bistatic CCD or NCCD images are referred to as ‘max’, ‘mean’ or ‘min’ in the results plots depending upon the procedure implemented.

For the CCD images, a maximum image has the maximum coherence value for each pixel between the different CCD images being compared (a maximum image results in the minimum number of detections). Conversely a minimum image has the lowest coherence (and the highest number of detections). This nomenclature is also used for the NCCD images.

The Combined Incoherence Coherent Change Detection (CI-CCD) images are named after the CCD images used in the formation. However, in the NCCD images a higher value corresponds to a greater change.

Therefore, to maximise the coherence or detections the following combinations were used for the CI-CCD images:

- Max two-stage - Max CCD, Min NCCD
- Mean two-stage - Mean CCD, Mean NCCD
- Min two-stage -Min CCD, Max NCCD

Here the max, mean or min of a CCD or NCCD image refers to taking the maximum, mean or minimum value at each pixel. So for example the Max two-stage maximises the coherence (thus the smallest number of changes). It is formed using the maximum CCD value and the minimum NCCD value.

5.2.4 Two-stage CI-CCD detector

5.2.4.1 Detector architecture

The detector architecture maintains similarities with the two-stage CI-CCD detector outlined in section 5.2.2, albeit with some modifications. As shown in Figure 5.3, a change detected in the NCCD image is classified as a change. If no change is detected, then the CCD image coherence value is compared against a threshold.

This architecture was modified to include four classes: definite change, probable change, probable no change and definite no change. The change detection for the NCCD images remains binary, as shown in section 5.2.2. This is because the NCCD process detects large scale changes. As the CCD process is more sensitive four classes have been used to reduce the impact of edge case detections on the performance metrics. These classes are outlined in equation (5.2). Here ρ is a change index separate from coherence, and represents the value of the CI-CCD detection pixel and T the change/no change threshold. t is the tolerance and defines the size of the probable change/no change bins. The aim of the tolerance value and the ‘probable’ category is to reduce the impact on performance metrics of an incorrect detection when the values are close but on opposite sides of the threshold. These thresholds and tolerances could be set using methodologies such as constant false alarm rate in an operational system. Here they were selected to produce CI-CCD images that matched the known ground truth. This is further explained in section 5.2.4.3.

$$\rho = \begin{cases} 1 & \hat{\gamma} \geq (T + t) \\ 0.5 & (T + t) > \hat{\gamma} \geq T \\ -0.5 & (T - t) < \hat{\gamma} < T \\ -1 & \hat{\gamma} \leq (T - t) \end{cases} \quad (5.2)$$

$$\rho = \begin{cases} 1 & \text{Def.no change} \\ 0.5 & \text{Prob.no change} \\ -0.5 & \text{Prob change} \\ -1 & \text{Def.change} \end{cases}$$

This is then shown visually in a flowchart in Figure 5.5.

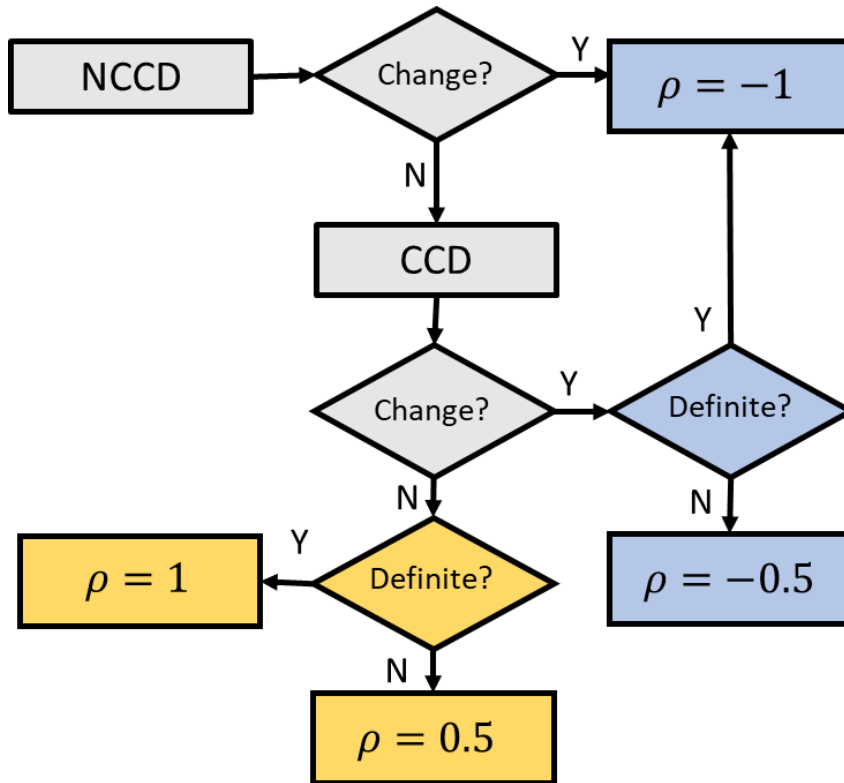


Figure 5.5 Flow diagram of the two-stage CI-CCD detector. Boxes in blue show where a change has been detected. Areas in yellow indicate no change. These reflect the colours in the CI-CCD images (such as Figure 5.8).

5.2.4.2 Pre and post CI-CCD sorting

Sorting occurs at two different stages. This sorting takes the maximum, mean or minimum value per pixel and forms new images. This occurs either before or after the CI-CCD detection. This is shown in two flowcharts (Figure 5.6 and Figure 5.7).

CI-CCD images formed when the sorting has occurred before the two-stage detection step are referred to as pre-2S-sorted. Multistatic CI-CCD image can be formed by sorting (maximum, mean or minimum) of bistatic CI-CCD images. These are referred to as post-2S-sorted images.

These two methodologies were used to show differences in behaviour and detection performance based on the chosen processing pipeline.

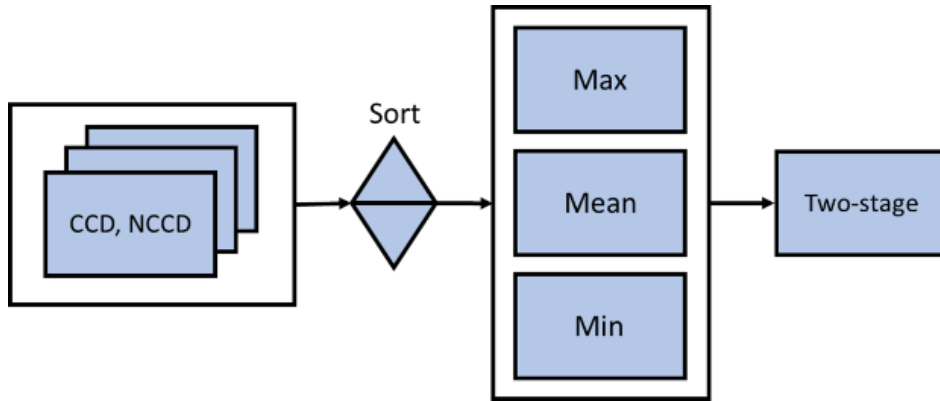


Figure 5.6 Flow chart showing the processing steps for forming ‘pre-2S-sorted’ CI-CCD images.

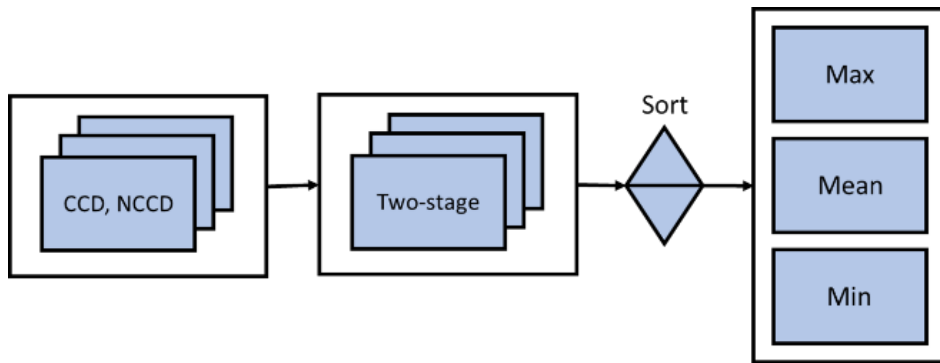


Figure 5.7 Flow chart showing the processing steps for forming ‘post-2S-sorted’ CI-CCD images.

5.2.4.3 Master image

The Master CI-CCD images were formed from exact repeated trajectories, unlike the test CI-CCD images which used dissimilar receiver positions. For example, TR1 against TR1, whereas the results use different trajectories such as TR1 against TR4. This resulted in very high coherence for the areas where no change occurred, as there would not be decorrelations present due to the baseline [146] or scattering term [177]. The master images were calculated from the mean of the individual bistatic master CI-CCD images. These were then discretised (see equation (5.3)). The letters ‘GBSAR’ were clearly visible in the master images.

$$\rho_{Discrete} = \begin{cases} 1 & \rho > 0.5 \\ 0.5 & 0 < \rho \leq 0.5 \\ -0.5 & 0 > \rho \geq -0.5 \\ -1 & \rho < -0.5 \end{cases} \quad (5.3)$$

Two master CI-CCD images were formed (Figure 5.8 and Figure 5.9), one for the pre-2S-sorted images and one for the post-2S-sorted images. These master images were formed with the same threshold for change, $T = 0.91$. The tolerance, t was set to 0.02.

This threshold was chosen as it resulted in two master images which closely matched the known ground truth. This value was chosen using qualitatively by inspecting the two stage images and comparing them to the known ground truth and the changes detected in CCD images. An operational system would use a more empirical method such as constant false alarm rate. At 0.91 both the Pre-2S-sorting and Post-2S-sorting images had a high Root Mean Squared (RMS) contrast values [232]. A lower threshold resulted in the ‘GBSAR’ letters in the pre-2S-sorting image being too large, and too many changes being detected on the lower area of the gravel. A higher tolerance resulted in too few detections of change in the Post-2S-sorting master image.

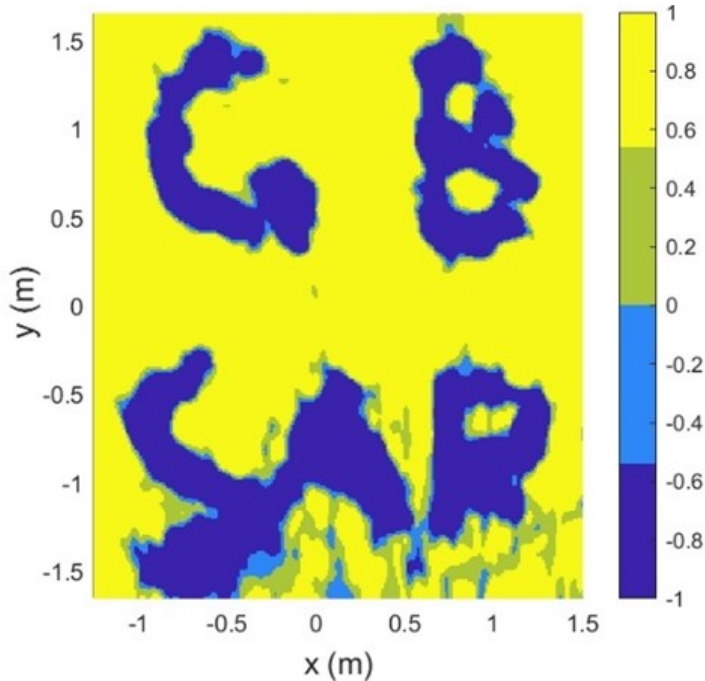


Figure 5.8 Two-stage master CI-CCD image for the pre-2S-sorting images. Here blue indicates a change and yellow indicates no change.

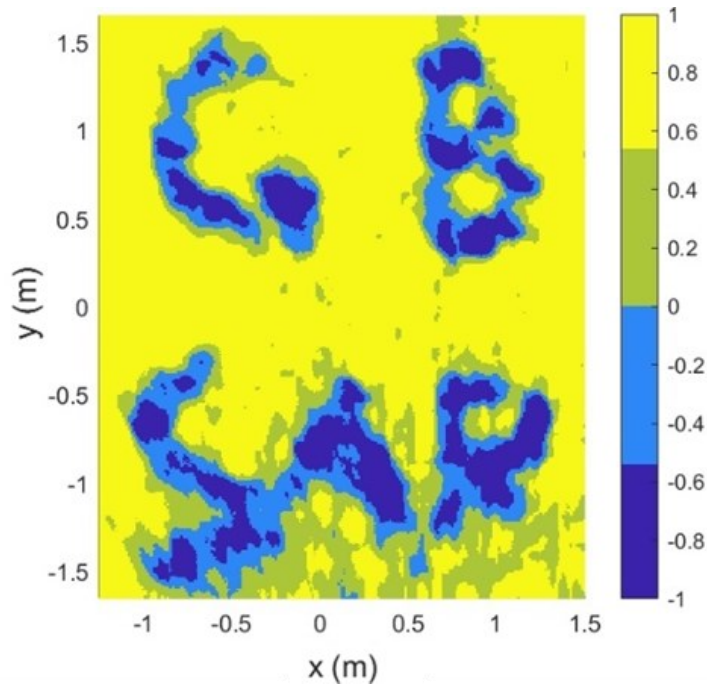


Figure 5.9 Two-stage master CI-CCD image for the post-2S-sorting images. Here blue indicates a change and yellow indicates no change.

5.2.5 Performance metrics

Performance metrics such as the Probability of Detection (POD), Critical Success Index (CSI) and the False Alarm Ratio (FAR) were used in the evaluation of the CCD images. These metrics are often used in the evaluation of space weather predictive models [223], [224]. These metrics were outlined in section 3.3.

5.3 Results

Two methods of forming the max, mean and min images were discussed in section 5.2.4.2. As such graphs are presented for both the pre-2S-sorting and post-2S-sorting. It should be noted that the bistatic and coherent summation multistatic CI-CCD images are the same, as they were not produced using the pre/post-2S-sorting method. Instead a single pair of SAR images was formed, and then change detection was performed. There will be some difference in the numerical values of the performance metrics due to the difference in master images.

5.3.1.1 Normalisation

The performance metrics were introduced in section 3.3. For the recollection of the reader the definitions for the metric symbols are provided below in Table 5-2, the full explanation and formulae for each term is located in section 3.3.

Table 5-2 Glossary of performance metrics

Symbol	Definition
PC	Proportion Correct
POD	Probability of Detection
CSI	Critical Success Index
MCC	Matthew's Correlation Coefficient
RMSE	Root Mean Squared Error
FAR	False Alarm Ratio
UIQI	Universal Image Quality Index

These metrics were plotted on spider plots. In order to improve the reader's ability to compare the performance of the different methodologies the performance values have been normalised to the maximum value.

This was done by finding the maximum value for each metric and dividing all values in that metric by the maximum value. The maximum values are shown below in Table 5-3. As such each spider plot uses values of 0-1.

The formula for the normalisation is shown in equation (5.4). Here x represents a particular performance metric (e.g. FAR, HSS, etc.). All the values of this particular metric (bistatic, multistatic, fully polarimetric etc.) are represented by X . x_i is the value of a given performance metric and a particular image formation technique. For example a maximum fully polarimetric multistatic image. This value is then normalised using the maximum value of X . The normalised value of x_i is represented by a tilde; $\tilde{x}_i$.

$$\tilde{x}_i = \frac{x_i}{\max(X)} ; \text{ where } X = [x_1, x_2 \dots x_N] \quad (5.4)$$

Table 5-3 Table showing the maximum values for each of the different performance metrics. This maximum value is the maximum value across all the different CI-CCD images.

PC	0.833	RMSE	1.655
POD	1.000	FAR	0.763
CSI	0.457	UIQI - Q	0.584
MCC	0.507	UIQI – Q1	0.682
HSS	0.500		

After the normalisation, the FAR and RMSE data presentation was modified further. The value of the normalised FAR and RMSE (now with values ranging from 0 to 1) was subtracted from 1. This was done so that a value closer to the outside of the spider plot (1) indicates better performance.

5.3.1.2 Bistatic & multistatic

Bistatic and multistatic performance can be compared. These are shown for the pre-2S-sorting (Figure 5.10) and the post-2S-sorting (Figure 5.11).

The pre-2S-sorting, for the VV polarisation (Figure 5.10) shows that the maximum multistatic performs well in many metrics, except the POD and CSI. This is likely because the high number of no-change events being classified, resulting in a high number of false

negatives. The coherent summation multistatic performs similarly to the best bistatic metrics. The max and mean exhibit quite poor performance, although do maintain a high POD. This shows the value of using multiple performance metrics.

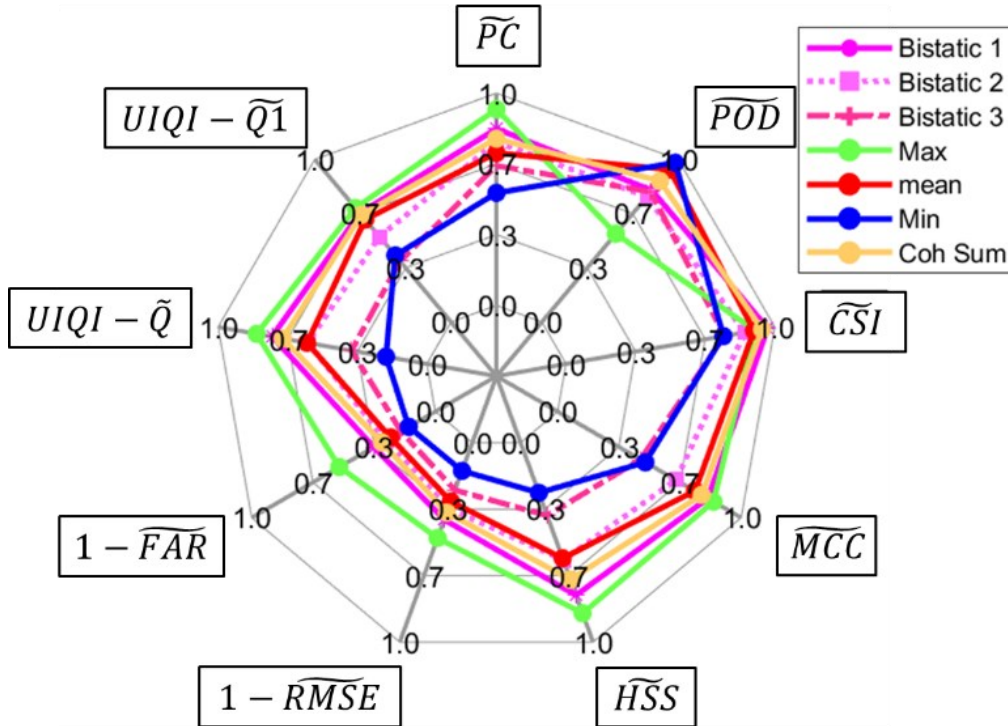


Figure 5.10 Spider plot showing the normalised performance of the three bistatic positions against the multistatic pre-2S-sorting and coherent summation. This is for the VV polarisation.

The behaviour of the post-2S-sorting (Figure 5.11) is different to the pre-2S-sorting. The minimum performs worse than in the previous set of images. The mean now demonstrates superior performance to the coherent summation. The performance of the max image is quite similar.

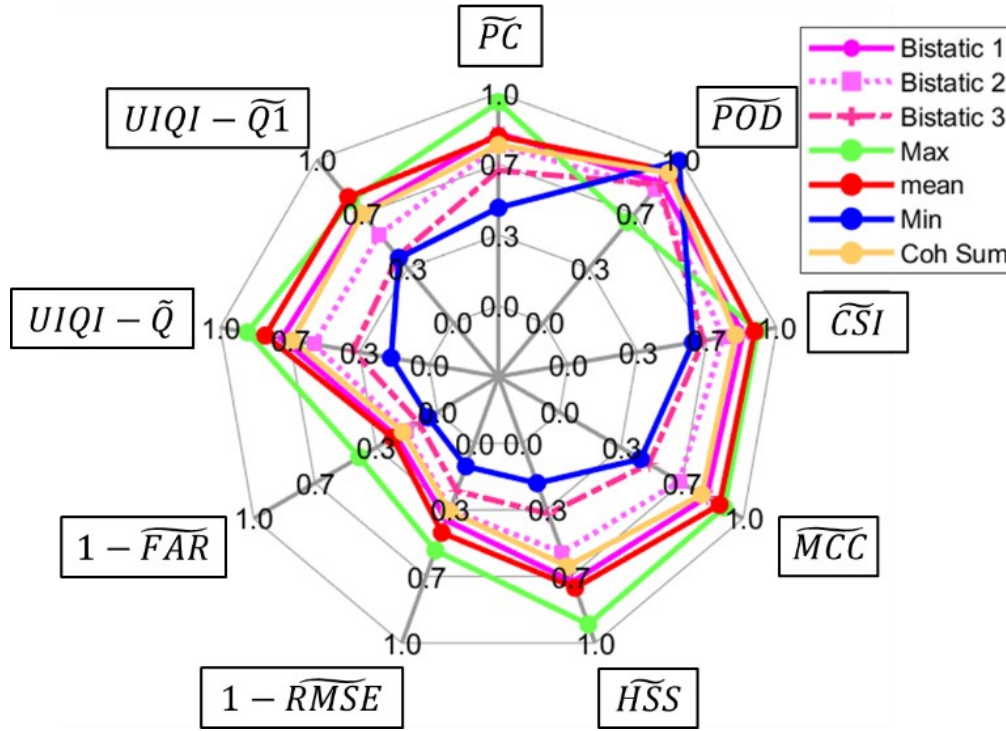


Figure 5.11 Spider plot showing the normalised performance of the three bistatic positions against the multistatic post-2S-sorting and coherent summation. This is for the VV polarisation.

It is also important when assessing performance to examine the outputs. This helps explain the performance seen in the graphs above. Figure 5.12 and Figure 5.13 show eight CI-CCD images. Comparing the output change detection images helps explain why the performance of the mean and min were quite similar (Figure 5.10). Inspecting the mean and min images in Figure 5.12 shows that they appear very similar. This shows that the pre-2S-sorting appears to lead to an increased number of detections. The mean image in Figure 5.13 however shows the ‘GBSAR’ more clearly and with a lower FAR. The letters are not particularly clear compared to the master image, however these results are indicative of the performance of the different methods. In the pre-2S-sorting many definite changes are detected, however in the post-2S-sorting significantly fewer are. It is also possible to see why the post-2S-sorting mean image outperforms the coherent summation image whereas the pre-2S-sorting mean performs worse than the coherent summation image.

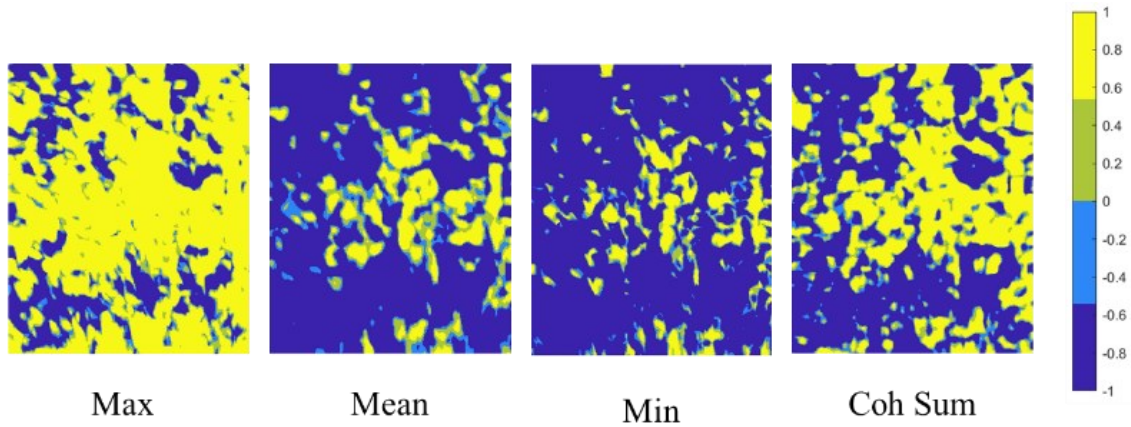


Figure 5.12 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the VV polarisation.

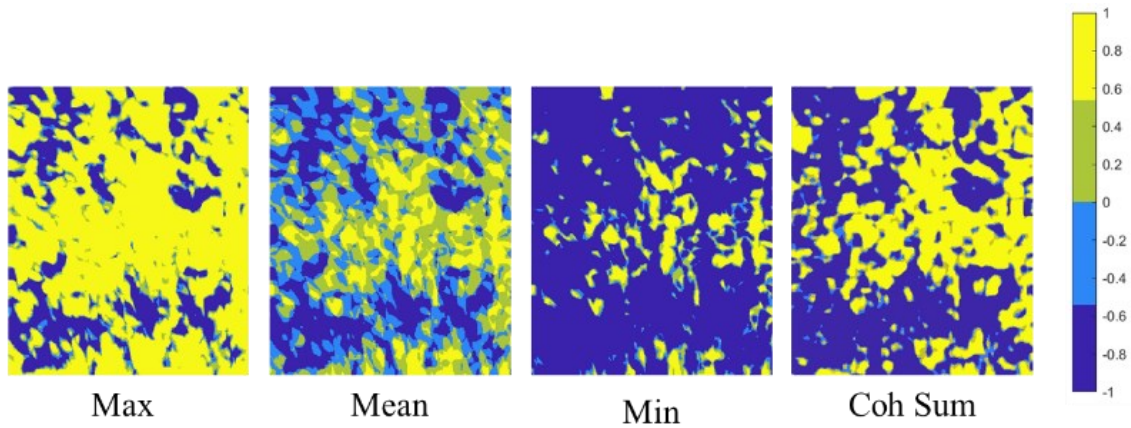


Figure 5.13 Set of four CI-CCD images formed using the post-2S-sorting dataset for the VV polarisation.

5.3.1.3 Multistatic comparisons

The different multistatic images can be compared. These are plotted in Figure 5.14 and Figure 5.15. These images show that whilst there is some polarimetric variation, the trend seen in section 5.3.1.2 holds true across the polarisations.

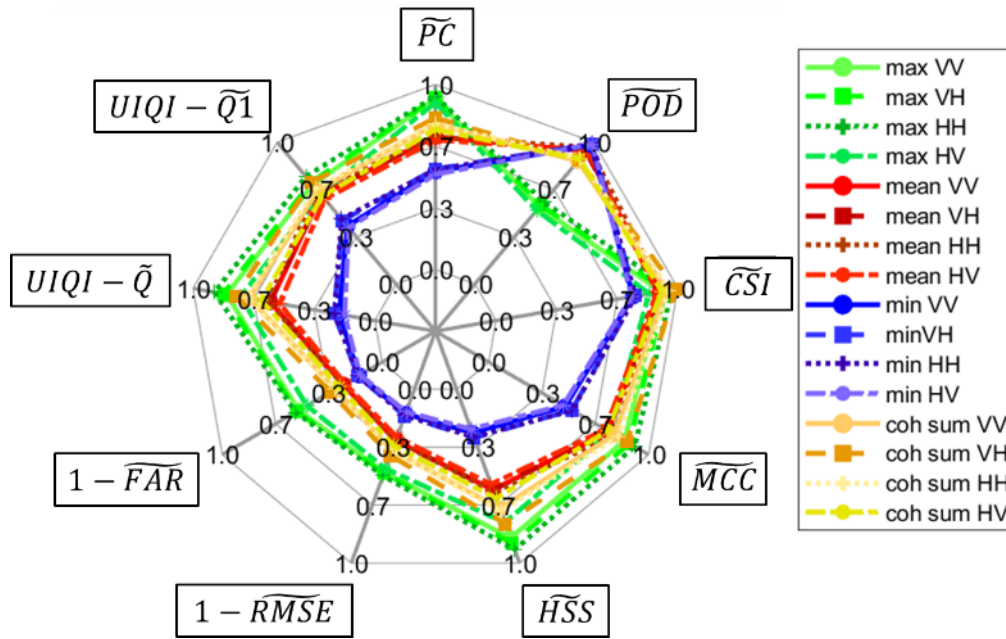


Figure 5.14 Spider plot showing the normalised performance of the pre-2S-sorting multistatic images across the four polarisations.

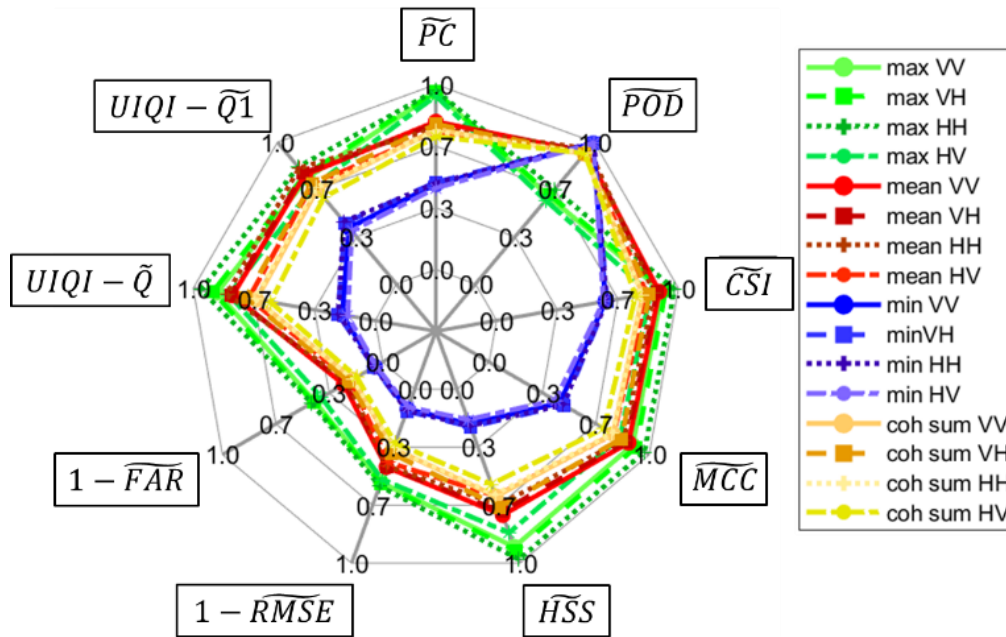


Figure 5.15 Spider plot showing the normalised performance of the post-2S-sorting multistatic images across the four polarisations.

5.3.1.4 Polarisations

The polarisations can also be investigated. Plotting the bistatic performance metrics in Figure 5.16 and Figure 5.17. This shows that there is a variance in performance across

polarisation and imaging geometry, although all polarisations perform quite similarly overall.

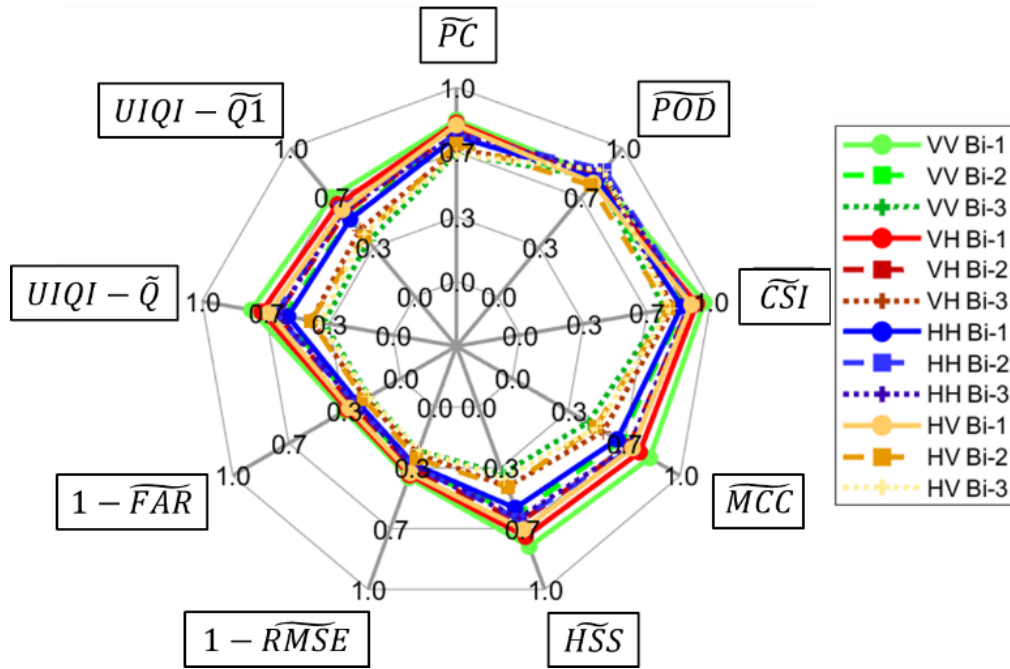


Figure 5.16 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared against the pre-2S-sorting master.

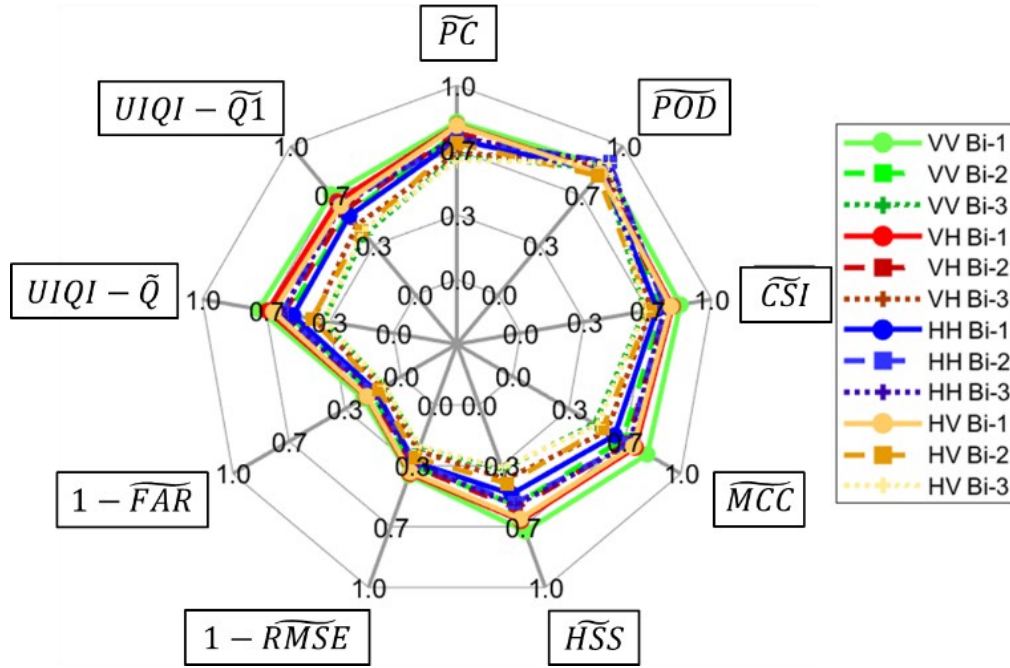


Figure 5.17 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared against the post-2S-sorting master.

Fully polarimetric images can be formed in the same way as the multistatic images. The results for these are presented in Figure 5.18 and Figure 5.19. These figures use TR1 as the reference and TR4 as the mission trajectory.

Similarly, to the bistatic results, the minimum images performed worse than the single polarisation images, except for POD. The coherent summation performs at a similar level to the poorest single polarisation (HH). The maximum performs well, except for POD. It has high PC, UIQI, MCC and HSS values. The mean varies in performance as seen in section 5.3.1.2. For the pre-2S-sorting it exhibits similar performance to the single polarisation, however for the post-2S-sorting it performs similarly to the max, although it has a higher POD at a cost of a lower PC and higher FAR.

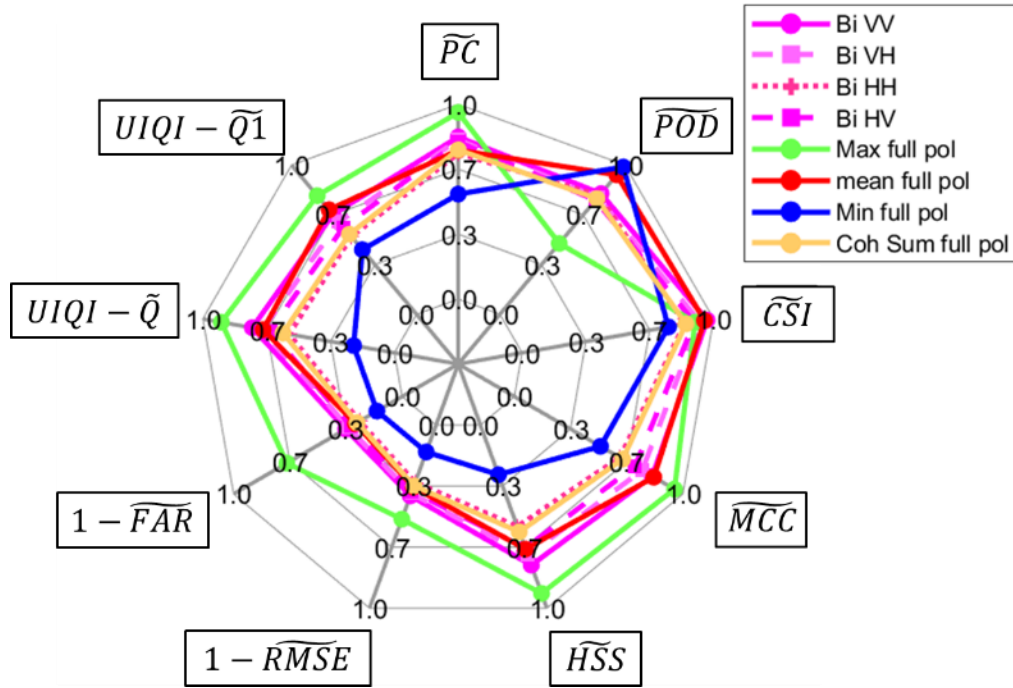


Figure 5.18 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using pre-2S-sorting and radar positions TR1 and TR4.

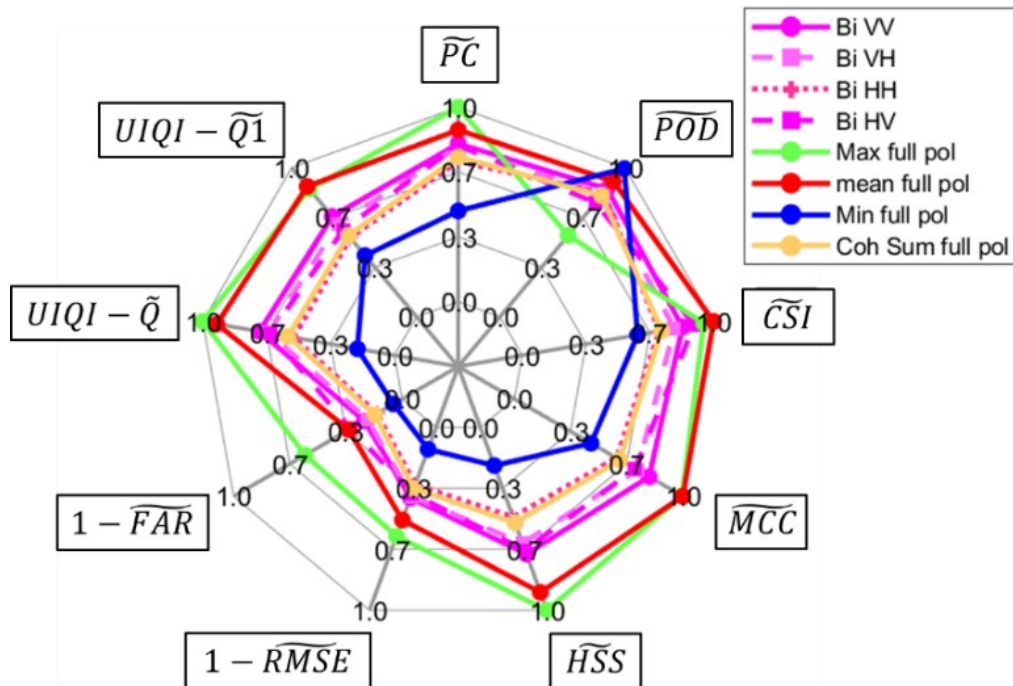


Figure 5.19 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using post-2S-sorting and radar positions TR1 and TR4.

Fully polarimetric multistatic images can also be formed. Figure 5.20 and Figure 5.21 compare the bistatic fully polarimetric performance metrics with the multistatic fully polarimetric performance.

In the pre-2S-sorting results (Figure 5.20) the max multistatic performs significantly worse than the bistatic maximum. It is believed this is due to too many images being used and thus changes being obscured. This effect is lessened in the post-2S-sorting results (Figure 5.21). In both the pre- and post-2S-sorting results the multistatic minimum performs worse than the bistatic. This is likely for the same reason as the maximum; too many images, which in this case cause too many changes to be detected.

The mean performs quite poorly for the pre-2S-sorting results (Figure 5.20), with the multistatic performing worse than the bistatic means. In the post-2S-sorting results (Figure 5.21) the performance is quite good, particularly with regards to the UIQI, CSI and POD. It also has a low FAR and RMSE. The multistatic is worse than some bistatic max and mean images for the HSS and FAR and is outperformed by the maximum in PC.

The coherent summation performs similarly to the maximum (bistatic and multistatic). It shows improvement over the bistatic coherent summation. For the pre-2S-sorting results (Figure 5.20), it exceeds it in POD and CSI, but performs worse for the other metrics. It has a higher HSS and MCC than the multistatic pre-2S-sorting, but not the bistatic. In the post-2S-sorting results (Figure 5.21) it is additionally outperformed by the bistatic and multistatic mean.

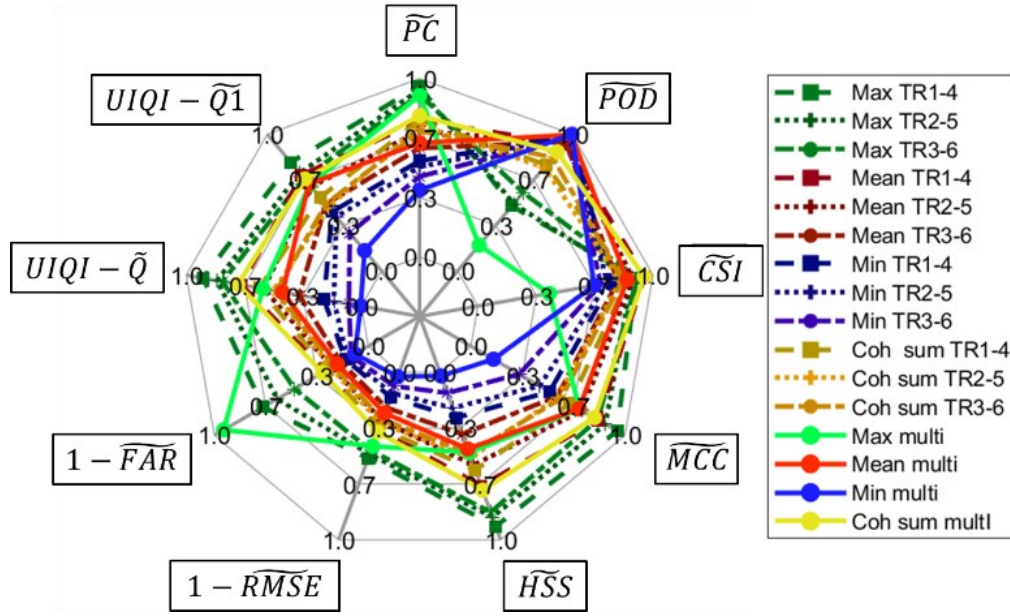


Figure 5.20 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using pre-2S-sorting.

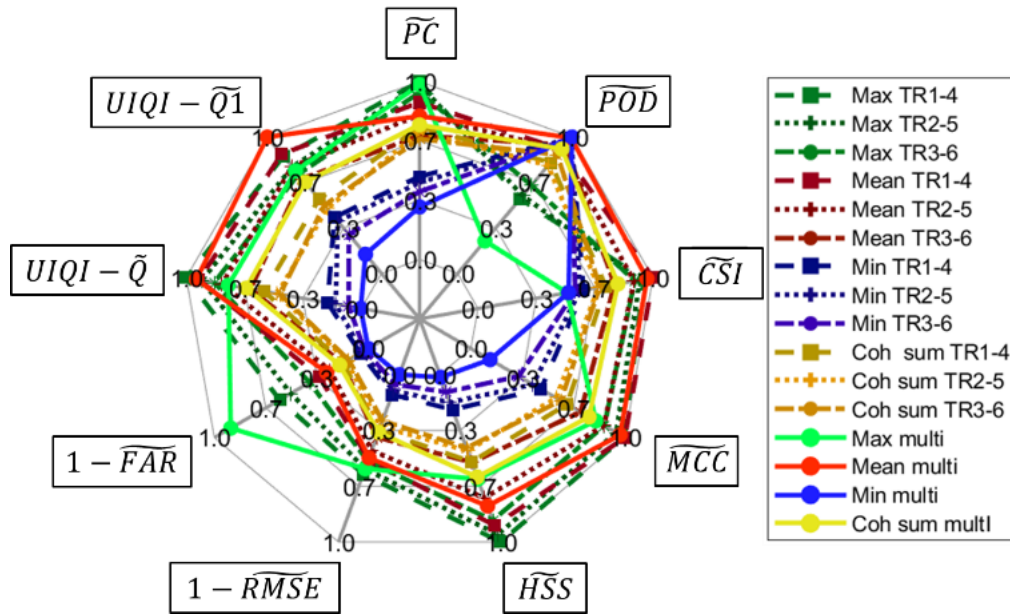


Figure 5.21 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using post-2S-sorting.

The output of the fully polarimetric and multistatic CI-CCD images are shown in Figure 5.22 (pre-2S-sorting) and Figure 5.23 (post-2S-sorting). The letters ‘GBSAR’ are quite

visible in the maximum image, so despite a relatively low POD, it is readable. It is also clearer than in the single pol (VV) images (Figure 5.12 and Figure 5.13).

The minimum images perform very poorly and are covered in strong detections of change. As such it is clear why the metrics are so poor.

The mean for the pre-2S-sorting (Figure 5.22) is quite similar to the minimum of the two figures below, as such it is clear why the performance metrics are similar to the minimum. The post-2S-sorting mean image (Figure 5.23) however clearly shows the ‘GBSAR’ letters. The four classes help here in making the letters more legible.

The coherent summation images do show the letters, although the false alarms make the G and S hard to make out.

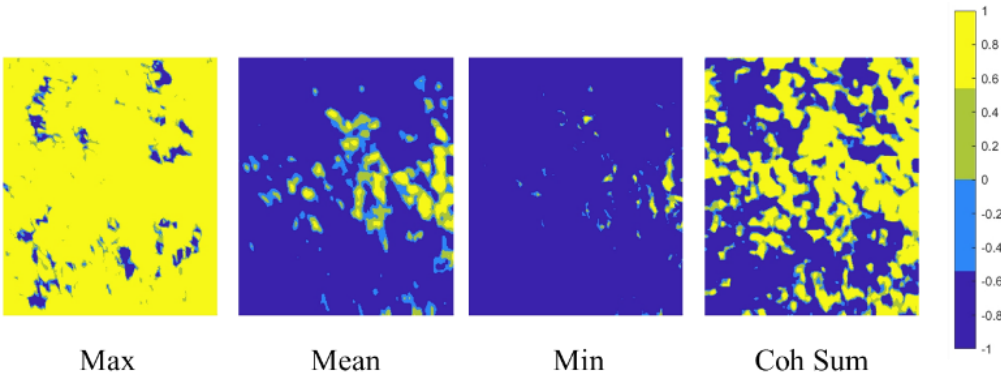


Figure 5.22 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the full polarisation multistatic.

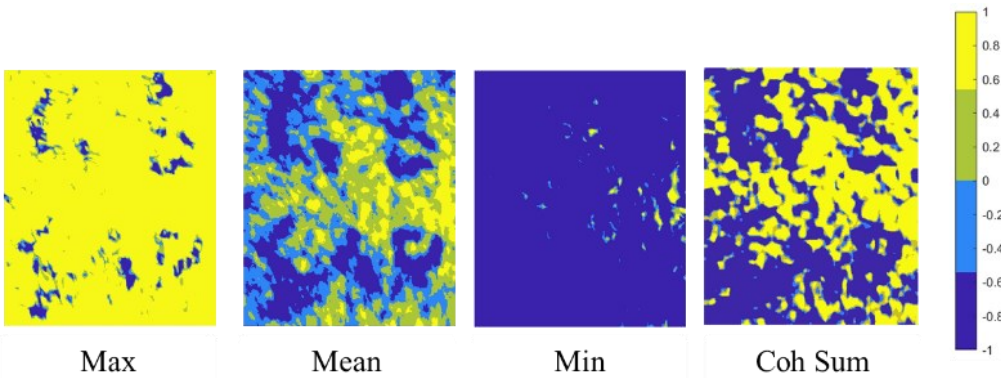


Figure 5.23 Set of four CI-CCD images formed using the post-2S-sorting dataset for the full polarisation multistatic.

An enlarged image of the mean full polarisation multistatic post-2S-sorting (from Figure 5.23) is shown in Figure 5.24.

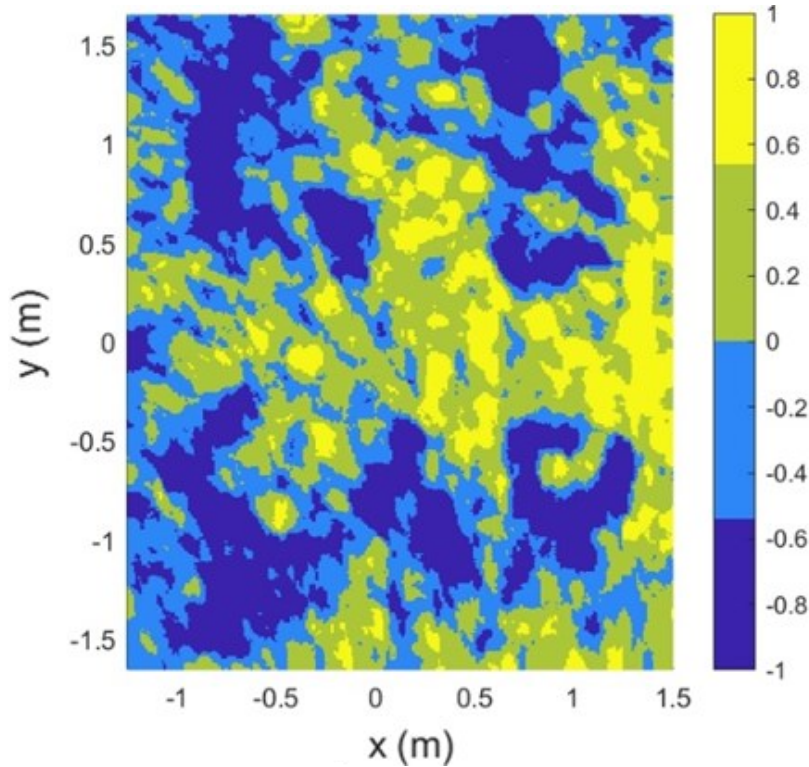


Figure 5.24 CI-CCD for the mean full polarisation multistatic post-2S-sorting (from Figure 5.23).

The master images and the mean pre- and post-2S-sorting mean images are formed in a similar manner. Although the number and geometry of trajectories, were significantly different. In the master images (Figure 5.8 & 8) the pre-2s-sorting image has a higher contrast and appears visually clearer than the post-2S-sorting master image. This is reversed when looking at the results (Figures & 24). Here the post-2S-sorting image is significantly clearer. This is believed to be from the input images. It is hypothesised this is due to the image formation pipeline. The bistatic master images have a high degree of similarity as they were formed using exactly repeated trajectories. Thus, averaging before image formation, results in a high contrast result. The post-2S-sorting averages a series of discrete values rather than a continuous series within 0-1, as such there is a greater possibility of a reduced contrast.

However, for the test images, the trajectories are no longer repeating, as such additional decorrelations are present. These additional decorrelations lower the coherence of the CCD images used in the pre-2S-sorting, which then results in a higher number of changes being detected.

5.3.1.5 Results Summary

In order to provide an overview and summary the mean of the values of the performance indices was taken for each of the CI-CCD images. These are shown in the tables below and use the colormap provided below.

This provides a single value of performance to summarise the results, however it is biased by the choice of metrics.

Table 5-4 and Table 5-5 present the bistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting respectively. These results are presented for all four polarisations.

Table 5-6 and Table 5-7 present the multistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting respectively. It can be seen that the highest values for the averaged performance metrics are found in Table 5-7. These are higher than those found in the other tables.

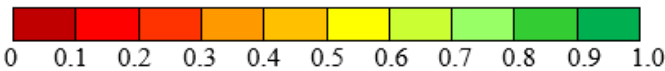


Table 5-4 Table showing the averaged performance metrics of the bistatic images compared to the pre-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.7	0.67	0.58	0.64
TR2-TR5	0.59	0.62	0.62	0.5
TR3-TR6	0.47	0.52	0.52	0.49

Table 5-5 Table showing the averaged performance metrics of the bistatic images compared to the post-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.67	0.63	0.54	0.61
TR2-TR5	0.57	0.58	0.58	0.49
TR3-TR6	0.45	0.48	0.59	0.46

Table 5-6 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the pre-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.79	0.68	0.45	0.59
	TR2-TR5	0.74	0.61	0.41	0.54
	TR3-TR6	0.72	0.5	0.35	0.55
Multi single pol	VV	0.73	0.63	0.43	0.67
	VH	0.75	0.62	0.45	0.72
	HH	0.78	0.64	0.45	0.68
	HV	0.68	0.6	0.42	0.64
Multi fully polarimetric		0.58	0.58	0.27	0.68

Table 5-7 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the post-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.84	0.81	0.31	0.56
	TR2-TR5	0.79	0.72	0.36	0.51
	TR3-TR6	0.74	0.61	0.31	0.52
Multi single pol	VV	0.76	0.72	0.38	0.64
	VH	0.78	0.71	0.4	0.67
	HH	0.82	0.71	0.4	0.63
	HV	0.71	0.66	0.36	0.59
Multi fully polarimetric		0.68	0.8	0.23	0.63

The maximum bistatic fully polarimetric for TR1-TR4 resulted in the highest average performance metric value. This image is shown in Figure 5.25. Compared to Figure 5.24, which also performed well it shows a lower number of detections.

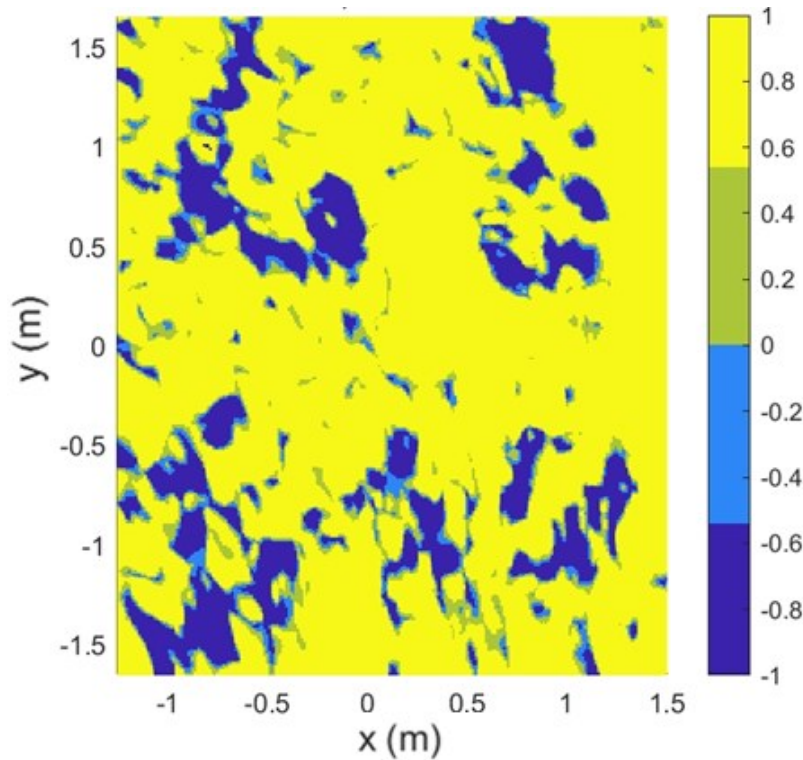


Figure 5.25 CI-CCD image for the bistatic TR1-TR4, fully polarimetric maximum (post-2S-sorting). This image showed a high average performance of 0.84 in Table 5-7.

5.3.2 Discussion

This chapter has investigated the performance of different multistatic combinations for change detection quantitatively using a variety of performance metrics as well as qualitatively. A large number of results were presented graphically and then summarised numerically in the pervious section.

The use of multiple performance metrics combined with inspecting the output images has been shown to help characterise performance. These metrics do not just show how well a detector performed, but its tendency towards over or under detection and how well it captures the structure of the disturbance. For example, the metrics showed how the performance of the mean images was improved in the post-2S-sorting compared to the

pre-2S-sorting (section 5.3.1.2), with the average performance metric rising from 0.58 to 0.8. This could then be visually seen as well in the CI-CCD images.

It has been shown that multistatic and multipolar change detection can lead to improved change detection performance. The average performance metric could rise to 0.8, compared to 0.5-0.7 for the bistatic images. However, the manner in which the multistatic CI-CCD image was formed has a significant impact on performance.

Coherent summation did not lead to the best performing change detection images, with an average performance metric of 0.63-0.67. In the case of pre-2S-sorting it could lead to similar performance to the mean, however for the post-2S-sorting it was outperformed by the mean, with an average performance metric of 0.8. Multistatic change detection images formed incoherently using stacks of bistatic images were shown to perform better. This was true in both cases for the maximum images, and true for the mean images for the post-2S-sorting. In both cases however the minimum images performed very poorly with an average performance metric of around 0.4 except for the fully polarimetric multistatic means where performance was under 0.3.

Consideration must thus be given to when the sorting is performed. Whether this is at the pre or post the CI-CCD stage, and what manner of sorting (max mean or min) was chosen. The variance in performance due to the former was most clearly demonstrated by the mean images which performed much better for the post-2S-sorting than for the pre-2S-sorting. The variance due to the type of sorting was evident in all the CI-CCD images, where the max, mean and min images displayed significant variation in detections.

Overall, the multistatic maximum and mean Post-2S-sorting images performed the best with an average performance metric as high as 0.81. The fully polarimetric multistatic mean Pos-2S-sorted image also exhibited good performance (0.8), with very high Q values, although was outperformed in some metrics by some fully polarimetric bistatic images.

The minimum images were the best at detecting the presence of a change (high POD). However, the minimum images suffered from a poor FAR and did not capture the shape of the disturbance as shown by the Q, MCC and HSS values. The maximum images

resulted in a significantly lower POD, however the shape of the GBSAR letters was much more evident. This was reflected in high Q, MCC and HSS values.

The maximum and minimum images however showed a degradation in performance for the fully polarimetric multistatic images. This is hypothesised to be from too many images being used, this leading to a dominance of outliers (either change or no change) in the sorting. This would then obscure the structure of the disturbance track. In the multistatic fully polarimetric case the mean post-2S-sorting image performed well and was more robust at negating the impact of outliers.

5.4 Conclusion

This chapter has investigated the performance of different multistatic combinations for change detection.

From the spider plots and the averaged performance tables (section 5.3.1.5) some conclusions can be drawn. Post-2S-sorting results in improved performance compared to pre-2S sorting. Maximum post-2S-sorting images could offer good performance as shown in Table 5-7, however for the fully polarimetric multistatic maximum image, the outliers (no change) become too dominant and degrade performance. As such the maximum may be vulnerable to missing a large number of possible detections (low POD) when large numbers of images are used. The mean images post-2S-sorting images performed quite well and were more robust to outliers.

The difference between the best performing maximum and mean images in Table 5-7 is quite small and does not represent a significant difference in performance.

The coherent summation performed worse than the maximum and mean images. This suggests processing a multistatic dataset bistatically, then forming a multistatic CI-CCD image will improve detection performance. The minimum images performed very poorly.

Overall, the mean post-2S-sorting performed well and is robust against outliers for larger volumes of images. Maximum post-2S-sorting images can perform well too but are more vulnerable to outliers and a low POD.

It is acknowledged that the values of the performance metrics relate to the master image used, and the number of detections present. Additionally, whilst it is hypothesised these conclusions are valid for other multistatic change detection scenarios, only a single scene and disturbance investigated here.

Future work should investigate scenes of greater complexity, layover and/or varying topography. Multiband or multispectral change detection could also be investigated w.r.t multistatic SAR. Change detection algorithms trimmed, weighted or winsorized means [233], [234] may offer improved performance by eliminating outliers.

6 Discussion & Conclusion

6.1 Discussion

This thesis has investigated two main areas. The first was the coherence of bistatic CCD images (chapter 4) and the second was multistatic and multidimensional change detection (chapter 5).

In chapter 4 two sets of geometries and ground types were used. In the first the spatial frequency domain overlap was maximised. In the second set of trajectories there was still a high degree of overlap, however the transceivers were restricted to three heights to reduce the impact of a difference in grazing angle and two ground types were used. A difference in spatial frequency domain overlap was accounted for with the use of spatially variant incoherence trimming.

Using these trajectories, it was shown there is a significant mismatch between the expected coherence when calculated using existing equations, and measured coherence in a bistatic scenario with different trajectories. This expected value for coherence matched the value of coherence from isotropic simulations. These isotropic simulations did not exhibit angle dependant scattering, shadowing or multipath.

The coherence of surfaces exhibiting speckle or near-speckle was found to be lower than the forecast coherence. It was hypothesised that this reduction in coherence was due to a change in the scattering, shadowing and multipath between the two SAR images due to the difference in geometry. This was termed the scattering parameter; γ_{scat} . Additionally, the results in 4.4 that the bistatic angle difference extent for any particular CCD performance band broadly varies inversely with the terrain height variation (so long as it is above the Rayleigh Roughness Criterion).

It was shown that this parameter could be modelled as a function of the bistatic angular difference. It was found that larger stones, which resulted in a brighter backscatter, lead to a greater loss of coherence.

The use of laboratory data allowed for a high degree of control and the minimisation of other sources of decorrelation. This improved confidence in the results and conclusions presented.

In chapter 5 a two-stage change detector which used four classes was presented for different combinations of multistatic and bistatic images. The performance was assessed quantitatively using a variety of performance metrics as well as qualitatively. This chapter investigated how well these methods of combining different SAR images together were able to combat the impact of different bistatic geometries as no trajectory was repeated.

The SAR collection was multidimensional, consisting of different geometries and polarisations. As such these images could be combined in different orders and sorted (maximum, mean and minimum) in different ways. Final images could be bistatic, multistatic (coherent sum or sorted) and single or fully polarimetric.

It was shown that using multiple performance metrics provided a good characterisation of the performance. These metrics did not only describe the correct detections of changes or the number of false alarms but also the structure of the change. This chapter also introduced a methodology for using standard performance metrics with a four class change detector.

It was shown that multistatic and multipolar change detection could lead to improved change detection performance. However, the manner in which the multistatic CI-CCD image was formed had a significant impact on performance. Coherent summation did not lead to the best performing change detection images. Instead multistatic change detection images formed incoherently using bistatic images was shown to perform better. An additional consideration is whether the sorting is performed pre or post the CI-CCD stage, and what manner of sorting was chosen.

Overall, the multistatic maximum and mean Post-2S-sorting images performed the best. The fully polarimetric multistatic mean Post-2S-sorted image also exhibited good performance, with very high Q values, although was outperformed in some metrics by some fully polarimetric bistatic images.

The minimum images were the best at detecting the presence of a change (high POD), although with a poor FAR and Q, MCC and HSS values.

The maximum and minimum images however showed a degradation in performance for the fully polarimetric multistatic images. This is hypothesised to be from too many images being used, this leading to a dominance of outliers (either change or no change) in the sorting. This would then obscure the structure of the disturbance track. In the multistatic fully polarimetric case the mean post-2S-sorting image performed well and was more robust at negating the impact of outliers.

[159][203], [235], [236]The findings in this thesis are applicable to spaceborne and airborne SAR systems such as satellites and drone swarms.

The findings relating to the scattering parameter (γ_{Scat}) show that for a bistatic or multistatic SAR system it is not sufficient to simply maintain a high spatial frequency domain overlap for repeated passes. It has been shown that in addition to the degradation in coherence due to non-overlap in K-space, there is also an angle dependant backscatter component. This component can dominate for some geometries.

This adds a constraint onto the possible geometries of a multistatic SAR system wishing to conduct CCD. However, some of the loss in performance due to the reduced coherence can be regained using multidimensional change detection.

6.2 Future work

Future work however may seek to investigate bistatic coherence in a real-world environment and to better characterise the behaviour of the scattering parameter (γ_{Scat}). This could be done with the use of ray tracing simulations, real world experiments and additional laboratory measurements.

Future work may also investigate polarimetric change detection. This may be simple polarimetric parameters as were investigated in [159] or more complex parameters, such as the Huynen fork [203], [235], [236]. This may aid in the identification of changes in scattering mechanism. This could help identify targets in a cluttered environment.

Research can also be conducted on multi-class change detectors. These detectors could have classes expanded to include the presence of new objects, or the removal of old ones rather than just changes on the ground.

6.3 Conclusion

This thesis has investigated bistatic and multistatic SAR change detection and interferometry.

The coherence of bistatic geometries was investigated, and a new decorrelation parameter (γ_{Scat}) proposed. This parameter represents for effects not accounted for in current formulas for estimating CCD coherence. Whilst some papers have made reference to volumetric decorrelation, that term is applicable to forests, not ground level speckle or near-speckle surfaces. This parameter was only investigated for two types of ground and over a certain set of trajectories. Future research might investigate more scenarios to better characterise the behaviour of this parameter.

Additionally the processing of multistatic and multipolarimetric SAR change detection images was investigated. This investigation found that the coherently combining all images in a multistatic collection did not lead to the best results. Additionally, the order of operations and type of sorting had a significant impact on the performance. This is a very under researched area of SAR, and future research could investigate other processing methods which might improve performance.

This work is relevant for future multistatic SAR systems such as those on satellites (with a significant baseline) or drone swarms operating in the near field or with significant baselines. It has shown the limitations of relying on the spatial frequency overlap to forecast coherence, and put forward a backscatter dependant parameter which should be considered (γ_{Scat}). This work has also shown some of the possible opportunities of multistatic systems, which can offer improved change detection performance. Although this is dependent on the processing chosen.

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Appendices

Appendix A Ethical approval letter



10 September 2024

Dear Mr Hagelberg ,

Reference: CURES/23663/2024

Project ID: 26958

Title: Bistatic and Multistatic Synthetic Aperture Radar Interferometric Phenomenology and Change Detection

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your CURES application, reference CURES/23663/2024 has been reviewed. You may now proceed with the research activities you have sought approval for.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team

Appendix B Journal papers

B.1 Laboratory bistatic SAR CCD investigation

Laboratory bistatic SAR CCD investigation

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Synthetic Aperture Radar (SAR) Coherent Change Detection (CCD) allows for the detection of very small scene changes. This is particularly useful for reconnaissance and surveillance as small changes such as vehicle tracks can be identified. In some situations, it is desirable to rapidly collect repeat pass SAR images for use in change detection, and multistatic geometries may facilitate this. Such repeat passes may however have significant baselines, particularly for satellite-based platforms, though CCD products are reliant on high coherence for good interpretability. This work investigates the sources and levels of incoherence associated with bistatic SAR imagery with increasing baselines using simulations and measured laboratory data.

Introduction: Synthetic Aperture Radar (SAR) allows high resolution images to be formed. SAR data can also be used interferometrically to determine a Digital Elevation Map (DEM) or to sensitively detect changes within a scene [1]. SAR Coherent Change Detection (CCD) has the potential to detect very small changes such as the tracks made by a vehicle. Typically, the two radar platform trajectories are closely repeated, with a low baseline, for the best possible CCD results [1, 2]. For satellites, this may necessitate long revisit times which may for example lead to decorrelations due to natural processes such as wind and rain [2]. This would reduce CCD interpretability. If planned multistatic SAR satellite constellations[3] come into existence, the ability to utilize trajectories with greater baselines could help reduce revisit times. Such image pairs may potentially have low coherence. This paper investigates the sources and levels of SAR bistatic geometry incoherence through both simulation and laboratory radar measurements.

Background: SAR image information can be represented in the spatial frequency domain, also known as K-space, where it is given the name “image support” [1]. The extent of the image support is a composite of incident minus scattered wave vectors from transceivers, $\bar{K} = \bar{k}_t - \bar{k}_s$, to the different scene positions. The length of $\bar{K}$ is proportional to frequency, and to the cosine of the bistatic angle [1]. In the context of coherence between SAR images

of horizontal terrain the proportion of the overlapping vertically projected image support area to total projected areas (K-space overlap) [4] can be used to predict coherence. In the SAR far-field it is straightforward to calculate K-space overlap. In the SAR near-field, the K-space overlap varies significantly across the scene, complicating the estimation of coherence [1, 5]. The SAR near-field is defined as the regime where the range $d < 2L_{cr}^2/\lambda_c$ for centre wavelength λ_c and for a scene with cross range extent L_{cr} .

SAR coherence between two collections γ_{true} has a value between 0 and 1 and is a little different from the coherence estimated directly from the images $\hat{\gamma}$, which is biased dependent on calculation features such as the CCD estimation window size [4]. γ_{true} can be decomposed into factors which are also in the range 0-1 [1, 2, 4, 6, 7]:

$$\gamma_{true} = \gamma_{temp} \gamma_{SNR} \gamma_{proc} \gamma_{geom} \quad (1)$$

$$\gamma_{proc} = \gamma_{alg} \gamma_{reg} \quad (2)$$

$$\gamma_{geom} = \gamma_{baseline} \gamma_{RCS} \quad (3)$$

In (1) the factors correspond to decorrelations due to: temporal changes between the two collections γ_{temp} ; signal to noise ratio (SNR) γ_{SNR} ; signal processing effects γ_{proc} ; and SAR geometry effects γ_{geom} . In (2) the signal processing term γ_{proc} accounts for decorrelations due to the image formation algorithm accuracy γ_{alg} and image registration accuracy γ_{reg} . In (3) the geometry term is decomposed into a calculated baseline correlation term $\gamma_{baseline}$ which accounts for K-space overlap; and a Radar Cross Section (RCS) term γ_{RCS} .

The RCS term introduced in [8], accounts for a difference in backscattering dependent on imaging geometry, and could incorporate many effects including variation in shadowing, multipath and polarization. The temporal and baseline correlation terms are typically of most interest for imaged scenes with developed speckle and low baseline [6, 9], however at least for bistatic geometries with high baseline, the RCS term is hypothesized to play a significant role.

Methodology: Bistatic SAR measurements were conducted at the Cranfield University Ground Based SAR laboratory (GBSAR lab) [10]. The scene (Fig 1) consisted of a gravel square 2.7 x 2.7 m. The measurements were conducted with a Vector Network Analyzer (VNA), with centre frequency of 10 GHz and bandwidth of 4 GHz. Due to the use of a single VNA, there were no signal synchronization issues associated with the bistatic measurements – often a significant issue for practical remote bistatic SAR sensing. The SAR geometries used were constrained by the available transmitter and receiver vertical scanning rectangular apertures pictured in Fig 2 (black), where the scene dimensions and SAR geometries measured are also shown.

For each bistatic SAR geometry, transceiver heights were kept the same and a horizontal aperture of 1.2 m was scanned for both the receiver and transmitter antennas, which gave equivalent monostatic apertures of length 1.12-

1.18 m. The six bistatic SAR geometry designations used ranged from “TR1” to “TR6”, with the height progressively decreasing with increasing index (1 to 6) and bistatic angle progressively increasing – crucially, these geometries were chosen, to maintain a substantial K-space overlap between the SAR geometries. It is noted that in previous measurements, variation in grazing angle between bistatic collections did not greatly influence coherence [8].

Transceiver scan geometry parameters are listed in Table 1. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the table are calculated to the centre of the scene and gravel region. For TR1 and TR6, there is only a 20cm overlap (17% of the aperture). The K-space overlap between the six SAR geometries was high, with $\gamma_{baseline}$ ranging from 0.83 to 0.98 as seen in Fig 3.



Fig 1 Image showing the gravel square scene.

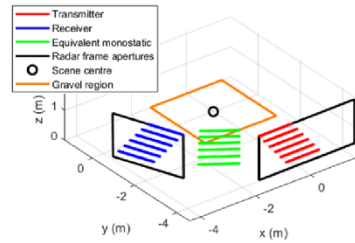


Fig 2 Diagram showing measured bistatic SAR geometries and scene dimensions. Each bistatic SAR geometry has transceivers at equal heights and the scene centre is denoted by “O”.

Table 1 Scan geometry parameters for the six bistatic collections. Tx denotes the transmitter, Rx the receiver, and BEM the Bistatic Equivalent Monostatic values for the transceiver trajectories. Ranges are in the respective slant planes. Resolutions are in the ground plane and estimated at the scene centre.

		TR1	TR2	TR3	TR4	TR5	TR6
Bistatic angle, β (°)		36.5	41.5	46.7	52.1	57.6	63.2
Grazing angle, ψ (°)	Tx	22.1	19.7	17.2	14.6	11.8	8.9
	Rx	22.8	20.4	17.8	15.1	12.2	9.2
	BEM	23.7	21.5	19.2	16.6	13.8	10.7
Range (m)	Tx	5.16	5.02	4.91	4.81	4.73	4.67
	Rx	5.00	4.87	4.75	4.65	4.57	4.51
	BEM	5.08	4.95	4.83	4.73	4.65	4.59
BEM aperture length (m)		1.12	1.14	1.15	1.17	1.18	1.18
Transceiver height (m)		1.94	1.70	1.45	1.21	0.97	0.73
BEM resolution	Range (cm)	4.1	4.0	4.0	4.0	3.9	3.8
	Cross-range (cm)	6.8	6.5	6.3	6.1	6.0	5.9

In addition to the measurements, simulations were undertaken assuming isotropic point scatterers with a

density of approximately 26 scatterers per resolution cell. This provided fully developed SAR speckle. The SAR and CCD processing undertaken was the same for both simulated and measured data.



Fig 3 Heatmap showing the $\gamma_{baseline}$ values for the different trajectories.

Results: The coherence of SAR image pairs was calculated as the mean over the CCD image. These mean coherence values were then plotted as a function of the bistatic angle (and by extension grazing angle) difference between the mission and reference trajectories. The measured coherence values are shown in Fig 4. As the separation (baseline) between bistatic trajectories increases, the coherence drops. The coherence also exhibits variation between the polarizations. Additionally, the coherence values of the measured results were then compared against the coherence of the simulated results and with the baseline correlation ($\gamma_{baseline}$). These are also shown in Fig 4. The simulated coherence shows a close match to the $\gamma_{baseline}$, however the measured results exhibit a coherence which becomes lower with increasing bistatic and grazing angle difference.

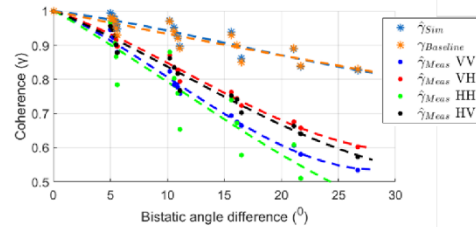


Fig 4 Graph of distribution of coherence and $\gamma_{baseline}$ as a function of the difference in the bistatic angle. The measured coherence values for all polarizations are shown in blue. Simulated coherences are shown in red and the baseline correlation in green. A curve of best fit was plotted for each.

Due to the nature of the laboratory environment, equations (1)-(3) can be simplified to estimate the RCS component: the SNR was high and approximated to 1; no scene changes were present so $\gamma_{temp} = 1$; the measurement ground truth was well known due to the well-controlled antenna positioning and accurate curved wavefront bistatic back-projection image formation was

used, so $\gamma_{algorithm}$ and γ_{reg} are approximated to 1. Hence the following equation is used to give an estimate for γ_{RCS} .

$$\hat{\gamma}_{RCS} = \langle \hat{\gamma}_{Meas}(x, y) / \gamma_{baseline}(x, y) \rangle \quad (4)$$

The triangular brackets indicate an averaging of the quantities over the scene. It is noted that due to the SAR near-field nature of the measurements, both the $\gamma_{baseline}$ and $\hat{\gamma}_{meas}$ (evaluated within a square sliding window) vary spatially. Hence, they are functions of image coordinates (x, y) . Therefore $\hat{\gamma}_{RCS}$ is evaluated as a mean over the spatially varying fraction in (4). “Meas” denotes that the coherence value is from the measured data.

An alternative method to estimate $\hat{\gamma}_{RCS}$ is to use the simulated and measured CCD images directly, that is without the use of $\gamma_{baseline}$. We have,

$$\gamma_{Sim} = \gamma_{baseline} \gamma_{alg} \quad (5)$$

$$\gamma_{Meas} = \gamma_{RCS} \gamma_{baseline} \gamma_{alg} \quad (6)$$

Where “Sim” denotes the simulated values (where $\gamma_{RCS Sim}=1$ due to the isotropic scatterer assumption). Hence,

$$\hat{\gamma}_{RCS} = \langle \hat{\gamma}_{Meas}(x, y) / \hat{\gamma}_{Sim}(x, y) \rangle \quad (7)$$

As in equation (4), an averaging over the spatially varying fraction is performed in (7) due to the SAR near-field nature of the measurements. The results for $\hat{\gamma}_{RCS}$ generated through (7), match those of (4) very closely, owing to the close correspondence of $\hat{\gamma}_{Sim}$ and $\gamma_{baseline}$ as was seen in Fig 5.

In Fig 5, $\hat{\gamma}_{RCS}$ is plotted for the different geometries and polarizations. $\hat{\gamma}_{RCS}$ can be seen to drop significantly, with increasing bistatic and elevation angular difference. The decorrelation may be so great that discriminating changes on the ground may not be possible for the greater bistatic angle differences. For bistatic angle differences greater than 10° , coherence is seen to be generally greater in the cross-polarization channels. The HH channel has the least coherence and most variability, which may be due to ground-multipath effects. The two $\hat{\gamma}_{RCS}$ estimates, (4) and (7), can also be compared with the estimated coherence of spatially variant incoherence trimmed (SVIT) images $\hat{\gamma}_{trimmed}$, which should have a similar value. The K-space incoherence-trimming excludes non-K-space overlap data from SAR images and is performed for each bistatic collection pair in a computationally intensive spatially variant manner [5, 11].

The comparison of the three approaches is shown in Fig 5 and shows good agreement. The difference between the results may be due to numerical errors in the calculation of $\gamma_{baseline}$ and in the spatially variant K-space trimming process. These are both computationally intensive processes requiring discretization choices.

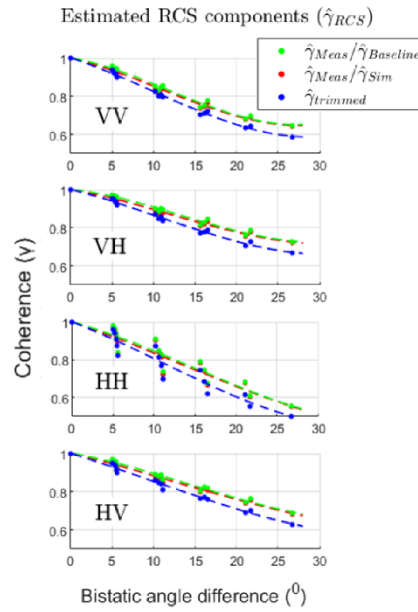


Fig 5 Graph showing $\hat{\gamma}_{RCS}$ estimated with three different methods, plotted against the difference in the bistatic angle. A point was plotted for each pair of radar positions and polarization. A curve of best fit was plotted for each. All four polarizations are shown.

Conclusion: The results presented show that SAR image speckle regions can suffer significant decorrelation due to differences in bistatic and elevation angles. This is interpreted to be due to the related changes in scattering properties (RCS), even in the presence of high K-space overlap. The effect is seen to be an important factor that should be considered when choosing bistatic SAR CCD geometries. For the bistatic geometries, frequencies and terrain considered, a difference in bistatic angle of 22° or greater led to a drop in coherence below 0.8, and in some cases below 0.7 (for some in HH polarization). For these bistatic angle differences, there were regions of low coherence which could mistakenly be taken for regions of scene change. When combined with a loss in resolution from the SVIT process, discerning temporal changes with these geometries may become challenging.

Some differences in coherence were seen between the polarimetric channels, such that above a 10° difference in bistatic angle the cross-polarizations showed the highest coherence. This result follows preliminary predictions [12] and it is possible that there may be another polarimetric decomposition that increases coherence further for this type of terrain. Further investigation into the behavior of the bistatic RCS factor is required, particularly with regard to different ground types and the impact of grazing angle differences, frequency band and polarimetric decomposition. Corresponding CCD performance analysis experiments [4] would further aid in interpretation of results.

Acknowledgments: This paper was produced as a part of research for a PhD sponsored by the Defence Science & Technology Laboratory (DSTL).

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Received: xx January 2021 *Accepted:* xx March 2021

doi: 10.1049/ell2.10001

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B.2 Combined Intensity and Coherent Change Detection with four classes for Multistatic Polarimetric Synthetic Aperture Radar

Received: 11 January 2024 | Revised: 15 April 2024 | Accepted: 11 May 2024
DOI: 10.1049/rsn2.12588

IET Radar, Sonar & Navigation



ORIGINAL RESEARCH

Combined intensity and coherent change detection with four classes for laboratory multistatic polarimetric synthetic aperture radar

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Defence Science and Technology Laboratory

Abstract

Satellites and drone swarms can be used to collect multistatic Synthetic Aperture Radar (SAR) images. Synthetic Aperture Radar images can be used for Intelligence Surveillance and Reconnaissance. One method is to use Coherent Change Detection (CCD) to identify changes such as objects or tracks in the scene. This paper investigates a two-stage change detector, formed using intensity change and CCD images, extended to laboratory measured multistatic SAR data. A variety of performance metrics are used to quantitatively assess the results. Bistatic results are compared to a variety of multistatic and fully polarimetric results. The improvement in performance of multistatic and fully polarimetric images over bistatic images is shown. Additionally challenges and limitations of using multistatic datasets are highlighted.

KEYWORDS

multistatic radar, polarimetric radar, radar imaging, radar interferometry, synthetic aperture radar, ultra wideband radar

1 | INTRODUCTION

Synthetic Aperture Radar (SAR) provides reconnaissance and surveillance of the earth's surface for all weather, during the day and night. Synthetic Aperture Radar Coherent Change Detection (CCD) allows for the detection of very small scene changes between two SAR images, such as vehicle tracks [1–4].

This research is applicable to multistatic satellite constellations. A multistatic SAR satellite constellation being developed by the United Kingdom Ministry of Defence under the name Project Oberon [5]. This work is also relevant to multistatic SAR drone swarms, which operate in SAR near field configurations [6, 7].

The research is supported by measurements at the Cranfield University Ground-Based Synthetic Aperture Radar (GBSAR) laboratory [8, 9], where antennas are scanned within two vertical rectangular apertures, which allow a great deal of flexibility and fine control of SAR geometries for the scene.

This paper investigates the use of a two-stage change detector [10–12] extended to multistatic and fully polarimetric

(near field) data [13, 14]. Several methods of forming the multistatic and fully polarimetric change detection images are used. These are presented in Sections 3.2 and 3.3. These images are analysed using a variety of performance metrics, which are presented in Section 3.4. The multistatic trajectories have a baseline between the mission and reference trajectories. This baseline leads to additional decorrelations [8, 15], which can be detected by the change detection algorithm. This can result in the actual change being obscured. This paper investigates how well different methods of forming multistatic change detection images are able to compensate for these decorrelations and produce a change detection image which is easy to interpret and captures the structure of the change.

1.1 | Coherent Change Detection

Coherent Change Detection is calculated as a normalised cross correlation [15–17]. The magnitude, $\hat{\gamma}$, is referred to as the sample coherence. Where S_1 and S_2 are the two complex

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images being compared and N is the number of pixels within a window sampled over the two images. The pixel index is k .

$$\hat{\gamma} = \frac{\sum_{k=1}^N S_1(k) S_2^*(k)}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

Forming good quality high contrast CCD results are reliant on high coherence between the SAR images [17, 18]. This coherence can be reduced by natural processes such as wind and rain [15, 18–20].

Conducting rapid repeated passes would allow for monitoring developing situations in a timely manner.

Bistatic (and multistatic) radar geometries involve having the transmitter and receiver substantially separated, and multistatic geometries are comprised of multiple simultaneous bistatic collections. Multistatic SAR can have several advantages, such as providing improved cross range resolution [21, 22], and Signal-to-Noise Ratio [23], although the choice of which trajectories to combine significantly affects these [24].

Multistatic SAR satellite constellations may allow the collection of more timely change detection images to be formed using SAR image collections from differing trajectories, thus reducing the repeat pass time [25, 26]. However, the CCD's may be subject to varying degrees of coherence due to differing baselines and other effects such as multipath and different scattering due to a change in geometry [8].

For high coherence and an improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support overlap [17, 27, 28], yet it has been found that this alone is insufficient to guarantee high coherence and good CCD contrast [8].

Multistatic CCD images can be formed in two ways. Either as a coherent summation where multiple SAR images are combined or using 'sorting'. This paper uses sorting to refer to taking the maximum, mean or minimum sorting [13, 14] for each pixel and is explained in detail in Section 3.3.2. The use of sorting multiple bistatic CCD images rather than coherent summation multistatic may be useful in certain scenarios. These may be where a multistatic collection is conducted but the positioning accuracy of the antennas is poor. This could be, for example, a swarm of Uncrewed Air Systems with a transmitter [6, 29, 30] in the swarm or with a large illuminator [29, 31].

1.2 | Non-coherent change detection

Non-coherent change detection (NCCD) allows for the detection of large scene changes. It is a comparison of the backscatter powers (amplitude squared) [15].

$$NCCD = |S_1(k)|^2 - |S_2(k)|^2 \quad (2)$$

2 | MULTIDIMENSIONAL CHANGE DETECTION

2.1 | Multidimensional Coherent Change Detection

The multistatic fully polarimetric SAR data is multidimensional and can be combined in different ways [13, 24]. In this paper, multidimensional is used to describe a scenario where several change detection images are available for the same change and area. In this paper, the dimensions for the multistatic data consist of multiple bistatic collections and four polarisations.

Prior work has investigated the performance of different multistatic combinations [13] as well as augmenting the CCD and NCCD with polarimetric decompositions [14].

2.1.1 | Polarimetric Coherent Change Detection

Polarimetry relates to the incident and scattered orientation of the Electro-Magnetic (EM) waves [2, 13, 32]. These are often described in terms of two orthogonal vectors; vertical (V) and horizontal (H). By convention, the nomenclature received-transmitted is used. Thus, a wave transmitted in the vertical and received in the horizontal polarisation would be called HV. This dataset employed here is fully polarimetric and uses the two co-polar polarisations VV and HH as well as the cross-polar polarisations HV and VH.

Radar polarimetry uses the vector nature of EM waves to produce and analyse the content of images. Polarimetry can provide information on the scattering mechanisms present in the scene [2]. Polarimetric SAR CCD has also been shown to improve CCD images [2, 13, 32].

2.2 | Two-stage detector definition

A two-stage change detector was presented in [10, 12], with Ref. [11] performing analysis on the theoretical performance. These detectors are described as 'combined intensity and CCD', shortened to CI-CCD in this paper. For the NCCD, changes are detected due to a difference in amplitude in the images. This typically indicates large scale scene changes. Smaller scene changes typically do not result in a change in intensity, but rather phase [15, 17]. To detect these changes, CCD is used.

The two-stage CI-CCD detector, introduced in Refs. [10, 12], is shown below in Figure 1 (replicated from [10]). Here S_1 and S_2 represent the reference and mission trajectories.

For the intensity change detection, the difference in intensities (σ) is calculated. This difference is then compared against a threshold T_{NCCD} . Differences exceeding this threshold are labelled as changes. The CCD, as described in Section 1.1 results in a coherence value, $\hat{\gamma}$. This value is also

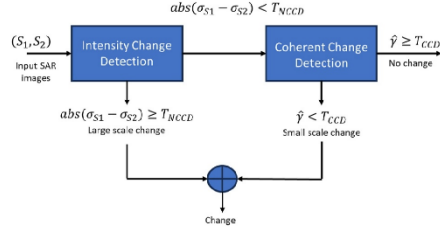


FIGURE 1 The block diagram of the CI-CCD detector introduced in [10, 12]. The figure is replicated from [10]. The figure is replicated from [10]. The figure shows the Intensity and Coherent Change Detection (CCD) stages as well as how thresholding is used.

compared against a threshold T_{CCD} . In this case, values exceeding the threshold (close to 1) are labelled as unchanged, whereas pixels with a value below the threshold are labelled as changes. If a change is detected in either the CCD or NCCD images, then the output image shows a change for that pixel. The output of the detector is a binary value indicating a change or no change.

3 | METHODOLOGY

3.1 | GBSAR laboratory

Bistatic SAR measurements were conducted at the Cranfield University Ground-Based SAR laboratory (GBSAR lab) [33]. The scene consisted of a gravel rectangle of 3.4 × 4 m and is shown in Figure 2. The measurements were conducted with a Vector Network Analyser (VNA), with a centre frequency of 8.3 GHz and bandwidth of 3.4 GHz. Due to the use of a single VNA, there were no signal synchronisation issues associated with the bistatic measurements, often a significant issue for practical remote bistatic SAR sensing [26]. The SAR geometries used were constrained using the available transmitter and receiver rectangular apertures pictured in Figure 3, where the scene dimensions and SAR geometries measured are also shown. The transmitter aperture had a width of 3.5 m, and the receiver aperture a width of 2.4 m. The vertical extent of both apertures was 1.46 m.

The multistatic data was collected for several geometries. In each case, the transmitter moved along the red trajectory. The receivers were located in one of the 6 positions. These are referred to as R1-6 (see Figure 3). The bistatic geometries are referred to as TR1-6.

The SAR data was collected for two collections. In the first, the reference, the scene was unchanged. In the second, called the mission, the letters 'GBSAR' were traced onto the scene. This was done by gently disturbing the gravel for use in change detection performance evaluation.

For the reference collection TR1, TR2 and TR3 were used. For the mission collection TR4, TR5 and TR6 were used.



FIGURE 2 Image shows the Ground-Based Synthetic Aperture Radar (GBSAR) system in a bistatic configuration, with a gravel rectangle as the scene.

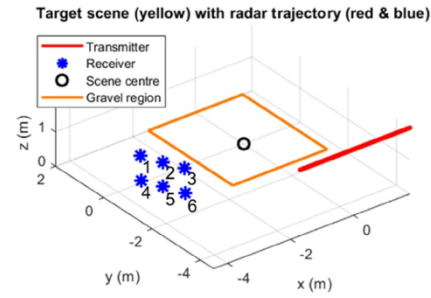


FIGURE 3 Diagram showing the radar trajectories used in the data collection. The transmitter trajectory is shown in red, the multiple fixed receiver positions in blue and the gravel region is shown in orange. The receivers are numbered 1-6 and are referred to as R1 through to R6.

Transceiver scan geometry parameters are listed in Table 1. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the table are calculated to the centre of the scene and gravel region. The resolutions were calculated using the Bistatic Equivalent Monostatic rather than the midpoints. This results in different co-ordinates to the transceiver midpoints. Using the incorrect geometry can lead to image distortions or incorrect resolution estimates [34, 35].

From the Reference and Mission multistatic collections, three pairs of bistatic geometries were used for CCD creation as follows: TR1 and TR4, TR2 and TR5, and TR3 and TR6 (effectively receiver columns). These allowed the formation of three bistatic CCD images for each of the two collections. The three CCDs were combined to form multistatic CCD images in different ways.

3.2 | Multistatic image formation

A multistatic SAR image is formed using the coherent summation of bistatic SAR images. These SAR images were formed using a bistatic generalisation of the Back Projection Algorithm [36]. In addition to multistatic SAR images,

		TR1	TR2	TR3	TR4	TR5	TR6
Bistatic angle, β ($^\circ$)		64.2	57.4	50.8	66.6	59.6	52.8
Grazing angle, ψ ($^\circ$)	Tx	22.9	22.9	22.9	22.9	22.9	22.9
	Rx	22.1	22.1	22.8	14.5	14.5	14.2
Range (m)	Tx	4.95	4.95	4.95	4.95	4.95	4.95
	Rx	5.24	5.25	5.32	5.01	5.00	5.08
Transmitter height (m)		1.92	1.92	1.92	1.92	1.92	1.92
Receiver height (m)		1.97	1.97	1.97	1.50	1.50	1.50
BEM resolution	Range (cm)	4.21	4.17	4.13	4.06	4.03	4.01
	Cross-range (cm)	4.36	4.38	4.40	4.40	4.41	4.41

Tx denotes the transmitter, Rx the receiver, and Bistatic Equivalent Monostatic (BEM) the BEM values for the transceiver trajectories. Ranges are in the respective slant planes. Resolutions are in the ground plane and estimated at the scene centre.

TABLE 1 Table showing the scan geometry parameters for the six bistatic trajectories.

multistatic CCD and NCCD images are used in this paper. These may be either from multistatic SAR images or a combination of bistatic CCD/NCCD images from a multistatic SAR collection. A multistatic CCD or NCCD image formed from (coherent summation) multistatic SAR images is referred to as a ‘Coh sum’ image in the results plots. Multistatic CCD images formed using multiple bistatic CCD or NCCD images are referred to as ‘max’, ‘mean’ or ‘min’ in the results plots depending upon the procedure implemented.

For the CCD images, a maximum image has the maximum coherence value for each pixel between the different CCD images being compared (a maximum image results in the minimum number of detections). Conversely, a minimum image has the lowest coherence (and the highest number of detections). This nomenclature is also used for the NCCD images.

The CI-CCD images are named after the CCD images used in the formation. However, in the NCCD images, a higher value corresponds to a greater change.

Therefore, to maximise the coherence or detections, the following combinations were used for the CI-CCD images:

- Max two-stage - Max CCD, Min NCCD
- Mean two-stage - Mean CCD, Mean NCCD
- Min two-stage - Min CCD, Max NCCD

3.3 | Two-stage CI-CCD detector

3.3.1 | Detector architecture

The detector architecture maintains similarities with the two-stage CI-CCD detector outlined in Section 2.2, albeit with some modifications. As shown in Figure 1, a change detected in the NCCD image is classified as a change. If no change is detected, then the CCD image coherence value is compared against a threshold.

This architecture was modified to include four classes: definite change, probable change, probable no change and

definite no change. The change detection for the NCCD images remains binary, as shown in Section 2.2. This is because the NCCD process detects large scale changes. As the CCD process is more sensitive four classes have been used to reduce the impact of edge case detections on the performance metrics. These classes are outlined in Equation (3). Here ρ is the value of the CI-CCD detection pixel and T the change/no change threshold. t is the tolerance and defines the size of the probable change/no change bins.

$$\rho \left\{ \begin{array}{l} 1 \\ 0.5 \\ -0.5 \\ -1 \end{array} \right. \begin{array}{l} \hat{\gamma} \geq T - t \\ T - t > \hat{\gamma} \geq T \\ T - t < \hat{\gamma} < T \\ \hat{\gamma} \leq T - t \end{array} \rho \left\{ \begin{array}{l} 1 \\ 0.5 \\ -0.5 \\ -1 \end{array} \right. \begin{array}{l} \text{Def. no change} \\ \text{Prob. no change} \\ \text{Prob. change} \\ \text{Def. change} \end{array} \quad (3)$$

This is then shown visually in a flowchart in Figure 4.

3.3.2 | Pre and post CI-CCD sorting

Sorting occurs at two different stages. This sorting takes the maximum, mean or minimum value per pixel and forms new images. This occurs either before or after the CI-CCD detection. This is shown in two flowcharts (Figures 5 and 6).

CI-CCD images formed when the sorting has occurred before the two-stage detection step are referred to as pre-2S-sorted. Multistatic CI-CCD image can be formed by sorting (maximum, mean or minimum) of bistatic CI-CCD images. These are referred to as post-2S-sorted images.

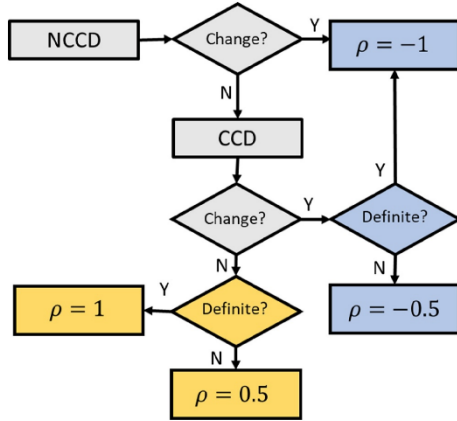


FIGURE 4 Flow diagram of the two-stage CI-CCD detector. Boxes in blue show where a change has been detected. Areas in yellow indicate no change. These reflect the colours in the CI-CCD images (such as Figure 7).

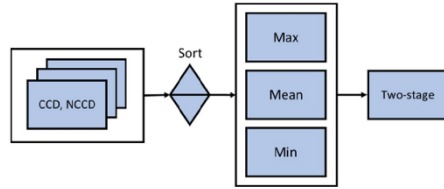


FIGURE 5 Flow chart showing the processing steps for forming 'pre-2S-sorted' CI-CCD images.

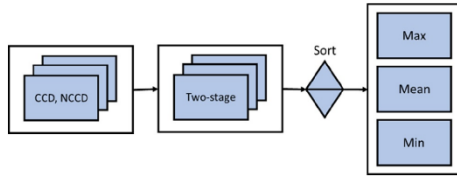


FIGURE 6 Flow chart showing the processing steps for forming 'post-2S-sorted' CI-CCD images.

3.3.3 | Master image

The Master CI-CCD images were formed from exact repeated trajectories, unlike the test CI-CCD images which used dissimilar receiver positions. For example, TR1 against TR1, whereas the results use different trajectories such as TR1 against TR4. This resulted in very high coherence for the areas where no change occurred, as there would not be decorrelations present due to the baseline [15] or Radar Cross Section,

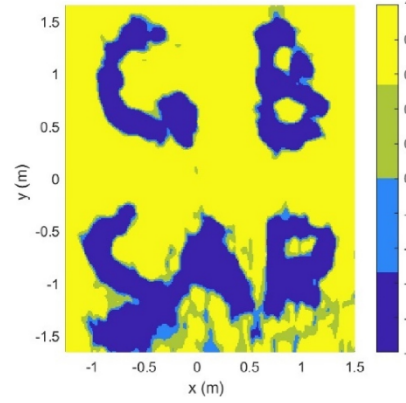


FIGURE 7 Two-stage master CI-CCD image for the pre-2S-sorting images. Here blue indicates a change and yellow indicates no change.

term [8]. The master images were calculated from the mean of the individual bistatic master CI-CCD images. These were then discretised (see equation (4)). The letters 'GBSAR' were clearly visible in the master images.

$$\rho_{Discrete} = \begin{cases} 1 & \rho > 0.5 \\ 0.5 & 0 < \rho \leq 0.5 \\ -0.5 & 0 > \rho \geq -0.5 \\ -1 & \rho < -0.5 \end{cases} \quad (4)$$

Two master CI-CCD images were formed (Figures 7 and 8), one for the pre-2S-sorted images and one for the post-2S-sorted images. These master images were formed with the same threshold for change, $T = 0.91$. The tolerance, t was set to 0.02.

This threshold was chosen as it resulted in two master images which captured the change. This value was chosen using both qualitative and quantitative measures of quality. At 0.91, both the Pre-2S-sorting and Post-2S-sorting images had a high Root Mean Squared (RMS) contrast values [37]. A lower threshold resulted in the 'GBSAR' letters in the pre-2S-sorting image being too large, and too many changes being detected on the lower area of the gravel. A higher tolerance resulted in too few detections of change in the Post-2S-sorting master image.

3.4 | Performance metrics

Performance metrics such as the Probability of Detection (POD), Critical Success Index (CSI) and the False Alarm Ratio (FAR) were used in the evaluation of the CCD images. These

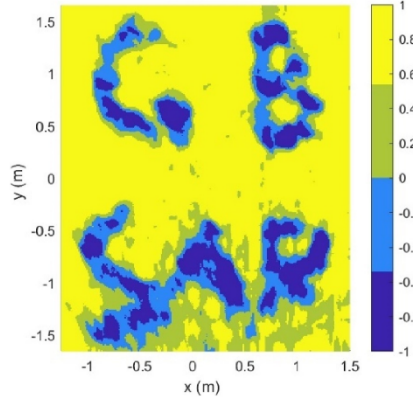


FIGURE 8 Two-stage master CI-CCD image for the post-2S-sorting images. Here blue indicates a change and yellow indicates no change.

metrics are often used in the evaluation of space weather predictive models [38, 39].

These were calculated using a confusion matrix (Table 2). Here *T* and *F* mean true and false respectively, and *P* and *N* mean positive (change) and negative (no-change) in the CCD image [38, 40].

3.4.1 | Adjustments to the performance metrics

Conventionally, a two-class detection is used. This leaves no room for ambiguous cases. As such, this paper utilises a four-class system. This was done to better take advantage of the multidimensional data available, and to reduce the impact of borderline cases. This necessitated a new confusion matrix, shown in Table 3.

3.4.2 | Performance metrics

Using the confusion matrix (Table 3), several performance metrics can be calculated. The formulae for the metrics are shown in Table 4. Additional metrics such as the Root Mean Squared Error (RMSE) (to be defined below) use the difference in CI-CCD (ρ) image values between the test and master images, instead of a confusion matrix. These formulae are defined below [38–44]:

Probability of Detection (POD). This metric gives a value of [0,1] and is the proportion of true positive predictions compared to the number of events. A value approaching 1 indicates most events were detected, and a value approaching 0 indicates most events were missed. The Critical Success index (CSI) shares some similarities with the POD. It compares the number of correct forecasts to the number of correct forecasts, false alarms and misses. It is not

TABLE 2 Confusion matrix, showing the conditions that correspond to TP, TN, FP and FN.

Confusion Matrix		Event Observed	
		Yes	No
Event Forecast	Yes	TP	FP
	No	FN	TN

Note: Here TP means true positive and TN means true negative. FP means false positive and FN means false negative.

TABLE 3 Modified confusion matrix for the four class images.

Confusion Matrix		Master image			
		$\rho = -1$	$\rho = -0.5$	$\rho = 0.5$	$\rho = 1$
Test image	$\rho = -1$	TP = 1	TP = 0.75	FP = 0.75	FP = 1
	$\rho = -0.5$	TP = 0.75	TP = 1	FP = 0.5	FP = 0.75
	$\rho = 0.5$	FN = 0.75	FN = 0.5	TN = 1	TN = 0.75
	$\rho = 1$	FN = 1	FN = 0.75	TN = 0.75	TN = 1

Note: Here TP means true positive and TN means true negative. FP means false positive and FN means false negative.

TABLE 4 Table showing the different performance metrics used in this paper.

Probability of Detection (POD)	
Value range: [0,1]	
$POD = \frac{TP}{TP + FN}$	(5)
Critical Success Index (CSI)	
Value range: [0,1]	
$CSI = \frac{TP}{TP + FP + FN}$	(6)
False Alarm Ratio (FAR)	
Value range: [0,1]	
$FAR = \frac{FP}{TP + FP}$	(7)
Proportion Correct (PC)	
Value range: [0,1]	
$PC = \frac{TP + TN}{TP + TN + FP + FN}$	(8)
Heidke Skill Score (HSS)	
Value range: $[-\infty, 1]$	
$HSS = \frac{2 * (TP * TN - FP * FN)}{(TP + FN)(FT + TN) + (TP + FP)(FP + TN)}$	(9)
Matthews's Correlation Coefficient (MCC)	
Value range: $[-1, 1]$	
$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}}$	(10)
Root Mean Squared Error (RMSE)	
Value range: $[0, \infty]$	
$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Predicted_i - Actual_i)^2}$	(11)

affected by the number of correct negative forecasts. A value approaching 1 indicates a perfect forecast.

The False Alarm Ratio (FAR) compares the number of false alarms with the number of forecast events. Here a value of 1 indicates all forecast events were false. This is sometimes confused with the False Alarm Rate $FAR_{rate} = FP / (TN + FP)$ [45].

The Proportion Correct (PC) provides a measure of the number of accurate forecasts of events compared to the total number. A value approaching 1 indicates most forecasts were true, a value approaching 0 indicates most were wrong.

The Heidke Skill Score (HSS) shares some similarities with the Success Rate ($SR = 1 - FAR_{rate}$); however, it also accounts for the random forecasts. The HSS outputs a value of $-\infty$ to 1. No incorrect forecasts would result in a value of $-\infty$. No correct forecasts would give a value of $-\infty$. A value of 0 would indicate 'no skill', and performance close to random guesses. The Matthew's Correlation Coefficient (MCC) is an alternative to Pearson's Correlation Coefficient (R) but is less affected by unbalanced datasets. A value of 1 represents perfect classification, and -1 represents perfect misclassification. Similarly, to the HSS, a value of 0 represents a classification similar to the expected value (random or no skill).

The RMS Error (RMSE) quantifies the error between the test and master images. It is commonly used to evaluate performance precision, although does not indicate whether errors are in positive or negative.

The Universal Image Quality Index (UIQI) UIQI was also used [4, 46, 47]. It consists of four metrics:

$$Q = Q_1 \cdot Q_2 \cdot Q_3 \quad 12$$

Here Q is a measure of the overall similarity. Q_1 can be seen as a measure of the structural similarity of the images. Q_2 represents the similarity of the image mean. Q_3 denotes the similarity of the image constants [4, 46, 47].

4 | RESULTS

Two methods of forming the max, mean and min images were discussed in section 3.3.2. As such graphs are presented for both the pre-2S-sorting and post-2S-sorting. It should be noted that the bistatic and coherent summation multistatic CI-CCD images are the same, as they were not produced using the pre/post-2S-sorting method. Instead a single pair of SAR images was formed and then change detection was performed. There will be some difference in the numerical values of the performance metrics due to the difference in master images.

4.1 | RGB colour composite images

Colour composite images can be formed to illustrate the impact of using multiple radar geometries and polarisations.

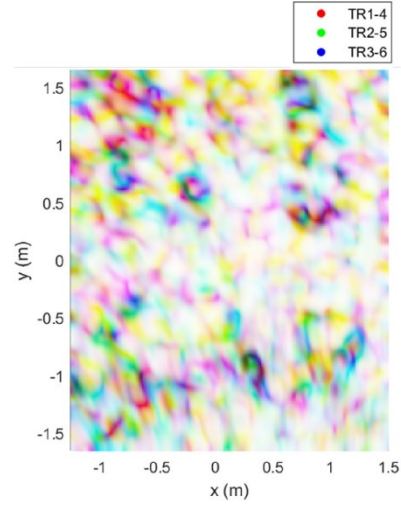


FIGURE 9 Colour composite (RGB) Coherent Change Detection (CCD) image for the three bistatic transceiver pairs. The image is VV polarised.

Three CCD images are used; thus, each pixel has three sets of values ranging from zero to one. These then define the Red Green Blue (RGB) value of each pixel.

In Figure 9, each colour RGB corresponds to a pair of receiver positions. Pixels that are white exhibit high coherence across all radar position pairs. However, inspecting the image shows that the coherence in a given pixel may be lower for one or two positions, leading to a brightly coloured image.

Figure 10 shows another colour composite, this time for all polarisations, but only one position. This again shows a significant degree of variability between the two co-polar terms (VV and HH) and the combined cross-polar terms ((VH + HV)/2).

4.2 | Normalisation

The performance metrics were plotted on spider plots. To improve the reader's ability to compare the performance of the different methodologies the performance values have been normalised to the maximum value.

This was done by finding the maximum value for each metric and dividing all values in that metric by the maximum value. The maximum values are shown below in Table 5. As such, each spider plot uses values of 0–1.

The formula for the normalisation is shown in Equation (6). Here x represents a particular performance metric (e.g. False Alarm Ratio, HSS, etc.). All the values of this particular metric (bistatic, multistatic, fully polarimetric, etc.) are represented by X . x_i is the value of a given performance metric and a particular image formation technique. For example, a maximum fully polarimetric multistatic image. This value is

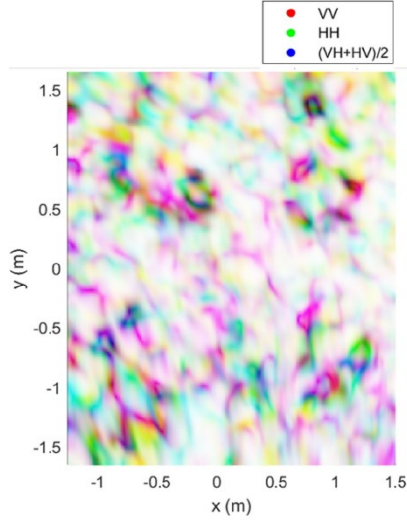


FIGURE 10 Colour composite (RGB) Coherent Change Detection (CCD) image for the four polarisations. Image is formed using TR1-4. The co-polar polarisations VV and HH are shown in red and green respectively. An average of the two cross-polar CCD images is shown in blue.

TABLE 5 Table showing the maximum values for each of the different performance metrics.

PC	0.833	RMSE	1.655
POD	1.000	FAR	0.763
CSI	0.457	UIQI - Q	0.584
MCC	0.507	UIQI - Q1	0.682
HSS	0.500		

then normalised using the maximum value of X . The normalised value of x_i is represented by a tilde; $\tilde{x}_i$.

$$\tilde{x}_i = \frac{x_i}{\max X}; \text{ where } X = x_1, x_2, \dots, x_N \quad 13$$

After the normalisation, the FAR and RMSE data presentation was modified further. The value of the normalised FAR and RMSE (now with values ranging from 0 to 1) was subtracted from 1. This was done so that a value closer to the outside of the spider plot (1) indicates better performance.

4.3 | Bistatic and multistatic

Bistatic and multistatic performance can be compared. These are shown for the pre-2S-sorting (Figure 11) and the post-2S-sorting (Figure 12).

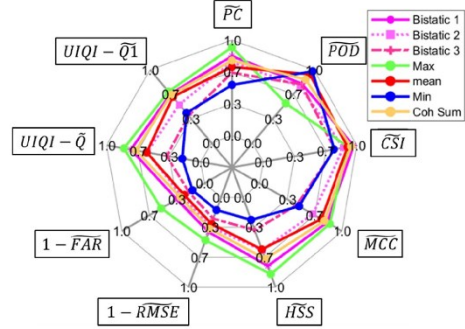


FIGURE 11 Spider plot showing the normalised performance of the three bistatic positions against the multistatic pre-2S-sorting and coherent summation. This is for the VV polarisation.

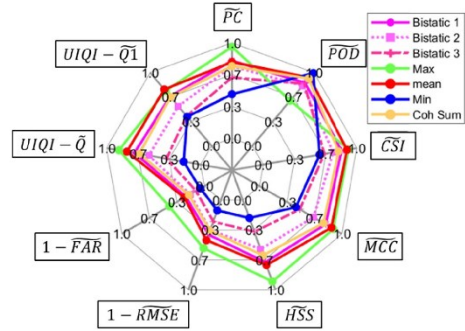


FIGURE 12 Spider plot showing the normalised performance of the three bistatic positions against the multistatic post-2S-sorting and coherent summation. This is for the VV polarisation.

The pre-2S-sorting, for the VV polarisation (Figure 11), shows that the maximum multistatic performs well in many metrics, except the POD and CSI. This is likely because the high number of no-change events being classified, resulting in a high number of false negatives. The coherent summation multistatic performs similarly to the best bistatic metrics. The max and mean exhibit quite poor performance, although do maintain a high POD. This shows the value of using multiple performance metrics.

The behaviour of the post-2S-sorting (Figure 12) is different to the pre-2S-sorting. The minimum performs worse than in the previous set of images. The mean now demonstrates superior performance to the coherent summation. The performance of the max image is quite similar.

It is also important when assessing performance to examine the outputs. This helps explain the performance seen in the graphs above. Figures 13 and 14 show eight CI-CCD images. Comparing the output change detection images

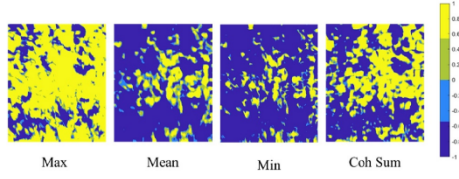


FIGURE 13 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the VV polarisation.

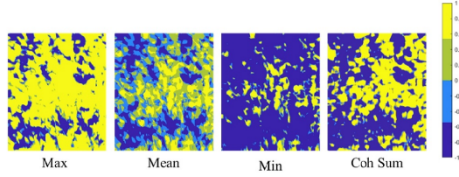


FIGURE 14 Set of four CI-CCD images formed using the post-2S-sorting dataset for the VV polarisation.

helps explain why the performance of the mean and min were quite similar (Figure 11). Inspecting the mean and min images in Figure 13 shows that they appear very similar. The mean image in Figure 14 however shows the ‘GBSAR’ much more clearly. In the pre-2S-sorting, many definite changes are detected, however in the post-2S-sorting significantly fewer are.

4.4 | Multistatic comparisons

The different multistatic images can be compared. These are plotted in Figures 15 and 16. These images show the trend seen in Section 4.1.3 holds true across the polarisations.

4.5 | Polarisations

The polarisations can also be investigated. Plotting the bistic performance metrics in Figures 17 and 18. This shows that there is a variance in performance across polarisation. This is particularly evident for the MCC and HSS metrics.

Fully polarimetric images can be formed in the same way as the multistatic images. The results for these are presented in Figures 19 and 20. These figures use TR1 as the reference and TR4 as the mission trajectory.

Similarly, to the bistic results, the minimum images performed worse than the single polarisation images, except for POD. The coherent summation performs at a similar level to the poorest single polarisation (HH). The maximum performs well, except for POD. It has high PC, UIQI, MCC and HSS values. The mean varies in performance as seen in Section 4.1.3. For the pre-2S-sorting, it exhibits similar performance to

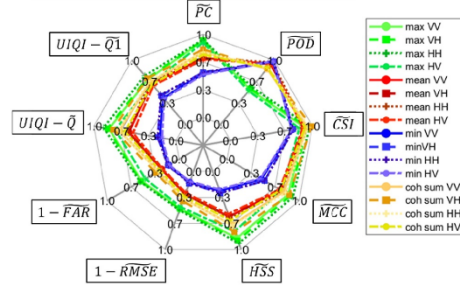


FIGURE 15 Spider plot showing the normalised performance of the pre-2S-sorting multistatic images across the four polarisations.

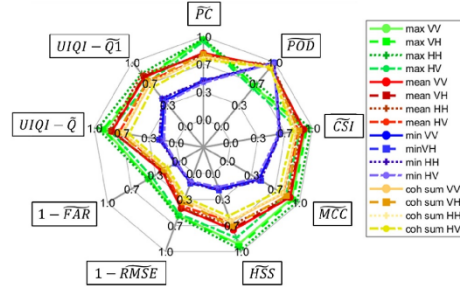


FIGURE 16 Spider plot showing the normalised performance of the post-2S-sorting multistatic images across the four polarisations.

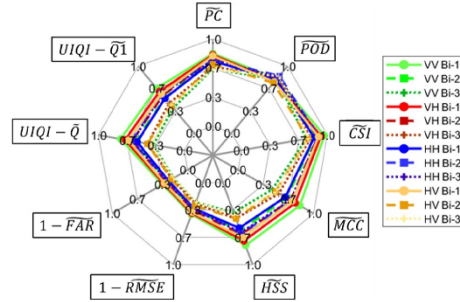


FIGURE 17 Normalised spider plot for bistic CI-CCD images for four different polarisations compared against the pre-2S-sorting master.

the single polarisation; however, for the post-2S-sorting, it performs similarly to the max, although it has a higher POD at a cost of a lower PC and higher FAR.

Fully polarimetric multistatic images can also be formed. Figures 21 and 22 compare the bistic fully polarimetric

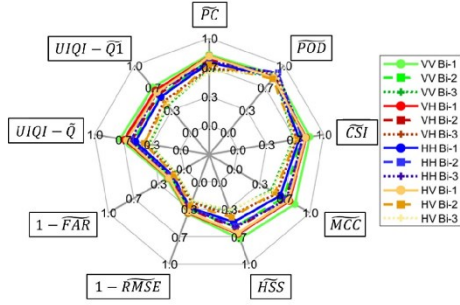


FIGURE 18 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared against the post-2S-sorting master.

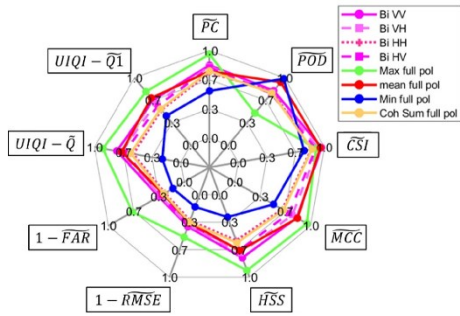


FIGURE 19 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using pre-2S-sorting and radar positions TR1 and TR4.

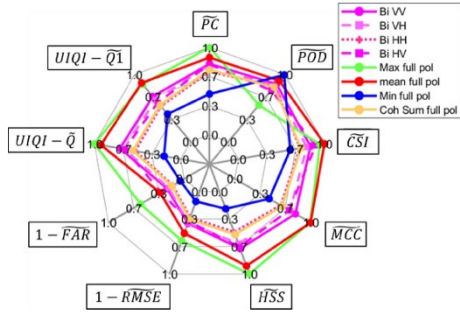


FIGURE 20 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and four fully polarimetric CI-CCD images. Formed using post-2S-sorting and radar positions TR1 and TR4.

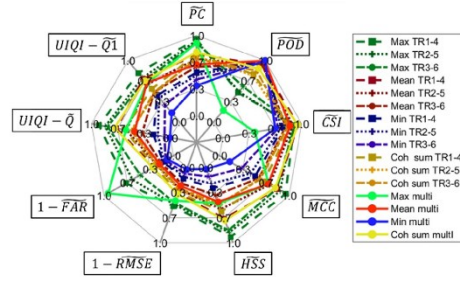


FIGURE 21 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using pre-2S-sorting.

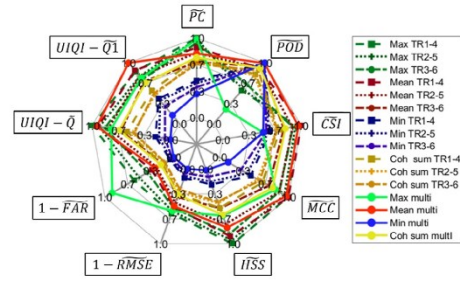


FIGURE 22 Normalised spider plot for bistatic CI-CCD images for four different polarisations compared and multistatic fully polarimetric CI-CCD images. Formed using post-2S-sorting.

performance metrics with the multistatic fully polarimetric performance.

In the pre-2S-sorting results (Figure 21), the max multistatic performs significantly worse than the bistatic maximum. It is believed this is due to too many images being used and thus changes being obscured. This effect is lessened in the post-2S-sorting results (Figure 22). In both, the pre- and post-2S-sorting results the multistatic minimum performs worse than the bistatic. This is likely for the same reason as the maximum; too many images, which in this case cause too many changes to be detected.

The mean performs quite poorly for the pre-2S-sorting results (Figure 21), with the multistatic performing worse than the bistatic means. In the post-2S-sorting results (Figure 22), the performance is quite good, particularly with regards to the UIQI, CSI and POD. It also has a low FAR and RMSE. The multistatic is worse than some bistatic max and mean images for the HSS and FAR and is outperformed by the maximum in PC.

The coherent summation performs similarly to the maximum (bistatic and multistatic). It shows improvement over the bistatic coherent summation. For the pre-2S-sorting

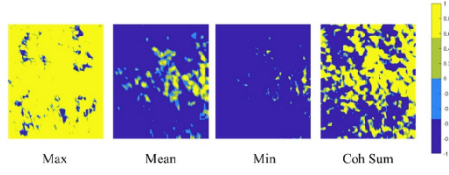


FIGURE 23 Set of four CI-CCD images formed using the pre-2S-sorting dataset for the full polarisation multistatic.

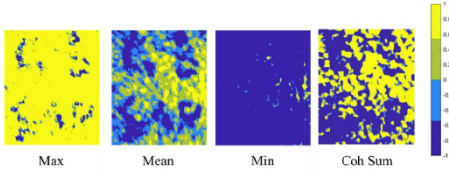


FIGURE 24 Set of four CI-CCD images formed using the post-2S-sorting dataset for the full polarisation multistatic.

results (Figure 21), it exceeds it in POD and CSI but performs worse for the other metrics. It has a higher HSS and MCC than the multistatic pre-2S-sorting, but not the bistatic. In the post-2S-sorting results (Figure 22), it is additionally outperformed by the bistatic and multistatic mean.

We can again inspect the output fully polarimetric and multistatic CI-CCD images shown in Figure 23 (pre-2S-sorting) and Figure 24 (post-2S-sorting). The letters ‘GBSAR’ are quite visible in the maximum image, so despite a relatively low POD, it is readable. It is also clearer than in the single pol (VV) images (Figures 13 and 14).

The minimum images perform very poorly and are covered in strong detections of change. As such, it is clear why the metrics are so poor.

The mean for the pre-2S-sorting (Figure 23) is quite similar to the minimum of the two figures below, as such it is clear why the performance metrics are similar to the minimum. The post-2S-sorting mean image (Figure 24) however clearly shows the ‘GBSAR’ letters. The four classes help here in making the letters more legible.

An enlarged image of the mean full polarisation multistatic post-2S-sorting (from Figure 24) is shown in Figure 25.

The coherent summation images do show the letters, although the false alarms make the G and S hard to make out.

The master images and the mean pre- and post-2S-sorting mean images are formed in a similar manner. Although the number and geometry of trajectories were significantly different. In the master images (Figures 7 and 8), the pre-2S-sorting image has a higher contrast and appears visually clearer than the post-2S-sorting master image. This is reversed when looking at the results (Figures 23 and 24). Here the post-2S-sorting image is significantly clearer. This is believed to be from the input images. It is hypothesised this is due to the

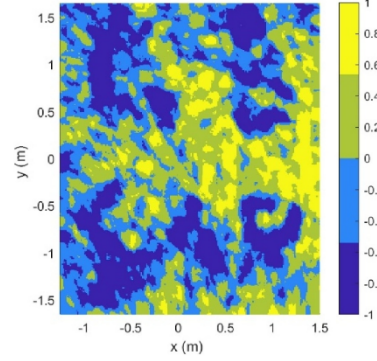


FIGURE 25 CI-CCD for the mean full polarisation multistatic post-2S-sorting (from Figure 24).

TABLE 6 Table showing the averaged performance metrics of the bistatic images compared to the pre-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.7	0.67	0.58	0.64
TR2-TR5	0.59	0.62	0.62	0.5
TR3-TR6	0.47	0.52	0.52	0.49

image formation pipeline. The bistatic master images have a high degree of similarity as they were formed using exactly repeated trajectories. Thus, averaging before image formation, results in a high contrast result. The post-2S-sorting averages a series of discrete values rather than a continuous series within 0–1, as such there is a greater possibility of a reduced contrast.

However, for the test images, the trajectories are no longer repeating, as such additional decorrelations are present. These additional decorrelations lower the coherence of the CCD images used in the pre-2S-sorting, which then results in a higher number of changes being detected.

4.6 | Results summary

To provide an overview and summary the mean of the values of the performance indices was taken for each of the CI-CCD images. These are shown in the tables below and use the colourmap provided below.

This provides a single value of performance to summarise the results; however, it is biased by the choice of metrics.



Table 6 and Table 7 present the bistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting,

TABLE 7 Table showing the averaged performance metrics of the bistatic images compared to the post-2S-sorting master image.

	VV	VH	HH	HV
TR1-TR4	0.67	0.63	0.54	0.61
TR2-TR5	0.57	0.58	0.58	0.49
TR3-TR6	0.45	0.48	0.59	0.46

TABLE 8 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the pre-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.79	0.68	0.45	0.59
	TR2-TR5	0.74	0.61	0.41	0.54
	TR3-TR6	0.72	0.5	0.35	0.55
Multi single pol	VV	0.73	0.63	0.43	0.67
	VH	0.75	0.62	0.45	0.72
	HH	0.78	0.64	0.45	0.68
	HV	0.68	0.6	0.42	0.64
Multi fully polarimetric		0.58	0.58	0.27	0.68

TABLE 9 Table showing the averaged performance metrics of the multistatic and fully polarimetric CI-CCD images formed using the post-2S-sorting.

		Max	Mean	Min	Coh-Sum
Bistatic full pol	TR1-TR4	0.84	0.81	0.31	0.56
	TR2-TR5	0.79	0.72	0.36	0.51
	TR3-TR6	0.74	0.61	0.31	0.52
Multi single pol	VV	0.76	0.72	0.38	0.64
	VH	0.78	0.71	0.4	0.67
	HH	0.82	0.71	0.4	0.63
	HV	0.71	0.66	0.36	0.59
Multi fully polarimetric		0.68	0.8	0.23	0.63

respectively. These results are presented for all four polarisations.

Table 8 and Table 9 present the multistatic averaged performance metrics for the post-2S-sorting and pre-2S-sorting, respectively.

It can be seen that the highest values for the averaged performance metrics are found in Table 9. These are higher than those found in Tables 6–8.

The maximum bistatic fully polarimetric for TR1-TR4 resulted in the highest average performance metric value. This

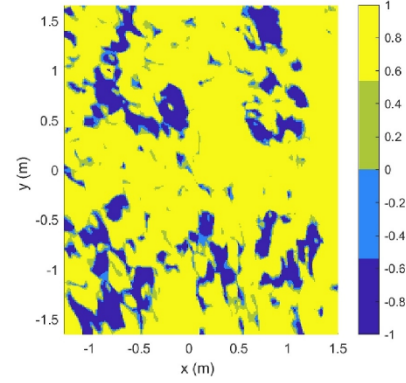


FIGURE 26 CI-CCD image for the bistatic TR1-TR4, fully polarimetric maximum (post-2S-sorting). This image showed a high average performance of 0.84 in Table 9.

image is shown in Figure 25. Compared to Figure 26, which also performed well it shows a lower number of detections.

5 | DISCUSSION

This paper has investigated the performance of different multistatic combinations for change detection quantitatively using a variety of performance metrics as well as qualitatively.

The use of multiple performance metrics combined with inspecting the output images has been shown to help characterise performance. These metrics do not just show how well a detector performed, but its tendency towards over or under detection and how well it captures the structure of the disturbance. For example, the metrics showed how the performance of the mean images was improved in the post-2S-sorting compared to the pre-2S-sorting (Section 4.1.3). This could then be visually seen as well in the CI-CCD images.

It has been shown that multistatic and multipolar change detection can lead to improved change detection performance. However, the manner in which the multistatic CI-CCD image was formed has a significant impact on performance. Coherent summation did not lead to the best performing change detection images. Instead multistatic change detection images formed incoherently using bistatic images was shown to perform better. An additional consideration is whether the sorting is performed pre or post the CI-CCD stage, and what manner of sorting was chosen. The variance in performance due to the former was most clearly demonstrated by the mean images which performed much better for the post-2S-sorting than for the pre-2S-sorting. The variance due to the type of sorting was evident in all the CI-CCD images, where the max, mean and min images displayed significant variation in detections.

Overall, the multistatic maximum and mean Post-2S-sorting images performed the best. The fully polarimetric multistatic mean Pos-2S-sorted image also exhibited good performance,

with very high Q values, although was outperformed in some metrics by some fully polarimetric bistatic images.

The minimum images were the best at detecting the presence of a change (high POD). However, the minimum images suffered from a poor FAR and did not capture the shape of the disturbance as shown by the Q , MCC and HSS values. The maximum images resulted in a significantly lower POD; however, the shape of the GBSAR letters was much more evident. This was reflected in high Q , MCC and HSS values.

The maximum and minimum images however showed a degradation in performance for the fully polarimetric multistatic images. This is hypothesised to be from too many images being used, this leading to a dominance of outliers (either change or no change) in the sorting. This would then obscure the structure of the disturbance track. In the multistatic fully polarimetric case, the mean post-2S-sorting image performed well and was more robust at negating the impact of outliers.

6 | CONCLUSION

This paper has investigated the performance of different multistatic combinations for change detection.

From the spider plots and the averaged performance tables (Section 4.1.6), some conclusions can be drawn.

Post-2S-sorting results in improved performance compared to pre-2S sorting.

Maximum post-2S-sorting images could offer good performance as shown in Table 9; however, for the fully polarimetric multistatic maximum image, the outliers (no change) become too dominant and degrade performance. Therefore, the maximum may be vulnerable to missing a large number of possible detections (low POD) when large numbers of images are used.

The mean images post-2S-sorting images performed quite well and were more robust to outliers.

The difference between the best performing maximum and mean images in Table 9 is quite small and does not represent a significant difference in performance.

The coherent summation performed worse than the maximum and mean images. This suggests processing a multistatic dataset bistatically, then forming a multistatic CI-CCD image will improve detection performance. The minimum images performed very poorly.

Overall, the mean post-2S-sorting performed well and is robust against outliers for larger volumes of images. Maximum post-2S-sorting images can perform well too but are more vulnerable to outliers and a low POD.

It is acknowledged that the values of the performance metrics relate to the master image used, and the number of detections present. Additionally, whilst it is hypothesised, these conclusions are valid for other multistatic change detection scenarios, only a single scene and disturbance investigated here.

Future work should investigate scenes of greater complexity, layover and/or varying topography. Multiband or multispectral change detection could also be investigated w.r.t multistatic SAR. Change detection algorithms trimmed,

weighted or winsorised means [48, 49] may offer improved performance by eliminating outliers.

AUTHOR CONTRIBUTION

Alexander Hagelberg: Conceptualization; Formal analysis; Investigation; Methodology; Software; Validation; Writing – original draft; Writing – review & editing. **Daniel Andre:** Funding acquisition; Methodology; Project administration; Resources; Software; Supervision; Writing – review & editing. **Mark Finnis:** Resources; Software.

ACKNOWLEDGEMENTS

This research was produced as a part of a PhD funded by Defence Science and Technology Laboratory.

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest that we are aware of.

DATA AVAILABILITY STATEMENT

Radar trajectory co-ordinates will be made available on the CORD repository. Synthetic Aperture Radar data is the subject of ongoing research but may be made available on request to the corresponding author or the Cranfield GBSAR group.

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How to cite this article: Hagelberg, A., Andre, D., Finnis, M.: Combined intensity and coherent change detection with four classes for laboratory multistatic polarimetric synthetic aperture radar. IET Radar Sonar Navig. 1–14 (2024). <https://doi.org/10.1049/rsn2.12588>

B.3 Bistatic Multi-polarimetric Synthetic Aperture Radar coherence investigation with Spatially Variant Incoherence Trimming

Bistatic Multi-polarimetric Synthetic Aperture Radar coherence investigation using Spatially Variant Incoherence Trimming

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Keywords: Synthetic Aperture Radar (SAR), bistatic radar, radar interferometry, Coherent Change Detection (CCD), polarimetric radar

Abstract: Synthetic Aperture Radar (SAR) Coherent Change Detection (CCD) allows for the detection of very small scene changes. This is particularly useful for Intelligence, Surveillance and Reconnaissance (ISR) as small changes such as vehicle tracks can be identified. Rapidly collecting repeat pass SAR imagery is important in these applications. For space-borne platforms, such repeat passes may however have significant differences, or baselines. CCD products are reliant on high coherence for good interpretability. This work investigates the sources and levels of incoherence associated with bistatic SAR imagery for a variety of baselines using simulations and measured laboratory data for two ground types. Additionally, spatially variant incoherence trimming is implemented. The paper shows the importance of angle dependant backscatter on the coherence of sub-resolution cell scatterers.

1. Introduction

High resolution Synthetic Aperture Radar (SAR) images enable detailed reconnaissance and surveillance of the Earth's surface for all weather, during the day and night. SAR interferometry can be used to determine a Digital Elevation Maps (DEM) [1, 2] and can be used for the detection of very small scene changes, such as vehicle tracks, using Coherent Change Detection (CCD) [3–6].

For high quality CCD results, typically two radar platform trajectories are closely repeated, with a low baseline, [7–9]. For satellites, this may necessitate long revisit times which may for example lead to decorrelation due to natural processes such as wind and rain [8], which would reduce CCD interpretability.

The research presented here is applicable to multistatic/bistatic satellite constellations, such as that being developed by the UK MOD under the name Project Oberon [10]. For such constellations, the ability to utilize trajectories with greater baselines and differing bistatic geometries could help reduce revisit times. However, such image pairs may potentially have low SAR coherence. This work is also relevant to multistatic Uncrewed Air System (UAS) swarms with either a transmitter [11–13] as part of the swarm or with a stand-off large illuminator [11, 14].

Forming good quality high contrast CCD results is reliant on high coherence between SAR images [7, 15]. This coherence can be reduced by natural processes such as wind and rain [15–18]. Thus, conducting rapid repeated passes would help mitigate this effect and allow for monitoring developing situations in a timely manner.

Bistatic (and multistatic) radar geometries involve having the transmitter and receiver(s) substantially separated, with multistatic geometries being comprised of multiple simultaneous bistatic collections. Multistatic SAR can have

several advantages, such as providing improved cross-range resolution [19, 20] and Signal to Noise Ratio (SNR) [21], although the choice of which SAR trajectories to combine significantly affects these [22].

Multistatic SAR satellite constellations may allow the collection of more timely change detection images to be formed using SAR image collections from differing trajectories, thus reducing the repeat pass time [23, 24]. However, the CCD's may be subject to varying degrees of coherence due to differing baselines and other effects such as different radar scattering due to a change in geometry, such as due to varying multipath or shadowing [25].

For high coherence and an improved change detection capability over nominally horizontal ground, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support vertical projection overlap [7, 9, 26], though it has been found that this alone is insufficient to guaranty high coherence and good CCD contrast [25].

This research is supported by measurements at the Cranfield University Ground Based Synthetic Aperture Radar (GBSAR) laboratory [25, 27, 28], where antennas are scanned within two vertical rectangular apertures, which allow a great deal of flexibility and fine control of SAR geometries for the scene.

This paper investigates the sources and levels of incoherence in ultra-wideband (UWB) SAR [29] bistatic geometries through both simulation and laboratory radar measurements. These SAR measurements are of two ground types.

In section 2, a background discussion of CCD and the spatial frequency domain is provided. Methodology is described in section 3, covering the GBSAR laboratory, SAR and CCD processing and the estimation of the scattering factor. Results are presented in section 4. Discussion and

conclusions are provided in section 5. References are provided in section 6 and SAR geometry information is provided in the appendices in section 7.

2. Background

2.1. Coherent Change Detection

Coherence between SAR images can be provided by a measure of the similarity between the two images, ranging from 0 to 1. It can be calculated via a normalised cross correlation [7, 17, 30] over corresponding samples of the images to provide a Coherent Change Detection (CCD) image product,

$$\hat{\gamma} = \frac{|\sum_{k=1}^N S_1(k) S_2^*(k)|}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

where the magnitude, $\hat{\gamma}$, is referred to as the sample (estimated) coherence, S_1 and S_2 are the two complex images being compared, N is the number of pixels within a window sampled over the two images and k is the pixel index.

A value approaching zero indicates low coherence, for example from a scene change, whereas values approaching 1 indicate areas of no change. An example CCD image is shown in Figure 1. The image was produced using exactly repeated SAR trajectories of a gravel rectangle. The letters ‘GBSAR’ were traced on the gravel, leaving legible incoherence tracks.

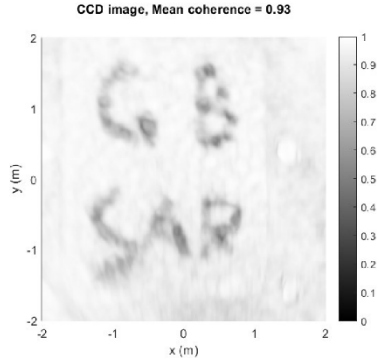


Figure 1 An example SAR laboratory CCD image.

2.2. Spatial frequency domain

SAR image information can be represented in the spatial frequency domain, also known as K-space, where it is given the name “image support” [7, 26, 31]. The extent of the image support is a composite of incident minus scattered wave vectors from transceivers, $\mathbf{K} = \mathbf{k}_i - \mathbf{k}_s$, to the different scene positions, where $\mathbf{k}_i = \frac{2\pi}{\lambda} \hat{\mathbf{i}}$ and $\mathbf{k}_s = \frac{2\pi}{\lambda} \hat{\mathbf{s}}$, and $\hat{\mathbf{i}}$ and $\hat{\mathbf{s}}$ are normalized incident and scattered directions. The length of $\mathbf{K}$ is proportional to frequency, and to the cosine of the bistatic angle, β [7]. These vectors can be plotted to trace out annulus segments within the K-space. An example is shown in Figure 2, for two different trajectories. The vertically projected areas corresponding to each collection are referred to as Projected Fourier Supports (PFS),

and the PFS’s corresponding to the collections in Figure 2 can be seen in Figure 3.

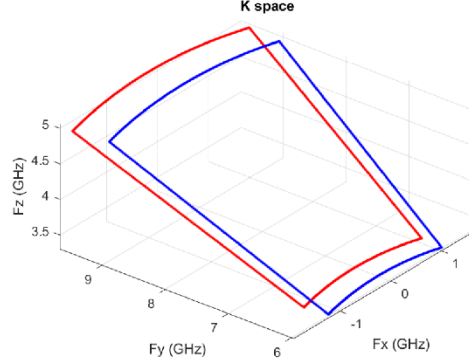


Figure 2 Spatial frequency plot showing the outline of two spatial frequency domain image supports.

In the context of coherence between SAR images of horizontal rough terrain, the proportion of the overlapping PFS areas to the square rooted product of the total PFS areas [17, 26] can be used to predict coherence (see section 2.3). In Figure 3, the overlapping area A_c is defined as $A_c = A_1 \cap A_2$, where A_1 and A_2 are the PFS areas of the two radar collections.

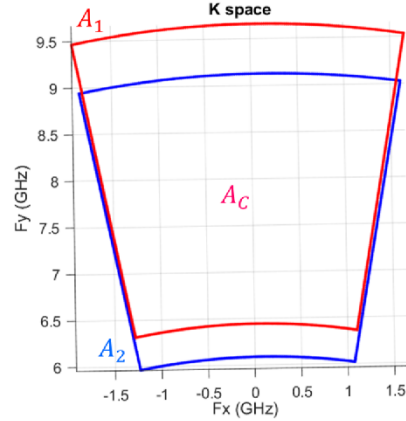


Figure 3 Projected Fourier supports of two radar collections. The two PFS areas are labelled A_1 and A_2 , and have the intersecting area A_c .

In the SAR far-field it is straightforward to calculate K-space overlap as the PFS areas are constant over the scene. However, in the SAR near-field, the PSF areas and their overlap varies significantly across the scene, complicating the estimation of coherence [7, 26]. The SAR near-field is defined as the regime where the range $d < 2L_{cr}^2/\lambda_c$ for centre wavelength λ_c and for a scene with cross-range extent L_{cr} . For the GBSAR system the far-field distance $d \approx 150$ m. The ranges in the laboratory are in the range of 4 – 10 m.

This can be further complicated by undulating or non-flat terrain, where the PFS projection directions are to the local terrain normal [32, 33].

The impact of the SAR near-field on the K-space is demonstrated in Figure 4. Here the K-space segments are plotted for the four corners of the scene as well as for the scene centre. It can be seen that in the SAR near-field, the PFS is spatially variant over the scene.

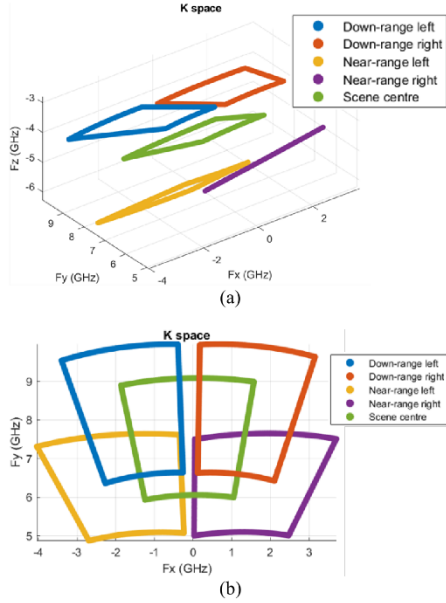


Figure 4 Spatial frequency plots showing the outline of five spatial frequency domain segments in the SAR near-field regime, corresponding to the four corners and centre of the measured scene. A three-dimensional view is shown in (a) and ground plane projection in (b).

2.3. Factors affecting coherence

The formula for calculating the sample (estimated) coherence, $\hat{\gamma}$, was presented in (1) section 2.1. It is referred to as the estimated coherence because it differs from the *true* coherence. The estimated coherence, $\hat{\gamma}$, is biased dependent on calculation features such as the CCD estimation window size [17, 34]. γ_{true} can be decomposed into factors which are also in the range 0-1 [7, 8, 17, 18, 35]:

$$\gamma_{true} = \gamma_{temp} \gamma_{SNR} \gamma_{proc} \gamma_{geom} \quad (2)$$

$$\gamma_{geom} = \gamma_{baseline} \gamma_{scat} \gamma_{reg} \quad (3)$$

Temporal decorrelation, γ_{temp} , refers to the change in the scene between the two SAR collection times. This may be the changes we wish to detect such as vehicle tracks or objects being placed in or removed from the scene. γ_{temp} can also be reduced by natural processes such as wind and rain [15–18].

The Signal to Noise Ratio (SNR) coherence factor γ_{SNR} also affects coherence [8, 17] and is given follows,

$$\gamma_{SNR} = \frac{1}{1 + SNR^{-1}} \quad (4)$$

γ_{proc} and γ_{geom} represent the decorrelations due to the processing and imaging geometries respectively. γ_{proc} accounts for decorrelations due to the image formation algorithm accuracy and assumptions, and the geometry term includes terms which are a function of the SAR imaging geometries. This includes $\gamma_{baseline}$ which accounts for K-space overlap [7, 9, 17, 26] and γ_{scat} which accounts for differences in electromagnetic backscatter, which would include shadowing and multipath effects [27, 36]. γ_{reg} refers to the image registration decorrelations due to differential layover [17].

The baseline correlation factor is [17, 18]

$$\gamma_{baseline} = \frac{A_c}{\sqrt{A_1 A_2}} \quad (5)$$

where A_1 and A_2 are the PFS areas corresponding to the two radar collections and $A_c = A_1 \cap A_2$ is the area of their intersection (see Figure 3). For the near-field the $\gamma_{baseline}$ must be evaluated on a per pixel basis, and then the values are averaged. $\gamma_{baseline}$ is sometimes referred to as the *spatial* correlation term. Alternative formulae for the spatial term in the monostatic far-field case are found in [8, 18], though these are not applicable to the SAR near-field data examined in this paper.

The Scattering term γ_{scat} was introduced in [27] and discussed further in [25], though originally referred to as the RCS term. It accounts for a difference in backscattering dependent on imaging geometry, and includes effects such as variation in shadowing, multipath and scattering due to polarisation. The temporal and baseline correlation terms are typically of most interest for imaged scenes with developed speckle and low baseline [15, 35], however at least for bistatic geometries with either high baseline or significantly different bistatic angles, the scattering term is hypothesized to play a significant role.

The misregistration term, γ_{reg} corresponds to the decorrelation due to a difference in layover [17],

$$\gamma_{reg} = \text{sinc}\left(\frac{h_s(\tan \psi_1 - \tan \psi_2)}{\rho_{res}}\right) \quad (6)$$

where h_s corresponds to the scatterer height, ψ the grazing angle and ρ_{res} is the resolution cell size.

3. Methodology

The Back Projection Algorithm (BPA) [37, 38], extended to the bistatic case, was used due to the SAR near-field and bistatic nature of the dataset collected.

3.1. GBSAR Laboratory

Bistatic SAR measurements were conducted at the Cranfield University Ground Based SAR laboratory (GBSAR lab) [25, 39] (see Figure 5).

The measurements were conducted with a Vector Network Analyzer (VNA), with centre frequency of 10 GHz and bandwidth of 4 GHz. Due to the use of a single VNA, there were no signal synchronization issues associated with the bistatic measurements – often a significant issue for practical remote bistatic SAR sensing.



Figure 5 The GBSAR laboratory in a bistatic configuration. The transmitter is circled in red and labelled Tx; the receiver is circled in blue and labelled Rx.

3.1.1. Scene ground types

Two scenes were used. Each was surrounded by spheres and top hat scatterers, used to verify the alignment of the SAR images.

The first measured scene is shown in Figure 6 and was a rectangle of gravel (2.7 m x 1.5 m). The gravel consisted of approximately 1 cm sized pieces of gravel, significantly smaller than the resolution cell size. A smaller rectangular area (1.5 m x 1.4 m) was used for the calculation of coherence and will be referred to as the Region Of Interest (ROI).

The second scene was a rectangle (1.6m x 1.5m) of densely packed stones, seen in Figure 7. This scene was less wide than the gravel scene, but encompassed the ROI used for this investigation.



Figure 6 Image showing the gravel rectangle, together with spheres and top hat scatterers used to ensure image alignment.



Figure 7 Image showing the stone rectangle. The spheres and top hat scatterers shown in Figure 6 are also present.

3.2. SAR images and background subtraction

Example SAR images of the two scenes are shown in Figure 8 and Figure 9. To increase the Signal to Clutter Ratio

(SCR) and to better estimate the Signal to Noise Ratio (SNR), background scans, free of gravel and stones, were carried out, and these were subtracted from the desired scene measurement data.

From these SAR images the SCR was estimated as 21 dB for the gravel measurements and 25 dB for the stones measurement. This clutter represents scattering from the laboratory itself and some multipath, and most of it was removed by the background subtraction. Some multipath signature remained visible after the subtraction, and because it was associated with the stones and gravel, it could not be removed with a background subtraction. However, the SAR geometry and the arrangement of the gravel and stones was designed such that the multipath appeared down-range of the ROI, so that it did not affect the coherence results.

The SNR was estimated as 30dB for the gravel and 38 dB for the stones. The difference in the SNR and SCR between the gravel and stones is due to the stones reflecting more strongly than the gravel.

SAR Bistatic image VV pol, Gravel BS, TR1 000

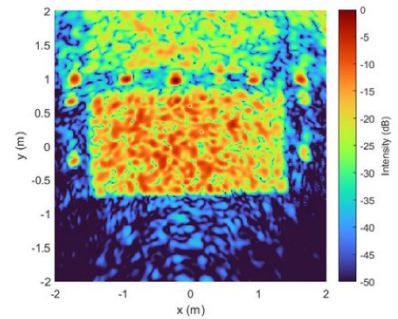


Figure 8 SAR image (VV, TR1 000) of the gravel scene with background subtraction.

SAR Bistatic image VV pol, Stones BS, TR1 000

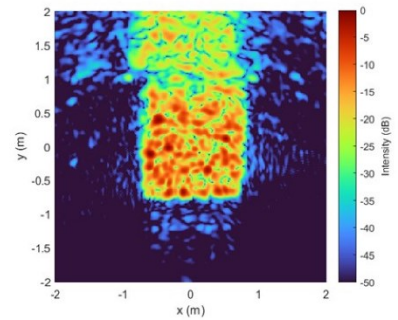


Figure 9 SAR image (VV, TR1 000) of the stone scene after background subtraction.

3.3. SAR geometries

The SAR geometries used were constrained by transmitter and receiver vertical rectangular scanning

apertures 0.4 m high by 2.4 m wide, seen in the SAR geometry overview in Figure 10. The red lines correspond to the transmitter positions used, and the blue to receiver positions.

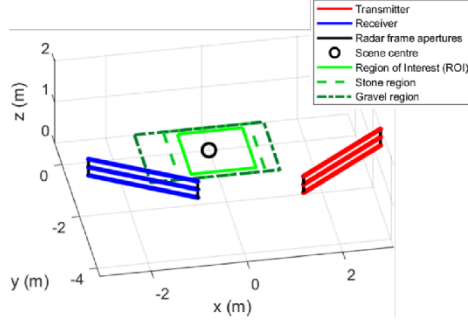


Figure 10 Diagram showing the radar geometries used. The transmitter and receiver geometries are shown in red and blue respectively. The scene centre is marked by the black circle. The stone and gravel regions are outlined with dashed green lines. The region of interest is outlined by the solid green line.

Fifteen bistatic SAR geometries were measured, and in each of them the transceiver heights were kept the same. For each of them, a 1.6 m horizontal aperture was scanned by both the transmitter and the receiver, and with five different horizontal positions labelled TR1 to TR5, and with three vertical positions, labelled 000, 200, 400, corresponding to vertical distances in millimetres to the scanner origin, with “000” corresponding to the highest trajectories and 400 corresponding to the lowest. The individual transmitter apertures are shown in Figure 11 and the corresponding receiver apertures in Figure 12, with local scanner axis coordinates – in these, the “X” marker colours denote the scanned aperture extents for each geometry, where TR1 form the outer pair of transceiver positions and TR5 form the inner pair.

The chosen SAR geometries allow the bistatic angle to be progressively increased, whilst maintaining a substantial K-space overlap between them. The K-space overlap between the six SAR geometries was high, with $Y_{baseline}$ ranging from 0.7 to 0.96 for non-repeating trajectories.

Transceiver scan geometry parameters are listed in the appendices in section 7. It is noted that the grazing and bistatic angles are spatially variant over the scene, and the values provided in the tables are calculated to the centre of the scene and gravel region. The SAR resolutions were estimated using the Bistatic Equivalent Monostatic (BEM) antenna positions, calculated along the antenna bisecting direction to the scene centre [40, 41].

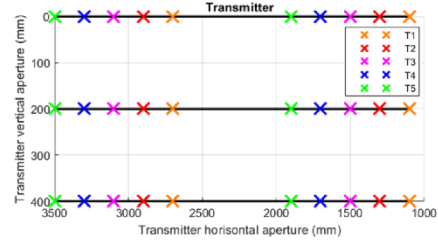


Figure 11 Diagram showing the horizontal extent of the transmitter apertures for each height, in the local axis coordinate system.

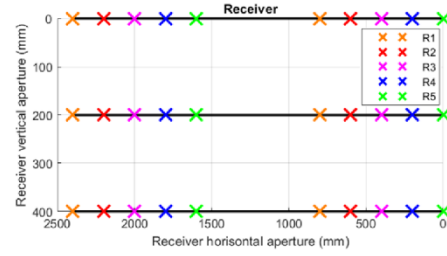


Figure 12 Diagram showing the horizontal extent of the receiver apertures for each height, in the local axis coordinate system.

The bistatic angle difference between the different trajectories and the grazing angle differences are shown in Figure 13 and Figure 14.

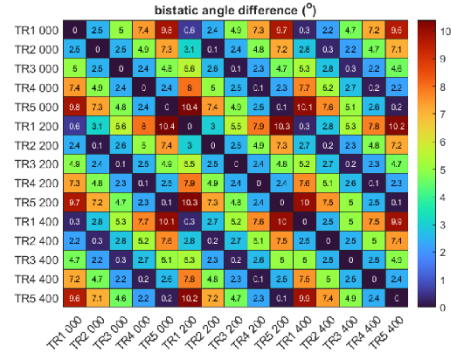


Figure 13 Heatmap and table showing the bistatic angle difference between the SAR geometries measured.

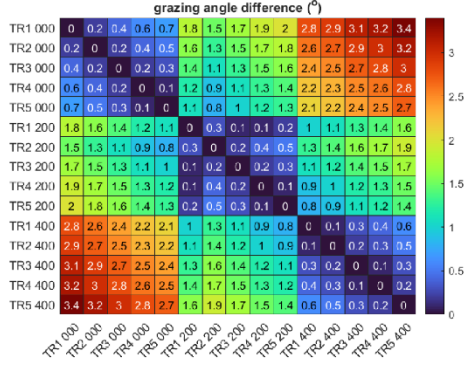


Figure 14 Heatmap and table showing the grazing angle difference between the SAR geometries measured.

3.4. Spatially Variant Processing

As discussed in section 2.2, spatial frequency domain projections of the radar collection data vary substantially across the scene when in the SAR near-field. Hence the calculation of $\gamma_{baseline}$ should be performed in a spatially variant manner. Additionally, Spatially Variant Incoherence Trimming (SVIT) can be implemented for increased coherence between images [26, 32, 33, 36, 42, 43].

The SVIT process omits / removes incoherent energy from the non-overlapping PFS data for each SAR image pixel for both SAR collections, during the image formation stage, resulting in two SAR images with greater coherence between them. The PFS areas alone are used to calculate $\gamma_{baseline}$.

Figure 15 and Figure 16 are outputs from the SVIT algorithm corresponding to the laboratory measurements undertaken, showing the PFS outlines of a master and reference image for a single point in the scene, plotted in red and blue respectively. These images compare the K-space overlap of SAR geometries TR1 000 and TR4 000. The greyscale figure backgrounds show a running sum of the intersecting PFS regions, in Figure 15, and non-intersecting, in Figure 16, where each PFS contributes values of one to the summation image (which is then normalized). The figures show significant variation in k-space of overlapping and non-overlapping regions as a function of scene position (or SAR pixel position).

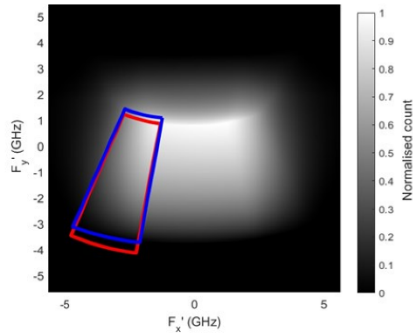


Figure 15 SVIT algorithm output for TR1 000 and TR4 000. The red and blue lines show the PFS for the reference and mission collections for a single scene position and collection pair. The grayscale background shows the sum over the scene of all intersecting regions, each given a value of 1.

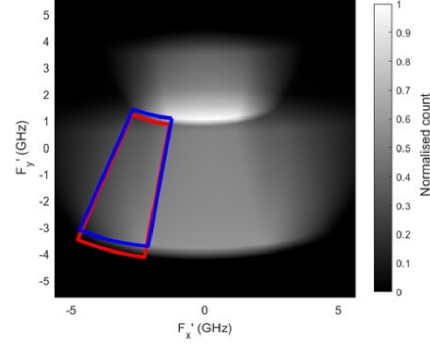


Figure 16 SVIT algorithm output for TR1 000 and TR4 000. The red and blue lines show the PFS for the reference and mission collections for a single scene position and collection pair. The grayscale background shows the sum over the non-intersecting regions, each given a value of 1.

3.5. Simulation

Two types of SAR image simulation were used. The first used isotropic point scatterers with a density of approximately 14.3 scatterers per resolution cell. This provided fully developed SAR speckle (see section 3.6).

For the purposes of modelling bistatic coherence for rough ground, the second set of simulations added a random phase contribution to each scatterer, which was scaled using the bistatic angle. This resulted in an additional decorrelation between SAR images, function of the difference between bistatic angles. The additional phase factor contribution to scatterer n took the following form,

$$\exp(i\pi C_{sim}\beta_n A_n) \quad (7)$$

where C_{sim} is a parameter to be determined empirically, β_n is the bistatic angle in radians at scatterer n , and A_n is a uniformly distributed random real number assigned to scatterer n such that $-1 \leq A_n < 1$. The values A_n were fixed across the simulations. The values of C_{sim} corresponded to a minimum Root Mean Squared Error (RMSE) between the simulation coherence and the measured data coherence.

The SAR and CCD processing undertaken was the same for both simulated and measured data.

A function of the difference in bistatic angle ($\Delta\beta$) was also used to fit coherence curves, as follows:

$$\gamma_{curve fit} = (1 + C_{cf1}\Delta\beta + C_{cf2}\Delta\beta^2 + C_{cf3}\Delta\beta^3)\gamma_{baseline} \quad (8)$$

The coefficients C_{cf} were chosen so that they resulted in the lowest Root Mean Squared Error (RMSE) when compared with the measured data, with their chosen values for the two measured scenes presented in Table 1.

Table 1 Parameter values used to add a decorrelation factor to the simulation (7), or to fit the overall coherence (8) as a function of bistatic angle difference for the two measured scenes.

	Bistatic decoherence simulation parameter	Coherence fitting coefficients		
	C_{sim}	C_{cf1}	C_{cf2}	C_{cf3}
Gravel	1.8	-0.72	-21.87	76.19
Stones	4.8	-8.23	16.62	50.85

The simulations and curve fitting were used to show that the behaviour of γ_{Scat} can be characterised and predicted.

3.6. Intensity distribution and surface roughness

A surface is considered rough when the size of the scatterers is small in comparison to the wavelength, and there are a large number of scatterers per resolution cell [44]. Additionally, the following roughness criterion should be met [45, 46]:

$$\Delta h > \frac{\lambda}{8 \cdot \cos \theta} \quad (9)$$

where, Δh (cm) is the surface height variation, λ (cm) the wavelength and θ the electromagnetic wave incidence angle (it is expected that this formula extends to bistatic back-scattering geometries).

The surface height variation (Δh) is around 1-2 cm for the gravel and 5-10 cm for the stones. These heights give values larger than the value of the criterion: $\frac{\lambda}{8 \cdot \cos \theta} = 0.41$ cm so that they are considered to be rough.

The intensity ($|I|$) Probability Density Function (PDF) of Rayleigh speckle takes the form of the negative exponential [7, 47-49].

$$P(|I|) = \frac{1}{\langle |I| \rangle} \exp \left(-\frac{|I|}{\langle |I| \rangle} \right) \quad (10)$$

where $|I|$ is the intensity and $\langle |I| \rangle$ is the mean intensity [7, 47, 48].

The pixel intensity distribution of the isotropic simulation is plotted in Figure 17 and closely follows the negative exponential distribution (red line), indicating that surface roughness has been well simulated.

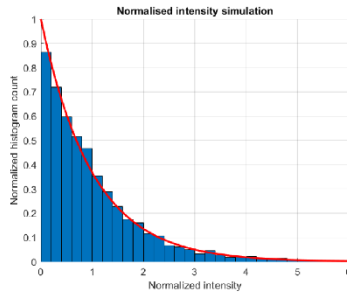


Figure 17 Normalised intensity distribution (histogram) for the isotropic simulations and negative exponential distribution (red).

Similar distributions can be plotted for the stone and gravel SAR images. The RMSE can be calculated between the measured intensity values and the negative exponential distribution. These are presented below in Table 2.

Table 2 RMSE calculated for the normalised intensity of the measured SAR images and the negative exponential distribution.

RMSE	Polarisation			
	VV	VH	HH	HV
Gravel	0.33	0.23	0.19	0.25
Stones	0.61	0.43	0.55	0.52

The gravel shows a closer alignment than the stones with the negative exponential distribution, as shown in Table 2.

The 1 cm diameter gravel stones give rise to complex scattering, including multipath as well as direct scattering, however the radar wavelength is significantly larger than the scatterers themselves which may change the nature of the scattering away from the simpler and more intuitive Physical Optics (PO) regime.

The stones exhibit a greater deviation from the ideal rough (speckle) scattering response than for the gravel scene, which may be due to the presence of fewer scatterers per resolution cell, as the stones are larger. The stones are approximately 10 cm in size, larger than the centre wavelength of 3 cm.

3.7. Estimation of γ_{Scat}

Due to the nature of the laboratory environment, equations (2) and (3) can be simplified and the terms calculated to estimate the scattering component.

No scene changes were present so $\gamma_{temp} = 1$. From the background subtraction images, (section 3.2), the SNR was estimated at 35 and 41 dB for the gravel and stones respectively. Thus, using equation (4) γ_{SNR} was estimated at 0.98 and 0.99 for the gravel and stones respectively. The measurement ground truth was accurately known due to the well-controlled antenna positioning and accurate curved wavefront bistatic back-projection image formation used, so $\gamma_{Proc} = 1$. The minimum γ_{reg} was calculated using equation (6) as $0.9968 \approx 1$.

Hence the following equation is used to give an estimate for γ_{Scat} :

$$\hat{\gamma}_{Scat-baseline} = \left(\frac{\hat{\gamma}_{Meas}(x, y)}{\gamma_{baseline}(x, y) \gamma_{SNR} \gamma_{reg}} \right) \quad (11)$$

The angled brackets indicate an averaging of the quantities over the scene. It is noted that due to the SAR near-field nature of the measurements, both the $\gamma_{baseline}$ and $\hat{\gamma}_{meas}$ (evaluated within a square sliding window) vary spatially. Hence, they are functions of image coordinates (x, y) . Therefore $\hat{\gamma}_{Scat}$ is evaluated as a mean over the spatially varying fraction in (11) and (12). "Meas" denotes that the coherence value is from the measured data.

An alternative method to estimate $\hat{\gamma}_{Scat}$ is to use the simulated and measured CCD images directly, that is without the use of $\gamma_{baseline}$. This is shown in equation (12). Here "Sim" denotes the simulated values (where $\hat{\gamma}_{Sim-isotropic} \approx$

$\gamma_{baseline}$ due to the isotropic scatterer assumption). The γ_{scat} for the isotropic simulations is ≈ 1 . Thus,

$$\hat{\gamma}_{Scat-Sim-isotropic} = \left(\frac{\hat{\gamma}_{Meas}(x, y)}{\hat{\gamma}_{Sim-isotropic}(x, y) \gamma_{SNR} \gamma_{reg}} \right) \quad (12)$$

As in equation (11), an averaging over the spatially varying fraction is performed in (12) due to the SAR near-field nature of the measurements.

After the spatially variant incoherent trimming process, it is assumed that the resulting coherence between images $\hat{\gamma}_{Trimmed}(x, y) = \hat{\gamma}_{Meas}(x, y) / \gamma_{baseline}(x, y)$, hence the following relation is assumed:

$$\hat{\gamma}_{Scat-Trimmed} = \left(\frac{\hat{\gamma}_{Trimmed}(x, y)}{\gamma_{SNR} \gamma_{reg}} \right) \quad (13)$$

Thus three formulae will be used to calculate γ_{scat} (11)-(13) to improve confidence in the results.

4. Results

4.1. Overall Coherence Results

The coherence between SAR images is evaluated as the mean of the absolute value of $\hat{\gamma}$ (1), over the ROI. For the measurements conducted, these are plotted in Figure 18, against the bistatic angle difference. Figure 13 and Figure 14 show that across the SAR geometries measured, the maximum bistatic angle difference is 10.3° , and the maximum grazing angle difference is 0.7° . All four polarisations are plotted, blue and cyan for the cross-polar and red and magenta for the co-polar. Crosses were used to represent the gravel scene data and circles the stone scene data, with curves of best fit added. The $\gamma_{baseline}$ values are plotted in green.

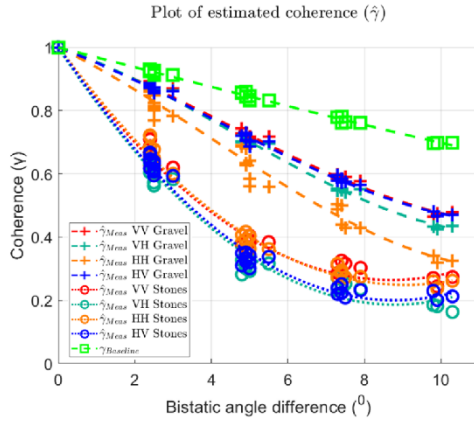


Figure 18 Coherence plotted against bistatic angle difference for the gravel and stone scene datasets, with $\gamma_{baseline}$.

For differing bistatic angles, the coherence for SAR images from both measured scenes is less than $\gamma_{baseline}$, with an increased difference as the bistatic angle difference increases. These results support previous findings [25] and indicate that there is a geometry dependant decorrelation other than that due to PFS overlap.

The coherence for the stones is below that for the gravel scene, indicating that the decoherence is terrain type specific. Reasons for the difference may include a greater variability in bistatic RCS for the larger stones, due to their larger sizes compared to the radar wavelengths (approximately 10 cm compared to a centre wavelength of 3 cm). This would also affect the relative prominence and variability of multipath and shadowing effects. Additionally, the larger stones have a lower number of scatterers per SAR resolution cell, leading to the SAR speckle not being quite as fully developed (see 3.6).

The coherence for the stones plateaus at $8-10^\circ$, this behaviour is attributed to the biasing seen in CCD processing at low coherence levels [17, 50], which increases estimated coherence ($\hat{\gamma}$) above true coherence γ_{true} , dependant on the CCD window size [17, 50].

Figure 18 shows there is a variation in coherence between the different polarisations, which will be seen in greater detail in sections 4.2 and 4.3.

It is noted that a simulation using isotropic scatterers $\hat{\gamma}_{sim-isotropic}$ provides an overall good match for $\gamma_{baseline}$, seen in Figure 19, as was the case in prior publications [25, 27].

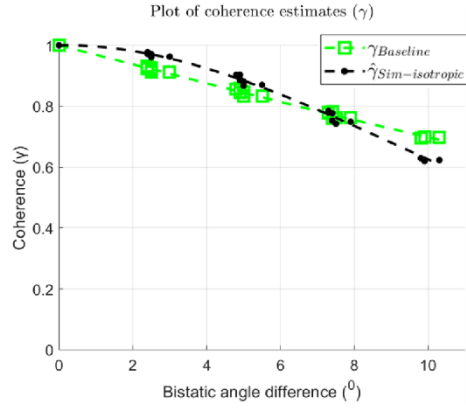


Figure 19 Graph showing the correspondence between $\gamma_{baseline}$ and $\hat{\gamma}_{sim-isotropic}$.

Although there is a good match between the $\gamma_{baseline}$ and $\hat{\gamma}_{sim-isotropic}$, there are however some differences. $\hat{\gamma}_{sim-isotropic}$ gives coherence values below $\gamma_{baseline}$ up to around 7 degrees, after which it gives higher coherence values. This difference may be due to numerical errors and additionally the effects of CCD coherence estimation for the simulation [17, 50]. This results in slightly different corresponding values for $\hat{\gamma}_{scat}$ in the following sections. The results are further described in section 4.2 for the gravel scene, and section 4.3 for the stones scene.

4.2. Gravel scene results

This section presents the coherence results for the gravel scene. The measured scene coherence is plotted in Figure 20. It includes measured and simulated coherence as well as $\gamma_{baseline}$ and a curve fitted to all of the measured data,

$\gamma_{Curve\ fit}$. The simulated coherence incorporated the bistatic decoherence model phase factor in (7) (see section 3.5) and is referred to as $\hat{\gamma}_{sim-decorrelation}$. The parameters used for the fitted curve and for the decoherence simulation are provided in Table 1.

For differing bistatic angles, the $\gamma_{baseline}$ values are significantly higher than for the measured data for all polarisations. The bistatic decorrelation simulation $\hat{\gamma}_{sim-decorrelation}$ matches the measured coherence better than the isotropic scatterer simulation $\hat{\gamma}_{sim-isotropic}$ (compare with Figure 19). The fit of $\hat{\gamma}_{sim-decorrelation}$ could be improved by replacing β with a polynomial function of β in equation (7), however the computationally intensive exercise of finding the optimal coefficient values is beyond the scope of this paper.

Of the four polarisations, HH shows the least coherence, for the gravel scene, and VV the most.

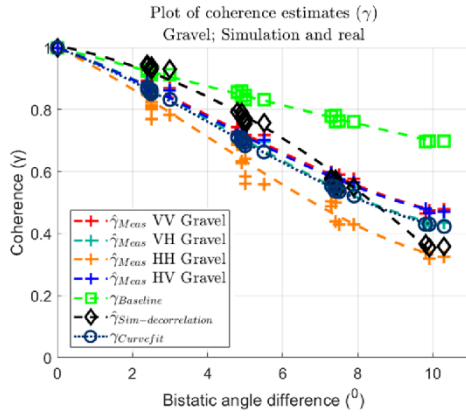


Figure 20 Coherence plots against bistatic angle difference for the gravel scene, including all four polarisations, $\gamma_{baseline}$, the bistatic decoherence simulation and the fitted curve, whose parameters are provided in Table 1.

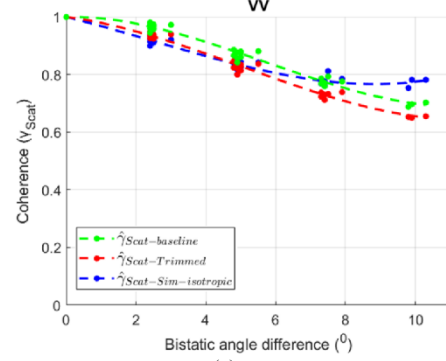
Using equations (11)-(13) the coherence scattering component associated with a departure from bistatic isotropy, $\hat{\gamma}_{Scat}$, can be estimated with three approaches.

Figure 21 shows $\hat{\gamma}_{Scat}$ for each of the four polarisations. In the case of the gravel scene, polarisation HH exhibits the steepest decrease in $\hat{\gamma}_{Scat}$ as a function of the bistatic angle difference. The three different methodologies for estimating $\hat{\gamma}_{Scat}$ result in only slightly different coherence values.

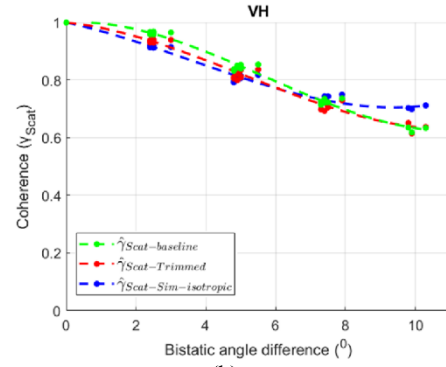
The values for $\hat{\gamma}_{Scat-baseline}$ (11) and for $\hat{\gamma}_{Scat-Sim-isotropic}$ (13) are plotted in green and blue respectively. $\hat{\gamma}_{Scat-Trimmed}$ (13) is shown in red and represents the coherence of the incoherence trimmed image coherence $\hat{\gamma}_{Trimmed}$ (with compensations for the SNR and registration errors).

The three $\hat{\gamma}_{Scat}$ curves mostly show close alignment except for the increased coherence of $\hat{\gamma}_{Scat-Sim-isotropic}$ at the most extreme bistatic angle difference of 10° . This is due

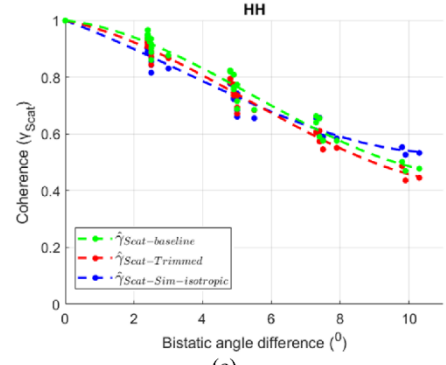
to the difference between $\hat{\gamma}_{sim-isotropic}$ simulated coherence and $\gamma_{baseline}$, seen in Figure 19.



(a)



(b)



(c)

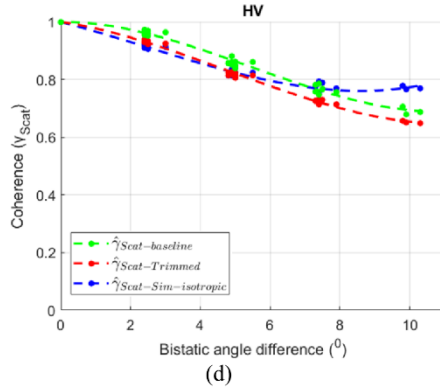


Figure 21 Gravel scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (11)-(13).

- In summarizing results, it has been found useful to divide the coherence into three performance bands [36]:
- *Good* CCD performance, occurs where changes are easily detected, and is associated with coherences above 0.8;
 - *Moderate* CCD performance, occurs where useful detection information may still be available but is unreliable due to an elevated false alarm rate, and is associated with coherence below 0.8 and above 0.6;
 - *Poor* CCD performance, occurs where changes are not discernible due to a very high false alarm rate, and is associated with coherence values below 0.6.

In the summarizing of results, the angular differences are rounded here to the nearest 1°.

For the gravel, “good” $\hat{\gamma}_{Scat}$ coherence is achieved for bistatic angle differences from 0° up to 4-6°, depending on polarisation. This corresponds to 0-6° for VV and HV, 0-5° for VH and 0-4° for HH.

“Moderate” CCD performance occurred at least for bistatic angle differences of 6-10° for VV and HV, 5-10° for VH and 4-7° for HH. The experimental setup did not allow for angular differences larger than 10°. “Poor” CCD performance occurred beyond these angular values.

The results are listed in the summary Table 3, and presented graphically in section 4.4.

Table 3 Summary of bistatic angular difference extents of coherence ($\hat{\gamma}_{Scat}$) performance bands for the gravel, where angles are rounded to the nearest 1°.

Scene	Pol	$\hat{\gamma}_{Scat} > 0.8$	$0.8 \geq \hat{\gamma}_{Scat} > 0.6$	$0.6 \geq \hat{\gamma}_{Scat}$
Gravel	VV	0-6°	6-10°	N/A
	VH	0-5°	5-10°	N/A
	HH	0-4°	4-7°	7-10°
	HV	0-6°	6-10°	N/A

4.3. Stone scene results

This section presents the coherence results for the stones scene. The coherence results are presented in Figure 22. The coherence for the stones is lower than for the gravel, and the difference increases as the bistatic angle difference increases, so that at 10° the difference is around 0.2. There is less variation with polarisation in the measured stones scene than with the gravel and HV is the polarisation in which coherence is least (whereas for the gravel, HH gave the least coherence).

The non-isotropic simulation $\hat{\gamma}_{sim-decorrelation}$ (see section 3.5) is plotted in black and the fitted coherence curve $\gamma_{Curve fit}$ is dark blue.

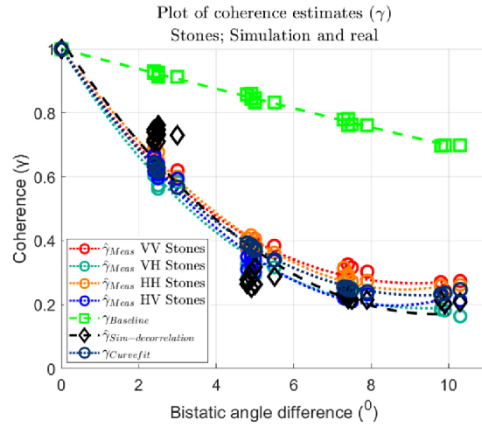
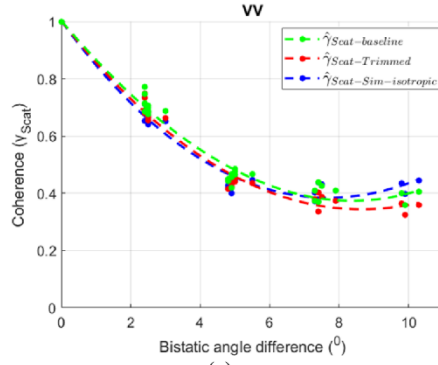


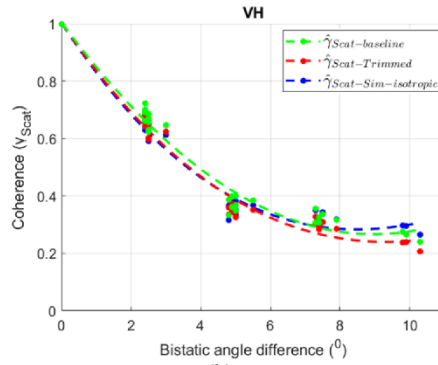
Figure 22 Coherence plots against bistatic angle difference for the stones scene, including all four polarisations, $\gamma_{baseline}$, the bistatic decoherence simulation and the fitted curve, whose parameters are provided in Table 1.

The estimates for $\hat{\gamma}_{Scat}$ (11)-(13) for the stones are plotted in Figure 23 for the four polarisations. The cross-polarization curves exhibit a steeper decrease in $\hat{\gamma}_{Scat}$ with respect to bistatic angle difference. The different methodologies result in only slightly different values.

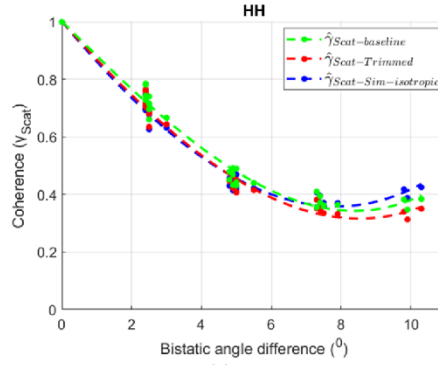
The slight rise or plateauing of the $\hat{\gamma}_{Scat}$ values for the stones seen at 10° is attributed to the biasing seen in CCD processing at low coherence levels [17, 50] and the steeper decrease in coherence of the isotropic simulation ($\hat{\gamma}_{sim-isotropic}$) compared to the baseline ($\gamma_{baseline}$) (Figure 19).



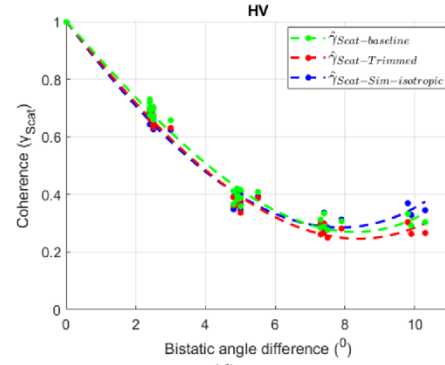
(a)



(b)



(c)



(d)

Figure 23 Stone scene coherence scattering component $\hat{\gamma}_{Scat}$ against bistatic angle difference, estimated with three methodologies presented in equations (11)–(13).

In comparison to the gravel results in Figure 21, the values of $\hat{\gamma}_{Scat}$ for stones in Figure 23 reduce at a faster rate.

Using the three performance bands defined in section 4.2: “good” $\hat{\gamma}_{Scat}$ coherence is achieved for bistatic angle differences from 0-1° for VV, VH and HH, and 0-2° for HV; “Moderate” CCD performance occurred for bistatic angle differences in the range 1-3° for VV, VH and HH, and 2-4° for HV; “Poor” CCD performance occurred for angles greater than 3°.

The results are listed in the summary Table 4, and presented graphically in section 4.4.

Table 4 Summary of bistatic angular difference extents of coherence ($\hat{\gamma}_{Scat}$) performance bands for the stones, where angles are rounded to the nearest 1°.

Scene	Pol	$\hat{\gamma}_{Scat} > 0.8$	$0.8 \geq \hat{\gamma}_{Scat} > 0.6$	$0.6 \geq \hat{\gamma}_{Scat}$
Stones	VV	0-1°	1-3°	3-10°
	VH	0-1°	1-3°	3-10°
	HH	0-1°	1-3°	3-10°
	HV	0-2°	2-4°	4-10°

4.4. Graphical summary section

The results presented in Table 3 and Table 4 are presented graphically in Figure 24. The curves of best fit in Figure 21 and Figure 23 were averaged and plotted with a colourmap based on the three performance bands defined in section 4.2. “Good” CCD performance is represented by green, “Moderate” by yellow and “Poor” by red.

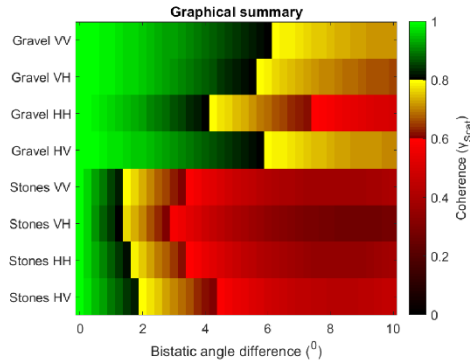


Figure 24 Graphical summary of results showing the bistatic angular difference extents of coherence ($\hat{\gamma}_{Scat}$) performance bands for the gravel and stone scenes. “Good” CCD performance is represented by green, “Moderate” by yellow and “Poor” by red.

5. Discussion and Conclusion

For two types of terrain, it has been shown that when the difference between bistatic angles is large enough for two bistatic collections, the coherence between the corresponding SAR images is less than would be expected from the degree of projected Fourier domain support overlap achieved.

It is hypothesised that the observed reduction in coherence is due to differences in the bistatic microwave scattering between the two SAR collections, which would include phenomena such as shadowing and multipath. These effects would be included within the proposed scattering coherence parameter γ_{Scat} .

The results presented build on those found in [25, 27] and provide improved characterisation of γ_{Scat} , now for two ground types. γ_{Scat} was calculated in three ways, which were in good agreement.

A CCD simulation was developed which modelled a decorrelation as a function of bistatic angle difference, implemented via a decorrelation phase factor controlled by one coefficient. Whilst matching to the experimental results was achieved, it is assumed that the match could be further improved by use of a polynomial function of the bistatic angle. The determination of the polynomial coefficients would be highly computationally intensive and a subject for future research. Additional further work could include the determination of improved curve fitting functions for γ_{Scat} .

It was shown that for bistatic SAR trajectories where there is a significant bistatic angle difference, the decorrelation due to γ_{Scat} dominates the coherence and can reduce it to a level where CCD interpretability becomes very poor. This shows that even when terrain has undergone little change, selection of bistatic SAR collections with high spatial frequency domain overlap may not be sufficient for forming good quality CCD images, and that the bistatic angle difference can have a major effect, which is terrain dependent. These considerations would affect the choice of useful interferometric imaging geometries obtained from a multistatic SAR system.

Table 3, Table 4 and Figure 24 summarise the $\hat{\gamma}_{Scat}$ coherence results and show that the CCD performance that can be expected depends upon the scene being imaged and the measured polarisation.

The two terrain surfaces investigated can be considered rough, with their surface height variations being above the Rayleigh Roughness Criterion height of 0.41 cm: the gravel with a surface height variation just above the criterion (1–2 cm), and the stones about an order of magnitude above it (5–10 cm).

Having investigated only two terrain types, it is difficult to extrapolate the results to general terrain, however the experiments conducted indicate that the bistatic angle difference extent for any particular CCD performance band broadly varies inversely with the terrain height variation (so long as it is above the Rayleigh Roughness Criterion). For example, for “Good” CCD performance, in the gravel case the angular extent reached 6°, whereas for the stones case it reached 2°.

Overall, however, it has been shown that the terrain surface has a significant impact on what different bistatic geometries can be used to form useful CCD images when an exact repeated pass is not possible, for example due to time or mission constraints.

An approach to simulating the decorrelation has been demonstrated, and matched to two types of terrain, controlled by one empirically determined parameter, however other ground types may respond differently. Future work could investigate additional ground types and how the combination of multistatic collections might be used to reduce the impacts of coherence loss [28]. To improve the understanding of the behaviour of the $\hat{\gamma}_{Scat}$ parameter, future experiments could utilise metal spheres or higher fidelity simulations using scene CAD model instead of point scatterers.

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7. Appendices

The appendices contain information about the antenna SAR trajectories used in this paper. The co-ordinates of the trajectories are available on the Cranfield Online Research Data (CORD) repository:
<https://dspace.lib.cranfield.ac.uk/handle/1826/20712>

In Table 5 several angles are presented. The first is the bistatic angle between the mean transmitter and receiver positions. Grazing angles for the mean transmitter, receiver and BEM positions are also presented. The BEM direction is the bisectrix of the vectors joining the antenna positions and the scene centre [40, 41].

The slant ranges to the scene centre, and heights for the mean transmitter, receiver and BEM positions are presented in Table 6. The BEM range is given by the bistatic range.

The ground-range and cross-range resolutions are presented in Table 7.

Table 5 Bistatic and Grazing angles

Trajectory	Bistatic angle, β (°)	Grazing angle (°)		
		Tx	Rx	BEM
TR1 000	63.4	25.3	26.0	30.6
TR2 000	58.6	25.2	26.1	29.8
TR3 000	53.8	25.1	26.1	29.0
TR4 000	49.1	24.9	26.0	28.2
TR5 000	44.4	24.7	25.9	27.5
TR1 200	64.7	22.9	23.8	28.0
TR2 200	59.8	22.9	23.8	27.2
TR3 200	54.9	22.8	23.8	26.5
TR4 200	50.0	22.6	23.8	25.8
TR5 200	45.2	22.4	23.7	25.1
TR1 400	65.9	20.5	21.4	25.3
TR2 400	60.9	20.5	21.5	24.5
TR3 400	55.9	20.4	21.5	23.9
TR4 400	50.9	20.2	21.4	23.2

TR5 400	46.0	20.1	21.3	22.6
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Table 6 Ranges and Heights

Trajectory	Range (m)			Height (m)		
	Tx	Rx	BEM	Tx	Rx	BEM
TR1 000	4.55	4.63	4.59	1.94	2.03	2.34
TR2 000	4.56	4.63	4.59	1.94	2.03	2.28
TR3 000	4.58	4.63	4.60	1.94	2.03	2.23
TR4 000	4.60	4.64	4.62	1.94	2.03	2.19
TR5 000	4.64	4.65	4.65	1.94	2.03	2.15
TR1 200	4.47	4.55	4.51	1.74	1.83	2.11
TR2 200	4.48	4.54	4.51	1.74	1.83	2.06
TR3 200	4.50	4.54	4.52	1.74	1.83	2.01
TR4 200	4.52	4.55	4.54	1.74	1.83	1.97
TR5 200	4.56	4.57	4.57	1.74	1.83	1.94
TR1 400	4.39	4.47	4.43	1.54	1.63	1.89
TR2 400	4.40	4.46	4.43	1.54	1.63	1.84
TR3 400	4.42	4.46	4.44	1.54	1.63	1.80
TR4 400	4.45	4.47	4.46	1.54	1.63	1.76
TR5 400	4.49	4.49	4.49	1.54	1.63	1.73

Table 7 Resolutions

Trajectory	Resolution (cm)	
	Ground range	Cross-range
TR1 000	5.11	5.34
TR2 000	4.95	5.19
TR3 000	4.80	5.09
TR4 000	4.67	5.02
TR5 000	4.57	4.99
TR1 200	5.02	5.24
TR2 200	4.86	5.10
TR3 200	4.72	4.99
TR4 200	4.59	4.92
TR5 200	4.48	4.88
TR1 400	4.93	5.16
TR2 400	4.78	5.01
TR3 400	4.64	4.91
TR4 400	4.52	4.84
TR5 400	4.41	4.79

Appendix C Conference papers

C.1 Polarimetric bistatic SAR image coherence

Polarimetric bistatic SAR image coherence

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Abstract

Synthetic Aperture Radar (SAR) Coherent Change Detection (CCD) allows the detection of very small scene changes, such as from ground subsidence or vehicle tracks, with applications both civilian and military. This high sensitivity to small changes can mean that differences in collection geometry or in polarisation can lead to significant changes in image coherence. This paper investigates the coherence between different bistatic SAR image geometries and their corresponding spatial frequency supports. It also investigates methods used to model coherence. The investigation employed both simulations and measured multistatic data collected at the Ground Based SAR Laboratory at Cranfield University.

1 Introduction

Synthetic Aperture Radar (SAR) allows the formation of high-resolution radar images, however without additional processing they can be hard to interpret and compare, when looking at two images from different times. Coherent Change Detection (CCD) between two SAR images, however, can highlight subtle changes between them [1]. Whilst CCD offers the potential for picking out small changes, it is reliant on a high degree of coherence between the two images.

The choice of bistatic geometry and polarimetric decomposition will affect the corresponding Radar Cross Section (RCS) values over SAR images and is thus likely to have an effect on the coherence between different bistatic SAR images [2].

This paper investigates bistatic polarimetric coherence with a view to improving CCD results for multistatic collections and is based on measured data collected with the Ground Based SAR (GBSAR) system at Cranfield University [3, 4].

Multistatic and bistatic CCD geometries are becoming an increasingly viable proposition for remote sensing of large areas of land. The cost of launching payloads to orbit has reduced to below \$2000 per Kg depending on the launch vehicle [5]. This makes the possibility of large SAR satellite constellations, more feasible. It is however important to be able to understand and predict the expected coherence.

This paper begins by providing some background information and then describing the laboratory environment and methodology used in the experiment. Results, discussion, and a conclusion are then provided.

2 Background

The scattering response, or RCS, of a scatterer, changes depending on the SAR geometry bistatic angle, and the polarisation measured [2].

There are four linear polarisations HH, VV, HV and VH, from which all other polarimetric decompositions can be formed. In general, for bistatic geometries, the two cross-polarisation (HV and VH) RCS values are different.

Understanding the dependence of SAR image coherence between different bistatic geometries and how it relates to

the spatial frequency domain is likely to prove beneficial in the detection of changes between multistatic SAR collections.

The SAR coherence between two images is calculated using the standard equation for CCD [6, 7, 8], giving the sample coherence, γ , which is the absolute value of a correlation between 2 images,

$$\gamma = \frac{|\sum_{k=1}^N S_1(k) S_2^*(k)|}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

Where S_1 and S_2 are the two complex images being compared and N is the number of pixels within a window sampled over the two images. The coherence is presented on a pixel-by-pixel basis to produce a coherence “CCD” image, and an average can be taken for the desired image area.

2.1 GBSAR laboratory measurements



Figure 1. The GBSAR laboratory in a bistatic configuration, measuring a gravel scene.

The GBSAR laboratory performs microwave measurements with a Vector Network Analyser (VNA), which generates a stepped frequency waveform. The system was set up for indoor use, with the VNA attached to two Ultra-Wideband horn antennas allowing measurements within the range 1-10 GHz. 6.6-10 GHz was the bandwidth selected for images in the investigation. The Antennae can be mounted in a bistatic or a pseudo monostatic configuration. When in a bistatic configuration, each antenna is mounted on a different two-dimensional vertical SAR aperture scanner. One SAR aperture is 3.5 m wide by 1.5 m high, mounted on a brown frame, and the other is 1.3 m

wide by 1.5 m high, mounted on a yellow frame, as seen in Figure 1. The measured target scene consisted of gravel, which provides a speckled SAR image suitable for the coherence investigation.

The data collection involved the transmitter antenna, mounted on the brown frame, traversing horizontally for each of nine fixed receiver antenna positions, mounted on the yellow frame.

When the scene is undisturbed, and the scans are repeated with the receiver in a new location, the combination of scans are equivalent to a single multistatic scan with multiple receivers operating simultaneously. As there are two separate trajectories for the transmitter, the GBSAR system has effectively collected two different multistatic SAR geometries. Figure 2 presents a diagram of the two multistatic scan SAR geometries. Red and green show the transmitter paths for upper and lower scan heights respectively; blue and yellow show the corresponding receiver positions when the geometry is monostatic and is partly obscured. The magenta stars show the 9 receiver positions for the various bistatic geometries collected. The black circle represents the scene centre.

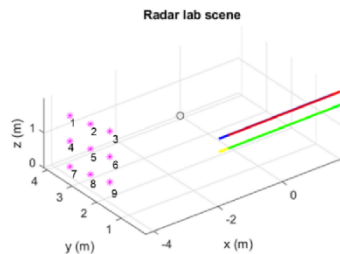


Figure 2. Monostatic and multistatic SAR geometries.

The scene used was a gravel rectangle, approximately 3.5×4 m, made up of approximately 1 cm sized gravel, which is around $1/3$ - $1/5$ the size of the wavelengths measured. This allowed for the appearance of speckle and would appear similar to rough flat terrain or an unsurfaced road. Had the smooth laboratory floor been left uncovered by gravel, it would have resulted in low signal to noise/clutter ratios.

In addition, the scene was disturbed between some of the multistatic collections, allowing a further validation of the CCD approach and measurements.

2.2 Spatial frequency domain

The spatial frequency domain, also called K-space, can be conceptualised in two ways. The first is as a Fourier transform of a reflectivity map of the scene, and the other as a composite of incident and scattered ray vectors with a length proportional to frequency [8].

The vector method allows the K-space image support outlines to be plotted for evaluation of SAR geometry properties, with an example shown in Figure 3.

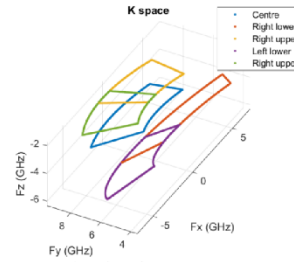


Figure 3. Image showing the Image support outlines in the spatial frequency domain, for the four corners of the gravel area and the centre (blue). This shows the large degree of radar geometry variation in the near-field SAR collection.

Data pertaining to a SAR collection can be represented in spatial frequency (K-space) as an image support. In the SAR far-field, this takes the form of a single image support [8], whereas in the more general SAR near-field case, there is an image sub-support associated with each scene position.

Here, the SAR near-field is defined as the regime where the range $d < 2L_{cr}^2\lambda_c^{-1}$ for an image cross range extent L_{cr} and centre wavelength λ_c .

In Figure 3 the image sub-support outlines for the four corners of the scene and for the centre of the scene are presented.

Due to the SAR geometry, SAR images taken from two different radar trajectories will have different overlap when corresponding K-space sub-supports are projected vertically. For the case of a horizontal ground scene, the overlap is associated with data which is coherent between the two collections and the non-overlap is associated with incoherent energy. This association is well-known for the monostatic case [6, 8], and is investigated here for the bistatic case.

The incoherent energy can be removed from the SAR imagery, or alternatively can be excluded at the image formation step, in principle resulting in new image pairs with improved coherence between them [6, 8].

An algorithm has been developed to calculate the vertically projected K-space sub-supports for each image pixel position, and to then find corresponding overlapping and non-overlapping projected areas.

As an illustrative example, in Figure 4, vertically projected sub-supports are presented. These are associated with the image centre position, and are for three bistatic collections, where the receiver is at three different heights. Three possible collection pairings are possible, and corresponding degrees of support overlap and non-overlap indicate that some pairings will have more coherence than others.

When all image pixel positions are considered, the sum of the overlap areas and corresponding non-overlap areas can be calculated. For the specific laboratory measurement scenario, the ratio of these areas will be presented in section 4.2, for comparison with image coherence results.

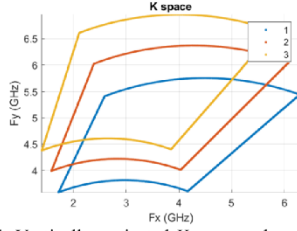


Figure 4. Vertically projected K-space sub-supports, for the scene centre, for receiver positions 1, 2 and 3 (see Figure 2).

2.3 Coherence

Coherence can be described of as the product of three main effects, described by factors in the range 0 to 1, where 0 corresponds to low coherence, and 1 corresponds to high [6, 9]. This is typically used for the far-field monostatic case; however, this paper investigates the generalisation to the near-field bistatic case.

$$\gamma = \gamma_{temp} \gamma_{SNR} \gamma_{proc} \quad (2)$$

Where, γ_{temp} refers to temporal changes within the scene, such as the movement of scatterers. These might be natural such as those caused by the rain and wind or by human interaction, such as a vehicle creating tracks. If there were no changes in the scene this value would tend to 1. If there were significant change in the scene, then the value would be close to 0. γ_{SNR} refers to losses in coherence due to noise; γ_{proc} refers to effects due to processing, and can be described as follows,

$$\gamma_{proc} = \gamma_{algorithm} \gamma_{registration} \gamma_{RCS} \gamma_{baseline} \quad (3)$$

The processing term encompasses errors arising from approximations in the SAR imaging algorithm, $\gamma_{algorithm}$, image registration errors, $\gamma_{registration}$, changes to the RCS, γ_{RCS} , and SAR geometry effects, $\gamma_{baseline}$.

The baseline factor $\gamma_{baseline}$ refers to decorrelation due to differences with the radar platform trajectories and in principle can be increased (brought closer to 1) through incoherent energy trimming (discarding) [2, 6, 8].

$$\gamma_{baseline} = \frac{A_c}{\sqrt{A_r A_m}} \quad (4)$$

Where A_c is the area of the overlap in the K-space supports. A_r and A_m are the areas for the reference and mission K-space supports respectively.

The γ value is regarded as *true* values, whereas the values obtained from the ROI in the CCD images are slightly different, in that they are measured and are a biased estimate of the true values [6, 9, 10]

3 Methodology

This paper employs simulated data and experimental data for validation. The simulation employs the laboratory ground truth and SAR geometries.

The simulation assumes perfect isotropic point scatterers and does not account for shadowing or multipath.

It was ensured that fully developed speckle was present in the images by comparing simulated images with the known position of scatterers, as seen in Figure 5, and also by verifying that the intensity distribution across the Region of Interest (ROI) conformed to the Rayleigh distribution (see Figure 6):

$$P(I) = \frac{1}{\langle I \rangle} \exp\left(-\frac{I}{\langle I \rangle}\right) \quad (5)$$

Here I is the intensity and $\langle I \rangle$ is the mean intensity [8, 11].

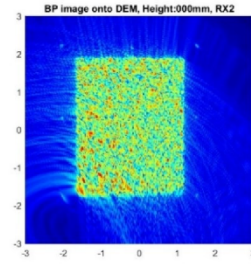


Figure 5 (a). Example simulated bistatic SAR image, with the transmitter in the upper track and receiver at position 2.

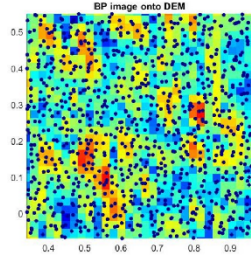


Figure 5 (b). Zoomed in view of a simulated SAR image with scatterer positions overlaid with dark blue dots.

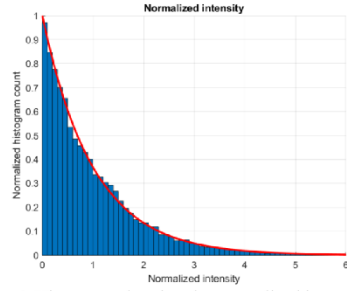


Figure 6. Histogram showing the normalised intensity of a simulated SAR image, with the Rayleigh distribution curve in red.

The CCD algorithm was then applied to find the coherence between the scans at different heights and between the geometries with different bistatic receiver positions. All coherence averaging was done over the gravel ROI only.

4 Results

After formation of monostatic and bistatic SAR images, the CCD process is applied between pairs of images, providing both CCD image results and an overall coherence value for each pair of images. The coherence values are listed in tables in sections 4.1 and 4.2.

4.1 Monostatic results

The overall coherence for the gravel covered ROI in the measured monostatic images are shown in Table 1. The table shows the mean coherence over the ROI between the different linear polarisation channels and for the two different grazing angles. The antenna scanner travels at two heights, an upper “u” and a lower “l” (1.925 m & 1.543 m) giving the grazing angles 25.1° and 20.6° to the scene centre respectively.

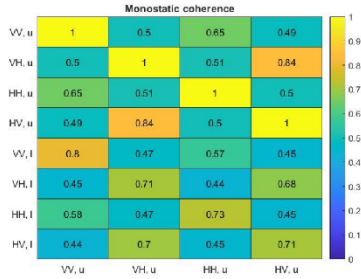


Table 1. Heat map showing the estimated mean coherence between measured monostatic image pairs in different linear polarisations. The height is shown as “u” for the upper scan position and “l” for the lower position. The coherence value is for the gravel ROI only.

Within the upper scan heights, the table is symmetric and demonstrates several patterns. Coherence between co-polarisations (HH and VV) is better than that between co-polarisations and cross-polarisations (HV and VH). The cross-polarisations correlate well with each other, ($\gamma = 0.84$), however the two channels are not identical. This could be due to the pseudo-monostatic geometry, where the transmitter and receiver horns are side-by-side, and due to the SAR near-field nature of the geometry.

Comparisons can then be made between the two heights. These are shown in Table 2. Using the radar platform trajectories, $\gamma_{baseline}$ could be calculated from the K-space overlap [6]. Then the following approximation:

$$\gamma_{RCS} \approx \gamma / \gamma_{baseline} \quad (6)$$

was used to calculate γ_{RCS} . This approximation could be used as $\gamma_{temp} = 1$ as there was no change; $\gamma_{algorithm}$ and γ_{reg} both have values approaching 1; $\gamma_{SNR} \approx 1$ using an estimated SNR of -45 dB, although this will vary across the scene. There is a significant level of clutter present from multipath and is included under γ_{RCS} , which varies with polarisation. The VV images had a greater coherence than the VH, HH and HV images when compared across the different heights within the same polarisation. With a coherence of 0.8 as opposed to 0.71-0.73. This is reflected in a corresponding higher γ_{RCS} . This may be due to H polarised waves being more susceptible to ground multipath effects [12].

Simulations resulted in an estimated coherence of 0.89 when comparing the two different monostatic geometry heights and $\gamma_{baseline}$ was evaluated as 0.93. However, in the simulation γ_{RCS} would be equal to one, hence in the simulation, it would be expected that $\gamma_{baseline} = \gamma$. It is possible that the observed small difference is due to random nature of the set scatterer distribution in the simulation or due to the pixelized approach used to find the projected area of the K-space sub-supports.

	γ	$\gamma_{baseline}$	γ_{RCS}
VV	0.8	0.93	0.86
VH	0.71	0.93	0.76
HH	0.73	0.93	0.78
HV	0.71	0.93	0.76
Average	0.74	0.93	0.79

Table 2. Table showing coherence values when comparing different monostatic heights. These were used to calculate γ_{RCS} (equation (6))

4.2 Bistatic results

The multistatic collections contained two transmitter heights and for each of these, nine bistatic SAR geometries with individual receiver positions. These were used to form bistatic pairs to perform CCD analysis on; the geometries are shown in Figure 2. The measurements were fully polarimetric, with all four linear polarisations collected.

For each generated CCD image, an average coherence value over the ROI was generated. For each pair of SAR geometries, the mean value of the coherence across the four

polarisations was found. This mean was then subtracted from the coherence values for the different polarisations. The histogram in Figure 7 shows the distribution of coherence minus mean across the four polarisations, for all SAR geometry pairs.

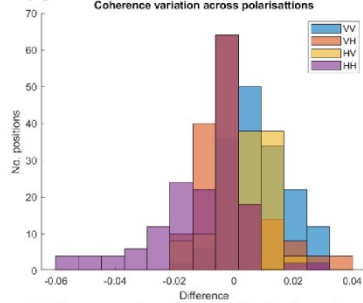
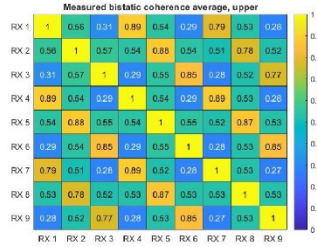


Figure 7. Histogram showing the distribution of variation from the mean coherence for each SAR geometry pair, across the four polarisations.

Figure 7 shows that despite having a very low standard deviation, the effect of RCS is still significant. $\gamma_{baseline}$ is still the dominant factor as it resulted in the coherence varying from 0.3-1, when looking at different receiver positions within any given polarimetric channel, as seen in Table 3. Whilst the average standard deviation may only have been around 1% of the maximum coherence, Figure 7 shows that HH tends to have a below average coherence, with VV having a higher than average. VH and HV where both close to the mean.

It is noted that the scene was relatively homogenous, consisting only of gravel and it is likely that more complex targets could result in a greater degree of difference in γ_{RCS} .



closely with the measured polarisation averaged coherence.

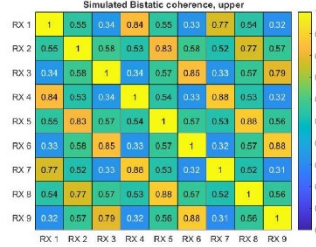


Table 4. Table showing the coherence between the simulated nine receiver position bistatic SAR images, with the transmitter in the upper position.

The difference between the measured coherence values (averaged across polarisations) and the simulated coherence values can be calculated. For both the upper and lower tracks. A histogram of these difference values is shown in Figure 8.

Figure 8. Histogram of the differences between the measured polarisation averaged coherence results in Table 3 and the simulated coherence results in Table 4. The mean difference value is -0.03.

With the knowledge of the SAR geometries, the K-space projected sub-support overlap values can be used to calculate $\gamma_{baseline}$ as shown in equation (4). The $\gamma_{baseline}$ values are shown in Table 5. These are evaluated for the ROI only. As discussed in section 2.2, because the collections are in the SAR near-field regime, the calculation is performed for every scene position, or pixel, so that the overlap across the whole ROI may then be estimated.

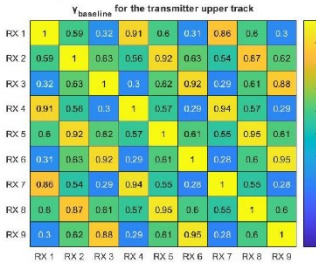


Table 3. Table showing the coherence between the measured nine receiver position bistatic SAR images collected with the transmitter in the upper position, averaged across polarisations.

In Table 3, a pattern emerges where, noting that the receiver positions are in a 3 X 3 square grid (see Figure 2) the grid receiver columns have a good coherence of 1-0.8. A step away in the receiver row direction for an image pair lowers the coherence to 0.5-0.6, and a second step away lowers it to around 0.3.

Table 4 presents the *simulated* SAR image coherence results. These results do not only exhibit the same pattern as for the measured data, but their values also align very

Table 5. Table showing $\gamma_{baseline}$ values for the upper transmitter trajectory. These were calculated for each pixel and then averaged across the ROI.

The measured coherence values can also be used to estimate the γ_{RCS} using equation (6). This then allows the γ_{RCS} values to be plotted on a histogram. These values then had the mean γ_{RCS} for each bistatic geometry pair subtracted, to show a distribution (in a similar manner to Figure 7).

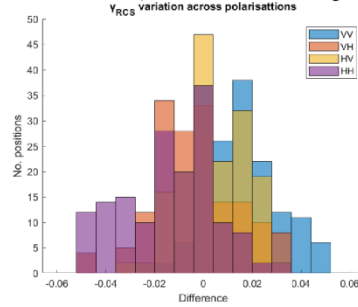


Figure 9 Histogram showing the distribution of γ_{RCS} from the mean γ_{RCS} for each SAR geometry pair, across the four polarisations.

Estimation of γ_{RCS} shows that it varies depending on polarisation. For this particular scene the HH tends to result in a lower value and the VV tend to be higher. This reflects the pattern in Figure 7.

5 Conclusion

The monostatic and bistatic results demonstrate that the proportion of coherence due to the SAR geometry is a dominating factor in these laboratory experiments. This can be seen in the similarity between the measured data coherence and $\gamma_{baseline}$, which acts as an upper bound on the true coherence.

It's noted that the measured coherence was very similar to the simulated coherence, despite the simplicity of the simulation, which relied upon isotropic point scatterers.

However $\gamma_{baseline}$ cannot be thought of as the only factor with a significant impact. γ_{RCS} still effects the coherence, even when the radar platform trajectories were very similar, and targets very simple. This was shown in Figure 7 and Figure 9. It is also likely that a more complex terrain, where the RCS varies significantly depending on the viewing angle, could lead to this component being more significant. The value of γ_{RCS} varied between polarisations and positions, this is not only due to the varying RCS of the gravel but also may have been due to the laboratory clutter and layout, leading to multipath echoes. Multipath is stronger in some polarisations as opposed to others [12]. It is possible that a fully polarimetric collection may offer improved coherence overall, using polarimetric decompositions or polarimetric CCD algorithms, as this could reduce the overall impact of γ_{RCS} in reducing coherence.

Overall, the results show that the equations for coherence found in [6, 9] (equations (2) and (3)) do apply to the bistatic case.

Future work could focus on comparing across polarisations and polarimetric decompositions. Additionally using multistatic images, as opposed to individual bistatic images from a multistatic collection, which could provide finer resolution SAR images. Additionally, more complex terrain with varying RCS could be investigated.

6 Literature

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C.2 Non-overlapping trajectory Multistatic SAR Coherent Change Detection

Non-overlapping trajectory Multistatic SAR Coherent Change Detection

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Keywords: SYNTHETIC APERTURE RADAR (SAR), K-SPACE, FOURIER DOMAIN, COHERENT CHANGE DETECTION (CCD), MULTISTATIC

Abstract

Synthetic Aperture Radar (SAR) Coherent Change Detection (CCD) allows the detection of very small scene changes but is typically reliant on a high degree of similarity in the radar trajectories, with a small baseline. In the case of multistatic SAR imagery, such as those formed by a constellation of SAR satellites, the radar trajectories may have a greater baseline than those collected by a monostatic system such as an aircraft. This paper investigates the effects of multistatic trajectories on the measured coherence between imagery, and how this relates to the spatial frequency (K-space). In particular, the case where radar platform trajectories are greatly dissimilar, but where the K-space image supports still contains a high degree of overlap, is investigated. This paper uses multistatic SAR collections measured at the Ground Based SAR Laboratory at Cranfield University.

1. Introduction

Synthetic Aperture Radar (SAR) allows the formation of high-resolution radar images, and Coherent Change Detection (CCD) between two SAR images can highlight subtle changes between them [1]. Whilst CCD offers the potential for detecting small changes in the scene, it is reliant on a high degree of coherence between the two images. If there is a large degree of incoherence, then changes will be obscured and difficult to detect.

The choice of SAR imaging geometry will affect the corresponding complex Radar Cross Section (RCS) values over the imaged scene and will thus have an effect on the coherence between different bistatic SAR images [2, 3]. The coherence of scene areas dominated by speckle is due to scatterers within a resolution cell interfering, contributing to the amplitude and phase in the imagery. As the radar platform path changes so do these values [4]. If information from SAR radar platforms travelling different tracks could be used to accurately detect changes, this could allow for more rapid return scans of target locations. This work investigates the use of disparate bistatic radar trajectories for the collection of coherent SAR data, and is validated with measured data collected with the Ground Based SAR (GBSAR) system at Cranfield University [3, 5, 6] as well as simulations.

Multistatic and bistatic CCD geometries are becoming an increasingly viable proposition for remote sensing. The cost of launching payloads to orbit has reduced to below \$2000 per Kg [7] depending on the launch vehicle. This makes the possibility of large SAR satellite constellations [8], or a powerful SAR satellite and ground-based aircraft receivers, a

more feasible possibility. The current improved density and lower cost of high-performance computer components make processing large volumes of data possible in a reasonable timeframe. [3]

This paper begins with introducing some background concepts. The paper then discusses the methodology used (both experimental and simulation). There is then a results and discussion section followed by a conclusion.

2. Background

2.1. Coherent Change Detection

The coherence between two SAR images is calculated using the standard equation for CCD [3], giving the normalized complex cross correlation, whose magnitude γ is referred to as the sample (estimated) coherence.

$$\gamma e^{i\phi} = \frac{\sum_{k=1}^N S_1(k) S_2^*(k)}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

Where S_1 and S_2 are the two complex images being compared and N is the number of pixels within a sample window which slides over the two images. The magnitude and phase of the complex correlation are γ and ϕ . The coherence is presented on a pixel-by-pixel basis to produce a coherence "CCD" image with values lying between 0 and 1, where 0 indicates no coherence, and 1 represents full coherence. An average can be taken over the CCD image representing overall coherence. The value of the estimated coherence varies with the choice of window size [4].

2.2. Spatial frequency (K-space)

The image support represented in the spatial frequency domain is typically in the form of an annulus segment. The spatial frequency can be conceptualised in two ways. The first is as a Fourier transform of an image, and the other as a composite of all incident and scattered wave vectors ($\mathbf{k}_i$ and $\mathbf{k}_s$) associated with the data collection, and here with a length proportional to frequency, for convenience.

$$\mathbf{k}_i = \hat{\mathbf{i}} \frac{2\pi f}{c} \quad (2)$$

$$\mathbf{k}_s = \hat{\mathbf{s}} \frac{2\pi f}{c} \quad (3)$$

$$\mathbf{K} = \mathbf{k}_i - \mathbf{k}_s \quad (4)$$

Here $\hat{\mathbf{i}}$ and $\hat{\mathbf{s}}$ represent the unit vectors of the incident and scattered wave directions respectively. $\mathbf{K}$ is the total wavenumber vector, which will be plotted in spatial frequency figures with units of GHz (multiplying $\mathbf{K}$ wavenumber value by $c/4\pi$). Each position in K-space corresponds to a single scattering measurement at a given frequency and for a given combination of receiver and transmitter positions.

When a whole SAR collection is presented in this way, this leads to characteristic image support shapes for SAR far-field measurements. However, when in the SAR near-field regime, wavefronts are significantly curved across the scene so that separate areas of the image have significantly different Fourier domain image supports, which we refer to as sub-supports. Here, the SAR near-field regime is defined to occur at ranges $d < 2L_{cr}^2\lambda_c^{-1}$ for an image cross range extent L_{cr} and a centre wavelength λ_c .

Figure 1 shows five constituent sub-supports from a monostatic collection taken in the SAR near field projected onto the ground plane. These supports exhibit significant variation. Thus, for SAR near-field collections, processes such as trimming of incoherent energy [6, 10] will need to be spatially variant over the scene.

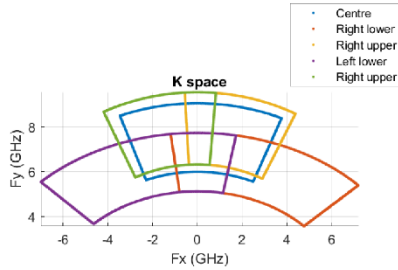


Figure 1. A plan view of the K-space sub-support outlines for the four corners of the gravel area and the centre (blue). This shows the variation in ground-plane resolution.

A key point to be noted for the current work, is that whilst two SAR platform trajectories may have little overlap in the spatial domain, the image supports may have a high degree of overlap

in the spatial frequency domain, which could lead to high coherence between collections. This is a hypothesis which will be tested here.

2.3. Coherence estimation

The coherence in an image can be thought of as the product of three main effects. [4, 11]. These equations and papers were originally developed for monostatic geometries, we hypothesise that they remain valid for bistatic and multistatic scenarios.

$$\gamma = \gamma_{temp} \gamma_{snr} \gamma_{proc} \quad (5)$$

Here γ is *true coherence*, which differs from the *estimated* coherence in equation (1). The temporal correlation, γ_{temp} , is from changes in the scene. If there were no change in the scene, including environmental effects such as rain or wind, this would take a value tending to 1. If there were significant change in the scene, then the value would be close to 0. The other correlations contributing to the sample coherence are due to noise, γ_{snr} , and due to processing and spatial effects, γ_{proc} [4]

$$\gamma_{proc} = \gamma_{algorithm} \gamma_{baseline} \gamma_{RCS} \gamma_{registration} \quad (6)$$

Where, $\gamma_{algorithm}$ refers to errors arising from the SAR imaging algorithm approximations; the baseline effects, $\gamma_{baseline}$ arise from the mismatch in radar platform trajectories and in the resulting different imaging angles; and γ_{RCS} is the change in scatterer RCS as a function of SAR geometry and polarisation [2, 3]. The baseline factor $\gamma_{baseline}$ is related to the degree of overlap of the projected K-space image sub-supports. $\gamma_{baseline}$ can be increased (brought closer to 1) through the process of removing radar data which is not part of the two image support overlap areas in K-space, when these are projected onto the ground surface plane. This is a process known as incoherent energy trimming [2, 4, 10].

There is then a contribution due to the registration, $\gamma_{registration}$ [4]. These are typically seen as arising from the layover effect or an inaccurate ground truth/radar trajectory.

3. Methodology

3.1. GBSAR laboratory

The GBSAR laboratory performs microwave measurements with a Vector Network Analyser (VNA), which generates a stepped frequency waveform. The system is currently set up for indoor use, with the VNA attached to two Ultra-Wideband horn antennas allowing measurements within the range 1-10 GHz. The Antennae can be mounted in a bistatic or a pseudo monostatic configuration. When in a bistatic configuration, each antenna is mounted on a different two-dimensional vertical SAR aperture scanner. One SAR aperture is 3.5 m wide by 1.5 m high and is used for the transmitter. The other aperture is 1.285 m wide by 1.5 m high and is used for the receiver. These are shown in Figure 2. The measured target scene consisted of gravel (Figure 2), which provides a

developed speckle SAR image suitable for the coherence investigation. [3, 6]

3.2. Laboratory measurement

The data collection involved transmitter and receiver antenna mounted onto rails with two axis movement. The scene consisted of a rectangular gravel area with metal spheres positioned around it for alignment and validation of the images. When the scene is left untouched, and the scans are repeated with the receiver in a new location, the collection of scans are equivalent to a single multistatic scan with multiple receivers operating simultaneously. The full collection consisted of the transmitter scan at two heights for each of nine receiver positions (see Figure 4). For change detection 'GBSAR' was traced lightly with a stick in the gravel.



Figure 2. The GBSAR laboratory in a bistatic configuration, measuring a gravel scene. The locations of the transmitter (Tx) and receiver (Rx) are marked. Several metal spheres are positioned around the gravel to aid alignment checks.

3.3. Simulations

This paper employs simulated data and measured experimental data for validation. The simulation employs the laboratory ground truth and measured SAR geometries.

The simulation assumes perfect isotropic point scatterers and does not account for shadowing or multipath [3]. It was ensured that fully developed speckle was present and that the intensity distribution across the Region of Interest (ROI) conformed to the Rayleigh distribution [3, 10]. A disturbance in the form of 'GBSAR' was used in simulated images.



Figure 3. Plot showing the disturbance used in the simulated results.

3.4. Radar trajectories

When considering the trajectories to be used for CCD analysis it is typical to aim for these to be as similar as possible to improve the coherence. This paper uses collections and trajectories which have a significant difference in the spatial domain but maintain a significant K-space overlap [3].

The transmitter trajectories were chosen to have no positions in common, covering different sectors in Azimuth, whereas the grid of 9 fixed receiver positions remained the same (see Figure 4). The transmitter track was split into two halves, Tx1 and Tx2. The receivers were labelled 1-9 and are here referred to as Rx1-9.

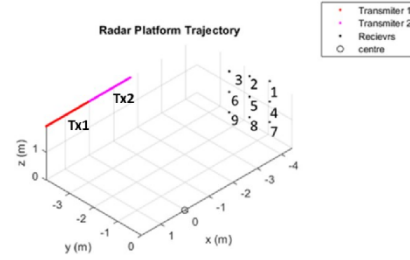


Figure 4. The radar trajectories in the data collection, shown split into two half apertures Tx1 and Tx2. The scene centre is also shown at (0,0).

There were 9 bistatic SAR geometries associated with each transmitter half aperture, hence there was 81 possible combinations for measuring SAR coherence. The 81 $\gamma_{baseline}$ coherence values were calculated for the 81 pairs and presented in Figure 5. It can be seen that the majority of trajectories exhibit zero overlap, thus only a few bistatic geometry were used in this study.

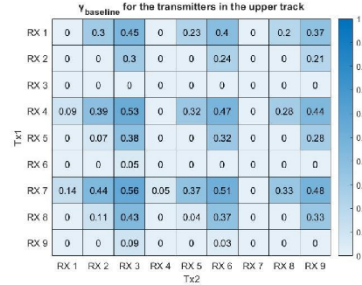


Figure 5. Heatmap showing calculated $\gamma_{baseline}$ for different bistatic geometry pairs.

3.5. Data processing & incoherence trimming

The SAR data, whether simulated or real is processed in the same manner and used the same frequency range of 6.6-10GHz. Consider a particular set of bistatic reference and mission trajectories. For these trajectories, the K-space

frequency sub-supports would vary across the scene, and an encompassing region of K-space is designated for analysis. Whether a K-space area in this region is occupied or not by a given sub-support, is calculated. The overlapping (coherent) and non-overlapping (incoherent) K-space sub-supports for the reference and mission collections are then found for each SAR image spatial position / imaging pixel. The non-overlapping areas can then be excluded from newly formed incoherence trimmed SAR images. This leaves trimmed reference and mission image pair [6, 12].

This process was implemented for all the bistatic SAR geometry pairs within the chosen multistatic collection. A trimmed multistatic reference image could then be formed as the coherent sum of all trimmed reference images, and a mission image in the same manner.

CCD algorithms were run, both on the full multistatic images and on the individual bistatic SAR image pairs.

4. Results

4.1. Low resolution simulations

A problem could be seen with some of the results where the K-space support overlap was low. In this case a large number of pulses were removed, giving the SAR image results with very poor cross-range resolution. This leaves large smears along ellipses of equal range, across the SAR images, instead of well-defined points. This effect was also seen in the spatially variant trimmed CCD images. Where large smears of incoherence are present, shown in Figure 6.

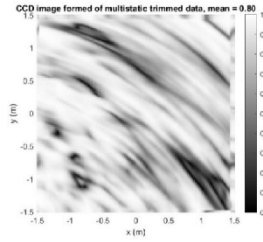


Figure 6. Simulated CCD image formed between Tx1-Rx8 and Tx2-Rx2. This clearly shows ‘smears’ of incoherence across the image.

These smears had the effect of adding large incoherence signatures to the multistatic images. The multistatic CCD images, such as in Figure 7, exhibited a speckly appearance and low coherence when including trajectories with a low overlap. These multistatic trimmed images were formed as coherent sums of the bistatic geometry SAR images, as explained in section 3.5. After all incoherent energy had been removed, the measured coherence was only around 0.64, substantially lower than the 0.8-0.9 expected if there were no scene disturbance. The disturbance ‘GBSAR’ (Figure 3) is not possible to identify in the CCD result.

This did demonstrate that simply adding bistatic geometries does not necessarily lead to improved CCD products. A careful choice of trajectories with an improved overlap would likely result in a significantly improved CCD image. This is shown in the next section.

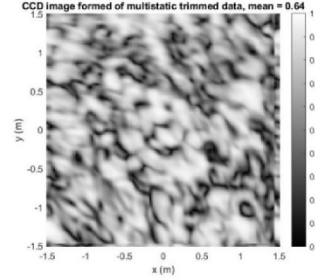


Figure 7. Simulated multistatic CCD image, showing a speckly result with the disturbance (Figure 3) indistinguishable. Formed using Tx1-Rx7&8 as the reference geometries and Tx2-Rx2&3 as the mission geometries.

4.2. High resolution simulation

Higher resolution simulations were next carried out, with Tx1 and Rx 7 against Tx2 and Rx 2&3. Tx1-Rx8 was omitted as it resulted in smearing, and as seen in Figure 5, has a very low overlap in the K-space. The trajectories are shown in Figure 8. In this case the multistatic CCD image had a high coherence of 0.91. The issue with cross range resolution remained to a degree, with some small smearing. This resulted in the disturbance being obscured somewhat.

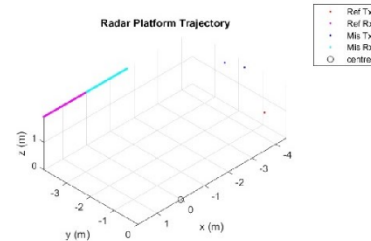


Figure 8. Radar trajectory used in forming the high resolution simulate multistatic images. Tx1-Rx7 was the reference geometry and Tx2-Rx2&3 were the mission geometries.

The resulting multistatic trimmed CCD image, seen in Figure 9, was of good quality, however some letters were difficult to make out. This is particularly evident on the S and A. The disturbance is however clearly distinct from the undisturbed gravel background.

Additional CCD results could be produced in addition to the multistatic CCD image. Multiple CCD images were produced for the bistatic SAR geometries within the multistatic collection. Each pixel within the CCD image would now have multiple complex correlation values associated with it from the

multiple bistatic CCD images produced. Forming a new image using the average per pixel value resulted in Figure 10 (a). This CCD image had a lower coherence than the multistatic CCD (0.77 compared to 0.83), however the letters were more legible. Taking the maximum per pixel value resulted in Figure 10 (b). This CCD image exhibited a higher coherence than the multistatic CCD image (0.88 compared to 0.83), whilst the disturbance is clear, the shapes of some of the letters remain hard to identify.

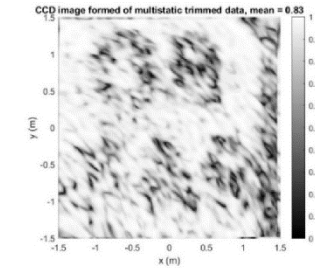


Figure 9. CCD image of simulated multistatic fully trimmed SAR images. The disturbance is visible, but it is difficult to identify the shapes.

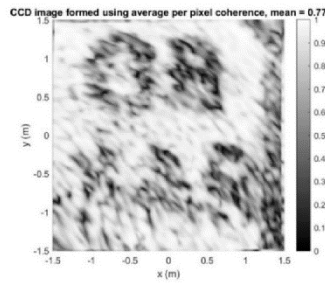
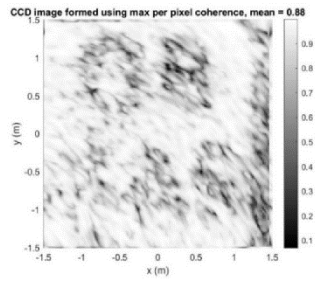


Figure 10. CCD products formed using the averaged (a) or maximum (b) per pixel values from fully trimmed bistatic images.

It is possible that using multiple passes leads to an improvement as each image had a different cross range direction. This may have resulted in the effect of the elongated speckle components being reduced. Resolution will not have

been improved as the bandwidth and azimuth angles remained the same. It is possible that multipass algorithms may be beneficial in detecting small changes when compared to using multistatic images.

4.3. Measured results

Attempting CCD analysis of the measured data proved more difficult as the gravel stones were not isotropic scatterers. As such, despite trimming off incoherent energy there was still a substantial decorrelation. This is likely caused by the change in the path of the backscatter and thus a phase change. In the best-case scenario, where the reference and mission trajectories were the same, the CCD image was of high quality. This is shown in Figure 11. The VV polarisation was used for the measured results in this paper.

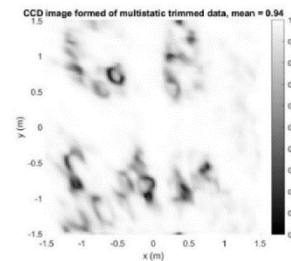


Figure 11. CCD image for measured data. Tx1Rx7 and VV polarisation. The 'GBSAR' disturbance is quite clear against the background.

When a resolution cell contains multiple scatterers, each contributing an unstable amplitude and phase, any change in radar geometry can be expected to lead to decorrelation [4] as the path taken by backscatter changes. When combined with the changing RCS of the gravel with respect to azimuth angle, the measured CCD results were of poorer quality. The multistatic CCD image shown in Figure 12 is significantly less clear than the simulated results or exact repeating trajectory shown in Figure 11. This is also true for the results in Figure 13 show that using average or maximum per pixel values of CCD's formed using bistatic geometries did not provide any improvement in legibility.

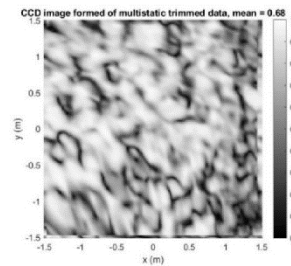


Figure 12. Multistatic measured (real) CCD image. This image shows a higher degree of decorrelation and results in the 'GBSAR' being obscured and not legible.

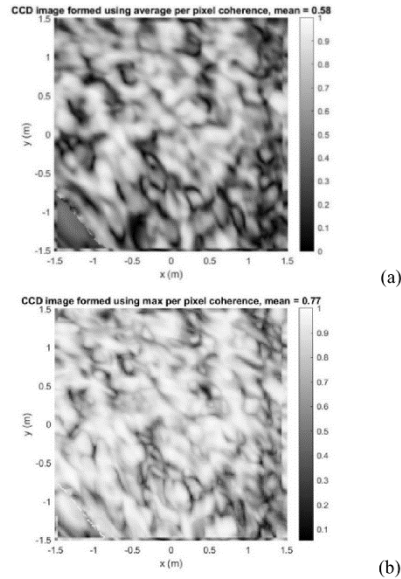


Figure 13. CCD products formed using the averaged (a) or maximum (b) per pixel values from fully trimmed measured bistatic images.

5. Discussion & Conclusion

The simulated results were promising, showing the disturbance clearly, the real results however were much less clear. This can partly be attributed to the disturbance, as the measured data had a smaller and less severe disturbance which made it much more difficult to identify when the surrounding gravel had a low coherence. The non-isotropic nature of the gravel will also have contributed to the quality of the results. It is recognised that these factors make it more difficult to accurately compare the simulated and measured results.

This can also be explained in terms of the components in equation (6). Whilst the trimming of SAR images results in $\gamma_{baseline} = 1$ other components such as γ_{RCS} would have played a significant role in reducing the coherence.

So whilst it is possible to achieve good coherence using non-overlapping transmitter trajectories (shown in the simulations) this was not demonstrated in the measured data.

Multistatic collections may provide improved CCD results, however if the component SAR geometries are not carefully chosen then the coherence may decrease. It is possible that the multiple passes (with additional viewing angles) inherent to multistatic images could prove beneficial in change detection, meaning it may not be necessary to form multistatic images for the most interpretable results.

Future work investigating multistatic (and multipass) collections and interferometry may achieve better results with

a more tailored change detection algorithm, or potentially using polarimetry and scattering mechanisms to help detect the changes. Such methods might even make the disturbance clear in the measured data. Some of the problems with the measured images may be resolved using a stronger disturbance and improved resolution (bandwidth) measurements in order to achieve similar results to the simulation.

6. Acknowledgements

This paper was produced as part of a PhD project sponsored by the Defence Science and Technology Laboratory (DSTL).

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C.3 Laboratory Multistatic and Multipolar SAR CCD Investigation

Proceedings of the Institute of Acoustics

LABORATORY MULTISTATIC AND MULTIPOLAR SAR CCD INVESTIGATION

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1 INTRODUCTION

Synthetic Aperture Radar (SAR) provides reconnaissance and surveillance of the earth's surface for all weather, during the day and night. SAR Coherent Change Detection (CCD) allows for the detection of very small scene changes between two SAR images, such as vehicle tracks [1,2]. However, good quality high contrast CCD results are reliant on high coherence between the SAR images [3].

To reduce the effect of decorrelation from natural processes such as wind and rain, and to monitor developing situations in a timely manner, it is desirable to rapidly collect the required repeated pass SAR collections. Bistatic radar geometries involve having the transmitter and receiver substantially separated, and multistatic geometries are comprised of multiple simultaneous bistatic collections. Multistatic SAR satellite constellations may allow collection of more timely change detection images to be formed using SAR image collections from differing trajectories, thus reducing the repeat pass time [4,5], however the CCD's may be subject to varying degrees of coherence due to differing baselines. The multistatic SAR data is multidimensional and can be combined in different ways. For high coherence and an improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support overlap [3,6,7], yet it has been found that this alone is insufficient to guaranty high coherence and good CCD contrast [8].

The research is aligned to derisking the multistatic SAR satellite constellation being developed by the UK MOD under the name Project Oberon [9], however it is also relevant to multistatic SAR drone swarms, which operate in SAR near field configurations [10,11]. The research is supported by measurements at the Cranfield University Ground Based Synthetic Aperture Radar (GBSAR) laboratory, where antennas are scanned within two vertical rectangular apertures, which allow a great deal of flexibility and fine control of SAR geometries for the scene.

This work investigates the levels of coherence between bistatic and multistatic SAR CCD imagery and approaches to improve change detection performance. The multistatic images are formed in a variety of ways including multipass and multi-polarimetric.

2 BACKGROUND

Multistatic SAR can provide several advantages, such as providing improved cross range resolution [12,13], and Signal to Noise Ratio (SNR) [14], although the specific geometries have a strong influence on these [15]. Polarimetric SAR CCD has also been shown to improve CCD images [2,16]. The coherence value of a CCD image is referred to as the estimated coherence $\hat{\gamma}$, and differs slightly from the true value γ_{true} . The deviation is biased and dependent on calculation features such as the CCD estimation window size [17]. The true coherence can be decomposed into factors which are also in the range 0-1 [3,8,17-22],

$$\gamma_{true} = \gamma_{temp} \gamma_{SNR} \underbrace{\gamma_{alg}}_{\gamma_{proc}} \underbrace{\gamma_{reg}}_{\gamma_{geom}} \gamma_{baseline} \gamma_{RCS} \quad (1)$$

The factors correspond to temporal changes between the two collections γ_{temp} ; signal to noise ratio (SNR) γ_{SNR} ; signal processing effects γ_{proc} ; and SAR geometry effects γ_{geom} . The signal processing term γ_{proc} accounts for decorrelations due to the image formation algorithm accuracy γ_{alg} and image

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registration accuracy γ_{reg} . The geometry term is decomposed into a calculated baseline term $\gamma_{baseline}$ which accounts for K-space overlap; and a Radar Cross Section (RCS) term γ_{RCS} , which is a function of the polarization [8,21].

3 METHODOLOGY

3.1 GBSAR laboratory and experimental setup

The GBSAR laboratory performs microwave measurements with a Vector Network Analyser (VNA), which generates a stepped frequency waveform. The system was set up for indoor use, with Ultra-Wideband horn antennas used here in the range 6.6-10 GHz. The two antenna horns are mounted on rails allowing motion in separate two-dimensional apertures, shown in Figure 1. Due to the high positional accuracy of the rail system, the transmitter trajectory could be repeated precisely, which combined with use of different receiver positions, allowed multistatic data to be collected. The geometry is shown in Figure 1b), with transmit aperture in red, and the six labelled receiver positions in blue, and referred to as R1 through to R6.

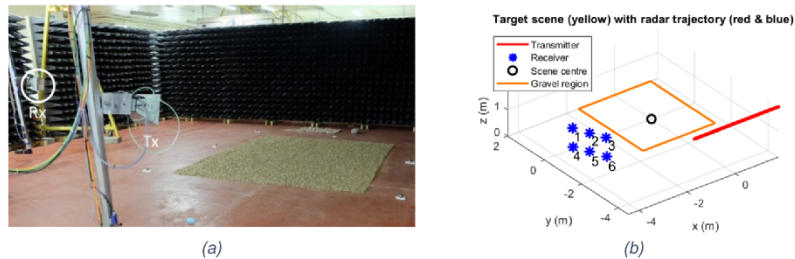


Figure 1 Image (a) shows the GBSAR system in a bistatic configuration, with a gravel rectangle as the scene. Image (b) shows the radar trajectories used in the data collection. The transmitter trajectory is shown in red, the multiple fixed receiver positions in blue and the gravel region is shown in orange. The receivers are numbered 1 to 6 and are referred to as R1 through to R6.

A gravel rectangle, approximately 3.5 x 4 m in size, was created at the centre of the scene, allowing speckle SAR image collection suitable for coherence investigation with gravel disturbance tracks drawn in. The letters 'GBSAR' were traced onto the scene by gently disturbing the gravel for use in change detection performance evaluation.

Three multistatic collections were measured: the first, the *Reference* collection, comprised the three bistatic geometries with receivers R1, R2, R3; the second and third were the *Mission* collections, comprising the three bistatic geometries R4, R5, R6 (see Figure 1b). The Mission multistatic geometries were collected at a later time to the Reference, one of them having had a disturbance track applied to the gravel terrain – Mission 2.

From the Reference and Mission multistatic collections, three pairs of bistatic geometries were used for CCD creation as follows: R1 and R4, R2 and R5, and R3 and R6 (effectively receiver columns). These allowed the formation of three bistatic CCD images for each of the two missions. The three CCDs were combined to form multistatic CCD images in different ways.

3.2 Data processing

Both bistatic and multistatic (coherent summation) SAR images were formed using the back projection image formation algorithm (BPA). The SAR images, reference and mission, were then used to form CCD images. Two sets of CCD images were formed, one for each of the two Missions: one where the gravel was undisturbed between SAR images (Mission 1), and another where the gravel had a track traced (Mission 2).

Performance metrics such as the Probability of Detection (POD), Critical Success Index (CSI) and the False Alarm Rate (FAR) were used in the evaluation of the CCD images. These were calculated using a confusion matrix. Here T and F mean true and false respectively, and P and N mean positive (change) and negative (no-change) in the CCD image [23],

$$POD = \frac{TP}{TP + FN} ; \quad CSI = \frac{TP}{TP + FP + FN} ; \quad FAR = \frac{FP}{TP + FN} \quad (2)$$

Five master images were used to calculate the performance metrics. Four were formed from single polarisation multistatic datasets, and the remaining one was formed using all four polarisations. The fully polarimetric master CCD image is shown in Figure 2 (a) with values ranging from 0 to 1. Figure 2 (b) shows a binary image where pixels with a coherence value below the threshold of 0.87 were detected as a change and set to 0, and those with a coherence above the threshold were set to 1. This shows where detections of a change or no change would be made for the master image. The threshold for the master image was chosen to most accurately replicate the ground truth of the disturbance. The threshold was kept constant for all master images, however it was varied for the comparison images, and this produced a series of curves presented in section 4. Performance metrics (equation 2) can be calculated by comparing the detections in the master and comparison images.

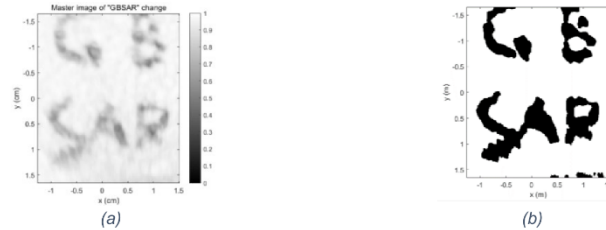


Figure 2 Fully polarimetric master images used for the performance metrics. Image (a) is a CCD image formed from the mean of fully polarized multistatic data collections. Image (b) is a binary image formed from applying a threshold to (a).

4 RESULTS

4.1 Polarimetric variation

Different polarisations give rise to different CCD images and coherence. This has been previously demonstrated in [21]. This is shown in Figure 5 and Figure 7, where coherence shows some variance with polarisation.

The variation with coherence can also be seen in the performance indices. These are presented in Figure 3 and Figure 4. In these figures individual datapoints are represented by dots. The dotted lines are quadratic curves fitted to the data.

In Figure 3 (a) & (b) the FAR is presented, for the bistatic and multistatic case respectively. This graph shows that the HH polarisation had a lower FAR. This is despite the lower coherence. This low value is likely due to a higher number of true positive detections, rather than a reduction in false positives. Figure 4 shows the CSI and POD. In Figure 4 (a) the HH polarisation outperformed the other polarisations with a higher CSI. In Figure 4 (b) the POD is shown, where all polarisations display a similar performance.

Analysis of these performance metrics demonstrate that coherence is not the only factor that should be considered when assessing the quality of CCD images. Such analysis is however difficult in non-laboratory environments, where environmental decorrelations effect the scene and there are trajectory errors.

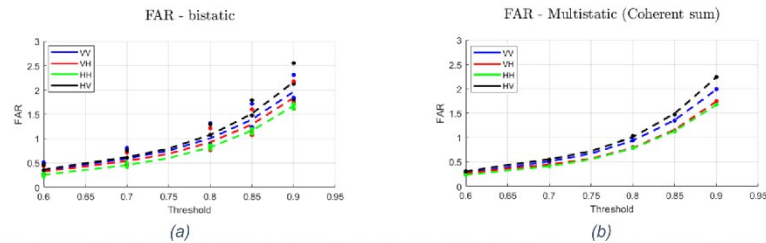


Figure 3 Images showing the FAR for (a) bistatic and (b) multistatic for four polarizations. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

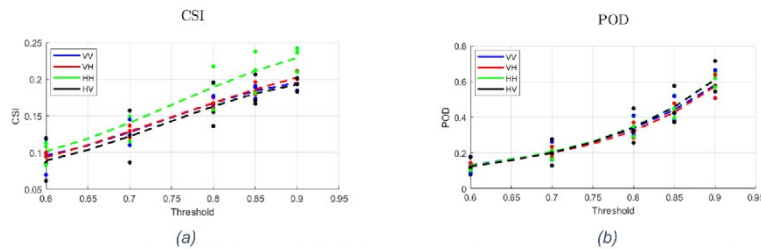


Figure 4 Images showing the CSI (a) and POD (b) for the bistatic images across four polarizations. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

4.2 GBSAR track - Qualitative analysis

In the tessellated image of bistatic CCD images in Figure 5, parts of the 'GBSAR' disturbance can be made out. Different polarisations and position pairs detect different parts of the disturbances. Compared to the master image (Figure 2) the CCD products are of a poorer quality. This is partly due to false detections caused by a low RCS coherence factor as the two SAR images are formed using different radar trajectories. Additionally, there will be a decorrelation across the CCD images due to the k-space non-overlap.

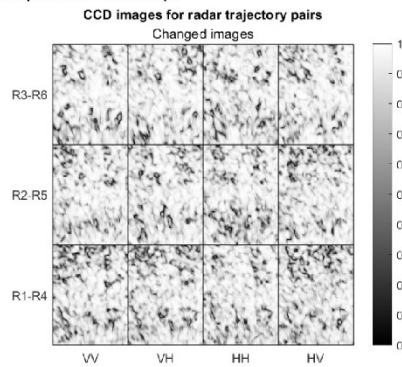


Figure 5. Tessellation of bistatic CCD images. Each row contains the CCD images for a particular trajectory pair. These correspond to receiver positions shown in Figure 1(b). Each column corresponds to a polarization.

Multistatic CCD images were formed in two manners. The first was to take the maximum, mean and minimum for each pixel across the individual bistatic CCD images formed across the two multistatic collections. Alternatively, coherent summation was applied to the SAR images in each multistatic collection, and then a CCD algorithm was applied across the two multistatic SAR images. The results are shown in Figure 6 for the VV polarisation.

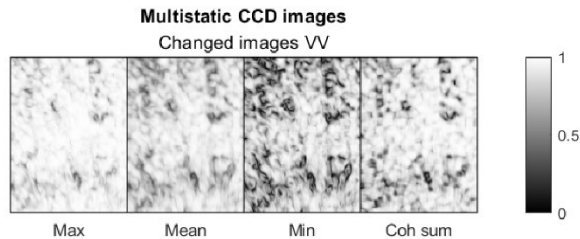


Figure 6. Tesselation image of multistatic CCD images formed for the VV polarization.

In the multistatic images the 'GBSAR' track is visually clearer than in the individual bistatic images. Visually, the mean and coherent summation images show some similar performance. For these images the multistatic CCD "minimum" appears to offer the clearest 'GBSAR' track representation. It is possible however, that altering the contrast and colour scale of the images could alter the qualitative performance perception, thus a variety of thresholds are used for the performance metrics in the quantitative analysis results shown in section 4.3.

4.3 GBSAR track - Quantitative analysis

The CCD coherence estimated over the image pixels is presented in Figure 7. The individual bistatic CCD coherence estimates are shown, together with their mean, min and max. Additionally, SAR coherent summation was performed for each of the two multistatic collections, providing two SAR images with finer resolution, from which a CCD was formed and its coherence estimated, designated "coherent sum CCD" in Figure 7.

It can be seen that the coherence of some individual bistatic geometries and the mean and coherent sum multistatic CCD images are quite similar. With the maximum and minimum CCD images giving the extreme values. Also, the HH images have a lower spread in coherence values compared with VV (excluding min and max).

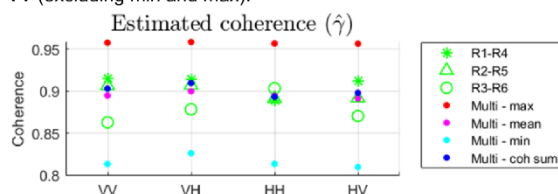


Figure 7 Estimated coherence of individual bistatic (green) and corresponding multistatic CCD images across four polarizations.

The detection performance metrics are compared in Figures 8-10. The green line is the minimum multistatic; the blue the maximum; the red is mean; the black is the coherent sum SAR image multistatic estimated coherence. These metrics are plotted for all four polarizations. These show variation in performance with polarization.

The metrics show that the trend lines for the individual bistatic, the mean and coherent sum multistatic are quite close. The minimum multistatic images perform significantly better, and the maximum images perform significantly worse. These behaviors are consistent for the POD, FAR and CSI.

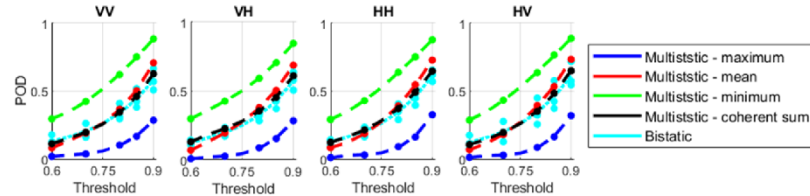


Figure 8 Graphs showing the POD for different multistatic images compared against bistatic images for four polarizations. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

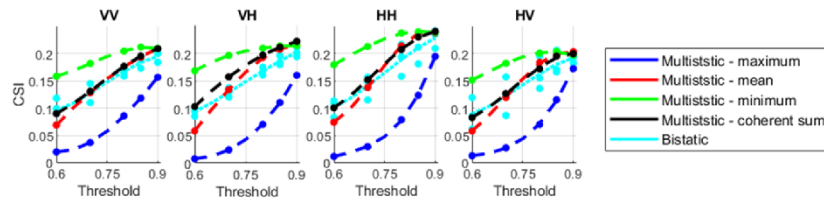


Figure 9 Graphs showing the CSI for different multistatic images compared against bistatic images for four polarizations. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

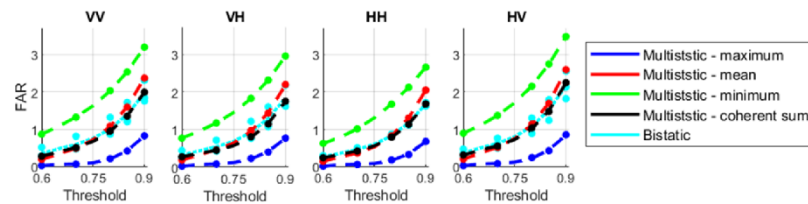


Figure 10 Graphs showing the FAR for different multistatic images compared against bistatic images for four polarizations. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

4.4 Polarimetric

Polarimetric images can be presented as a colour composite of several CCD images represented by RGB values or as a single greyscale CCD image. Two examples are shown in Figure 11. Polarimetric multistatic CCD images can be formed in a similar manner to the approaches taken previously. Maximum, mean and minimum images were compared: each pixel is given the value of the maximum, mean or minimum of 12 images (4 polarisations and 3 position pairs). Compared to the individual polarisation (black), the minimum and mean images resulted in an improved POD but also in increased FAR. The maximum image showed a very low FAR, however this was accompanied by very poor POD and CSI results.

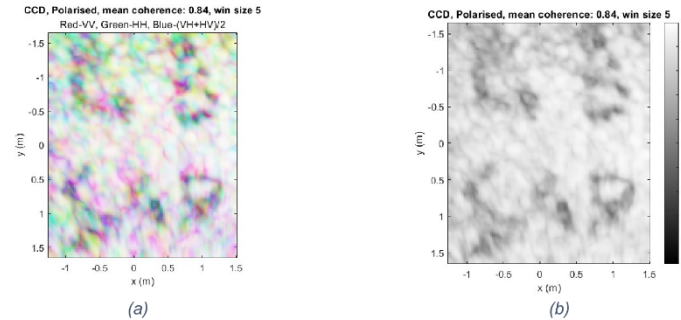


Figure 11 Fully polarimetric multistatic CCD colour composite image (a) and greyscale multistatic CCD (b). Greyscale CCD was formed as the average of the four polarized multistatic CCD images.

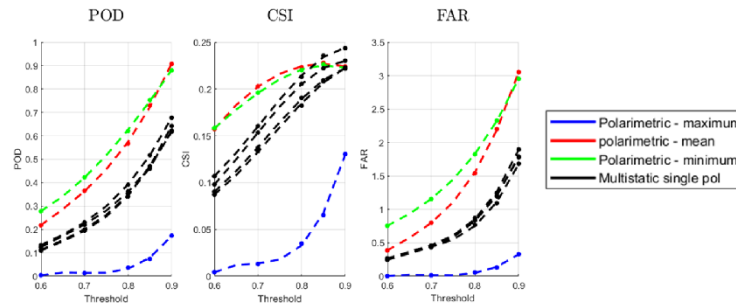


Figure 12 Graphs showing the POD, CSI and FAR for different multistatic images. Blue, red and green are formed from all four polarizations and 3 bistatic position pairs. These produced the max, mean or minimum value for each pixel. These are compared with the single polarization multistatic CCD images formed from coherent summation multistatic SAR images. Datapoints are plotted with dots, and polynomial fitted curves are added to show the data trends.

5 CONCLUSIONS

Qualitative and quantitative methods have been used to assess the performance of bistatic and multistatic CCD images against master images.

It has been shown that multidimensional (multistatic and multipolar) CCD can offer improved performance over single bistatic (figures 8-10 & 12), using qualitative and quantitative analysis. It has also been shown that the manner in which the multidimensional CCD image is formed has a significant impact on performance.

Additionally, different polarizations result in different levels of coherence and performance at detecting tracks. This variation was however quite minor, but was shown in figures 3, 4(a) and 7-10. Despite the minor variation in performance between polarisations, fully polarimetric CCD images showed a significantly improved POD compared with single polarization bistatic images, albeit with a higher FAR.

The value of the performance metrics is dependant on the threshold set for the comparison image, as such multiple thresholds and performance metrics should be used to characterise performance.

Future work will explore the impact of polarimetric decompositions on coherence and change detection performance. Additional work will investigate the impact of greater baselines and trajectory differences.

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C.4 Polarimetrically augmented Coherent Change Detection three stage detector for laboratory multistatic Synthetic Aperture Radar

Polarimetrically augmented Coherent Change Detection three stage detector for laboratory multistatic Synthetic Aperture Radar

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1 Introduction

Synthetic Aperture Radar (SAR) is an image formation technique that uses a moving transmitter and/or receiver to form high resolution radar images [1]. Because SAR uses microwave frequency electromagnetic (EM) waves rather than visible light, and is an active sensor, it allows for reconnaissance and surveillance for all weather, during the day and night. SAR Coherent Change Detection (CCD) allows for the detection of very small scene changes between SAR images, such as vehicle tracks[2, 3]. However, high contrast CCD results are reliant on high coherence between the SAR images [1].

In a CCD image a change is detected as a ‘*decorrelation*’ over corresponding SAR image patches. These decorrelations originate from several sources [1, 4–7]. One of these is natural processes such as wind and rain which lead to greater decorrelation for longer greater times between repeat passes. To reduce the decorrelation from natural processes such as wind and rain, and to monitor developing situations in a timely manner, it is desirable to rapidly conduct the required repeated pass SAR collections.

In a monostatic SAR system the transmitter and receiver are co-located. In a bistatic system they are separated by a significant distance. A multistatic system utilises multiple transmitters or receivers. Multistatic SAR has several advantages, such as providing improved cross range resolution [8, 9], and Signal to Noise Ratio (SNR) [10], although the choice of which trajectories to combine significantly affects these [11].

Multistatic constellations may allow change detection images to be formed using SAR image collections from a wide variety of different trajectories, thus potentially reducing the repeat pass time [12, 13], however these may be subject to varying degrees of interferometric baseline and therefore coherence. This data is multidimensional and can be combined in different ways. For high coherence and improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency support overlap [1, 14, 15], yet it has been found that this alone is insufficient to guaranty high coherence and good CCD contrast.

Applications include the multistatic SAR constellation being developed by the UK MOD under the name Project Oberon [16]. Such constellations may be able to provide timely repeat pass imagery. This research can also be applied to drone SAR swarms currently under development, which are intended to operate in SAR near field multistatic configurations [17, 18].

Polarimetric SAR CCD has also been shown to improve CCD images [3, 19, 20]. A two-stage intensity and CCD change detector has been demonstrated in [21–23]. This paper combines polarimetric decompositions and scattering mechanisms with CCD images to investigate the improvement in detection performance using multistatic and multipolarimetric SAR data. The detector performance will be quantified using performance metrics (see section 3.3).

This research is supported by measurements at the Cranfield University Ground Based Synthetic Aperture Radar (GBSAR) laboratory, where the antennas are scanned within two vertical rectangular apertures, allowing for a great deal of flexibility and control of SAR geometries for the scene.

2 Background

2.1 Coherent Change Detection (CCD)

Forming good quality high contrast CCD results is reliant on high coherence between the SAR images [1, 20, 24]. This coherence can be reduced by natural processes such as wind and rain [4, 7, 24, 25]. Conducting rapid repeated passes would allow for monitoring developing situations in a timely manner and provide better coherence.

For high coherence and an improved change detection capability, the repeat pass geometries should be chosen to provide a high degree of spatial frequency (K-space) support overlap [1, 14, 15], yet it has been found that this alone is insufficient to guaranty high coherence and good CCD contrast [5].

Coherent Change Detection (CCD) is calculated as a normalised complex cross correlation [1, 4, 26]. The magnitude, $\hat{\gamma}$, is referred to as the sample coherence. Where S_1 and S_2 are the two complex images being compared and N is the number of pixels within a window sampled over the two images.

$$\hat{\gamma} = \frac{|\sum_{k=1}^N S_1(k)S_2^*(k)|}{\sqrt{\sum_{k=1}^N |S_1(k)|^2 \sum_{k=1}^N |S_2(k)|^2}} \quad (1)$$

2.2 Multidimensional CCD and two Stage detectors

The multistatic SAR data is multidimensional and can be combined in different ways. In this case multistatic data consists of three bistatic collections and four polarisations. This data can be processed in a variety of ways [11, 20].

A two-stage detector was presented in [21, 23], with [22] performing analysis on the theoretical performance. These detectors are described as ‘combined intensity and coherent change detection’. For the Non-Coherent Change Detection (NCCD), changes are detected due to a difference in amplitude in the images. This typically indicates large scale scene changes. Smaller scene changes typically do not result in a change in intensity, but rather phase [1]. To detect these small-scale changes CCD is used.

The two-stage detector, introduced in [21, 23], is shown below in Figure 2.1 (replicated from [21]). Here S_1 and S_2 represent the reference and mission trajectories.

For the Intensity change detection, the difference in intensities (σ) is calculated. This difference is then compared against a threshold T_{NCCD} . Differences exceeding this threshold are labelled as changes. The coherent change detection, as described in section 2.1 results in a coherence value, $\hat{\gamma}$. This value is also compared against a threshold T_{CCD} . In this case values exceeding the threshold (close to 1) are labelled as unchanged, whereas pixels with a value below the threshold are labelled as changes. The output of the detector is a binary value indicating a change or no change.

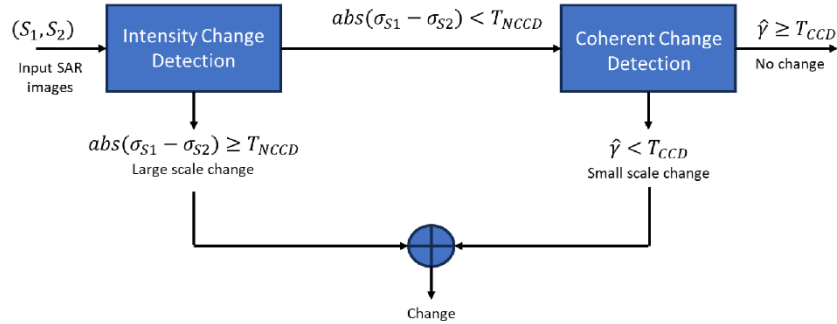


Figure 2.1 The block diagram of the two-stage detector introduced in [21, 23]. Image is replicated from [21], where it is figure 3. Image shows the Intensity and Coherent change detection stages as well as how thresholding is used.

2.3 Polarimetry

Radar polarimetry uses the vector nature of electromagnetic waves to produce and analyse images. The main benefit of partial or fully polarimetric data collections is that the additional information provides a more detailed characterisation of the scatterer or target [3, 19, 26, 27], this is because the scattering of a target is dependent on the polarization and imaging geometry [28, 29]. Electromagnetic waves can be decomposed into vertical “V” or horizontal “H” polarisations. These are orthogonal to one and other.

These polarisations are used to describe the orientation of the EM waves as they are transmitted and received. VV means the antenna horns were set up to transmit and receive in the vertical polarisation. HH would mean the same but for the horizontal polarisation. VV and HH are referred to as the co-polar polarisations. There are also two cross-polar polarisations, VH and HV. In this case there is a mismatch between the transmit and receive polarisations. The nomenclature is to write received-transmitted. So a VH polarisation would be transmitted in horizontal and received in vertical.

Polarimetric decompositions are combinations of polarisations. Often these are used to characterise different scattering mechanisms [30].

The Scattering matrix, $\mathbf{S}$, is a 2x2 matrix. It describes the backscattering response and polarising properties of a target [31, 33]. This matrix is populated by complex variables called the complex scattering amplitude. The first column is for the scattering from horizontally transmitted waves, and the second for vertically transmitted waves. The Scattering matrix, $\mathbf{S}$ is defined as follows [26]:

$$\mathbf{S} = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} \quad (2)$$

It can be decomposed using the Pauli basis as follows:

$$\mathbf{S} = \begin{bmatrix} a+b & c-jd \\ c+jd & a-b \end{bmatrix} = a \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + b \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} + c \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} + d \begin{bmatrix} 0 & -j \\ j & 0 \end{bmatrix} \quad (3)$$

Here the factors a, b, c and d are all complex, and represent the contribution of canonical scattering mechanisms [26]. These can be determined from the scattering matrix.

- a, corresponds to the single (odd) bounce scattering from a plane or sphere.
- b, corresponds to double (even) bounce scattering from a dihedral.
- c, corresponds to double (even) bounce scattering from a dihedral, rotated 45 degrees with respect to the line of sight.
- d, corresponds to anti-symmetric helix type scattering. These transform the incident wave to its orthogonal polarisation state.

Rearranging (3) we get the formulas for a, b, c and d:

$$a = \frac{S_{hh} + S_{vv}}{2}; \quad b = \frac{S_{hh} - S_{vv}}{2}; \quad c = \frac{S_{hv} + S_{vh}}{2}; \quad d = \frac{S_{vh} - S_{hv}}{2j}; \quad (4)$$

A change in the value of the a, b, c or d variables is indicative of a change between the reference and mission trajectories. These polarimetric decompositions are used in the three-stage change detection process, see section 3.2.

3 Methodology

3.1 GBSAR laboratory

The GBSAR laboratory performs microwave measurements with a Vector Network Analyser (VNA), which generates a stepped frequency waveform. The system is currently set up for indoor use, with the VNA attached to two Ultra-Wideband horn antennas allowing measurements within the range 1-10 GHz. The two antenna horns are mounted on rails and are moved in two dimensional vertical apertures. These are shown in Figure 3.1. Because of the high positioning accuracy of the rail system, trajectories could be repeated and multistatic images formed.

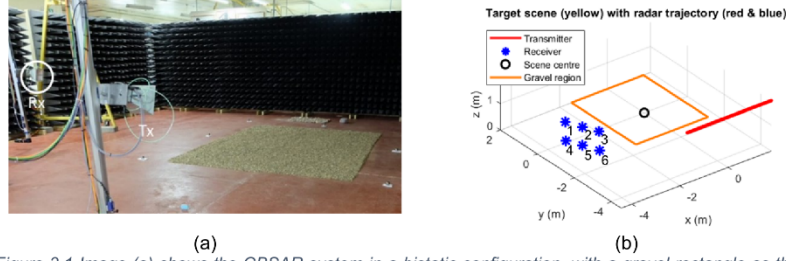


Figure 3.1 Image (a) shows the GBSAR system in a bistatic configuration, with a gravel rectangle as the scene. Image (b) shows the radar trajectories used in the data collection. The transmitter trajectory is shown in red, the multiple fixed receiver positions in blue and the gravel region is shown in orange. The receivers are numbered 1 to 6 and are referred to as R1 through to R6.

In this experiment the 6.6-10 GHz band was used. A gravel rectangle, approximately 3.5 x 4 m, was located at the centre of the scene. This would provide speckled SAR images suitable for a coherence investigation and allow tracks to be drawn. The letters 'GBSAR' were traced on the gravel for use in change detection images.

3.2 Polarimetrically augmented three stage detector

A new three stage detector is proposed in this paper. Unlike previous examples it uses multistatic, fully polarimetric data.

"Maximum", "mean" and "minimum" are used to refer to the detections in the images, where the naming convention comes from CCD images: a maximum image has the maximum coherence value for each pixel between the different CCD images being compared (a maximum image results in the minimum number of detections). Conversely a minimum image has the lowest coherence (and the highest number of detections). This nomenclature is also used for the NCCD and polarimetric decomposition images.

However, in the NCCD and polarimetric decomposition images a higher value corresponds to a greater change. Therefore, to maximise the coherence or detections the following combinations were used for the two and three stage images:

- Max CCD – Min NCCD, Min Pol change
- Mean CCD – Mean NCCD, Mean Pol change
- Min CCD – Max NCCD, Max Pol change

3.2.1 Order of operations

The formation of the three-stage images is presented in this section. The processing has been broken down into three flow diagrams to aid in clarity.

The formation of a bistatic two-stage image is presented below in Figure 3.2. The multistatic case will be similar, albeit with additional images generated. First four sets of SAR images are compared using CCD and NCCD. This forms a CCD and NCCD image for each polarisation. For the multistatic case this would involve 12 sets of SAR images. The maximum, mean and minimum of the pixels in the CCD and NCCD images are then found.

This then allows for the two stage images to be formed. The two stage image is formed by applying a threshold to the CCD and NCCD images. T_{CCD} is applied to the CCD images and T_{NCCD} is applied to the NCCD images. The max two-stage image is named after the max CCD image maximises the coherence. This results in a lower number of detections, and the highest value for the two-stage image. The maximum CCD and minimum NCCD

images are used to form it. The mean two-stage is formed using the mean images. The minimum CCD image minimises the coherence and thus has the highest number of detections of change. As such, to form the minimum two-stage image the minimum CCD is used alongside the maximum NCCD.

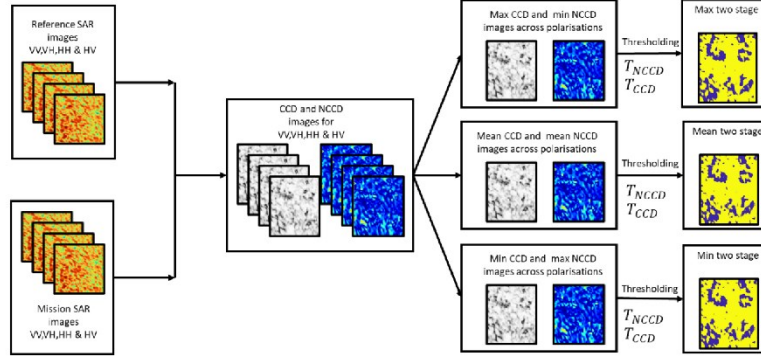


Figure 3.2 Flow diagram showing the formation of the two-stage change detection images.

The fully polarized SAR images are also used to form the polarimetric change images. This is shown in Figure 3.3. First the VV, VH, HH and HV images are decomposed into the a, b, c and d parameters (see equation (4)). The difference is then found between the reference and the mission images. This results in four images of the differences in polarimetric parameters. The maximum, mean and minimum of each pixel is then taken. For the multistatic case this would be done three times, resulting in 12 polarimetric change images that would then have the maximum, mean or minimum applied across them.

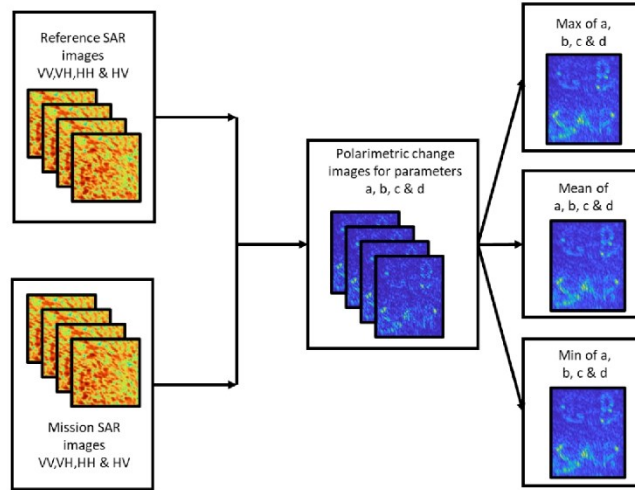


Figure 3.3 Flow diagram showing the formation of the polarimetric change images.

Finally the three-stage detector is presented. In this a threshold is applied to the two-stage detector images (Figure 3.2) and the polarimetric decomposition change images (Figure 3.3). The threshold $T_{2\text{ stage}}$ is applied to the two-stage images and T_{pol} is applied to the polarimetric decomposition change images. The result is referred to as the three-stage image. This processing stage is the same for the bistatic or multistatic case as the two-stage and polarimetric change images are already either bistatic or multistatic.

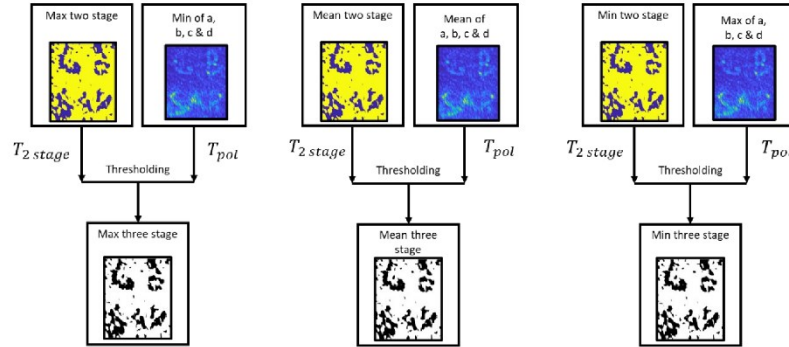


Figure 3.4 flow diagram showing the three-stage detector. It shows how the two-stage images and polarimetric decomposition change images are thresholded.

3.3 Data processing

The SAR images will be used to form CCD images. There were two sets of CCD images, one where the gravel was undisturbed, and another where the gravel had a disturbance track traced.

Performance metrics will be used in the evaluation of the CCD images. These metrics are often used in the evaluation of space weather predictive models [32, 34]. These are calculated using a confusion matrix. Here T and F mean true and false respectively, and P and N mean positive (change) and negative (no-change) in the CCD image [32, 35]. These are shown in a confusion matrix in Table 1.

Confusion Matrix		Event Observed	
		Yes	No
Event Forecast	Yes	TP	FP
	No	FN	TN

Table 1 Confusion matrix, showing the conditions that correspond to TP, TN, FP and FN.

Using the Confusion matrix several performance metrics can be calculated. The formulae for the metrics are shown in Table 2. Additional metrics such as the RMSE (to be defined below) use the coherence values of the images. These formulas are defined below [32, 34–39]:

- Probability of Detection (POD). This metric gives a value of [0,1] and is the proportion of true positive predictions compared to the number of events. A value approaching 1 indicates most events were detected, and a value approaching 0 indicates most events were missed.
- The Critical Success index (CSI) shares some similarities with the POD. It compares the number of correct forecasts to the number of correct forecasts, false alarms and misses. It is not affected by the number of correct negative forecasts. A value approaching 1 indicates a perfect forecast.
- The False Alarm Rate (FAR) compares the number of false alarms with the number of forecast events. Here a value of 1 indicates all forecast events were false.
- The Proportion Correct (PC) provides a measure of the number of correct forecasts of events compared to the total number. A value approaching 1 indicates most forecasts were true, a value approaching 0 indicates most were wrong.
- The Heidke Skill Score (HSS) shares some similarities with the Success Rate ($SR = 1 - FAR$), however it also accounts for the random forecasts. The HSS outputs a value of $-\infty$ to 1. No incorrect forecasts would result in a value of +1. No correct forecasts would give a value of $-\infty$. A value of 0 would indicate 'no skill', and performance close to random guesses.
- The Matthew's Correlation Coefficient (MCC) is an alternative to Pearson's Correlation Coefficient (R) but is less effected by unbalanced datasets. A value of 1 represents perfect classification, and -1 represents perfect miss-classification. Similarly to the HSS, a value of 0 represents a classification similar to the expected value (random or no skill).

- The root mean squared error (RMSE) is a measure of the difference in values rather than the forecasting of events. In this case 0 indicates no error, and any other positive value indicates an error.

Name	Formula	Value range	Eq. No.
Probability of Detection	$POD = \frac{TP}{TP + FN}$	[0,1]	(5)
Critical success Index	$CSI = \frac{TP}{TP + FP + FN}$	[0,1]	(6)
False Alarm Rate	$FAR = \frac{FP}{TP + FP}$	[0,1]	(7)
Proportion Correct	$PC = \frac{TP + TN}{TP + TN + FP + FN}$	[0,1]	(8)
Heidke Skill Score	$HSS = \frac{2 * (TP \cdot TN - FP \cdot FN)}{(TP + FN)(FP + TN) + (TP + FP)(FP + TN)}$	$[-\infty, 1]$	(9)
Matthews's Correlation Coefficient	$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}}$	$[-1, 1]$	(10)
Root Mean Squared Error	$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Predicted_i - Actual_i)^2}$	$[0, \infty]$	(11)

Table 2. Table shows the formulas and range of values for different performance metrics and skill scores.

Master CCD images will be used to calculate the performance metrics. A master two stage image is shown in Figure 3.5 (a) with values ranging from -1 to 1. Figure 3.5 (b) shows a binary image where pixels with a coherence below a threshold were detected as a change and set to 0. Those with a coherence above the threshold were set to 1. This shows where detections of a change or no change would be made for the master image. The threshold for the master image was chosen as it most accurately replicated the ground truth of the disturbance. A lower threshold would have resulted in too large an area of detected changes, whereas a higher threshold would have resulted in parts of the letters being missed out.

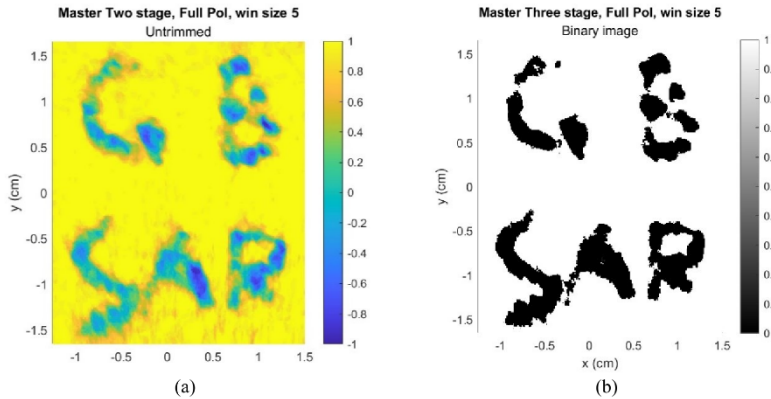


Figure 3.5 Master images used for the performance metrics. Image (a) is a two-stage change image formed from fully polarized multistatic data collections. Image (b) is a three-stage change detection binary image formed from applying a threshold to (a) and the polarimetric decomposition change images.

4 Results

The performance of the three-stage change detection process can be plotted on a spider plot. This allows for the easy visualization of many separate variables. A higher value generally indicates good performance with the exception of FAR and RMSE, where high values indicate poor performance.

The performance of the bistatic images is plotted in Figure 4.1. Here it can be seen that the performance varies significantly depending on whether the bistatic image is formed from the maximum mean or minimum of the fully polarimetric data. It is also clear that using multiple variables is key to understanding the performance. Looking at the proportion correct and the RMSE the maximum and mean appear to perform very well. However, the POD shows that the maximum is missing a large number of the changes. The minimum images result in the best POD, and a decent PC, however, perform very poorly in all other metrics. Overall the mean images appear to perform the best for the bistatic case.

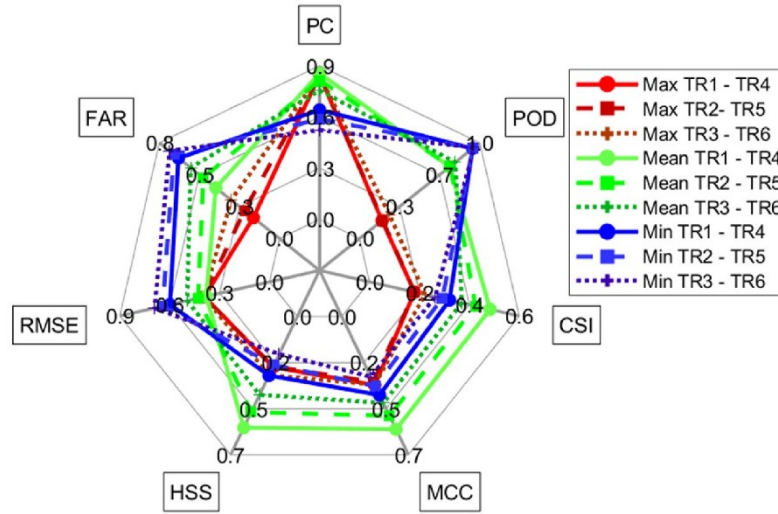


Figure 4.1 Spider plot of the three stage bistatic performance metrics. Maximum images are represented by red, mean by green and minimum by blue.

The trend shown in Figure 4.1 is repeated in

Figure 4.2. Here the mean images are clearly performing better than the maximum and minimum images. There are differences between the multistatic and bistatic performance metrics and these are shown in Figure 4.3, Figure 4.4 and Figure 4.5.

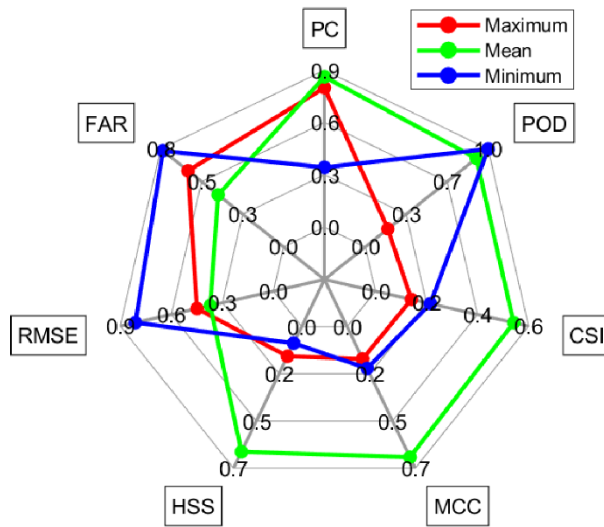


Figure 4.2 Spider plot of the three stage multistatic performance metrics. Maximum is represented by red, mean by green and minimum by blue.

In the case of the maximum (Figure 4.3) the performance of the HSS and PCC drop closer to zero indicating that the performance is approaching that of a random guess. The FAR however increases significantly from around 0.3 to 0.6.

The mean images (Figure 4.4) show an improvement in performance for all metrics. With a reduction in RMSE and FAR, and an increase in all other metrics.

The minimum images (Figure 4.5) show a drop in performance. In particular PC shows a significant drop from 0.6 to 0.3. Additionally, the HSS, CSI and MCC also show drops. The RMSE and FAR also increase. The POD does improve, however.

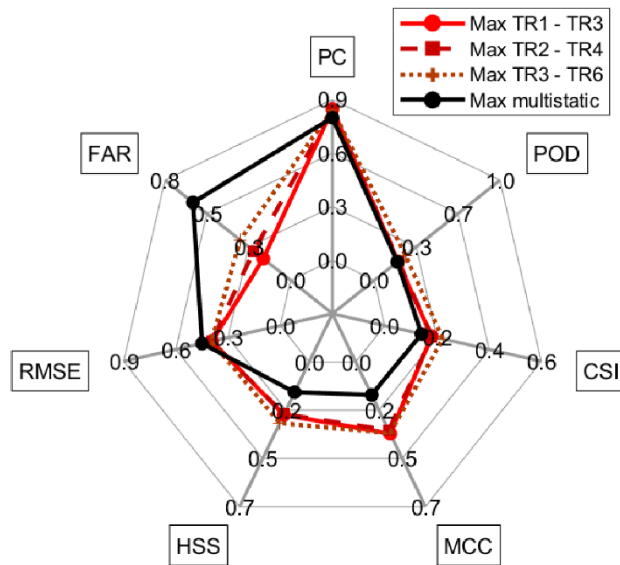


Figure 4.3 Spider plot showing the change in performance metrics between the three bistatic maximum images and the multistatic maximum image. The bistatic images are represented by red, and the multistatic image by black.

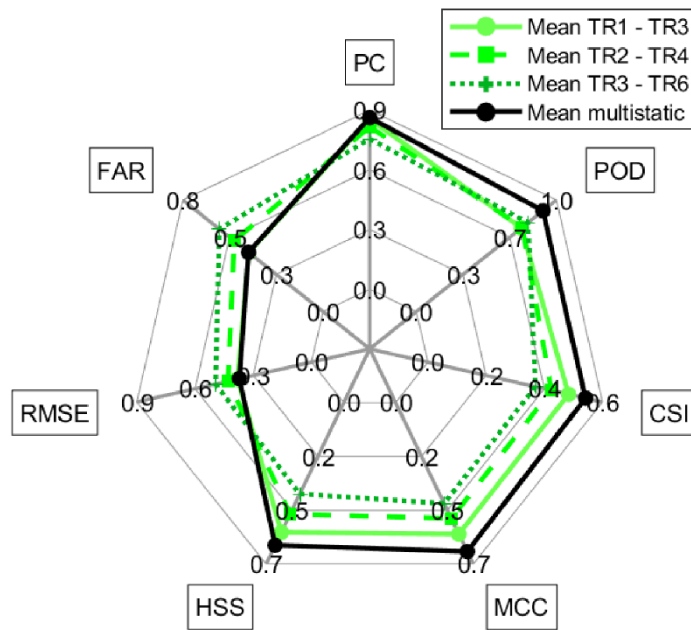


Figure 4.4 Spider plot showing the change in performance metrics between the three bistatic mean images and the multistatic mean image. The bistatic images are represented by green, and the multistatic image by black.

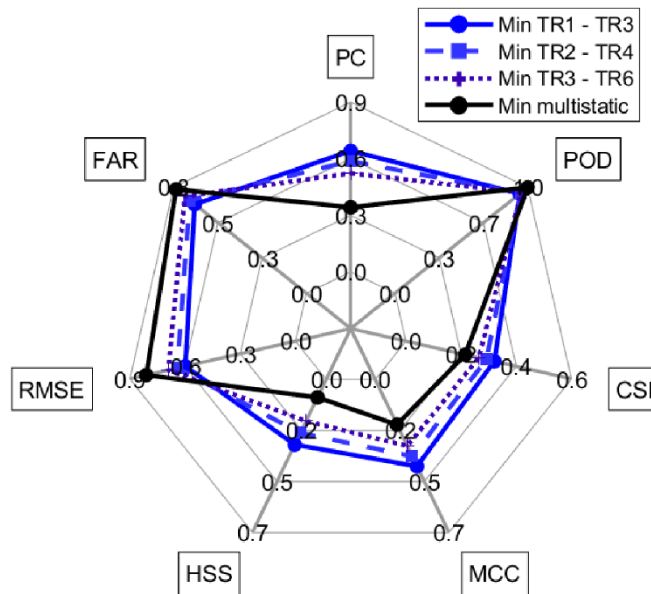


Figure 4.5 Spider plot showing the change in performance metrics between the three bistatic minimum images and the multistatic minimum image. The bistatic images are represented by blue, and the multistatic image by black.

The change in performance discussed above between the bistatic and multistatic collections can also be visualized using the 3 stage binary images. A tessellation of these is presented in Figure 4.6. Here white is a detection of no change and black a detection of a change. In the maximum images, the multistatic image contains significantly more detections of change than the bistatic images. This visualizes the drop in performance seen in Figure 4.3. The mean multistatic is visually more similar to the master (Figure 3.5), than the bistatic mean images. Finally, the minimum image appears quite similar to the bistatic minimum images, although it appears to have additional false detections. This aligns with the change in performance seen in figure Figure 4.5.

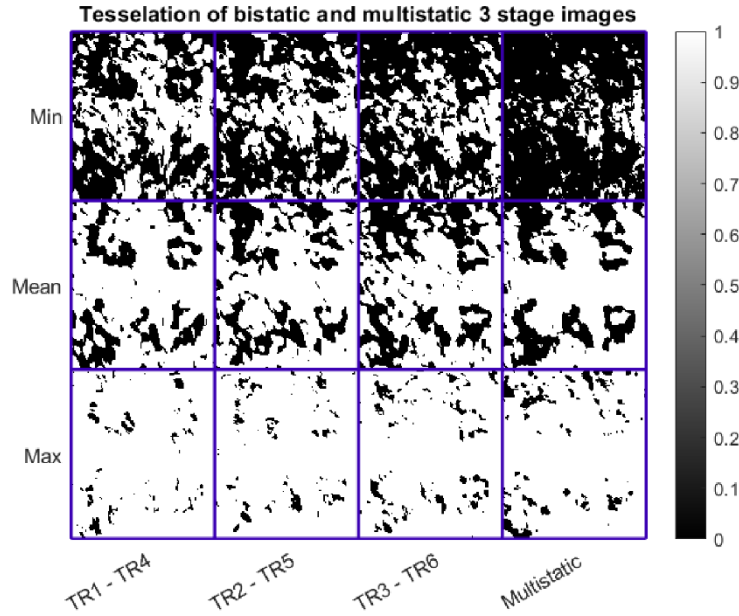


Figure 4.6 Tessellation of bistatic and multistatic three stage change images. The top row shows the minimum, the middle the mean and the bottom row the maximum. The minimum images have the most detections, and the 'GBSAR' becomes illegible for the multistatic. The maximum images have the fewest detections, and the 'GBSAR' remains unclear throughout. The minimum images show the 'GBSAR', although the multistatic bears greater resemblance to the master than the bistatic images.

5 Conclusion

In conclusion this paper has shown the feasibility of a three-stage change detector, using coherent and incoherent change detection data as well as polarimetric decompositions.

It has also investigated the performance of this change detector. It has been shown that simply relying on common performance metrics such as POD and FAR is insufficient to properly characterize the performance of a detector/forecast. Utilizing multiple performance metrics is advisable. Additionally inspecting the detector or model output (as was done for Figure 4.6) can also aid in the analysis of performance.

For this dataset, the mean multistatic performed best. This is a different result compared to [20], where the minimum appeared to perform best. It is believed that this is due to the change in the detector used. This suggests that attaining optimal detection is dependent on the processing used, and that attempting to maximize the detections in multistatic data does not always lead to the best results.

The polarimetric decomposition used was not roll-invariant, and future work could investigate the use of roll-invariant decompositions or parameters such as the Huynen fork.

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