

ORIGINAL RESEARCH

Modelling real-world effects in near-field SAR collections for compressive sensing

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Abstract

The ability to control sidelobes in a SAR image is critical to forming images that are useful for interpretation and exploitation. QinetiQ has developed the RIBI sensing system, which utilises a distributed coherent array of sensors to produce multistatic images. These systems require techniques from outside the traditional radar domain to utilise the theoretical resolution possible in synthesising a coherent aperture from multiple disparate collections. This paper develops previously published work on using compressive sensing techniques to suppress sidelobes in SAR images to develop a higher-fidelity measurement model. Using Cranfield University's GBSAR System a series, experimental measurements are conducted, and image estimation techniques are applied to this real data. It demonstrates an improvement in recovery performance over an isotropic measurement matrix, and discusses areas which require further development.

KEYWORDS

compressed sensing, multistatic radar, synthetic aperture radar

1 | INTRODUCTION

1.1 | Overview

Radio frequency (RF) imaging is a long-established technique for surveillance and reconnaissance. In particular, synthetic aperture radar (SAR) provides a long-range all-weather ground imaging capability which has seen both military and civilian use for over 60 years [1, 2].

In recent years the capability of unmanned air system (UAS) to provide a suitable platform for SAR sensors has dramatically improved. QinetiQ's RIBI system [3] is one example of such a system, where a multi-function sensor has been integrated with a Vulcan Raven X8 multirotor UAS to produce a highly-capable SAR collection system. When combined with a sensor designed around a modern software-defined radio, these platforms allow for a massive increase in the frequency, spatial, and temporal diversity available to the system. Combining these into a wider multistatic collection theoretically yields significant improvements to resolution, however the disjointed nature of these collections will lead to

strong sidelobes which require management to form actionable imagery. Through a number of programmes QinetiQ have designed, constructed, and gathered data with the RIBI system in a number of collection schemes. There are a number of challenges that are the subject of ongoing research including timing accuracy, three-dimensional exploitation, and sidelobe suppression when combining collections.

Cranfield's ground-based SAR (GBSAR) system [4] is a lab-based radar system capable of capturing multistatic SAR data with a high accuracy motion solution, and is therefore an extremely capable collection system to use for developing processing algorithms and tools. In comparison, the RIBI system produces images with a high degree of complexity, and as such research into novel processing techniques is far more complex. The additional complication added by timing errors, motion profile of a UAS, and higher data bandwidths generates significant additional complexity which is not desirable for assessing novel algorithms.

In this work, the GBSAR system is used to collect SAR data in order to support algorithm development. This data is then used to assess the performance of a number of image estimation

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algorithms to suppress sidelobes in data representative of RIBI data. Improvements to the image reconstruction algorithms are presented, along with the resulting enhanced images, for simple canonical scatterers and more complex objects.

1.2 | Previous work

SAR is a broad field with numerous research areas including receiver design [5], signal processing [6], and collection methodology [7]. As discussed, multistatic SAR involves multiple sensing systems transmitting and/or receiving with techniques required to fuse this data into a single collection. In this process there are a number of challenges such as clock accuracy [8] and geolocation accuracy [9].

Gaps in SAR imagery have been a subject of research for many years, with gaps in apertures [10, 11] due to interference or corruption and frequency [12] considered. Traditional radar techniques would consider techniques such as windowing for sidelobe control, however previous work by the authors have demonstrated that for multistatic collections from the RIBI sensors development beyond these techniques is required. Compressive sensing (CS) [13, 14] provides a mathematical technique for signal reconstruction based on assumed sparsity, even for signals sampled below the Nyquist rate [15].

For SAR, CS has previously been shown to have promise as a technique for mitigating strong extended sidelobes in a number of challenging collection regimes.

- Background separation and Ground Moving Target Indication (GMTI) [16, 17].
- Sparse multistatic collections.
- 3D imaging from a single pass (with complex trajectory) or few repeat passes [7, 18].
- Gaps in frequency to avoid interference/jamming [19].

The grounds for using sparse processing techniques in SAR has been previously discussed, for example, Ref. [20]. A typical SAR scene would not be considered to be sparse, therefore a number of approaches have been considered to create a basis for use with CS techniques. These include decomposing the image into bright, sparse, scatterers and lower backgrounds [21], man-made environments such as building interiors [3], and low frequency collections [7, 22].

In this work three CS algorithms will be utilised: orthogonal matched pursuit (OMP) [23], iterative hard thresholding (IHT) [24], and ElasticNet [25]. These were all previously demonstrated in our 2023 paper [26] to have merit in their application to isotropic simulated images, and are thus carried forward to this research. Backprojection [27] will be considered as part of this, representing traditional radar processing techniques.

1.3 | Contribution

This work builds on previously published simulated results through developing the following original ideas.

- Utilises Cranfield's GBSAR system to collect near-field SAR data to enable research of near-field scattering phenomena.
- Develops a new measurement matrix which utilises a frequency-dependent anisotropic scattering model (referred to as the "modified" model) obtained from the GBSAR data.
- Applies CS algorithms, previously tested on simulated isotropic scatterers, to real data involving simple scatterers, comparing performance between an isotropic model and the modified model.
- Further develops the IHT algorithm to address issues with convergence.
- Applies CS algorithms to a model T-64 to represent a more complex scattering object.

This paper concludes with a discussion of the main results, practical considerations for implementation, and an exploration of future areas of research.

2 | COMPRESSIVE SENSING THEORY FOR SAR

2.1 | SAR processing

This paper further develops previous work by the authors, where a number of CS algorithms were applied to multistatic SAR images using a perfect point scatterer (isotropic) model. Reconstruction accuracy and run-times were assessed, and expansions to real-world imagery were considered. A more complete discussion of the image formation methods can be found in the previous work [26], however the main results are replicated here.

The total phase history captured during a SAR collection is given using Equation (1):

$$\Phi = \sum_{k=1}^K \zeta_k e^{-i \frac{4\pi f(t_f)}{c} R_k(t_s)} \quad (1)$$

Where f is the transmitted frequency, R_k is the two-way path length from transmitter, to scatterer, and back to receiver, t_f and t_s are fast- and slow-time, respectively, and c is the speed of light. This model assumes a sum over K scatterers which are all independent of each other. Previously these scatterers were assumed to be isotropic, and thus ζ_k was a scalar value of RCS.

This isotropic scattering model was therefore a simplification that omitted a number of factors which would impact the RCS of a scatterer, including the following.

- Angles of incidence and reflection.
- Frequency.
- Polarisation.
- Material properties.
- Physical dimensions and geometry.

This work uses data collections performed using the GBSAR system to explore three of these features: azimuth angle, elevation angle, and frequency.

The phase history calculated from Equation (1) can be rewritten in a matrix format to express a SAR collection as a linear equation:

$$\Phi = A\Gamma + n \quad (2)$$

Where the A matrix, known as the forward projection, is defined as follows:

$$A = \begin{bmatrix} e^{-i\frac{4\pi f_1}{c}R_k(t_1, x_1, y_1)} & \dots & e^{-i\frac{4\pi f_1}{c}R_k(t_1, x_{N_x}, y_{N_y})} \\ \vdots & \ddots & \vdots \\ e^{-i\frac{4\pi f_{N_f}}{c}R_k(t_{N_t}, x_1, y_1)} & \dots & e^{-i\frac{4\pi f_{N_f}}{c}R_k(t_{N_t}, x_{N_x}, y_{N_y})} \end{bmatrix} \quad (3)$$

The matrix A is applied to a ground truth, Γ , to form a phase history, Φ , with Gaussian IQ noise n applied.

$$\Gamma = \begin{bmatrix} a(x_1, y_1), & \dots, & a(x_{N_x}, y_{N_y}) \end{bmatrix} \quad (4)$$

$$\Phi = \begin{bmatrix} \varphi(f_1, t_1), & \dots, & \varphi(f_{N_f}, t_{N_t}) \end{bmatrix} \quad (5)$$

An image Γ' can be formed by applying A' , known as the backwards projection, to Equation (2):

$$\Gamma' = A'(A\Gamma + n) \quad (6)$$

In the ideal case A' would be the inverse of A , however when the aperture is sampled sparsely A^{-1} does not exist, (and without regularisation will have a high sensitivity to noise) and as such techniques for estimating A' must be used.

2.2 | Compressive sensing

A number of algorithms from traditional radar, linear regression, and compressive sensing were used in the previous paper to attempt to reconstruct the ground truth from the multistatic data. The key results from this work showed that ElasticNet, OMP, and IHT all showed that they are effective at estimating Γ' . This was quantified both in terms of reconstructing scatterer RCS and suppressing. These three algorithms are carried forward to this work.

ElasticNet is a regularised linear regression approach that combined L_1 and L_2 norms to produce an approach that combines the relative strength of the widely used RIDGE [28, 29] and LASSO [30] algorithms. The tuning parameter β selects between these two norms, where the L_2 component acts to preferentially select smaller values and the L_1 component prefers a sparse solution. It is fully expressed as follows:

$$\min_{\Gamma} \frac{1}{2N_{\text{samples}}} \|\Phi - A\Gamma\|_2^2 + \alpha\beta\|\Gamma\|_1 + \frac{\alpha(1-\beta)}{2}\|\Gamma\|_2^2 \quad (7)$$

Here α is a learning rate parameter that has been optimised against a specified training dataset (along with β).

OMP is a greedy algorithms with an explicit number of non-zero coefficients in Γ that produces a low residual r :

$$\min_{\Gamma} \|\Phi - A\Gamma\|_2 \text{ subject to } \|\Gamma\|_0 \leq N_{>0} \quad (8)$$

IHT imposes a hard limit on the number of non-zero coefficients on each iteration, running until the error between Γ and Γ' is suitably low.

$$\Gamma_{n+1} = H_s(\Gamma_n + A^T(\Phi - A\Gamma_n)) \quad (9)$$

Both OMP and IHT have explicit limits on the number of non-zero coefficients that they allow in their solutions, given by $N_{>0}$ and H_s respectively. Whilst simulated imagery is trivial to estimate these limits, given the ground truth is controlled, real data is likely to provide a much more complex response.

The data used in this work is collected by a monostatic system with gaps in the data inserted later by zeroing areas of the slow-time aperture. This allows for a direct comparison between theoretical full monostatic collections had that been available.

3 | EXPERIMENTAL MEASUREMENT

3.1 | Collection system

The GBSAR system is a rail-based RF sensing capability for researching novel airborne and spaceborne remote-sensing techniques. It is capable of three-dimensional SAR [31] in monostatic, bistatic, and multistatic configurations with high resolutions, and can be used to study coherent change detection (CCD) [4, 32] and hyperspectral SAR.

Figure 1 shows the near-monostatic antennas on the rail mount in the centre and, while a second mounting exists for bistatic measurements (yellow frame, just out of picture), this was the system used for the collections. The full range of motion gives an aperture of range 3.5 m in azimuth and range 1.5 m in elevation. For the 2D datasets in this work the azimuth aperture used was 3.5 m long at an elevation of 1.94 m, with the scene centre approximately 4 m from the aperture centre. A 3D dataset of a single scatterer was also collected to examine elevation responses (see Section 3.5), which used the full azimuth and elevation ranges of the system.

The full GBSAR system is capable of operating from 2 to 25 GHz in a stepped-frequency CW imaging mode. For the following experiments a bandwidth of 4 GHz was used with a centre frequency of 10 GHz. Sampling rates were calculated to give a sufficiently large non-ambiguous imaging region. As shown in Figure 1 the radar is in an indoor space which has

been had a large amount of radar-absorbing materials applied to potentially large sources of reflection, however through performing background scans and subtracting that from any

subsequent collections the imaging area can be suitably low-background for sensitive techniques to be evaluated.

In support of this work a number of datasets have been collected using the GBSAR system.

- Individual scatterers (trihedrals and spheres).
- Multiple scatterers.
- Background scans (as appropriate).
- 3D trihedral response.

A subset of these datasets have been selected for this paper as detailed in Table 1.

The dataset used in question is show in Figure 2, with three trihedrals placed in a row parallel to the radar's direction of motion. The background has been subtracted from the data prior to processing, thus the model T-64, ducting, and other artefacts are not present in the final image. This image has been formed using a functional backprojection processor to allow for higher resolution images to be produced, as the memory requirements of the matrix method outlined previously are too great to allow this, however all of the other imaging parameters are identical to the matrix processing used in following sections. In this case, the available bandwidth has been reduced and downsampled, leading to increased range

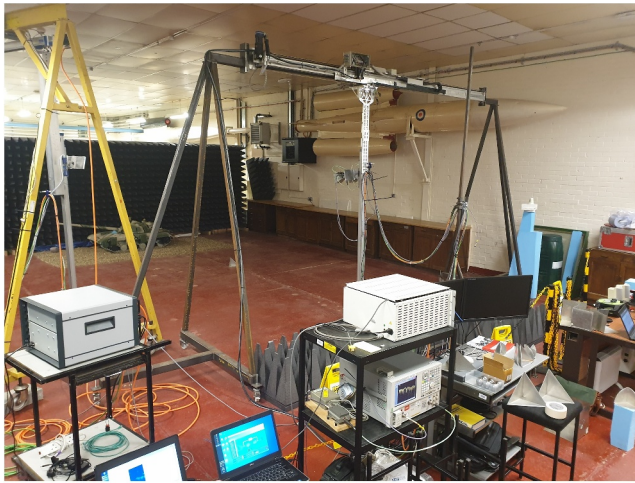


FIGURE 1 GBSAR system in the laboratory with the metallic model T-64 in a gravel bed to the left (behind the yellow A-frame).

TABLE 1 Key of experimental collections undertaken, with the scene centre assumed to be (0,0,0) for the purposes of relative scatterer locations in a (range, cross-range, and elevation) coordinate system.

Collection serial	Summary	Object 1	Object 2	Object 3
C01	Single square trihedral	250 mm square trihedral (Scene centre)	—	—
C02	Single triangular trihedral	171 mm triangular trihedral (Scene centre)	—	—
C03	Single curved trihedral	120 mm curved trihedral (Scene centre)	—	—
C10	Single spherical reflector	280 mm sphere (Scene centre)	—	—
C11	Two beating trihedrals	171 mm triangular trihedral (Scene centre)	171 mm triangular trihedral (0, -1, 0)	—
C12	Three beating trihedrals	171 mm triangular trihedral (Scene centre)	171 mm triangular trihedral (0, -1, 0)	171 mm triangular trihedral (0, -2, 0)
C14	Wide-spaced trihedrals	171 mm triangular trihedral (Scene centre)	171 mm triangular trihedral (0, 2, 0)	171 mm triangular trihedral (0, -2, 0)
C18	Mixed trihedral models	171 mm triangular trihedral (Scene centre)	120 mm curved trihedral (0, -1, 0)	150 mm square trihedral (0, 1, 0)
C31	3D scan	171 mm triangular trihedral (Scene centre)	—	—
B01	Background scan	—	—	—
B05	3D background scan	—	—	—

sidelobes, as a necessary step to make the matrix processing viable within hardware limitations. Other datasets available used a number of different canonical scatterers (spheres and alternative trihedrals) with different arrangements, whereas the T-64 remains available as a complex object if an image is formed directly from the background scan data.

In Section 3.2 the response of an individual scatterer is applied to these results, as was previously simulated, as an isotropic point in free space, and as such the collections were

designed to investigate a number of areas where this assumption does not hold true. This work focuses on the observed frequency (Section 3.3) and azimuth (Section 3.4) responses of the scatterers under test, as these are most applicable to the 2D pseudo-multistatic imaging case outlined in Section 2. The elevation response is also considered (Section 3.5) as well as other effects that are noted but were not measured or accounted for in this work (Section 3.7).

3.2 | Perfect point scatterer processing

Before any adjustments are made to the processing method the original isotropic matrix is applied first, to examine what recovery performance is possible without assuming any angular or frequency dependency. For this, dataset C12 is used with three equal trihedrals as per Table 1. The collection was modified to produce a pseudo-multistatic collection by deleting the central 50% of the azimuth collection.

Backprojection, given by applying A^T as A' , represents the standard image processing technique within the radar domain. Previous work on simulated data demonstrated that this exhibits the high sidelobes expected, and therefore is suitable as a control formation algorithm to compare recovery attempts to. In this case three scatterers are present in the imaging area, and OMP, ElasticNet, and IHT are applied to this dataset to produce their own estimations of A' . Figure 3 contains their recovered imagery from applying A' to the multistatic phase history Φ_S as well as the backprojection case.

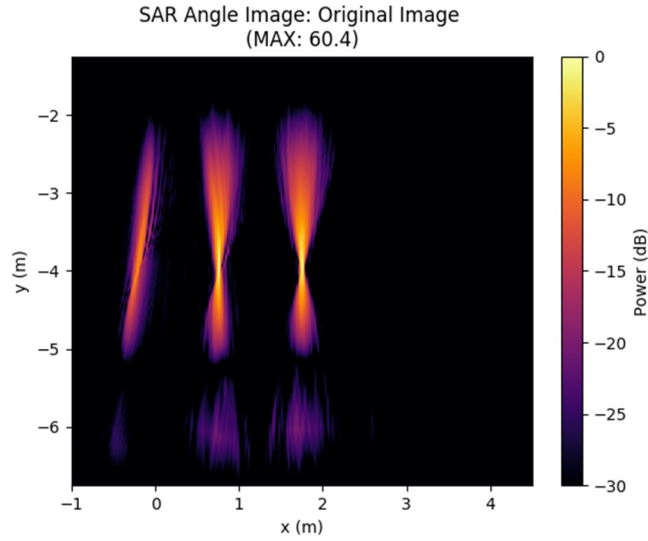


FIGURE 2 A dB plot of dataset C12 used for Sections 3 and 4 formed using a functional backprojection processor.

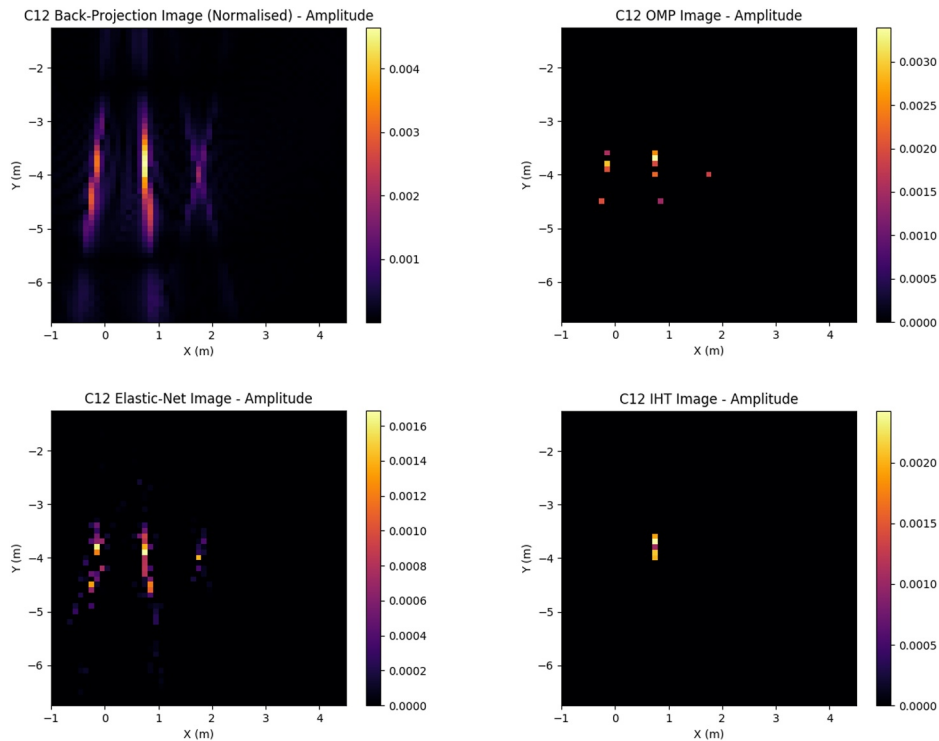


FIGURE 3 Backprojection and recovery algorithm outputs for the isotropic A matrix model.

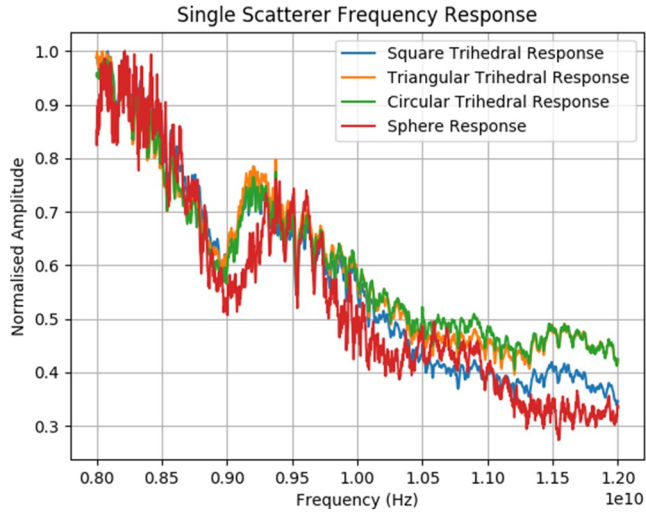


FIGURE 4 Normalised frequency response of four different scatterers across full 4 GHz bandwidth of the radar.

The isotropic A matrix omits the ζ term that encodes the azimuth response, however the frequency response of the radar is still removed from the phase history prior to commencing image formation (discussed in the following section).

When evaluating the recovery performances of the respective algorithms it is obvious that the amplitude of the central scatterer is reduced in each, however this data collection has three trihedrals of equal physical size which should, therefore, have equal RCS. In addition the extended range sidelobes have led to the scatterers spreading across multiple pixels. This makes it clear that the isotropic model is not capable of giving the correct solution for real data, despite its strong performance on idealised simulated data in previous research. As such the rest of this section will consider what improvements can be made to the A matrix in order to improve CS performance.

3.3 | Frequency response

The overall frequency response will be a combination of the frequency-dependent scatterer reflection and impact of hardware. Figure 4 shows the normalised mean frequency response obtained from three trihedrals and a sphere at the centre of the scene.

The four scatterers all exhibit a similar trend in frequency response, which is likely due to the hardware as opposed to frequency dependency in the scatterer itself as typically RCS will increase with frequency.

This response can be applied to Φ directly as a characteristic of the radar, by creating a mean response from the four plots shown and dividing each slow-time aperture point by this frequency response to remove it from Φ . As such, frequency response will not be encoded within A , however applying this response to the terms of A would also be entirely valid.

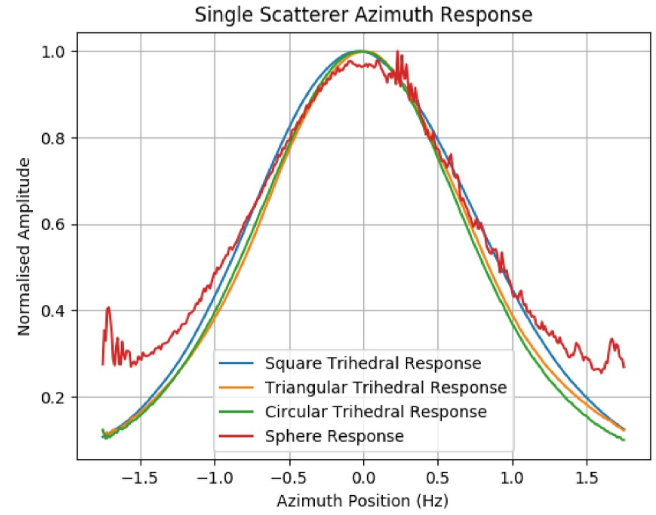


FIGURE 5 Normalised azimuth response of four different scatterers for full azimuth extent of collections.

3.4 | Azimuth response

The azimuth response observed will be a combination of the antenna beam pattern and the response of the scatterer under test. The results for the azimuth response using a sum across the frequency dimension of the phase history can be found in Figure 5. The responses here have been normalised to their brightest point. The sphere's peak RCS is far lower than that of the trihedrals, and as such noise is more evident in the collection, hence the raised tail regions either side of the peak.

The angular extent of this peak is approximately equal for all four scatterers, and this is not the expected result if the azimuth response is dominated by the scatterers. It is expected that a sphere will have an equal RCS at all azimuth/elevation angles, whereas a trihedral will have a limited angle of acceptance. The conclusion must be that this response is due to the beam pattern of the antenna at close range not illuminating the scatterers full as it sweeps across the scene.

To match the experimentally observed azimuth response in Figure 5 a zero-mean Gaussian function, ϕ , can be used:

$$C_a = \phi(\beta|x_k - x_{Tx}|) + n_a \quad (10)$$

The Gaussian function uses the difference in cross-range position between each pixel (x_k) and the along-track position of the radar (x_{Tx}), with a width control parameter β , to model the azimuth beampattern response and noise floor addition given by n_a . Through use of a zero-mean this produces a maximum response when the pixel is in the centre of the aperture, with the amplitude decaying as the cross-range separation increases. Figure 6 gives a comparison of experimental and modelled azimuth responses using this Gaussian for a single trihedral at the centre of the aperture.

This is a clear departure from the isotropic scattering model used previously, representing a highly azimuth-

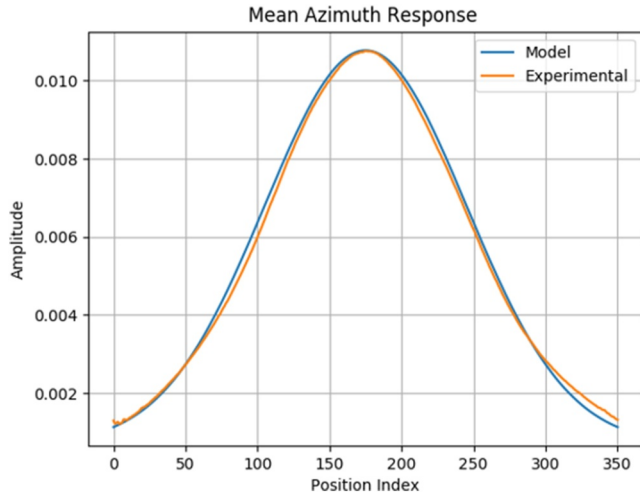


FIGURE 6 Modelled and experimental azimuth responses of a single triangular trihedral.

dependent response, and is therefore a key feature to be added into the measurement model used.

3.5 | Elevation response of a triangular trihedral

A 2-dimensional aperture was collected utilising the entire imaging space of the GBSAR system, collected at the full 4 GHz bandwidth. The response of this summed across the bandwidth is displayed in Figure 7. All other datasets are collected at an elevation of 1.94 m, corresponding to the top row of this plot.

The overall shape of the azimuth response for each potential aperture height is similar, however there is a variation in peak amplitude if a slice through the centre of the aperture is taken. This appears to be due to the sidelobe pattern of the antenna in elevation.

3.6 | Matrix improvements

The work undertaken in Sections 3.3 to 3.5 can be used to improve the A matrix described in Section 2 (Equation 3), and this improved A matrix can then be applied to the recovery algorithms to improve performance. As noted in Section 3.3 the frequency response is removed from the captured phase history rather than being encoded in A , however this could be added to the coefficients of A as the correction term C_f as below. The azimuth correction, C_a , from Section 3.4 is applied to the individual elements of A in Equation (3):

$$A_{(f,t,x,y)} = C_f C_a e^{-i \frac{4\pi f c}{R_k(t,x,y)}} \quad (11)$$

This yields a second version of the A matrix, which will be referred to as the "Modified" model when results are

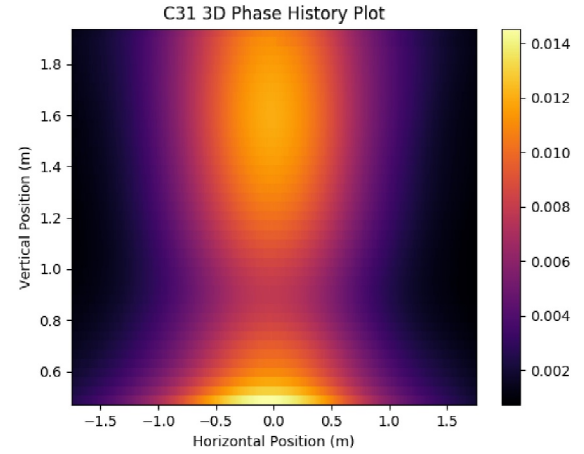


FIGURE 7 3D frequency-summed response.

presented. Note, that elevation has not been considered in this work in order to limit the number of free parameters to model, and accordingly collections have been constrained to a height of 1.94 m throughout.

3.7 | Other effects

There are a number of other factors which have been considered and later omitted in order to limit the complexity of the A matrix at this stage, which will now be discussed.

For all of the collections displayed a single polarisation (VV) was collected. Whilst HH and cross-polarisation measurements can also be made for a full polarimetric solution for the scope of this work, and to facilitate a range of collections without introducing significant time constraints, a single polarisation was collected.

The physical dimensions of a trihedral will lead to a more complex response than a Gaussian curve can model. One would expect a dominant trihedral response with smaller dihedrals either side as the radar illuminated only two planes of the trihedral shape. Had this been the dominant factor in the azimuth response a sinc-like function could have been used to replicate this effect.

Material properties will have an impact on the observed RCS of a scatterer, and so a thorough model would include terms to account for this. The scatterers used were all assumed to be of a uniform metal with no difference in reflectivity, and so this is noted as an assumption and not modelled further.

Spherical and cylindrical objects were not the key scatterers under test in this work, however multipath effects between scatterers and between scatterers and the surface will all contribute to artefacts observed in the final SAR image. In the case of two cylinders a response will be observed between the two objects. The original A matrix does not account for this, and adding this into the measurement model will represent complexity beyond the scope of this work.

A functional approach to simulation and image formation would be an alternative to the matrix approach utilised in this

work, the merits of this will be discussed as part of the analysis following the results (Section 5.2).

4 | MODIFIED A MATRIX RESULTS

4.1 | Reconstruction performance

The following section takes the improvements to the A matrix as outlined in Section 3.6 and applies them to the same dataset as used in Section 3.2. All of the imaging parameters—sample rates, bandwidth, and trajectories—are identical and the same amount of data has been removed from the centre of the aperture.

The results of applying the modified A matrix are shown in Figure 8 for, OMP, ElasticNet, and IHT. The backprojection image retains the isotropic A matrix to be used as a comparison.

In the cases here the recovery performance has improved in two ways when compared to the isotropic results in Section 3.2. Firstly, the centre scatterer does not have its amplitude suppressed relative to the two scatterers on its left. Though the amplitudes are not equal the ability to recover a central scatterer which is not evident in a regular backprojection image is an important result. Secondly, the extended range sidelobes are not as pronounced in these images, with ElasticNet and IHT both limiting the amount of energy estimated in these regions, although there is some variation in the position of the

scatterers in the range direction for the two left scatterers. The range resolution of these image is relatively poor compared to the pixel size, and this produces long range sidelobes directed at each subaperture. The central scatterer sits at an intersection of two range sidelobes and thus can be resolved, however those on the left cannot be accurately placed within the sidelobes.

4.2 | Further IHT development

The techniques used will be sensitive to any discrepancies between A and A' , and so whilst the modified model has yielded a performance gain it has not been able to achieve the performance demonstrated on perfect simulated data. The OMP and ElasticNet algorithms used are coded as part of Python's SKLearn module, however IHT was implemented based on Davies' work and therefore offers a chance to look for performance gains. This section therefore examines the IHT algorithm and identifies three ways in which the performance shown in Figure 8 can be improved.

The first of these is to add a normalisation term, μ , in order to account for amplitude changes as a result of passing Γ_n through the forwards and backwards operators. During optimisation it was observed that the IHT parameters required careful selection, else issues with coefficients accelerating to large values were observed. This was due to the residual difference becoming larger at each step, with increasingly large

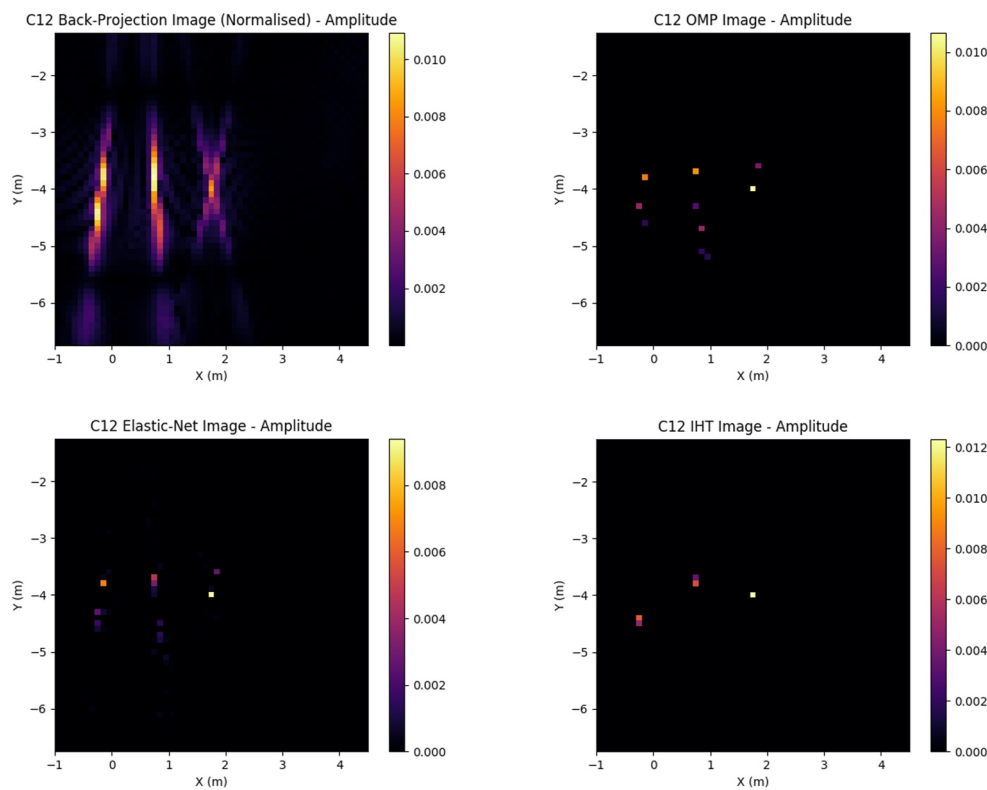


FIGURE 8 Backprojection and recovery algorithm outputs for the modified A matrix model.

coefficient values being required to attempt to control this. This has already been included in the regular IHT results in Figure 8.

Finally, through the use of ideas similar to the CLEAN algorithm [33], the IHT algorithm can be modified so that H_s varies with the iteration number. This can take the form of either a fixed number of iterations per increment of H_s , or waiting until the difference in errors between iterations is suitably low. Each time a scatterer is added a significant increase in the residual error is observed which, while possible in regular IHT, required a measure of "best versus current" error to be checked to see if adding an additional scatterer fails to achieve better error than a previous result.

This leads to the IHT algorithm being fully expressed as follows:

$$\Gamma_{n+1} = H_s(n) \left(\Gamma_n + \mu \lambda A^T (\Phi - A \Gamma_n) \right) \quad (12)$$

In testing, a learning rate of 0.1 was successful in guarding against the coefficients accelerating in value, with H_s being initialised as 1 and increasing by 1 every 5 iterations. The normalisation value λ is calculated to preserve a coefficient's magnitude after being passed through $A^T A$.

The results for implementing these three additions and rerunning the same dataset, and processing case, as Section 4.1 are shown in Figure 9. In this case the IHT algorithm has produced a result at $H_s = 3$, a case which previously did not converge on a solution, and was able to produce a solution of three approximately equal scatterers. The algorithm can be allowed to postulate $H_s > 3$, however lower errors are observed for $H_s = 3$ and so this is the selected output. The scatterer's amplitudes are all approximately equal and in-line with the backprojection result, and as H_s only allows three non-zero coefficients there is no excess energy placed into the range sidelobes.

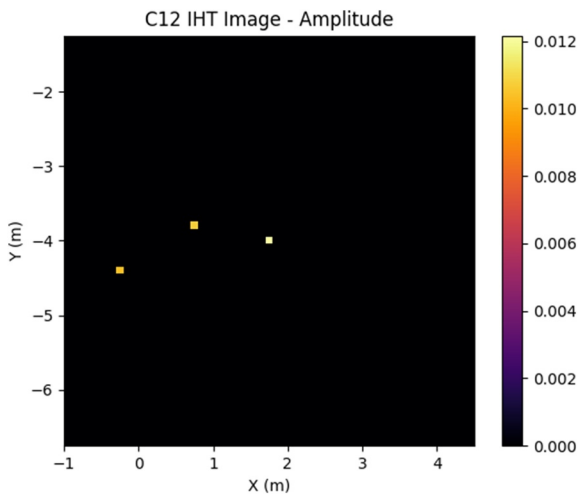


FIGURE 9 IHT2 reconstruction of the same dataset as Figure 8.

4.3 | Quantitative performance assessment

Until this point the recovery performance has been assessed purely visually. In order to give a more detailed comparison of the algorithms a number of metrics are presented in this section, and applied to results in Table 2.

Two metrics are used which do not require a ground truth estimation, which was required for the metrics used in previous work. The N_{99} value gives the number of pixels in the resultant image that account for 99% of the total power in the image. This is to give a comparison between ElasticNet, which does not have an explicit limit on the number of non-zero pixels, and OMP/IHT. The L_2 error is also used on the residual between the data captured Φ and the reconstructed data $A\Gamma$. Neither of these metrics are dependent on knowing the ground truth of the image. The reference value for this is the L_2 error of the original Φ data.

As the data for these experiments was collected in a well-controlled environment ground truth was measured and used to derive two further metrics, which are developments on those used previously.

The first metric of this type is a computation of the sum of the distances between each scatterer in the ground truth array and the closest scatterer in the estimate, referred to from this point as total scatterer distance error (TSDE). If the sidelobes have been sufficiently suppressed this will lead to a lower value indicated a more accurate placement of the scatterer. This is vulnerable to large extended sidelobes putting some energy close to (or on) the original position, so it is not suitable as a metric by itself. The range and cross-range components have been individually highlighted, as this assists with determining whether the error is due to the extended range sidelobes from the bandwidth-induced resolution, or if it is due to the cross-range sidelobes from the multistatic apertures. From this, an error in cross-range is less desirable than an error in range, although in the ideal case the total error should be zero.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (13)$$

The second metric, total excess energy (TEE), is carried over from the previous work, and this is to sum the total energy in the image estimate that has not been attributed to a ground truth position. This is after the ground truth to estimation step has been executed, which is the key difference between this and the scatterer position mean-squared error used in the 2023 work. A lower value is preferred, as this would indicate there is little energy in the image that is not directly attributable to a scatterer. The mean-squared error calculation for a ground truth Y_i and image estimate $\hat{Y}_i$ is shown in Equation (13). The reference value in this column is the TEE value for the regular backprojection image.

The results in Table 2 show the recovery performances of the four algorithms across the metrics outlined above for three datasets: C12, C14, and C18. These datasets consist of trihedrals in different combinations placed along the 4 m range

TABLE 2 Quantitative recovery performance results for datasets C12, C14, and C18. Best performance numbers are in bold with reference values excluded.

Dataset	Error metric	N_{99}	$\ \Phi - \mathbf{A}\Gamma^V\ _2$	TSDE (range, m)	TSDE (cross-range, m)	TSDE (m)	TEE
Simple model							
C12	Reference	896	0.757	0.0	0.0	0.0	7.7
	OMP	10	0.373	0.1	0.1	0.14	1.2×10^{-8}
	ElasticNet	59	0.185	0.1	0.0	0.10	2.0×10^{-8}
	IHT	10	0.441	0.1	0.2	0.223	6.07×10^{-9}
	IHT2	9	0.396	0.1	0.1	0.141	1.24×10^{-8}
C14	Reference	1245	0.643	0.0	0.0	0.0	5.5
	OMP	10	0.325	0.2	0.4	0.458	1.67×10^{-8}
	ElasticNet	60	0.187	0.1	0.1	0.20	5.63×10^{-9}
	IHT	10	0.424	2.0	0.3	2.144	3.54×10^{-9}
	IHT2	10	0.343	0.1	0.3	0.341	9.34×10^{-9}
C18	Reference	821	1.228	0.0	0.0	0.0	19.9
	OMP	10	0.562	0.9	0.4	1.21	4.29×10^{-8}
	ElasticNet	69	0.232	0.0	0.0	0.0	2.16×10^{-8}
	IHT	9	0.728	1.0	0.3	1.30	1.15×10^{-8}
	IHT2	9	0.595	1.0	0.3	1.30	4.15×10^{-8}
Modified model							
C12	Reference	896	0.757	0.0	0.0	0.0	7.7
	OMP	9	0.188	0.1	0.5	0.524	4.19×10^{-8}
	ElasticNet	19	0.133	0.1	0.2	0.223	2.0×10^{-8}
	IHT	10	0.313	1.1	0.1	1.14	1.87×10^{-8}
	IHT2	8	0.210	0.1	0.5	0.524	4.49×10^{-8}
C14	Reference	1245	0.643	0.0	0.0	0.0	5.5
	OMP	9	0.121	0.2	0.1	0.30	4.55×10^{-8}
	ElasticNet	15	0.098	0.1	0.3	0.324	1.91×10^{-8}
	IHT	10	0.262	2.0	0.3	2.14	1.98×10^{-8}
	IHT2	7	0.155	0.1	0.4	0.424	1.66×10^{-8}
C18	Reference	821	1.228	0.0	0.0	0.0	19.9
	OMP	8	0.308	0.0	0.5	0.50	6.14×10^{-8}
	ElasticNet	34	0.202	0.0	0.1	0.10	9.04×10^{-8}
	IHT	9	0.414	0.0	0.3	0.30	3.62×10^{-8}
	IHT2	7	0.341	0.0	0.5	0.50	3.82×10^{-8}

line. Any tuning parameters for the algorithms were set on C12, with C14 and C18 considered to be test datasets. For the IHT2 results the "best" iteration was chosen rather than the final one.

The "Reference" row refers to use of traditional back-projection techniques for all columns except the L_2 error of the residual. In this column, the reference value is the L_2 norm of the phase history, Φ , alone. The reference row shows the backprojection gives an accurate determination of scatterer

positions, however this is based on a large amount of scatterers in the image and a significant amount of excess energy.

Looking at overall trends and comparing the simple and modified models.

- Regardless of whether the simple or modified models are used all of the algorithms were able to produce significant decreases in the L_2 error and TEE compared to the

reference values, with a significant decrease in the number of point-like scatterers required in the estimation.

- Given the increase in TSDE an interpretation of this is that the fit given by the estimation algorithms is not necessarily better than backprojection, as the scatterers are not always in the correct positions, but the lower N_{99} and L_2 values mean we have a good fit nonetheless.
- In all cases the modified Model produced lower L_2 errors than the Simple Model with the image energy concentrated in fewer scatterers. This was frequently accompanied by a rise in the TEE, however the TEE is vulnerable to errors in the ground truth.

When comparing between the three algorithms.

- ElasticNet had the lowest L_2 error across all datasets and methods however it achieved this by spreading power out among a greater number of scatterers, as seen by the N_{99} column. It was also best at positioning the scatterers accurately, as shown by achieving the lowest TSDE values, but this was because it is fitting a large number of scatterers to the extended range sidelobes, tending to have some energy close to the ground truth as a result.
- OMP produced the second-best L_2 error after ElasticNet, however its limited number of non-zero coefficients combined with the range sidelobes to generate larger TSDE values. These errors are far greater than could be reasonably attributed to ground truth alone.
- IHT2 outperformed IHT on L_2 error with fewer scatterers, however both IHT algorithms were consistently worse than

OMP and ElasticNet. It showed the same issue as OMP where a hard limited number of coefficients meant it could generate comparable L_2 errors while misplacing scatterers in the range sidelobe (when compared to the ground truth).

- Dataset C18 with its mixed types of trihedrals did have the highest L_2 errors on the residuals for all of the algorithms, while C12 and C14 were broadly similar in across both models.

4.4 | Complex scattering objects

The final imagery presented considers the model T-64 observed at the back of the imaging scene in Figure 1. The datasets to this point have all contained simply canonical scatterers, so this represents an object of significant scattering complexity to recover.

Figure 10 shows four different views of the model tank. Top-left is a close-in photograph of the tank for referring back to. The bottom two images show resultant SAR images of the tank with 100% (left) and 50% (right) of the aperture remaining with the aperture centred on the tank. In the left image the barrel can be clearly identified, along with a bright spot moving along the left side of the hull. There is an increased response around the turret, and a bright spot where the right fender meets the upper glacis. In the reduced aperture version a number of changes are observed. Firstly, there is a large sidelobe generated by the side of the hull that extends far beyond the edge of the tank. Secondly, there is an interference pattern observed across the whole image leading to a beating

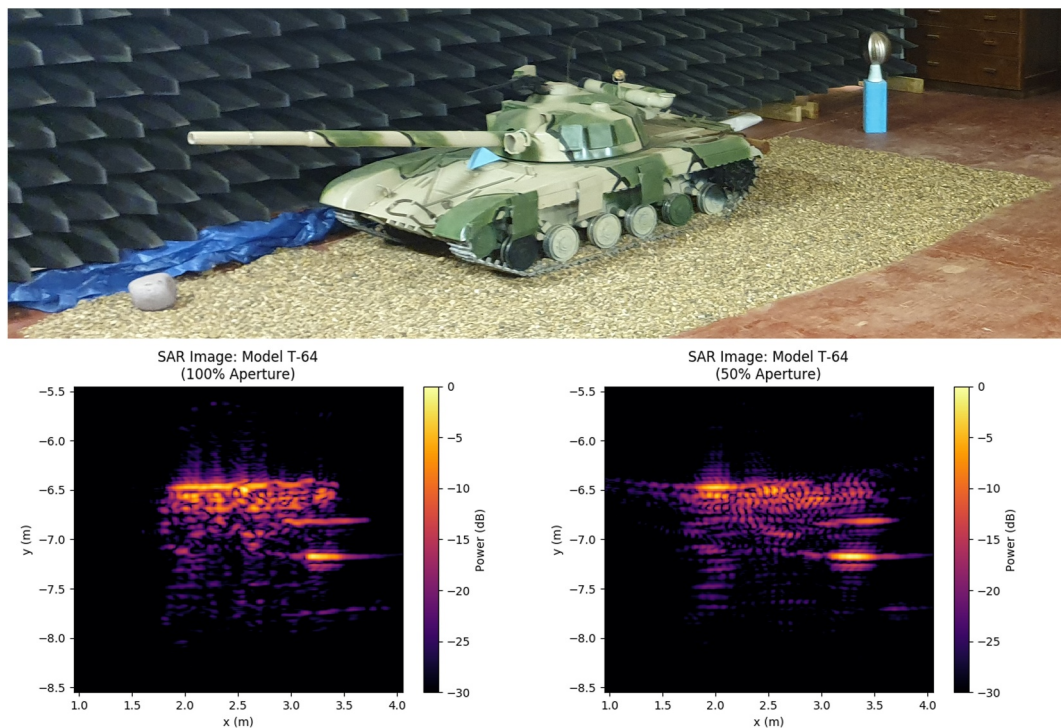


FIGURE 10 The model T-64 and resultant images: *top* photograph of the tank and gravel bed, *bottom left* 100% aperture image, *bottom right* 50% aperture image.

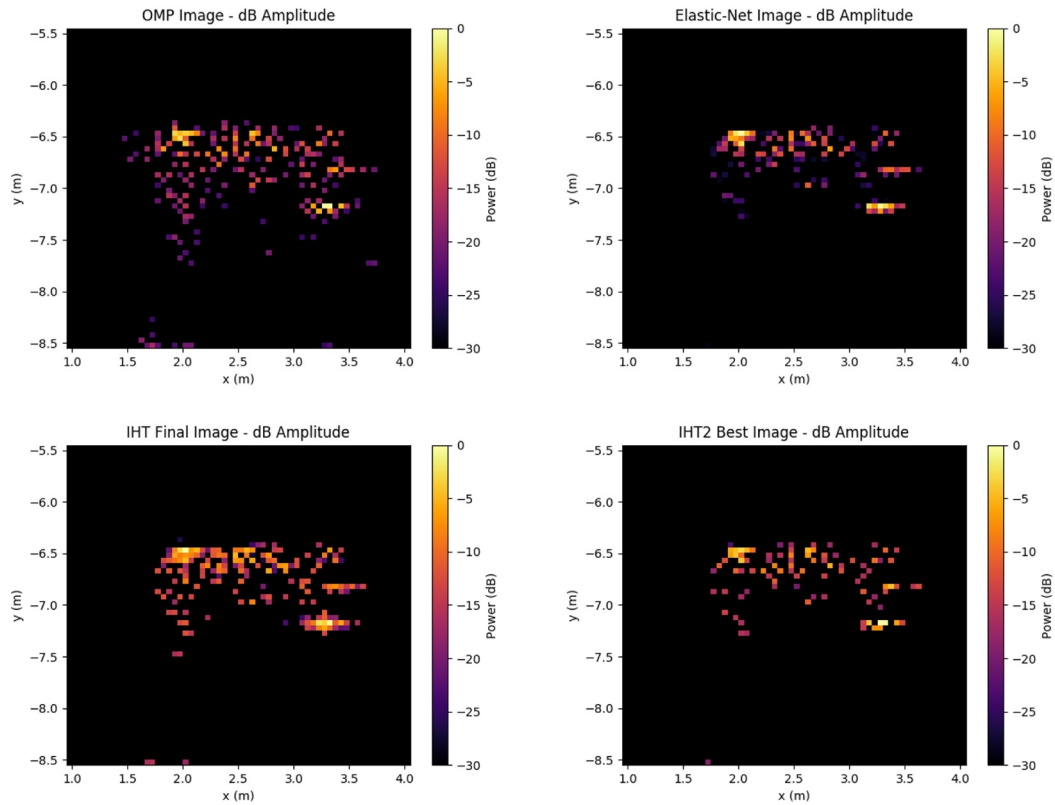


FIGURE 11 Image estimation results for OMP, ElasticNet, IHT, and IHT2 for the tank in Figure 10 using the Simple Model.

effect on the pixel power. Finally, the bright spot along the sidelobe is degraded in the centre, while the dihedral shape formed between the fender and upper glacis becomes significantly brighter.

The top-right figure gives a composite image, plotting the left and right apertures in green and red respectively scaled to the same maximum value to give comparable colour bars. This shows that the fender-glacis dihedral and barrel responses are far stronger in the right section of the aperture, while the left contains far stronger responses from the hull and turret. The gravel bed the tank is resting on is below the -30 dB clipping applied to these images, to focus on the response from the tank itself.

There are three key features of this collection worth noting which would differ in a typical X-Band SAR collection from an aircraft. Firstly, the frequency is not scaled to the model, and therefore the interactions are not of the correct scale for this to be fully representative. Secondly, the near-field nature of the collection will mean that the wavefront curvature will have an impact on the response, which would be negligible in the far-field collection. This latter effect is obvious in the shape of the sidelobe response in the 50% aperture image, where a far-field would expect the cross-range sidelobe to be parallel to the track (for a side-looking array). Finally, for a spotlight SAR image typically the beam footprint is both far larger than the scene and steered to maintain a relatively equal power across the scene. In these experiments the beamwidth is narrower than the scene, thus the Gaussian shape added to correct for the beampattern may not be necessary in a far-field scene.

These assumptions noted, this dataset demonstrates the complexity of attempting to move these techniques onto a detailed compound scattering object with a 50% central aperture reduction.

Figures 11 and 12 show the algorithms attempting to recover the tank using the same settings as previously with the simple and modified models respectively, with the N_{99} and L_2 residual values given in Table 3.

As in Section 4.3 the modified model produces lower L_2 errors than the simple model, however the improvements are very slight. Any type of image estimation produces a far lower L_2 error than the reference values. For this dataset the ground truth was not estimated as its accuracy was unlikely to be high enough to produce meaningful results. Visually, the images in Figures 11 and 12 have all successfully reduced the large cross-range sidelobe seen in the 50% aperture image in 10 and yielded an image where the tank has approximately the correct dimensions and features, such as the barrel and fender-glacis dihedral. Comparing simple and modified models does not yield significant differences in the imagery.

When comparing between the algorithms, one striking observation is that the L_2 values are all remarkably close together, despite the algorithms producing images that appear visually very different. It is also noticeable that the trend that ElasticNet showed in Section 4.3 of having a better L_2 error and higher N_{99} than OMP and IHT is no longer the case in Table 3. For a complex scattering scenario such as this there are likely many solutions that produce low errors which are challenging to

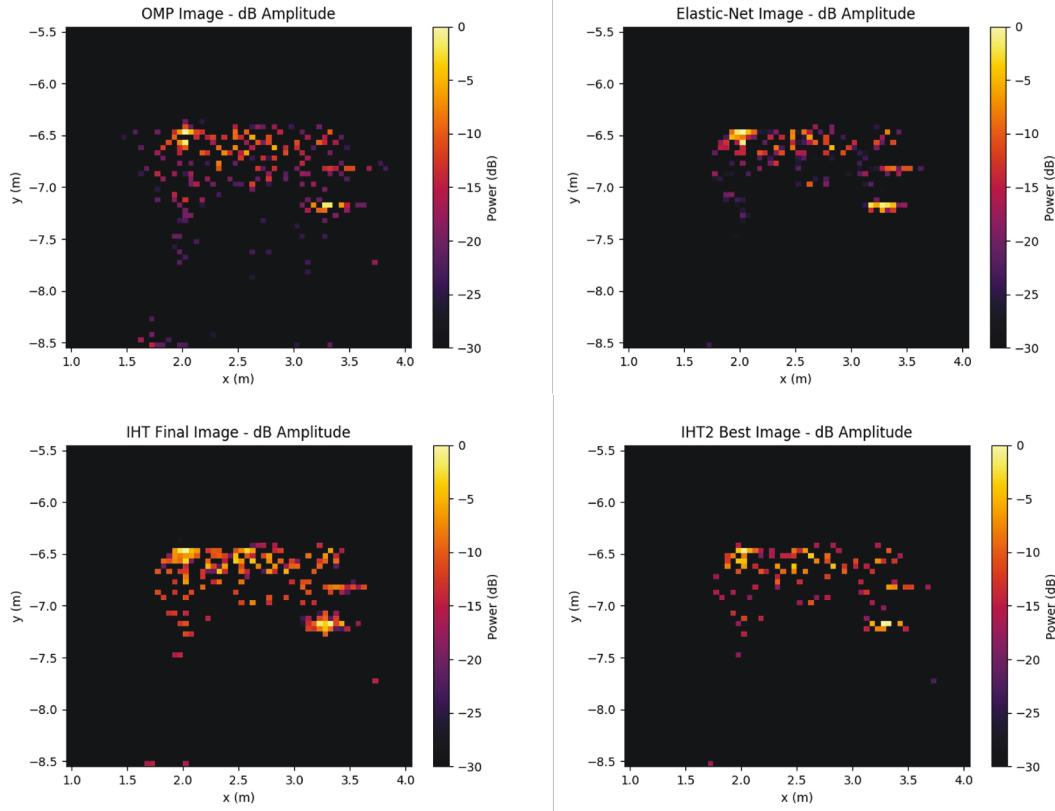


FIGURE 12 Image estimation results for OMP, ElasticNet, IHT, and IHT2 for the tank in Figure 10 using the modified model.

TABLE 3 Scatterer count and L_2 errors for the tank reconstructions in Figures 11 and 12.

Simple model Algorithm	Isotropic		Modified model	
	N_{99}	$\ \Phi - A\Gamma^v\ _2$	N_{99}	$\ \Phi - A\Gamma^v\ _2$
Reference	-	1.282	-	1.282
OMP	166	0.558	162	0.550
ElasticNet	101	0.659	108	0.646
IHT	150	0.581	146	0.575
IHT2	84	0.626	87	0.609

distinguish between. It is also possible that the scale of frequency interactions at this scale (1:4 scale) is causing more complex interactions that does not approximate well to point-like scatterers.

5 | ANALYSIS

5.1 | Reconstruction performance

When comparing the results from Sections 3.2 and 4.1 a few conclusions can be drawn.

- Despite strong simulated performance the isotropic model is not capable of fully accounting for the complexities of real

data. In this case, the beampattern producing a directional response was a significant factor that was unaccounted for and therefore the performance of the recovery algorithms suffered.

- It is possible to create a more detailed model of a collection to improve performance, based on measurements of simple scatterers and applying those to the measurement matrix. This model, when applied to compressive sensing techniques, is able to produce improved results compared to the simple isotropic model.
- Through examining the algorithms and further development performance improvements can be made for this specific case.

The range sidelobes do require careful consideration, as they do challenge the algorithms where a scatterer extends over a large number of pixels. Table 2 show the impact on scatterer placement accuracy that the sidelobes can have. The ability to place multiple scatterers whose sum satisfies the observed data gives the potential for confusion and, for OMP and IHT, require estimations of the number of non-zero coefficients to be greater than the number of scatterers in order to account for these errors.

The datasets presented in Section 4.3 demonstrate that the excess energy is able to be successfully suppressed compared to a backprojection collection regardless of the scattering model used. Errors in cross-range can be accounted for

through use of the modified model, and the modified model outperforms the simple model in all cases. Of the four recovery algorithms tested ElasticNet performed the best on the trihedral datasets.

Finally when looking at the T-64 results in Section 4.4, and using the algorithm metrics from the trihedral datasets, an improvement in the L_2 error can be observed when using the modified model for recovery, however the improvement is relatively slight.

The improvements to the A matrix, and modifications to the IHT algorithm, have shown that it is possible to add further complexity to the simple measurement model previously used and see gains in visual and quantitative performance.

5.2 | Further A matrix improvements

When analysing these results further the original assumptions made as part of the A matrix design should be reconsidered for their impact. This section refers back to assumptions and exclusions made in Section 3.7 to examine what impact they may have had on the results and their viability for inclusion in further work.

All of the results presented are for a single polarisation (VV), despite GBSAR's capability to collect a fully polarimetric scene. In this work this was the only polarisation collected, however there is no reason why a full polarimetric dataset could not be processed. A suitable matrix decomposition, such as the Krogager [34] or Pauli [35] decompositions could be used, as inputs to the CS techniques.

The modified A matrix, as implemented, considers only objects that give an azimuth Gaussian response due to the beam-pattern limitation. Prior to this being demonstrated to be the limiting factor, the A matrix was expected to encode only trihedrals facing a given angle as Γ encoded RCS. It was hypothesised that a method of concatenating A and Γ matrices could be used as a way of distinguishing multiple scatterers, in a similar manner to polarisation, however this was only briefly attempted due to the memory issues leading to images that either had insufficient pixels or theoretical SAR resolution to be useful.

The impact of being in the near-field is also worth discussing. The extended sidelobes of scatterers are partly because of the processing, but also their physical size leading to them extending over multiple pixels. At present the geometric approach has been applied to this, however for objects that are close/large a physical optics regime may be more appropriate, which will be beyond the mathematical approach employed at present. Considering now Figure 10 as an example of a complex object, being the model T-64, it is obvious that this is a far more complex scattering scenario. Simulating an object such as this is computationally expensive, and whilst entirely achievable will not fit into the A matrix method of computing all of the elements of A in advance.

5.3 | Practical application

Whilst the performance of the recovery algorithms has been demonstrated, a brief discussion of the practicalities of these for data gathering tasks is warranted for completeness.

A complex object would require a more detailed analysis in order to produce an image suitable for further intelligence use than the simple trihedral models used earlier. In order to instil confidence that the recovery process is successful a much clearer idea of the scattering phenomenology would be necessary. This would ultimately require evaluation of a greater volume of more diverse data, with robust metrics for determining recovery performance.

If employed on a single platform, the reduced-aperture concept employed here the platform would still be required to visit the extreme edges of the full aperture to determine the resolution. A large gap would allow for time-dependent interference/jamming to be mitigated and potentially recover back to a full-resolution image, however without a pressing reason to not collect that data it may be an easier proposition to collect as much as possible. If multiple platforms are employed there would be challenges involved in timing synchronisation, data transfer, and computational cost, and this would be closer to the RIBI concept.

There is also the computational cost to consider when looking for a practical application of these algorithms. Whilst a sparse collection may reduce the time required taking measurements this may shift an unsatisfactory burden onto recovery computation. For low-cost sensors this may place requirements on the processing capability that are simply not feasible within size, weight, and power constraints.

5.4 | Future work

The matrix approach is ultimately limited by the memory required to hold and manipulate the large matrices formed, and the A matrix also requires significant calculation time to initialise. Adding in the additional modelling discussed in the previous section and it becomes obvious quickly that, with currently processing power, there is a limitation on the performance that can be obtained using this approach.

One could examine a functional approach to this, where A and A' become abstracted as more complex forward and backward projection functions. A functional version of A would not require all of the elements to be calculated prior to recovery, and so could utilise a higher-fidelity simulation and add some of the exclusions highlighted here. The disadvantage of this is that every projection step is slow, which contrasts with the matrix approach which, once initialised, is able to rapidly transform between Φ and Γ . Balancing fidelity and computational cost would be critical in a functional approach, however having the option for greater fidelity would be welcome.

One additional development of the IHT algorithm could be to use a second algorithm, such as ElasticNet, to produce an estimate of the number of non-zero coefficients. This would remove the challenge of determining this value on unseen data, however it would clearly be an increase in computational cost to effectively run two CS algorithms sequentially. Alternative approaches to compressive sensing are also available to replace the recovery stage of image formation such as machine learning.

6 | CONCLUSIONS

This work has demonstrated that, whilst an isotropic model might provide acceptable results, it is possible to create a more representative model of RF propagation that improves the performance of CS recovery algorithms when applied to real data. The first set of result focused on trihedrals, and ElasticNet, OMP, and IHT all performed better when using this modified model, according to both visual inspection and the image quality metrics presented.

When comparing the performance of the algorithms used, ElasticNet was the most consistently effective algorithm according to the quantitative metrics used. The results for OMP and IHT demonstrated the difficulty in setting a pre-determined number of non-zero coefficients for an unknown image, although they also have comparable performance with ElasticNet. The IHT2 algorithm developed, including a learning rate and an increasingly hard threshold, was able to produce comparable L_2 errors as IHT with fewer non-zero coefficients.

The paper focused on accounting for azimuth and frequency variation in improving the model, however the results on a more complex scattering object showed that these do not necessarily increase the fidelity of the model to noticeably improve performance. Effects such as elevation angle, polarisation, and physical optics may be required, however this would involve balancing performance with the increased computational cost of running multiple iterations of a more complex mode.

AUTHOR CONTRIBUTIONS

George A. J. Price: Investigation; Formal Analysis; Writing - Original Draft. **Daniel Andre** Conceptualisation; Resources; Supervision. **Chris Moate** Conceptualisation; Methodology; Writing - Review and Editing. **Peter Yuen** Supervision. **Mark Finnis** Software; Data Curation.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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Modelling realworld effects in nearfield SAR collections for compressive sensing

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