

Multi-modal analysis of barely visible impact damage in carbon fibre composites through the fusion of Pulsed Thermography and Phased Array Ultrasonic Testing

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ABSTRACT

The increasing use of composite materials in modern aircraft structures has necessitated more efficient and reliable inspection techniques to ensure structural integrity and operational safety. Barely visible impact damage (BVID) poses a significant challenge in composite maintenance due to its subtle nature, requiring advanced non-destructive testing and evaluation (NDT&E) methods for accurate detection and characterisation. This study explores a multi-modal inspection approach that integrates phased array ultrasonic testing (PAUT) and pulsed thermography (PT) to enhance BVID detection in carbon fibre-reinforced polymer (CFRP) composites. By leveraging complementary fusion strategies, the proposed framework improves defect localisation beyond the limitations of individual techniques. The results demonstrate that fusion increased PAUT-detected sizes by up to 7% for thin specimens and 8% for thick ones, while PT-detected sizes improved by as much as 71% and 53%, respectively. These findings highlight the synergistic advantages of multi-modal NDT&E, showcasing its potential to provide complementary defect assessment and reduce uncertainty in damage evaluation. The results of this study contribute to the development of more sophisticated inspection methodologies, which ultimately support more efficient and reliable maintenance strategies in aviation.

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1. Introduction

Air transportation might be considered a shining star of global trade, with an annual growth rate of 5.1% for passenger traffic and 5.6% for cargo traffic [1], respectively. Airlines have focused on contemporary approaches to maintaining flight operations and supportive actions, such as scheduling and maintenance. Maintenance is one of the most revolutionised phenomena that struggles with the compensation of more than 2000 actions per year for an ordinary passenger aircraft [2]. Among these actions, maintaining structural integrity is a crucial engineering application working under dynamic stress and environmental conditions, requiring a high standard of reliability and durability [3].

The growing portions of composite structures in modern aircraft reveal the need for protection against particular damages caused by the layered nature of composite structures [4]. Composite structures are highly susceptible to barely visible impact damage (BVID), which generally occurs during ground services. BVID might considerably endanger the structure due to the invisible internal effect may induce vital delamination between the plies, or matrix cracks in composites [5]. Once subjected to structural stresses, this defect can accelerate dramatically, potentially leading to component failure.

To mitigate the hazards connected with BVIDs, it is critical to diagnose them accurately in the early stage. In addition, understanding the location and extent of the defect is significant to assess aircraft components properly [6]. Traditional inspection techniques rely on frequent scanning, such as C-scan which might often face challenges in accurately detecting and characterising defects, particularly in complex composite materials. However, this kind of routine maintenance schedule requires service

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interruptions grounding the aircraft in a certain period that reduces profitability [7]. Advanced signal processing methods, such as data/image fusion, can provide a powerful solution by integrating complementary information from multiple inspection techniques, thereby enhancing detection accuracy and reliability as well as potentially decreasing ground time. In particular, the combination of deep effective ultrasonic and surface-efficient thermography inspections might ensure a holistic detection of such subtle and critical BVIDs.

Current literature has a number of research articles to address difficulties regarding BVID detection, especially on aviation composites. Each NDT&E technique has a distinct capability to investigate BVID. In the last decade, ultrasonic [8–19], X-ray tomography [12,18], optical profilometry [12,18], guided waves [20–24], acoustic emission [25] and thermographic [26–29] methods have already been applied successfully accordingly to their ability to sense. Ultrasonic inspection is commonly used for internal structures due to its accurate imaging capabilities. In addition, several studies have utilised various strategies to check BVID, but these strategies have been employed to confirm, compare, or assess each other rather than combining them [12,18].

Alternatively, the literature has few investigations combining different modalities to get their synergistic effect of sensing ability. One recent example of that is [30]. The authors present a comprehensive methodology for constructing a parametric model of BVID in carbon fibre-reinforced composite structures. The approach integrates data from experimental tests, including X-ray computed tomography (CT) scans and ultrasonic B and C-Scans, with numerical simulations of low-velocity impact loading. By combining these methods, the realistic geometry and delamination patterns of BVID were accurately reconstructed, while numerical simulations validated and refined the damage extent. An original procedure for reconstructing BVID from non-destructive testing data was developed to create parametric computer-aided design (CAD) models. This enabled the characterisation of generic BVID shapes across a range of impact energies and impactor types. In a similar but older study, the same research group analysed the discrepancies between ultrasonic testing (UT) and CT results and proposed a correction factor to improve UT's accuracy [31]. The findings revealed that UT underestimates the damage extent, and the proposed correction factor significantly enhances its reliability for BVID evaluation.

Another example study introduces an integrated nonlinear ultrasound (NU) and vibrothermography (VT) non-destructive testing (NDT) method to detect BVID in CFRP components [32]. In this method, a continuous ultrasound wave is transmitted through the CFRP and received by a piezoelectric sensor. Any damage in the propagation path modulates the received signal, causing variances in high-frequency harmonic components, which forms the basis of ultrasonic testing. Simultaneously, an infrared (IR) camera captures surface temperature changes in the transmission area. Damage in the ultrasonic path causes localised heating due to frictional and conduction effects, enabling VT detection. The method was tested on CFRP plates with visible impact damage (VID) at 5, 15, and 25 J and BVID at 12 and 16 J. Signal processing, including fast Fourier transform, demonstrated improved detection capability, highlighting the potential of this approach for efficient and precise inspection of CFRP structures.

A further example of combination trials is unimodal but using multiple damage indices (DIs) based on amplitude variation, symbolic dynamics, and root mean square deviation, combined via data fusion across excitation frequencies [33]. An imaging algorithm was employed for localisation, while a distance-based classification approach achieved over 91 percent accuracy in most cases. It was emphasised that combining frequencies and DIs improved the robustness and consistency of the damage assessment process.

Building on these advancements in combinatory non-destructive testing (NDT) techniques, this study proposes a novel approach combining Phased Array Ultrasonic Testing (PAUT) and Pulsed Thermography (PT) for the inspection of barely visible impact damage (BVID) in composite structures. This integrated methodology leverages the complementary strengths of PAUT and PT, PAUT's ability to accurately detect and localise subsurface damage and PT's sensitivity to surface-level and near-surface anomalies. By fusing data from these two techniques, the approach aims to improve detection reliability, provide a more comprehensive characterisation of damage, and address limitations inherent to single-modality inspections. The aforementioned examples indicate that it is possible to have a number of papers dealing with unimodal NDT&E on BVID assessment of carbon fibre composites, but the research regarding the combination of those NDT&E methods is rarely available in current literature. In particular, although a lot of research papers have inspected BVID characteristics using thermography and ultrasonic methods, the majority of these studies have preferred to evaluate and compare their results employing an accompanying inspection modality. It should be stated that the combination of individual NDT&E modalities has not been widely presented, namely the fusion of PT and

PAUT specifically. This combined framework is designed to enhance both the precision and efficiency of BVID evaluation in advanced composite materials.

2. Methodology

2.1. Material and specimen description

Modern aerospace structures increasingly rely on fibre-reinforced plastic composites due to their high specific mechanical properties [34]. However, these materials are prone to barely visible impact damage (BVID), caused by low-velocity impacts that create internal delaminations while leaving the surface visibly intact. BVID significantly reduces local strength and can propagate under fluctuating stresses, leading to potentially catastrophic failures [35].

To investigate barely visible impact damage (BVID) in this study, two sets of carbon fibre-reinforced polymer (CFRP) specimens were tested with defects introduced at varying energy levels in accordance with ASTM impact testing standards [36]. The CFRP material used was unidirectional (UD) pre-preg IMS-977-2. The specimens were fabricated as laminates and cut into coupon dimensions of $100 \times 150 \text{ mm}^2$, with the fibre direction aligned parallel to the longer edge to replicate the structural characteristics of composite aircraft fuselages.

The first group of specimens consisted of nine plies with an average cured thickness of 1.65 mm. This group included five specimens subjected to impact energies of 2.5, 4, 8, and 12 joules (J). To ensure repeatability in the experimental procedure, two coupons were impacted at 8 J. They will be called 8 Ja and 8 Jb in further steps. The second group comprised laminates with 18 plies, resulting in an average cured thickness of 3.8 mm. This set was impacted with energies of 4, 8, 12, and 20 J. The selected energy levels are based on prior knowledge of generating barely visible impact damage in the specimens. These impacts are expected to create internal defects that cannot be seen by the naked eye. All specimens were impacted at the central region of their front surface, while the back side remained unaffected. Throughout the article, the front side is referred to as the 'surface', and the back side as the 'back wall'. While they are discussed collectively, they will be referred to as 'thin' and 'thick' specimens in the following sections, and summarised in Table 1.

2.2. Experimental procedures

2.2.1. PAUT data acquisition and processing for BVID inspection

The Phased Array Ultrasonic Testing (PAUT) system used in this study was the Sonatest PA X3 series, equipped with a 10 MHz frequency transducer. This transducer is a 64-element linear phased array with an element pitch of 0.6 mm, and it is mounted with a custom flat elastomer wedge to ensure consistent contact with the specimen. The active aperture used in the scanning process consists of eight elements from the total array, allowing dynamic control of the ultrasonic beam for focusing and steering. The system captures waveform data at a sampling frequency of 125 MHz, providing high temporal resolution.

The PAUT system recorded A-scans at discrete locations along the specimen during a linear scan. The total number of A-scans (M) in a single scan is calculated as follows:

$$M = (\text{total number of elements} - \text{active sub-aperture size} + 1) = 64 - 8 + 1 = 57$$

This results in a linear scan width of 34.2 mm, where each frame represents a 1 mm slice of the specimen alongside the longer edges of specimens. The data for each scan consists of 57 A-scans (1 mm frame), each containing 504 amplitude values, forming a 3D matrix of dimensions $57 \times 504 \times 150$ for a single specimen.

Table 1. Description of BVID specimens.

Specimens	Defect	Layup	Number of Plies	Thickness (mm)	Sizes (mm)
BVID thin specimens	2.5, 4, 8, 12 Joules Impact damages	[45/ – 45/90/0/90/0/90/ – 45/45]	9	1.65	100 x 150
BVID thick specimens	4, 8, 12, 20 Joules Impact damages	[45/ – 45/90/0/90/0/90/ – 45/45] _s	18	3.8	100 x 150

The scanning distance is analogous to the longer side of an image, with a total scan length depending on the size of the specimen (150 frames for 150 mm).

The specimens were prepared and scanned in accordance with guidelines to ensure accurate alignment and full surface coverage. The scanning process was designed to produce linear scans that were straight and evenly spaced, based on the transducer's acquisition area. This approach facilitated the whole surface coverage, thereby ensuring that all regions of interest were captured during data collection.

To avoid interference from excessive coupling media, the scans were performed on dry, flat surfaces with a thin layer of water spray as the coupling agent. An encoder was employed to track the probe's movement, ensuring precise measurement of the scanning distance. The specimens were aligned according to strict guidelines to ensure complete surface coverage, enabling comprehensive analysis.

The processing framework ensures robust and precise extraction of defect information from the scanning of composite materials through a systematic methodology. Pre-processing involves A-scan alignment to minimise surface roughness effects and Time Gain Compensation (TGC) to compensate for signal attenuation with depth [37]. Echo localisation utilises wavelet transforms to identify prominent echoes, windowing to focus on signals above a threshold, and cross-correlation with a reference model to extract key characteristics like amplitude and time lag. Iterative subtraction further isolates significant echoes. Thresholding optimises defect detection by balancing sensitivity and specificity, distinguishing defect signals from structural noise. The final output includes accurately localised defect echoes with their peak amplitudes and time locations. This processing framework provides a robust and accurate methodology for extracting defect information, with iterative analysis ensuring high-quality localisation and characterisation of defects within the composite material.

2.2.2. PT data acquisition and processing for BVID inspection

To obtain thermograms in this study, a high-definition cooled infrared camera (FLIR X8501sc, $NE\delta T < 20mK$, InSb, 3–5 μm , 1280 $\times$ 1024 pixels, linear Sterling cooling, 50 mm focal length) was utilised alongside two xenon flashes (Balcar, 6.2 kJ per flash, 2 ms pulse duration @ FWHM), all synchronised via a PC and a custom-made controller unit. The camera was positioned about 60 cm from the specimens (to cover the whole surface), while the flashes were placed 50 cm from the specimens and 50 cm between each other, forming a 45° angle to the sample surface (reflection mode). In reflection mode, the flashes were positioned in front of the specimens, capturing surface-level thermal responses critical for identifying near-surface defects. In transmission mode, the flashes were placed behind the specimens to enable through-thickness heat propagation analysis, providing insights into thermal diffusivity [38]. Thermograms were recorded from the surface via reflection and from the back wall via transmission, enabling different perspectives on internal features. All specimens were inspected individually in both modes, with thermographic sequences comprising 1100 frames at 145 Hz frequency, during approximately 7.6 s. Figure 1 presents the experimental setup for PT data recording in reflection mode. In transmission mode, the excitation sources (flash lamps) should be placed on the other side of the specimen.

Selecting the optimal frame for defect visualisation was a critical challenge in thermographic analysis. To address this, adaptive thresholding was applied, a technique that dynamically adjusts the threshold value



Figure 1. PT experimental setup in reflection mode with a BVID specimen.

Table 2. Selected PT reflection frames and their corresponding times based on specimen and impact energy levels (frame rate: 145 hz).

Energy Level	Thin Specimens	Time (s)	Thick Specimens	Time (s)
2.5 J	Frame 15	0.103	Not applicable	–
4 J	Frame 31	0.214	No defect	–
8 Ja	Frame 51	0.352	Frame 56	0.386
8 Jb	Frame 43	0.297	Frame 94	0.648
12 J	Frame 35	0.241	Frame 112	0.772
20 J	Not applicable	–	Frame 105	0.724

based on the statistical analysis of pixel intensity histograms. This approach ensures that the threshold is tailored to the specific characteristics of each frame, improving the accuracy of defect detection. Following this, the thermogram exhibiting the largest defect area was selected as the most representative image. This decision was made based on a visual inspection of the sequence images, with a particular focus on the temporal evolution of defect detection marks following the flash pulse. Initially, the detection marks exhibited an increase, corresponding to the heating and cooling phases of the specimen. After reaching a peak, the marks began to decrease as the thermal contrast lowered. The frame with the maximum thermal contrast and most pronounced detection mark was selected as the most representative thermogram, as it provided the clearest and most significant indication of defect presence, ensuring optimal defect characterisation for subsequent analysis. The selected PT frames and their corresponding time values for different specimens and impact energy levels are presented in Table 2. Since transmission PT did not yield distinguishable results at the corresponding time points, frames from the first second (frame 145) and third second (frame 435) were selected to represent the thin and thick specimens, respectively.

Line profile analysis played a pivotal role in interpreting the thermal response of materials and identifying anomalies. This approach involves plotting variations of the pixel values along a defined linear path within the thermographic image. Such profiles allow the visualisation of temperature gradients and the identification of irregularities associated with defects or structural features. The line profile's contour is indicative of heat diffusion patterns, which are influenced by both the thermal source configuration and the material properties. By systematically comparing defective and sound areas along the line profile, defect parameters such as size, location, and thermal contrast were quantified. This methodology, integrated with adaptive thresholding, provided a comprehensive approach for defect identification and characterisation in thermographic inspections.

The data processing framework for Pulsed Thermography (PT) incorporates several critical steps aimed at accurately detecting and characterising anomalies. A key initial step is adaptive thresholding, where the threshold value is dynamically adjusted. For each frame in the dataset, the mean (Threshold) and standard deviation (sd) of pixel intensity values are dynamically computed within a defined region of interest (ROI). This step ensures that defects are effectively isolated from the background (defect-free region). These statistical parameters are then adjusted to create a new threshold, calculated as the original mean plus a scaled factor of the standard deviation ($2 \times \text{sd}$), which enhances sensitivity to variations in the data. Figure 2 illustrates the main steps of processing for PAUT and PT from raw data to obtaining extracted features of related defects.

Subsequently, the entire dataset is iteratively processed for each frame, where the intensity values of each pixel are normalised by subtracting the adjusted threshold. This operation yields a residual matrix, which highlights deviations from the threshold and facilitates the detection of anomalies. The resulting residuals are stored sequentially in a 3D matrix, maintaining the spatial and temporal structure of the original data. This methodology effectively amplifies defect-related signals while suppressing background variations.

2.3. Fusion strategies

2.3.1. Centroid-based image alignment method

The centroid-based image alignment method involves aligning two images by calculating and matching their centroids, based on extracted defects. This approach assumes that the centroid of a defect or object within an image serves as its geometric centre. By aligning the centroids of the reference and target images, we can translate one image to align with the other [39]. Here, PAUT inspection images have been selected as

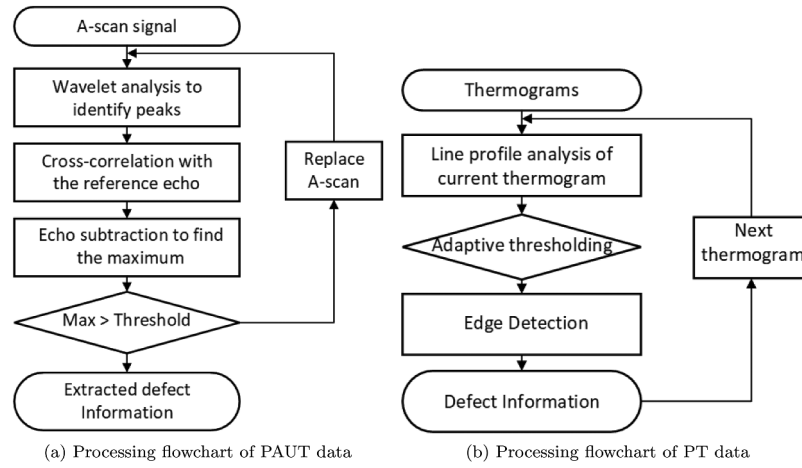


Figure 2. PAUT and PT flowcharts from raw data to defect extraction.

references and PT inspection images as targets. This alignment has been implemented for each fusion method in further stages.

The centroid of a binary image can be computed as the centre of mass of all nonzero pixels in the image. For a binary image $I(x, y)$, the centroid C is calculated using the equations:

$$C_x = \frac{\sum_{x,y} x \cdot I(x, y)}{\sum_{x,y} I(x, y)} \quad (1)$$

$$C_y = \frac{\sum_{x,y} y \cdot I(x, y)}{\sum_{x,y} I(x, y)} \quad (2)$$

where (C_x, C_y) are the coordinates of the centroid, and $I(x, y)$ is the pixel intensity at location (x, y) .

To align the reference image $I_r(x, y)$ with the target image $I_t(x, y)$, their centroids are first computed. The centroid of each image is represented by the coordinates (C_{rx}, C_{ry}) for the reference image and (C_{tx}, C_{ty}) for the target image. A translation vector T is then determined by subtracting the target image's centroid from the reference image's centroid. This vector T represents the necessary shift to align the centroids. The target image is subsequently translated by the computed vector T , producing the transformed (aligned) target image $I'_t(x, y)$, where each pixel is repositioned according to the translation. To visualise the alignment, the reference and transformed target images are overlaid. The overlay combines the images using color channels: The reference image is displayed in red, and the aligned target image is displayed in green (Figure 3).

The centroid-based method provides a straightforward approach to image alignment by leveraging the geometric centre of the objects within the images. It should be emphasised that the data collection of each specimen has been performed in a delicate manner using full-area capturing for the whole surface. It means that individual inspection results should be almost aligned before this step except for slight displacement or shift. Here, it has been assumed that the centroids adequately represent the objects' geometry. In addition, after this alignment stage, the data has been assumed to be perfectly registered for further applications.

2.3.2. Fusion rules

Union (Logical OR). This method combines all the defect regions from both images. If either image has a defect in a particular pixel, that pixel will be marked as a defect in the final image. It ensures that no defects are missed from either image. The fused image shows all the defects present in either the reference or target image.

$$F_{\text{union}}(x, y) = A(x, y) \vee B(x, y) \quad (3)$$

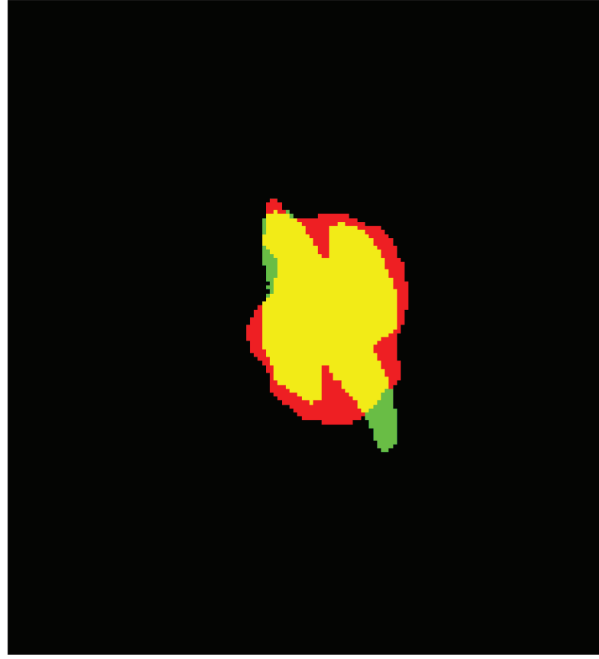


Figure 3. Representative registered image pair based on center-of-mass matching. Red color refers to the reference PAUT image, and green refers to the transformed PT image.

Intersection (Logical AND). The intersection method only highlights the defect regions that appear in both images. If a defect exists in one image but not in the other, it is excluded. This method focuses on finding defects that are common to both images. It is useful when you want to highlight only the most certain and consistent defects that appear in both images.

$$F_{\text{intersection}}(x, y) = A(x, y) \wedge B(x, y) \quad (4)$$

Clustering-based fusion. The process of combining the defect information from PAUT and PT images involves the following steps:

- **Normalisation of Data:** To ensure comparability between the depth data from PAUT and temperature data from PT, normalisation is applied. Using the min-max normalisation technique, both datasets are scaled to the range $[0, 1]$:

$$X_{\text{norm}} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (5)$$

where X represents the original dataset, and X_{norm} is the normalised data. This step standardises the datasets for subsequent clustering and fusion processes.

- **Reversing PT Data:** Since PAUT identifies defects as regions with lower values, while PT highlights defects as regions with higher temperature values, the PT data is inverted to align the interpretation of defects. This inversion is computed as:

$$X_{\text{reversed}} = \max(X_{\text{PT}}) - X_{\text{PT}} \quad (6)$$

where X_{PT} is the original PT data, and X_{reversed} represents the inverted data. This transformation ensures consistent defect identification between the two modalities.

- **Application of K-Means Clustering:** After normalisation and reversing, k-means clustering is applied to segment the PAUT and PT datasets into k clusters. The objective function of the k-means algorithm minimises the intra-cluster variance [40]:

$$\underset{C_1, C_2, \dots, C_k}{\text{minimize}} \sum_{i=1}^N \sum_{j=1}^k r_{ij} \|x_i - \mu_j\|^2 \quad (7)$$

where:

- N : Number of data points,
- x_i : Feature vector of the i -th data point,
- μ_j : Mean of the j -th cluster,
- r_{ij} : Binary indicator (1 if x_i belongs to cluster C_j , 0 otherwise).

The clustering segregates defect and non-defect regions for each dataset. By combining the PAUT depth-based data and PT temperature-based data through clustering, defect regions are consistently identified, leveraging the complementary characteristics of PAUT and PT inspection techniques.

In the absence of labelled data, which is a common limitation in defect detection tasks, the fusion of different inspection techniques requires the use of *unsupervised* learning methods. These techniques are capable of extracting patterns, relationships, and structures directly from the data, without relying on ground truth labels. In particular, the defect detection problem can be approached by leveraging various unsupervised learning methods, such as clustering, thresholding, and anomaly detection, to identify regions of interest (i.e. defects) in the inspection images.

Thus, the fusion methodology in this study is designed to combine defect information from both inspection techniques, utilising unsupervised techniques to overcome the lack of labelled data while preserving the structural integrity of the defects identified through PAUT and PT inspection.

Principal component analysis (PCA) for fusion.

- **Preprocessing:** Both datasets are normalised, and PT data are inverted as described in the clustering process.
- **PCA Computation:** First, the normalised datasets from both modalities (PAUT and PT) are combined into a single matrix, $\mathbf{D}$. In this case, the rows of the matrix represent different data points (e.g. individual image pixels or regions of interest), and the columns represent the different datasets (PAUT and PT).

$$\mathbf{D} = [\hat{X}_{\text{PAUT}} \quad \hat{X}_{\text{PT}}] \quad (8)$$

where $\hat{X}_{\text{PAUT}}$ is the normalised data from PAUT images and $\hat{X}_{\text{PT}}$ is the normalised data from PT images.

Next, a covariance matrix $\mathbf{C}$ is calculated to capture the relationships between the data points from both modalities. The covariance matrix measures how much two random variables (in this case, image data points) vary together. The covariance matrix is calculated using the following formula [41]:

$$\mathbf{C} = \frac{1}{n-1} \mathbf{D}^T \mathbf{D} \quad (9)$$

where $\mathbf{C}$ is the covariance matrix of the combined dataset $\mathbf{D}$. n is the number of data points (e.g. the number of pixels or regions in your dataset). $\mathbf{D}^T$ is the transpose of the combined dataset matrix, $\mathbf{D}$. The covariance matrix $\mathbf{C}$ helps identify the directions (principal components) along which the data varies the most.

PCA works by finding the eigenvectors and eigenvalues of the covariance matrix. Eigenvectors represent the directions of maximum variance in the data, while eigenvalues indicate the magnitude of variance along these directions.

The first principal component $\mathbf{PC}_1$ is derived by projecting the original data $\mathbf{D}$ onto the eigenvector $\mathbf{v}_1$, which corresponds to the largest eigenvalue. This projection captures the maximum variance in the data and represents the most significant feature in the dataset.

$$\mathbf{PC}_1 = \mathbf{D} \mathbf{v}_1 \quad (10)$$

where $\mathbf{PC}_1$ is the first principal component, representing the most significant feature extracted from both PAUT and PT data. $\mathbf{v}_1$ is the eigenvector corresponding to the largest eigenvalue from the covariance matrix $\mathbf{C}$.

The principal component $\mathbf{PC}_1$ is used as the fused representation of the defects detected in both the PAUT and PT images.

- **Binarisation of PCA Output:** The principal component output is thresholded:

$$B(x, y) = \begin{cases} 1, & \text{if } \mathbf{PC}_1(x, y) < T, \\ 0, & \text{otherwise,} \end{cases} \quad (11)$$

where T is the mean value of the PCA output.

Wavelet-based image fusion.

- **Preprocessing:** Both datasets are normalised, and PT data are inverted as described in the clustering process.
- **Wavelet Decomposition:** Wavelet decomposition and fusion are powerful techniques used in image processing, especially when dealing with multi-modal data, such as images obtained from different inspection methods like PAUT and PT. The goal is to enhance important features of the images by decomposing them into different frequency bands and then applying fusion rules to combine the relevant information from each modality.

Each image is decomposed into wavelet sub-bands [42]:

$$\text{Wavelet Decompose}(I) \rightarrow \{A, H, V, D\} \quad (12)$$

where A is approximation coefficients, representing the smooth or low-frequency components of the image. H, V, D are horizontal, vertical, and diagonal details, capturing horizontal edges and fine details.

- **Fusion Rules:** Fusion is applied at each sub-band:
- Approximation coefficients (A): Averaging:

$$A_{\text{fused}} = \frac{A_{\text{PAUT}} + A_{\text{PT}}}{2} \quad (13)$$

- Detail coefficients (H, V, D): Maximum selection:

$$C_{\text{fused}} = \max(C_{\text{PAUT}}, C_{\text{PT}}) \quad (14)$$

where C is a detail coefficient.

- **Wavelet Reconstruction:** After the fusion of the coefficients, the final fused image is obtained by reconstructing the image from the fused approximation and detail coefficients. The reconstruction process involves applying an inverse wavelet transform to the fused coefficients, resulting in a final image that incorporates the most relevant features from both modalities. Fused coefficients are reconstructed by:

$$I_{\text{fused}} = \text{Wavelet Reconstruct}(A_{\text{fused}}, H_{\text{fused}}, V_{\text{fused}}, D_{\text{fused}}) \quad (15)$$

- **Binarisation:** The fused image is thresholded to produce a binary mask highlighting defect regions, as described in the PCA section.

2.4. Evaluation

Evaluating BVID poses significant challenges due to the inherent lack of ground truth, which complicates the validation of inspection results. To address this, the fusion results of this study are compared with Pulsed Phase Thermography (PPT) and Principal Component Thermography (PCT), both of which rely on signal processing techniques derived from non-destructive testing data. These methods produce their own interpretations of defects through specific transformations and analyses, making them comparable to fusion-

based methodologies, which might similarly be considered an NDT-based signal processing application to integrate multiple data sources. Given this shared reliance on NDT-derived processing, it is appropriate to evaluate our fusion approach against PPT and PCT to understand its relative performance and potential advantages.

2.4.1. Pulsed phase thermography (PPT)

Pulsed Phase Thermography (PPT) is a non-destructive evaluation (NDE) technique that analyses thermal data in the frequency domain. The core principle involves transforming time-domain data into frequency components using the Discrete Fourier Transform (DFT). In the context of an image matrix, where $I(m, n)$ represents the pixel values of an image of size $M \times N$, the DFT of the image can be written as [43]:

$$F(k_x, k_y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(m, n) \exp\left(-j2\pi\left(\frac{k_x m}{M} + \frac{k_y n}{N}\right)\right) \quad (16)$$

where:

- $F(k_x, k_y)$ is the DFT of the image at frequency indices k_x and k_y , corresponding to the horizontal and vertical frequency components, respectively.

- j is the imaginary unit ($j^2 = -1$).

- M and N are the number of rows and columns of the image matrix.

- k_x and k_y are the frequency indices in the horizontal and vertical directions, respectively.

The amplitude A_{k_x, k_y} is then computed as the magnitude of the complex DFT result:

$$A_{k_x, k_y} = \sqrt{\text{Re}(F(k_x, k_y))^2 + \text{Im}(F(k_x, k_y))^2} \quad (17)$$

where $\text{Re}(F(k_x, k_y))$ and $\text{Im}(F(k_x, k_y))$ are the real and imaginary parts of the DFT at k_x and k_y .

The phase ϕ_{k_x, k_y} is given by:

$$\phi_{k_x, k_y} = \tan^{-1}\left(\frac{\text{Im}(F(k_x, k_y))}{\text{Re}(F(k_x, k_y))}\right) \quad (18)$$

In the case of Pulsed Phase Thermography, the phase is of particular interest because it is less affected by external factors like surface reflections and geometry variations.

2.4.2. Principal component thermography (PCT)

The Fourier transform is a powerful tool that converts a signal from the temperature-time space to a phase-frequency space, using sinusoidal basis functions. However, sinusoidal functions may not be ideal for representing transient signals, such as the temperature profiles typically observed in pulsed thermography. An alternative approach to extracting spatial and temporal data in a compact form is Singular Value Decomposition (SVD). Unlike the Fourier transform, which relies on sinusoidal basis functions, SVD is an eigenvector-based technique that forms an orthonormal space. SVD is similar to Principal Component Analysis (PCA), with the key difference being that SVD simultaneously provides PCA in both row and column spaces [44].

The SVD of an $M \times N$ matrix A (where $M > N$) is given by:

$$A = URV^T \quad (19)$$

where:

- U is an $M \times N$ orthogonal matrix,

- R is a diagonal $N \times N$ matrix containing the singular values of A on its diagonal,

- V^T is the transpose of an $N \times N$ orthogonal matrix, which represents the characteristic time.

To apply SVD to PT data, the 3D thermogram matrix, which represents both spatial and temporal variations, must be reorganised into a 2D matrix A . This is done by rearranging the thermograms such that the temporal variations are represented column-wise, and the spatial variations are represented row-wise. In this configuration, the columns of U correspond to a set of orthogonal statistical modes known as empirical orthogonal functions (EOFs), which describe the spatial variations of the data. Meanwhile, the principal components (PCs), which represent the temporal variations, are arranged row-wise in the matrix V^T .

The first EOF captures the most significant spatial variability of the data. In many cases, only a few EOFs are required to adequately represent the original data. For example, a sequence of 1000 thermograms can often be approximated by just 10 or fewer EOFs. The first EOF has been used in this study to compare fusion results.

3. Results and discussion

This section details the inspection results of two sets of composite specimens, categorised as thin and thick, evaluated using PAUT and PT. The analysis encompasses raw inspection images, their corresponding binary representations to highlight defect regions, and the fused outcomes generated through five distinct fusion rules. These fusion approaches aim to enhance the detection and visualisation of defects by leveraging complementary information from both modalities. In addition, pulsed phase thermography and principal component thermography analysis results have been presented with the results to compare current results with different signal processing operations. These methods have already been previously validated regarding their ability to detect even if the defects are in different scales or depths [44,45]. The section is structured to facilitate a comprehensive comparison, emphasising the effectiveness of each fusion method across varying material thicknesses. By systematically presenting these results, the section aims to provide insights into the advantages and challenges of integrating multi-modal inspection techniques for BVID detection and characterisation in CFRP composite structures.

3.1. Set of thin specimens

Colour-coded imaging is used in C-scan imaging to show the raw signal obtained by an ultrasonic phased-array transducer, providing information on the various levels of the examined material. Furthermore, C-scan images are planar views that reveal details about the dimensions and appearance of the defect plane [46]. The PAUT inspection C-scan results of thin specimens (actual thickness is 1.65 mm) impacted by 2.5, 4, 8 (a,b) and 12 J impact energies have been presented in Figure 4. The PAUT results reveal a detailed depth profile of the examined composite specimens. The greyscale images, calibrated to represent the specimen's depth, range from black (indicating the surface layer) to white (corresponding to the back wall). The scale has been set higher than the actual thickness to see the fluctuation in the grey back surface. The defects are predominantly located near the surface layer, as evidenced by the darker regions in the depth profile.

Most defects exhibit an elongated orientation, extending diagonally from the upper left to the bottom right of the inspection images. Their forms are generally close to a spherical shape in the middle side. This alignment may be indicative of stress distribution patterns based on the manufacturing layout of the specimens. The greyscale variations within the defect regions suggest a complex internal structure, with partial delamination occurring in the intermediate plies. The grey-toned defect marks, situated between black and white regions, imply that some defect features spread multiple layers, penetrating into the internal plies but not fully reaching the back wall. In addition, all specimens have confirmed that the defects are in the middle region, even if scans might have slight drifts because of the manual scanning deviations.

This observation highlights the ability of PAUT to detect and visualise defects with varying depth extents and orientations. Figure 5 also indicates that the thickness of the specimen from a representative signal of PAUT measured 1.72 mm which is 96 percent accuracy with the actual thickness of 1.65 mm (totally 256 data samples for 3 mm acquisition). Thickness values for the specimen fluctuate around this value through all signals. Showing defect points and signals in different depths is not necessary to avoid prolonging and deviation from the main topic. Figure 6 has exemplified the 3D defect distribution from the surface to the back wall of the specimen (8Ja specimen). It is evident that the main defect is quite close to the surface and black colour (Figure 4(a)). However, it is understood that there are obvious separations/delaminations in the internal structure below the surface damage. Similar to this example, there are several tones of grey in other specimens' images, indicating subsurface defects (Figure 4(b-e)).

The defect size clearly increases with the impact energy levels, as shown by the consistent progression of defect dimensions across the specimens. This trend underscores the sensitivity of PAUT in capturing varying levels of internal defects caused by different impact energies. The similarity in defect shapes and sizes for the 8J (a,b) impacted specimens further supports the repeatability of the inspection technique. These

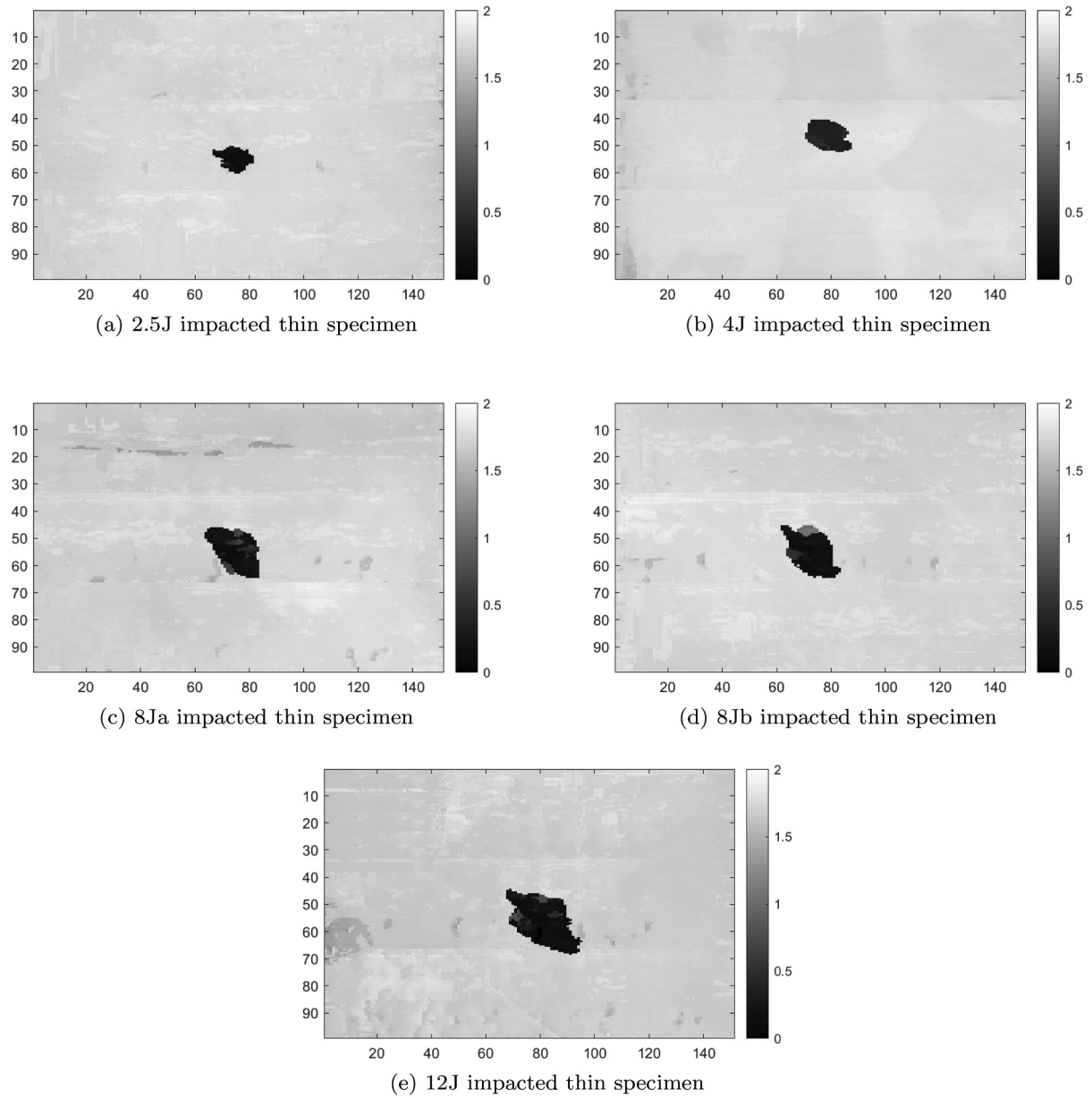


Figure 4. PAUT inspection results for 1.65 mm thickness (thin) composite specimens showing black shallow and white deep regions (color bar is the thickness in mm).

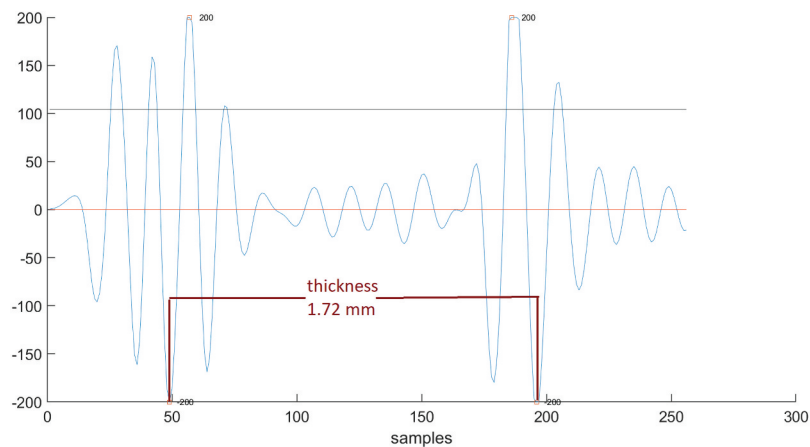


Figure 5. An arbitrary defect-free signal from PAUT indicating the measured thickness of the specimen.

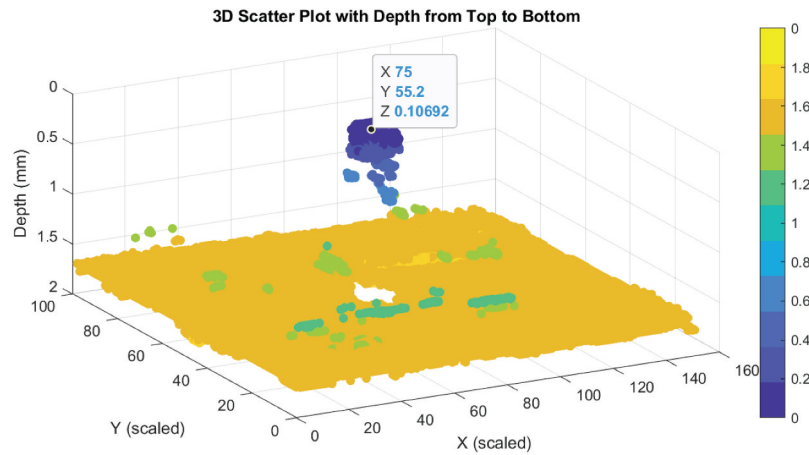


Figure 6. 3D defect depth plot for thin specimen 8Ja.

observations reinforce the reliability of PAUT in detecting and visualising defects, particularly in cases where energy inputs produce consistent damage patterns.

In summary, the PAUT results are consistent with the expectation that damage in composite structures often originates near the surface after such low-velocity impact events. Furthermore, the subtle greyscale transitions in the defect zones emphasise the capability of PAUT to capture fine-scale variations in defect morphology, which is critical for characterising barely visible impact damage in CFRP composites.

On the other hand, the pulsed thermography results provide complementary insights into the characterisation of defects. In reflection mode (Figure 7), the images exhibit a higher visual clarity than transmission images (Figure 8) due to their strong colour contrast, which allows for more definitive identification of defect marks. This should be attributed to the measurement sensitivity to the illuminated side of the specimen in the reflection mode. It means a higher absorptivity causing a lower penetration in depth might have a stronger thermal contrast because the heat is more readily absorbed and redistributed around the defect [47]. However, the transmitted signal reaching the sensor is weaker due to the longer path length, leading to noisier images with less distinct defect boundaries. The presented thermograms include false colour temperature scales (greyscale) that depict relative surface temperature distributions at selected time frames by assigning distinct colours to varying intensity levels (Figures 7, 8, 13, 14).

In transmission mode, PT appears noisier, with weaker defect marks, particularly for the lower impact energy specimen (e.g. the 2.5 J impacted specimen in Figure 8(a)). This noise could stem from the longer path the thermal waves need to traverse through the material, leading to attenuation and diffusion. The weakened signal in transmission mode often blurs the borders of defects, making it challenging to identify their exact size and shape. Although defect contrast is better in Figure 8(b-e), it is hard to discriminate defect borders. Despite these challenges, transmission thermography retains some utility for confirming defect presence and orientation, especially in deeper regions where surface-based reflection thermography might not be as effective [48].

For higher-impact energy specimens, the defect signatures are notably more pronounced in both reflection and transmission thermography modes, representing the increased extent of damage. 8J (a,b) specimen results in both modes also support the repeatability of the inspections. These observations underscore the potential of pulsed thermography to reliably detect and characterise defects across varying damage levels. By providing complementary insights to PAUT findings, PT validates defect locations and orientations, thereby enhancing the overall defect characterisation process. The integration of these techniques highlights the value of a multi-modal approach, combining the surface sensitivity of PT with PAUT's ability to detect subsurface defects. This synergy emphasises the importance of leveraging the strengths of both techniques for comprehensive damage assessment, particularly in advanced applications where accurate characterisation of surface and deep defects is critical. In particular, reflection mode results have been selected to combine with PAUT data for further steps of this study, due to its higher contrast and detection capability of shallow regions.

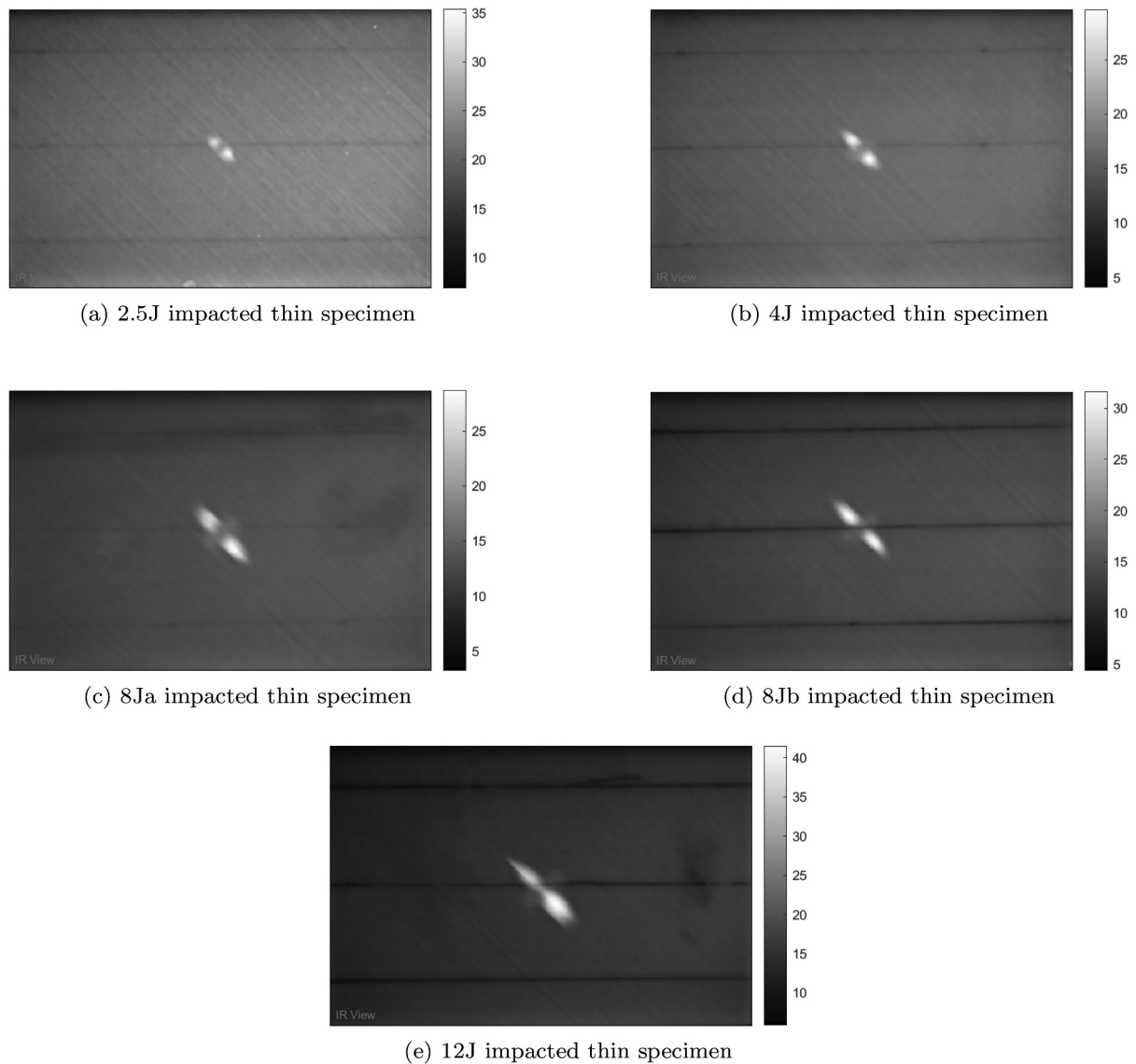


Figure 7. Pulsed thermography results in reflection mode for 1.65 mm thickness (thin) specimens at 145 Hz image acquisition frequency.

Besides previous discussions of PAUT and PT results, it should be considered that individual inspection modalities have specific limitations. In particular, the dead zone effect occurs when a defect or flaw is located near the surface of a material, ultrasonic signals such as tip-diffracted waves can overlap with other waves, like the lateral wave or back-wall wave. This overlap creates a 'dead zone', where poor time resolution makes it difficult to distinguish and measure these signals accurately [49,50]. On the other hand, poor thermal penetration ability into the material for thermography analysis is already mentioned while discussing reflection and transmission modes. This brings a restriction in PT inspection to detect deep defect marks [47].

The anisotropic nature of composites is another significant challenge, and the subtle variations caused by different damage mechanisms may make precise defect characterisation inherently difficult. Especially anisotropy might affect the material properties, such as electrical and thermal conductivity, resulting in accuracy lack in detection or characterisation, unlike successful applications in isotropic materials [51,52].

The absence of definitive ground truth for BVID observed in these specimens introduces another difficulty in assessing the accuracy of individual modalities. To address these challenging points and issues for the inspection of BVID, a complementary fusion has been proposed for PAUT and PT, and a comparative analysis of the techniques serves as an evaluation. It is evident that each modality brings unique strengths to defect characterisation in CFRP specimens. PAUT is skilful in detecting subsurface and internal defects with high

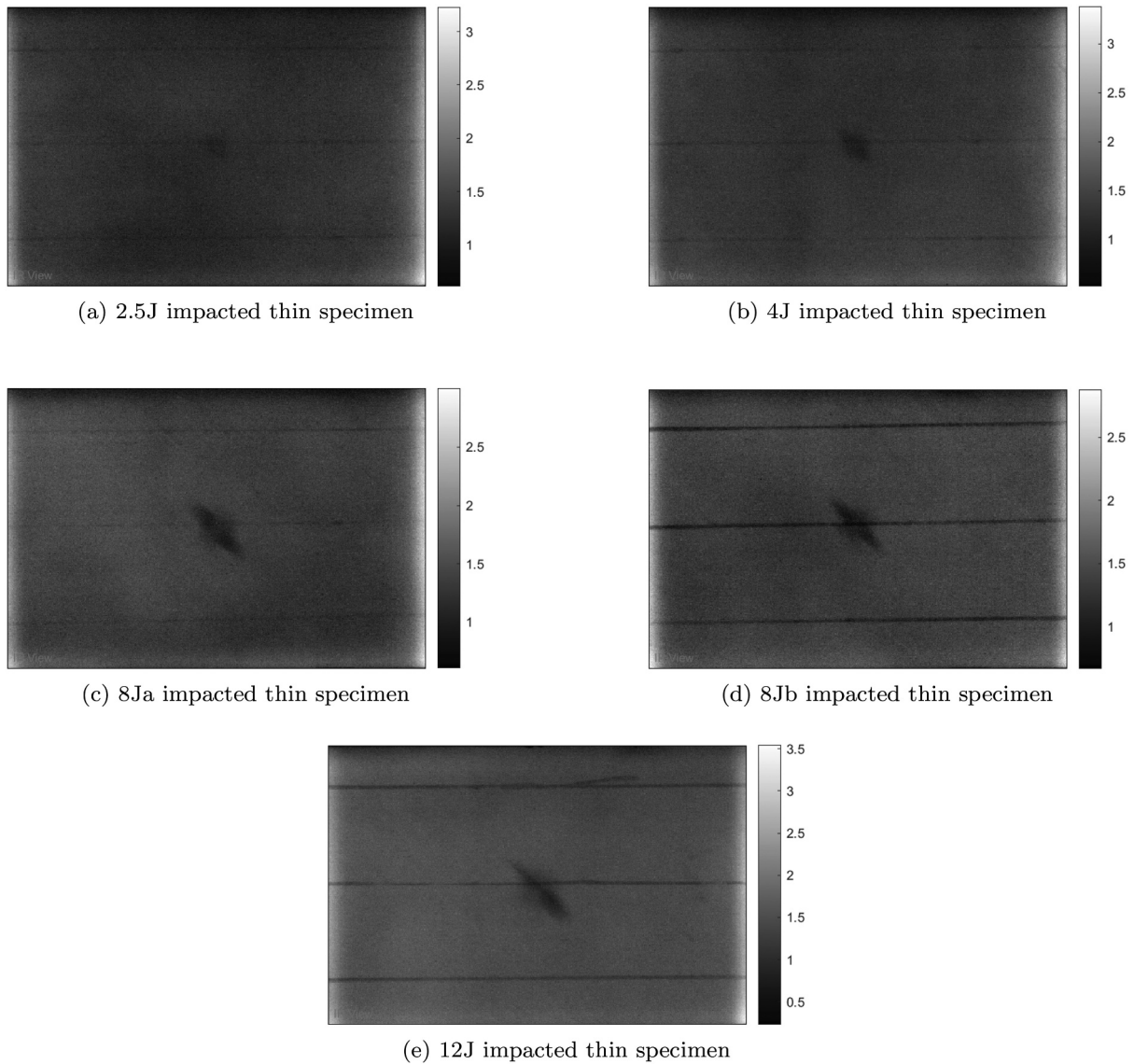


Figure 8. Pulsed thermography results in transmission mode for 1.65 mm thickness (thin) specimens at 145 Hz image acquisition frequency.

spatial resolution, while PT provides valuable thermal signatures that reveal surface and near-surface anomalies.

Figure 9 represents a holistic comparison of individual inspection results given in the first two rows of the figure, fused results given between rows 3–7 and PPT/PCT images in the last two rows. After extracting binary forms of individual inspection results (PAUT and PT in reflection mode), the study incorporates multiple fusion rules, including Logical OR, Logical AND, Clustering, PCA, and Wavelet, to enhance defect sizing.

Particularly, the Logical OR rule emphasises inclusivity by highlighting regions detected by any modality. It might also be considered as a sum or superposition of source images to get complementary defect marks. It ensures that no potential defects are missed, detected by source methods. Besides, the Logical OR combination rule has provided the largest defect sizes calculated for each specimen (Table 3). The fused images have shown distinctive detection marks from PAUT and PT, showing the dual contribution of sources.

In contrast, the Logical AND rule enforces strict conditions for defect identification, highlighting only regions detected by all contributing modalities. This selective approach enhances specificity and tends to reduce false positives (a defect detected, but not present in reality), as it focuses only on the most reliable detections. However, its rigid requirements may exclude subtle defects or signals that are inconsistently

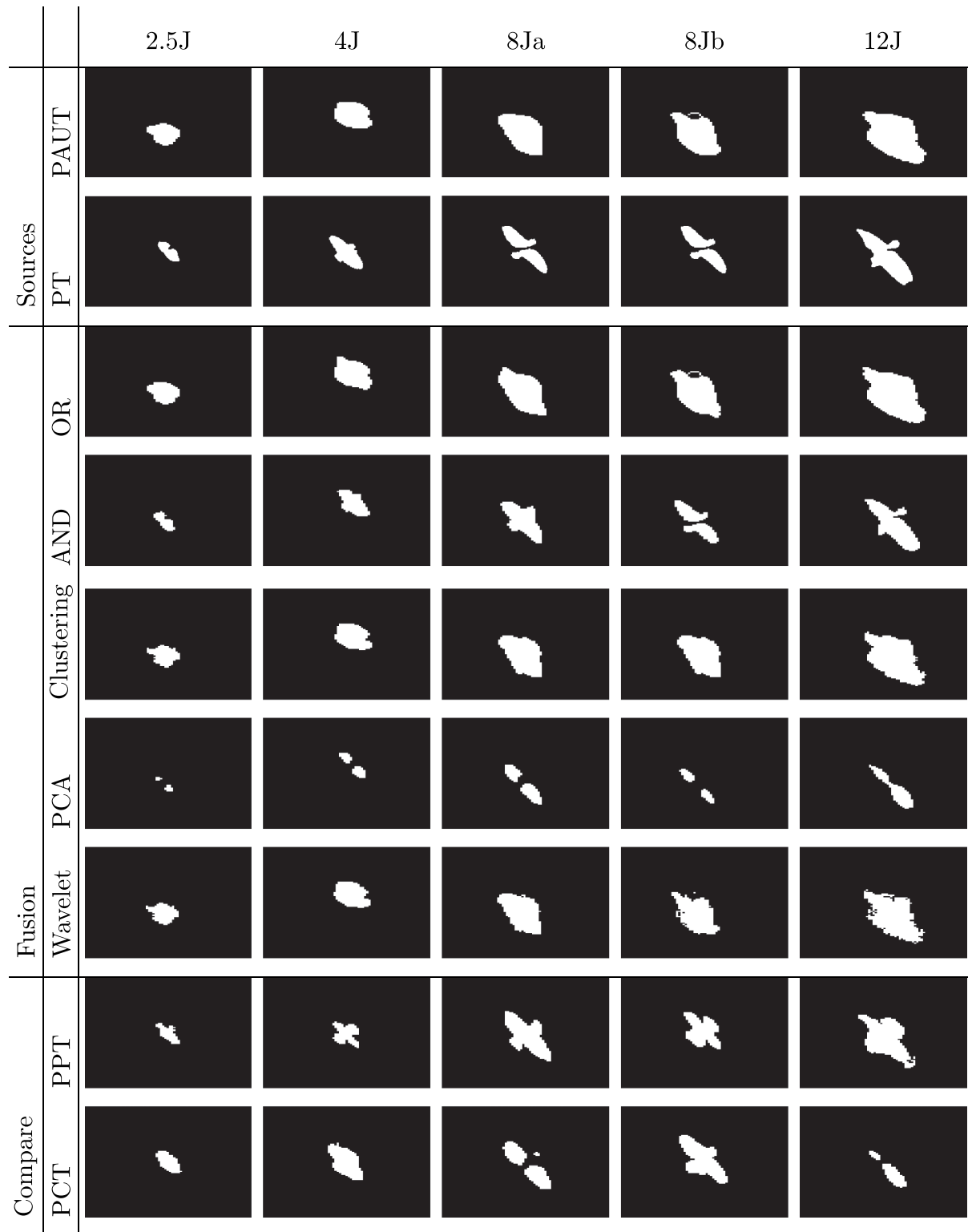


Figure 9. Source images (rows 1–2) of thin specimens, fused images under Logical or, Logical and, clustering, PCA and Wavelet combination rules (rows 3–7), and PPT/PCT results (rows 8–9) to compare with sources and fusion results (images are focused in middle defected zone).

Table 3. Defect sizes of thin specimens for sources, different fusion methods and PPT-PCT for comparison according to the impact energy levels (in mm^2).

Energy	PAUT	PT	Logical OR	Logical AND	Clustering	PCA	Wavelet	PPT	PCT
2.5J	105.96	48.77	108.97	45.76	93.92	13.25	89.10	52.98	73.45
4J	164.96	120.41	177.60	107.77	150.51	45.15	137.87	88.50	161.95
8Ja	270.92	211.92	290.79	192.05	256.47	98.13	233.59	243.83	165.56
8Jb	284.77	160.14	295.00	149.91	256.47	42.14	227.57	173.99	239.61
12J	428.06	254.67	434.68	248.04	394.34	98.74	350.39	306.44	78.27

captured across modalities. Consequently, Logical AND fusion often results in smaller defect sizes compared to other fusion rules, reflecting its conservative nature. However, PCA gave the lowest sizes contrary to expectations.

The Clustering technique applies data-driven grouping to localise defects by analysing pixel properties and spatial distributions. By aggregating adjacent regions with similar characteristics, clustering helps refine defect boundaries and minimises the influence of noise. This approach strikes a balance between inclusivity and specificity, capturing defect regions with a high degree of spatial coherence. Its effectiveness lies in providing well-defined defect shapes and sizes, which are critical for accurate characterisation. This rule represented slightly lower sizes than Logical OR, confirming its nature of balance.

Principal Component Analysis (PCA) enhances defect visualisation by reducing the dimensionality of the combined data while retaining the most significant features. Through this transformation, PCA extracts dominant patterns from the fused inputs, highlighting defects that are prominent across modalities. While this method excels in distinguishing clear defect signals from background noise, it may underrepresent subtle features that do not contribute significantly to the principal components. The fused defect sizes from PCA were generally smaller than those identified by PT and, in most instances, closely resembled PT's outcomes. This pattern suggests that PCA predominantly captures surface-level characteristics, is heavily influenced by PT data, and does not effectively integrate the complementary subsurface information provided by PAUT.

Finally, the Wavelet Transform fusion rule utilises the multi-resolution capability of wavelet analysis to detect defects across different scales. By decomposing the source images into frequency components, the wavelet approach identifies both fine and coarse defect features. This technique is particularly useful for capturing subsurface details and structural variations, making it a valuable complement to PAUT and PT. However, its performance depends on the choice of wavelet parameters, which require careful optimisation for specific applications. Here, the decomposition level is selected as two, and it is considered sufficient for this case, which is not extremely complex in nature with only defected and defect-free regions. This rule showed similar sizes as Clustering, having relatively smaller areas. The defect sizes obtained for all specimens and methods are comprehensively presented in Table 3.

Pulsed Phase Thermography (PPT) and Principal Component Thermography (PCT) are advanced signal processing techniques derived from thermography data, similar to fusion operation, which is considered a signal processing tool. However, unlike fusion rules that integrate multiple modalities, PPT and PCT focus on thermographic responses, highlighting hidden features of the inspection.

PPT, based on Fourier analysis, decomposes thermal signals into phase and amplitude components across different frequencies. The phase component effectively isolates defect regions by emphasising thermal contrasts that correlate with subsurface anomalies. Its frequency-based analysis enables PPT to suppress noise and enhance the clarity of defect features, particularly for deeper defects with thermal propagation delays. It is evident that PPT results are highly different from PT results, having additional defect clues coming from the internal structure, close to PAUT results in particular regions. The defect shapes and sizes were significantly improved by PPT, providing seamless and more spherical shapes in the middle of the defects. In comparison with the fusion results, PPT provided better spatial resolution than logical AND and PCA fusion rules, having close similarities with clustering and wavelet results in terms of size calculations and shapes. It might be considered that the fusion application was able to provide expected outcomes, confirming complementary contributions from multi-modal analysis.

Similarly, PCT employs principal component analysis to extract dominant patterns from a series of thermographic images. By emphasising the most significant thermal variations, PCT might highlight defects, particularly subsurface anomalies with high signal contrast while reducing the influence of noise and irrelevant features. However, PCT images have not indicated the expected outcomes like PPT, especially for 8 Ja and 12 J specimens. These images did not have sufficient enhancement in detection, while 2.5 J, 4 J, and 8 Jb specimens showed better spatial resolution and increased defect sizes. It might be attributed to the illumination differences during heating or environmental disturbances such as motion or excessive touch for holding the specimen.

The results presented here for thin (1.65 mm thickness) specimens highlight the promising potential of fusion techniques in the Non-Destructive Testing domain. By integrating complementary data from multiple inspection modalities, fusion enhances the detectability, and reliability facilitating defect characterisation. Techniques like Logical OR, Clustering and Wavelet transformation effectively combine the strengths of individual methods, providing a comprehensive view of defect distributions while minimising the limitations inherent to single-modality inspections.

3.2. Set of thick specimens

The evaluation of thick composite samples (actual thickness is 3.8 mm) introduces unique challenges compared to thin samples, primarily due to the increased material volume, which affects signal propagation and defect visibility. The specimens were inspected by 4, 8 (a,b), 12 and 20 J energy levels. The main point to start with is that the first specimen, 4 J impacted, does not show any defect marks in both inspections, PAUT and PT. It might be claimed that thick specimens are more resistant to applied energies. Figure 10 has shown the PAUT results for all specimens with the colour bar depicting the depth, and transition from dark (surface layer) to light (back wall). It is obviously seen that the main defect colour is black, but they have also some variations of grey tones indicating subsurface defects.

Unlike thin specimens, the results have shown circular shapes rather than representing defect orientations. This might be attributed to the raised volume of the specimen, supporting the higher resistance of thick specimens. Defects are clearly found in the middle region of the specimens in both inspection methods, confirming the location. Greyscale changes in the defect regions indicate a complex internal structure with partial delaminations at depths exceeding the middle of the section. The grey tones suggest defects scattering multiple layers but not extending to the back wall, similar to thin specimens. On the other hand, defect sizes are getting larger with the increasing impact energy, except for the 4J impact-resistant specimen.

In addition to these generic PAUT findings, the PAUT effectively detected defects at varying depths as shown in Figure 11. It shows the measured thickness of the specimen as 3.97 mm, 96 percent accurate compared to the actual thickness of 3.8 mm (based on 424 data samples for 5 mm acquisition). Thickness was calculated between the first maximum peak (front wall) and the last one (back wall), and the values fluctuated around this measurement.

Figure 12 has demonstrated 3D scattering example of the defect in the 8Ja specimen. It can be seen that the back wall is fluctuating quite close to 4 mm, supporting the measuring thickness above. According to colour bar, the deepest part of the defect is around 1.2–1.4 mm in thickness, which can be considered as 'defect depth', and the majority of the defect is scattered near the surface. These observations have underlined again the capability of PAUT to detect and visualise defects with varying depth extents and distribution.

On the other hand, pulsed thermography results have confirmed the PAUT results in terms of locations. In addition, the first specimen impacted by 4 J has been found undamaged. Figure 13 has represented the PT images in reflection mode. Among the specimens, 4 J and 8 Jb specimens exhibit notable variations in brightness across the entire sample, not just within the defect regions, but the whole surface. These specimens showed excessively high reflection intensities, leading to overly bright areas that may obscure finer details. This widespread brightness could result from the material's surface quality, which enhances the reflection of thermal energy back to the imaging system. Conversely, the remaining three samples exhibit darker overall appearances with bright content for just defected areas, allowing for better visualisation of defect features. These darker regions may indicate lower reflection and higher thermal absorption, which could enhance heat diffusion for sound areas.

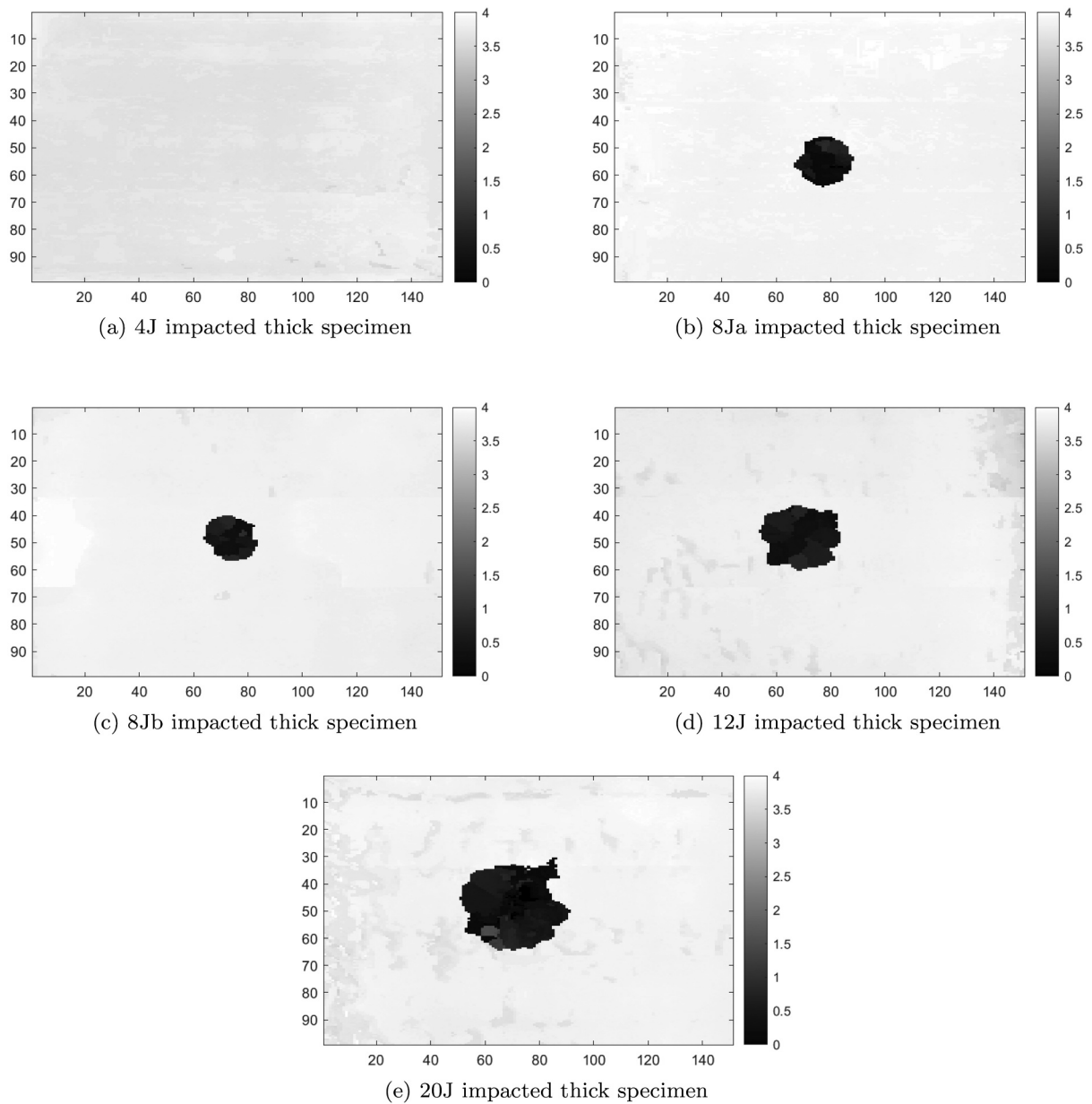


Figure 10. PAUT inspection results for 3.8 mm thickness (thick) composite specimens showing black shallow and white deep regions (color bar is the thickness in mm).

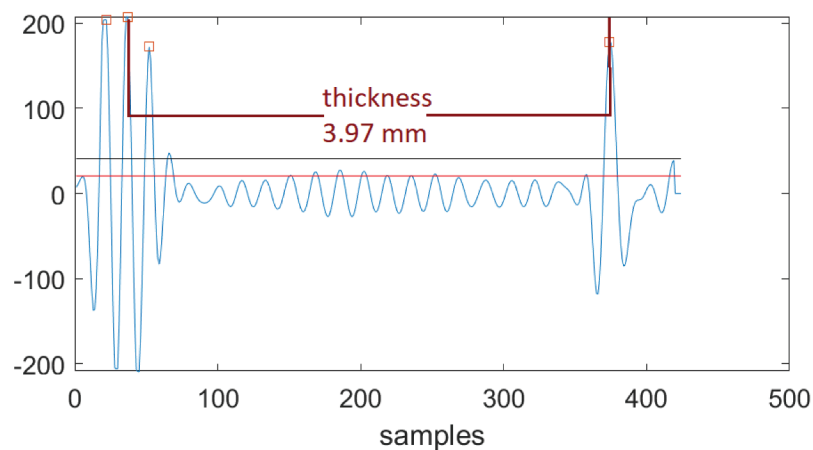


Figure 11. An arbitrary defect-free signal from PAUT indicating measured thickness of the thick specimen.

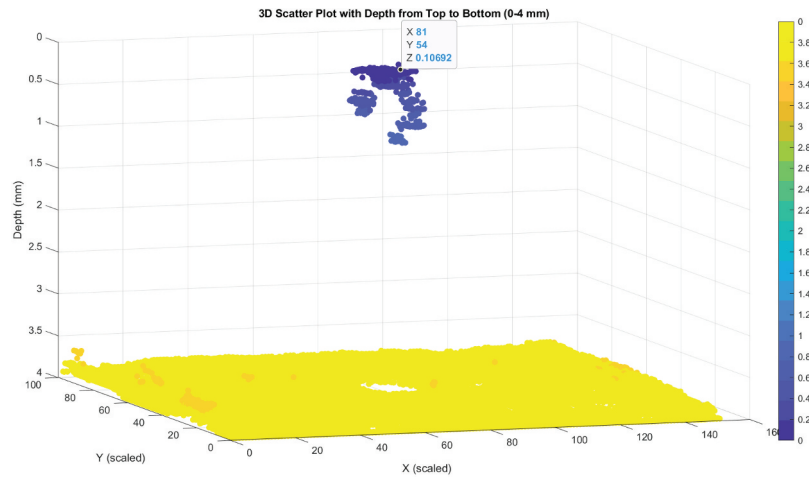
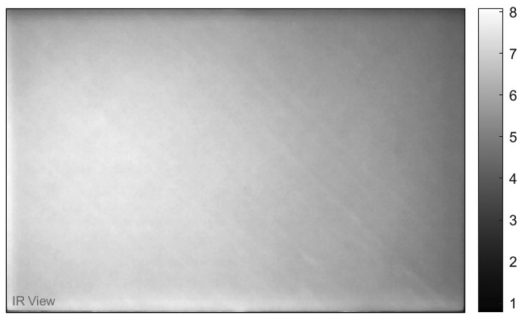


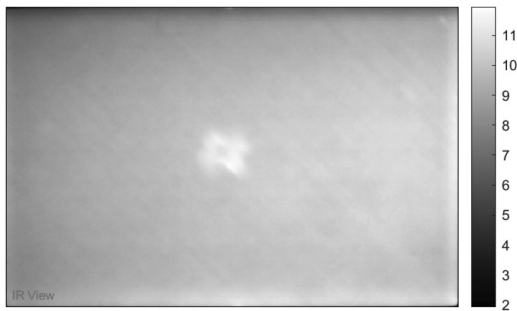
Figure 12. 3D defect depth plot for thick specimen 8Ja.



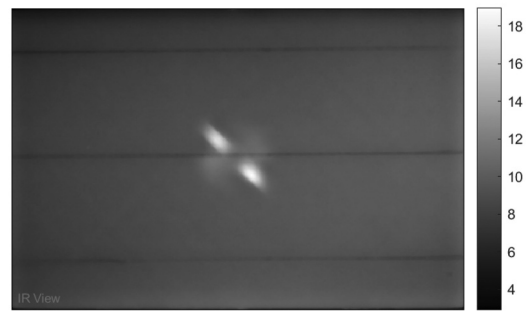
(a) 4J impacted thick specimen



(b) 8Ja impacted thick specimen



(c) 8Jb impacted thick specimen



(d) 12J impacted thick specimen



(e) 20J impacted thick specimen

Figure 13. Pulsed thermography results in reflection mode for 3.8 mm thickness (thick) specimens at 145 Hz image acquisition frequency.

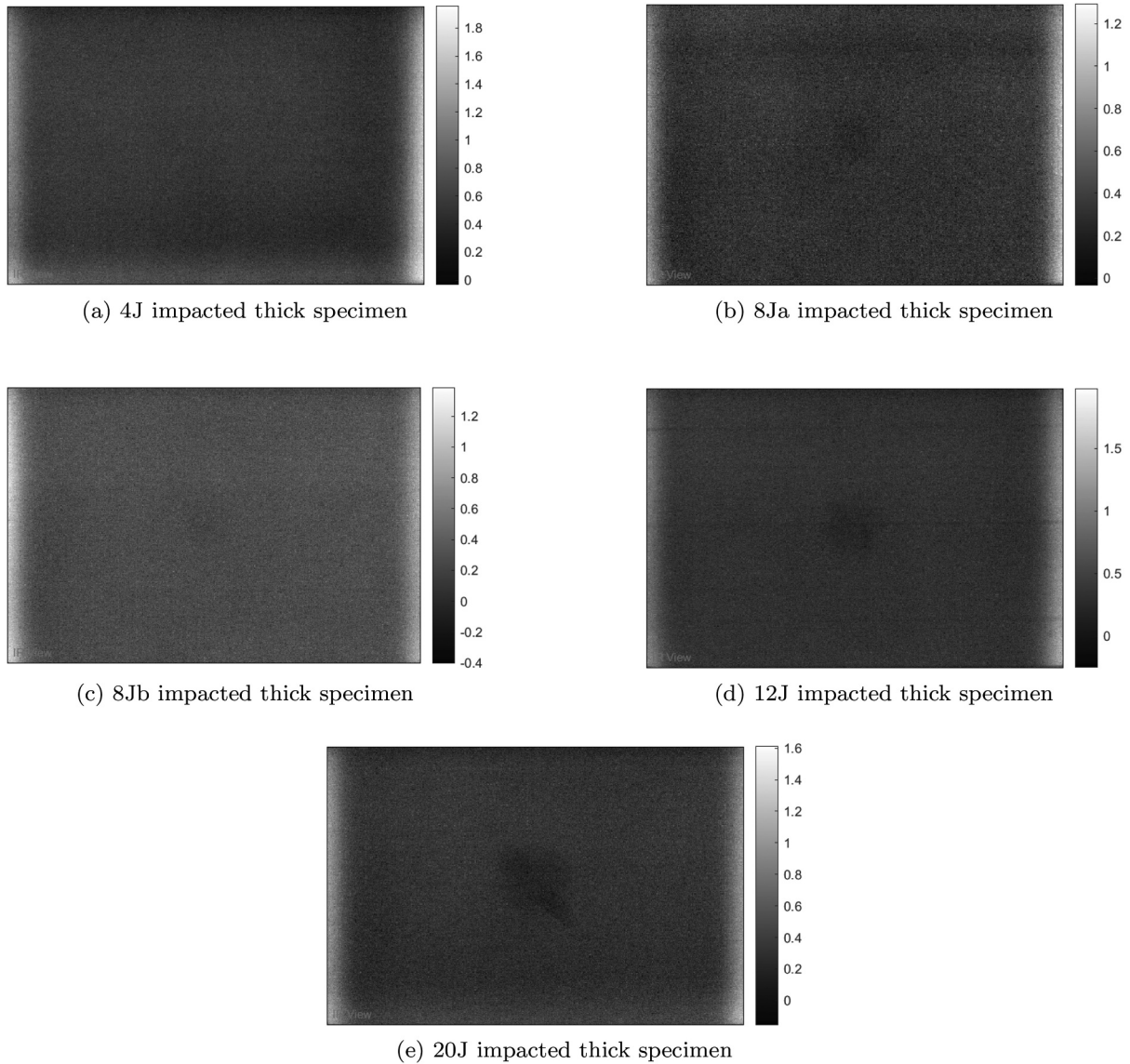


Figure 14. Pulsed thermography results in transmission mode for 3.8 mm thickness (thick) specimens at 145 Hz image acquisition frequency.

In the transmission mode of Pulsed Thermography (PT), defect visualisation becomes increasingly challenging as specimen thickness rises. The PT transmission images are shown in [Figure 14](#) for thick specimens. With thicker materials, the thermal signal transmitted through the specimen decreases significantly, reducing the overall signal-to-noise ratio. This attenuation makes it nearly impossible to distinguish defect features from the noisy background, as the thermal contrast weakens substantially. Here, except for the 20 J impacted specimen, it is difficult to identify and differentiate defect borders to extract defect information. For the 12 J impacted specimen, although the defected area has partially darker evidence for the defect, it is still hard to distinguish for the human eye. Besides, defects are not apparent in the 4 J and 8 J (a,b) specimens. A primary factor contributing to this is that the defects are placed close to the surface layer. In such cases, the transmitted thermal energy has minimum interaction with the defect regions, as the location of the energy source is opposite from the defected side of the specimen. Consequently, deeper layers of the specimen dominate the thermal signal in transmission mode, masking the already weak defect indicators. This highlights a limitation of the PT transmission mode for inspecting thick materials, emphasising the need for complementary techniques or enhanced signal processing methods to improve defect detection in such scenarios.

To further enhance defect detection and overcome the limitations observed in individual inspection methods, the fusion of Pulsed Thermography (PT) in reflection mode and Phased Array Ultrasonic Testing (PAUT) data was employed. Given that the 4J specimen was found to be undamaged in both PT and PAUT inspections, it is excluded from the subsequent analysis to maintain a focus on defected samples and ensure efficient use of space. Figure 15 has displayed the fusion results corresponding to the aforementioned fusion rules with the source images and in comparison with PPT/PCT images. The analysis continues with the reflection mode PT results, as this mode demonstrated better contrast and defect visualisation in the thick

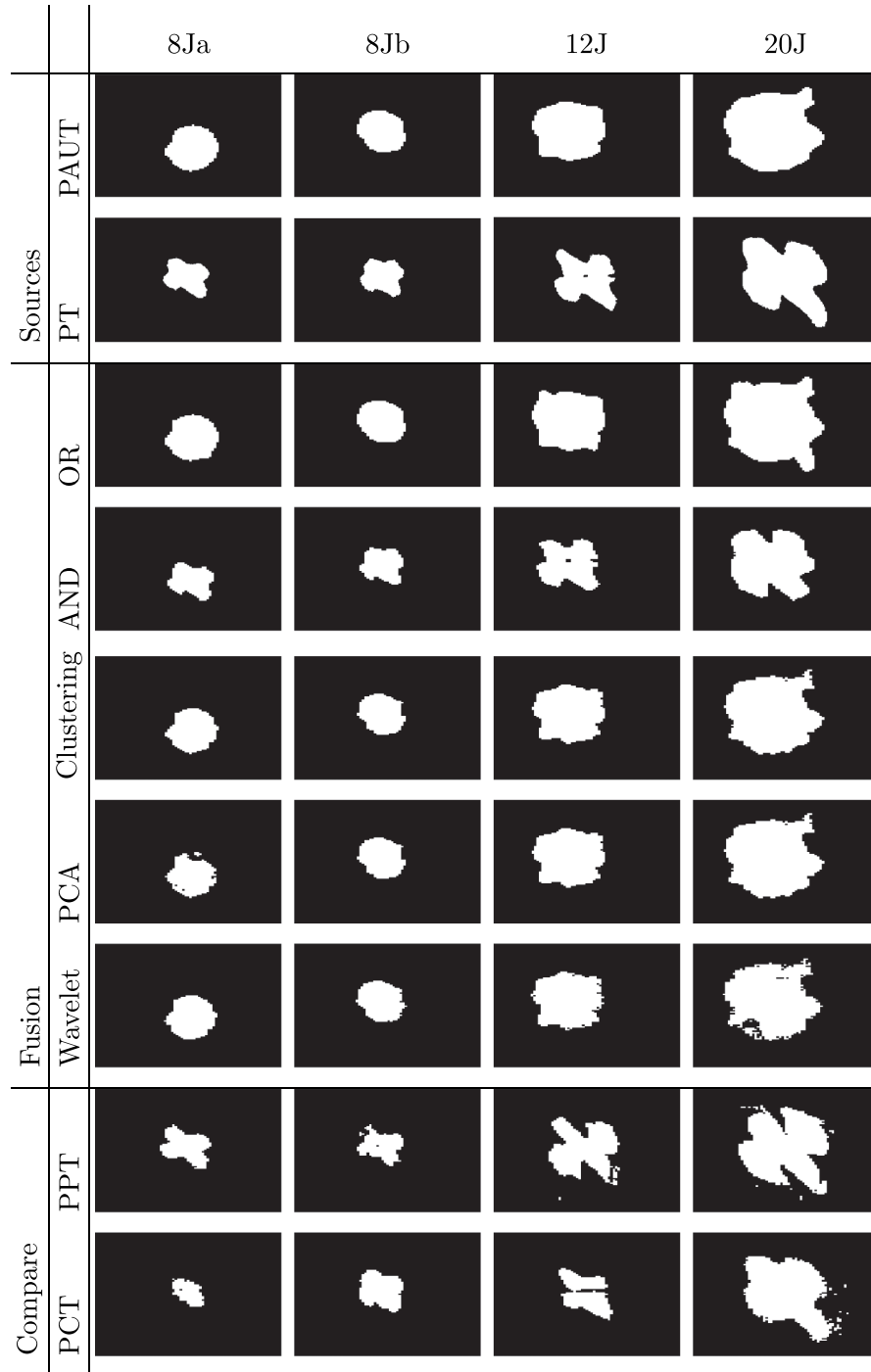


Figure 15. Source images (rows 1–2) of thick specimens (except 4 J energy resistant one), fused images under Logical or, Logical and, clustering, PCA and Wavelet combination rules (rows 3–7), and PPT/PCT results (rows 8–9) to compare with sources and fusion results (images are focused in middle defected zone).

Table 4. Defect sizes of thick specimens for sources, different fusion methods and PPT-PCT for comparison according to the impact energy levels (in mm^2).

Energy	PAUT	PT	Logical OR	Logical AND	Clustering	PCA	Wavelet	PPT	PCT
8Ja	302.83	201.08	308.25	195.67	279.35	246.24	261.89	217.94	101.75
8Jb	263.70	198.07	266.10	195.67	242.62	242.62	239.01	175.80	228.18
12J	575.56	398.56	596.03	378.09	544.25	544.25	512.34	484.65	255.27
20J	1010.23	813.37	1093.92	729.68	953.64	953.64	862.73	853.70	810.36

specimens compared to the transmission mode. The fusion results aim to consolidate defect information from both techniques, enabling a detailed evaluation of defect morphology, and spatial distribution.

The analysis of the extracted binary images and the fused images under different methodologies, Logical OR, Logical AND, Clustering, PCA, Wavelet, and PPT/PCT, revealed fewer variations for thick specimens in defect visualisation and better consistency across the samples. Each method exhibited distinct strengths and limitations based on its fusion logic and processing approach. Mainly, all PAUT images have larger sizes than PT images. After registration of images based on PAUT reference, fusion results have demonstrated complementary defect marks from both individual inspection modalities.

When examined separately, the Logical OR method provided a slight inconsistency for the 20 J specimen than other combination rules, where a strongly oriented elongation from the PT reflection mode was retained. This inconsistency arises because Logical OR considers any region identified as a defect by either PT or PAUT. Here, this feature preserved from PT may be an indication of more serious damage detected near the surface. Other fusion methods have suppressed this feature due to their more sophisticated integration of the input data, which reduces false positives. Nevertheless, the logical Or rule has provided the largest areas for defects for each energy level, as expected (Table 4).

Logical AND fusion results that diverged from the other methods, particularly in its strict overlap criterion. As a result, this rule has indicated the smallest defect sizes for each energy level. Consequently, Logical AND may exclude defect regions captured by only one method, leading to a more conservative defect representation. This behaviour could explain the deviation observed compared to other techniques, as it emphasises only the most certain defect regions.

Interestingly, PCA and Clustering produced identical defect results for 8 Jb, 12 J and 20 J impacted specimens. This similarity could stem from their reliance on statistical patterns and feature grouping within the non-complex data. Employing two distinct clusters or features as 'defect' and 'sound' might cause this similarity, having insufficient variation. Mainly, both methods aim to reduce dimensionality and cluster similar features, which can lead to comparable outcomes. Fortunately, wavelet results have also represented fairly similar defect shapes and areas, assisting PCA and clustering results. This alignment and similarity suggest that the defect features in these specimens were statistically consistent and distinguishable, enabling PCA, Clustering and wavelet rules to identify close regions with each other.

In addition, the wavelet exhibits a coarser, rougher shape, which highlights the finer and more detailed information that comes from the nature of the application. Furthermore, the separate damage traces in the lower left region of the 20 J impacted sample, which is likely to come from different layers, confirm this detailed capability of the wavelet.

When comparing the results from thick specimens with thin specimens, the PPT and PCT methods exhibit more consistent detection. Specifically, defect indications in thick specimens display a more spherical morphology and closer sizing similar to those detected by fusion rules. This contrasts with the results for thin specimens might be attributed to the increasing thickness and energy levels which may have enabled deeper damage to be better detected by PAUT and included in the combination. As a reminder, for thin specimens, these methods gave predominantly PT-like results. Detailed size information for detected defects by individual techniques, fusion rules and to compare with PPT/PCT can be seen in Table 4.

4. Overall discussion

Overall, this study has been customised for BVID defects which is one of the most vital defects seen in complex composite structures. The combination possibilities of PAUT and PT inspections have been investigated, stating unique limitations and advantages of individual rules applied for specified specimens

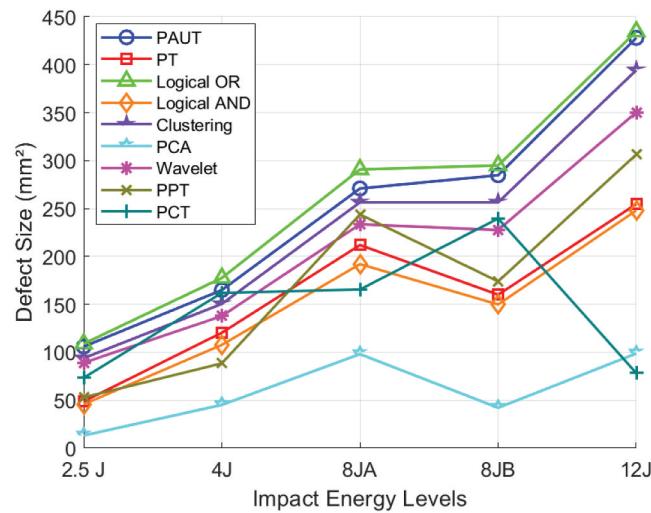


Figure 16. Defect sizes of thin specimens for detected inspection sources, fusion and in comparison with PPT/PCT results.

of two different thicknesses. The study employs various fusion techniques, Logical OR, Logical AND, Clustering, Principal Component Analysis (PCA), and Wavelet decomposition, to enhance defect visualisation and assess the performance of PAUT and PT. The results are compared with Pulsed Phase Thermography (PPT) and Principal Component Thermography (PCT) for further validation.

PAUT proved highly reliable in detecting defects of varying depths, with good sizing and localisation. PT, particularly in reflection mode, was effective for detecting surface and near-surface defects but less reliable in transmission mode. The fusion of PAUT and PT data showed promising results, with each fusion rule offering distinct advantages: Logical OR maximised defect coverage, Logical AND provided high confidence in defect identification, Clustering enabled detailed localisation, PCA simplified the fusion process, and Wavelet decomposition captured multi-scale features for improved detection. PPT and PCT, as signal processing tools, offered additional insights into defect characterisation by comparison.

Figure 16 compares defect sizes (in mm^2) detected by different inspection methods across various impact energy levels for thin specimens (2.5 J, 4 J, 8 Ja-b, and 12 J). The analysis focuses on understanding how the defect sizes vary across energy levels for each method and highlights the differences in performance of these methods in detecting and quantifying BVID damage in CFRP composite materials.

Defect sizes generally increase with higher impact energy levels, as expected. This is observed in almost all methods, with defect sizes consistently becoming larger as the energy level increases. For example, PA shows a rise from 105.96 mm^2 at 2.5 J to 428.06 mm^2 at 12 J. This suggests that higher energy levels cause larger damage to the material, which can be detected through various methods. For some methods (e.g. PA, PT, and Logical OR), the increase in defect size with impact energy is quite pronounced, whereas others (e.g. PCA and PCT) show more moderate changes.

Figure 17 also presents defect sizes (in mm^2) for various inspection methods at different impact energy levels for thick specimens (8 Ja, 8 Jb, 12 J, and 20 J). As expected, defect sizes broadly increase with higher impact energy levels. This is consistent across most methods, with larger defects being observed for higher energy impacts, particularly noticeable in the 12 J and 20 J energy levels. For example, the defect size for PAUT ranges from 302.83 mm^2 at 8 Ja to 1010.23 mm^2 at 20 J, showing a clear increase. Given similar sizes for 8 Ja and 8 Jb specimens have also supported the repeatability of proposed detection methods not only for individual sources but also for advanced signal processing tools as fusion, PPT and PCT.

Finally, the integration of PAUT and PT with fusion methods demonstrated that well-optimised fusion could enhance defect detection, sizing, and boundary definition for BVID in particular, advancing non-destructive testing (NDT) capabilities. By bridging the gap between PAUT and PT, this study establishes a foundation for future studies aimed at refining fusion strategies,

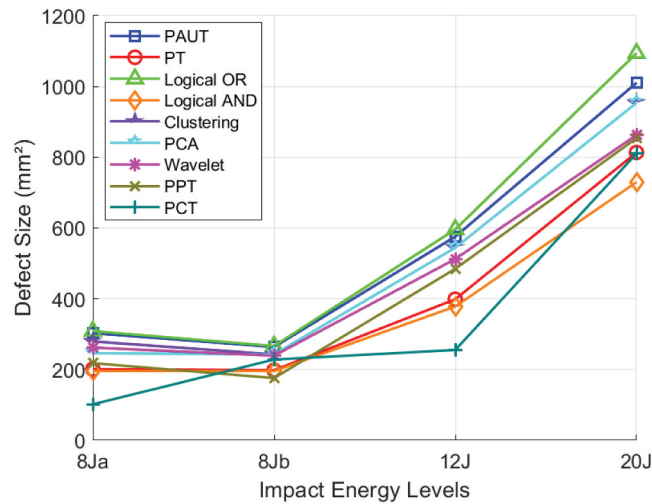


Figure 17. Defect sizes of thick specimens for detected inspection sources, fusion and in comparison with PPT/PCT results.

incorporating advanced signal processing, and exploring applications in diverse composite structures and inspection scenarios.

5. Conclusions and future works

This study investigated Barely Visible Impact Damage (BVID) in CFRP composite specimens, focusing on defect sizing and localisation using Phased Array Ultrasonic Testing (PAUT) and Pulsed Thermography (PT). Adopted fusion rules, including Logical OR, Logical AND, Clustering, Principal Component Analysis (PCA), and Wavelet decomposition methods, were employed to enhance defect visualisation and analyse the performance of PAUT and PT. The results were further compared with defect detection outcomes from Pulsed Phase Thermography (PPT) and Principal Component Thermography (PCT) which are considered signal processing tools similar to fusion.

Precise inspections using PAUT and PT methods were conducted. Specimens were marked properly to facilitate clearer surface identification. To ensure consistent data collection across all inspection types, data was acquired in a uniform direction. Specimen alignment was performed in two steps, first a full surface coverage was followed matching image edges, then using centroid matching to eliminate possible human operator-induced drifts.

PAUT consistently demonstrated high reliability in detecting defects with varying depth extents, offering reasonable sizing and localisation. PT in reflection mode was particularly effective for identifying surface and near-surface defects, with sufficient contrast to identify defects. However, PT transmission results did not ensure adequate contrast to differentiate between defect and sound regions.

The complementary analysis of PAUT and PT using the aforementioned fusion rules has revealed promising detection results, integrating distinct detection marks from individual sources. The findings confirm that the fusion approach enhanced the defect size detection, with increases of up to 7% and 8% for PAUT in thin and thick specimens, respectively, while PT detection accuracy improved significantly by up to 71% for thin specimens and 53% for thick ones. This synergistic effect has also confirmed the idea that fusion might have the potential to improve BVID defect characterisation.

Fusion rules have offered distinct advantages for defect detection and characterisation. Logical OR maximises coverage by combining all detected features, while Logical AND ensures high confidence by highlighting common regions but may miss subtle defects. Clustering effectively segments defects based on similarity metrics and enables detailed defect localisation and shape analysis. PCA simplifies detection by retaining key features, handling the fusion process similar to dimensionality reduction. Wavelet decomposition captures multi-scale features with finer details, improving the detection of both small and large defects. Finally, PPT and PCT have provided functional results to compare source and fused results, taking advantage of advanced signal processing applications.

The ability of fusion to incorporate diverse data sources, such as ultrasonic and thermographic insights, further highlights its adaptability and utility across a range of applications. This study demonstrates that well-optimised fusion rules not only enhance defect visualisation but also improve defect sizing and boundary definition that enables advanced NDT solutions. Moving forward, the integration of data-driven fusion techniques with emerging technologies, such as machine learning and artificial intelligence, holds huge promise for revolutionising defect detection and material assessment in industrial and aerospace contexts.

Recommendation of future research is for enhancing defect detection and characterisation using additional unsupervised methods, such as advanced machine learning algorithms or statistical approaches. A detailed comparison of these methods with clustering techniques could provide further insights into their relative strengths and limitations for defect characterisation. Additionally, Finite Element Method (FEM) simulations could be utilised to simulate impact scenarios and provide a benchmark for experimental results, offering a deeper understanding of damage mechanisms. Finally, developing a mathematical model to establish a correlation between impact energy levels and resulting defect sizes could enable predictive capabilities, supporting a more comprehensive evaluation of BVID in composite materials.

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Multi-modal analysis of barely visible impact damage in carbon fibre composites through the fusion of pulsed thermography and phased array ultrasonic testing

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