

Article

Low-Power Vibrothermography for Detecting Barely Visible Impact Damage in CFRP Laminates: A Comparative Imaging Study

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Abstract

This study explores the application of low-power vibrothermography (LVT) for detecting barely visible impact damage (BVID) in carbon fibre-reinforced polymer (CFRP) laminates. Composite specimens with varying impact energies (2.5–20 J) were excited using a single piezoelectric transducer with a nominal centre frequency of 28 kHz, operated at a fixed excitation frequency of 28 kHz. Thermal data were captured using an infrared camera. To enhance defect visibility and suppress background noise, the raw thermal sequences were processed using principal component analysis (PCA) and robust principal component analysis (RPCA). In LVT, RPCA and PCA provided comparable signal-to-noise ratios (SNR), with no consistent advantage for either method across all cases. In contrast, for pulsed thermography (PT) data, RPCA consistently resulted in higher SNR values, except for one sample. The LVT results were further validated by comparison with PT and phased array ultrasonic testing (PAUT) data to confirm the location and shape of detected damage. These findings demonstrate that LVT, when combined with PCA or RPCA, offers a reliable method for identifying BVID and can support safer, more efficient structural health monitoring of composite materials.

Keywords: barely visible impact damage; vibrothermography; principal component analysis; robust principal component analysis



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1. Introduction

Composite materials such as CFRP have gained widespread adoption in the aerospace industry [1,2] as well as in various other industries, including wind turbines [3], automotive [4], pressure vessels [5], sports and leisure [6], and construction sectors [7] due to their exceptional strength-to-weight ratio, corrosion resistance, and design flexibility [8,9]. Despite their remarkable properties, CFRPs are not immune to defects [10]. One of their critical vulnerabilities lies in their sensitivity to low-energy impacts, which can cause BVID [11,12]. BVID is a type of internal damage characterised by cracks, delamination, or fibre fracture, frequently difficult to detect with visual inspection [13]. This form of internal damage is critical, as it can initiate further damage when there are multiple cycles of loading, which could cause a major failure if it is not identified and fixed [13]. Meeting this challenge requires the adoption of non-destructive testing (NDT) technique designed to detect and assess

BVID [14]. Active thermography has emerged as one of the promising NDT approaches to tackle this problem [15]. Active thermography requires external excitation sources such as optical radiation (halogen lamp and laser), electromagnetic stimulation (induced eddy currents and microwaves), and mechanical ultrasonic waves to induce localised heating within the material [15–17]. These excitation sources generate thermal contrast between defective and non-defective areas, which an infrared camera can capture [17].

Among the various active thermography techniques, vibrothermography stands out for its ability to use vibration and/or ultrasonic excitation to generate heat at damage sites. This process is coupled with monitoring the sample using an infrared camera to assess the structural health of the material [18,19]. As explained by Renshaw et al. [20], heat is produced at cracks and defects primarily through mechanisms such as friction, localized plastic deformation, and viscoelastic effects.

Recent work by Liu et al. [21] demonstrated that optimizing the excitation frequency and sweep duration in low-power vibrothermography, using a laser Doppler vibrometer and a variable-frequency PZT transducer, can significantly improve the detection of BVID in CFRP by enhancing thermal contrast at defect sites. While their approach provides valuable insight into the role of excitation parameters and advanced instrumentation, it requires more complex equipment and procedures that may limit practicality for routine inspections.

In contrast, this study employs a fixed-frequency (28 kHz) transducer for low-power vibrothermography (LVT), representing a more accessible and industry-relevant experimental setup. A key feature of this work is the systematic comparison of principal component analysis (PCA) and robust principal component analysis (RPCA) as image processing tools to enhance defect detection in thermal images. By evaluating both techniques through quantitative signal-to-noise ratio (SNR) analysis, we provide new insights into their relative performance for identifying subtle damage.

This research also explores the effect of sample positioning by comparing detection results when CFRP specimens are placed in upper and lower positions within the experimental setup. Understanding how the orientation of the sample affects detection outcomes offers valuable practical guidance for future inspections.

Moreover, this study goes further by directly comparing the effectiveness of low-power vibrothermography with PT and PAUT for BVID detection and quantification. To the best of our knowledge, this is the first work to validate LVT findings using both PT and PAUT, allowing for a more comprehensive and reliable evaluation of each method's capabilities.

Together, these approaches advance the understanding of non-destructive testing methods for composites and contribute to the development of more accurate and robust strategies for detecting barely visible impact damage in CFRP materials.

2. Literature Review

Conventional vibrothermography techniques rely on a high-power excitation source to introduce sufficient energy into the specimen [22]. Although effective in detecting the defect, high-energy excitation sources pose a significant risk, as they can potentially introduce additional damage to the material under inspection [23]. This limitation has spurred interest among researchers to develop an LVT technique as a safer alternative. Solodov et al. [24,25] demonstrated that local defect resonance (LDR) can significantly enhance vibrothermography efficiency by producing noticeable temperature increases using low acoustic power input. However, one of the main challenges in applying LVT is the need for prior knowledge of the LDR frequency. To address this, Solodov et al. [25] developed a model that relates the LDR frequency to the defect geometry, material properties (Young's modulus, density, and Poisson's ratio), and the thickness of the material. Both the residual thickness at the defect and the overall plate thickness influence how the defect resonates.

Meanwhile, Segers et al. [26] used low-power ultrasonic excitation together with scanning laser vibrometry to detect LDR frequencies by analysing the vibrational response of composite specimens. Zhang et al. [27] demonstrated that micro-ultrasonic excitation thermography could successfully detect submillimetre porosities in CFRP composites, highlighting its complementary potential for low-power defect characterisation. Rahammer et al. [28,29] introduced an alternative way to estimate the LDR frequency without relying on laser scanning vibrometry. Their method, known as Resonance Frequency Sweep Thermography (RFST), uses a wideband frequency sweep to excite a broad range of possible defect resonances. This approach simplifies the testing process and lowers equipment costs by removing the need to know the exact resonance frequency of a defect in advance. However, wideband sweep excitation often includes frequencies outside the operating range of the transducer, which leads to reduced heat generation and a lower SNR in thermal images [21].

Recent advancements in LVT have demonstrated its efficacy in detecting and quantifying various defects in CFRP composites, including corrosion, delamination, and BVID. Liu et al. [22] developed a framework for detecting corrosion defects in CFRP-strengthened steel structures using LVT. By combining this technique with advanced image processing algorithms such as fast fourier transform (FFT) and partial least squares regression (PLSR), the authors significantly enhanced defect detectability and quantification. Huang et al. [23] investigated the detection of artificial delaminations in CFRP composites using ultrasonic thermography. This study employed PCA, FFT, and TSR algorithms to process thermal image sequences, effectively improving SNR and enabling the quantification of delamination areas using Otsu's thresholding method. In another study, Zhang et al. [30] explored the application of low-power ultrasonic thermography combined with manifold learning for the detection of BVID in CFRP specimens. The manifold learning algorithm extracted intrinsic features from thermal image sequences, effectively isolating damage information and suppressing thermal noise. This method demonstrated its capability to enhance sensitivity and reliability in detecting BVID. These studies highlight the critical role of integrating LVT with advanced image processing techniques, such as PCA, FFT, TSR, and manifold learning, to enhance defect visualisation and quantification. Compared to other active thermography methods, such as PT, significant research has been dedicated to optimising the processing of thermal image sequences. The combination of low-power excitation and sophisticated data analysis presents a promising pathway for improving the accuracy and efficiency of CFRP defect detection, paving the way for more reliable and effective NDT methods. PCA has been widely used in the field of active thermography to enhance defect detection. Among them are Marinetti et al. [31], where they leveraged PCA to process infrared (IR) image sequences gathered from the application of optical thermography (flash thermography and harmonic thermography) to the steel plate, opaque plastic, and carbon fibre-reinforced plastic, aiming to extract meaningful features and reduce redundancy in thermal NDT. Rajic et al. [32] introduced principal component thermography to improve the defect contrast and depth characterisation. Although principal component thermography is effective for feature extraction and dimensionality reduction, it does not promote sparsity, complicating result interpretation [33]. It is also sensitive to the noise and outliers in the dataset [34].

To address these limitations, various PCA variants have been introduced. Yousefi et al. [35] applied low-rank sparse principal component thermography (Sparse-PCT) to enhance defect segmentation in infrared thermographic data, demonstrating significantly improved accuracy in detecting subsurface defects, particularly in composite materials. Ebrahimi et al. [36] demonstrated RPCA outperformed conventional PCA, or principal component thermography (PCT), in terms of contrast-to-noise ratio when applied to PT

data from CFRP samples containing artificial defects. Huang et al. [37] demonstrated that RPCA outperformed conventional PCA, sparse PCA, and kernel PCA in detecting defects on building surfaces, particularly under challenging conditions such as shadow interference and image noise.

While prior studies have demonstrated the potential of PCA and RPCA in thermographic inspection, their comparative performance in LVT for detecting barely visible impact damage (BVID) in CFRP materials remains underexplored. This study addresses that gap by evaluating and comparing PCA and RPCA for thermal data enhancement in LVT and quantifying their effectiveness using SNR. To ensure the reliability of the findings, the results are also cross-validated using PT and PAUT.

3. Materials and Methods

3.1. Specimen Specification

The experimental specimens used in this study are the same CFRP laminates previously examined by Alhammad et al. [38] and Torbali et al. [39]. Two different thicknesses of CFRP samples were used in this study: a thin laminate and a thick laminate. Both sample types were manufactured using unidirectional pre-preg material (IMS-977-2) with a symmetrical stacking sequence of $[45/-45/90/0/90/0/90/-45/45]$. The thin laminate consisted of 9 plies, resulting in an average cured thickness of 1.65 mm, while the thick laminate was made by stacking the same sequence in a symmetric fashion (denoted as $[45/-45/90/0/90/0/90/-45/45]_s$), producing a total of 18 plies with a cured thickness of 3.8 mm. The corresponding per-ply thickness was approximately 0.183 mm for the thin laminates and 0.211 mm for the thick laminates, accounting for slight variations due to manufacturing tolerances. The laminates were cut into rectangular samples measuring 100 mm × 150 mm [38].

The specimens were subjected to BVID, created using a 13 mm steel hemispherical impactor and following the ASTM impact testing standard. Impact energies ranged from 2.5 J to 20 J, with specific drop heights and impactor masses calibrated to achieve the desired energy levels [38]. This approach ensured controlled damage conditions for studying the application of vibrothermography.

The experiment involved 10 samples: five thin samples (1.6 mm thickness) and five thick samples (3.8 mm thickness). For the thin samples, one specimen received 2.5 J of impact energy, one received 4 J, two specimens received 8 J, and one received 12 J. For the thick samples, one specimen received 4 J, two received 8 J, one received 12 J, and one received 20 J of impact energy. Two samples were prepared at the 8 J impact level for both thicknesses to allow assessment of the repeatability and consistency of barely visible impact damage (BVID) under conditions considered critical for BVID formation in aerospace-grade CFRP. Figure 1 depicts one of the experimental samples.



Figure 1. Photographs of the CFRP specimen: (left) front surface and (right) back surface, where the transducer was bonded for ultrasonic excitation; this surface also faced the infrared camera during testing.

3.2. Experiment Set-Up

This study aimed to detect BVID in CFRP laminates using LVT. The experimental design was inspired by recent research on identifying LDR frequencies through thermal responses. In particular, Rahammer et al. [29] showed how repeated frequency sweeps could be used to extract periodic thermal patterns caused by defect activation, while Hedayatrasa et al. [40] developed a thermal spectroscopy approach that relies on upward and downward frequency sweeps, combined with signal derivative analysis, to estimate LDR frequencies while correcting for thermal latency.

In this work, instead of using one broadband transducer, we used commercially available narrowband transducers with a centre frequency of 28 kHz (Hesentec HS-4SS-3528). The transducer was attached to the surface of the CFRP sample using couplant and excited one at a time using a function generator (TTI TG550) and a voltage amplifier (Piezo System EPA-104). Because automated sweeping was not possible, we manually adjusted the excitation frequency in small steps and monitored the surface temperature response live with an infrared camera.

To address the limited sample size (150 mm × 100 mm) and the relatively large diameter of the ultrasonic transducer, a dual-sample setup was employed. One CFRP specimen (the “lower sample”) was clamped vertically in a bench vice with a protective cork layer to prevent surface damage, while a second specimen (the “upper sample”) was placed horizontally on top. The transducer was positioned such that half of its contact surface was bonded to the vertical sample and the other half to the horizontal sample, as shown in Figure 2. This configuration prevented the transducer from overlapping a defect area on a single sample, allowed simultaneous excitation of both specimens and enabled direct comparison of their thermal responses under identical excitation conditions. A lightweight clamp ensured consistent contact without obstructing the thermal camera’s view.

For all CFRP specimens, a 28 kHz piezoelectric transducer was used as the sole excitation source, chosen based on preliminary tests which showed strong thermal contrast in a 1.6 mm-thick sample impacted at 12 J. However, since each sample has a different LDR frequency, the raw thermal response varied, some samples showed clear defect signatures, while others did not.

Thermal measurements were captured using a long-wave infrared (LWIR) camera (FLIR T560) placed approximately 1 metre from the sample surface. To minimise vibration artefacts and ensure a stable thermal signal, the recording procedure was standardised: the infrared camera was activated first and recorded for five seconds before ultrasonic excitation began. The signal generator then excited the specimen for five seconds, after which the camera continued recording until a total of 25 s had elapsed. Only frames captured between 5 and 15 s were used for data processing, discarding the first and last ten seconds to improve signal clarity and reduce computational time. Figure 2 illustrates the arrangement of the samples during LVT testing.

To improve the visibility of BVID in the thermal image sequences, we applied two processing techniques: PCA and RPCA. These methods help reduce background noise and enhance localised heating signals that may indicate defects.

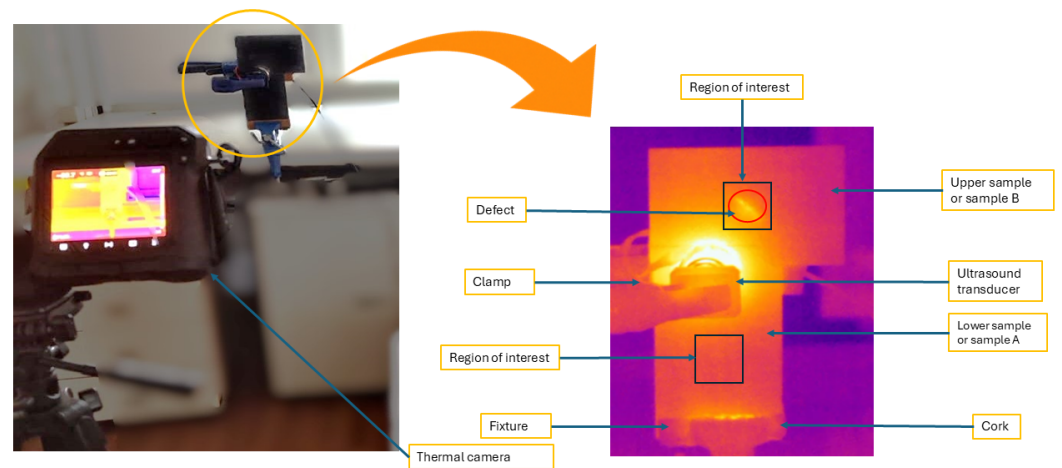


Figure 2. Schematic of the experimental setup. A large-diameter ultrasonic transducer is placed across the top of two CFRP specimens: one clamped vertically (lower sample) and one resting horizontally (upper sample). This configuration allows excitation of both samples simultaneously.

3.3. Image Processing of Thermal Images

3.3.1. Principal Component Analysis (PCA)

Because raw thermal images are often affected by noise, background radiation, and 3D thermal diffusion, image processing techniques are commonly applied to enhance contrast between defective and sound areas, thereby improving the accuracy of defect detection [41,42]. In this study, each frame was first converted to greyscale and then reshaped into a one-dimensional vector. This resulted in a data matrix $M \in \mathbb{R}^{T \times N}$, where T is the number of frames and N is the number of pixels per frame. Each row of M represents a thermal frame in time, while each column corresponds to the temporal evolution of a single pixel's intensity.

PCA is a widely used statistical method for dimensionality reduction and noise suppression. It transforms the original high-dimensional data into a set of orthogonal components that capture the most significant variance in the dataset [23,43]. Prior to PCA, the data matrix M was mean-centred along each pixel's time series. PCA was then performed by applying singular value decomposition (SVD) directly to the mean-centred matrix, or equivalently, by performing eigen-decomposition on the covariance matrix $M^T M$ [23,43]. This process yields a set of principal components, ordered by descending variance, that represent the underlying structure of the thermal data in a lower-dimensional subspace [37]. After decomposition, the selected principal components (e.g., PC1 to PC5) are reshaped back into 2D image frames for visual analysis. These component images often reveal defect-related features with improved contrast compared to the original raw thermal frames [37,43].

3.3.2. Robust Principal Component Analysis (RPCA)

While PCA is effective in reducing dimensionality and extracting dominant patterns in thermal data, it is known to be sensitive to noise and outliers [44,45]. To overcome this limitation, RPCA offers a more resilient framework for separating meaningful thermal features from undesired background interference [45].

RPCA decomposes the thermal video data matrix $M \in \mathbb{R}^{T \times N}$, where T is the number of frames and N is the number of pixels per frame, into two components [44–47]:

$$M = L + S \quad (1)$$

where L is a low-rank matrix and S is a sparse matrix. This decomposition is obtained by solving the following convex optimisation problem [46]:

$$\min_{L,S} \|L\|_* + \lambda \|S\|_1 \quad \text{subject to} \quad M = L + S \quad (2)$$

Here, $\|L\|_*$ denotes the nuclear norm (sum of singular values) that promotes low-rankness, and $\|S\|_1$ is the element-wise ℓ_1 -norm that encourages sparsity in S . The regularisation parameter λ balances the trade-off between the low-rank and sparse components and was selected based on established recommendations in the literature [23,45].

In this study, RPCA was applied to enhance defect visibility in CFRP thermographic video sequences. After decomposition, the low-rank component L preserved the dominant thermal feature associated with the defects, while reducing background variations and random noise. As a result, the L component was selected for further analysis and compared with the PCA outputs.

To solve the decomposition efficiently, the inexact augmented lagrangian multiplier (IALM) method was employed due to its balance between computational speed and convergence reliability [36,47].

3.4. Quantitative Evaluation Using SNR

SNR is a critical metric in infrared thermography, commonly used to assess the performance of image processing algorithms for defect detection in NDT [48–50]. It quantitatively compares the intensity of a signal originating from a defect region with the level of background noise, thereby serving as an indicator of image quality and defect visibility [49].

The most widely used formulation for SNR in thermographic applications is defined as follows [48,49]:

$$\text{SNR (dB)} = 20 \log_{10} \left(\frac{|\mu_{\text{defect}} - \mu_{\text{background}}|}{\sigma_{\text{background}}} \right) \quad (3)$$

where μ_{defect} is the mean intensity value within the defect region, $\mu_{\text{background}}$ is the mean intensity in a nearby sound area, and $\sigma_{\text{background}}$ is the standard deviation of the background noise [48,49].

In the study by Hidalgo-Gato et al. [48], the SNR was used to quantitatively compare several thermographic image processing techniques. These included differential absolute contrast (DAC), pulsed phase thermography (PPT), thermographic signal reconstruction (TSR), principal component thermography (PCT), as well as statistical approaches such as skewness and kurtosis. The authors demonstrated that SNR is a useful metric for evaluating the effectiveness of each method in enhancing defect visibility. By calculating the difference in average intensity between a defect region and a nearby background region and normalising it by the background noise level, SNR provides an objective measure of image contrast and quality.

Madruga et al. [49] demonstrated the application of this SNR metric in lock-in thermography, comparing discrete Fourier transform (DFT) and harmonic approximation (HA) methods for phase image generation. Their results highlighted the importance of sufficient SNR (e.g., >0 dB) to ensure reliable automatic defect detection.

In this study, SNR was employed to quantitatively evaluate the effectiveness of PCA and RPCA in enhancing defect visibility in the upper CFRP specimens.

3.5. Methodology

This study explores the potential of LVT for detecting BVID in CFRP materials by combining thermal image enhancement and quantitative evaluation techniques. The workflow

is structured into three main stages: data acquisition, image processing, and performance assessment using SNR analysis.

To start, thermal data were collected using an LVT setup. A 28 kHz piezoelectric transducer was used to apply continuous ultrasonic excitation to the CFRP specimens. A FLIR T560 long-wave infrared (LWIR) camera, operating at 30 Hz, recorded the resulting surface thermal response. The captured thermal video was converted into grayscale image frames for further processing.

In the image processing stage, the data were analysed using two enhancement techniques, PCA and RPCA. These methods are designed to suppress variations in the thermal response of the sound area (i.e., undamaged regions within the specimen) and enhance the visibility of subtle thermal anomalies associated with damage.

For performance evaluation, the effectiveness of each image processing method was quantified using SNR metric. An 80×80 pixel region of interest (ROI) was manually selected to avoid areas too close to the ultrasonic transducer, as localised heating from the transducer itself could interfere with defect contrast and bias the PCA and RPCA results. For SNR calculation, a rectangular patch corresponding to the defect area was placed within the visible defect, while a separate patch was designated in a sound (undamaged) area of the specimen. Both defect and sound patch locations remained identical for PCA and RPCA to facilitate strict and objective comparison. This approach allowed for consistent, objective comparison of defect visibility across different enhancement methods.

To validate the experimental results and benchmark the LVT approach, additional datasets from pulsed thermography (PT) and phased array ultrasonic testing (PAUT) were included. These PT and PAUT datasets were previously obtained and described by Torbali et al. (2025) [39], who is a co-author of the present study.

The PT measurements were performed using a high-sensitivity cooled infrared camera (FLIR X8501sc, InSb, spectral range 3–5 μm , 50 mm focal length, 1280×1024 pixels, NEDT < 20 mK, linear Stirling cooling). Unlike the LVT experiments, where two CFRP samples were tested simultaneously within the setup, PT measurements were performed on a single-sample basis. Two xenon flash lamps (Balcar, 2 ms pulse duration at FWHM, 6.2 kJ per flash) served as the excitation source, with all components synchronised via a PC. For each measurement, the camera was placed approximately 40 cm from the specimen to ensure full surface coverage. The two flashes were positioned 10 cm behind the camera, separated by a distance of 50 cm, and angled at 45 degrees with respect to the sample surface [39].

The PT thermal data were processed using the same PCA and RPCA techniques as applied to the LVT data, while the PAUT data served as a reference for confirming the presence and location of subsurface defects.

The PAUT was carried out using a Sonatest PA X3 system with a 64-element linear array transducer operating at 10 MHz and an element pitch of 0.6 mm. A flat elastomer wedge was used to maintain consistent contact with the specimen. For each scan, eight elements were activated as the aperture, which allowed the ultrasonic beam to be focused and steered as needed. Waveform data were collected at a sampling frequency of 125 MHz to ensure high temporal resolution [39].

This combined approach enables a comparative evaluation of LVT's performance relative to established inspection methods, particularly in terms of thermal contrast and defect detectability. A summary of the methodology is illustrated in Figure 3.

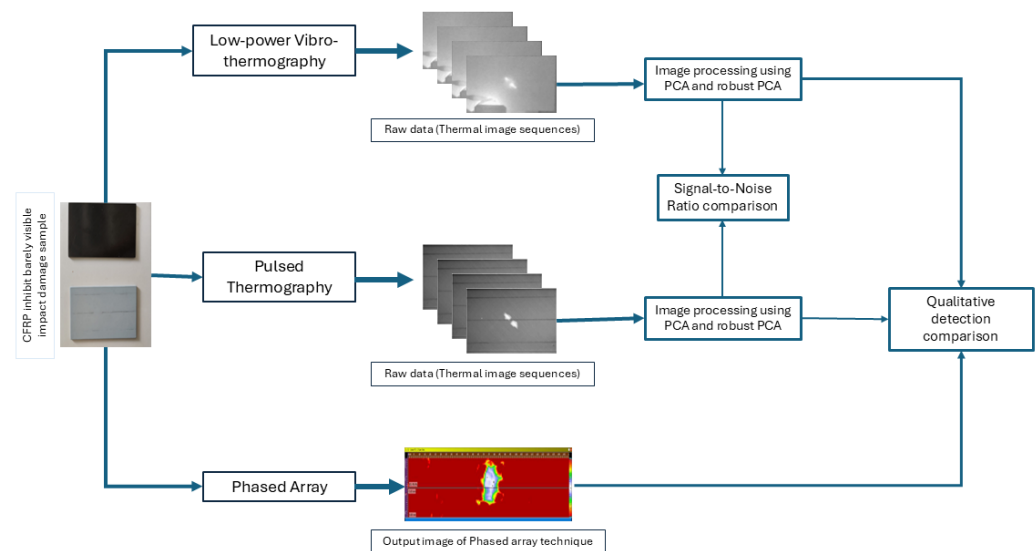


Figure 3. Overview of the experimental methodology.

4. Result

The results presented in this section were obtained using the dual-sample arrangement and LVT experimental configuration described in the section experiment set-up (see also Figure 2). This arrangement enabled the simultaneous excitation and thermal monitoring of both an upper and a lower CFRP specimen using a single transducer.

Analysis focused on comparing the thermal response and defect detectability between the upper and lower samples under identical excitation conditions. The following results illustrate how sample positioning, impact energy, and thickness influence defect visibility, as revealed through PCA and RPCA image processing.

4.1. Variability in Defect Detection Across Dual-Sample Configuration

This section highlights differences in defect detectability observed during tests using a dual-sample setup. In this configuration, an upper and a lower CFRP sample were bonded to a single piezoelectric transducer and excited simultaneously using the same ultrasonic signal at 28 kHz. Although both samples experienced the same excitation conditions, the ability to detect defects differed between them. In some cases, defects were clearly detected in both samples. In others, only one sample, showed a visible defect. This behaviour may be influenced by the relationship between each sample's LDR frequency and the fixed excitation frequency.

Each CFRP sample has a unique LDR frequency, which depends on material properties, defect geometry, and thickness [25]. If a sample's LDR is close to the applied excitation frequency (28 kHz), it is more likely to resonate and generate a strong thermal response, making the defect detectable. Conversely, if the LDR is significantly different from the excitation frequency, little or no resonance occurs, reducing thermal response and rendering the defect invisible [24]. Figure 4 compares two dual-sample configurations, captured 5 s after excitation. In the thick-sample setup (left), defects are visible in both the upper (12 J) and lower (20 J) samples. In contrast, the thin-sample setup (right) shows a detectable defect only in the lower sample (12 J), while the upper sample (2.5 J) shows no visible response.

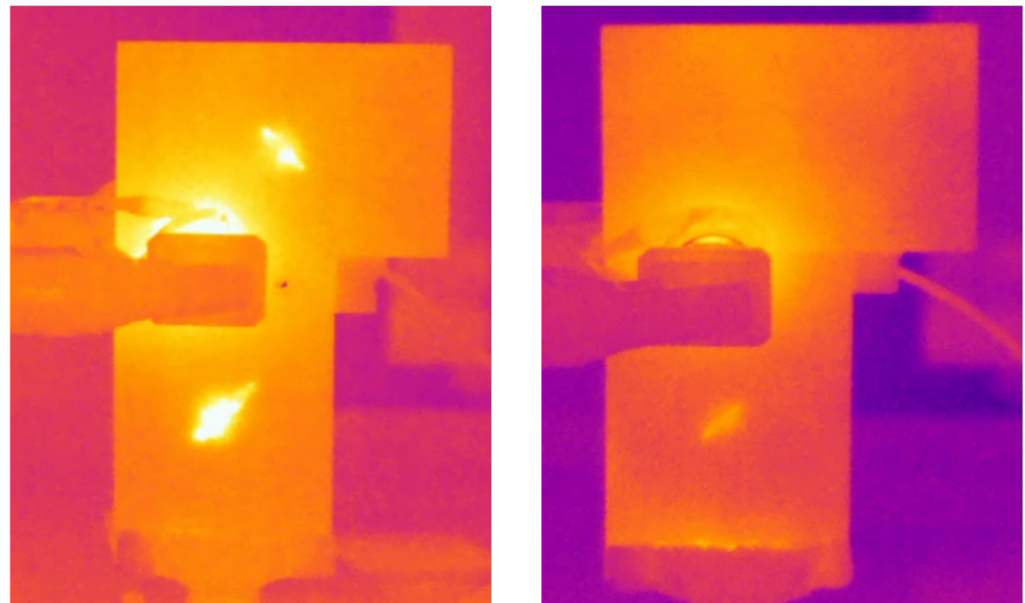


Figure 4. Comparison of defect visibility in dual-sample configuration: **(Left)** defects in both the upper and lower samples are visible; **(Right)** only the lower sample defect is visible.

4.2. Effect of Sample Positioning on Detection

Initially, the upper sample in the dual-sample arrangement was intended solely to support the transducer placement. However, experimental results revealed that the upper sample, positioned horizontally above the transducer, often exhibited superior defect detection performance compared to the lower (vertically clamped) sample. This section evaluates the effect of sample positioning on thermal image-based detection across all specimens.

Ten CFRP samples were tested, five thin (1.6 mm) and five thick (3.8 mm), each subjected to various impact energies ranging from 2.5 J to 20 J. For each sample, thermal data were processed using both PCA and RPCA. From each method, the first five principal components (PC1 to PC5) were extracted for evaluation. This resulted in a total of 100 processed images for the upper-sample configuration and another 100 for the lower-sample configuration.

As shown in Figures 5 and 6, the defect was only detectable when the sample was positioned in the upper configuration. Notably, in this 2.5 J thin sample, the BVID was only revealed in Principal Component 3, indicating that the thermal response was too subtle to be captured in the dominant PC1 or PC2. This highlights the importance of evaluating multiple components, especially in low-energy impact cases where defect signals are weak. In contrast, the same defect remained undetectable in the lower configuration regardless of the processing method or principal component.

A similar result was observed in a thick CFRP sample subjected to an 8 J impact, where the defect was not clearly detected when the sample was positioned below another material (see Figures 7 and 8). In contrast, the defect became visible in PC3 when the same sample was positioned above another material. This consistency across multiple samples suggests that the sample position significantly influences defect detectability in vibrothermographic testing.

In contrast, samples with higher impact energies or more prominent damage, such as the thin 12 J specimen, exhibited clear defect visibility in both configurations. However, even in these cases, the upper configuration often resulted in marginally higher contrast or more defined defect shapes. (See Figures 9 and 10).

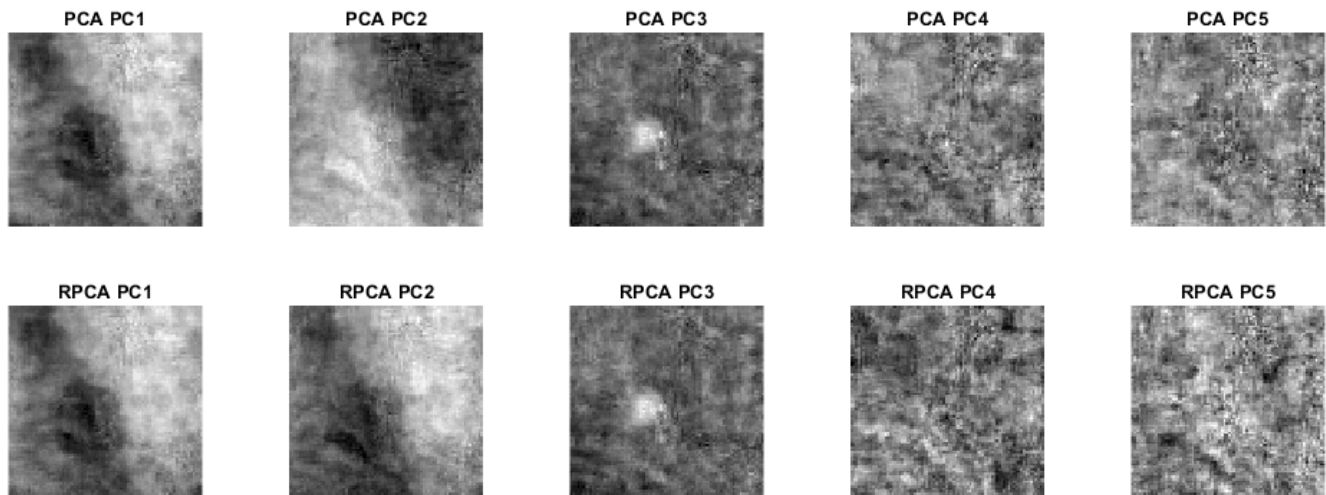


Figure 5. RPCA and PCA applied to a thin CFRP sample with a 2.5 J BVID, positioned above another material (upper configuration).

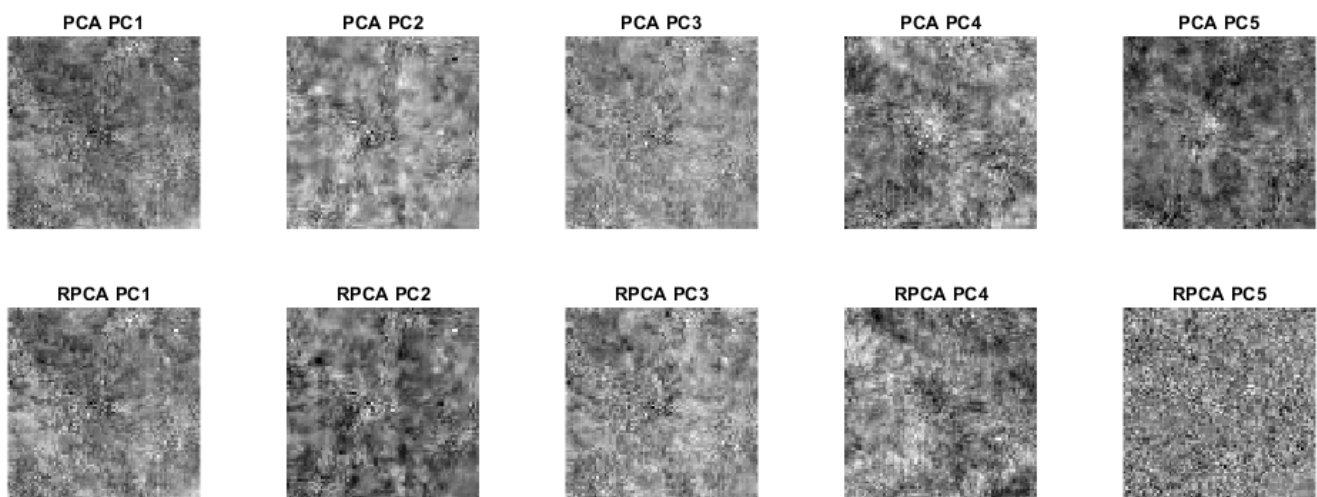


Figure 6. RPCA and PCA applied to a thin CFRP sample with a 2.5 J BVID, positioned below another material (lower configuration).

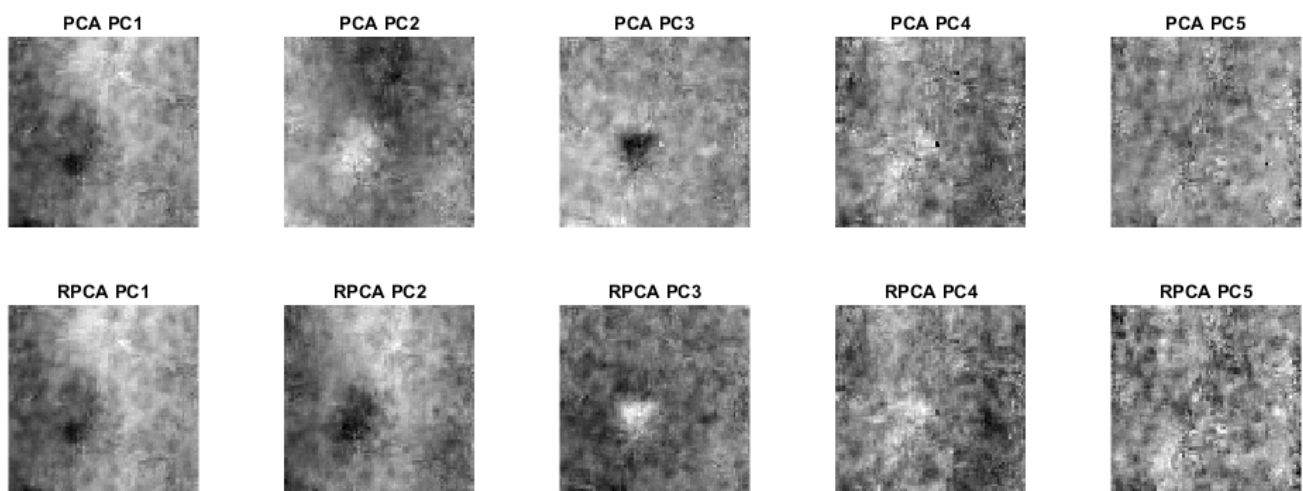


Figure 7. RPCA and PCA applied to a thick CFRP sample with an 8 J BVID, positioned above another material (upper sample).

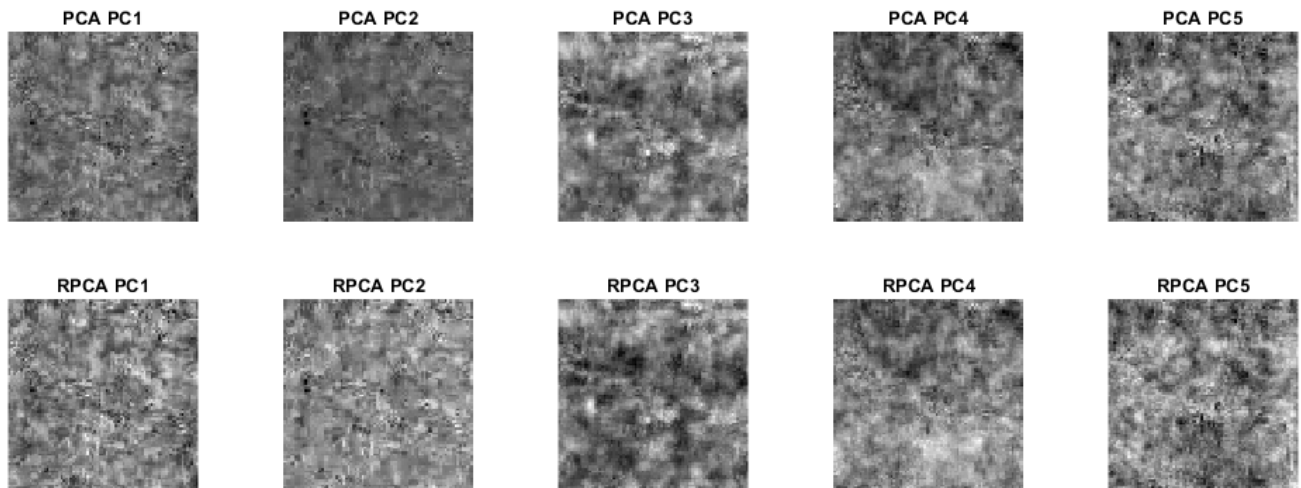


Figure 8. RPCA and PCA applied to a thick CFRP sample with an 8 J BVID, positioned below another material (lower sample).

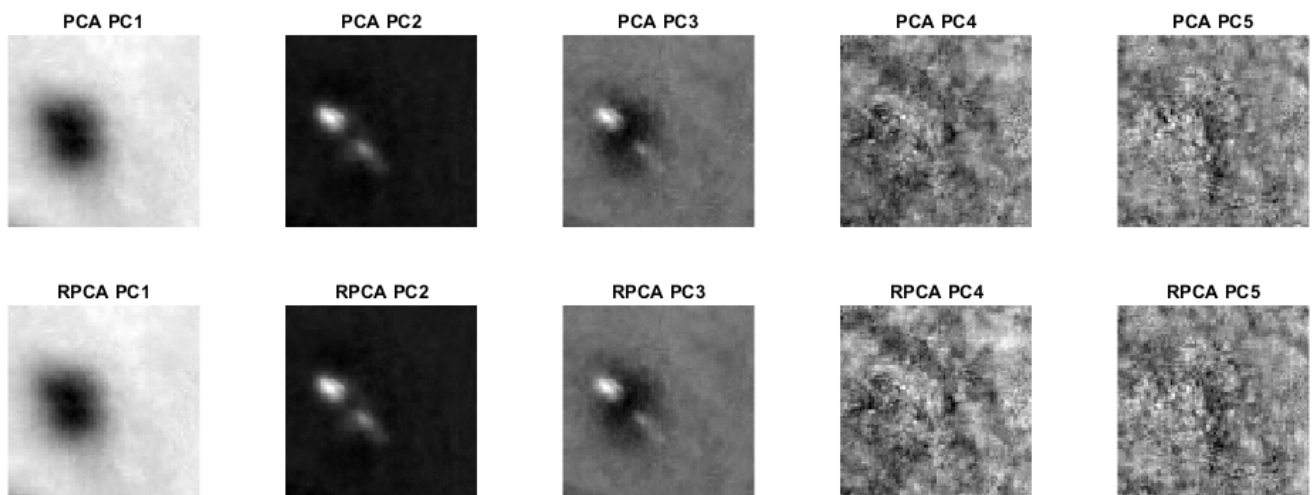


Figure 9. RPCA and PCA applied to a thick CFRP sample with an 12 J BVID, positioned above another material (upper sample).

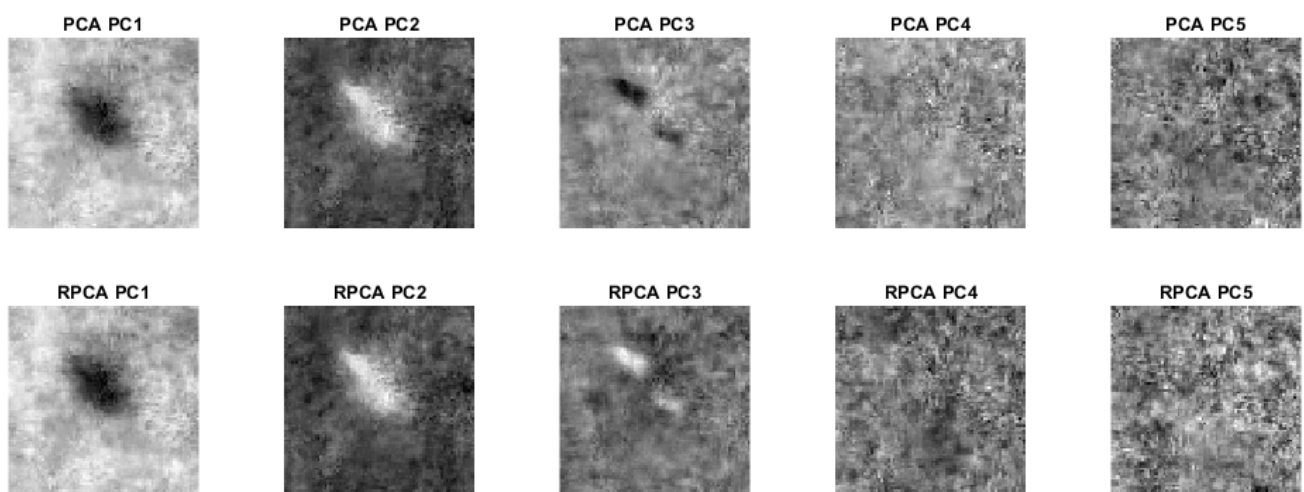


Figure 10. RPCA and PCA applied to a thick CFRP sample with a 12 J BVID, positioned below another material (lower sample).

4.3. SNR-Based Evaluation of Detection Performance

To complement the visual observations, a quantitative analysis was performed using SNR for each processed image. The SNR provides an objective metric for evaluating how well a defect can be distinguished from the surrounding background. This approach enables direct comparisons between different conditions, including processing method (PCA vs RPCA), impact energy, and sample positioning.

Table 1 and the bar chart on Figure 11 summarise the SNR values for all tested CFRP samples across both upper and lower configurations.

Table 1. SNR for PCA and RPCA across all tested CFRP samples.

Type	Impact Energy (J)	Label	Position	SNR RPCA (dB)	SNR PCA (dB)	Best PC
Thin	2.5		upper sample	14.13	13.62	PC3
Thin	2.5		lower sample	not detected	not detected	not detected
Thin	4.0		upper sample	23.13	22.84	PC2
Thin	4.0		lower sample	6.42	5.94	PC3
Thin	8.0	A	upper sample	28.12	28.29	PC1
Thin	8.0	A	lower sample	25.61	25.60	PC1
Thin	8.0	B	upper sample	31.75	31.54	PC1
Thin	8.0	B	lower sample	18.69	19.16	PC2
Thin	12.0		upper sample	27.90	28.04	PC1
Thin	12.0		lower sample	32.32	33.15	PC1
Thick	4.0		upper sample	not detected	not detected	not detected
Thick	4.0		lower sample	not detected	not detected	not detected
Thick	8.0	A	upper sample	21.16	22.31	PC2
Thick	8.0	A	lower sample	9.54	9.89	PC2
Thick	8.0	B	upper sample	17.23	17.16	PC3
Thick	8.0	B	lower sample	not detected	not detected	not detected
Thick	12.0		upper sample	29.59	29.90	PC1
Thick	12.0		lower sample	15.20	15.00	PC1
Thick	20.0		upper sample	31.26	30.98	PC1
Thick	20.0		lower sample	36.93	37.04	PC1

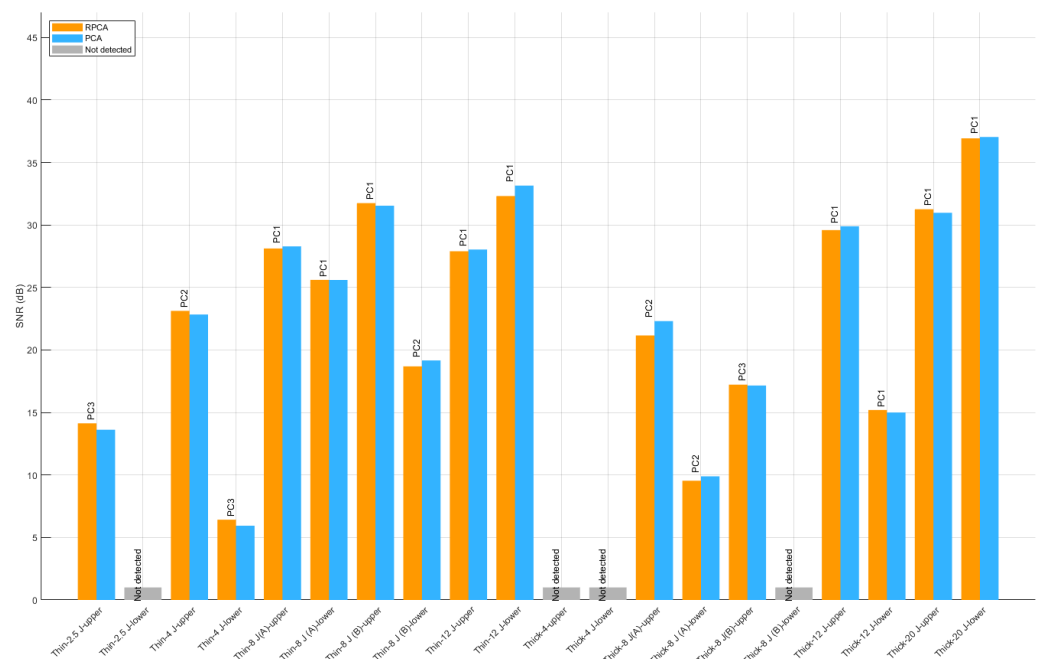


Figure 11. Bar chart of SNR (dB) for RPCA and PCA across CFRP samples.

The results presented in the bar chart offer an overview of SNR (dB) values obtained through both RPCA and PCA processing for a range of CFRP samples subjected to various impact energies and configurations. A prominent trend observed in the data is that samples placed in the upper position, closer to the transducer, generally exhibit higher SNR values, regardless of the image processing method or sample type. This highlights the significant effect of sample positioning and transducer proximity on defect detectability.

As impact energy increases, there is a clear tendency for the SNR values to rise as well, especially in the thin samples. Both RPCA and PCA methods achieve their highest SNR value for the thin-12 J and thick-20 J samples. For these samples, the lower position yields a higher SNR than the upper position.

In comparing the two image processing approaches on the LVT data set, it becomes evident that RPCA and PCA deliver comparable SNR values in most cases. An examination of the principal components further reveals that PC1 most often corresponds to the highest SNR, particularly for samples with large or clear defects. In cases where the defect is less distinct, the best SNR may be achieved using PC2 or PC3, indicating that relevant defect information can be captured in higher-order components when the variance associated with the defect is not dominant.

There are several notable anomalies in the dataset. In particular, the Thick-4 J sample, both in upper and lower positions, shows an SNR marked as “not detected” for both RPCA and PCA. This absence of a detectable signal is not a result of image processing limitations but rather reflects the physical reality of the sample. Validation using both PT and PAUT inspection confirmed that the thick-4 J sample did not sustain any measurable damage during impact testing. “not detected” outcomes are also seen in some lower-positioned thin and thick samples. This may be attributed to several factors, such as the defect not being in close proximity to the transducer or an imperfect match between the transducer excitation frequency and the sample’s local defect resonance (LDR) frequency. Both factors can diminish the thermal response associated with a defect, making detection more challenging.

4.4. Comparison Between LVT and PT for BVID Detection in CFRP

To better understand the capability of LVT in detecting BVID in CFRP composites, its results were compared with those from PT, a well-established thermal NDT method. Both techniques were applied to the same set of impacted CFRP samples. The thermal data from each technique were processed using a consistent approach that included both PCA and RPCA. The best principal component (PC) selected based on the visual contrast of the defect was then used to calculate the SNR, providing a quantitative basis for comparison.

In this context, PT serves as a benchmark. PT uses a strong, short-duration heat pulse that typically results in high thermal contrast [51]. LVT, in contrast, relies on mechanical excitation to generate heat at internal defect sites through vibration or friction. These distinct excitation mechanisms result in different thermal responses, which in turn affect image contrast and the effectiveness of PCA-based defect isolation.

For consistency, only upper-positioned samples of LVT were included in the analysis. Earlier findings indicated that defect visibility in LVT was mostly better when the specimen was positioned as the upper sample in the dual-sample setup.

For the calculation of PT data, a region of interest (ROI) measuring 130×130 pixels was defined. Rectangular patches were selected within the defect region and the sound (undamaged) area. The result of the calculation of SNR can be seen in Table 2.

The comparative analysis of SNR values for PCA and RPCA across various PT CFRP samples demonstrates that both methods achieve their optimal defect contrast in the first principal component (PC1). RPCA consistently provides slightly higher SNR than PCA for

most samples, confirming its effectiveness in suppressing background noise. However, a clear anomaly is observed for the Thin 2.5 J sample, in this case, PCA outperforms RPCA.

Table 3 summarizes how well both LVT and PT performed in detecting impact damage across various CFRP samples. For each case, the table presents the highest SNR value achieved by each technique, alongside representative thermal images that illustrate defect visibility.

Table 2. Comparison of RPCA and PCA SNR values (dB) for PT samples.

Sample	RPCA (SNR) (dB)	PCA SNR (dB)	Best PC
Thin 2.5 J	28.62	29.36	PC1
Thin 4 J	35.87	34.68	PC1
Thin 8A J	42.11	40.36	PC1
Thin 8B J	42.07	40.77	PC1
Thin 12 J	38.63	37.97	PC1
Thick 4 J	not detected	not detected	not detected
Thick 8A J	42.31	41.22	PC1
Thick 8B J	35.01	34.58	PC1
Thick 12 J	41.07	40.16	PC1
Thick 20 J	49.16	47.56	PC1

From the table, it is clear that PT consistently provides higher SNR values than LVT, sometimes by a considerable margin. For instance, in the Thin 2.5 J sample, the SNR for PT is more than two fold of SNR for the LVT (29.36 dB versus 14.13 dB), and this pattern persists across both thin and thick samples at different impact energies. The visual images reinforce this finding, defects generally appear sharper and more distinct in the PT images, whereas in LVT some defects are less obvious or harder to distinguish, particularly in samples with lower SNR.

Table 3. Comparison of best PCs and defect visibility using LVT and PT.

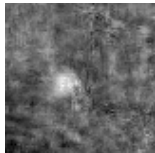
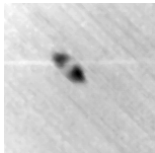
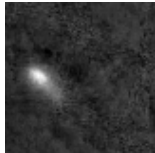
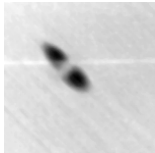
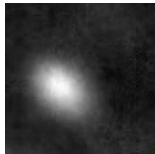
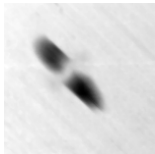
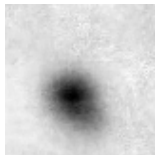
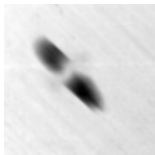
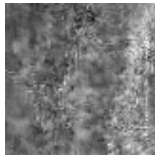
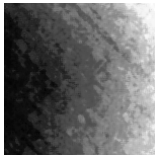
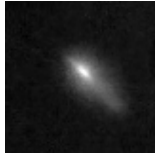
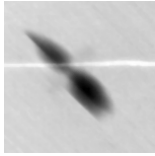
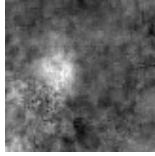
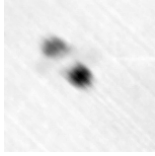
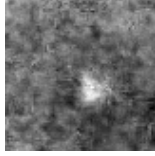
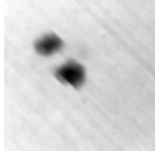
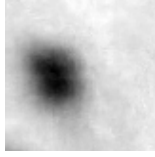
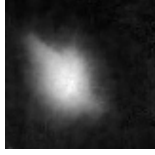
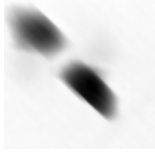
Sample (Type + J)	LVT SNR	LVT Image	PT SNR	PT Image
Thin 2.5	14.13		29.36	
Thin 4.0	23.13		35.87	
Thin 8.0 (A)	28.12		42.11	
Thin 8.0 (B)	31.75		42.07	

Table 3. *Cont.*

Sample (Type + J)	LVT SNR	LVT Image	PT SNR	PT Image
Thick 4.0	not detected		not detected	
Thin 12.0	33.15		38.63	
Thick 8.0 (A)	22.31		42.31	
Thick 8.0 (B)	17.23		35.01	
Thick 12.0	29.90		41.07	
Thick 20.0	37.04		49.16	

4.5. Comparative Analysis of LVT, PT, and PAUT for BVID Detection

Table 4 presents a visual comparison of defects identified using LVT, PT, and PAUT (shown as C-scan images). For LVT and PT, the thermal images were captured from the front surface of the samples, the same side where the impact was applied. In contrast, the C-scan measurements were taken from the back surface of each specimen. The comparison of defect images from PT, LVT, and PAUT (C-scan) shows clear differences in the appearance and shape of BVID. In PT images, defects generally appear as two distinct dark lobes, particularly in samples with lower impact energy. These lobes are well separated and show a sharp contrast against the background. In LVT images, the defects are typically seen as a single, more continuous region, either darker or brighter than the surrounding area, often with sharper outlines and more compact shapes compared to PT.

C-scan images, obtained from PAUT, consistently show a single rounded or elliptical defect area. The defect shapes in C-sans are generally smooth, centred, and compact, with no splitting or multiple lobes observed. In most cases, the VT results more closely resemble the C-scan images, both in terms of shape and position. PT often shows more visual complexity, with multiple lobes or elongated patterns, while C-sans and LVT images indicate a single, centralised area of damage.

Table 4. Qualitative comparison of defect visibility using LVT, PT, and PAUT (C-scan) imaging (only upper-positioned samples are included).

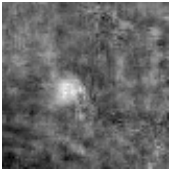
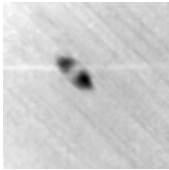
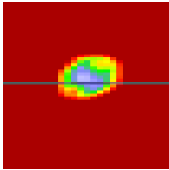
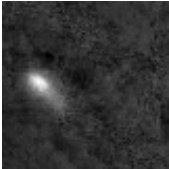
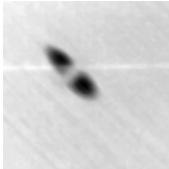
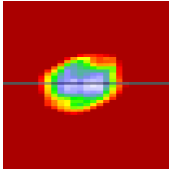
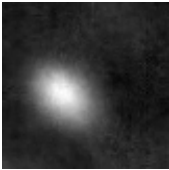
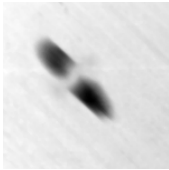
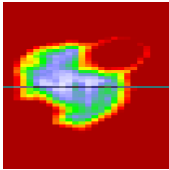
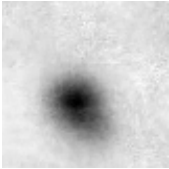
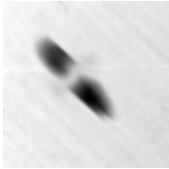
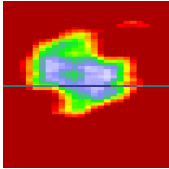
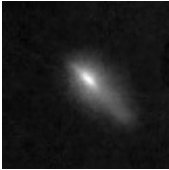
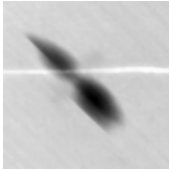
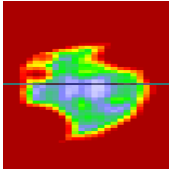
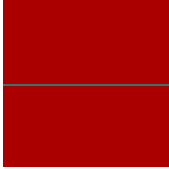
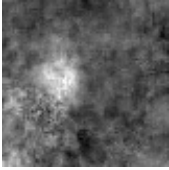
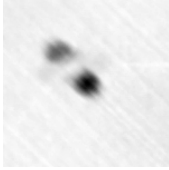
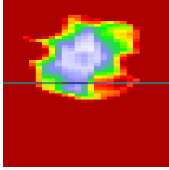
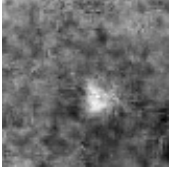
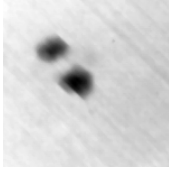
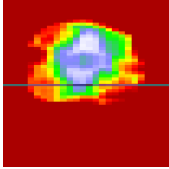
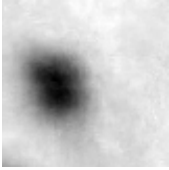
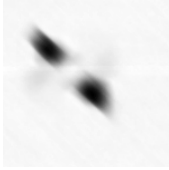
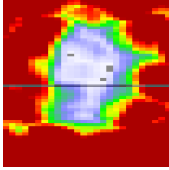
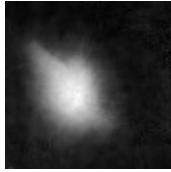
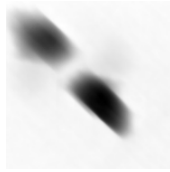
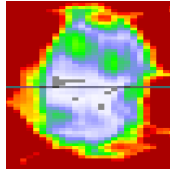
Sample (Type + J)	LVT Image	PT Image	C-scan Image
Thin 2.5			
Thin 4.0			
Thin 8.0 (A)			
Thin 8.0 (B)			
Thin 12.0			
Thick 4.0			
Thick 8.0 (A)			
Thick 8.0 (B)			
Thick 12.0			

Table 4. *Cont.*

Sample (Type + J)	LVT Image	PT Image	C-scan Image
Thick 20.0			

5. Discussion

This study explored the effectiveness of LVT in detecting BVID in CFRP laminates, supported by a comparative analysis against PT and PAUT. Advanced image processing techniques, namely PCA and RPCA, were applied to enhance defect visibility and evaluate detection performance through SNR metrics.

5.1. Effectiveness of PCA and RPCA in Enhancing Thermal Contrast

In LVT, both PCA and RPCA yielded similar SNRs, with only minor, sample-specific variations and no clear evidence that one consistently outperformed the other.

For PT data, the situation was different. Here, RPCA generally provided higher SNR values than PCA across most CFRP samples, confirming its advantage in suppressing background noise and isolating defect-related signals, especially in data with complex or structured background variations. The only notable exception was the thin 2.5 J sample, in which PCA outperformed RPCA by a small margin. In all other PT cases, RPCA yielded the highest defect contrast. These results align with previous studies showing that robust decomposition techniques, such as RPCA, can offer tangible improvements in thermal contrast for PT, where spatial and temporal noise components can otherwise obscure subtle defect signatures.

It is also important to consider the computational trade-offs associated with each method. The improvements in defect contrast offered by RPCA, particularly in PT, come at the cost of substantially higher processing times. For instance, when processing PT data consisting of 1000 frames, conventional PCA required only 1.32 s, whereas RPCA required 73.93 s for the thin 4 J sample, over fifty times longer. Given that SNR improvements with RPCA are often modest in PT, the additional computational cost should be carefully considered in practical applications. The use of RPCA may be most justified when maximum contrast enhancement is critical for defect detectability [36,37].

5.2. Implications for NDT of CFRP Structures

These findings have practical implications for nondestructive testing of CFRP structures, particularly in aerospace and transport sectors where detection of subsurface damage is critical. LVT, combined with RPCA or PCA-based image enhancement, offers a low-power method, capable of revealing BVID with high contrast, especially in thicker and higher impact energy laminates. The ability to isolate defect signals using RPCA and PCA also reduces reliance on high excitation energy or complex thermal stimulation, offering safer and more energy efficient alternatives to conventional methods.

5.3. Limitations and Future Work

Despite promising results, this study has several limitations. The transducer frequency was fixed at 28 kHz, which may not match the LDR frequency for all specimens, potentially resulting in suboptimal energy transfer and reduced sensitivity in certain configurations. Additionally, the sample set included only 10 specimens, which limits the statistical reliability and generalizability of the findings. The ROI for image analysis was also selected

manually, introducing subjectivity that could affect the consistency of defect quantification, particularly in larger or more diverse datasets.

Future work should address these limitations, by exploring variable or adaptive excitation frequencies, incorporating larger and more diverse sample sets, including different defect types and evaluating advanced image processing techniques to further enhance defect segmentation and quantitative accuracy. Furthermore, the development and implementation of automated ROI selection methods, such as those based on computer vision, would greatly improve the objectivity, efficiency, and repeatability of the analysis process. Additionally, future studies should include a thorough analysis of measurement uncertainty and result repeatability, such as repeated measurements and uncertainty quantification, to strengthen confidence in the robustness and reliability of the detection results. For the next study, it is also important to investigate the effect of the fixture itself, such as potential thermal stress or reflected waves.

6. Conclusions

This study explored the use of LVT combined with advanced image processing methods for detecting and quantifying BVID in CFRP laminates. By processing thermal image sequences with PCA and RPCA, and benchmarking the results against PT and PAUT, the research provides new insights into the comparative strengths and limitations of these approaches for NDT applications.

The results show that both PCA and RPCA substantially improve defect visibility in LVT thermal images, enabling reliable detection of BVID. For LVT data, the overall difference between RPCA and PCA was not significant, in some cases, RPCA gave slightly higher SNR values, while in others, PCA performed marginally better. There was no consistent trend favoring one method over the other, suggesting that either technique can be applied effectively in LVT, depending on the data quality and computational constraints.

In contrast, RPCA offered a clear advantage over PCA in the analysis of PT data, generally achieving higher SNR values and superior suppression of background noise, with only minor exceptions. These findings reinforce the value of robust decomposition techniques, particularly in thermographic applications where complex or structured background noise may obscure defect signatures. The study also highlights the influence of specimen positioning in the dual-sample LVT setup, with defects more readily detected in the upper sample.

Cross-validation with PAUT confirms that both LVT and PT are capable of accurately identifying the location and shape of subsurface defects in CFRP samples. However, it is important to recognize that RPCA comes with a substantial computational cost: for example, processing a typical PT dataset with RPCA and PCA may take over seventy seconds, compared to less than two seconds for PCA alone. This difference in processing time should be considered when selecting image processing strategies.

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Low-power vibrothermography for detecting barely visible impact damage in CFRP laminates: a comparative imaging study

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