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Event-triggered passive–active guided wave monitoring for a PZT-embedded smart composite panel

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Abstract

Composite structures are vulnerable to impact-induced local anomalies that are often difficult to detect visually, necessitating structural health monitoring (SHM) methods capable of both impact localization and post-impact assessment. This study proposes an event-triggered passive-active SHM framework for a piezoelectric transducers (PZT)-embedded smart composite panel. The embedded PZT array functions as a unified sensing and actuation network, enabling a continuous procedure of passive impact localization and active damage detection. A PZT-embedded smart composite panel was fabricated, and tensile tests were performed to verify the mechanical compatibility of the sensor integration scheme. In the passive stage, impact localization was achieved through continuous wavelet transform, first-peak extraction, Gaussian-windowed cross-correlation, and probabilistic imaging. In the active stage, two time-frequency features, the energy ratio (ER) and the normalized residual entropy (NRE), were extracted from differential guided-wave responses, and a Mahalanobis-distance (MD)-based indicator was constructed within a healthy reference space for state discrimination. Experimental results demonstrate that the passive method achieves high-accuracy impact localization. Furthermore, while ER characterizes the energy of damage-induced scattering waves, NRE provides complementary information regarding the temporal energy redistribution of the residual signals. By synthesizing ER and NRE, the proposed MD-based indicator is shown to effectively separate healthy and local-anomaly states. Compared with conventional damage indices, the proposed method more effectively suppresses healthy-state fluctuations and improves discrimination stability.

1. Introduction

Carbon-fiber-reinforced polymers (CFRPs) have been widely used in high-performance engineering structures, particularly in aerospace applications, owing to their high specific strength, high specific stiffness, corrosion resistance, and design flexibility [1]. However, CFRPs are susceptible to transient service loads (e.g. low-velocity impacts, tool drops, debris strikes), which may induce internal damage such as delamination, matrix cracking, fiber breakage, and local debonding [2, 3]. Unlike metallic structures that exhibit visible plastic dents, CFRPs develop barely visible impact damage (BVID), impeding timely detection. If undetected, such damage may propagate under cyclic or complex service loads, compromising residual strength and structural safety [2–4]. Therefore, online structural health monitoring (SHM) for composite structures is of critical engineering significance [5, 6].

Among various SHM methods, guided-wave-based approaches have gained wide attention due to their large-scale monitoring capability and high sensitivity to damage [6–11]. Guided-wave SHM methods fall into two categories by working mode: passive and active monitoring [12, 13]. Passive monitoring detects transient stress-wave responses generated by impacts or acoustic-emission events, making it suitable for event perception and impact-source localization [12–14]. To enhance the accuracy and robustness of impact localization in complex composite structures, various algorithms have been developed, such as neural-network-based methods, time-reversal focusing, multi-frequency probabilistic imaging, adaptive time-reversal imaging, and Lamb-wave-mode-based approaches, among others [14–19]. Among these approaches, time-reversal-based methods exploit the spatial focusing property of reversed wavefields for impact localization, and virtual implementations can perform the corresponding back-propagation or wavefield reconstruction numerically under complex propagation conditions [14, 16, 19–21]. De Marchi L proposed a passive monitoring technique based on dispersion compensation to locate impacts in plate-like structures, demonstrating that dispersion compensation can be effectively applied even without knowing the exact time of impact [22]. Recent studies have further extended passive impact monitoring from source localization toward joint impact characterization and uncertainty-aware estimation. Deng *et al* proposed simultaneous impact localization and energy estimation using ensemble learning and approximate Bayesian computation [23]. By combining data-driven forward models with Bayesian inference, the method provides probabilistic estimates of both impact position and energy. Bayesian data fusion and ANN-assisted updating have also been introduced to improve localization robustness in composite structures [21, 24], while a recent sensor-learning framework enabled simultaneous localization and impact-force estimation [25]. Earlier work has also demonstrated real-time impact localization in anisotropic aerospace composite structures without *a priori* knowledge of material properties [26]. Nevertheless, passive monitoring indicates whether and where an impact occurred, but does not directly determine if it caused internal damage or local structural anomalies. Active guided-wave monitoring compensates for this limitation by detecting damage via changes in wave propagation, reflection, mode conversion, and scattering relative to a healthy baseline [7–11]. For example, De Luca *et al* showed that guided-wave responses effectively reveal local structural changes induced by low-velocity impact in composite plates [27]. Nevertheless, continuous full-time and full-area active scanning may lead to high power consumption, data redundancy, and unnecessary occupation of the monitoring system when no impact event occurs.

Passive and active monitoring are thus complementary, passive for event triggering and localization, active for post-event state assessment, driving passive-active integration as a key SHM direction [13, 28–30]. For example, Chandarana *et al* used piezoelectric transducers (PZTs) for both passive acoustic emission monitoring and active pitch-catch guided-wave inspection in composite pipes, demonstrating the feasibility of reusing the same sensor network in a multimodal manner [28]. Wang *et al* showed that fusing active and passive monitoring in Lamb-wave-based SHM reduces the data burden of continuous active monitoring while improving efficiency [29]. Kessler and Flynn proposed a hybrid passive/active impact detection and localization system for aerospace structures, in which a PZT array was used to detect and localize impact-induced signals in the passive mode and was subsequently switched to active guided-wave interrogation for post-impact assessment [30]. These studies demonstrate that an event-triggered passive-active strategy can organize impact monitoring into a sequential procedure of event perception, spatial localization, and state discrimination.

In guided-wave-based SHM, PZTs are widely used due to their dual actuation and sensing capabilities. Most existing studies employ surface-bonded PZT patches, which are convenient for laboratory installation and sensor replacement but pose limitations for long-term service in composite structures. The adhesive layer may age, debond, or degrade under temperature, humidity, fatigue loading, and operational environments, thereby altering the electromechanical coupling with the host structure. Moreover, surface-mounted sensors and exposed wires are vulnerable to abrasion, accidental impact, and handling damage. Additionally, externally attached sensors can compromise surface integrity. This motivates the development of PZT-embedded smart composite structures, in which transducers are incorporated into the laminate during fabrication.

Studies have confirmed the feasibility and potential of embedded PZT for SHM applications. Lin and Chang embedded a piezoceramic network in composite structures using printed-circuit techniques, creating a thin flexible layer for distributed sensing and actuation [31]. Su *et al* further designed a built-in active sensor network which supports guided-wave-based monitoring for laminated composites [32]. Dziendzikowski *et al* compared surface-mounted and embedded PZT transducers for *in situ* BVID detection and localization, showing that the integration scheme affects both transducer behavior and damage-indication performance [33]. Ren *et al* further demonstrated *in-situ* integration of a large-scale PZT network into an aerospace composite wing-box panel, verifying signal repeatability and damage monitoring

capability under realistic conditions [34]. Feng and Aliabadi assessed the structural integrity of composite plates with embedded PZT transducers and emphasized that sensor embedding should be evaluated not only from a sensing perspective but also from the viewpoint of host-structure integrity [35]. Ren *et al* examined temperature effects on embedded PZT signals in composite structures of varying thicknesses, underscoring the need to account for environmental sensitivity in embedded sensing systems [36]. Reviews on smart composite manufacturing and embedded sensors indicate that embedding sensors enhances integration and protection, yet introduces challenges in manufacturing reliability, local material discontinuity, sensor survivability, and mechanical compatibility [37, 38].

Despite these successful attempts, most existing studies on PZT-embedded SHM for composite structures focus on either passive or active damage detection alone, and have not adequately integrated mechanical compatibility verification, passive impact localization, active guided-wave monitoring, multidimensional feature construction, and statistical state discrimination into a continuous workflow. Moreover, active damage detection still faces challenges in feature stability and decision reliability. Conventional damage indices are often constructed from single scalar features such as amplitude, energy, correlation coefficient, or root-mean-square deviation (RMSD). Although simple to implement, these indices may compress path-dependent variations, time-frequency redistribution, and local scattering information [39, 40]. Recently, statistical decision methods based on healthy reference spaces have attracted increasing attention. Among them, the Mahalanobis distance (MD) can account for both scale differences and correlations of multidimensional features, making it suitable for healthy-data-driven anomaly detection and damage identification [41, 42]. The sensitivity of such statistical features to noise and damage severity has been systematically evaluated, providing a theoretical basis for reliable decision-making [43]. Nevertheless, its effectiveness for active SHM applications remains underexplored.

Motivated by these issues, this study proposes an event-triggered passive-active SHM method for a PZT-embedded smart CFRP panel. The same embedded PZT array serves as a unified sensing and actuation network. In the passive stage, impact detection and localization are performed; upon event triggering, the system switches to active guided-wave monitoring to discriminate between the healthy state and post-impact local anomalies. The main contributions of this work are summarized as follows: 1) A complete SHM workflow is proposed, encompassing fabrication of a PZT-embedded smart panel, mechanical testing, passive impact localization, and event-triggered active monitoring. 2) A state-evaluation indicator is established using the MD of constructed multi-dimensional signal features to enhance the robustness of damage detection.

The remainder of this paper is organized as follows. Section 2 describes the fabrication of the PZT-embedded smart composite panel, the verification of its mechanical compatibility and the event-triggered passive-active monitoring strategy. Section 3 presents passive impact localization method and active guided-wave-based state evaluation method. Section 4 provides the experimental results and comparative analysis. Section 5 concludes the paper and discusses future work.

2. Smart composite panel and experimental setup

This section describes the experimental platform for the proposed PZT-embedded passive-active monitoring study. A PZT-embedded smart composite panel is first fabricated to integrate a transducer network. Mechanical compatibility tests are then performed to evaluate the influence of PZT embedment on the strength of the composite structure. Finally, the measurement system is described, providing the structural and hardware foundation for the monitoring methods presented in the following section.

2.1. Fabrication of the PZT-embedded smart panel

The fabrication process is illustrated in figure 1(a). PZT discs were used as transducers, and flexible printed circuit boards were adopted to connect the PZT elements with external wires. Specifically, the PZT discs and wires were first soldered to the predefined positions on the flexible printed circuit board. The solder joints located inside the panel were insulated using thin fabric tape to ensure electrical insulation while controlling the added thickness, whereas the external wire solder joints were encapsulated with latex to improve the insulation reliability and operational stability of the exposed connection regions. T700 carbon-fiber prepreg was used to fabricate a square panel with a side length of 250 mm and a $[0/90]_{2S}$ layup. Four packaged PZT transducers were inserted between the fourth and fifth layers at the four corners. The panel was manufactured using vacuum-bagging and oven hot-press curing.

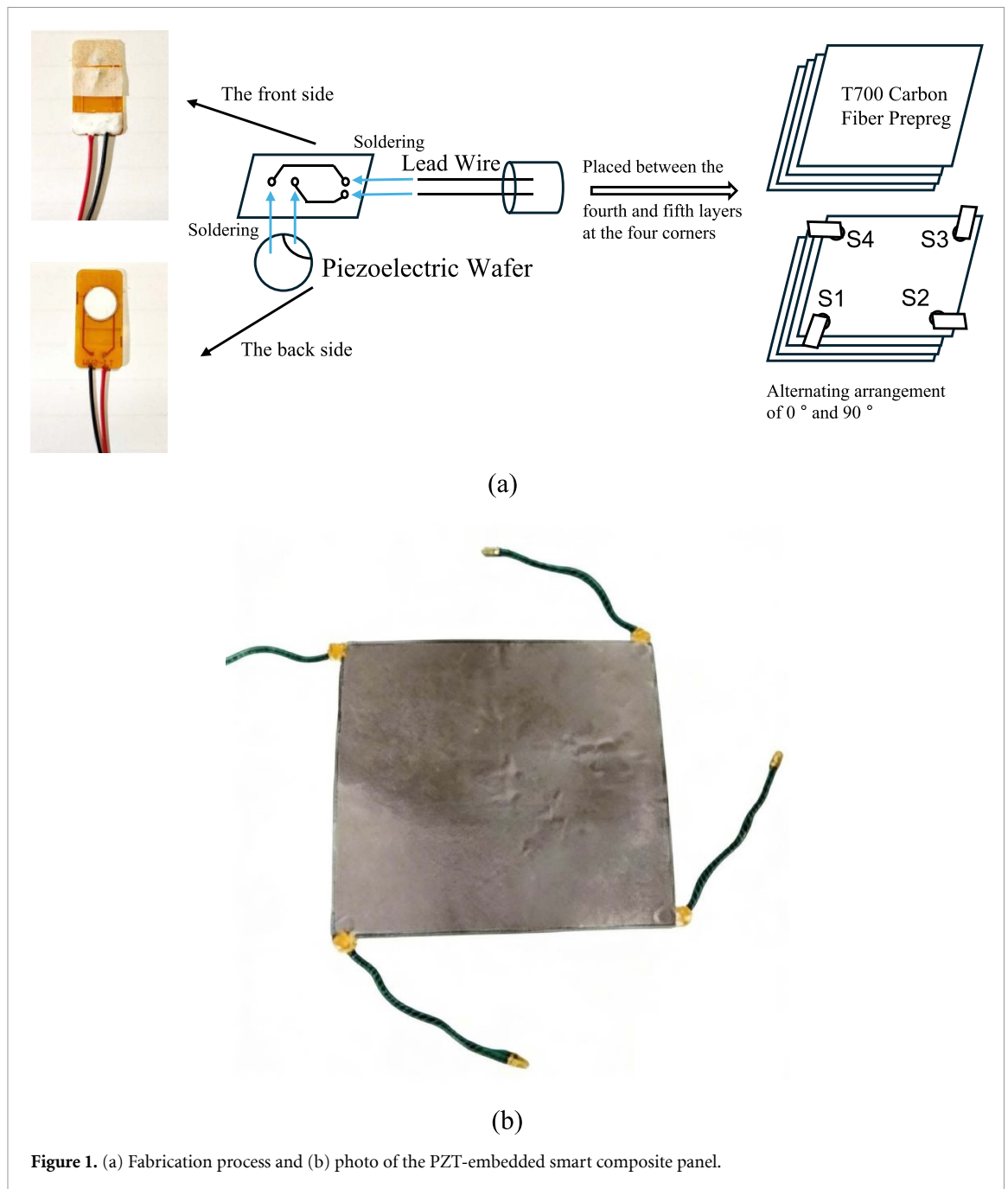


Figure 1. (a) Fabrication process and (b) photo of the PZT-embedded smart composite panel.

The curing cycle consisted of holding at 80 °C for 0.5 h, heating to 130 °C and holding for 1.0 h, followed by furnace cooling to room temperature before demolding. This fabrication process enabled stable embedding of the PZT sensing units inside the laminate and produced an integrated smart structure shown in figure 1(b) for subsequent impact perception and active guided-wave detection.

From the perspective of structural functionality, the proposed design has two main considerations. First, embedding PZT sensors inside the laminate can avoid the susceptibility of surface-mounted sensors to abrasion, debonding, and adhesive-layer ageing during service, while improving the consistency of coupling between the sensors and the composite matrix [31, 33, 35]. Second, placing the sensing units near the middle layer rather than on the surface helps achieve structural-sensing integration without significantly compromising the surface integrity of the panel. However, embedded PZT sensors may also introduce heterogeneous material interfaces, local geometric discontinuities, and stress concentrations. Therefore, before conducting passive-active monitoring experiments, it is necessary to verify the influence of this sensing integration scheme on the basic load-bearing capacity of the composite structure [35, 36].

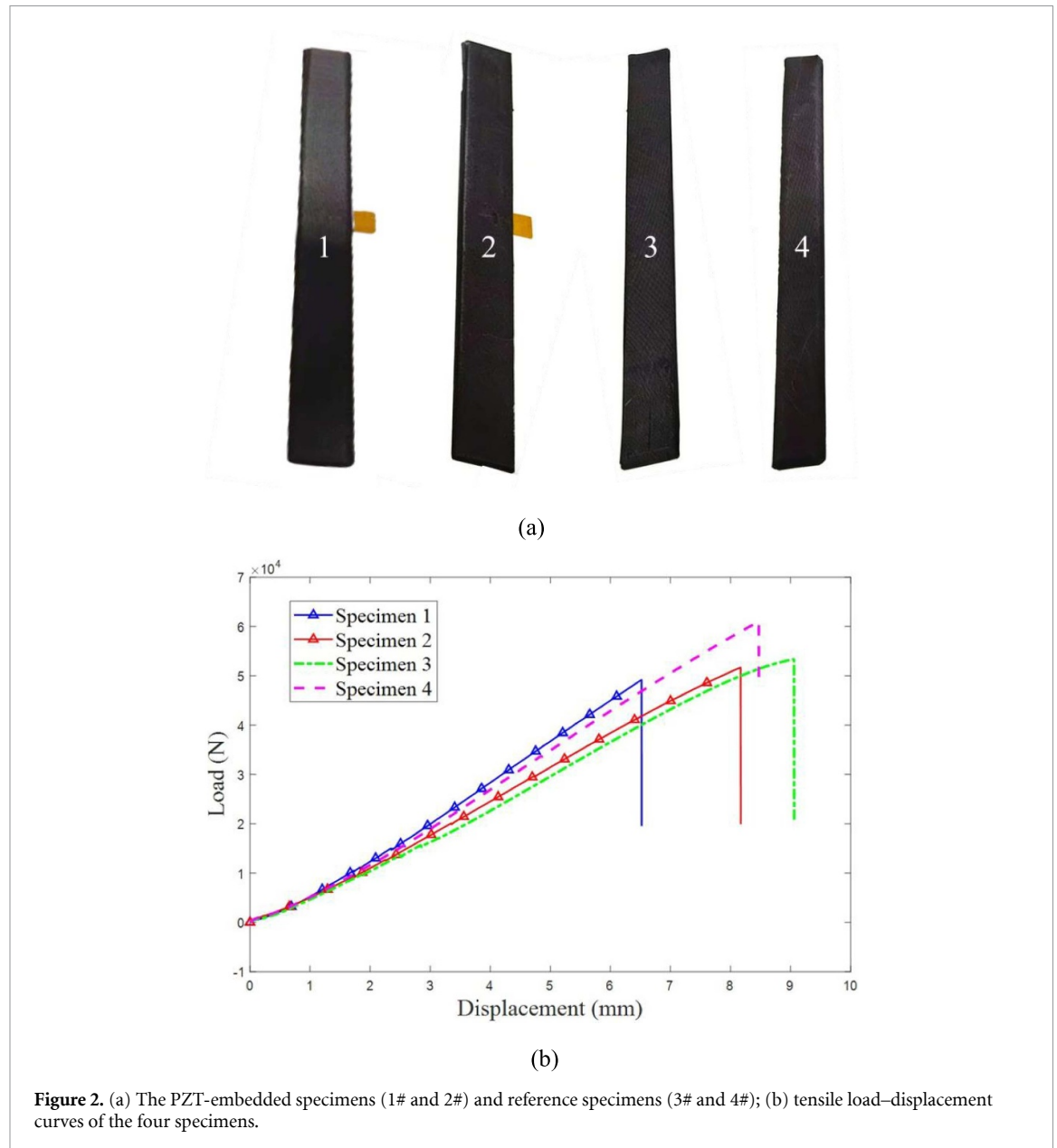


Figure 2. (a) The PZT-embedded specimens (1# and 2#) and reference specimens (3# and 4#); (b) tensile load–displacement curves of the four specimens.

2.2. Mechanical compatibility verification

To evaluate the influence of embedded PZT on the mechanical properties of smart panels, tensile tests were conducted in accordance with ASTM D3039/D3039M [44]. Notably, the purpose of these tests was not to establish a statistical mechanical-property database for PZT-embedded composites, but rather to perform a preliminary mechanical compatibility verification of the smart panel. Four specimens were fabricated using the same T700 carbon-fiber prepreg with the same process as described in section 2.1. The dimensions of the specimens are 250 mm × 25 mm × 2.5 mm with the layup sequence of $[0^\circ/90^\circ]_{4S}$. Two groups of specimens were prepared: a PZT-embedded group (with a PZT assembly embedded between the eighth and ninth layer) and a reference group without PZT embedding. Each group contained two parallel specimens, as shown in figure 2(a). The tensile tests were carried out with an electronic universal testing machine under displacement control, with a loading rate of 2 mm min⁻¹. During the tests, an extensometer was used to measure the deformation in real time, and the load–displacement data were recorded simultaneously. The tests were conducted at room temperature of 23 °C and a relative humidity of 50%.

The load–displacement curves of all four specimens exhibited typical tensile response characteristics of cross-ply carbon-fiber composite laminates. As shown in figure 2(b), the curves were approximately linear in the elastic stage, displayed no obvious yield plateau, and showed rapid brittle fracture upon reaching the peak load. From the measured loads and specimen dimensions, the tensile strengths of the two PZT-embedded specimens (1# and 2#) were 789.6 MPa and 827.1 MPa respectively, with a mean

strength of 808.35 MPa, whereas the reference specimens (3# and 4#) gave 853.9 MPa and 975.9 MPa, with a mean strength of 914.90 MPa, indicating an average reduction of approximately 11.65% due to PZT embedding. Given the limited number of samples, a statistically significant conclusion cannot yet be drawn; nonetheless, the embedded PZT generally does not markedly impair the overall tensile strength. This suggests that the fabricated smart panel is mechanically compatible for structural carrier applications.

2.3. Experimental set-up for SHM applications

An SHM monitoring system was designed to enable both passive impact event monitoring and post-impact active damage detection based on a National Instruments® platform. The monitoring process followed an event-triggered passive-active workflow shown in figure 3(a), and the corresponding experimental setup is shown in figure 3(b).

The system initially operated in passive mode. The embedded PZT transducers were connected via a wiring hub to a PXIe-5105 acquisition module, which recorded the transient voltage responses of all sensing channels. Upon external impact on the composite panel, Lamb waves were generated and captured by the PZT array. The passive module then identified the impact event and estimated its location from the multichannel impact responses.

Upon detection of an impact event, the system was switched to active mode by a predefined experimental sequence. A predefined excitation signal generated by the PXIe-5423 module was amplified and applied to a selected PZT transducer, while the remaining PZT transducers synchronously captured the guided wave responses; the acquired signals were recorded by the PXIe-5105 module for subsequent analysis. For the four-PZT array used in this study, each PZT patch was sequentially actuated during active inspection. This sequential actuation was achieved through the PXIe-2529 matrix switch module, which reconfigured the electrical connections of the array without manual rewiring, thereby realizing 12 effective pitch-catch paths for damage detection (figure 3(c)).

This configuration seamlessly integrates passive impact monitoring and active damage detection into a single experimental workflow: the passive mode handles event triggering and impact localization, while the active mode evaluates the post-impact condition.

3. Impact localization and damage detection algorithms

Based on the fabricated smart panel and developed experimental system, this section designs the monitoring algorithms employed in the two stages. A probability-based imaging method is first briefly introduced for impact localization. Subsequently, a MD-based damage evaluation method is highlighted with enhanced robustness.

3.1. Impact localization method

An impact on the PZT-embedded smart composite panel generates broadband guided waves. Due to different propagation distances, the waves reach distinct sensors with varying arrival times. The impact location can thus be estimated from the time differences of arrival (TDOAs), the sensor coordinates, and wave velocity. TDOA-based localization has been widely used for impact monitoring in plate-like structures, often combined with sensor arrays, cross-correlation, wavelet time-frequency analysis, and imaging algorithms [12, 15, 18, 19]. The flowchart of the localization algorithm is shown in figure 4.

In this study, four embedded PZT transducers were used as shown in figure 3(c). The in-plane coordinate of the i -th sensor $\mathbf{s}_i$ is defined as

$$\mathbf{s}_i = (x_i, y_i), i = 1, 2, 3, 4 \quad (1)$$

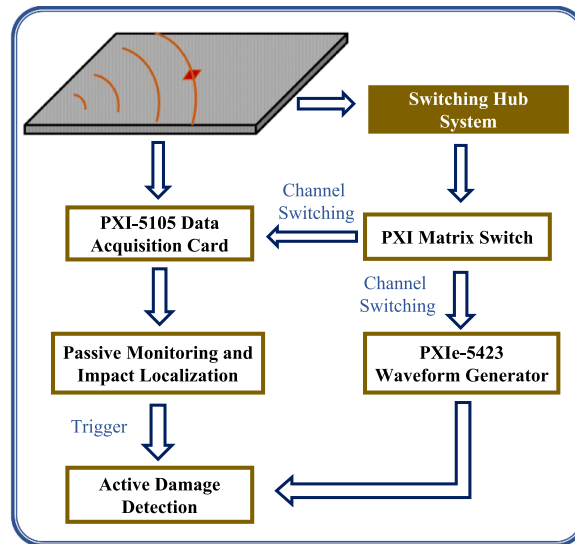
and the coordinate of an arbitrary candidate impact point $\mathbf{p}$ is defined as

$$\mathbf{p} = (x, y) \quad (2)$$

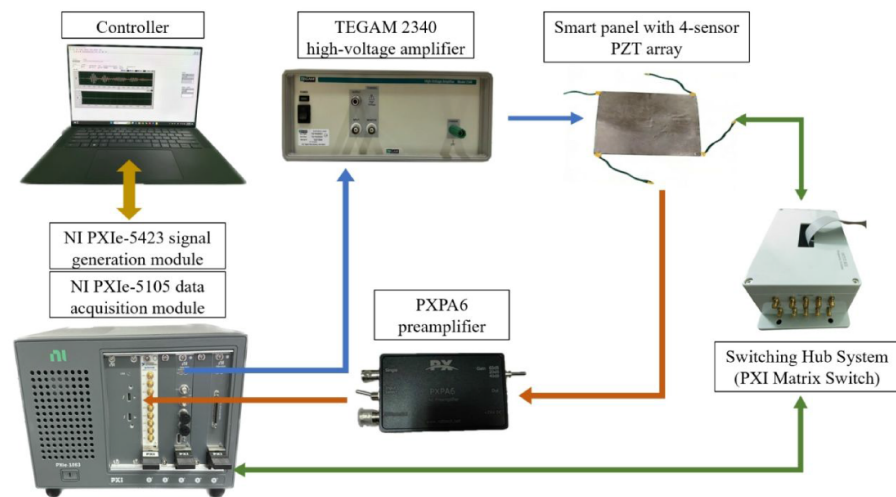
The theoretical propagation distance from the candidate point to the i -th sensor $d_i(\mathbf{p})$ is then calculated as

$$d_i(\mathbf{p}) = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (3)$$

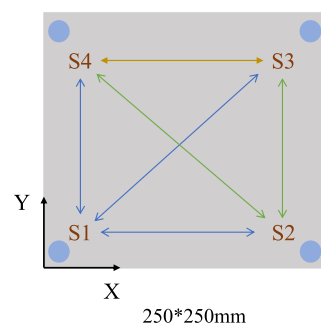
For a sensor pair (i, j) , the propagation distance difference $d_i(\mathbf{p})$ and $d_j(\mathbf{p})$ corresponding to the candidate point is defined as $\Delta d_{ij}(\mathbf{p})$. Given the wave propagation velocity v_{eq} , the theoretical time difference



(a)



(b)



(c)

Figure 3. Passive-active experimental system for the PZT-embedded smart composite panel: (a) event-triggered passive-active workflow, (b) experimental setup and (c) embedded PZT layout of the smart composite panel with corresponding definition of paths.

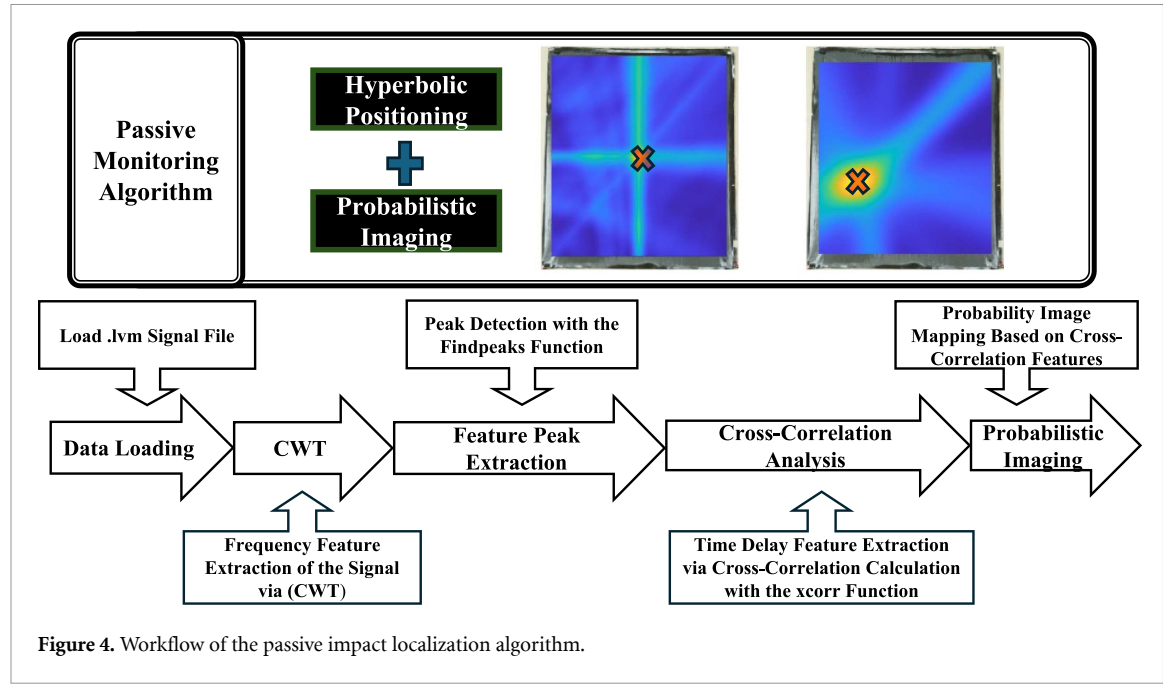


Figure 4. Workflow of the passive impact localization algorithm.

of arrival $\Delta t_{ij}^{\text{th}}(\mathbf{p})$ for the candidate point can be expressed as

$$\Delta t_{ij}^{\text{th}}(\mathbf{p}) = \frac{\Delta d_{ij}(\mathbf{p})}{v_{\text{eq}}} = \frac{d_i(\mathbf{p}) - d_j(\mathbf{p})}{v_{\text{eq}}} . \quad (4)$$

Ideally, the set of points satisfying the same time-difference constraint forms a hyperbola with the two sensors as foci. When multiple sensor pairs are used, several hyperbolic constraints can jointly determine the impact location. In practice, impact responses are usually broadband, non-stationary, and multimodal, and are affected by dispersion, mode conversion, boundary reflection, and noise [7, 8, 10–12, 15]. As a result, the hyperbolas corresponding to different sensor pairs usually do not intersect at a single point. To improve localization robustness, a grid-scanning-based delayed correlation imaging method was adopted [15, 18, 19].

The response induced by low-velocity impact is broadband and contains multiple guided-wave components [12, 15]. Continuous wavelet transform was used to extract the time of flight (TOF) of impact-induced Lamb waves. Let the time-domain signal acquired by the i th sensor be $x_i(t)$. The wavelet coefficient of $x_i(t)$ is defined as

$$W_i(a, b) = \int_{-\infty}^{+\infty} x_i(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-b}{a} \right) dt \quad (5)$$

where a is the scale parameter, b is the time-shift parameter, $\psi(t)$ is the mother wavelet, and $(\cdot)^*$ denotes the complex conjugate. The complex Morlet wavelet was used for time–frequency enhancement of the impact responses. The magnitude $A_i(t)$ of the wavelet coefficient was used to obtain an envelope-type response representing the energy variation of the dominant wave packet in each channel:

$$A_i(t) = |W_i(a_0, t)| \quad (6)$$

where a_0 corresponds to a specific frequency of interest. The envelope $A_i(t)$ was then smoothed to reduce the influence of local noise and small fluctuations on peak identification. The TOF of the first arrival waves can be then extracted.

The equivalent propagation velocity was calibrated using impact tests at several known positions on the panel. For each calibration point, the TOF of the first arrivals were extracted corresponding to different channels. The distance difference from the known impact point to each sensor pair was divided by the corresponding arrival-time difference to obtain a velocity estimate. The velocity v_{eq} was obtained as

the average of all valid estimates from different calibration points and sensor pairs. Although the propagation velocity varies with direction owing to laminate anisotropy, an experimentally calibrated equivalent velocity is adopted here as an engineering approximation to reduce the complexity of the localization procedure. The influence of the directional velocity variation on the present localization results is further discussed in section 4.1.

After extracting the first-arrival time t_i and the corresponding CWT-envelope amplitude α_i for the i -th channel, a Gaussian window was constructed to emphasize the local arrival information and suppress the influence of subsequent reflections and tail oscillations. The discrete Gaussian window $g_i[n]$ centered at t_i is defined as

$$g_i[n] = \exp\left[-\frac{(t_n - t_i)^2}{2\sigma^2}\right], \quad t_n = \frac{n}{f_s} \quad (7)$$

where f_s is the sampling frequency, n is the sample index, and σ controls the temporal width of the Gaussian window. The local arrival representation $z_i[n]$ is then defined as

$$z_i[n] = \alpha_i g_i[n] . \quad (8)$$

This converts the time-domain response in each channel into a local Gaussian-kernel representation.

For each sensor pair (i, j) , the cross-correlation sequence between the two local arrival representations is calculated as

$$R_{ij}[\tau] = \sum_n z_i[n + \tau] z_j[n] \quad (9)$$

where τ is the discrete sample delay. Under this definition, a positive delay indicates that the first arrival at sensor i occurs later than that at sensor j . Because the two representations are restricted to the neighborhoods of their respective first arrivals, the resulting correlation sequence generally exhibits a smooth single-peak distribution, with its peak position corresponding to the measured TDOA.

For an arbitrary candidate point $\mathbf{p}$, the theoretical arrival-time difference $\Delta t_{ij}^{\text{th}}(\mathbf{p})$ given by equation (4) is converted into the corresponding discrete sample delay $\tau_{ij}^{\text{th}}(\mathbf{p})$. The correlation contribution of sensor pair (i, j) $C_{ij}(\mathbf{p})$ is then obtained as

$$\tau_{ij}^{\text{th}}(\mathbf{p}) = \text{round}\left[f_s \Delta t_{ij}^{\text{th}}(\mathbf{p})\right] \quad (10)$$

$$C_{ij}(\mathbf{p}) = R_{ij}\left[\tau_{ij}^{\text{th}}(\mathbf{p})\right] . \quad (11)$$

When the candidate point approaches the actual impact location, its theoretical delay becomes consistent with the measured correlation-peak delay, resulting in a relatively high value of $C_{ij}(\mathbf{p})$.

To improve the robustness of multi-channel fusion, the pairwise correlation contributions are weighted according to the first-arrival amplitudes. The final imaging function is defined as

$$I(\mathbf{p}) = \sum_{i < j} C_{ij}(\mathbf{p}) . \quad (12)$$

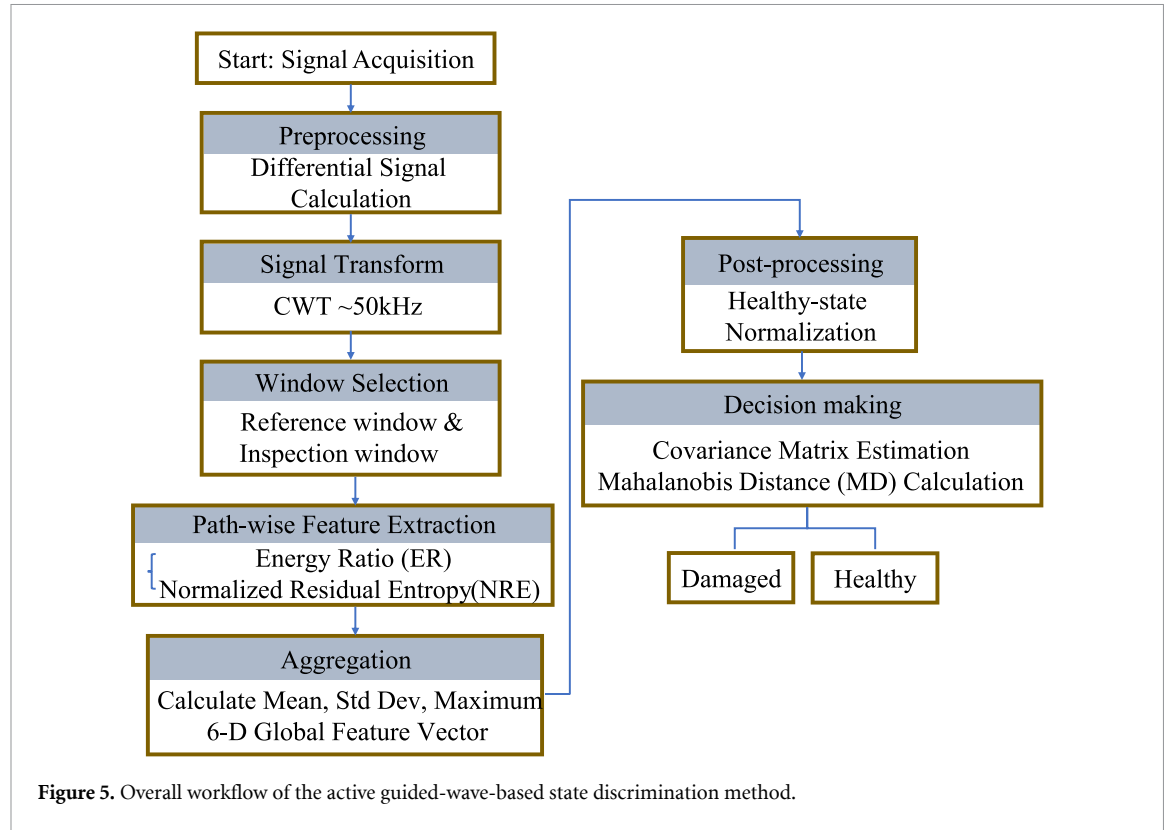
After all candidate grid points within the panel are traversed, a two-dimensional impact-localization image is obtained. The estimated impact location $\hat{\mathbf{p}}$ is determined as the grid point corresponding to the maximum imaging value:

$$\hat{\mathbf{p}} = \arg\max_{\mathbf{p}} I(\mathbf{p}) . \quad (13)$$

3.2. Post-impact damage evaluation method

A guided-wave-based method is proposed for post-impact evaluation of PZT-embedded smart composite panels. Through a hierarchical mapping process, guided-wave responses are progressively transformed into a MD-based anomaly discrimination indicator. The overall workflow is depicted in figure 5.

Following the proposed passive-active SHM scheme, guided-wave responses are captured before and after an impact event is detected, and the differential responses between these two states are extracted for damage evaluation.



For any actuation–reception channel, the baseline signal and the current-state signal before and after impact are denoted as $x_p^H(t)$ and $x_p^C(t)$, respectively, where p is the path index and t is the time variable. First, the differential signal $\Delta x_p(t)$ is constructed as

$$\Delta x_p(t) = x_p^C(t) - x_p^H(t) . \quad (14)$$

Subsequently, the continuous wavelet transform is applied to the differential and baseline signals, respectively. A reference window and an inspection window are defined in the time domain for further feature extraction. The reference window Ω_r characterizes the first arrivals in the baseline signals, while the inspection window Ω_s , applied to the differential signals, extracts signal variations and energy redistribution caused by local anomalies.

Based on the dual-window, two complementary features are extracted from the response signals. The first feature is the energy ratio (ER). For the p -th path, ER is defined as

$$ER_p = \frac{\int_{\Omega_s} |C_{d,p}(\tau)|^2 d\tau}{\int_{\Omega_r} |C_{b,p}(\tau)|^2 d\tau} \quad (15)$$

where the numerator and denominator denote the wavelet energy of the differential signal $C_{d,p}(\tau)$ within the inspection window and the baseline signal $C_{b,p}(\tau)$ within the reference window, respectively. Physically, ER quantifies the normalized residual wavelet energy of damage-scattered signals relative to the baseline signals, with a larger value indicating stronger scattering caused by structural anomalies.

Although ER captures the degree of signal variation between the two states, it cannot characterize its temporal distribution. To address this limitation, Shannon entropy is further introduced to formulate a second feature, the normalized residual entropy (NRE) [45]. For the p -th path, the normalized residual-energy probability distribution over the samples within the inspection window $p_{d,p}(\tau)$ is first defined as

$$p_{d,p}(\tau) = \frac{|C_{d,p}(\tau)|^2}{\sum_{\tau' \in \Omega_s} |C_{d,p}(\tau')|^2} . \quad (16)$$

The corresponding Shannon entropy is then calculated as

$$NRE_p = \frac{-\sum_{\tau \in \Omega_s} p_{d,p}(\tau) \cdot \log_2[p_{d,p}(\tau)]}{\log_2 N_s} \quad (17)$$

where N_s is the number of samples within the inspection window. NRE ranges from 0 to 1 and a larger value indicates that the residual energy is distributed over a broader time interval, characterizing the temporal concentration or dispersion of the residual response.

ER and NRE form a complementary feature pair: ER captures local-anomaly-induced scattering intensity, whereas NRE provides a supplementary measure of the accompanying variation in distribution complexity. Together, they enhance the completeness of post-impact damage evaluation across distinct physical dimensions.

The response of an individual propagation path may be affected by the propagation distance, propagation direction, and local transducer coupling. Therefore, the path-level ER and NRE are statistically aggregated to construct a global representation of the structural state.

For a monitoring sample containing N_p effective pitch-catch paths, the path-level ER and NRE vectors are defined as

$$\mathbf{ER} = [\text{ER}_1 \quad \text{ER}_2 \quad \cdots \quad \text{ER}_{N_p}]^T \quad (18)$$

and

$$\mathbf{NRE} = [\text{NRE}_1 \quad \text{NRE}_2 \quad \cdots \quad \text{NRE}_{N_p}]^T \quad (19)$$

where $N_p = 12$ for the PZT array used in this study, and the same set of 12 paths is used for all monitoring samples, independent of the estimated impact location.

Three statistical quantities, namely mean μ , standard deviation σ , and maximum value m , are calculated for the two vectors and concatenated into a six-dimensional global feature vector $\mathbf{x}$:

$$\mathbf{x} = [\mu_{\text{ER}}, \sigma_{\text{ER}}, m_{\text{ER}}, \mu_{\text{NRE}}, \sigma_{\text{NRE}}, m_{\text{NRE}}]^T \quad (20)$$

Multiple measurements in the healthy status are used to construct the reference space. Let

$$\mathbf{x}_H^{(i)} = [x_{H,1}^{(i)} \quad x_{H,2}^{(i)} \quad \cdots \quad x_{H,6}^{(i)}]^T, i = 1, 2, \dots, N_H \quad (21)$$

denote the global feature vector of the i -th healthy reference sample, where N_H is the number of healthy samples. The mean of the j -th feature dimension is calculated as

$$\mu_{H,j} = \frac{1}{N_H} \sum_{i=1}^{N_H} x_{H,j}^{(i)}, j = 1, 2, \dots, 6. \quad (22)$$

Consistent with the numerical implementation, the corresponding standard deviation used for feature scaling is calculated as

$$\sigma_{H,j} = \sqrt{\frac{1}{N_H} \sum_{i=1}^{N_H} (x_{H,j}^{(i)} - \mu_{H,j})^2}, j = 1, 2, \dots, 6. \quad (23)$$

For an arbitrary sample with global feature vector $\mathbf{x}$, the j -th standardized feature is obtained as

$$z_j = \frac{x_j - \mu_{H,j}}{\sigma_{H,j}}, j = 1, 2, \dots, 6. \quad (24)$$

The standardized feature vector is therefore expressed as

$$\mathbf{z} = [z_1 \quad z_2 \quad \cdots \quad z_6]^T. \quad (25)$$

The same healthy-reference means and standard deviations are used to standardize all subsequent monitoring samples.

Let $\mathbf{z}_H^{(i)}$ denote the standardized global feature vector of the i -th healthy sample. The center of the standardized healthy reference space is calculated as

$$\boldsymbol{\mu}_z = \frac{1}{N_H} \sum_{i=1}^{N_H} \mathbf{z}_H^{(i)}. \quad (26)$$

The covariance matrix of the standardized healthy samples is then given by

$$\mathbf{C}_H = \frac{1}{N_H - 1} \sum_{i=1}^{N_H} \left(\mathbf{z}_H^{(i)} - \boldsymbol{\mu}_z \right) \left(\mathbf{z}_H^{(i)} - \boldsymbol{\mu}_z \right)^T . \quad (27)$$

Because the number of healthy samples is limited relative to the six-dimensional feature space, the sample covariance matrix may be ill-conditioned. A diagonal regularization term is therefore introduced:

$$\mathbf{C}_{H,\text{reg}} = \mathbf{C}_H + 10^{-3} \mathbf{I} \quad (28)$$

where $\mathbf{I}$ is the 6×6 identity matrix.

The MD of a monitoring sample from the healthy reference distribution is calculated as

$$\text{MD} = \sqrt{(\mathbf{z} - \boldsymbol{\mu}_z)^T \mathbf{C}_{H,\text{reg}}^{-1} (\mathbf{z} - \boldsymbol{\mu}_z)} . \quad (29)$$

The MD accounts for both the variance of each feature dimension and the correlations among different features. A larger MD indicates a greater multidimensional deviation from the healthy reference distribution.

A decision threshold is determined offline using receiver operating characteristic (ROC) analysis [46]. The MD values of the healthy and seeded-anomaly calibration samples are used as the negative and positive scores, respectively. A set of candidate thresholds is generated between the minimum and maximum MD values of all calibration samples. For a candidate threshold t , a sample is classified as anomalous when

$$\text{MD} > t . \quad (30)$$

The true-positive rate is calculated as

$$\text{TPR}(t) = \frac{\text{TP}(t)}{\text{TP}(t) + \text{FN}(t)} \quad (31)$$

and the false-positive rate is calculated as

$$\text{FPR}(t) = \frac{\text{FP}(t)}{\text{FP}(t) + \text{TN}(t)} \quad (32)$$

where TP, FN, FP, and TN denote the numbers of true-positive, false-negative, false-positive, and true-negative classifications, respectively.

The ROC curve is constructed from the pairs $(\text{FPR}(t), \text{TPR}(t))$ obtained at different candidate thresholds. The Youden index corresponding to threshold t is defined as

$$J(t) = \text{TPR}(t) - \text{FPR}(t) . \quad (33)$$

The ROC-derived calibration threshold is selected as

$$T_{\text{ROC}} = \arg \max_t [\text{TPR}(t) - \text{FPR}(t)] . \quad (34)$$

During state discrimination, a monitoring sample is classified as a local-anomaly state when

$$\text{MD} > T_{\text{ROC}} . \quad (35)$$

The threshold is determined from the calibration data before online monitoring and remains fixed during subsequent state evaluation. After an impact triggers active interrogation, the extracted ER and NRE features are mapped to an MD score and compared directly with this threshold; a value exceeding the threshold indicates a significant deviation from the healthy reference state.

4. Results and discussions

This section validates the proposed SHM framework from passive impact localization to active anomaly detection. The impact localization results are first analyzed to provide both event-triggering cues and spatial information of impact events. The presentation of the active guided-wave-based SHM results starts with a representative seeded-anomaly case to clarify the dual-window selection strategy and the construction of ER and NRE features. The statistical behavior of the extracted features is then evaluated across all healthy and local-anomaly samples, followed by state discrimination verification using the healthy reference space and MD. Finally, comparative analyses with conventional time-domain, frequency-domain, and energy-based approaches are conducted to evaluate the feature representation capability and discrimination stability of the proposed method.

4.1. Passive impact localization

To verify the effectiveness of the passive impact localization method, impact tests were conducted at five representative positions on the smart composite panel, as listed in table 1. A steel ball (with a diameter of 7 mm) drop test was used to simulate external impact events, and the drop height was approximately 30 mm. Four embedded PZT sensors were used to synchronously acquire the impact response signals at a sampling rate of 10 MHz. Each impact position was tested four times to evaluate the repeatability and stability of the localization results.

Figure 6(a) shows the time-domain responses of the four sensing channels for a typical impact event. The raw signals contain the first-arrival wave packet, noise, and boundary reflections, making direct identification of the first arrival difficult. CWT was applied to the impact responses with the center frequency set to 40 kHz, and the modulus of the wavelet coefficients was extracted as shown in figure 6(b). Although the impact response is broadband in nature, the wave packets at 40 kHz can be clearly distinguished from low-frequency structural vibrations, high-frequency noise, and later boundary reflections. Moreover, this frequency provides a favorable balance between temporal resolution and signal quality: lower frequencies tend to produce broader wave packets, thus degrading temporal resolution, whereas higher frequencies are more susceptible to attenuation, dispersion, and noise.

The equivalent velocity v_{eq} corresponding to the 40 kHz waves was set as 900 m s^{-1} by calibration tests for cross-correlation delay matching. To assess the influence of laminate anisotropy and the calibration accuracy, the direction-dependent A_0 -mode energy velocity at 40 kHz was additionally calculated for the T700/M21 [0/90]_{2s} laminate. The calculated energy velocity varies from approximately 828 to 1009 m s^{-1} over the propagation directions, with an average value of approximately 894 m s^{-1} , which is close to the experimentally calibrated result. Moreover, although directional velocity variations may introduce localization uncertainty, the proposed method integrates the correlative contributions from multiple sensor pairs. The multi-path averaging effect can further mitigate the impact of moderate velocity variations on localization accuracy.

An adaptive peak detection method was then used to identify the peak position and amplitude of the first-arrival wave packets. The minimum peak height was set to 10% of the maximum amplitude of the corresponding channel, and the minimum peak width was set to 20 sampling points. The peak positions were used to construct the TDOA between different sensing channels, while the normalized first-arrival amplitudes were used as channel weights. By combining Gaussian-windowed cross-correlation with the weighted imaging algorithm, the impact localization probability map was obtained, as shown in figure 6(c). The peak position in the probability map was taken as the predicted impact location.

Table 1 summarizes the localization results for the five impact positions. The proposed method achieved effective localization for all tested positions, with an overall average localization error of approximately 3.25 mm. The average errors of position 1 and position 4 were relatively low, as 1.00 mm and 1.81 mm, respectively. Nevertheless, position 5 exhibited a larger maximum error of 14.56 mm. The relatively large maximum error at position 5 was caused by one outlying localization result, which may be associated with uncertainty in first-arrival identification, multimodal interference, and local variations in wave propagation. Overall, the passive localization module can accurately identify the impact location and provide triggering information and spatial prior knowledge for subsequent active guided-wave inspection. Compared with VTR-based approaches [19–21], the present cross-correlation imaging method avoids wavefield reconstruction and is simpler to implement. The average localization error of 3.25 mm demonstrates sufficient accuracy for the present event-triggered monitoring framework.

4.2. Active damage detection

To evaluate the performances of the active damage detection, we introduced artificial damage by bonding a piece of damping rubber (approximately 10 mm in diameter and 2 mm in height) at different impact

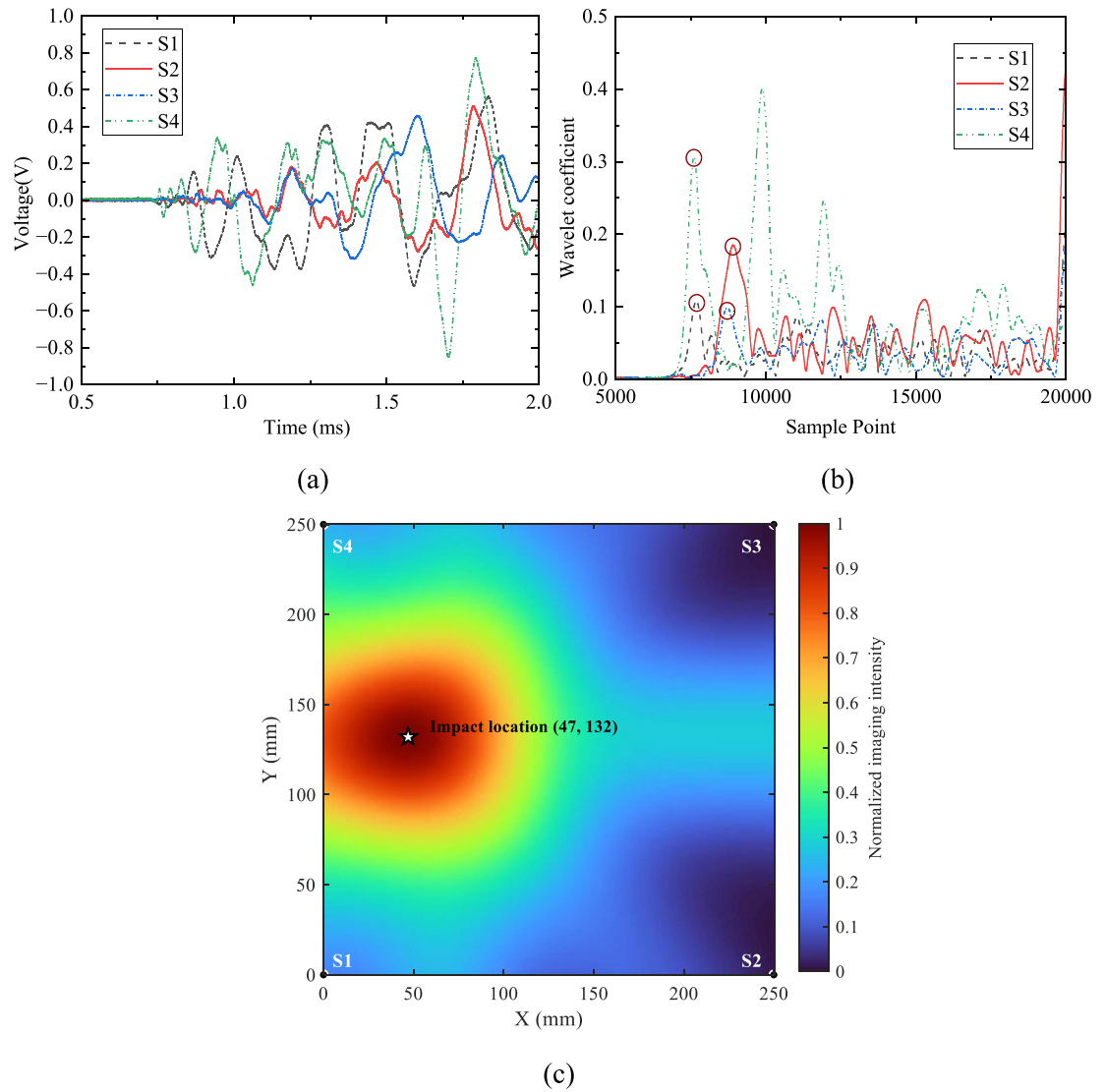


Figure 6. (a) Original time-domain impact response signals of the four sensing channels; (b) wavelet-coefficient envelopes with the first peaks marked; (c) impact localization probability map.

Table 1. Summary of impact localization results.

Measurement point ID	Actual coordinates	Estimated coordinates	Mean error(mm)	Maximum error(mm)	Minimum error(mm)
1	(48,93)	(48,91), (48,93) (47,93), (48,94)	1.0000	2.0000	0.0000
2	(178,80)	(180,87), (181,82) (180,80), (180,76)	4.3394	7.2801	2.0000
3	(104,170)	(104,177), (104,174) (104,165), (101,168)	4.9014	7.0000	3.6056
4	(46,130)	(44,129), (45,130) (46,131), (49,130)	1.8090	3.0000	1.0000
5	(172,143)	(172,143), (172,143) (176,129), (170,144)	4.1991	14.5602	0.0000

locations shown in figure 7(D1–D7), enabling the proposed method to be evaluated in a non-destructive manner.

4.2.1. Selection of the reference window and inspection window

According to the proposed method described in section 3.2, we first selected proper windows for subsequent feature extraction. Through theoretical arrival-time estimation and measured healthy baseline

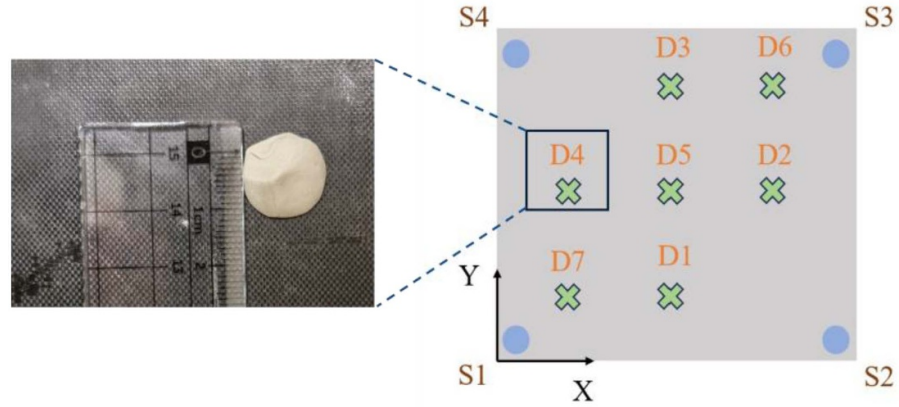


Figure 7. The distribution of seeded-damage samples on the smart panel.

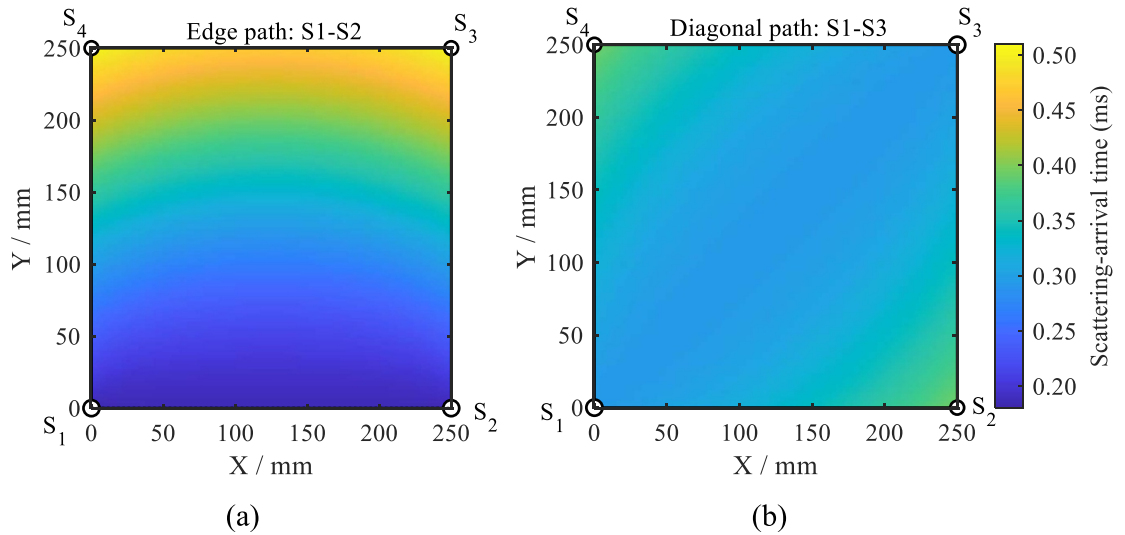


Figure 8. Theoretical scattering-arrival time maps for representative pitch-catch paths: (a) Edge path: S1-S2; (b) Diagonal path: S1-S3.

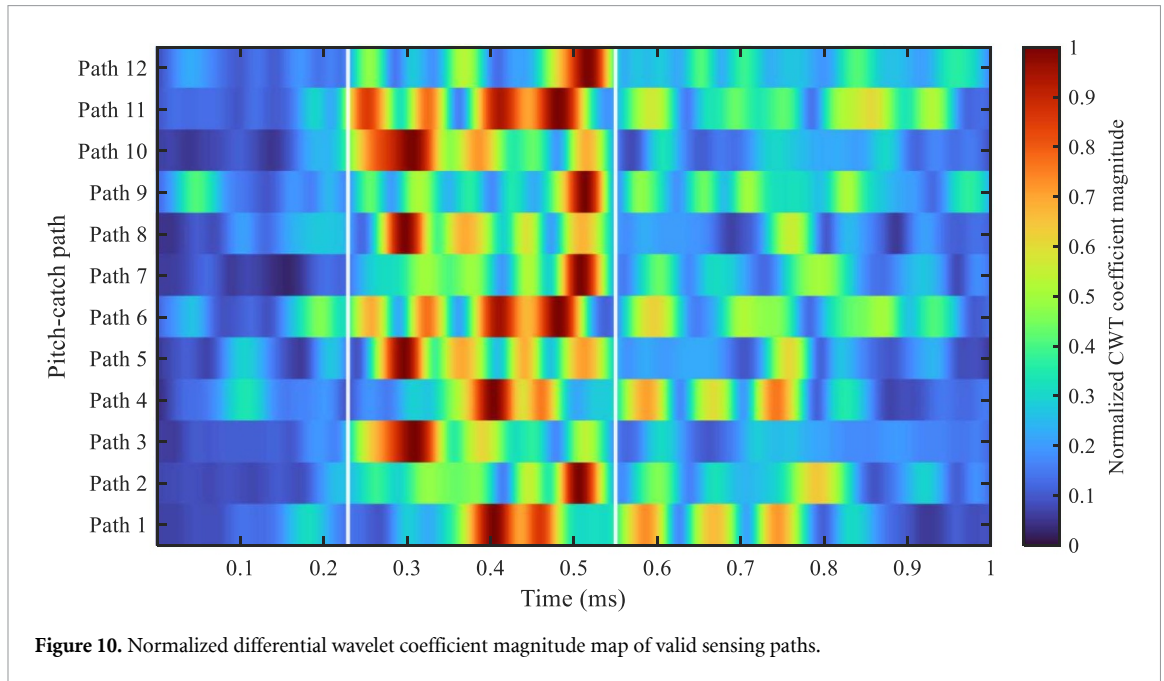
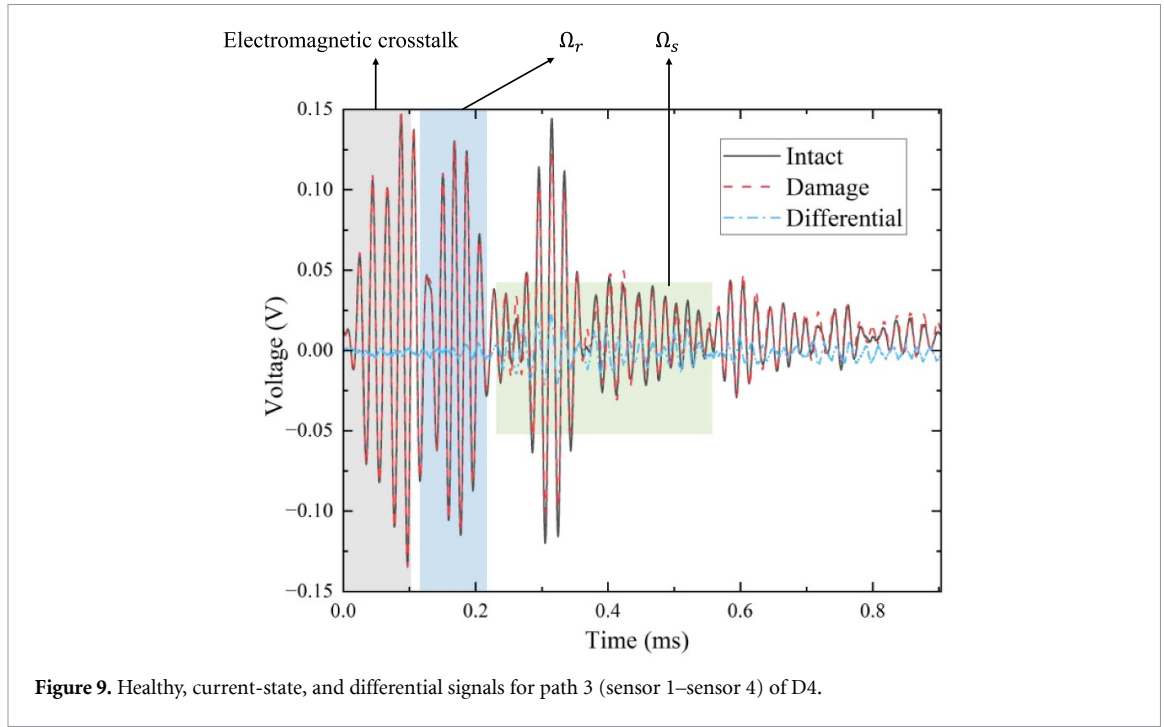
responses, we defined the reference window $\Omega_r = [0.11 \text{ ms}, 0.22 \text{ ms}]$, which contains the first arrivals to provide a stable normalization baseline.

The theoretical arrival time of scattering waves was estimated for representative pitch-catch paths as shown in figure 8. For an arbitrary candidate scattering point q on the panel, the corresponding scattering propagation time $t_{ij}^{\text{sc}}(q)$ was calculated as

$$t_{ij}^{\text{sc}}(q) = \frac{|q-s_i|}{v_{iq}} + \frac{|q-s_j|}{v_{qj}} \quad (36)$$

where s_i and s_j are the actuator and receiver coordinates, respectively, and v_{iq} and v_{qj} are the direction-dependent A0-mode group velocities of the two propagation segments. The maps indicate that the onsets of the scattering waves in the monitored region are mainly located before approximately 0.55 ms, so we defined the inspection window $\Omega_s = [0.23 \text{ ms}, 0.55 \text{ ms}]$.

Representatively, figure 9 shows the healthy baseline signal, the current-state signal, and the differential signal of Path 3 under the D4 condition. The reference window Ω_r is located after the electromagnetic crosstalk and is used to extract a stable early healthy-response baseline. The damage-scattering waves appear in the later part of the waveform, which are covered by the selected inspection window. We further calculated the normalized differential wavelet coefficient magnitude distribution of the D4 sample over the 12 effective pitch-catch paths in figure 10. Results confirm that the selected inspection window allows to cover most of the damage-scattering waves.



The path-level ER and NRE distributions of the D4 sample were further calculated. As shown in figure 11(a), the ER distribution is highly non-uniform over the 12 effective paths. A few paths close to the local anomaly show obvious peak values. The NRE values remained at a relatively high level but also varied across paths shown in figure 11(b). Paths with higher NRE values exhibited more temporally dispersed residual-energy distributions, which may be associated with multiple scattered wave packets, dispersive broadening, mode conversion, or reflections.

4.2.2. Behavior of ER and NRE features

These path-level ER and NRE distributions are then aggregated into a six-dimensional global feature vector consisting of the mean, standard deviation, and maximum values of ER and NRE, as described in section 3.2. Figure 12 presents a comprehensive comparison of aggregated ER/NRE-based statistical features for all the healthy and damaged samples.

For the ER family, all three statistics exhibit strong and consistent discrimination capability. In the healthy state, μ_{ER} , σ_{ER} and m_{ER} remain close to zero while the damaged state shows a pronounced and

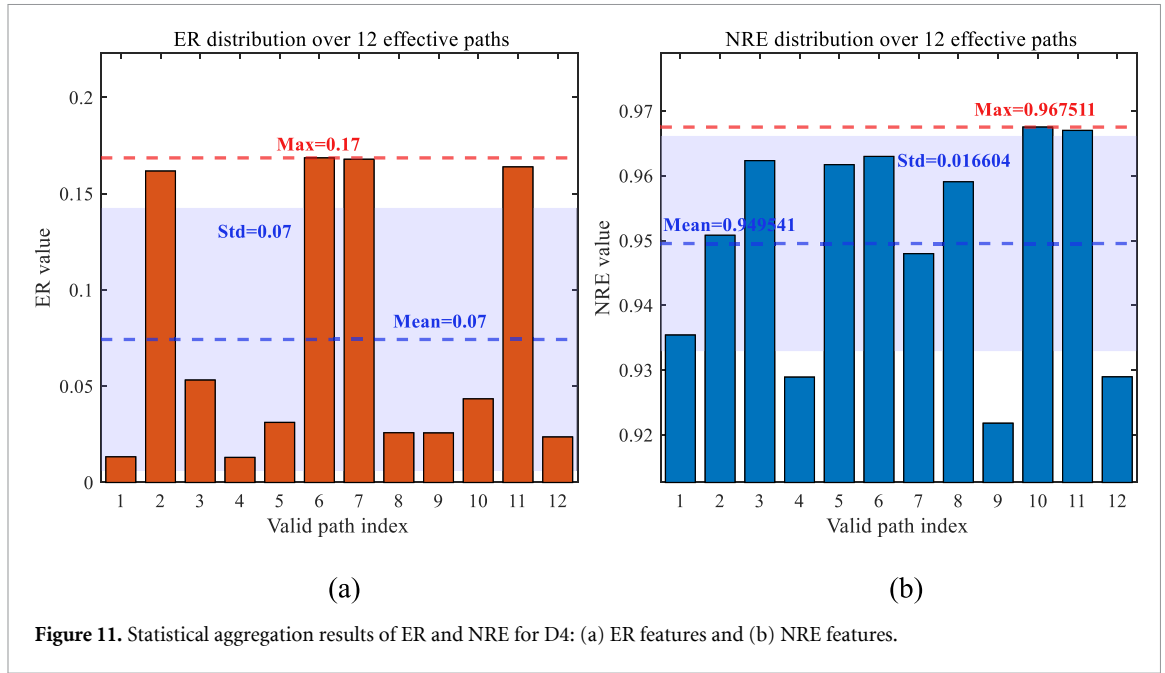


Figure 11. Statistical aggregation results of ER and NRE for D4: (a) ER features and (b) NRE features.

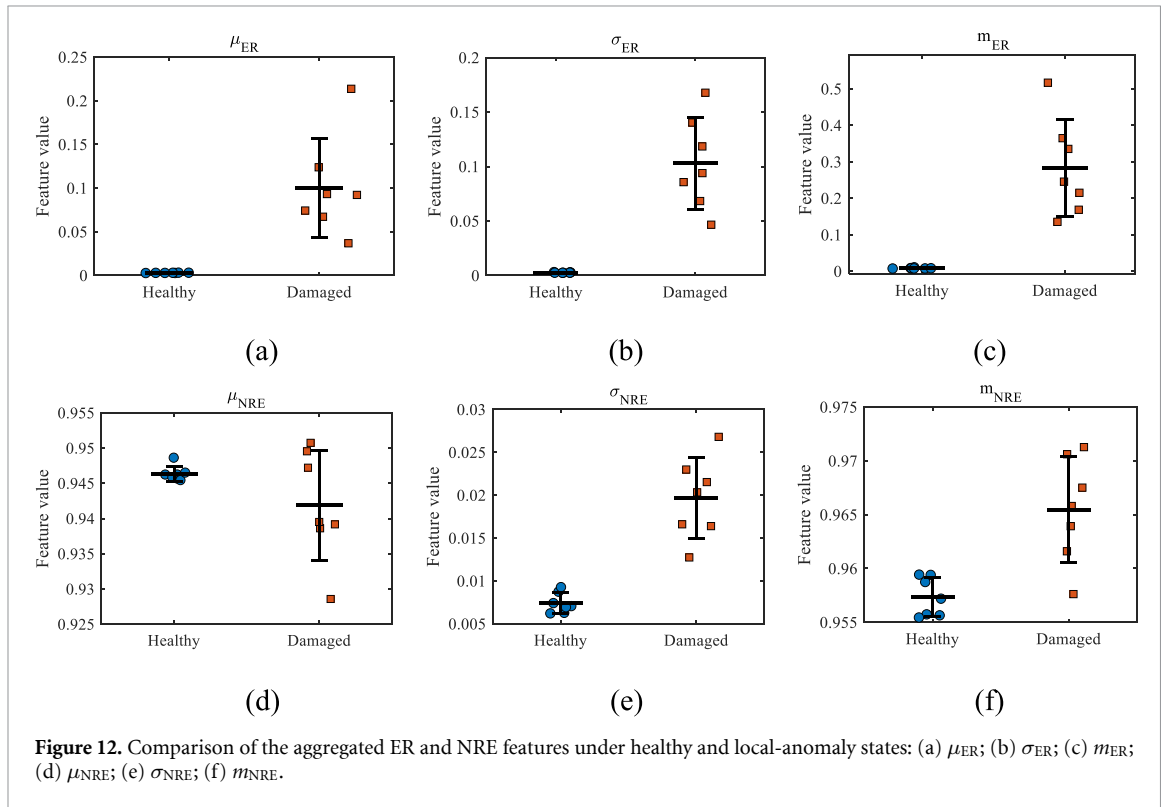


Figure 12. Comparison of the aggregated ER and NRE features under healthy and local-anomaly states: (a) μ_{ER} ; (b) σ_{ER} ; (c) m_{ER} ; (d) μ_{NRE} ; (e) σ_{NRE} ; (f) m_{NRE} .

systematic increase in all ER metrics. In contrast, the NRE features exhibit a fundamentally different behavior. The standard deviation σ_{NRE} reveals a clear and robust separation: healthy samples cluster tightly around low variance values, whereas damaged samples exhibit significantly increased dispersion. This indicates that damage does not uniformly alter signal complexity across all paths; instead, it introduces strong path-dependent variability in the temporal distribution of residual wave energy. Physically, some paths experience concentrated scattering (low entropy dispersion), while others exhibit multi-path scattering, mode conversion, or extended wave packets (high entropy dispersion), leading to increased inter-path heterogeneity.

Overall, the results highlight a clear functional distinction between ER and NRE features. ER primarily captures energy amplification and scattering intensity changes induced by structural anomalies, resulting in strong and stable class separation. NRE, on the other hand, characterizes the redistribution

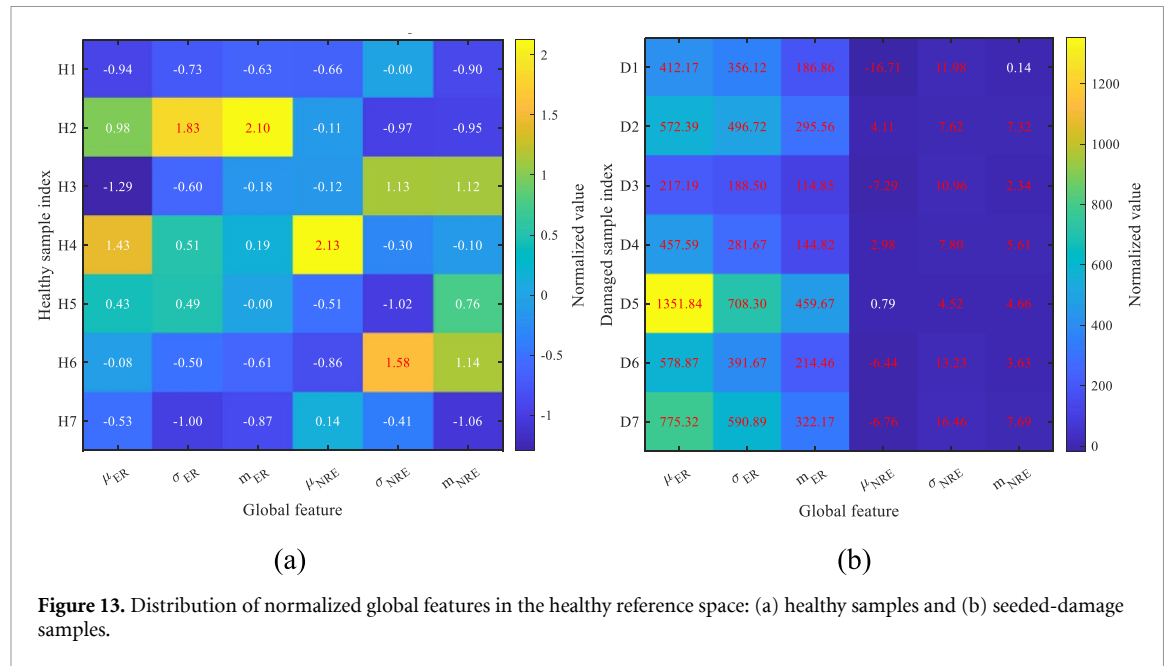


Figure 13. Distribution of normalized global features in the healthy reference space: (a) healthy samples and (b) seeded-damage samples.

complexity of residual signals in the time domain. Importantly, the complementary nature of these two feature families indicates that combining ER (magnitude-driven) and NRE (distribution-driven) indicators enhances both physical interpretability and statistical robustness for structural anomaly detection in guided-wave-based SHM systems.

4.2.3. Damage separation in the healthy reference space and MD calculation

Following the feature construction process, the six-dimensional ER–NRE global feature vector was further mapped into the healthy reference space, and raw feature differences were converted into standardized deviations relative to the healthy reference distribution. A MD-based deviation score was subsequently calculated on this basis.

Figure 13 presents the standardized six-dimensional feature distributions of healthy and seeded-damage samples in the healthy reference space according to equation (24). It can be observed that healthy samples fluctuate around zero across all six standardized dimensions, indicating that they form a relatively compact reference distribution. In contrast, seeded-damage samples exhibit systematic deviations across multiple dimensions, rather than being confined to a single feature.

In particular, deviations in ER-related dimensions are highly consistent, suggesting that the differential energy enhancement induced by local anomalies has exceeded the inherent variation range of healthy samples. By contrast, deviations in NRE-related dimensions are generally milder than those in ER-related dimensions, with noticeable inter-sample variability observed. The NRE, together with ER, forms a complete deviation pattern in the healthy reference space and provides a direct transition from raw feature differences to reference-space deviations, which lays out the foundation for subsequent MD score calculation.

The MD scores were then calculated with the six-dimensional ER–NRE features, with sample-wise values displayed in figure 14. Healthy samples yield concentrated, low-level MD scores, while seeded-damage samples exhibit significantly elevated values, forming a clear separation between the two groups. This indicates that local-anomaly samples deviate holistically from the healthy reference distribution in the six-dimensional feature space, rather than presenting isolated changes in a single dimension. This verifies the effectiveness of healthy reference space modeling and MD calculation in integrating high-dimensional feature information.

Owing to the limited sample size, the threshold marked in figure 14 merely serves to verify the state discrimination capability of the proposed MD indicator within the current experimental dataset. For practical long-term service applications, the threshold should be updated and validated using larger datasets covering diverse impact energies, impact locations, anomaly configurations, environmental temperatures and boundary conditions. This can subsequently be used for online state evaluation as long as the operating conditions remain within the validated envelope. Periodic validation or recalibration may nevertheless be necessary when long-term environmental drift, sensor ageing, structural modification, or other significant changes occur.

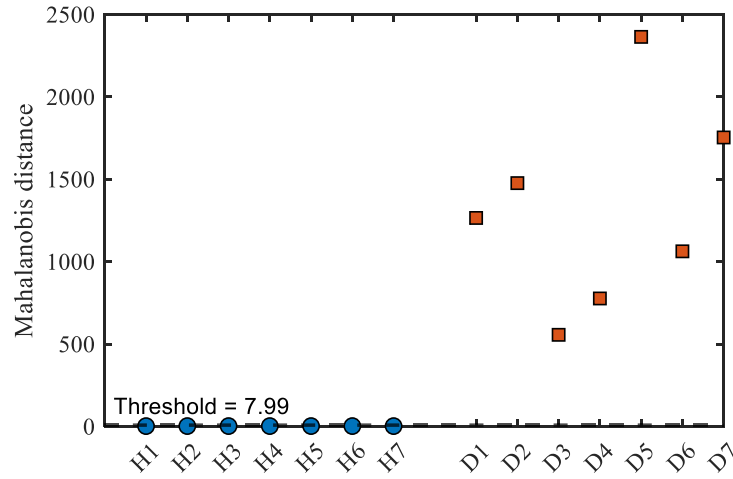


Figure 14. Distribution of the MD scores of all samples.

4.2.4. Method evaluation

To evaluate the proposed method, comparative analyses were conducted at two levels. First, the representation capability of the proposed ER–NRE features was compared with conventional time-domain and frequency-domain indicators under the same healthy-reference-based MD framework. Second, an indicator-level comparison was performed to assess the respective contributions of healthy-reference statistical mapping and NRE feature fusion.

Normalized RMSD was selected as a representative time-domain indicator, and spectral RMSD (S-RMSD) was adopted as a representative frequency-domain indicator. For the p -th pitch–catch path, RMSD was calculated over the effective response interval as

$$\text{RMSD}_p = \sqrt{\frac{\int_{\Omega} [x_p^C(t) - x_p^H(t)]^2 dt}{\int_{\Omega} [x_p^H(t)]^2 dt}} \quad (37)$$

where $x_p^H(t)$ and $x_p^C(t)$ denote the healthy baseline and current-state responses, respectively. The corresponding frequency-domain S-RMSD was defined as

$$\text{S-RMSD}_p = \sqrt{\frac{\int_B (|X_p^C(f)| - |X_p^H(f)|)^2 df}{\int_B |X_p^H(f)|^2 df}} \quad (38)$$

where $X_p^H(f)$ and $X_p^C(f)$ are the Fourier spectra of the two responses. The frequency band B was determined independently from the healthy baseline spectrum before the comparison. The spectra of the 12 effective pitch–catch paths were individually normalized and averaged, and the -6 dB bandwidth around the dominant spectral component was approximately 41–62 kHz. This fixed band was subsequently used for all healthy and local-anomaly samples. For a consistent comparison, RMSD and S-RMSD were calculated over the same effective response interval of 0.11–0.55 ms for all valid paths. Principal component analysis (PCA) visualization was used solely for qualitative visualization of the feature distributions, whereas the quantitative comparison was performed using the MD scores calculated according to the same healthy-reference procedure described in section 3.2, with the corresponding results added as figure 15.

As shown in figures 15(a)–(c), all three feature representations contain useful information for distinguishing the healthy and local-anomaly states. The RMSD representation exhibits relatively larger sample dispersion, whereas S-RMSD and ER–NRE provide clearer clustering between the two states. The separability between healthy and local-anomaly states was quantified by separation, which is defined as

$$\text{Separation} = \frac{\mu_D - \mu_H}{\sigma_D + \sigma_H} \quad (39)$$

where μ_H and μ_D are the mean indicator values of the healthy and local-anomaly groups, respectively, and σ_H and σ_D are the corresponding standard deviations. A larger Separation indicates stronger inter-class separation relative to the within-class variation. The quantitative results in figure 15(d) indicate

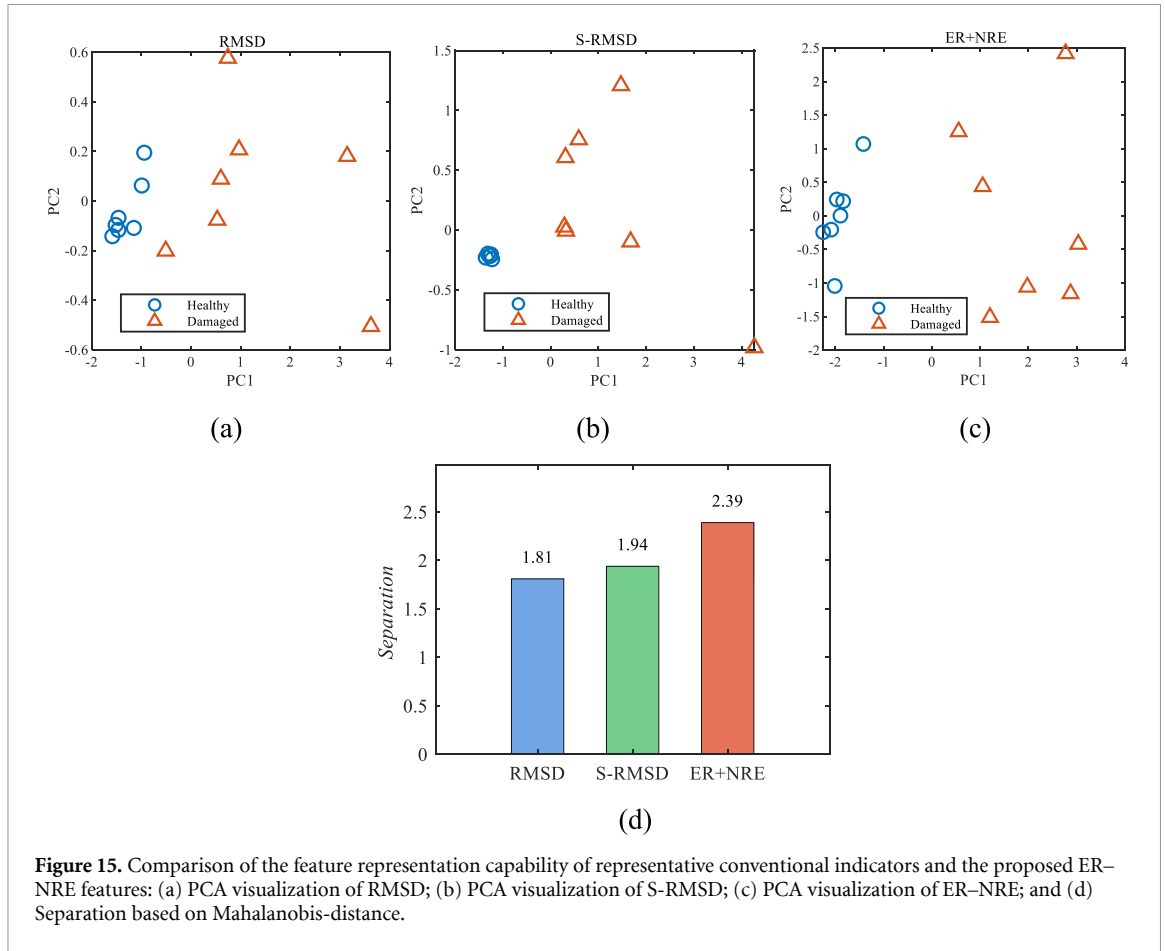


Figure 15. Comparison of the feature representation capability of representative conventional indicators and the proposed ER–NRE features: (a) PCA visualization of RMSD; (b) PCA visualization of S-RMSD; (c) PCA visualization of ER–NRE; and (d) Separation based on Mahalanobis-distance.

that the proposed ER–NRE representation provides stronger healthy/local-anomaly separation than either representative single-domain indicator, owing to the combination of residual scattering magnitude and its temporal energy-distribution characteristics.

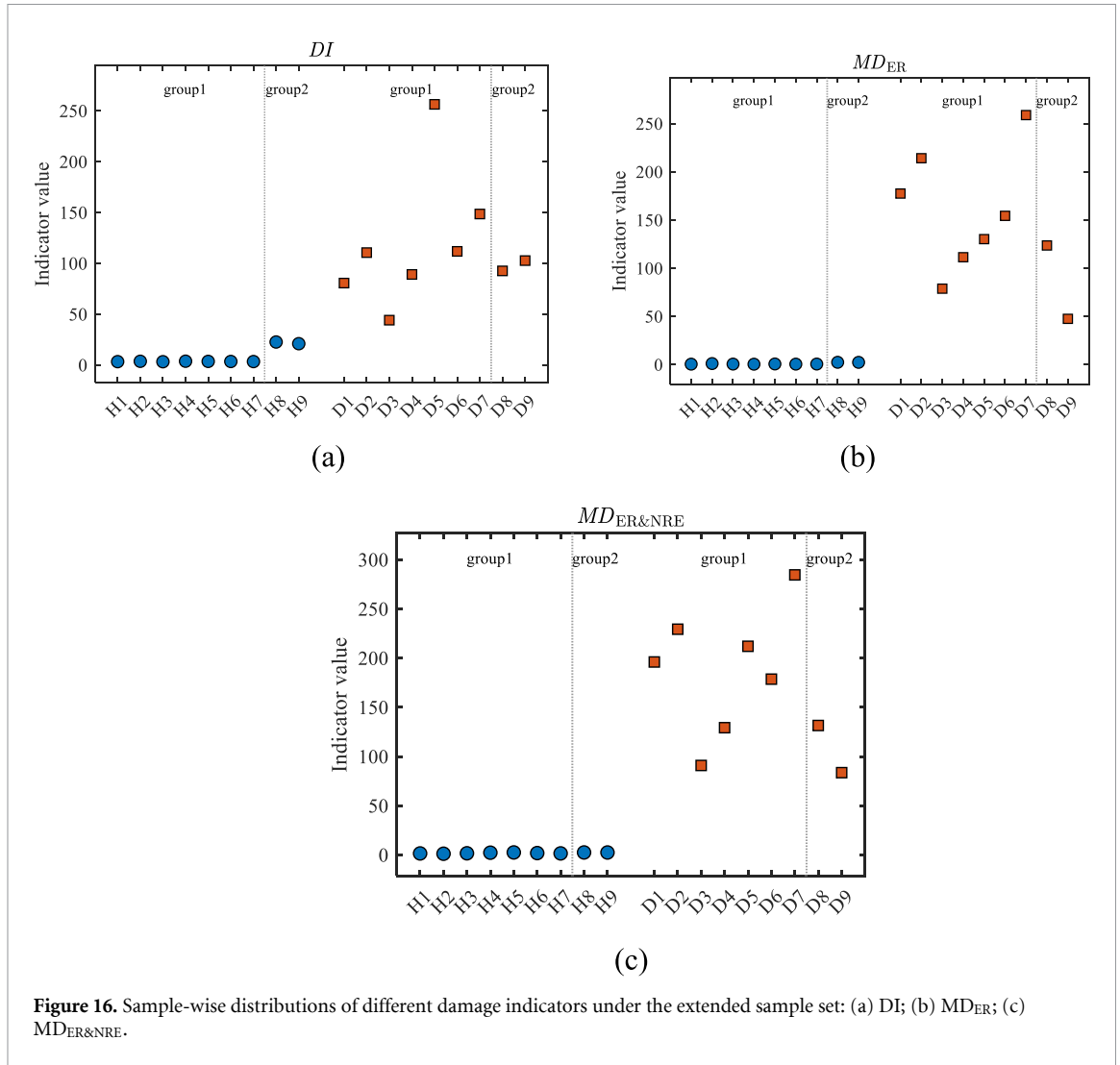
To further examine the contributions of healthy-reference statistical mapping and NRE fusion to the final indicator, an indicator-level comparison was subsequently conducted. In conventional active guided-wave SHM, a widely adopted strategy constructs a single damage indicator from differential responses and performs state classification via an empirical threshold [10, 11, 39, 40]. It aggregates multi-path differential responses into a scalar to characterize structural conditions, and identifies damage once the indicator exceeds a predefined value. Correspondingly, a damage index (DI) is typically defined by accumulating the ERs of the 12 effective pitch-catch paths as

$$DI = \left[\sum_{p=1}^{12} \frac{\int_{\Omega_s} |C_{d,p}(\tau)|^2 d\tau}{\int_{\Omega_r} |C_{b,p}(\tau)|^2 d\tau} \right] \times 100 . \quad (40)$$

For this indicator-level comparison, an ablation test was conducted on the proposed method, in which the features provided by the NRE were omitted and only ER was used. Accordingly, three indicators, DI, MD_{ER} , and $MD_{ER\&NRE}$, were constructed for comparison.

Section 4.2.3 has verified the effectiveness of ER&NRE feature construction, healthy reference space mapping, and the MD damage indicator using the seven samples which are marked as group1. To further compare the representation capability of different indicators under a wider range of healthy-state variations, two extra samples are introduced, namely group2, to both health and damaged scenarios.

Figure 16 compares the sample-wise distributions of three damage indicators. The conventional DI provides clear global separation between healthy and damaged states, as damaged samples exhibit consistently higher ERs. However, the additional samples in group 2 shift toward the lower bound of the



damaged distribution. This leads to reduced robustness under varying healthy-state conditions. In contrast, MD_{ER} significantly improves separability by projecting path-level ER features into a healthy reference space. Healthy samples are tightly clustered around the origin, while damaged samples are clearly displaced, confirming that statistical aggregation of path-wise ER combined with MD-based deviation measurement provides a more stable anomaly representation than DI. With the incorporation of NRE, $MD_{ER\&NRE}$ achieves the best discrimination performance. Healthy samples remain concentrated near zero, whereas damaged samples exhibit a distinctly higher and more dispersed distribution.

The same separation was used to quantify the inter-class separability of the three indicators. In addition, normalized gap was calculated to characterize the minimum margin between the healthy and local-anomaly groups as

$$\text{normalized gap} = \frac{\min(\mathcal{D}) - \max(\mathcal{H})}{\sigma_D + \sigma_H} \quad (41)$$

where $\mathcal{D}$ and $\mathcal{H}$ denote the sets of the damaged and healthy groups, respectively; σ is the corresponding standard deviations for each group.

Figure 17 presents the resultant metrics of the three indicators. The separations obtained for the three indicators are 1.583 (DI), 2.150 (MD_{ER}), and 2.496 ($MD_{ER\&NRE}$), respectively. This indicates that path-level statistical modeling enhances discrimination relative to global ERs, and that incorporating NRE provides additional non-redundant information, further enlarging the inter-class separation. Consistently, the normalized gap also demonstrates that the proposed method constitutes a more effective approach for active damage detection.

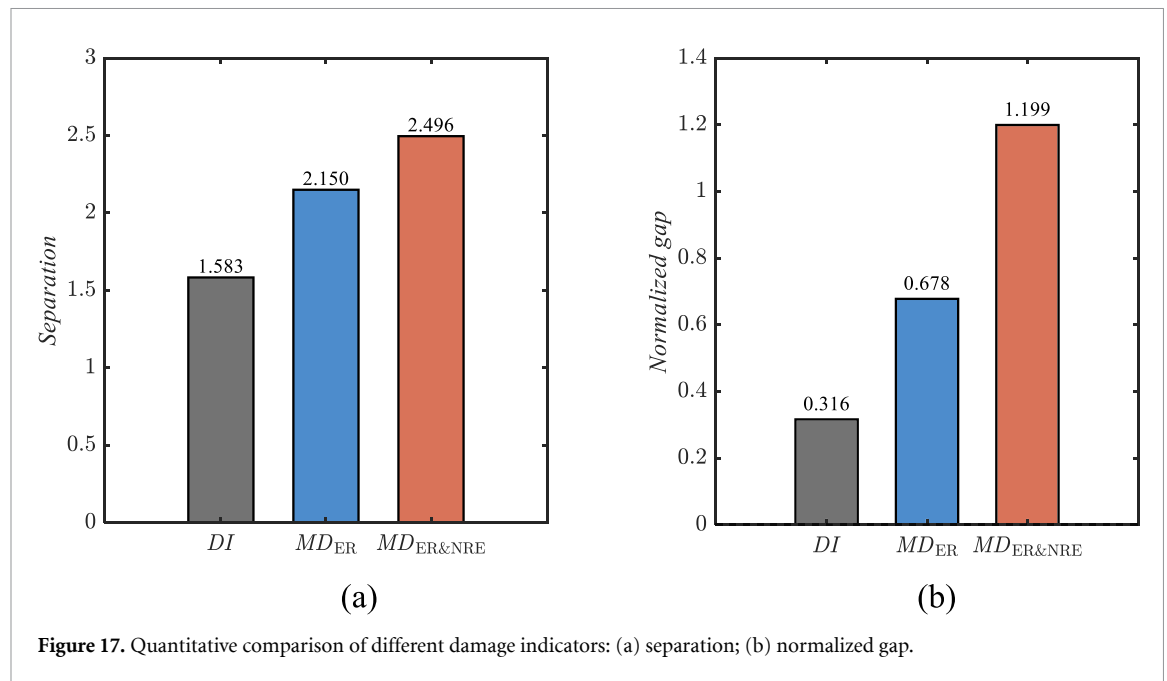


Figure 17. Quantitative comparison of different damage indicators: (a) separation; (b) normalized gap.

5. Conclusion

This study proposed an event-triggered passive-active SHM framework for a PZT-embedded smart composite panel to address the demand for continuous impact monitoring and post-impact state assessment. Smart panels with embedded PZT arrays are fabricated via flexible printed circuit integration. Tensile tests verify the basic mechanical compatibility of the integration scheme, while indicating that the balance between sensing functionality and mechanical performance deserves attention in practical engineering design.

A complete SHM workflow is then established from passive impact localization to active guided-wave state discrimination. In the passive stage, impact localization is achieved by combining continuous wavelet transform, first-peak extraction, Gaussian-windowed cross-correlation and weighted probabilistic imaging, yielding an overall average localization error of approximately 3.25 mm. This provides reliable event-triggering signals and spatial prior knowledge for subsequent active guided-wave interrogation. VTR-based localization for more complex structures with low-signal-to-noise conditions will be investigated in the future. In the active stage, a dual-window feature framework of ER and NRE is constructed based on differential guided-wave responses, and a MD anomaly indicator is further developed through multi-path statistical aggregation and healthy reference space mapping. Results demonstrate that ER characterizes damage-induced scattering energy enhancement, while NRE provides complementary information on the temporal redistribution of residual signal energy. The ER–NRE feature set provides greater MD-based separability than the conventional time- and frequency-domain indicators considered, while the fused indicator $MD_{ER\&NRE}$ outperforms conventional energy-based damage indices with clearer healthy-anomaly separation, stronger suppression of healthy-state fluctuations, and improved threshold-based discrimination stability. Notably, quantitative severity assessment is beyond the scope of the present study because only a single type and size of seeded local anomaly was considered. Future work will investigate multiple damage sizes, damage modes, and locations to establish whether the ER–NRE–MD response can support reliable severity assessment.

This study confirms the feasibility of PZT-embedded smart composite panels for integrated passive-active monitoring and validates the effectiveness of the proposed indicator for post-impact state assessment. By demonstrating that the same embedded sensor network can support both passive impact detection and active damage quantification, this work establishes a critical step toward truly integrated SHM for composite structures. Future work will also evaluate the statistical robustness of the indicator, develop compensation strategies for environmental and operational variations, and validate the method under diverse damage modes and complex structural configurations, thereby facilitating the translation of the proposed strategy from laboratory verification to practical SHM solutions.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Author contributions

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References

- [1] Soutis C 2005 Fibre reinforced composites in aircraft construction *Prog. Aerosp. Sci.* **41** 143–51
- [2] Abrate S 1998 *Impact on Composite Structures* (Cambridge University Press) (<https://doi.org/10.1017/CBO9780511574504>)
- [3] Richardson M O W and Wisheart M J 1996 Review of low-velocity impact properties of composite materials *Compos. Part A Appl. Sci. Manuf.* **27** 1123–31
- [4] Wronkowicz-katunin A, Katunin A and Dragan K 2019 Reconstruction of barely visible impact damage in composite structures based on non-destructive evaluation results *Sensors* **19** 4629
- [5] Hassani S, Mousavi M and Gandomi A H 2022 Structural health monitoring in composite structures: a comprehensive review *Sensors* **22** 153
- [6] Ricci F, Monaco E, Boffa N D, Maio L and Memmolo V 2022 Guided waves for structural health monitoring in composites: a review and implementation strategies *Prog. Aerosp. Sci.* **129** 100790
- [7] Qing X, Li W, Wang Y and Sun H 2019 Piezoelectric transducer-based structural health monitoring for aircraft applications *Sensors* **19** 545
- [8] Mitra M and Gopalakrishnan S 2016 Guided wave based structural health monitoring: a review *Smart Mater. Struct.* **25** 053001
- [9] Giurgiutiu V 2014 *Structural Health Monitoring with Piezoelectric Wafer Active Sensors* 2nd edn (Academics)
- [10] Rose J L 2014 *Ultrasonic Guided Waves in Solid Media* (Cambridge University Press) (<https://doi.org/10.1017/CBO9781107273610>)
- [11] Su Z and Ye L 2009 *Identification of Damage Using Lamb Waves: From Fundamentals to Applications (Lecture Notes in Applied and Computational Mechanics)* (Springer) Vol 48
- [12] Capineri L and Bulletti A 2021 Ultrasonic guided-waves sensors and integrated structural health monitoring systems for impact detection and localization: a review *Sensors* **21** 2929
- [13] Staszewski W J, Mahzan S and Traynor R 2009 Health monitoring of aerospace composite structures: active and passive approach *Compos. Sci. Technol.* **69** 1678–85
- [14] Ciampa F and Meo M 2012 Impact detection in anisotropic materials using a time reversal approach *Struct. Health Monit.* **11** 43–49
- [15] Deng D, Zeng X, Yang Z, Yang Y, Zhang S, Ma S, Xu H, Yang L and Wu Z 2025 Multi-frequency probabilistic imaging fusion for impact localization on aircraft composite structures *Struct. Health Monit.* **24** 185–201
- [16] Wu Z, Zeng X, Deng D, Yang Z, Yang H, Ma S and Yang L 2024 Impact localization on stiffened composite plate based on adaptive time reversal focusing *Acta Mater. Compos. Sin.* **41** 467–80
- [17] Wang Z, Zhang J, Cui H, Gorgin R and Zhang Y 2023 Non-contact impact source localization in composite symmetry panels based on A0 mode of Lamb waves *Symmetry* **15** 1836

- [18] Feng B, Ribeiro A L, Pasadas D J and Ramos H G 2022 Locating low velocity impacts on a composite plate using multi-frequency image fusion and artificial neural network *J. Nondestr. Eval.* **41** 34
- [19] Qiu L, Yuan S, Zhang X and Wang Y 2011 A time reversal focusing based impact imaging method and its evaluation on complex composite structures *Smart Mater. Struct.* **20** 105014
- [20] Yu Z, Xu C, Sun J and Du F 2023 Impact localization and force reconstruction for composite plates based on virtual time reversal processing with time-domain spectral finite element method *Struct. Health Monit.* **22** 4149–70
- [21] Deng D, Zeng X, Yang Y, Zhang S, Xu H, Yang Z, Yang L and Wu Z 2025 Data fusion based impact localization on aircraft composite structures using Bayesian estimation and weighted averaging *Mech. Syst. Signal Process.* **230** 112675
- [22] De Marchi L, Marzani A, Speciale N and Viola E 2011 A passive monitoring technique based on dispersion compensation to locate impacts in plate-like structures *Smart Mater. Struct.* **20** 035021
- [23] Deng D, Zeng X, Pang Q, Bai S, Tian T, Yang H, Yang Z, Yang L and Wu Z 2026 Simultaneous impact localization and energy estimation in composite structures using ensemble learning and approximate Bayesian computation *Thin-Walled Struct.* **225** 114754
- [24] Sun J, Tian K, Zhang H, Rui X, Xu L, Qi L and Zeng Z 2026 Impact localization method for composite laminates based on artificial neural networks and Bayesian updating *Compos. Struct.* **376** 119814
- [25] Oh G W, Choi B G, Kim S Y, Park S, Lee J W, Schulz M J, Kim S E, Kim C-J, Kim C and Kang I 2026 Impact localization and force estimation for structural health monitoring of composite structures using spray-deposited nano-carbon strain sensors and a neural network *Smart Mater. Struct.* **35** 065006
- [26] De Simone M E, Ciampa F, Boccardi S and Meo M 2017 Impact source localisation in aerospace composite structures *Smart Mater. Struct.* **26** 125026
- [27] De Luca A, Caputo E, Sharif Khodaei Z and Aliabadi M H F 2018 Damage characterization of composite plates under low velocity impact using ultrasonic guided waves *Composites B* **138** 168–80
- [28] Chandarana N, Gresil M and Soutis C 2018 Damage detection and monitoring in composite pipes using piezoelectric sensors. *9th European Workshop on Structural Health Monitoring (EWSHM 2018) (Manchester, UK)*
- [29] Wang Q, Hua J and Ji D C 2017 Research on active and passive monitoring fusion for integrated Lamb wave structural health monitoring *Commun. Comput. Inf. Sci.* **761** 442–51
- [30] Kessler S S and Flynn E B 2013 Hybrid passive/active impact detection and localization for aerospace structures *Structural Health Monitoring 2013: A Roadmap to Intelligent Structures—Proc. 9th Int. Workshop on Structural Health Monitoring (Stanford, CA)* vol 2 pp 2325–32
- [31] Lin M and Chang F K 2002 The manufacture of composite structures with a built-in network of piezoceramics *Compos. Sci. Technol.* **62** 919–39
- [32] Su Z, Wang X, Chen Z, Ye L and Wang D 2006 A built-in active sensor network for health monitoring of composite structures *Smart Mater. Struct.* **15** 1939–49
- [33] Dziendzikowski M, Kurnyta A, Dragan K, Kłysz S and Leski A 2016 *In situ* barely visible impact damage detection and localization for composite structures using surface-mounted and embedded PZT transducers: a comparative study *Mech. Syst. Signal Process.* **78** 91–106
- [34] Ren Y, Zhang S, Yuan S and Qiu L 2023 *In-situ* integration and performance verification of large-scale PZT network for composite aerospace structure *Smart Mater. Struct.* **32** 055010
- [35] Feng T and Aliabadi M H F 2021 Structural integrity assessment of composites plates with embedded PZT transducers for structural health monitoring *Materials* **14** 6148
- [36] Ren F, Giannakeas I N, Sharif Khodaei Z and Aliabadi M H F 2024 The temperature effects on embedded PZT signals in structural health monitoring for composite structures with different thicknesses *NDT & E Int.* **141** 102988
- [37] Carani L B, Humphrey J, Rahman M M and Okoli O I 2024 Advances in embedded sensor technologies for impact monitoring of composite structures *J. Compos. Sci.* **8** 201
- [38] Meyer Y, Lachat R and Akhras G 2019 A review of manufacturing techniques of smart composite structures with embedded bulk piezoelectric transducers *Smart Mater. Struct.* **28** 053001
- [39] Lu H, Chandran B, Wu W, Ninic J, Gryllias K and Chronopoulos D 2024 Damage features for structural health monitoring based on ultrasonic Lamb waves: evaluation criteria, survey of recent work and outlook *Measurement* **232** 114666
- [40] Cantero-chinchilla S, Aranguren G, Royo J M, Chiacchio M, Etxaniz J and Calvo-echenique A 2021 Structural health monitoring using ultrasonic guided-waves and the degree of health index *Sensors* **21** 993
- [41] Farrar C R and Worden K 2012 *Structural Health Monitoring: A Machine Learning Perspective* (Wiley) (<https://doi.org/10.1002/9781118443118>)
- [42] Worden K, Manson G and Fieller N R J 2000 Damage detection using outlier analysis *J. Sound Vib.* **229** 647–67
- [43] Yao R and Pakzad S N 2014 Damage and noise sensitivity evaluation of autoregressive features extracted from structure vibration *Smart Mater. Struct.* **23** 025007
- [44] ASTM International 2017 *ASTM D3039/D3039M-17 Standard Test Method for Tensile Properties of Polymer Matrix Composite Materials* (ASTM International) (https://doi.org/10.1520/D3039_D3039M-17)
- [45] Shannon C E 1948 A mathematical theory of communication *Bell Syst. Tech. J.* **27** 623–56
- [46] Fawcett T 2006 An introduction to ROC analysis *Pattern Recognit. Lett.* **27** 861–74