

Article

Structural Damage Localization via RPCA-Based Decomposition of Full-Field Responses with a Differential Damage Index

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Featured Application

This study provides a vision-based full-field damage localization framework for structural health monitoring, enabling robust identification of local damage regions from dense displacement responses under noise and reduced spatial sampling conditions.

Abstract

This study addresses the challenge of separating local damage information from full-field structural responses under complex environmental and noise conditions by proposing a structural damage localization method that integrates piecewise denoising, Robust Principal Component Analysis (RPCA), and a differential damage index. First, full-field responses obtained from vision-based measurement are processed through piecewise denoising and continuous displacement extraction, and then organized into a structural spatiotemporal response matrix. RPCA is subsequently employed to separate low-rank global response components from sparse local anomalies, and a damage index is constructed by differencing sparse-component statistical features between healthy and damaged states. Moving-load tests on a simply supported beam show that the DI peak in the damaged region is approximately 28 times higher than the non-damaged background level, and the identified DI peak accurately falls within the actual damage region. Compared with RMS, kurtosis, curvature index, wavelet energy, PCA residual, and RPCA sparse-energy indicators, the proposed method is the only one that achieves zero regional localization error. Under noise levels of 40–20 dB, all 30 repeated trials achieve a 100% localization success rate, and the success rate remains 93.33% even at 10 dB. Moreover, the localization results remain stable when λ/λ_0 varies from 0.50 to 1.50. Even when the number of spatial measurement points is reduced from 3401 to 128, the method maintains zero mean localization error and a 100% localization success rate. These results demonstrate that the synergy among piecewise denoising, RPCA decomposition, and state-difference enhancement effectively highlights damage-induced local anomalies, providing a robust and physically interpretable framework for full-field-response-based structural damage localization.

Keywords: structural health monitoring; full-field response; robust principal component analysis (RPCA); damage localization; differential damage index; spatial sampling density



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1. Introduction

Over the service life of bridges, buildings, and large-scale engineering structures, structural performance evolves under the combined effects of environmental loading, material degradation, and local damage. Accurate acquisition of structural state information is essential for safety assessment and early warning. Structural responses, such as displacement and vibration, are key physical quantities that reflect changes in global stiffness and stress states, and have therefore become key observables in Structural Health Monitoring (SHM) [1–4]. Although traditional point-sensor monitoring approaches can provide high-precision local response measurements, they remain limited in spatial coverage, deployment cost, and adaptability to complex structures [5].

In recent years, advances in computer vision and full-field measurement technologies have enabled the increasing use of vision-based, non-contact techniques for structural response measurement [6–9]. These methods allow synchronous acquisition of full-field structural responses without dense sensor deployment, thereby providing richer spatial information for structural state assessment and damage identification. Compared with traditional approaches, full-field response data capture not only global structural behavior but also potential localized anomalies, offering a new avenue for data-driven structural damage identification [10]. Representative full-field and non-contact structural response measurement techniques used in civil SHM mainly include three-dimensional laser scanning, radar-based displacement measurement, digital image correlation (DIC), optical-flow-based methods, template matching, and edge- or contour-based visual tracking. Three-dimensional laser scanning can provide dense geometric information and is suitable for static or quasi-static deformation measurement, but its scanning speed, equipment cost, and data-processing burden limit its applicability to rapid dynamic responses. Radar-based systems can realize long-distance displacement monitoring with high measurement sensitivity, but their spatial resolution and equipment cost may restrict dense full-field response acquisition. DIC and optical-flow-based methods can provide rich spatial displacement information from image sequences, but their performance is often affected by surface texture, illumination variation, decorrelation, and computational cost. Template matching and edge/contour tracking are relatively simple and efficient for structural components with clear visual features, and are therefore suitable for extracting dense displacement responses along structural edges. Considering the beam-like structure, the availability of a continuous edge feature, and the need to construct a dense spatiotemporal displacement matrix for subsequent RPCA decomposition, this study adopts a vision-based edge-response measurement strategy with segmented denoising and continuous edge-feature extraction. This strategy avoids dense contact sensor deployment while providing spatially continuous displacement responses required by the proposed full-field damage localization framework [11–16].

However, in practical engineering environments, structural responses are typically composed of multi-source superimposed signals, including global response components governed by overall structural dynamics and subtle perturbations induced by local damage or anomalies. These components are strongly coupled in both time and space, causing damage-related features to be masked by dominant background responses and making direct separation and identification from raw response data challenging [17–20]. This difficulty is further exacerbated by environmental noise, measurement errors, and operational variability, which increase response uncertainty and thereby limit the damage sensitivity and spatial resolution of traditional feature-based or statistical methods [21–23].

Therefore, effectively separating global structural responses from local anomalies in full-field response data without relying on complex structural models, and constructing

damage indices with high contrast and strong robustness, remains a critical challenge in structural damage identification [24–26].

To address these challenges, extensive studies have been conducted from various perspectives. Traditional approaches primarily rely on structural dynamic analysis or statistical feature extraction, including damage identification based on modal parameter variations, frequency response functions, energy-based indices, or response statistics [27–31]. Although these methods can be effective under linearity assumptions or ideal testing conditions, they typically depend on reliable prior models or stable test environments and are sensitive to environmental noise and operational variability, which limits their robustness in complex engineering scenarios [32,33].

In vibration-response-based structural damage identification, damage indices (DIs) are commonly used to transform structural response changes into spatially comparable damage descriptors. Existing damage indices mainly include those based on modal parameter variations, flexibility or curvature changes, frequency response functions, wavelet energy or local singularities, and statistical response features [34–36]. These indices generally localize damage by comparing response differences between healthy and damaged states or by extracting localized anomaly features [37–39]. However, in the presence of complex environmental noise, boundary effects, and non-damage-related disturbances, indices constructed directly from raw response amplitudes, energy measures, or single-state anomaly intensity are susceptible to background fluctuations, leading to reduced damage-feature contrast or spurious peaks. Therefore, constructing a differential damage index that highlights damage-induced changes while suppressing common background disturbances is critical for improving the stability of full-field-response-based damage localization.

In recent years, machine learning, deep learning, vision-based measurement, multi-sensor fusion, and optimization-assisted methods have significantly advanced structural health monitoring. Machine learning techniques have been widely applied to vibration-response classification, damage identification, feature selection, and structural state assessment. Deep learning further enhances the ability to extract nonlinear features from complex response patterns and has shown strong potential in vision-based defect detection, structural response prediction, vibration-response analysis, and data-driven damage diagnosis [40]. Meanwhile, optimization-assisted methods, including swarm intelligence, particle swarm optimization, whale optimization algorithms, and hybrid optimization schemes, have been used for crack identification, damage-parameter inversion, structural response prediction, and model updating, providing new tools for damage localization and quantification in complex structures. These studies indicate that modern SHM is shifting from traditional feature extraction toward intelligent, data-driven, and optimization-assisted paradigms [41–43].

However, existing machine learning and deep learning methods typically rely on large numbers of labeled samples and well-covered damage scenarios, and their generalization performance is often affected by structural type, environmental variability, sensor configuration, and training-data quality. Although optimization-assisted methods can be used for damage-parameter inversion and model updating, they generally require predefined structural models, objective functions, and substantial computational cost. In contrast, this study takes the data structure of full-field responses as the starting point. Low-rank-sparse decomposition is used to explicitly separate global structural responses from local anomalous perturbations, and a state-difference mechanism is further introduced to enhance damage-induced variations in sparse features. Rather than aiming at end-to-end classification or parameter inversion, the proposed method provides a physically interpretable framework for full-field response decomposition and damage localization, offering an interpretable

feature foundation for subsequent damage quantification, multi-damage identification, and physics-informed learning methods.

Beyond supervised learning, recent studies have explored unsupervised and weakly supervised approaches to reduce reliance on labeled data, such as extracting structural state variations through anomaly detection, matrix decomposition, low-rank–sparse modeling, and multi-source data fusion. Among these methods, RPCA and its variants offer inherent advantages in separating low-rank backgrounds from sparse anomalies and have been applied to signal denoising, anomaly detection, and structural damage identification [44,45]. These methods provide a promising route for separating global structural behavior from local anomalous perturbations in full-field responses [46,47].

However, although machine learning, deep learning, optimization-assisted identification, and low-rank–sparse decomposition methods have enriched the methodological toolbox for intelligent SHM, existing studies remain limited in full-field-response-based damage identification under complex environments. First, many vision-based measurement approaches and deep learning models focus primarily on structural response acquisition, image feature extraction, or end-to-end state classification, without explicitly modeling the coupling between global structural behavior and local damage-induced perturbations. This limits the physical interpretability and stability of damage features. Second, traditional statistical indicators and some data-driven methods often extract discriminative features directly from raw responses and are therefore susceptible to global background fluctuations, noise disturbances, and operational variability, making it difficult to reliably highlight localized damage information in complex environments.

Low-rank–sparse decomposition and RPCA provide a promising approach to addressing these issues, and previous studies have demonstrated their feasibility in separating the global structural response background from local anomalous perturbations. However, many existing studies directly use the sparse component, its amplitude, or sparse energy as damage-sensitive features. Although such indicators can partially highlight local anomalies, they essentially measure sparse-response intensity directly and are therefore susceptible to measurement noise, boundary effects, local non-damage-related disturbances, and differences in background responses across operating conditions. This limitation is particularly important for full-field response data, where global structural dynamics and local damage-induced perturbations are strongly coupled in both time and space. Relying solely on sparse-component amplitude or energy cannot sufficiently remove background fluctuations shared by healthy and damaged states. Therefore, it remains necessary to construct a differential damage index based on low-rank–sparse decomposition that emphasizes damage-state changes relative to the healthy baseline, thereby improving the separability and localization stability of local damage features.

To address these issues, this study proposes a structural damage localization method based on full-field response low-rank–sparse decomposition and differential enhancement of sparse features. A spatiotemporal matrix representation of structural responses is first constructed, upon which Robust Principal Component Analysis (RPCA) is employed to separate global structural responses from local anomalies. Statistical features of the sparse components are then extracted separately for healthy and damaged states, and a state-difference strategy is introduced to construct a Differential Damage Index (DI). This index suppresses common background disturbances while enhancing damage-specific localized anomalies, enabling stable damage localization in complex environments.

It should be emphasized that the novelty of this study lies neither in the use of RPCA alone nor in simply applying RPCA to full-field response data. Rather, it lies in establishing an integrated decomposition-based identification framework for vision-based full-field responses. In this framework, spatially continuous full-field displacement responses obtained

through segmental denoising, continuous edge-feature extraction, and pixel-to-physical scale conversion are used as inputs. Spatiotemporal matrix modeling, low-rank–sparse decomposition, sparse-component statistical feature extraction, and healthy/damaged state-difference enhancement are integrated to reformulate damage localization from direct sparse-anomaly detection into enhancement-based identification of damage-induced variations in sparse features.

The main contributions of this paper are as follows:

- (1) A spatiotemporal matrix decomposition framework for structural full-field responses is constructed. This framework takes spatially continuous full-field displacement responses obtained through segmental denoising, continuous edge feature extraction, and pixel-to-physical scale conversion as input, organizes the time-varying responses of dense spatial measurement points into a unified matrix form, and decouples the global dynamic response of the structure from local anomalous disturbances through low-rank–sparse decomposition. The low-rank component is used to represent the global response dominated by the overall dynamic behavior of the structure, while the sparse component is used to represent local anomalous disturbances that deviate from the overall response pattern.
- (2) A differential damage index based on statistical features of the sparse component is proposed. Unlike existing methods that directly use the amplitude of the sparse component or sparse energy for damage characterization, this paper separately extracts statistical features of the sparse components under healthy and damaged states, and constructs the damage index through differential calculation, thereby weakening background fluctuations and non-damage sparse disturbances commonly existing in the two states, and highlighting damage-induced local anomalous changes.
- (3) Through noise conditions and comparison with multiple benchmark damage indices, the advantages of the proposed differential damage index in terms of damage feature contrast, localization accuracy, and noise robustness are verified. This method combines the anomaly extraction capability of RPCA decomposition with the differential feature enhancement mechanism, providing an interpretable data-driven solution for full-field-response-based structural damage localization in complex environments. It should be noted that this paper mainly focuses on local damage location identification; for the quantitative inversion of physical quantities such as damage severity, crack depth, and stiffness reduction, further studies combining samples with multiple damage severities, structural models, or calibration relationships are still required.

2. Materials and Methods

2.1. Overall Framework of the Proposed Method

Under complex operating conditions and noise contamination, localized anomalies induced by structural damage are often masked by dominant global responses, making their direct extraction from raw response data challenging. This constitutes a key challenge in structural damage identification.

To address this challenge, this study proposes a structural damage localization method based on the decomposition of full-field response data. The core idea is to construct a unified spatiotemporal representation and employ low-rank–sparse decomposition to separate global structural responses from local anomalous perturbations, thereby enhancing damage-related information and enabling damage localization.

The overall framework of the proposed method is shown in Figure 1. First, videos of structural responses are acquired using a vision-based measurement system, and the raw video sequences are preprocessed using piecewise denoising and continuous edge-feature extraction [48]. Specifically, a region of interest (ROI) containing the beam edge is

selected from each video frame. Sequences of edge-pixel coordinates are then obtained through piecewise denoising and structural edge tracking. These edge-pixel coordinates are converted into pixel displacement time histories, which are further transformed into full-field displacement responses along the structural measurement line through pixel-to-physical scale conversion.

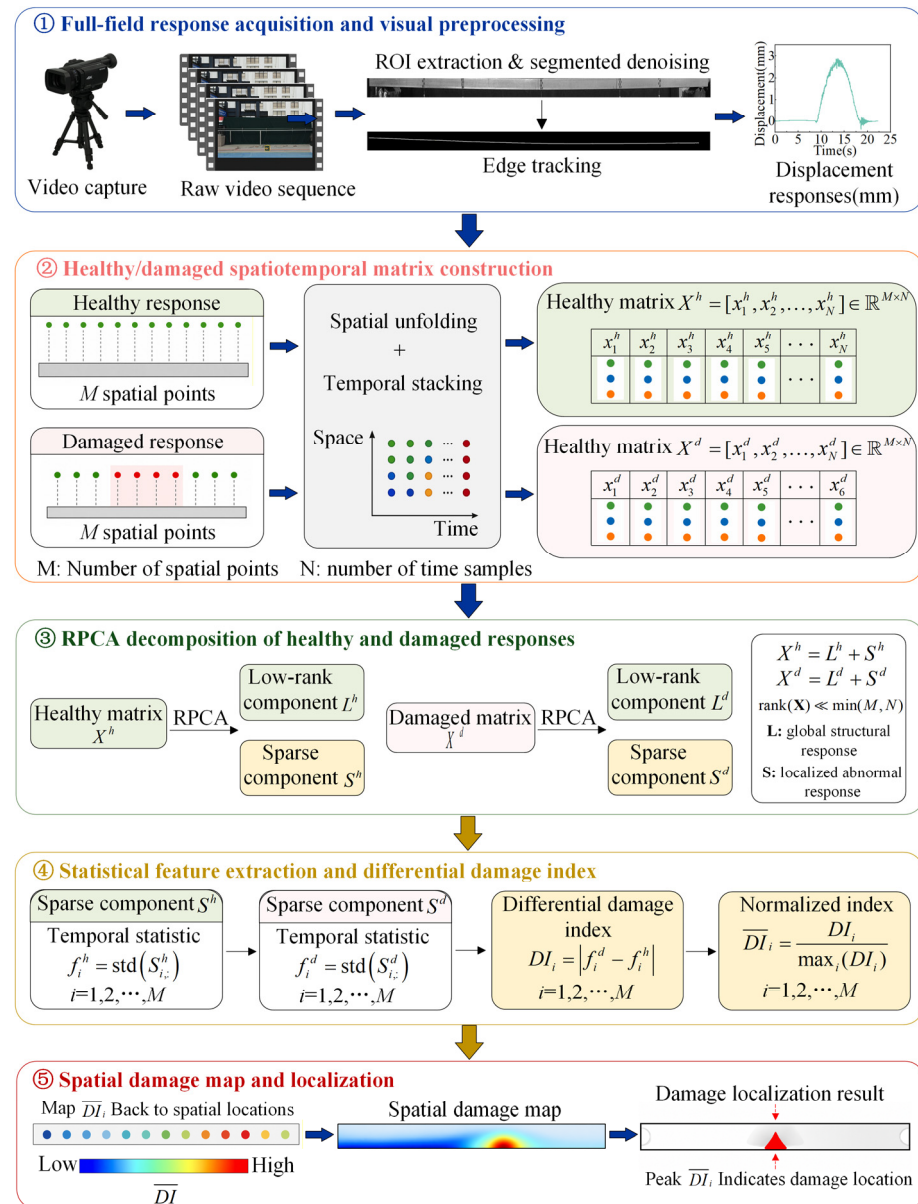


Figure 1. Data flow of the proposed full-field response decomposition and differential damage localization framework.

For the healthy and damaged states, the displacement time histories at all spatial measurement points are unfolded and stacked according to spatial position and temporal order to construct the healthy-state and damaged-state full-field response matrices, X^h and X^d , respectively. Low-rank–sparse decomposition is then performed separately on X^h and X^d , yielding low-rank components L^h and L^d , and sparse components S^h and S^d . The low-rank components characterize globally correlated structural responses, whereas the sparse components capture local anomalous perturbations that deviate from the global response pattern. Subsequently, statistical features f_i^h and f_i^d are extracted from the sparse components along the temporal dimension for the healthy and damaged states, respectively,

and the spatial damage index DI_i is constructed through state-wise differencing and normalization. Finally, the damage index is mapped back to the structural coordinates to obtain its spatial distribution, enabling spatial characterization and localization of damage.

From a methodological perspective, the proposed method consists of five consecutive processing stages: vision-based measurement and preprocessing, construction of healthy- and damaged-state spatiotemporal matrices, RPCA-based response decomposition, sparse-component statistical feature extraction and differential damage index construction, and spatial damage mapping and localization. Specifically, the vision-based preprocessing stage converts raw video data into full-field displacement responses; the matrix construction stage organizes time histories from multiple measurement points into a unified form; the response decomposition stage separates global and local components using a low-rank-sparse model; the feature extraction stage enhances damage-induced anomalies through healthy/damaged-state differencing; and the spatial mapping stage maps the damage index back to structural coordinates to identify the damage location. Following the experimental data flow, the proposed method reformulates structural damage localization as a problem of full-field response decomposition and differential feature enhancement, enabling damage-region identification without relying on complex structural models.

2.2. Full-Field Data Representation

To enable data-decomposition-based structural damage identification, the original structural response data must first be transformed into a unified mathematical representation. In practical engineering applications, full-field structural responses acquired using vision-based measurement systems are discretized in both space and time, making them not directly suitable for unified global response analysis and local anomaly extraction. Therefore, it is necessary to construct a spatiotemporal representation that captures both spatial distributions and temporal evolution characteristics.

Consider M spatial positions selected along the structural measurement line, with response data sampled at N time instants. The full-field displacement response at time t can be represented as a spatial response vector:

$$\mathbf{x}_t = [x_1(t), x_2(t), \dots, x_M(t)]^T \in \mathbb{R}^M \quad (1)$$

where $x_i(t)$ denotes the displacement response at the i -th spatial measurement position at time t . By stacking the response vectors across time, a spatiotemporal matrix representation of the full-field structural response can be constructed:

$$\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N] \in \mathbb{R}^{M \times N} \quad (2)$$

In this representation, each column of the matrix $\mathbf{X}$ corresponds to the spatial response distribution at a given time instant, while each row represents the temporal response evolution at a given spatial position. This spatiotemporal matrix representation provides a compact and structured form for structural responses, facilitating subsequent matrix-based analysis.

From a structural dynamics perspective, under the current testing conditions, structural responses are typically governed by a limited number of dominant modes or globally correlated motions, leading to strong correlations among different spatial measurement positions. Consequently, the full-field response matrix typically exhibits an approximately low-rank structure and can be expressed as:

$$\text{rank}(\mathbf{X}) \ll \min(M, N) \quad (3)$$

The spatiotemporal matrix organizes the original discrete response measurements into a unified form and transforms structural responses into a matrix representation that captures both spatial and temporal information. Its approximately low-rank structure reflects the fact that global structural responses are governed by a limited number of dominant modes or correlated motions, thereby providing the basis for subsequent separation of global responses from local anomalous perturbations.

2.3. Structural Response Decomposition and Damage Identification

Once the spatiotemporal matrix representation of the structural full-field response is obtained, the key challenge is to extract damage-related local anomalies from the overall response. To this end, the structural response is modeled as a superposition of global responses and local anomalies, which are separated through low-rank–sparse decomposition. Based on the spatiotemporal matrix X constructed in Section 2.2, the structural response can be expressed as:

$$X = L + S \quad (4)$$

where L denotes the low-rank component, capturing global structural response characteristics, and S denotes the sparse component, representing local anomalous perturbations. The key idea of this formulation is to recast structural damage localization as the separation of global responses from local anomalous perturbations, thereby avoiding the difficulty of directly extracting subtle damage features from complex response signals.

From a structural dynamics perspective, in the undamaged state, structural responses are governed by a limited number of dominant modes, leading to strong correlations among spatial measurement points and resulting in an approximately low-rank structure. When local damage occurs, changes in stiffness distribution introduce localized perturbations that deviate from the global response pattern. These perturbations are spatially concentrated and temporally nonstationary or abrupt, and thus manifest as sparse components in the overall response. Based on these properties, low-rank–sparse decomposition can effectively separate global structural responses from local anomalies.

To further illustrate the decomposition mechanism and damage characterization process of the proposed method, Figure 2 schematically presents the procedure for full-field response decomposition and damage localization.

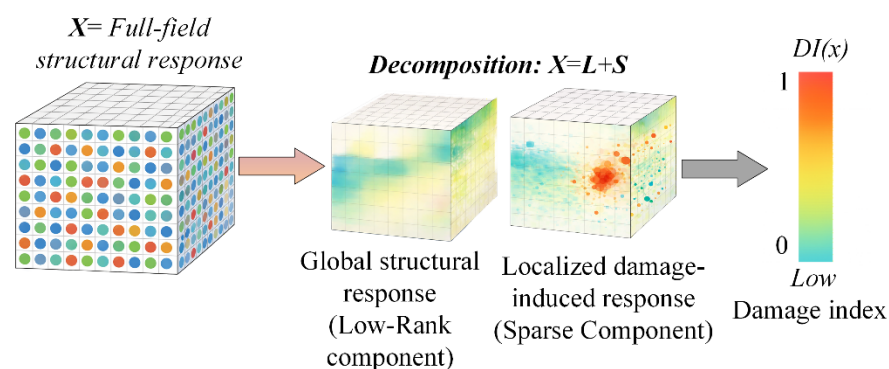


Figure 2. Illustration of low-rank and sparse decomposition for structural damage identification. Different colors are used to schematically distinguish the full-field response, low-rank global component, sparse localized anomaly component, and damage-index intensity.

As illustrated in Figure 2, the original full-field response can be decomposed into a low-rank component representing globally correlated structural behavior and a sparse component capturing local anomalous perturbations. Based on this decomposition, a

damage index is constructed through differencing between healthy and damaged states to enable spatial localization.

To obtain stable decomposition results, the decomposition is formulated as the following optimization problem:

$$\min_{L,S} \|L\|_* + \lambda \|S\|_1 \text{ s.t. } X = L + S \quad (5)$$

where $\|L\|_*$ denotes the nuclear norm that promotes low-rankness, $\|S\|_1$ denotes the L_1 norm that promotes sparsity, and λ is a regularization parameter. Through convex relaxation, this optimization model enables effective separation of low-rank components and sparse anomalies while maintaining computational tractability.

In terms of theoretical assumptions, RPCA is suitable for cases in which the original data can be approximated as the superposition of a low-rank background component and a sparse anomaly component. For full-field structural responses, this assumption means that the global structural dynamic response is mainly governed by a limited number of dominant modes or correlated global motions, and therefore appears as a low-rank or approximately low-rank structure in the space–time matrix. In contrast, local damage and other localized anomalies generally affect only limited spatial regions and may induce enhanced perturbations that deviate from the global response pattern over certain time intervals; thus, they can be approximated as sparse or spatially concentrated components in the space–time matrix. Based on this assumption, the low-rank component L represents the globally correlated structural response, whereas the sparse component S captures local anomalous perturbations that deviate from the global response pattern. Notably, this assumption does not require the structural response to be strictly low-rank or the damage-induced perturbation to be absolutely sparse. Rather, it requires sufficient spatiotemporal distinction between the two components so that low-rank–sparse decomposition can yield a physically meaningful approximate separation.

Regarding parameter selection, this study adopts the commonly used initial regularization parameter for the Principal Component Pursuit (PCP) problem:

$$\lambda_0 = \frac{1}{\sqrt{\max(M, N)}} \quad (6)$$

In this expression, M and N denote the numbers of spatial measurement points and temporal samples, respectively. The parameter λ controls the trade-off between the low-rank and sparse components: a larger λ imposes a stronger penalty on the sparse component, thereby retaining more response information in the low-rank component, whereas a smaller λ permits more local perturbations to be assigned to the sparse component. In this study, λ_0 is used as the default value, and different multiples of λ_0 are tested in subsequent experiments for parameter sensitivity analysis to evaluate the robustness of damage localization results to variations in the regularization parameter.

For numerical implementation, this study adopts an iterative augmented Lagrange multiplier strategy to solve the above convex optimization problem. In each iteration, the low-rank component is updated using singular value thresholding, the sparse component is updated using the soft-thresholding operator, and the Lagrange multiplier is updated to progressively reduce the reconstruction residual. The convergence criterion is defined as:

$$\frac{\|X - L^{(k)} - S^{(k)}\|_F}{\|X\|_F} < \varepsilon \quad (7)$$

In this criterion, k denotes the iteration index, $\|\cdot\|_F$ denotes the Frobenius norm, and ε is the convergence tolerance. In this study, $\varepsilon = 10^{-6}$ is adopted, and a maximum iteration

number is imposed as a safeguard to avoid infinite iterations in extreme cases. In practical computation, the iterative process is usually terminated once the relative reconstruction residual threshold is reached. This criterion ensures numerically stable reconstruction accuracy of the decomposition results.

It is worth noting that the RPCA framework used in this study differs fundamentally from classical Principal Component Analysis (PCA) in both its modeling objective and its mechanism for handling local anomalies. Classical PCA typically approximates the original response data using a low-dimensional principal subspace, with the primary objective of retaining the dominant variance components. The residual component, however, is not explicitly constrained to be sparse. Consequently, when local damage-induced anomalies are coupled with global structural responses or measurement noise, damage-related information may be partially absorbed into the principal components or mixed with noise in the residuals, leading to unstable characterization of local damage. In contrast, RPCA explicitly decomposes the response matrix into low-rank and sparse components: the low-rank component represents globally correlated structural responses, whereas the sparse component captures local anomalous perturbations that deviate from the global response pattern. Therefore, RPCA is more suitable for separating superimposed structures such as “global structural behavior–local anomalous perturbations” from full-field response data.

To account for measurement noise in practical engineering applications, this model can be extended to:

$$\mathbf{X} = \mathbf{L} + \mathbf{S} + \mathbf{E} \quad (8)$$

In this model, E denotes a small-magnitude random noise term. This extension improves the applicability and robustness of the proposed method for real measurement data.

The primary role of a damage index is to map structural state changes into spatially interpretable and comparable damage descriptors. For response-difference-based damage identification methods, index construction is generally based on two principles. First, damage alters the local dynamic response of a structure, leading to changes in statistical response features, energy distribution, or local singularities within the damaged region. Second, differencing between healthy and damaged states can suppress background responses and non-damage-related disturbances shared by the two states. Therefore, a differential damage index essentially measures damage-induced changes rather than directly evaluating the response amplitude of a single state.

Once the sparse component is obtained, its elements capture localized anomalous responses at each spatial position over time. For sparse-component-based damage identification, a common strategy is to directly construct a damage index using the amplitude or energy of the sparse component. For example, the sparse energy at the i -th spatial measurement point can be expressed as:

$$E_i^s = \sum_{t=1}^n S_{i,t}^2 \quad (9)$$

In Equation (9), $S_{i,t}$ denotes the entry of the sparse-component matrix at the i -th spatial measurement point and the t -th time instant. Such an index can reflect the strength of local anomalous responses. However, it is essentially a direct accumulation of sparse-component amplitudes and cannot distinguish whether the sparse response originates from structural damage or from measurement noise, local boundary effects, illumination variations, identification errors, or other non-damage-related disturbances. Therefore, when sparse background disturbances are also present in the healthy state, directly using a sparse-energy index may amplify background spurious peaks or provide insufficient contrast for damage characterization.

To overcome these limitations, this study does not directly use sparse-component energy as the damage index. Instead, sparse-component statistical features are extracted separately under healthy and damaged states, and the damage index is then constructed through state-wise differencing. The core idea of this strategy is that background disturbances shared by healthy and damaged states can be suppressed through differencing, whereas damage-induced local anomalies can be highlighted. Therefore, the proposed DI is not a conventional sparse-energy index, but a differentially enhanced damage index based on changes in sparse-component statistical features.

Specifically, standard-deviation features are extracted along the temporal dimension for the sparse components corresponding to the healthy and damaged states, respectively:

$$f_i^h = \text{std}(S_{i,:}^h), f_i^d = \text{std}(S_{i,:}^d) \quad (10)$$

Here, $S_{i,:}^h$ and $S_{i,:}^d$ denote the sparse-component time series at the i -th spatial measurement point in the healthy and damaged states, respectively, while f_i^h and f_i^d denote the corresponding sparse-component variability features. The standard-deviation feature reflects the temporal variability of local anomalous responses and provides greater robustness to transient noise than single-instant amplitude measures.

Based on this, the differential damage index is constructed as:

$$DI_i = |f_i^d - f_i^h| \quad (11)$$

This differencing operation suppresses sparse background disturbances shared by healthy and damaged states while highlighting newly introduced or enhanced local anomalies after damage. Therefore, relative to direct sparse-energy indicators, the proposed DI emphasizes damage-specific differences caused by structural state changes, thereby improving the spatial contrast between damaged and non-damaged regions. In this study, DI specifically refers to the Differential Damage Index. To avoid confusion with general damage indicators, this index is not constructed directly from raw responses, PCA residuals, or single-state sparse energy; rather, it is a state-difference-based index derived from differences in sparse-component statistical features between healthy and damaged states.

Furthermore, to remove scale effects and facilitate comparison across different operating conditions, the damage index is normalized as follows:

$$\overline{DI}_i = \frac{DI_i}{\max_i(DI_i)} \quad (12)$$

In Equation (12), $\max_i(DI_i)$ denotes the maximum value of the differential damage index across all spatial measurement points. The normalization places the index on a consistent scale, ensuring comparability across different noise levels and testing conditions. To improve the completeness and reproducibility of the method description, the main computational workflow of the proposed method is summarized in Algorithm 1.

To further clarify the distinction between the proposed method and classical PCA/CPCA, existing RPCA sparse-energy approaches, and conventional damage indicators, Table 1 provides a comparison in terms of core principle, damage characterization, and background-interference treatment. The proposed method does not directly use the amplitude or energy of the RPCA sparse component. Instead, it builds on preprocessing of vision-based full-field responses and low-rank-sparse decomposition, and enhances damage-induced changes through state-wise differencing of sparse-component statistical features between healthy and damaged states.

Algorithm 1. RPCA-Based Differential Damage Localization (Pseudocode of the proposed method)

Input:

Healthy-state full-field response matrix X^h ; damaged-state full-field response matrix X^d ; regularization parameter λ ; convergence tolerance ε ; spatial coordinates of measurement points $\Omega = \{\omega_i\}_{i=1}^M$

Output:

Normalized differential damage index $\bar{D}I$ and damage localization result ω^*

```

1    // Low-rank and sparse decomposition
2    for each structural state  $q \in \{h, d\}$  do
3      Set the input response matrix  $X^q$ 
4      Solve the RPCA optimization model to obtain  $L^q$  and  $S^q$  using Equation (5)
5      Set  $\lambda = \lambda_0$  according to Equation (6)
6      Iteratively update  $L^q$  and  $S^q$  using singular-value thresholding and
       soft-thresholding
7      Check the convergence criterion using Equation (7).
8    end for
9    // Sparse-component feature extraction
10   for each spatial measurement point  $i = 1, 2, \dots, M$  do
11     Extract the sparse-component time series  $S_{i,:}^h$  and  $S_{i,:}^d$ 
12     Compute the temporal statistical features  $f_i^h$  and  $f_i^d$  using Equation (10)
13     Construct the differential damage index  $DI_i$  using Equation (11)
14   end for
15   // Normalization and spatial localization
16   Normalize the damage index  $\bar{D}I_i$  using Equation (12).
17   Map  $\bar{D}I_i$  back to the structural spatial coordinates  $\Omega$ .
18   Identify the damage location by the peak of  $\bar{D}I_i$ :  $\omega^* = \omega_{\arg\max_i(\bar{D}I_i)}$ 
19   return  $\bar{D}I, \omega^*$ 

```

Table 1. Comparison of PCA/CPCA, RPCA, Damage Indices, and the Proposed Method.

Comparison Aspect	PCA/CPCA	RPCA Sparse-Energy	Conventional Damage Indices	Proposed Framework Proposed Full-Field
Core Principle	Low-dimensional subspace approximation	Low-rank–sparse decomposition	Damage-sensitive response features	Full-field preprocessing, RPCA decomposition, and state-difference enhancement
Damage characterization	Residual or unexplained components	Sparse-component amplitude or energy	Modal, statistical, curvature, or energy changes	Difference in sparse statistical features between healthy and damaged states
Background interference	Sensitive to outliers and noise	Sparse component may retain non-damage disturbances	Easily affected by background fluctuations	Preprocessing and state differencing suppress common background disturbances

As shown in Table 1, classical PCA/CPCA methods mainly capture anomalies through residuals or unexplained components. RPCA sparse-energy approaches can separate global responses from local anomalies, but the sparse component may still retain non-damage-related disturbances. Conventional damage indices strongly depend on the selected re-

sponse features and are susceptible to background fluctuations. In contrast, the proposed method integrates full-field response preprocessing, RPCA-based local anomaly separation, and healthy–damaged state differencing. By suppressing common background disturbances while enhancing damage-induced local variations, the proposed method improves both the contrast and interpretability of damage characterization.

3. Laboratory Verification

3.1. Experimental Setup and Objectives

To validate the proposed structural damage localization method integrating full-field response low-rank–sparse decomposition with a differential damage index, a laboratory experiment was conducted on a simply supported beam model. As shown in Figure 3, the experimental system consisted of a model beam, a moving-load excitation system, a vision-based measurement system, and a contact-based reference measurement system. The test beam had a span of approximately 5.5 m, with hinged and roller supports at its two ends to form simply supported boundary conditions. A traction device (YE2-90L-4, Xinling Motor, Taizhou, China) drove a model truck carrying an additional 5 kg mass to move along the beam surface at a constant speed of 0.19 m/s, thereby simulating moving-load excitation and inducing structural dynamic responses. Each test condition was repeated 10 times. To evaluate the capability of the proposed method to identify local damage anomalies, a predefined damage region was located at approximately $L/3$ of the beam, corresponding to spatial points 41–43 along the vision-based measurement line. A single-damage condition was first used as the baseline validation case, followed by noise, parameter, and spatial sampling sensitivity tests to further assess method stability.

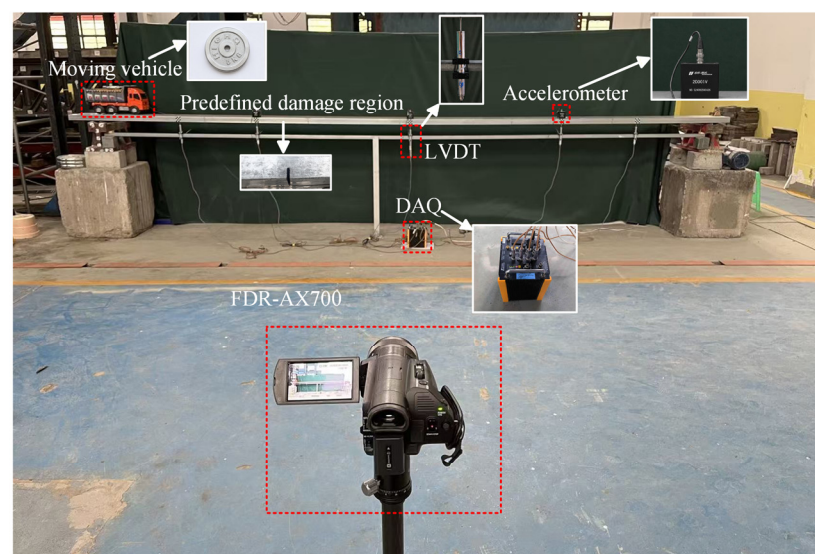


Figure 3. Experimental setup for full-field measurement and structural damage identification.

Full-field structural displacement responses were acquired using a vision-based measurement system. A Sony FDR-AX700 high-resolution camera (Sony Corporation, Tokyo, Japan) was used, with a video resolution of 3840×2160 , a frame rate of 30 fps, and a sensor size of $13.2 \text{ mm} \times 8.8 \text{ mm}$. The camera was mounted on a tripod, with its optical axis directed toward the measurement region on the beam side surface. The distance between the camera and the beam was approximately 5 m, and the focal length was set to 11 mm. Each test video lasted approximately 25 s, corresponding to about 750 time samples.

In the spatial dimension, discrete measurement points were not predefined. Instead, displacement responses were extracted from continuous valid edge-pixel columns within

the beam ROI. After pixel-to-physical scale conversion, spatially continuous full-field displacement time histories along the beam measurement line were obtained and used to construct the full-field spatiotemporal response matrix for RPCA analysis. The primary analysis used the complete full-field spatial response data. The subsequent spatial sampling density analysis was conducted by uniformly downsampling the complete full-field data to evaluate changes in damage localization performance under progressive sparsification of spatial information.

The raw video sequences were preprocessed using piecewise denoising and continuous edge-feature extraction. Through ROI extraction, illumination-field distribution analysis, local adaptive denoising, and structural edge tracking, this preprocessing method reduces the effects of non-uniform illumination, shadows, and image noise on edge-displacement estimation while preserving the continuity of the structural contour. The pixel displacement of the beam edge was then converted into actual displacement time histories at each spatial position through pixel-to-physical scale calibration, and the full-field spatiotemporal response matrices X^h and X^d were constructed for the healthy and damaged states, respectively. The detailed principles and parameter settings of this vision-based preprocessing method are provided in Ref. [48].

To verify the accuracy of the vision-based measurements, five LVDT displacement sensors DH-LVDT20, (Donghua, Taizhou, China) were placed along the beam span at $L/8$, $L/4$, $L/2$, $3L/4$, and $7L/8$ to provide high-precision displacement reference signals at different spatial locations. In addition, accelerometers (2D001V, Donghua, Jiangsu, China) were installed at $L/4$, $L/2$, and $3L/4$ to record structural vibration responses under moving-load excitation. All contact-sensor signals were synchronously acquired using a DH5902N data acquisition system at a sampling frequency of 200 Hz, and the vision-based and contact-based measurement systems were time-aligned via software synchronization. The LVDT measurements were primarily used to validate the accuracy of the vision-based full-field displacement responses, whereas the acceleration responses provided supplementary confirmation of the stability and repeatability of the structural dynamic responses under moving-load excitation.

3.2. Validation of Response Decomposition

To verify the effectiveness of the proposed RPCA-based response decomposition method for structural damage localization, its ability to separate components in full-field response data must be evaluated. For structural dynamic responses, measured signals typically consist of global structural responses and local damage-induced perturbations, which are strongly coupled in both space and time and thus make direct damage feature extraction difficult. Therefore, effective decoupling of global and local responses is a key prerequisite for subsequent high-precision damage localization.

To examine this issue, the RPCA decomposition results are first analyzed from the perspective of the spatial distribution of the full-field response. As shown in Figure 4, the original response matrix X contains continuous variations in the global structural response as well as local anomalies, with different components strongly coupled in both space and time and therefore difficult to distinguish directly. After decomposition, the low-rank component L exhibits a pronounced smooth structure, showing good spatial continuity and a consistent temporal evolution trend, and thus effectively captures the global response behavior of the structure. In contrast, the sparse component S exhibits low overall magnitude, with most regions close to zero and significant enhancement only in localized regions. In particular, near the actual damage region (spatial points 41–43), a clear localized concentration of high responses is observed, indicating that the sparse component effectively highlights damage-induced local anomalies. In terms of

amplitude distribution, the low-rank component remains mainly within a relatively stable fluctuation range, whereas the sparse component shows significant deviations only at localized positions. This “globally smooth–locally abrupt” contrast demonstrates that RPCA can effectively separate global and local information from full-field responses.

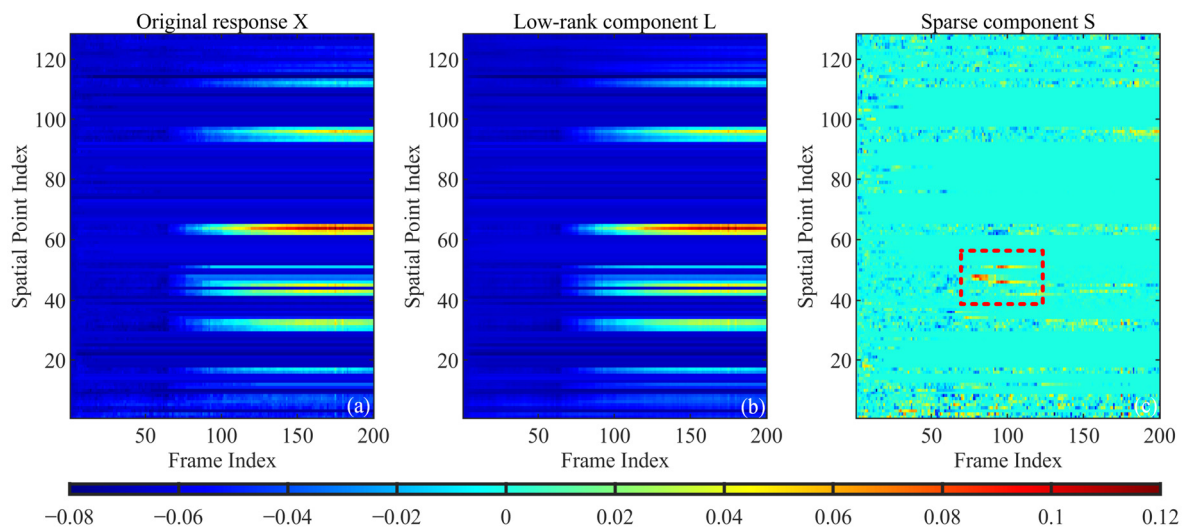


Figure 4. Decomposition results of the full-field response using RPCA: (a) original response matrix X , (b) low-rank component L , and (c) sparse component S highlighting the localized abnormal region. The red dashed box indicates the actual damage region.

Based on this analysis, a representative measurement point (No. 43) is selected to further verify the accuracy of the decomposition, and the original response is compared with its decomposed components, as shown in Figure 5. The low-rank component L closely matches the original signal X in terms of the overall variation trend, accurately capturing the dominant response evolution. In contrast, the sparse component S exhibits a relatively small overall amplitude and fluctuates only at localized time instants, indicating that it primarily captures anomalous disturbances in the original signal.

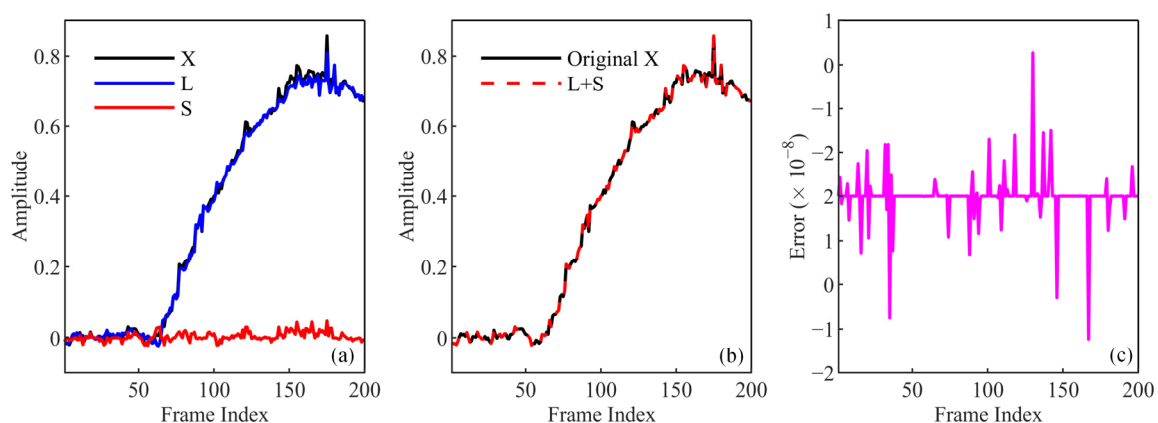


Figure 5. Decomposition validation of the response signal. (a) Signal decomposition at a representative spatial point, showing the separation into low-rank component L and sparse component S . (b) Reconstruction comparison between the original signal X and the reconstructed signal $L + S$. (c) Reconstruction error.

In terms of amplitude, the maximum absolute value of the original signal is approximately 8.56×10^{-1} , whereas that of the sparse component is 4.81×10^{-2} , corresponding to only 5.6% of the original signal maximum. The mean absolute value of the sparse compo-

ment further decreases to the order of 8.60×10^{-3} . These results indicate that the sparse component maintains a low background level over most of the time range and exhibits pronounced anomalous responses only at specific time instants, confirming its effectiveness in capturing local disturbances.

Furthermore, comparison between the original signal X and the reconstructed signal $L + S$ shows that they nearly perfectly overlap over the entire time range. The corresponding reconstruction error, shown in Figure 5c, has extremely small magnitude and fluctuates slightly around zero. Quantitatively, the maximum absolute reconstruction error is approximately 1.63×10^{-8} , and the mean absolute reconstruction error is approximately 9.46×10^{-10} , which is about seven orders of magnitude smaller than the maximum amplitude of the original signal. These results indicate that the RPCA solver achieves good numerical convergence and satisfies the reconstruction constraint $X = L + S$ within numerical precision. It should be noted that the near-zero reconstruction error mainly reflects the extent to which the algorithm satisfies the equality constraint, whereas the physical plausibility of the decomposition should still be assessed based on the spatial distribution characteristics of the low-rank and sparse components.

Overall, the results in Figures 4 and 5 support the validity of the RPCA decomposition from spatial-distribution and time-series perspectives, respectively. The low-rank component preserves the global response evolution, whereas the sparse component mainly captures local anomalous perturbations. Meanwhile, their sum reconstructs the original response within numerical precision. These results indicate that the RPCA method used in this study can preserve the main response information while highlighting local anomaly features, providing a reliable basis for subsequent sparse-component-based damage feature extraction and localization analysis.

3.3. Damage Localization and Index Analysis

After verifying that RPCA decomposition effectively decouples global and local responses, this section constructs damage indices based on the sparse component and evaluates their localization performance. Since the sparse component S primarily captures local anomalies in structural responses, its spatial statistical features can be used to quantify damage sensitivity at different measurement points. Accordingly, the standard deviation of the sparse component at each spatial measurement point is adopted as the basic feature for constructing the damage index, and potential damage regions are identified through comparison between healthy and damaged states.

As shown in Figure 6a, the spatial distribution of the sparse-component standard deviation, $\text{std}(S)$, is presented for the healthy and damaged states. The overall trends under the two conditions are largely consistent, and both exhibit random fluctuations, mainly due to inherent uncertainties in structural responses and environmental disturbances. However, near the actual damage region (spatial points 41–43), the damaged-state curve shows localized increases in amplitude and fluctuation intensity compared with the healthy-state curve. Although these differences are observable in the local region, their magnitudes remain comparable to the overall background fluctuations and therefore do not provide sufficient contrast for reliable damage identification.

To further improve the separability of damage features, a Differential Damage Index (DI) is introduced by computing the difference in feature values between damaged and healthy states, thereby highlighting regions with state changes. Figure 6b shows the spatial distribution of the differential index. Across most spatial locations, the DI values remain close to zero with minor random fluctuations, whereas a pronounced positive peak emerges near the damage region, forming a distinct localized feature.

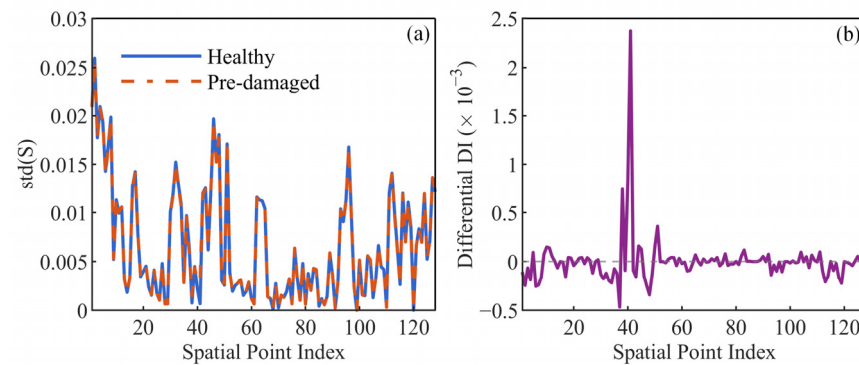


Figure 6. Damage feature extraction and localization using the sparse component S: (a) comparison of std(S) between healthy and damaged states; (b) differential damage index for localization. The dashed line in (b) denotes the zero-reference baseline.

Quantitatively, the peak DI value in the damage region is approximately 2.37×10^{-3} , whereas the average background level in non-damaged regions is only 8.46×10^{-5} , representing a 28-fold difference. This pronounced amplitude contrast demonstrates that the differential operation effectively suppresses global background fluctuations while substantially enhancing damage-induced local anomalous responses, allowing damage features to be clearly separated from complex backgrounds.

In terms of localization, the DI peak occurs at the 41st spatial point, which lies within the actual damage region spanning spatial points 41–43. According to the localization-error definition used in this study, an identified DI peak falling within the true damage region is defined as zero localization error. Thus, the localization error under this condition is 0 spatial points, indicating that the proposed differential damage index can accurately localize the damage region.

It is important to note that the above results do not arise solely from sparse-component amplitude enhancement, but from the joint effect of low-rank–sparse decomposition and the state-difference mechanism. RPCA first separates local anomalies from global responses, reducing the masking effect of dominant structural responses on damage features. Based on this separation, the DI further exploits differences in sparse-component statistical features between healthy and damaged states to suppress sparse background disturbances already present in the healthy state, thereby producing higher spatial contrast in the damaged region relative to non-damaged regions. Therefore, the proposed DI is not an indicator directly based on sparse-component energy, but a differentially enhanced indicator designed to capture damage-induced changes.

Overall, the results in Figure 6 demonstrate that the sparse-component-based damage characterization approach effectively enhances local anomalous features in the damaged region under the current experimental conditions. By introducing the differencing strategy between healthy and damaged states, the spatial contrast of damage features is markedly improved, enabling accurate localization of the actual damage region. These findings provide the basis for subsequent noise robustness analysis, parameter sensitivity analysis, and comparative evaluation.

3.4. Noise Robustness and Comparative Analysis

After demonstrating the localization capability of the proposed differential damage index, this section further evaluates its stability and relative performance in terms of noise robustness and comparison with benchmark methods. The benchmark methods include RMS, kurtosis, curvature index, wavelet energy, PCA residual, RPCA sparse-energy, and the proposed differential damage index. All methods are computed using the same full-field response data, with the same normalization procedure and localization-error definition

adopted to ensure fair comparison. By comparing the damage peak locations, localization errors, and error variation trends under noise-free and noisy conditions, the localization stability of the proposed method under noise disturbance is assessed.

Gaussian white noise corresponding to SNR levels of 40, 30, 20, and 10 dB is first added to the original response data, and 30 independent noise trials are conducted at each noise level. For each trial, the differential damage index, identified DI-peak location, and localization error are recalculated. Localization success is defined as the identified DI peak falling within the actual damage region, namely spatial points 41–43. The representative curve in Figure 7a corresponds to the trial whose relative DI error is closest to the mean value of the 30 trials at each SNR level. Figure 7b,c report the mean localization error, localization success rate, mean relative DI error, and corresponding 95% confidence intervals obtained from the 30 repeated trials.

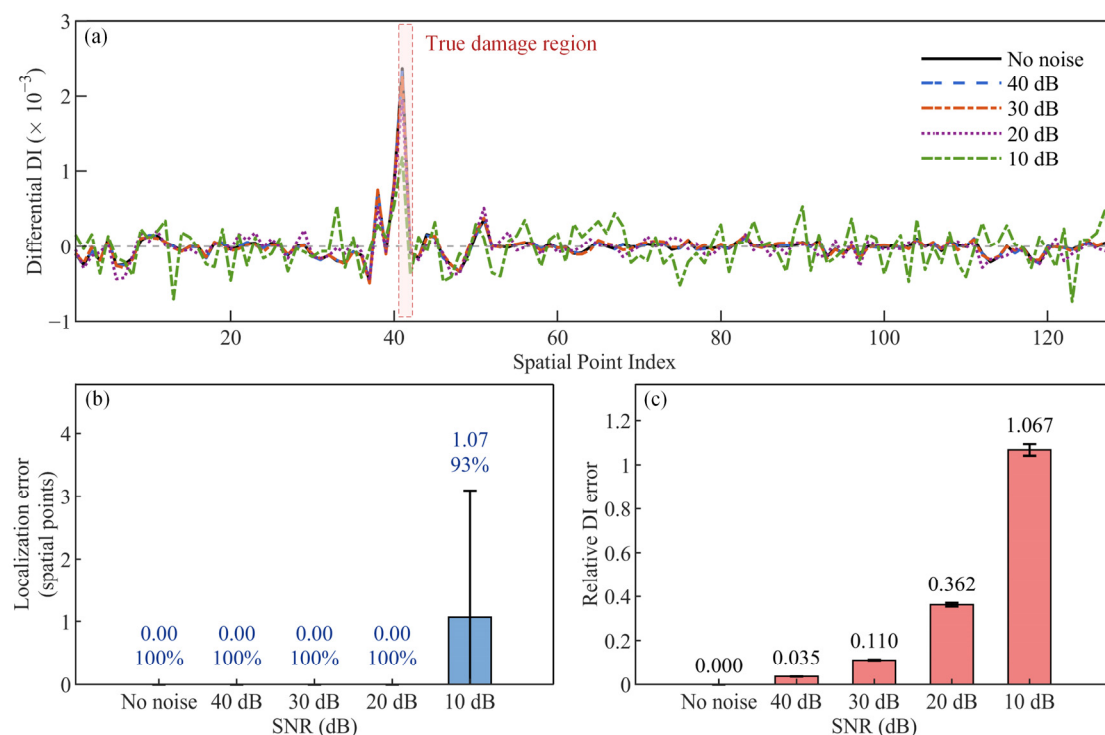


Figure 7. Noise robustness of the proposed differential damage index under repeated noise realizations: (a) representative DI curves under different SNR levels; (b) mean localization error with 95% confidence intervals and localization success rates; and (c) mean relative DI error with 95% confidence intervals.

As shown in Figure 7a, under noise-free, 40 dB, 30 dB, and 20 dB conditions, the differential damage index exhibits a distinct and concentrated positive peak near the actual damage region. As noise intensity increases, fluctuations in the background region gradually become stronger; nevertheless, the dominant peak near the damage region remains clear, and the peak location in the representative curves shows no noticeable shift. When the SNR further decreases to 10 dB, random fluctuations in non-damaged regions increase significantly and some localized spurious peaks become more pronounced. Even so, the dominant peak near the actual damage region remains identifiable. The corresponding statistical results show that, under 40, 30, and 20 dB conditions, the mean localization errors over 30 repeated trials are all zero, with localization success rates of 100%. When the SNR decreases to 10 dB, the mean localization error increases to approximately 1.07 spatial points, while the localization success rate remains 93.33%.

Based on the repeated-trial results, using the noise-free DI curve as the baseline, the mean relative DI errors under 40, 30, 20, and 10 dB noise conditions are 0.0354, 0.1102, 0.3618, and 1.0671, respectively. As the SNR decreases, the mean relative DI error and its 95% confidence interval gradually increase, indicating that noise increases background fluctuations and local deviations in the overall damage-index curve. It should be noted that the relative DI error reflects the variation in the entire spatial DI curve relative to the noise-free baseline, whereas the localization error is determined only by the distance between the identified DI-peak location and the actual damage region. Therefore, even when background fluctuations and curve errors increase with noise, the localization error is defined as zero as long as the identified DI peak remains within spatial points 41–43. This indicates that noise mainly affects the overall shape and background fluctuations of the DI curve, whereas the damage peak location exhibits greater stability.

Subsequently, the proposed method is compared with RMS, kurtosis, curvature index, wavelet energy, PCA residual, and RPCA sparse-energy. To eliminate the effects of differences in scale and amplitude range among indices, the spatial damage index of each method is normalized with respect to its maximum positive peak value. Figure 8a presents the normalized spatial distributions of the seven damage indicators, while Figure 8b reports the localization errors calculated based on the shortest distance between the identified DI-peak location and the actual damage region spanning spatial points 41–43.

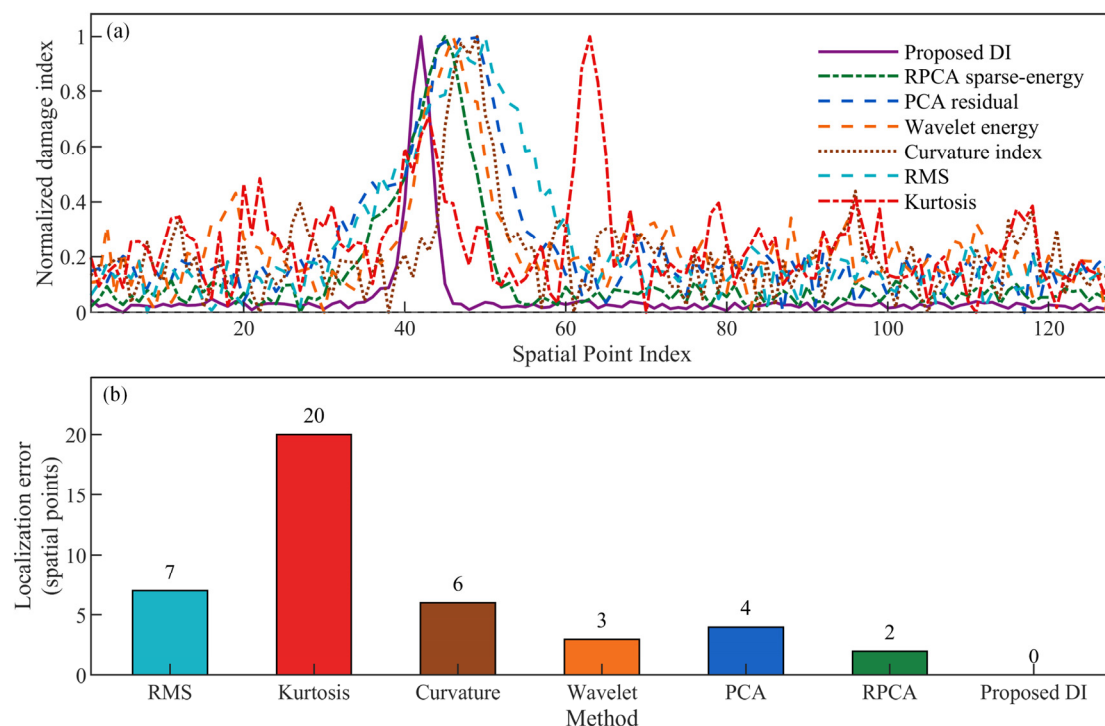


Figure 8. Comparative analysis of different damage localization indicators: (a) normalized spatial distributions of RMS, kurtosis, curvature index, wavelet energy, PCA residual, RPCA sparse-energy, and the proposed differential damage index; (b) localization errors of different methods.

As shown in Figure 8a, RMS and kurtosis exhibit relatively strong background fluctuations and multiple local peaks in non-damaged regions, with the maximum kurtosis peak clearly deviating from the actual damage region. The curvature index, wavelet energy, PCA residual, and RPCA sparse-energy indicators also produce responses near the damage region; however, they exhibit varying degrees of peak broadening, background disturbance, or spatial deviation. In contrast, the proposed differential damage index forms a concentrated dominant peak within the actual damage region while maintaining a relatively low

background level in non-damaged regions, demonstrating stronger spatial contrast and clearer localized characteristics.

Figure 8b further reports the localization errors of different methods. The localization errors of RMS, kurtosis, curvature index, wavelet energy, PCA residual, and RPCA sparse-energy are 7, 20, 6, 3, 4, and 2 spatial points, respectively, whereas the proposed differential damage index achieves a localization error of 0. It is the only method among all compared approaches that achieves zero-error region-level localization. Compared with RPCA sparse-energy, the proposed method further removes the remaining 2-point localization error. This improvement can be attributed to the synergistic effect of piecewise denoising, RPCA low-rank–sparse decomposition, and healthy–damaged state differencing: piecewise denoising reduces random disturbances, RPCA separates global responses from local anomalies, and state differencing further suppresses common background disturbances while highlighting damage-induced changes, thereby enabling accurate localization of the actual damage region.

Overall, Figure 7 demonstrates that the proposed differential damage index maintains good localization stability under repeated noise perturbations, while Figure 8 shows that it achieves lower localization errors than traditional statistical indicators, transform-domain indicators, and matrix-decomposition-based indicators. In the current single-damage experimental scenario, the combination of RPCA decomposition and state differencing effectively suppresses common background fluctuations while enhancing local damage features, providing the basis for subsequent parameter sensitivity analysis.

3.5. Sensitivity to the RPCA Regularization Parameter and Spatial Sampling Density

To investigate the sensitivity of the proposed method to variations in key parameters and spatial measurement resolution, this section analyzes the effects of the RPCA regularization parameter λ and the number of spatial sampling points on localization results. The evaluation metrics include the spatial distribution of the differential damage index, peak location, peak-to-background ratio, mean localization error, and localization success rate.

Based on the baseline regularization parameter λ_0 defined in Equation (6), five parameter settings, $\lambda/\lambda_0 = 0.50, 0.75, 1.00, 1.25$, and 1.50 , are examined while keeping the piecewise denoising, RPCA solution conditions, and DI calculation procedure unchanged. Figure 9a shows the corresponding normalized DI curves, and Figure 9b further compares the peak locations, localization errors, and peak-to-background ratios.

As shown in Figure 9a, varying the regularization parameter leads to certain differences in peak amplitude, peak width, and background fluctuations. Nevertheless, the dominant peaks remain concentrated near the actual damage region. Figure 9b shows that the peak locations under the five parameter settings are $x/L = 0.323, 0.320, 0.323, 0.324$, and 0.324 , respectively, all falling within the actual damage region; accordingly, the localization errors are all zero. These results indicate that damage-region identification remains stable even when λ varies from 0.5 to 1.5 times the baseline value.

Under the five parameter settings, the peak-to-background ratios are 35.8, 38.6, 41.2, 39.4, and 36.7, respectively, attaining the maximum value of 41.2 at $\lambda/\lambda_0 = 1.00$. This indicates that the baseline parameter setting provides a favorable balance between local damage peak enhancement and non-damage background suppression. Notably, even when $\lambda/\lambda_0 = 0.50$ and 1.50 , where the peak-to-background ratios are relatively lower, the values still reach 35.8 and 36.7, respectively, and no localization deviation occurs. Therefore, the regularization parameter mainly affects the prominence of damage features, but does not change the final localization result within the investigated range, indicating that the proposed method is not sensitive to a narrowly tuned parameter range.

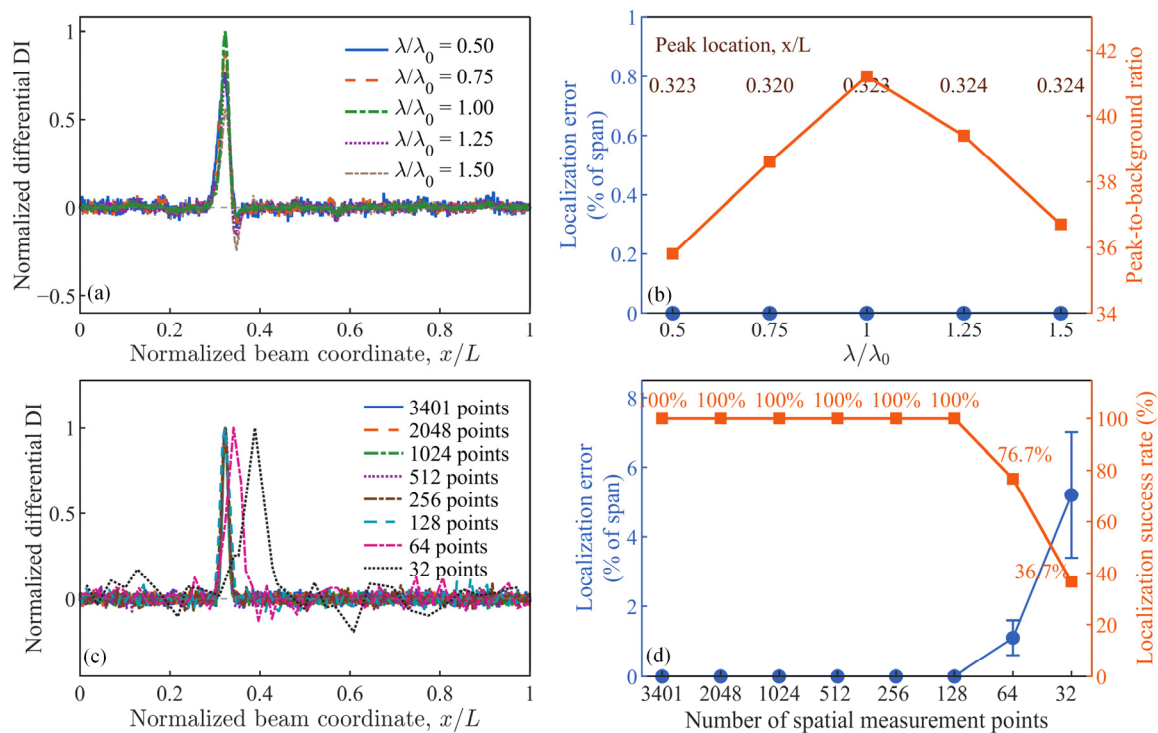


Figure 9. Sensitivity analysis of the proposed differential damage index with respect to the RPCA regularization parameter and spatial sampling density: (a) normalized DI curves under different values of λ/λ_0 ; (b) peak locations, localization errors, and peak-to-background ratios under different values of λ/λ_0 ; (c) normalized DI curves under different spatial sampling densities; and (d) mean localization errors, 95% confidence intervals, and localization success rates under different numbers of spatial measurement points.

The spatial sampling sensitivity analysis uses the full-resolution 3401 spatial points as the baseline and further considers 2048, 1024, 512, 256, 128, 64, and 32 sampling points. Under different sampling densities, the same beam coverage is maintained, and measurement points are selected using a stratified spatial sampling strategy. For each sampling density, 30 repeated trials are conducted. Localization is classified as successful when the identified DI peak falls within the actual damage region corresponding to spatial points 41–43. Figure 9c shows representative DI curves under different sampling densities, while Figure 9d presents the mean localization error, 95% confidence interval, and localization success rate.

As shown in Figure 9c, when the number of spatial points decreases from 3401 to 128, the location and overall shape of the dominant damage peak remain largely stable. Although reducing the number of sampling points slightly increases curve discretization and local background fluctuations, a concentrated and clear dominant peak is still formed near the damage region. In particular, under the 128-point condition, the peak location remains consistent with the full-resolution result, indicating that damage localization does not require all 3401 spatial points.

The statistical results in Figure 9d further confirm this observation. Under the 3401-, 2048-, 1024-, 512-, 256-, and 128-point conditions, the mean localization errors over 30 repeated trials are all zero, with localization success rates of 100%. In other words, compressing the spatial data from 3401 to 128 points causes no observable degradation in localization performance. Although only approximately 1/26 of the spatial data is retained, the damage region can still be reliably identified, demonstrating the tolerance of the proposed method to reduced spatial sampling density in high-density full-field data.

When the number of spatial points is further reduced to 64, the representative DI curve begins to exhibit peak broadening and a slight shift. The mean localization error increases to approximately 1.10% of the span, and the localization success rate decreases to 76.7%, with a corresponding 95% confidence interval of approximately 0.50% of the span. This indicates that 64 spatial points are still sufficient for localization in most trials, but the influence of sampling locations on the results is no longer negligible.

Under the 32-point condition, local peak shifts and background fluctuations become more pronounced. The mean localization error reaches 5.20% of the span, the localization success rate decreases to 36.7%, and the 95% confidence interval expands to 1.80% of the span. Compared with the 64-point condition, the mean localization error increases by 4.10% of the span, and the success rate decreases by 40 percentage points. These results indicate that insufficient spatial resolution degrades both localization accuracy and repeatability. This is mainly because, as the sampling interval increases, the number of effective measurement points available to describe the local peak shape near the actual damage region decreases substantially, making the peak location more susceptible to sampling-point distribution and background fluctuations.

Overall, Figure 9 reveals two types of sensitivity behavior. For the RPCA regularization parameter, all five settings within $\lambda/\lambda_0 = 0.50\text{--}1.50$ achieve zero-error localization, and the peak-to-background ratio remains above 35.8, indicating that the proposed method has a relatively broad robust parameter range. With respect to spatial sampling density, reducing the number of spatial points from 3401 to 128 still maintains a 100% localization success rate and zero mean localization error. However, when the number of points decreases to 64 or fewer, the localization error and variability of the results begin to increase significantly. Therefore, under the current experimental conditions, 128 spatial measurement points distributed along the beam length can be regarded as a reasonable lower bound that balances data compression and stable localization. These results demonstrate the stability of the proposed method with respect to regularization-parameter variation and provide quantitative evidence for spatial data compression and measurement-point layout in full-field measurement.

4. Conclusions

This study addresses the challenge of local damage information being masked by global structural responses under complex background and noise conditions by proposing a structural damage localization method based on vision-based full-field responses, RPCA low-rank-sparse decomposition, and state-wise difference enhancement. The method first extracts stable spatiotemporal response data through piecewise denoising and continuous full-field displacement extraction. RPCA is then employed to separate global structural responses from local anomalies, and a differential damage index is constructed from differences in sparse-component statistical features between healthy and damaged states. Experimental results demonstrate that the proposed method effectively suppresses common background fluctuations, enhances damage-induced local anomalies, and enables reliable damage-region localization. The main conclusions are summarized as follows:

- (1) The proposed full-field response low-rank-sparse decomposition framework effectively separates global structural responses from local anomalies. The low-rank component preserves the overall evolution trend of structural responses, whereas the sparse component shows clear localized enhancement near the actual damage region. At the representative spatial point, the maximum absolute value of the sparse component is approximately 5.6% of that of the original signal. The original response and the reconstructed signal $L + S$ are nearly identical, with a maximum absolute reconstruction error of 1.63×10^{-8} and a mean absolute reconstruction error

- of 9.46×10^{-10} . These results indicate that the RPCA solution has good numerical stability and provides a reliable data basis for subsequent damage feature extraction.
- (2) The differential damage index constructed from sparse-component statistical features significantly improves the spatial contrast and localization accuracy of the damaged region. The peak DI value in the damage region is approximately 2.37×10^{-3} , whereas the average background level in non-damaged regions is 8.46×10^{-5} , representing a 28-fold difference. The peak occurs at the 41st spatial point and falls within the actual damage region spanning spatial points 41–43, corresponding to a localization error of 0. Compared with RMS, kurtosis, curvature index, wavelet energy, PCA residual, and RPCA sparse-energy, the proposed method is the only approach that achieves zero-error region-level localization. This advantage can be attributed to the synergistic effect of piecewise denoising, RPCA-based anomaly separation, and healthy–damaged state-difference enhancement, rather than to any single processing step.
 - (3) Noise robustness tests, parameter sensitivity analysis, and spatial sampling sensitivity tests further verified the stability of the proposed method. Under 40, 30, and 20 dB noise conditions, the mean localization errors over 30 repeated trials were all zero, with localization success rates of 100%. Under the 10 dB condition, the mean localization error was approximately 1.07 spatial points, while the localization success rate remained 93.33%. When λ / λ_0 varied from 0.50 to 1.50, the localization errors under all five parameter settings were zero, and the peak-to-background ratio remained between 35.8 and 41.2, indicating that the localization results are robust to variations in the regularization parameter. Regarding spatial sampling density, reducing the number of measurement points from 3401 to 128 still maintained zero mean localization error and a 100% localization success rate over 30 repeated trials. When the number of points was further reduced to 64 and 32, the mean localization errors increased to 1.10% and 5.20% of the span, respectively, and the localization success rates decreased to 76.7% and 36.7%, respectively. Therefore, under the current experimental conditions, 128 spatial measurement points can be regarded as a reasonable lower bound for balancing data compression and stable localization.

Overall, the proposed method separates global structural behavior from local anomalies in vision-based full-field responses without relying on complex structural models or large labeled datasets, and further enhances damage-induced changes through state-wise differencing. The method demonstrates strong performance in damage-feature contrast, localization accuracy, noise robustness, and parameter adaptability, providing a physically interpretable framework for full-field-measurement-driven structural damage screening and damage-region localization.

It should be noted that the experimental validation in this study is limited to a single localized damage scenario and a laboratory-scale simply supported beam model. The current conclusions are mainly applicable to damage-region identification, and a quantitative relationship has not yet been established between DI features and physical quantities such as crack depth, damage area, or local stiffness degradation. In addition, the proposed DI is constructed from the state-wise difference between healthy and damaged responses, and thus the current formulation requires an available healthy-state baseline; its baseline-free extension remains to be further investigated. RPCA decomposition relies on the assumption that global responses are approximately low-rank and local anomalies are relatively sparse. Its applicability under complex environmental variations, strongly nonlinear responses, multiple-damage scenarios, or spatially distributed damage conditions requires further validation. Future work will involve tests with different damage severities, multiple damage locations, and complex operating conditions, investigate the relationship between DI features and physical damage severity, and further extend the method to damage quantifi-

cation and state assessment of complex engineering structures by incorporating structural prior information, machine learning, and physics-informed approaches.

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