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Robust Damage Detection and Localization Under Complex Environmental Conditions Using Singular Value Decomposition-based Feature Extraction and One-dimensional Convolutional Neural Network

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Abstract

Ultrasonic guided wave is an attractive monitoring technique for large-scale structures but is vulnerable to changes in environmental and operational conditions (EOC), which are inevitable in the normal inspection of civil and mechanical structures. This paper thus presents a robust guided wave-based method for damage detection and localization under complex environmental conditions by singular value decomposition-based feature extraction and one-dimensional convolutional neural network (1D-CNN). After singular value decomposition-based feature extraction processing, a temporal robust damage index (TRDI) is extracted, and the effect of EOCs is well removed. Hence, even for the signals with a very large temperature-varying range and low signal-to-noise ratios (SNRs), the final damage detection and localization accuracy retain perfect 100%. Verifications are conducted on two different experimental datasets. The first dataset consists of guided wave signals collected from a thin aluminum plate with artificial noises, and the second is a publicly available experimental dataset of guided wave signals acquired on a composite plate with a temperature ranging from 20°C to 60°C. It is demonstrated that the proposed method can detect and localize the damage accurately and rapidly, showing great potential for application in complex and unknown EOC.

Keywords Ultrasonic guided waves, Singular value decomposition, Damage detection and localization, Environmental and operational conditions, One-dimensional convolutional neural network

1 Introduction

Guided wave-based monitoring techniques for damage diagnosis in a large-scale plate and pipe structures have attracted much attention in recent years, owing to their large area inspection capability and high sensitivity to small damages. Since propagating guided waves will interact with the abnormalities or inhomogeneity near the wave propagation path, it provides an intuitive way to detect and localize the damages by extracting useful information related to the presence of damages. However, guided waves are characterized by a dispersive and multi-modal nature [1, 2], making it very difficult to interpret the complicated guide wave signal and extract the damage-related information.

Baseline comparison is a widely used damage feature extraction method, which uses a set of baseline records of a healthy structure to distinguish the damage-related information from a new record of the damaged structure.

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The time-of-flight (TOF) of a particular guided wave component scattered from the damage source can be highlighted to serve as the features to detect and localize the damage. In this way, the accuracy of the extracted temporal information plays a key role.

But guided wave signals are vulnerable to changes in environmental and operational conditions (EOC) such as temperature and noise, making the guided wave records deviate greatly from the original waveforms. Moreover, damage-related signal components are usually very weak and easily submerged in the noises, especially for minor damage in large-scale structures. A robust damage detection technique, which retains high accuracy under a complex environment, is thus of great significance.

Temperature is the most important EOC, since it is the most ubiquitous and greatly influences the guided wave waveform. Reliable damage detection must take into account the influence of temperature since the temperature effect would cause stronger signal changes than typical damage. Hence, many temperature compensation techniques have been developed, including the optimal baseline selection methods [3], local peak coherence [4], optimal signal stretch methods [5] and continuously growing baseline temperature compensation methods [6]. But these methods are limited in practical application since they only approximate the effect of temperature and required a lot of baseline records.

On the other hand, registered guided wave signals are always disturbed by various noises in the complex environment. The damage-related signal components are relatively weak and cause little signal waveform changes. For guided wave signals with low signal-to-noise ratios (SNRs), it becomes very difficult to implement damage detection and localization techniques. Recently, singular value decomposition (SVD) has been found very useful to process signals with low SNRs. An SVD-based signal processing approach [7] was proposed to detect the defect of large-scale structures such as long bridges and pipes. SVD is a linear decomposition method that is widely used for dimensionality reduction and it is the core of a well-known signal processing method: principal component analysis (PCA). Besides, SVD can also separate the changes caused by EOCs and typical damage. For example, by applying SVD on ultrasonic records, Liu et al. [2] proposed an SVD-based method to detect the damages of real-world piping systems experiencing significant variations in EOCs. Wang et al. [8] proposed a PCA-based method to eliminate the effects of temperature variation on the icing monitoring of a full-scale wind turbine blade. Sutthaweekul et al. [9] used PCA analysis to reveal flat bottom hole defects in coated glass fiber reinforced plastic pipes and eliminate the pipe curvature influence. Flat bottom holes are evaluated using the principal component feature and synthetic aperture radar tomography including the time-of-flight feature. The results show that the proposed method can clearly reveal the area of flat bottom holes. It has been proved that SVD is very useful for specific information extraction. This paper proposes a novel SVD-based feature extraction method for guided wave-based damage detection and localization under a complex environment. The feature extraction method aims to fully extract the damage-related information contained in signals under the influence of temperature variations and low SNRs. Also, it preserves the temporal information contained in signals to improve damage localization accuracy. So, the extracted damage-related information can be seen as a new damage index namely the temporal robust damage index (TRDI). TRDI removes the effect of EOC, but preserves the temporal damage-related information we need.

However, conventional physics-based imaging algorithms can not work on TRDI. In light of the complexity of TRDI, a one-dimensional convolutional neural network (1D-CNN) is proposed to correlate the TRDI directly with the damage localizations. Due to the sparse connections and equivariance properties of 1D-CNN, it can preserve the temporal information of TRDI, and further extract high-level features from TRDI.

For 1D-CNN, it is a kind of deep learning model, which extracts useful features from data and then uses those features to classify the status of the testing structure. To date, many deep learning techniques have been proposed for structural health and control monitoring based on ultrasonic guided waves [10–16]. But most of them fail the damage detection task in a complex environment. The large temperature variations and the low SNRs prevent the effective feature extraction of these methods. Few deep learning-based methods have considered the influence of external conditions. Recently, a WaveNet-based network [15] has been found to be useful for damage detection in large temperature variations but it is limited in damage localization.

In this paper, based on SVD-based feature extraction and the 1D-CNN model, we show that the proposed method achieves high damage detection and localization accuracy, even for the signals with low signal-to-noise ratios (SNRs) and in a large temperature-varying range. Verifications of the proposed method are conducted on two different experimental datasets. The first dataset consists of guided wave signals collected from a thin aluminum plate with artificial noises. The second is a publicly available experimental dataset of guided wave signals acquired on a composite plate with a temperature ranging from 20°C to 60°C. The results and discussions indicate that our method is very robust and practical for applications in complex and unknown environments.

2 Proposed Methods

The proposed method for damage detection and localization in a complex environment can be seen as a two-stage model, where TRDIs are extracted from original guided wave signals in stage 1, and then TRDIs are input into 1D-CNN to learn the correlation between TRDIs and damage states in stage 2.

2.1 SVD-Based Feature Extraction

For convenience, first, we demonstrate that the transducer configuration pitch–catch is used [17]. Assume that there are overall N guided wave signals collected from the experimental setup. These guided wave signals are arranged together with a fixed sequence, and expressed as

$$\boldsymbol{X}^{N*D} = \left[\boldsymbol{x}_1,\ \boldsymbol{x}_2,\ \ldots,\ \boldsymbol{x}_N\ \right]^{\mathrm{T}}, \tag{1}$$

where $\boldsymbol{X}^{N*D}$ is the total signal matrix, D indicates the signal length, $\boldsymbol{x}$ is the individual signal.

As shown in Figure 1, we first use a rectangular window to separate the total signal matrix into short time segments, and the window width is identical to the excitation signal length. This is due to the origin of the damage-related signal component being the ultrasonic echo from the damage. So, the damage-related signal component is similar to the excitation signal. By sliding the rectangular window along the whole signal, we decompose the guided wave signal into different temporal segments. It can be expressed as

$$\begin{cases} \boldsymbol{X}^{W}{}_{d} = \boldsymbol{X}_d * w(d), \\ d = \frac{\Delta t}{2}, \frac{\Delta t}{2} + 1, \ldots, N - \frac{\Delta t}{2}, \end{cases} \tag{2}$$

where $\boldsymbol{X}^{W}{}_{d}$ is the decomposed signal segment, $w(d)$ is the time window function, Δt is the window width.

Then, for each signal segment, the SVD-based feature extraction is performed:

$$cov\left(\boldsymbol{X}^{W}{}_{d}\right) \overset{\mathrm{SVD}}{\rightarrow} \boldsymbol{U} \sum \boldsymbol{U}^{\mathrm{H}}, \tag{3}$$

where $cov(\cdot)$ indicates the covariance operation, the superscript H indicates the conjugate transpose, $\boldsymbol{U}$ and $\sum$ are the corresponding eigenvector matrix and eigenvalue matrix after SVD, respectively. In other words, $\sum$ indicates the matrix containing singular values at the diagonal. Since these singular values are arranged in decreasing order, the first singular value will correspond to the most vital part.

We have decomposed the signal into various signal segments. Since we set the width of the rectangular window to be identical to the excitation signal length, each segment can contain a large proportion of one wave component, and can only capture the damage-scattered signals from a single damage source once. So, the largest eigenvalue in the matrix $\sum$ means the most correlated signal components, and other eigenvalues mean the independent variations.

Thus, we extract the damage-related features from diagonal terms of the matrix $\sum$ i.e., the singular values:

$$\lambda_d = \lambda_1 - \textstyle\sum_{n=2}^{N} \lambda_n/(N-1), \tag{4}$$

where λ_d is the extracted processed singular value, λ_n means the singular value of corresponding row of matrix $\sum$.

Through such signal processing, each segment of the signals will correspond to a processed singular value, and total processed singular values form a specific temporal sequence related to the damage information, i.e., TRDI.

All these guided wave signals are scattered from the same damage source, making the corresponding damage-related signal components strongly correlated, whereas the changes caused by EOCs such as noises or temperatures are little correlated. Thereby, TRDI can maximally preserve useful damage-related information but remove the effect of EOCs. TRDI also contains the temporal information associated with the damaged spatial location. Temporal damage-related information is highly important to guided wave-based damage localization. TRDI

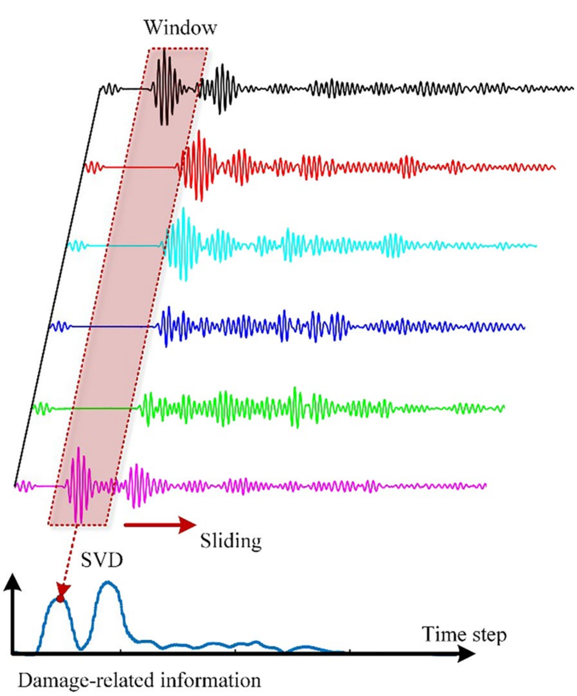

Figure 1 The process of the SVD-based feature extraction

can thus work as an effective feature to perform damage detection and localization in a complex environment.

2.2 Architecture of the 1D-CNN Model

After the SVD-based feature extraction, the obtained TRDI will be normalized and arranged as a feature vector named one sample. The corresponding damage location is then assigned to the sample, constructing a labeled dataset. So, the 1D-CNN model is used here as a complex function approximator to map the sample space (TRDI) to the label space (damage location). This process is commonly termed the training phase, indicating to fit the samples to their labels by updating the trainable parameters in the 1D-CNN model. To achieve the best training accuracy, reasonable model construction is essential.

The model architecture is constructed by a stack of convolution blocks and fully connected layers (FCLs), as shown in Figure 2. Each convolution block is equipped with one convolutional layer and one max-pooling layer.

A convolutional layer performs the convolution of the input with a specific number of filters. Due to the advantages of sparse connections and parameter sharing [14], the convolutional layer can extract high-level feature representation that preserves the time ordering with a few parameters. It can be formulated as [14]

$$x_{i'}^{l} = b_{i'}^{l} + \sum_{i=1}^{N_{l-1}} \mathrm{conv1D}\left(w_{ii'}^{l-1}, s_{i}^{l-1}\right), \tag{5}$$

$$y_{i'}^{l} = f\left(x_{i'}^{l}\right) \; and \; s_{i'}^{l} = y_{i'}^{l} \downarrow ss, \tag{6}$$

where $x_{i'}^{l}$ is the input, $y_{i'}^{l}$ is the intermediate output, $b_{i'}^{l}$ is the bias of the i' th neuron at layer l, s_{i}^{l-1} is the output of the i^{th} neuron at layer $l-1$, $w_{ii'}^{l-1}$ is the kernel weight connection between i^{th} neuron at layer $l-1$ to i' th neuron at layer l, $s_{i'}^{l}$ is the output of the neuron, $\downarrow ss$ represents the downsampling operation with the factor ss, and $f(\cdot)$ denotes the activation function i.e., leaky rectified linear unit (LReLU), here.

We select three types of convolution kernels for each convolution block with sizes 3, 5, and 7. Such multi-scale sets also enhance the robustness of the network to environmental noises. And, the number of filters of each CNN block is set as 16, 32, and 64.

Meanwhile, the max-pooling layer takes the maximum value of every two features from the prior layer [10], and improves the computational efficiency by downsampling the temporal information.

1D-CNN thus also preserves the temporal information represented by TRDI, where the high-level features of TRDI are further extracted with a few parameters.

Then, after flattening the features extracted by 1D-CNN, FCLs are utilized to approximate the relationship between the extracted features and the label set, i.e., damage locations. It should be noted that classification and regression are two options to predict the damage location. Classification is applicable for the case where the available damaged conditions are relatively few, while regression is applicable for the case with sufficient damaged conditions. In this work, classification is adopted considering the used experimental dataset and the *Softmax* function is employed. So, the first FCL has 64 filters, followed by the nonlinear

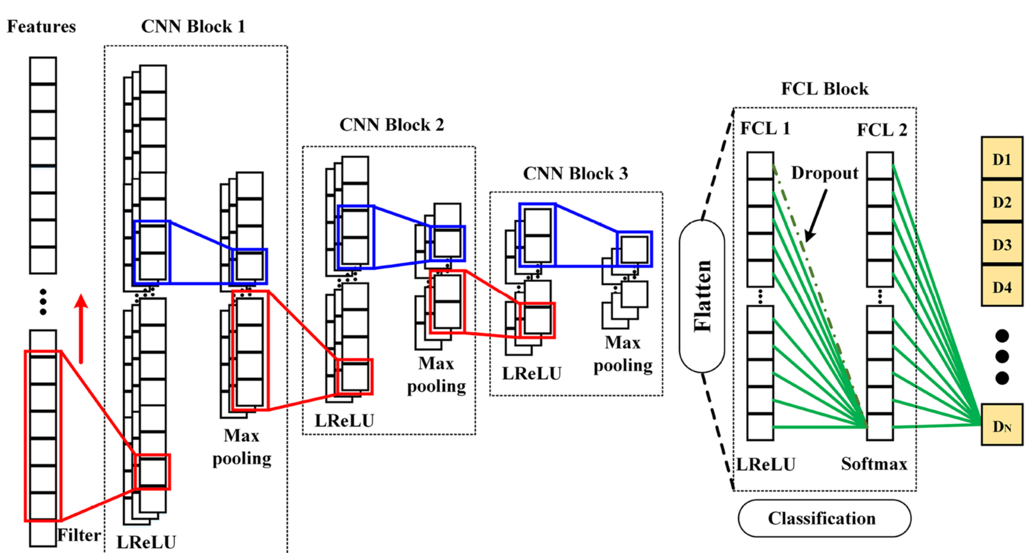

Figure 2 The architecture of the 1D-CNN model

activation LReLU and Dropout regularization [18]. The predictions of damage locations are output using the second FCL with the *Softmax* function.

For the loss function, which works as an objective function to minimize the discrepancy between the network output and label set, the cross-entropy (CE) loss is used for classification. Then, Adam [19] with adaptive learning rates for optimization is used, which is an algorithm for first-order gradient-based optimization of mini-batch stochastic gradient descent. Adam updates the trainable parameters of the whole network to obtain the optimal parameter set, which satisfies the minimum loss function value. The hyperparameters of Adam are set as: $\alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999$.

As a result, the constructed 1D-CNN model is trained for epochs until convergence. Then, the well-trained 1D-CNN model can be used to predict the damage locations with the testing data. In this way, the performance of our method can be evaluated through testing data.

3 Verifications and Discussions

3.1 Experimental Dataset for Aluminum Plate

Experimental investigations are first carried out on a thin aluminum plate with dimensions of 500 mm×500 mm×4 mm.

Guided wave signals are often generated and sensed using piezoelectric transducers (PZT). Here, we only use four PZTs for guided wave data collection to form 12 actuator-sensor pairs. The experiment setup is shown in Figure 3.

A waveform generator generates the excitation signal, and the sensed Lamb wave was recorded with an oscilloscope. Due to the limited resource, a mass with a diameter of 25 mm and a weight of 0.3 kg is utilized to simulate the damaging effect. A 5-cycle Hanning-windowed sinusoidal tone burst with a central frequency of 200 kHz is selected as an excitation signal. So, the exciting frequency is lower than the cut-off frequency of higher-order modes, and only fundamental modes (the first symmetric (S0) and the first anti-symmetric (A0) modes) generate.

Subsequently, the plate is divided into 25 uniform regions for damage classification, where four regions are selected for placing PZTs and other regions for damage simulations as shown in Figure 4. The mass is glued to the center of the corresponding region of the plate. So, we collect 12 signals from the 12 actuator-sensor pairs for each damage case. It should be noted that these signals have to be arranged together with a fixed sequence to form a sample processed by SVD-based feature extraction. Considering the operation error and noises, we repeat the data collection operation twenty times. In addition, twenty samples for the undamaged case are also collected. Hence, a total of 440 samples are obtained.

To verify the robustness of our model, different levels of additional Gaussian white noise are added to these samples. As shown in Figure 5, one selected sample with five different level of noise are displayed for illustration. To reduce the randomness, for each SNR, the results are averaged from 10 cases. It can be observed that with low SNR, the guided wave signal is totally hidden by the noises. Most existing methods for ultrasonic damage diagnosis fail this situation, whereas it is usually encountered in large-scale structures.

Then, we use 60% of the dataset for training, 20% for validation, and 20% for testing. So, there are relatively few samples for training (264 samples). Our validations

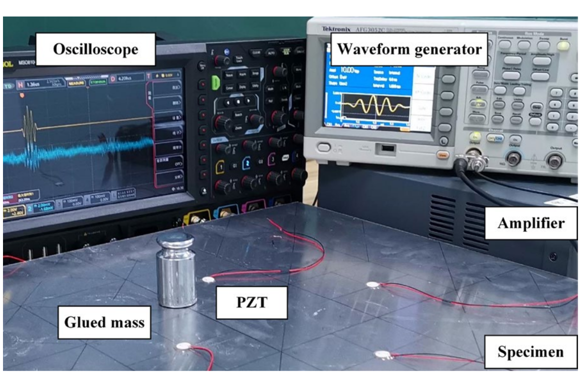

Figure 3 The experimental setup

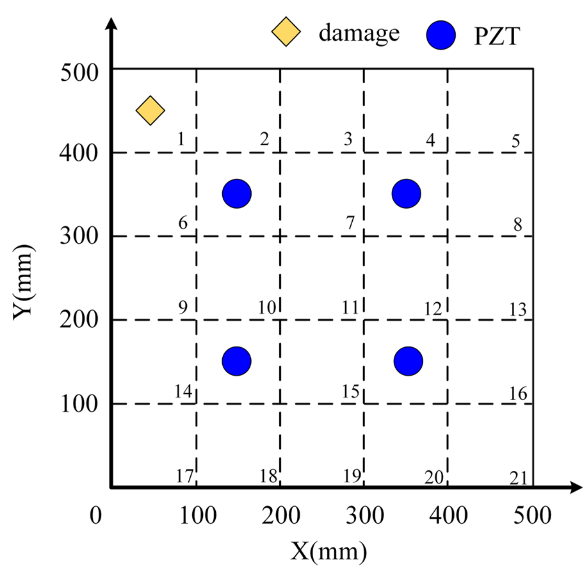

Figure 4 Regions for damage simulations and PZT

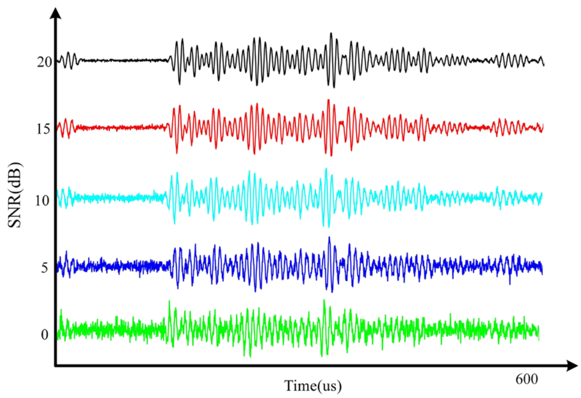

Figure 5 Comparisons of guided wave signals with different levels of SNRs

Table 1 The results of damage localization with different SNRs

SNRs (dB)	Accuracy (%)			Time (s)	Epoch
	Training	Validation	Testing		
20	100	100	100	5.40	12
15	100	100	100	3.78	10
10	100	100	100	5.92	17
5	100	100	100	3.99	11
0	100	100	100	4.24	11

are carried out with the Windows 10 operating system and hardware with Intel i5-7300HQ CPU and a GTX1060Ti GPU.

After SVD-based feature extraction, the damage-related time series corresponding to different damaged conditions, i.e., TRDIs are ready. TRDIs can share the same damage-related information, but a few differences can be observed due to the experimental and operational variations, making TRDIs more complicated. The constructed 1D-CNN model could be advantageous in handling this kind of damage-related time series.

A learning rate of 1×10^{-3} and a batch size of 4 is used for final damage localization model training. The model is trained until convergence, and the accuracy and training time are exhibited in Table 1.

The histories of accuracy and loss on the training and validation sets for the case 0 dB are given in Figure 6 for illustration. Then, the well-trained model is tested on the testing set and achieves 100% perfect accuracy. The test results are shown in Table 2.

It is clear that our model is rapid and robust to guided waves with different levels of noise. With the help of SVD-based feature extraction, our model achieves the best 100% accuracy.

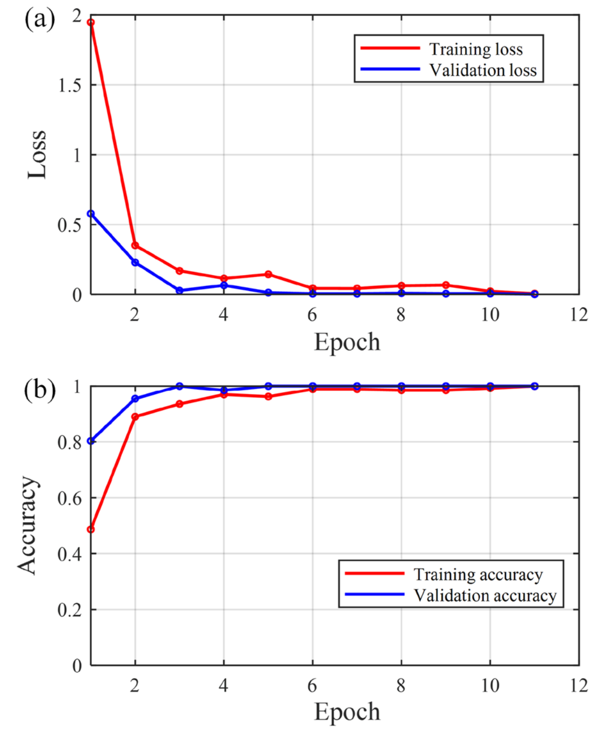

Figure 6 Accuracy and loss for training and validation

Table 2 Accuracy and loss for training and validation

Epoch	Loss		Accuracy	
	Training	Validation	Training	Validation
1	1.95	0.56	0.50	0.80
2	0.33	0.24	0.88	0.96
3	0.23	0.05	0.92	1.00
4	0.12	0.09	0.96	0.98
5	0.20	0.00	0.94	1.00
6	0.06	0.00	0.99	1.00
7	0.07	0.00	0.99	1.00
8	0.08	0.00	0.98	1.00
9	0.09	0.00	0.98	1.00
10	0.01	0.01	0.99	1.00
11	0.00	0.00	1.00	1.00

3.2 Experimental Dataset for Composite Plate

Our method is also verified on an open guided wave dataset [20, 21] conducted on a 500 mm×500 mm×2 mm composite laminate. The specimen comprises material Hexply®M21/34%/UD134/T700/300 and has a quasi-isotropic layup with a stacking sequence of [45/0/−45/90/−45/0/45/90] s.

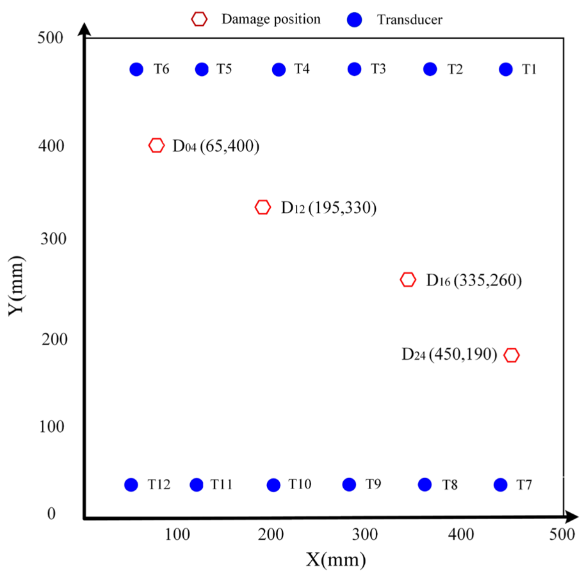

Figure 7 Schematic of the composite plate, the positions of the transducers and simulated damages

A total of 12 transducers were arranged in a pitch-catch configuration for data acquisition and the excitation signal was a 5-cycle, Hanning windowed tone burst at 200 kHz. Figure 7 shows the positions where the transducers were attached to the top surface of the plate for activating and receiving guided wave signals.

The reversible damage is an aluminum disk with a diameter of 10 mm and a height of 2.35 mm. The little disk mimics a damage to produce the wave scattering and mode conversions.

As one can see from Figure 7, four damaged conditions are provided and denoted as D04, D12, D16, and D24, respectively. Additionally, an undamaged plate provides an undamaged condition.

To verify our model, firstly, at each temperature level and each damaged condition, we picked out six signals in pitch-catch configuration with the actuator-sensor pair T1-T7, T2-T8, T3-T9, T4-T10, T5-T11, and T6-T12. So, there are overall 956×6 signals, where 159×6×4 signals for four damaged conditions and 320×6 signals for the undamaged condition are prepared for verification. The training dataset is collected under temperature variations ranging from 20 °C to 60 °C. We show that the temperature variations significantly affect the guided wave waveforms, and damage-related information is easy to be covered.

As shown in Figure 8(a), we compare the two signals acquired at 20 °C in the undamaged and D_{12}-damaged conditions. Figure 8(b) shows corresponding signals acquired at 20 °C and 40 °C in the D_{12}-damaged condition. Then, Figure 8(c) shows the corresponding wave differences between D_{12}-damaged signals and undamaged signals acquired at 40 °C and 20 °C, respectively. It is obvious that temperature has a stronger effect on the waveforms than the changes caused by damage, indicating that considering the effect of temperature variations is important for the ultrasonic damage diagnosis method.

After SVD-based feature extraction, the damage-related time series TRDIs corresponding to the same D_{04}-damaged condition are selected and plotted in Figure 9. Those TRDIs corresponding to the same damaged condition but different temperature levels are plotted in the same figure. So, these TRDIs share the same damage information, but small differences among these TRDIs can still be observed. This is due to the uncertainty in the process such as the inaccurate PZT configuration and imperfect plate geometry. In light of the uncertainty, the 1D-CNN model could be advantageous in handling this kind of damage-related time series.

Then, we also use 60% of the dataset for training, 20% for validation, and 20% for testing. A learning rate of 1×10^{-3} and a batch size of 4 is also used for damage localization. The overall training results are displayed in Table 3, and the histories of accuracy and loss on the training and validation sets are given in Figure 10. The test results are shown in Table 4. Then, the well-trained model is tested on the testing set and achieves 100% perfect accuracy.

It is clear that with limited training data, our model succeeds to detect and localize the small damages, even with low SNR and large temperature variations. The success of our model depends on the effective SVD-based feature extraction and 1D-CNN deep learning model. TRDI can effectively remove the effect of EOCs and retain important temporal damage-related information. Then, the 1D-CNN model can further extract the high-level features from TRDIs, and preserve the temporal damage-related information to perform damage detection and localization.

Additionally, to show the ability of SVD-based feature extraction, we perform the damage localization without the help of TRDIs. The results are displayed in Table 5.

It can be observed that the localization accuracy becomes much worse, and the validation and testing accuracy indicates that the pure 1D-CNN model fails the damage localization task.

4 Conclusions

(1) According to the extraction of effective guided wave signal in a complex environment, the robust guided wave-based method for damage detection and localization under complex environmental conditions using singular value decomposition-

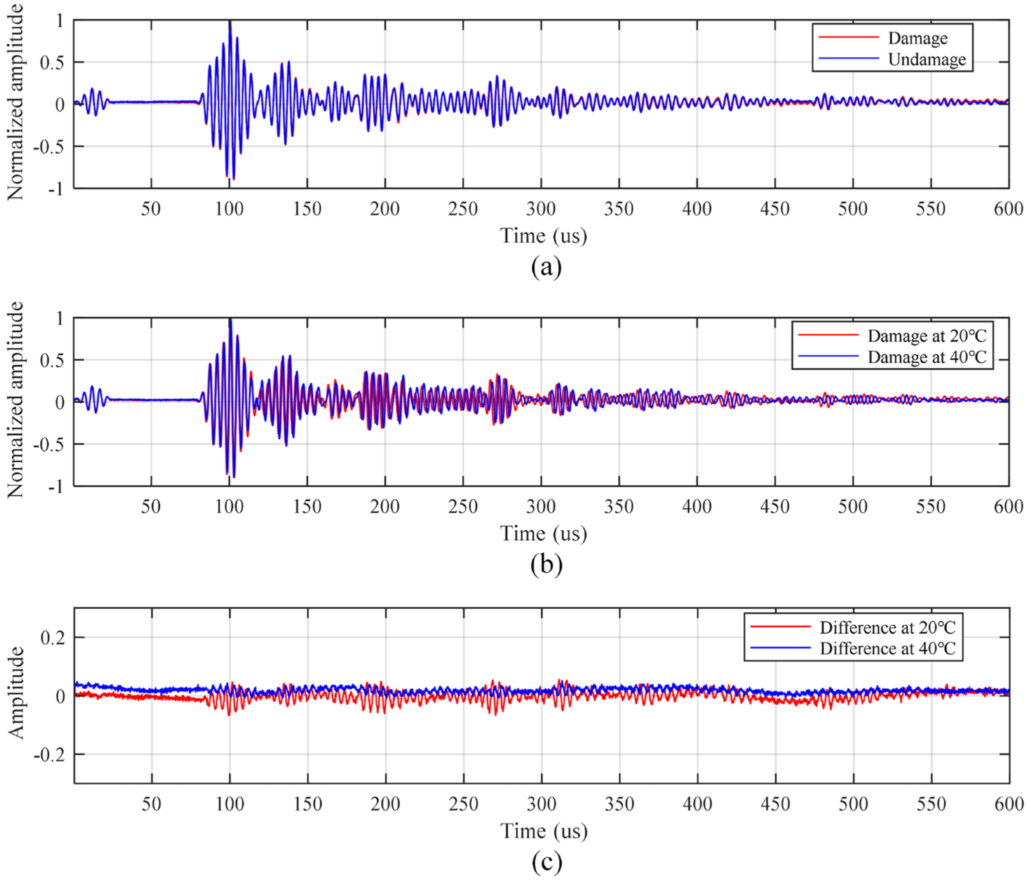

Figure 8 **a** Signals recorded at 20 °C in the undamaged condition and in the D_{12}-damaged condition, **b** Signals recorded at 20 °C and 40 °C in the D_{12}-damaged condition, **c** Signal differences between undamaged condition and D_{12}-damaged condition at 20 °C and 40 °C

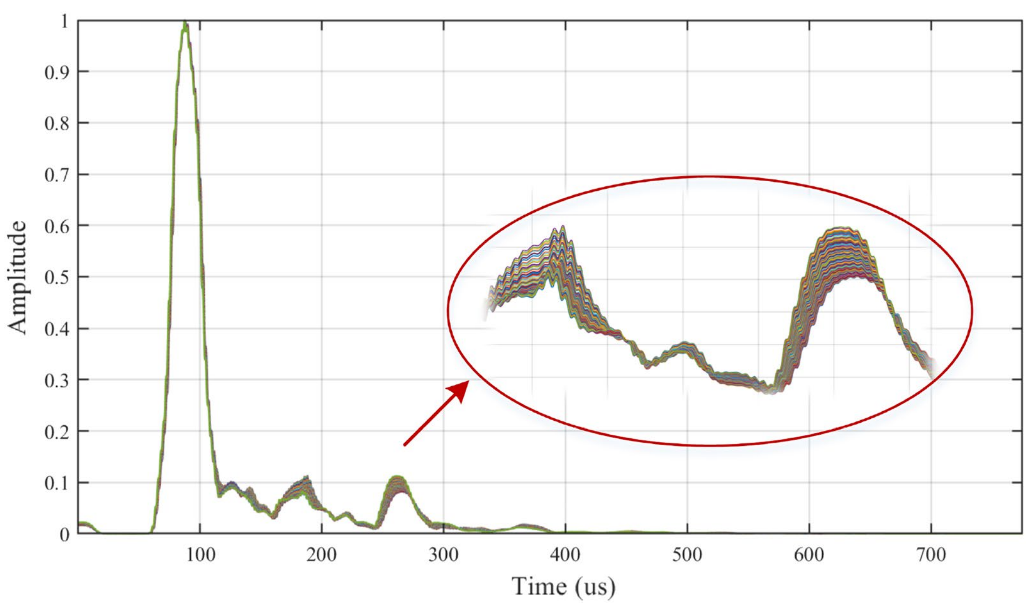

Figure 9 The damage-related time series TRDIs corresponding to the same damaged condition

Table 3 The results of damage localization with different temperatures

Temperature (°C)	Accuracy (%)			Time (s)	Epoch
	Training	Validation	Testing		
20–60	100	100	100	61.29	44

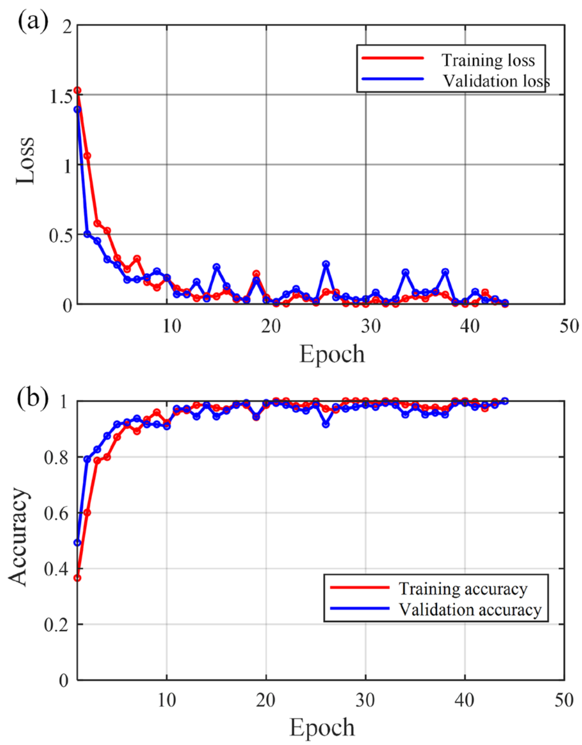

Figure 10 Accuracy and loss for training and validation

Table 4 Accuracy and loss for training and validation

Epoch	Loss		Accuracy	
	Training	Validation	Training	Validation
1	1.51	1.39	0.35	0.50
2	1.08	0.50	0.60	0.80
3	0.58	0.46	0.79	0.84
4	0.52	0.28	0.80	0.89
5	0.30	0.25	0.88	0.93
6	0.24	0.16	0.92	0.94
7	0.29	0.17	0.89	0.95
8	0.14	0.18	0.93	0.93
9	0.11	0.23	0.95	0.93
10	0.15	0.18	0.92	0.92
11	0.11	0.07	0.95	0.97
12	0.09	0.07	0.95	0.97
13	0.02	0.16	0.99	0.88
14	0.03	0.02	0.99	0.99
15	0.03	0.27	0.98	0.88
16	0.10	0.15	0.97	0.97
17	0.01	0.02	0.99	0.99
18	0.01	0.01	1.00	1.00
19	0.22	0.16	0.98	0.88
20	0.01	0.01	1.00	1.00

Table 5 The Results of Damage Localization without TRDIs

Temperature	Accuracy (%)			Time (s)	Epoch
	Training	Validation	Testing		
20–60°C	100	34.72	30.54	391.38	50

based feature extraction and the 1D-CNN model is presented. We remove the effect of complex environmental conditions through an SVD-based feature extraction method and correlate the extracted TRDIs directly with the presence of damages, thus realizing damage detection using guided waves in complex environments.

(2) In order to eliminate the need for signal interpretation and baseline records, and solve the shortcomings of traditional temperature compensation technology. A rectangular window function is used to slide the guided wave signals into short-time domain segments. Each short-time domain segment will correspond to an output value, which forms a specific time series TRDI related to damage information. TRDI will retain useful time-domain damage-related information while eliminating the adverse effects of EOCs.

(3) The 1D-CNN model is employed for the optimal design. Using the feature extraction ability of the 1D-CNN model, the nonlinear function mapping relationship between TRDI and defect location is established. As a result, a higher speed of damage detection in a complex environment is obtained. Once the model is constructed, damage diagnosis can be performed within a few milliseconds.

(4) The experiment is conducted in a noisy environment with different SNRs and a temperature difference between 20 °C and 60 °C. Through two experimental datasets, we have shown that our method is very robust to the influence of temperature and noises, and final damage localization accuracy retains perfect 100%.

(5) The proposed method should be tested on actual engineering structures or other real damaged conditions. Further studies on complex structures influenced by more environmental conditions are

ongoing. The paper still needs further research on improving the authenticity of guided wave signal waveform recovery. In future research, we will continue to consider the principle of multiple effects of EOC on guided wave signal waveform, and further improve the authenticity of guided wave signal waveform recovery based on efficient detection.

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Author Contributions
SZ, SW and HZ were in charge of the whole research designs; SW, SZ, HZ and ZL wrote the manuscript; XW and ZN assisted with sampling and data analyses. All authors read and approved the final manuscript.

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Declarations

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