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Improving autoencoder-based unsupervised damage detection in uncontrolled structural health monitoring under noisy conditions

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Abstract: Structural health monitoring is widely utilized in outdoor environments, especially under harsh conditions, which can introduce noise into the monitoring system. Therefore, designing an effective denoising strategy to enhance the performance of guided wave damage detection in noisy environments is crucial. This paper introduces a local temporal principal component analysis (PCA) reconstruction approach for denoising guided waves prior to implementing unsupervised damage detection, achieved through novel autoencoder-based reconstruction. Experimental results demonstrate that the proposed denoising method significantly enhances damage detection performance when guided waves are contaminated by noise, with SNR values ranging from 10 to −5 dB. Following the implementation of the proposed denoising approach, the AUC score can elevate from 0. 65 to 0. 96 when dealing with guided waves corrputed by noise at a level of −5 dB. Additionally, the paper provides guidance on selecting the appropriate number of components used in the denoising PCA reconstruction, aiding in the optimization of the damage detection in noisy conditions.

Keywords: structural health monitoring; guided waves; principal component analysis; deep learning; denoising; dynamic environmental condition

基于自编码器模型在复杂噪声环境中无监督式结构损伤检测算法的改进*

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摘　要:结构健康监测广泛应用于户外环境中,尤其是恶劣条件中的结构监测。这些恶劣的运行环境会使监测系统受到噪声的干扰。因此,设计有效的降噪策略以增强在噪声环境中利用导波进行损伤结构检测的性能至关重要。介绍了一种基于时序主成分分析(PCA)重构信号的方法用于降低波导的噪声,并将降噪后的信号与基于改进后的自编码器重建的模型来实现无监督损伤检测。对该降噪算法以及基于自编码器的无监督损伤检测模型的有效性在信噪比 10 dB 降到-5 dB 的环境中进行了测试。实验结果表明,所提出的降噪方法能够显著提高噪声环境中损伤检测性能,在信噪比为-5 dB 的噪声环境中实现 AUC score 从 0. 65 提升到 0. 96。与此同时,还提供了用于降噪的 PCA 重构信号中的主成分选择的策略,用于实现优化降噪以及无监督的损伤检测。

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关键词：结构健康监测；导波；主成分分析；深度学习；降噪；动态环境

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0 Introduction

A large scale of civil infrastructure and mechanical structures, face various external forces over their service life. Given these risks and fueled by the progress in sensing technology, there's a growing focus on utilizing structural health monitoring (SHM) technique for proactively detect damage and avert disasters in large-scale infrastructures[1]. Within the realm of SHM approaches, ultrasonic guided waves have been extensively utilized due to a series of advantages, including travel long distances without significant loss of energy enabling the assessment of large structures through a single point of access, and the exceptional sensitivity of guided waves to irregularities like cracks[2], and delamination[3] allowing for the prompt identification of potential defects, preventing them from escalating into more critical problems[4].

However, an inherent challenge in utilizing guided waves for structural health monitoring is the intricate nature of the collected signal[5]. Typically, these guided waves are dispersive, meaning their waveform evolves as they travel[2], and encompass multiple modes and reflections, complicating the task of discerning minor reflections triggered by variations, such as defects, in the complex guided wave signals[6]. In addition, ultrasonic guided waves are also easily distorted by environmental and operational condition (EOC) variations[6]. Such variations can modify the travel of guided waves, possibly obscuring actual damage or resulting in erroneous indications of damage[7].

To adapt guided wave-based damage detection to complex variations in environmental and operating conditions, researchers have explored unsupervised techniques for damage detection that do not rely on prior measurements from damaged structures. Motivated by the impressive advancements in deep learning, a novel strategy that leverages an autoencoder-based reconstruction method for detecting damage is proposed. Traditionally, anomaly detection methods based autoencoders involve training the network to learn normal behavior, such as the patterns of guided waves under intact conditions. Subsequently, anomaly detection is executed by assessing whether the test data can be accurately reconstructed by the trained model or not[8-9]. Consequently, guided waves that cannot be effectively reconstructed by the trained autoencoder model are identified as anomaly data, indicating potential damage or irregular environmental variations. In guided wave-based monitoring, Abbassi et al.[10] employed guided waves from a pristine structure under controlled temperature variations to train the autoencoder. They subsequently evaluated its performance using test data containing guided waves from both healthy and damaged structures. Similarly, Lee et al.[9] trained a deep autoencoder using guided waves from an intact composite plate and achieved fatigue damage detection by analyzing the reconstruction error statistics under a laboratory-controlled temperature. Despite the effectiveness of these autoencoder-based damage detection methods in experimental settings, their performance in detecting stable long-term damage under uncontrolled environments with irregular variations remains untested[9-11]. Additionally, the autoencoder reconstruction-based model mentioned above necessitates a comprehensive collection of historical guided waves as training data. The measurement conditions of this training data need to encompass those of the evaluation data to minimize false alarms[8-9]. However, gathering such data poses challenges as it requires long-term monitoring to cover various environmental conditions, rendering these methods less practical in real-world scenarios[11].

In response to this challenge, our previous research[12] devised a novel approach to train autoencoders without the need for collecting historical guided waves as training data. Instead, the model is directly trained using evaluation data. This method capitalizes on the bias learning property inherent in neural networks, wherein they tend to prioritize learning from large classes while overlooking smaller ones[13]. Consequently, the autoencoder model is inclined to better learn guided waves from regular environmental conditions compared to those from irregular environmental, such as rain and snow, and damage conditions, as guided waves from irregular environments and damage conditions typically exhibit anomalous signals that are underrepresented in the evaluation data. Additionally, this method leverages a local principal component analysis (PCA) reconstruction technique to aid in distinguishing guided waves from irregular environmental conditions and damage conditions[12]. Consequently, the proposed method achieves unsupervised damage detection solely using evaluation data, autonomously distinguishing guided waves in the evaluation data originating from regular environments, irregular environments, and damage variations.

However, guided wave structural health monitoring systems are often implemented in extremely harsh environments[14]. In such conditions, the guided wave measurement system may encounter noise that distorts the measurements over time, adversely affecting damage detection techniques, as discussed in various studies[15]. Consequently, the presence of noise might hinder the novel autoencoder's ability to accurately reconstruct guided waves. This issue could lead to inaccuracies in the reconstruction coefficients, rendering them ineffective for damage detection.

In practical considerations, it is essential to improve methods for accurately detecting damage within complex and noisy environments. A straightforward approach to accomplish this is to denoise the guided waves before implementing the damage detection process. Regarding denoising signals, it is common to reconstruct signals using sparse, such as wavelets[16] or low-rank representations, such as variational mode decomposition[16] and compressed sensing[17]. This is because noise typically does not align well with these sparse or low-rank structures, leading to its exclusion from the reconstructed signals when employing such representations[18]. Although sparsity and low-rank based methods are widely recognized for their denoising capabilities on structural health monitoring, they often do not constitute the primary focus of research and are seldom thoroughly investigated. Our previous study[19] first explores utilizing temporal correlations of guided waves for denoising through the temporal PCA reconstruction method. This research demonstrated the superior denoising capability of techniques such as the two-dimensional Fourier transform, random projection, and PCA, which exploit temporal correlations among guided waves, over the one-dimensional Fourier transform, which does not utilize these correlations. Among the methods evaluated, PCA-based reconstruction was found to offer the best denoising performance due to its effective leverage of temporal correlations within the guided waves.

1　Methodology

As depicted in Fig. 1, the proposed damage detection framework comprises three modules: denoising module, short-term PCA, and autoencoder reconstruction modules. The denoising module serves to clean guided waves by reconstructing them with local temporal PCA. Short-term PCA reconstruction, also accomplished through local temporal PCA, is utilized to identify irregular environmental variations. In contrast, autoencoder-based reconstruction is employed to detect damage variations, complemented by short-term PCA reconstruction.

1.1　Local (Temporal) PCA reconstruction

Both the denoising PCA reconstruction and short-term PCA reconstruction employ local (temporal) PCA reconstruction. This technique entails partitioning the evaluation data X with dimensions $N \times M$ (comprising N guided waves) into several non-overlapping local batches or time windows. Let X_t denote the t-th batch of guided waves, represented by a matrix with dimensions$L \times M$ (containing L days of guided waves with M samples each) In this study, each evaluation dataset spans 80 days of guided waves. Both the denoising PCA reconstruction and short-term PCA reconstruction are implemented with a 1- day time window size (batch). In other words, they partition each evaluation dataset into 80 non-overlapping batches, each (X_t) containing 1 000 guided waves in this paper. Local PCA reconstruction is accomplished using the transformation matrix V_t with a dimension of $P \times M$ and consists of P eigenvectors (principal components) that correspond to the P largest eigenvalues for the covariance matrix $\hat{\boldsymbol{X}}_t^{\mathrm{T}}\hat{\boldsymbol{X}}_t$for X_t where $\hat{\boldsymbol{X}}_t$ is obtained by subtracting the mean of each column from X_t[12]. The transformed representation is then computed as:

$$\boldsymbol{Y}_t' = \hat{\boldsymbol{X}}_t \boldsymbol{V}_t^{\mathrm{T}} \tag{1}$$

Table 1　Parameters for training autoencoder network
(自编码神经网络训练参数)

Parameters	Values in each layer
Neurons Number of Layers in Encoder Network	2,000 512 128 32
Neurons Number of Layers in Encoder Network	32 128 512 2,000
Learning Rate	0.000 5
Batch Size	256

The representation $\boldsymbol{Y}_t'$ with $L \times P$ dimension contains compressed information (when P is smaller than M). Guided waves are reconstructed according to the following equation:

$$\hat{\boldsymbol{X}}_t' = \boldsymbol{Y}_t' \boldsymbol{V}_t \tag{2}$$

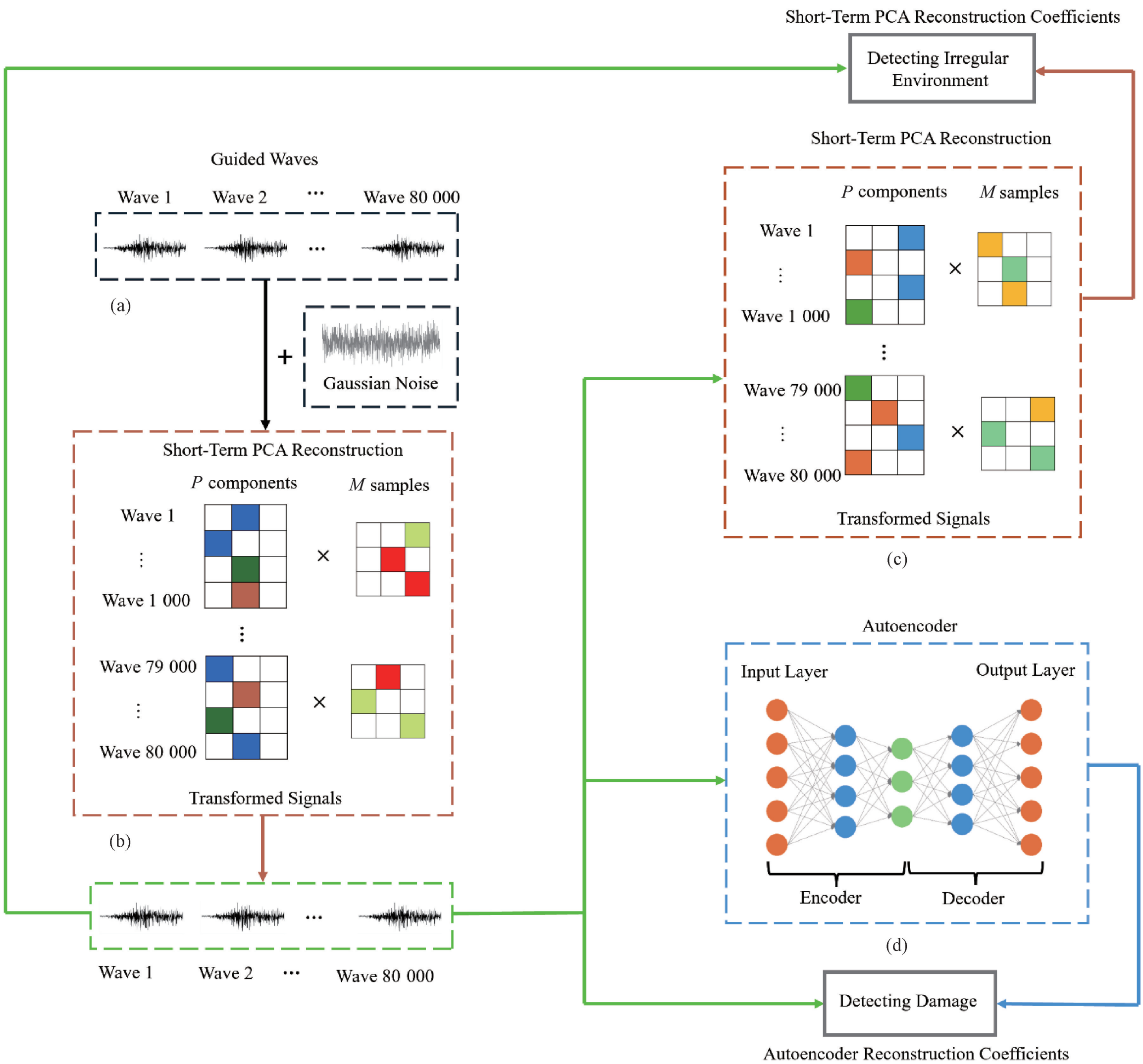

Fig. 1 The damage detection framework incorporating a denoising module is depicted (噪声环境中故障检测算法框架图): (a) Showcases guided waves utilized for assessing structural status, susceptible to corruption by noise stemming from harsh environments; (b) Demonstrates the denoising process for guided waves through denoising PCA reconstruction; (c) and (d) Illustrate short-term and autoencoder-based reconstruction methods, employed to derive short-term PCA and autoencoder-based reconstruction coefficients, facilitating the identification of guided waves amidst regular, irregular environmental variations and damage variations

denoising PCA module is utilized for reconstructing raw guided waves, whereas the short-term PCA reconstruction is employed for processing denoised (reconstructed) guided waves.

1.2 Autoencoder architecture

The autoencoder network architecture consists of both an encoder and a decoder, visualized in Fig. 1(d). It's important to note that the autoencoder module is employed to reconstruct denoised guided waves generated by the denoising PCA, rather than raw guided waves. The mean square error (MSE) is employed as the loss function to train the model. We optimize the autoencoder to minimize the average reconstruction error between the input and output in the network. The parameters employed for training the autoencoder are summarized in Table I. Within the encoder network, the number of neurons ranges from 2 000 in the first layer to 512, 128, and finally 32 in subsequent layers. Conversely, in the decoder network, the number of neurons is inversely proportional. The autoencoder is trained using the "Adam" optimizer with a learning rate of 0.000 5 and a batch size of 256[12].

1.3 Reconstruction coefficient

The reconstruction performance of both the autoencoder and short-term PCA method is assessed through the reconstruction coefficients for the guided waves. These coefficients represent the Pearson correlation coefficient between a (denoised) guided wave and its corresponding reconstructed guided wave, ranging from −1 to 1, which is defined as following equation:

$$r_i = \frac{(\boldsymbol{x}'_i - \bar{x}'_i)^{\mathrm{T}}(\boldsymbol{x}_i - \bar{x}_i)}{\| \boldsymbol{x}'_i - \bar{x}'_i \| \ \| \boldsymbol{x}_i - \bar{x}_i \|} \tag{3}$$

r_i represents our reconstruction coefficient, where $\| \cdot \|$ represents the Euclidean norm. The variable $\bar{x}_i$ and $\bar{x}'_i$ are scalars that represent the mean of the i−th (denoised) guided wave measurement x_{i} and the reconstructed guided wave x'_i[12].

These reconstruction coefficients $\boldsymbol{r} = [r_1 \ r_2 \ r_3 \cdots r_N]^{\mathrm{T}}$ obtained by the autoencoder and short-term PCA for each denoised guided wave will be used to detect damage in noisy conditions.

1.4 Irregular variation detection

Short-term PCA reconstruction coefficients can be used to detect irregular environmental variations, such as rain and snow. Guided waves with short-term PCA reconstruction coefficients below λ are inferred to originate from irregular environmental variations when they meet the condition:

$$r_i^{(\mathrm{S})} \leqslant \lambda \tag{4}$$

Where $r_i^{(\mathrm{S})}$ represents the short-term PCA reconstruction coefficients for the i−th measurement. As previous studies, λ corresponds to the 20−th percentile of all short-term PCA reconstruction coefficients[12].

1.5 Damage detection

Guided waves that cannot be reconstructed by the autoencoder and are not identified as irregular variations (as determined by short-term PCA reconstruction based on Equation (4)) are inferred to be from damage variations. Subsequently, the normalized reconstruction difference is employed to denoise guided waves between short-term PCA and autoencoder, computed using Equation (5). When these reconstruction coefficient differences deviate significantly from 0, the corresponding measurements are classified as damage variations. The damage detection indicator is defined as follows:

$$dr_i = \frac{r^{(S)} - r^{(L)}}{r^{(S)}_{\mathrm{median}} - {}^{(L)}_{\mathrm{median}}} \tag{5}$$

Where $r^{(S)}$ and $r^{(L)}$ represent the short-term PCA and autoencoder reconstruction coefficients, respectively, for the i−th measurement. $r^{(S)}_{\mathrm{median}}$ and $r^{(L)}_{\mathrm{median}}$ denote the medians of all short-term and autoencoder reconstruction coefficients for guided waves in an evaluation data. These two medians are utilized to normalize the reconstruction coefficients, aiming to minimize the reconstruction difference between short-term PCA and autoencoder during regular variations[12]. Therefore, damage is identified as follows:

$$dr_i \geqslant \eta \tag{6}$$

The threshold η is not explicitly predetermined in this paper. Instead, the study employs the receiver operating characteristic (ROC) curve, which involves sweeping across various threshold values η, to assess the performance of the unsupervised damage detection framework. To mitigate false alarms caused by irregular variations, we set dr_i to 0 for guided waves that satisfy Equation (4).

1.6 Damage detection evaluation

In this paper, we utilize the receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC) to evaluate the damage detection performance. This approach, widely employed in structural health monitoring research, calculates the true positive rate (TPR) and false positive rate (FPR) by sweeping across possible thresholds[20]. In this context, true positives (TP) represent the number of measurements accurately identified as damage, while false positives (FP) indicate the number of measurements incorrectly identified as damage.

2 Experimental setup

We employ the same experiment dataset used in study[12] to evaluate the performance of our strategy for selecting optimal components under a range of environmental conditions. The dataset includes ultrasonic guided waves collected from an aluminum plate, dimensions 53 cm×53 cm ×3 mm, located at the University of Utah in Salt Lake City. This plate was subjected to varying outdoor conditions, experiencing weather phenomena such as rain and snow. For the guided wave monitoring, each measurement involved the acquisition of 8 ultrasonic guided waves, together with environmental information like temperature, humidity, air pressure, and light levels. For more detailed information on how the measurements were collected, refer to the studies[21].

2.1 Synthetic damage guided wave generation

The dataset for this experiment encompasses 80 days of guided wave data, with a total of 80 000 measurements taken under diverse environmental and operational circumstances, recording one measurement every 86 seconds. The guided waves within this dataset experienced synthetic damage over 4 days. This synthetic damage was generated following methods previously established in the literature[20]. Such a method conceptualizes a guided wave affected by damage as a combination of a straightforward guided wave emitted directly and another wave that has been altered through its interaction with a simulated damage site[20]. Consequently, the guided waves that mimic damage variations are produced by combing waves from both the shortest and longest paths of transmission, presented in previous study[12].

2.2 Damage detection under noisy conditions

To evaluate the framework's ability to detect damage in the presence of noise, we introduce Gaussian noise $N(0,\sigma^2)$ to the guided waves. The intensity of the noise is regulated by the signal-to-noise ratio (SNR):

$$SNR_{dB} = 10\log\left(\frac{P_{signal}}{P_{noise}}\right) \text{ and } P_{x_i} = \frac{1}{M}\sum_{j=1}^{M} x_{ij}^2 \tag{7}$$

Our experiment assesses the framework's ability to detect damage in noisy conditions by analyzing the variation of AUC scores as the SNR of the guided waves changes from 10 to −5 dB.

3 Results and discussion

Anomaly detection performance is computed for raw and denoised guided waves across various signal-to-noise ratios, ranging from ∞ (Original) to −5 dB. These results illustrate the enhancement in damage detection under noisy conditions facilitated by our proposed denoising strategy.

3.1 Guided wave reconstruction under noisy conditions for PCA and autoencoder

In the first subplot of Fig. 2, reconstruction coefficients for short-term PCA and autoencoder are computed using original guided waves without noise. In Fig. 2, the reconstruction coefficients of guided waves by short-term PCA, denoted as "PCA (1d)," and autoencoder, denoted as "Enc (80d)," are depicted in subplots with varying signal-to-noise ratios (SNR): ∞ (Ori.), 5, 0, and −3 dB, as indicated in each subplot's title. It is important to highlight that in each scenario, the damage persists for 4 days, shaded in a gray region within each subplot. In all instances, short-term PCA utilizes the first 15 components for reconstructing guided waves, while the autoencoder-based reconstruction coefficients are generated through training the autoencoder for 10 epochs. A noticeable difference between the short-term PCA and autoencoder reconstruction coefficients emerges during damage moments, as indicated in the shadowed region. However, as additional noise is introduced into the original guided waves, reducing the signal-to-noise ratio from ∞ to 5 dB, the reconstruction difference between short-term PCA and autoencoder Still persists, although the overall reconstruction performance of both methods deteriorates due to noise interference. Consequently, the values of these reconstruction coefficients become lower and more variable, diminishing their ability to distinguish anomaly regions, as demonstrated in the second subplot.

Continuing to decrease the SNR of the guided waves, the values of these reconstruction coefficients further decrease (reducing to around 0.7 and 0.6 in the third and fourth subplots) and exhibit increased variability.

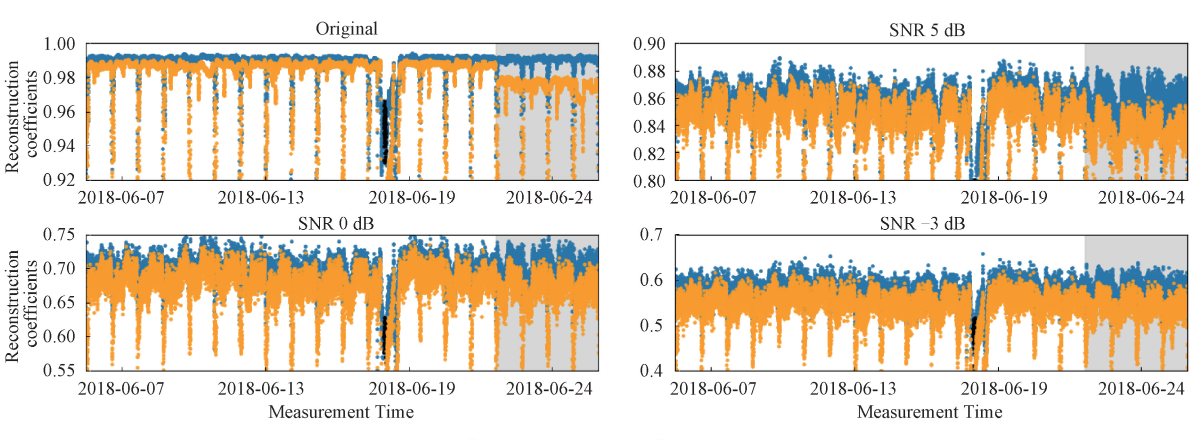

Fig. 2 The reconstruction coefficients of guided waves by short-term PCA and autoencoder with varying signal-to-noise ratios (噪声环境中自编码神经网络重建系数变化图)

Distinguishing the reconstruction difference between healthy and damaged moments for achieving anomaly detection in noisier conditions becomes nearly impossible, as illustrated in the third and fourth subplots of Fig. 2.

3.2 Anomaly detection performance using PCA reconstruction denoising strategy

Comparing the reconstruction coefficients in Fig. 2 with those in Fig. 3, it can be found that our proposed PCA reconstruction denoising strategy preserves the existence of the reconstruction difference between healthy moments and damage moments in noisy conditions. In Fig. 3, tall these reconstruction coefficients are computed using denoised guided waves, employing the first 30 components in the PCA denoising reconstruction, instead of raw guided waves. Also, the AUC scores computed using the short-term PCA and autoencoder reconstruction coefficients with raw guided waves decrease as the signal-to-noise ratio of these guided waves is reduced (by introducing stronger Gaussian noise into the original guided waves), as illustrated in the first-row subplots in Fig. 4. The first-row subplots depict AUC scores calculated using raw guided waves at varying signal-to-noise ratios (SNR): (Ori.), 10, 5, 0, −3, and −5 dB, with each SNR labeled in the title of the respective subplot. In contrast, the second-row subplots present AUC scores derived from denoised guided waves, utilizing the first 40 components in the PCA denoising reconstruction. In the computation of these AUC scores, the X-axis denotes the number of training epochs used for autoencoder training, labeled as "Train Epoch. (L)," and the Y-axis, labeled as "Comp. Num. (S)," signifies the number of principal components utilized in the short-term PCA reconstruction. However, when we employ PCA to first reconstruct (denoise) these guided waves and then use the PCA denoised guided waves to calculate the normalized reconstruction coefficients difference, high AUC scores are maintained even when the SNR of raw guided waves is reduced to −3 and −5 dB, as shown in the second-row subplots of Fig. 4.

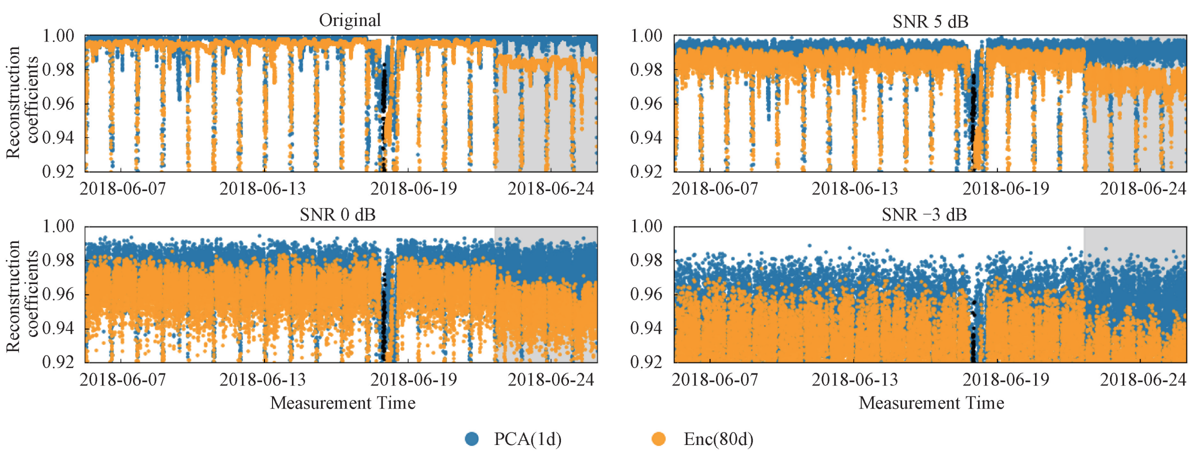

Fig. 3　The reconstruction coefficients of guided waves by PCA and autoencoder with varying signal-to noise ratios after using denoised (应用降噪算法后,噪声环境中自编码神经网络重建系数变化图)

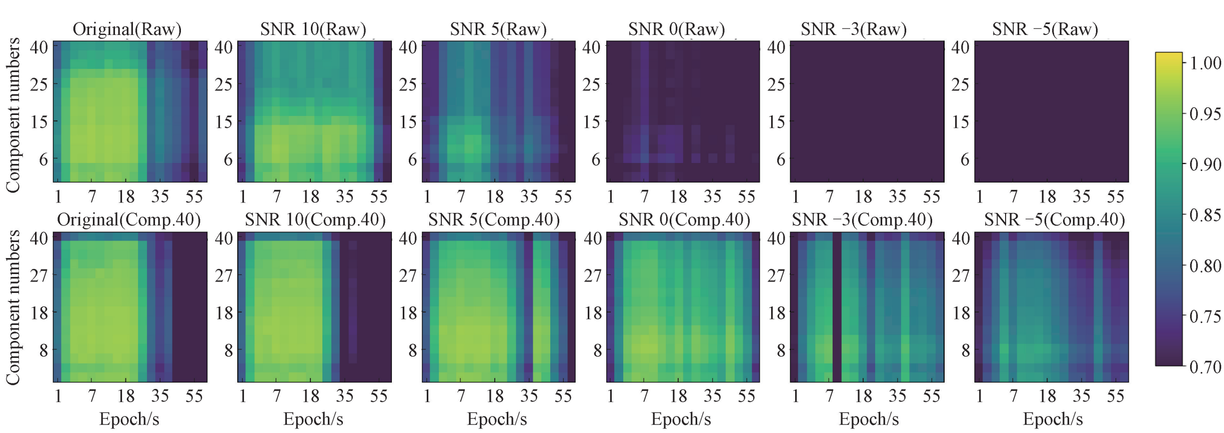

Fig. 4　The AUC are scores calculated without and with denoising strategy (降噪算法应用前后 AUC score 变化图)

An interesting observation is that both excessively large and excessively small training epochs, as well as the number of components used in the short-term PCA reconstruction, fail to yield high AUC scores for the anomaly detection method. Previous research has indicated that excessively large training epochs and a high number of components lead the autoencoder and PCA to reconstruct guided waves not only from healthy guided waves but also from damage conditions. Conversely, excessively small training epochs and a low number of components result in suboptimal reconstruction of all guided waves. In these instances, the distinct reconstruction difference between healthy moments and damage moments disappears, ultimately compromising the efficacy of anomaly detection.

3.3 Hyperparameter investigation for PCA reconstruction denoising strategy

Considering the PCA denoising reconstruction process, the key hyperparameter is the number of components used in the PCA denoising reconstruction process. Accordingly, we will vary the number of components from 4 to 60 to denoise guided waves, and then calculate the AUC scores with these denoised guided waves. It can be observed in Fig. 5, which illustrates the change in the optimal AUC score (the largest AUC score over training epochs) with different SNR values, the number of components used in the PCA denoising reconstruction, and the number of components used in the short-term PCA reconstruction. In each subplot, x represents the number of short-term PCA components used to calculate these optimal AUC scores. The number of components (4, 8, 15, 25, 40, and 60) used in the PCA denoising reconstruction is depicted in the legend at the bottom of this figure. It is evident that when the SNR is larger, such as above 0, using a small number of components to denoise guided waves results in lower optimal AUC scores, as shown in the first four subplots of Fig. 5. However, as the SNR continues to reduce, using a small number of components to denoise guided waves leads to higher optimal AUC scores compared to those using a larger number of components, as shown in the last two subplots of Fig. 5. This can be explained by the fact that using too small a number of components to denoise guided waves results in the reconstructed guided waves not only removing noise but also losing more information, including damage information. However, if the SNR is too low, using too large a number of components will not completely filter out this noise and then worsen the reconstruction coefficients, thereby compromising anomaly detection.

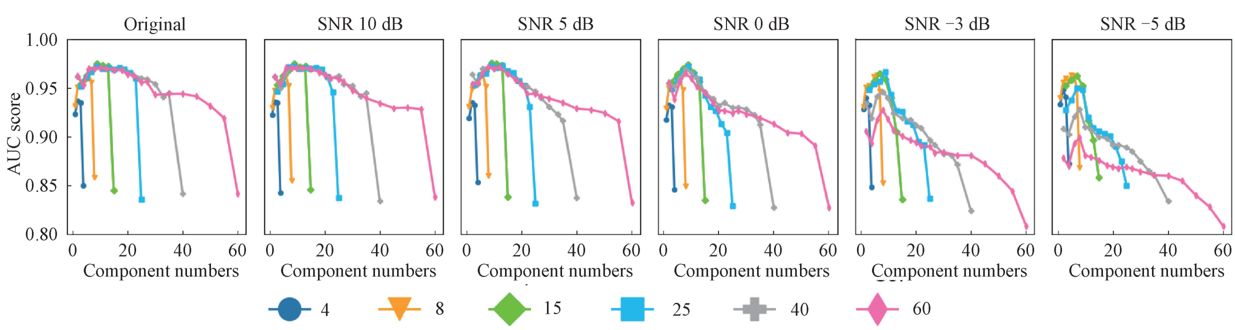

Fig. 5 The optimal AUC score are calculated with denoised guided waves, with the signal-to-noise ratio changing from ∞ (Ori.) to −5 dB(降噪算法中应用不同主成分数量情况下,最优 AUC score 变化图)

Another noteworthy point is that using too few components to reconstruct (denoise) guided waves diminishes the anomaly detection robustness to the number of components used in the short-term PCA reconstruction. Since the time window size of the denoising PCA reconstruction and the short-term PCA reconstruction is the same, the number of components used in the denoising PCA reconstruction determines the limit of components used in the short-term PCA reconstruction and the resolution of information for each component in the short-term PCA reconstruction. For example, if the number of components used in the PCA reconstruction is 4, using 4 components in the short-term PCA reconstruction will result in all short-term PCA reconstruction coefficients being 1 since the rank of the matrix consisting of denoised guided waves is 4. Consequently, the short-term Preconstruction will lack the ability to detect irregular environmental variations.

4 Conclusion

This paper proposes a denoising approach to enhance the performance of autoencoder-based damage detection under noisy conditions by utilizing a local temporal PCA reconstruction with a 1-day time window. Our findings indicate a significant improvement in the damage detection capabilities when applying our denoising strategy, with SNR values ranging from 10 to −5 dB.

The research further reveals that the optimal number of components for the local temporal PCA reconstruction, aimed at enhancing damage detection in noisy settings, is dependent on the noise level (SNR) of the guided waves. In highly noisy environments, it is advisable to use fewer components for denoising to prevent the inclusion of excess noise in the reconstructed guided waves, which could deteriorate the quality of both short-term PCA and autoencoder reconstructions. Conversely, in environments with lower noise levels, employing more components is beneficial as it incorporates more environmental and damage information into the denoised (reconstructed) guided waves, thereby improving damage detection. Therefore, for the practical application of temporal PCA reconstruction in improving damage detection, it is advisable to first estimate the noise level of the collected guided waves, which aids in choosing an appropriate number of components for the denoising PCA reconstruction process. Noise level estimation can be done through temporal correlation analysis of guided waves from adjacent locations.

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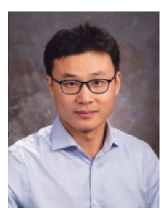

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