

Semi-supervised diagnostic method for abnormal vibration data in SHM via SCNs and Bayesian-optimized LSTM

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Abstract: Structural health monitoring (SHM) systems frequently operate under harsh environmental conditions, inevitably leading to data anomalies such as outliers, deviations, and drifts. This study develops a semi-supervised learning framework leveraging long short-term memory (LSTM) networks to systematically diagnose and categorize abnormal acceleration signals. The proposed method integrates an enhanced density-based spatial clustering of applications with noise (DBSCAN) algorithm to automatically assign labels to acceleration data, substantially reducing the need for labor-intensive manual annotation of raw datasets. A scattering convolution network (SCN) is employed to decompose raw acceleration signals. The first three orders of wavelet scattering coefficients are extracted as the training input features for the subsequent model. This approach achieves a 97.01% reduction in feature dimensionality compared with the original signal, thereby optimizing the computational efficiency and diagnostic accuracy of the LSTM model. The effectiveness and applicability of the methodology are rigorously validated through a case study involving the Suzhou Science and Technology Museum (SSTM). Experimental results confirm that when the minimum points threshold (M) and scanning radius (ε) of the enhanced DBSCAN algorithm are configured at 5 and 0.1, respectively, the unsupervised labeling module attains high data annotation accuracy. Furthermore, Bayesian optimization is utilized to fine-tune the hyperparameters of the LSTM model, yielding a missed detection rate of 0%, a false detection rate of 1.4%, and an overall diagnostic accuracy of 96%. These findings demonstrate the proposed method significantly enhances computational efficiency while preserving diagnostic accuracy, providing an effective

reference for anomaly diagnosis in measurement data.

Key words: semi-supervised diagnostic method; scattering convolution network; long short-term memory; density-based spatial clustering; structural health monitoring

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Structural health monitoring (SHM) systems serve a critical role in applications such as bridges, high-rise buildings, and industrial equipment^[1-2]. Their core function lies in real-time data collection (e.g., vibration, temperature, and strain) using sensor networks to assess structural conditions and provide early warnings of potential risks^[3-4]. However, monitoring sensors are frequently exposed to harsh environments (e.g., high temperatures, extreme cold, and strong winds), which shorten their operational lifespan relative to that of the monitored structures^[5]. Moreover, sensor faults (e.g., device aging, power interruptions, and hardware damage) can induce data noise or missing values, which severely interfere with structural diagnosis results and even cause false alarms and distorted decision-making. Therefore, developing robust fault diagnosis methods, particularly for vibration monitoring data, has become a core research topic for enhancing the reliability of SHM systems.

Sensor faults and data anomalies in SHM can be categorized into five types: bias, drift, gain error, precision degradation, and complete failure^[6]. Because different types of anomalous data exhibit distinct characteristics, the adoption of feature-classification-based methods for data anomaly diagnosis has emerged as a research hotspot. For example, Worden et al.^[7] applied outlier analysis methods to structural damage monitoring problems, which failed to account for the coexistence of multiple outlier types in monitoring data. Mallat et al.^[8] explored the relationship between the local regularity of monitoring data and the Lipschitz exponent. By tracking the local maxima of wavelet transforms across multiple scales, they detected/localized anomalous data, thereby enabling effective anomaly removal. Kullaa^[9] adopted a generalized likelihood ratio method grounded in multiple hypothesis testing to identify several types of data anomalies.

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lies. Huang et al. [10] employed a weighted principal component analysis approach to address the varying sensitivity of principal components to anomalous data and integrated weighted information of principal components via Bayesian inference to more accurately identify and diagnose anomalous data.

Deep learning is a robust technique for directly extracting features from large-scale measured datasets [11–12]. Deep learning methods typically enable precise separation between sensor fault patterns and normal operating conditions by leveraging discriminative features in the amplitude and time-series morphology of vibration data [13]. In this respect, Fu et al. [14] integrated distributed similarity testing with artificial neural networks to identify three types of anomalies (i. e., drift, outliers, and bias) in wireless sensor networks. Meanwhile, Bao et al. [15] employed raw data imaging processing integrated with deep learning methods to detect seven types of anomalous data in the monitoring system of a long-span bridge in China, achieving an overall identification accuracy of 86%. Ni et al. [16] exploited the inherent characteristics of time-series data and adopted a synergistic fusion strategy combining one-dimensional convolutional neural networks and autoencoder architectures to develop a deep learning model for engineering anomaly detection. Compared with traditional methods that require the conversion of measured dynamic response signals into the image domain for indirect processing, this method exhibits significant advantages in computational efficiency. Nevertheless, current research on multitype anomaly detection for practical monitoring data remains relatively limited. Moreover, deep learning-based methods often involve high computational loads and time con-

sumption when processing massive monitoring datasets, posing challenges to the realization of real-time online anomaly identification.

Although numerous studies have investigated deep learning-based data anomaly diagnosis methods and achieved promising accuracy and practicality, existing research has largely focused on improving classification accuracy and type distinguishability. To further improve the effectiveness and practicality of existing data anomaly detection methods, this study proposes a semi-supervised learning method based on long short-term memory (LSTM) networks for data anomaly diagnosis. The main contributions of this study are as follows: (1) the incorporation of dynamic time warping (DTW) to improve the clustering accuracy of the density-based spatial clustering of applications with noise (DBSCAN) algorithm for automated data labeling and (2) the adoption of a scattering convolution network (SCN) to effectively reduce the input dimension of the deep learning-based classification algorithm, thus improving model training efficiency. To validate the proposed method, acceleration data from the Suzhou Science and Technology Museum (SSTM) are employed as a case study to comprehensively investigate the accuracy and influencing factors of the proposed data anomaly detection method.

1 Methodology

This section primarily focuses on the computational workflow of the acceleration data anomaly diagnosis method based on the SCN-LSTM (S-LSTM) framework. As illustrated in Fig. 1, this method comprises five sequential steps: data preprocessing, feature extraction from vibration data, LSTM network construction, hyperparameter optimization, and vibration data fault diagnosis.

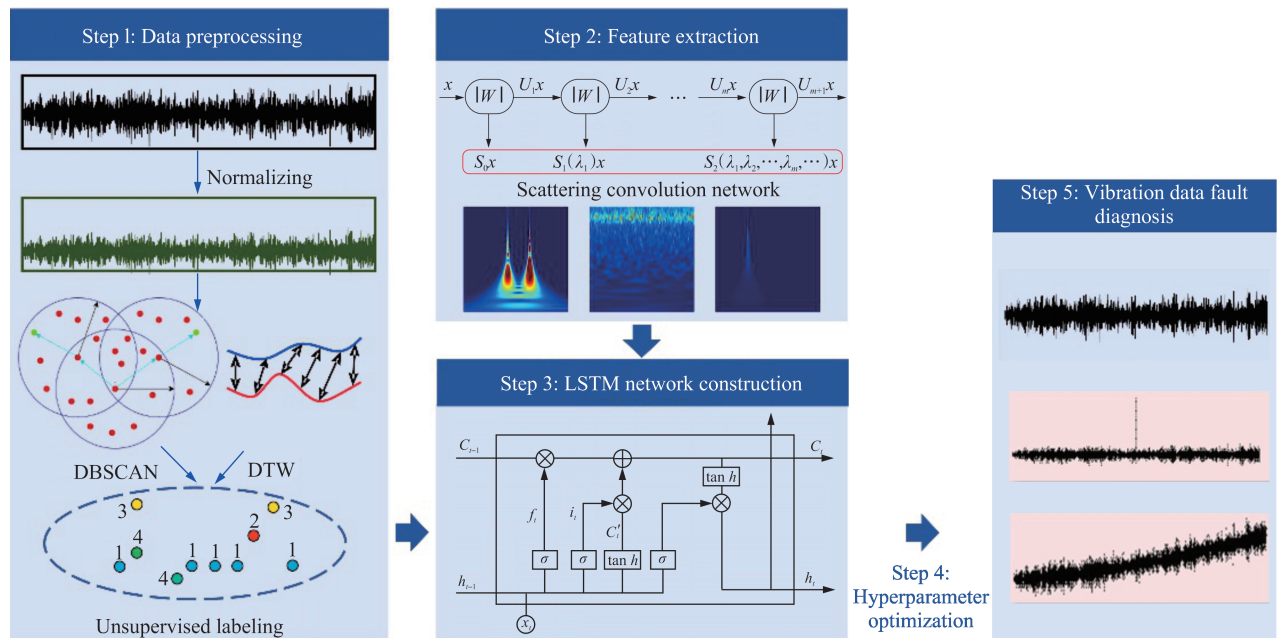


Fig. 1 Computational procedure of the proposed abnormal data diagnosis method

hyperparameter optimization, and vibration data fault diagnosis. The specific workflow is detailed as follows.

(1) Data preprocessing. A preliminarily organized vibration dataset is standardized using min-max scaling. Common types of anomalous vibration acceleration data are classified. Accordingly, an improved DBSCAN algorithm—with DTW incorporated to improve clustering accuracy—is employed to conduct unsupervised labeling on all data.

(2) Feature extraction from vibration data. SCN is first used to transform common anomalous data. Notably, the application of this network not only achieves dimensionality reduction of monitoring data, eliminates redundant information, and improves computational efficiency but also extracts essential data features (e. g. , implicit signal characteristics). Then, the first three orders of wavelet scattering coefficients are extracted as training data for LSTM.

(3) LSTM network construction. The dataset is split into training and testing sets at an 8:2 ratio. Labeled wavelet scattering coefficients are employed for network training, yielding an initial LSTM network.

(4) Hyperparameter optimization. The optimization ranges for the LSTM hyperparameters are specified, including the initial learning rate, maximum number of iterations, number of LSTM hidden layer nodes, and number of LSTM layers. Bayesian optimization (BO) is employed to optimize the network hyperparameters.

(5) Vibration data fault diagnosis. The optimized LSTM network is employed to diagnose anomalies in the unlabeled samples of the test set. The predicted labels are compared with the true labels to evaluate the network's classification performance. The accuracy and precision of classification are quantified using the false detection rate, missed detection rate, and accuracy. The calculation formulas for these metrics are as follows^[17]:

$$\varepsilon_m = \frac{N_F^R}{N_F^R + N_F^F} \times 100\% \quad (1)$$

$$\varepsilon_s = \frac{N_R^F}{N_R^R + N_R^F} \times 100\% \quad (2)$$

$$\varepsilon_a = \frac{N_F^F + N_R^R}{N_F^R + N_F^F + N_R^R + N_R^F} \times 100\% \quad (3)$$

where ε_m denotes the missed detection rate, defined as the percentage of unidentified anomalous monitoring data relative to the total number of anomalous samples; ε_s represents the false detection rate, defined as the percentage of normal monitoring data incorrectly identified as anomalous relative to the total number of normal samples; ε_a indicates the accuracy rate, defined as the percentage of correctly identified test data relative to the total number of monitoring samples; N_F^R is the count of true anomalies mispredicted as normal; N_F^F is true anomalies

correctly detected; N_R^R is true normal samples correctly identified; and N_R^F is true normal samples falsely flagged as anomalies.

2 Measurements from SSTM

2.1 SSTM and its monitoring system

SSTM and its Industrial Exhibition Hall serve as critical cultural-technological exhibition and experience facilities in Suzhou, with a total floor area of 68 940 m². They adopt a hybrid system that combines steel-concrete composite frames with giant steel trusses. The truss assembly spirals upward from the western facade, undergoes a 270° rotation, and spans the water body, thereby forming a large-curvature spatial configuration. Because of the significant cantilever span, the structure is prone to vibration serviceability issues during operation under dynamic loads. Accordingly, a full-lifecycle health monitoring system for SSTM is essential to capture real-time load and structural response data.

A building information modeling-based targeted safety monitoring platform was developed for SSTM. The primary monitoring parameters were stress, displacement, and acceleration of the main steel structure. In this study, measured acceleration data from the structure were employed as a case study for data anomaly diagnosis. Acceleration sensors were mainly installed on the second floor, third floor, roof layer, and cantilevered sections of the steel structure, with a total of 23 measurement points. The specific layout is shown in Fig. 2. Uniaxial acceleration sensors were utilized to acquire vertical acceleration data from the steel trusses at a sampling frequency of 50 Hz. The layout diagrams for each level indicate the local identification numbers assigned to the acceleration measurement points. Continuously recorded acceleration data were segmented into intervals, each with a duration of 3 000 s.

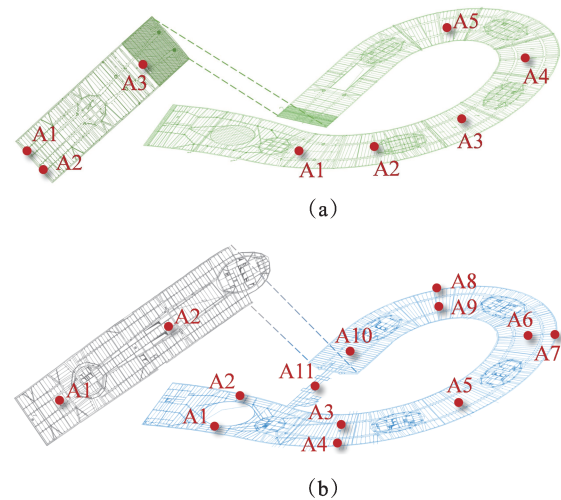


Fig. 2 Arrangements of acceleration measurement points. (a) 2nd layer; (b) 3rd layer

2.2 Typical abnormal vibration data

The classification of data fault types relies on the intrinsic characteristics of data signals. Common fault types include spikes, trend components, and excessive noise^[17]. Fig. 3 presents six typical categories of abnormal acceleration data. To assess the impact of different fault types on the frequency spectra of vibration monitoring data, the frequency distributions of these six abnormal data categories were analyzed. The frequency spectra of abnormal acceleration data exhibited distinct characteristics, enabling fault type classification based on frequency-domain properties. Because “data loss,” “trend components,” and “baseline drift” primarily affected the low-frequency segment of the signal spectrum, these three fault types were classified into a single category termed drift, bias, and complete failure (DBC). Meanwhile, the data characteristics of “multispikes” and “noise” were analogous to the superposition of limited-bandwidth white Gaussian noise, which uniformly affected the entire spectrum. Thus, these two fault types were jointly categorized as spikes and noise (SP). Data without the aforementioned fault types were classified as fault-free (FF).

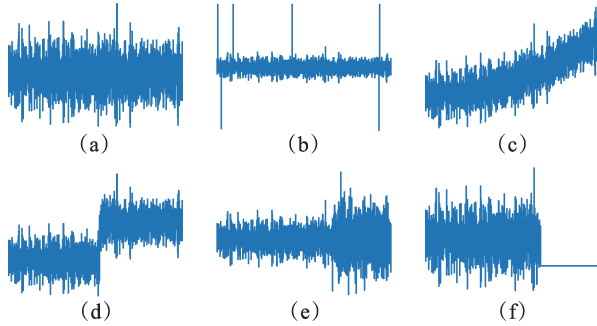


Fig. 3 Typical types of acceleration data. (a) Normal data; (b) Multispikes; (c) Trend; (d) Baseline drift; (e) Noise; (f) Data loss

3 Anomaly Diagnosis of SHM Data

3.1 Data annotation for training data

To validate the effectiveness of the improved DBSCAN algorithm, a segment of raw vibration monitoring data from SSTM collected in September 2022 was selected as an analytical case. This data segment included 12 acceleration measurement points sampled at a frequency of 50 Hz and a length of 20 000 sampling points, covering multiple fault types described in Section 2.2. Fig. 4 compares clustering results obtained using the traditional K-means method and the improved DBSCAN method on the same data segment, with data from September 7 and September 10, 2022, as examples. Numbers 1, 2 and 3 in Fig. 4 denote cluster IDs.

For the monitoring data from September 7, measure-

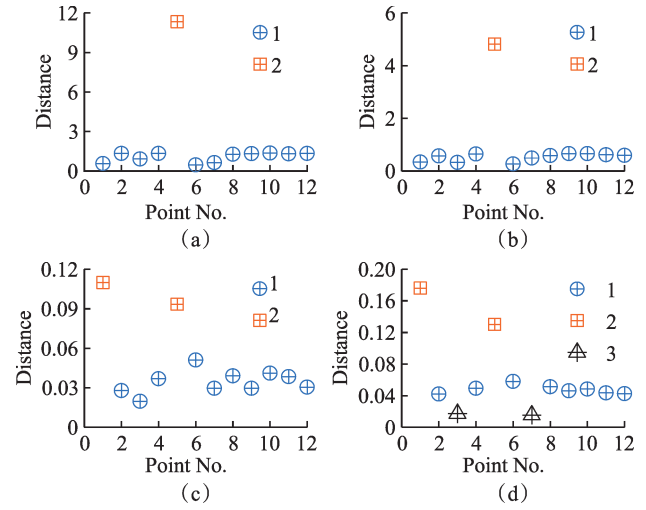


Fig. 4 Acceleration data clustering results. (a) K-means, September 7, 2022; (b) DBSCAN, September 7, 2022; (c) K-means, September 10, 2022; (d) DBSCAN, September 10, 2022

ment point No. 5 was consistently isolated by both methods. Based on its DTW time-series similarity distance, its spectral characteristics significantly differed from those of the majority of the dataset. According to prior analysis, it should be classified as a DBC-type fault. For the monitoring data from September 10, measurement points No. 3 and No. 7 exhibited different classification results between the two methods, indicating that their spectral characteristics were similar to those of normal data but still exhibited subtle discrepancies. Analysis revealed that such discrepancies stemmed from spectral distortions caused by multispikes or noise interference. The K-means method tends to misclassify such points as normal data, whereas the DBSCAN algorithm can effectively identify them as anomalous noise points. However, given that the spectra of SP-type faults are relatively close to those of normal data, measurement points No. 3 and No. 7 were ultimately categorized as normal data. Measurement points No. 1 and No. 5 were classified as DBC-type data, whereas the remaining points were identified as normal. The comparative analysis confirms that the improved DBSCAN algorithm can effectively classify monitoring data faults based on spectral features, providing a reliable data foundation for subsequent fault diagnosis.

The impact of two critical parameters of DBSCAN clustering—minimum points threshold (MinPts, M) and scanning radius (ϵ)—on data labeling outcomes was systematically analyzed. These hyperparameters significantly influenced classification results through parameter coupling effects. To identify optimal parameter configurations, 300 fault-containing monitoring response data points were randomly selected for unsupervised fault clustering validation. The classification results were rigorously benchmarked against manual screening outcomes

(Fig. 5). Note that ε is uniformly set to 0.1. The manual verification identified 276 normal samples, 8 DBC fault samples and 16 SP fault samples within the dataset. In addition, the ε_s corresponding to MinPts values of 4, 5 and 6 is 1.4%, 1.1% and 2.5%, respectively, the ε_m corresponding to MinPts values of 4, 5 and 6 is 0.3%, 0% and 0.7%, respectively. Visual comparison revealed substantial concordance between DBSCAN-based clustering and manual annotations, validating the algorithm's diagnostic reliability. Through iterative parameter tuning, the configuration of $M = 5$ and $\varepsilon = 0.1$ achieved optimal classification performance, particularly in distinguishing SP and DBC fault signatures.

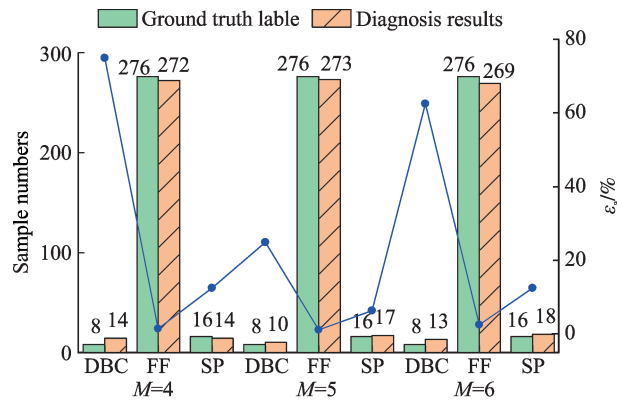


Fig. 5 Comparison of unsupervised clustering results with ground truth labels ($\varepsilon = 0.1$)

To quantify the effectiveness of the proposed outlier identification method, three metrics (described in Section 1) were used for evaluation. The calculation results indicated that a few normal data points were misclassified as abnormal data, with an average false detection rate of 1.67%. The parameter set selected in this study achieved the lowest false detection rate among all tested settings. The missed detection rate remained 0% across different parameter combinations. Through appropriate parameter setting, it can be ensured that no additional abnormal data are introduced into the normal dataset, thereby minimizing their impact on subsequent structural state analysis.

However, this method has a significant drawback related to the computational efficiency of the DTW algorithm. When calculating the similarity between two time series, the algorithm complexity is $\mathcal{O}(N^2)$, where N is the sequence length. When the response time series is long, and the number of monitoring points reaches a certain scale, computational efficiency faces the curse of dimensionality, preventing it from meeting the requirements for rapid fault diagnosis of anomalous monitoring data. The erroneous information introduced by abnormal data can distort subsequent analyses, leading to incorrect conclusions and reducing the reliability of the monitoring system. Therefore, to improve the efficiency of abnormal

data identification, this study utilized data labels obtained using the proposed method as a training dataset for supervised deep learning. By training an effective fault diagnosis classifier, rapid fault diagnosis can be achieved.

3.2 Training data preprocessing and network training

The raw vibration data collected during the operational monitoring phase of SSTM were selected as training and testing samples for the fault diagnosis classifier. The dataset comprised 400 samples for training and 100 samples for testing. To illustrate the computational process of the wavelet scattering transform, three representative samples were extracted from the original monitoring dataset: a normal data sample, an SP fault data sample, and a DBC fault data sample. Each sample had a length of 20 000 data points, with a calculated scattering invariance scale of 387.93 and a sampling frequency of 50 Hz. Through the wavelet scattering transform network, the original monitoring data underwent layer-by-layer decomposition. The first-layer zero-order scattering coefficients yielded a feature dimension of 1×10 , as shown in Fig. 6. After computing the first-layer scattering coefficients, the signal began to decompose progressively through convolution operations, ultimately resulting in a three-layer decomposition. The feature dimensions of the second- and third-layer scattering coefficients were 78×10 and 244×10 , respectively. After concatenating the features from all three layers, the feature length of the wavelet-scattered signal was reduced to 332, representing a 98.34% reduction relative to the original signal length. Fig. 7 visually displays the automatically extracted features of the three fault types processed by SCN.

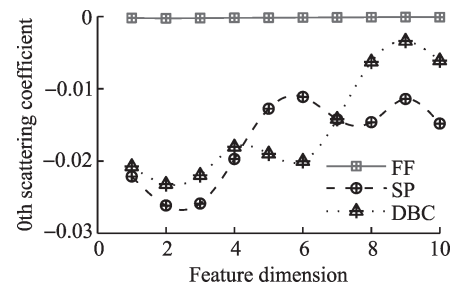


Fig. 6 Zero-order scattering coefficient of scattering convolution network

The signal progressively transitioned from high-frequency to low-frequency components as the wavelet scattering decomposition advanced layer by layer, until the energy of the scattering coefficients approached zero. The underlying principle is that during scattering, information lost at one stage due to the modulus operation is recovered in the subsequent stage. As scattering iterations increase, the energy of the scattering coefficients

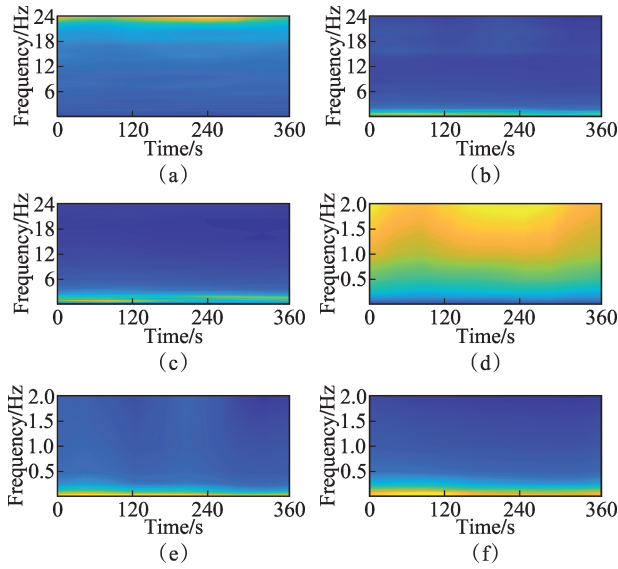


Fig. 7 SCN visualization features of various acceleration data. (a) Second scattering features (FF); (b) Second scattering features (SP); (c) Second scattering features (DBC); (d) Third scattering features (FF); (e) Third scattering features (SP); (f) Third scattering features (DBC)

rapidly converges to zero. Consequently, unlike traditional Fourier-transform-based signal decomposition, which can theoretically continue indefinitely, wavelet scattering requires only a few iterations to meet signal decomposition requirements. This approach significantly reduces the feature dimensionality of the input data and avoids feeding raw data indiscriminately into the LSTM network. Thus, features extracted from wavelet scattering effectively compress the input representation for network training, enabling the rapid training of the LSTM network for signal classification tasks.

The proposed method was employed to classify three pattern types: normal, SP, and DBC data. The training dataset consisted of normalized acceleration data. The model was trained using an Adam optimizer with a learning rate of 0.001, a batch size of 10, and a training duration of 100 epochs.

3.3 Anomaly diagnosis of vibration data

The trained LSTM classifier was evaluated using the test set. Fig. 8(a) presents the confusion matrix of the test set, which provides a fundamental, intuitive, and computationally efficient way to assess classification performance. Herein, the left and right columns represent the proportions of correctly (Corr) and incorrectly (Inco) classified samples, respectively, the corresponding ε_m , ε_s , and ε_a are 0%, 4.4% and 91.0%, respectively. However, the unoptimized LSTM model performed poorly in diagnosing anomalies in abnormal monitoring data, particularly for DBC-type fault cases. Among the three manually identified DBC-type fault samples, the LSTM model misclassified over half of the

DBC	1		2	33.3%	66.7%
FF	3	87	1	95.6%	4.4%
SP	3		3	50.0%	50.0%
	DBC	FF	SP	Corr	Inco

(a)

DBC	2		1	66.7%	33.3%
FF		90	1	98.9%	1.1%
SP	2		4	83.3%	16.7%
	DBC	FF	SP	Corr	Inco

(b)

Fig. 8 Confusion matrix of anomaly diagnosis. (a) Unoptimized S-LSTM; (b) Optimized S-LSTM

DBC-type fault data into other categories.

In the current framework, the lack of systematic optimization of adjustable parameters, such as the wavelet scattering invariance scale and the LSTM hyperparameters, adversely affects the fault classification accuracy. By scanning the wavelet scattering invariance scale and applying BO to determine the optimal combination of hyperparameters for the LSTM network, the accuracy of anomaly diagnosis can be further improved. This study applied the BO algorithm to tune key hyperparameters of the LSTM neural network, including the number of LSTM layers, hidden layer nodes, initial learning rate, and regularization coefficient. Herein, ε_m , ε_s , and ε_a are 0%, 1.1% and 96.0%, respectively. The optimized LSTM model significantly improved anomaly diagnosis accuracy while reducing the missed detection rate.

To evaluate the performance of the proposed algorithm, its anomaly diagnosis accuracy and reliability were comprehensively analyzed using the three metrics described in Section 1. Fig. 9 compares the diagnostic results of three models: classical LSTM, unoptimized

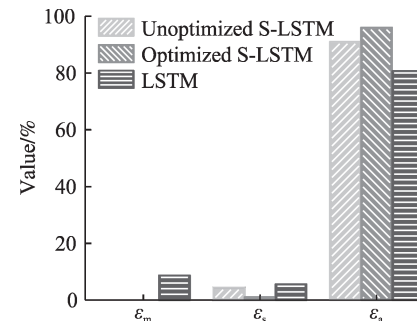


Fig. 9 Comparison of various anomaly diagnosis methods

S-LSTM, and Bayesian-optimized S-LSTM. Classical LSTM had the lowest diagnostic accuracy and exhibited false positives, where some abnormal data were misclassified as normal. Meanwhile, although the unoptimized S-LSTM model outperformed the classical LSTM, it still suffered from a certain rate of missed detections. In contrast, the optimized S-LSTM model achieved the best accuracy, significantly reduced the missed detection rate, and did not misclassify any abnormal data as normal, demonstrating superior anomaly identification capability and reliability.

Taking the acceleration monitoring data of the SSTM from September 5-21, 2022, as an example, the proposed method was applied for anomaly diagnosis. To facilitate statistical analysis of the results, the data were divided into daytime and nighttime periods. Fig. 10 presents the ground truth labels and the anomaly detection results of the test dataset, respectively. The spatiotemporal distribution of anomalies showed high consistency between the two subplots. The calculated anomaly diagnosis accuracy of the proposed method reached 95.7%, demonstrating the classifier's excellent anomaly identification capability. Sensors A1 and A5 exhibited data anomalies for over 90% of the time, indicating potential hardware faults in these two sensors. Furthermore, on September 15 and 17, SP-type faults were widespread across all sensors. These were primarily due to maintenance operations conducted on the construction site's power system during this period, which introduced abnormal voltages resulting in numerous sudden spikes or glitches in the data. Overall, more than 75% of the acceleration sensors operated normally, reliably providing structural dynamic response data that can be used for further structural state analysis and assessment studies.

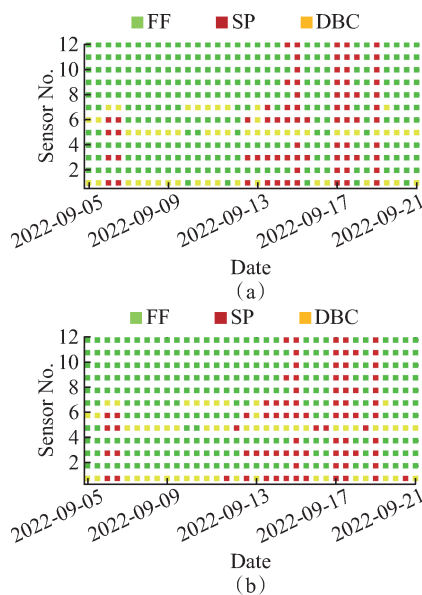


Fig. 10 Ground truth labels and diagnosis results of the test dataset. (a) Ground truth labels; (b) Diagnosis results

4 Conclusions

This study focused on fault diagnosis of acceleration data in SHM and proposed a semi-supervised learning-based method for fault diagnosis in vibration monitoring acceleration responses. Field monitoring data from SSTM were utilized as a case study to validate the effectiveness of the proposed method. The main conclusions are as follows.

(1) An anomaly data identification method based on an improved LSTM is proposed. For the SSTM acceleration data, the proposed method attained an anomaly diagnosis accuracy of 95.7%, demonstrating the classifier's excellent diagnostic performance.

(2) The classification results of the improved DBSCAN algorithm exhibited high consistency with manual screening results, confirming the algorithm's accuracy and reliability. In addition, the algorithm attained high classification accuracy when MinPts was configured as 5 and ϵ as 0.1. A few normal data points were misclassified as abnormal data, corresponding to an average false detection rate of 1.67%.

(3) SCN effectively reduced the input dimension of the LSTM model, resulting in a 97.01% reduction in feature size compared with the feature size of the original input signal. The Bayesian-optimized S-LSTM model attained an anomaly diagnosis accuracy of 96% on the test set, with a missed detection rate of 0% and a significantly lower false detection rate of 1.4%.

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基于SCN与贝叶斯优化LSTM的结构健康监测 异常振动数据半监督诊断方法

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摘要: 结构健康监测(SHM)系统通常在恶劣环境条件中运行,不可避免地会出现离群值、偏差和非线性漂移等数据异常。因此,本文提出了基于长短期记忆网络(LSTM)的异常数据半监督诊断方法。该方法利用改进的基于密度的空间聚类方法(DBSCAN),自动为加速度数据分配标签,解决了传统监督学习中标注成本高的问题。在此基础上,采用散射卷积网络(SCN)对原始加速度信号进行多尺度分解,利用前3阶小波散射系数作为训练数据,大幅降低了冗余信息(数据压缩率达97.01%),提升了LSTM的计算效率与分类精度。最后,通过苏州科技馆(SSTM)的振动监测数据验证了该方法的有效性。结果表明,当改进的DBSCAN算法的最小包含点数 M 和扫描半径 ϵ 分别设置为5和0.1时,可有效实现振动数据的高精度标注。此外,利用贝叶斯优化对LSTM模型的超参数进行调优后,漏检率降低至0%,误检率降低至1.4%,诊断准确率提升至96%。该方法在保证诊断精度的同时显著提升了计算效率,为结构健康监测数据异常诊断提供了有效参考。

关键词: 半监督诊断方法; 散射卷积网络; 长短期记忆网络; 基于密度的空间聚类方法; 结构健康监测

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