

Lamb Wave Damage Identification Method for Composites Based on Dual-domain Features and Interpretable Deep Network

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Abstract: Aiming at the problems of complex dispersion, insufficient feature representation and poor interpretability of deep learning models in Lamb wave signal processing for composite materials, a Lamb wave damage identification method based on time-frequency dual-domain feature fusion and interpretable deep learning is proposed to improve the accuracy and reliability of damage identification. Time domain and frequency domain features of Lamb wave signals are extracted to construct a dual-domain feature system with time domain features as the core, and a multi-branch 1D-CNN is designed for targeted learning and efficient fusion of the dual-domain features. A systematic data augmentation strategy is introduced to enhance the model's generalization ability under small sample conditions, and the SHAP method is adopted to analyze the model's feature importance and reveal its decision-making mechanism, thus solving the "black box" problem of deep learning models. Experimental results on the carbon fiber reinforced composite plate guided wave dataset show that the proposed method achieves an average classification accuracy of 93.62%, with all evaluation metrics significantly outperforming the single-branch 1D-CNN, LSTM and Transformer benchmark models. SHAP analysis verifies that time domain features are the core discriminant features of the model, and the model's decision-making logic is consistent with the physical mechanism of Lamb wave propagation in defective composite materials. The research shows that time-frequency feature fusion can fully mine defect discriminant information in Lamb wave signals, the multi-branch 1D-CNN is well adapted to guided wave signal feature learning, and SHAP effectively realizes the physical interpretability of the model. This method provides an interpretable technical approach for intelligent non-destructive testing of composite materials and has good engineering application potential.

Keywords: guided wave testing; dual-domain feature fusion; convolutional neural network; data augmentation; interpretable deep learning

1. Introduction

Composite materials have been widely used in aerospace, energy equipment, transportation and other fields due to their high specific strength, high specific stiffness and excellent fatigue resistance [1]. However, in long-term service, hidden damages such as delamination, cracks and debonding are prone to initiate and propagate rapidly, directly threatening structural safety and operational reliability [2]. Therefore, the research on efficient and accurate damage detection and identification of composite materials is of great engineering value. Lamb wave detection has become one of the mainstream technologies for non-destructive testing of composite materials owing to its long propagation distance, high sensitivity to defects and capability of large-area rapid inspection [3]. Nevertheless, Lamb wave signals exhibit obvious multimodal and dispersive characteristics, and the reflection, scattering and mode conversion caused by defects further increase signal complexity. Traditional single domain feature methods are difficult to fully capture multi-scale damage information, limiting identification accuracy and stability [4].

In recent years, deep learning has been widely applied in Lamb wave signal recognition. Convolutional neural networks can automatically perform feature learning and classification, showing prominent advantages in complex signal processing [5-6]. However, most existing methods adopt single features or raw signals as input, ignoring complementary information among features from different domains [7]. In addition, the model decision-making process lacks interpretability, making it difficult to correlate with Lamb wave propagation mechanisms, resulting in insufficient engineering applicability [8].

Although some studies have attempted time-frequency multi-domain fusion^[9], they generally fail to fully exploit the rich information within other critical signal domains. Meanwhile, the problems of weak generalization ability and easy overfitting of models under small samples have not been effectively solved.

To this end, this paper proposes a Lamb wave damage identification method for composite materials based on dual-domain feature fusion and interpretable deep learning. Time domain and frequency domain features are extracted to construct a dual-domain representation system, with time-domain features as the core discriminant features. A multi-branch one-dimensional convolutional neural network is designed to realize domain wise feature learning and efficient fusion. Data augmentation is integrated to improve model robustness, and the SHAP method is used to analyze the decision interpretability. The innovations of this paper are as follows: constructing a time-frequency dual-domain feature system with time-domain features as the core, proposing a multi-branch 1D-CNN fusion framework adapted to dual-domain features, and introducing SHAP to achieve physical interpretability of the model and clarify the core role of time-domain features in damage identification, providing a new approach for high-precision and interpretable intelligent non-destructive testing of composite materials.

2. Feature Engineering and Data Preparation

2.1. Experimental Setup

An open source guided wave dataset was adopted in this paper to verify the proposed method^[10]. Figure 1 shows the schematic diagram of the carbon fiber reinforced composite plate, transducer layout and simulated defect positions used in the experiment. The plate has dimensions of 500 mm × 500 mm with a thickness of 2 mm. The laminated plate was fabricated with a quasi-isotropic layup sequence of [45/0/45/90/-45/0/45/90]. Twelve piezoelectric ceramic transducers, numbered T1 to T12, were bonded to the surface of the plate in a parallel array configuration. In this study, seven defect positions (D1, D2, D3, D4, D5, D6 and D7) were selected for the experiments, and the specific locations of each defect are detailed in the schematic diagram.

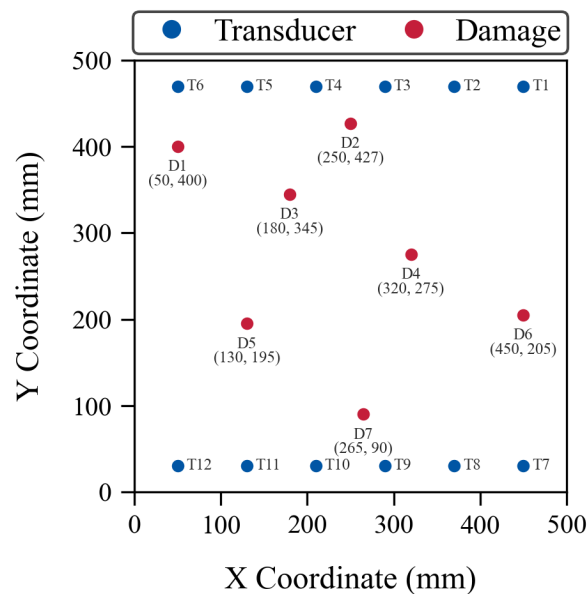


Figure 1: Schematic diagram of the structure of carbon fiber reinforced composite plate, transducer array layout and simulated defect positions.

2.2. Data Augmentation

To enhance the generalization ability of the model and alleviate the overfitting problem under small sample conditions, a systematic data augmentation strategy was applied to the original Lamb wave signals, as illustrated in Figure 2. Each original signal was sequentially subjected to four perturbation transformations: time shifting, noise addition, signal amplification and amplitude shifting. Five groups of synthetic samples were generated with different parameters for each transformation, which expands the sample size while preserving the defect-related physical features of the signals.

Time shifting simulates the excitation time delay and propagation time difference, Gaussian noise addition restores the interference in actual detection environments, signal amplification mimics the amplification effect of defect reflection, and amplitude shifting simulates the variation in measurement sensitivity. Among the five groups of samples generated by each transformation, three groups were randomly selected for the training set and two for the test set, and the original signals were directly added to the training set to retain the real data distribution. Ultimately, 13 training samples and 8 test samples were constructed from each original signal, resulting in a total of 6552 training samples and 4032 test samples in the dataset.

This augmentation strategy enables the construction of a dataset with balanced distribution and diverse samples, which fully reproduces the signal variations and noise characteristics in actual detection, avoids the introduction of invalid distortions, and effectively improves the model's robustness and ability to learn defect invariant features.

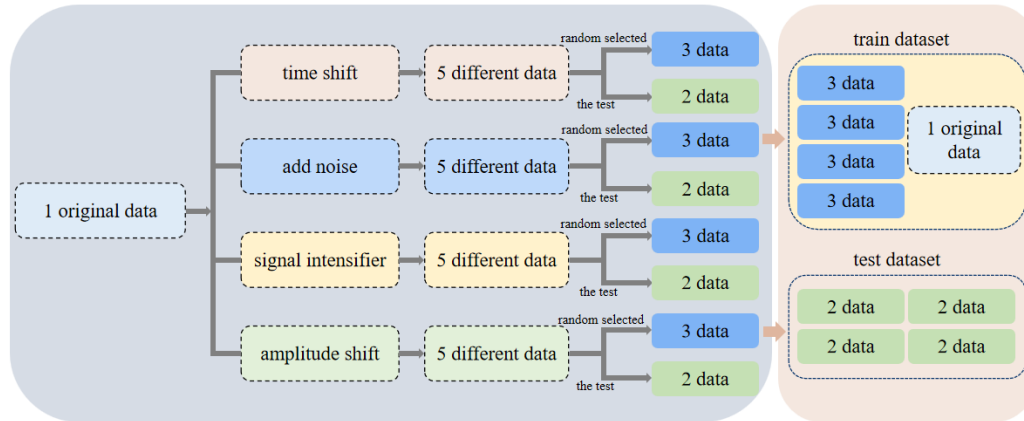


Figure 2: Schematic diagram of data augmentation methods and dataset division process.

2.3. Dual-domain Feature Extraction

To fully capture defect related information in Lamb wave signals, a handcrafted feature set was constructed from two dimensions: the time domain and frequency domain. A total of 27 physically meaningful feature parameters were extracted to characterize the interaction laws between signals and defects from the perspectives of statistical characteristics, energy distribution, and wave propagation characteristics, providing abundant discriminant information for multi-branch CNN classification.

Time domain features were directly extracted from the original time series without domain transformation, and can intuitively reflect the amplitude variation, energy intensity and distribution symmetry of signals. A total of 14 time domain statistical features were selected in this study, with their definitions shown in Table 1, where N is the number of signal sampling points and x_i is the signal amplitude at the i -th sampling point.

Table 1: Time domain features and their mathematical definitions.

Feature Index	Expressions	Feature Index	Expressions
mean_value	$\bar{X} = \frac{1}{N} \sum_{i=1}^N x_i$	kurtosis	$\beta = \frac{1}{N} \sum_{i=1}^N x_i^4$
rms	$X_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}$	variance	$\sigma_x^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{X})^2$
sqrt_amplitude	$X_r = \left(\frac{1}{N} \sum_{i=1}^N \sqrt{ x_i } \right)^2$	max_value	$X_{max} = \max\{ x_i \}$
absolute_mean_amplitude	$ \bar{X} = \frac{1}{N} \sum_{i=1}^N x_i $	min_value	$X_{min} = \min\{x_i\}$
skewness	$\alpha = \frac{1}{N} \sum_{i=1}^N x_i^3$	peak_to_peak	$X_{p-p} = \max(x_i) - \min(x_i)$
waveform_index	$S_f = \frac{X_{rms}}{ \bar{X} }$	kurtosis_index	$K_v = \frac{\beta}{x_{rms}^4}$
skewness_index	$S = \frac{\alpha}{x_{rms}^3}$	pulse_index	$I_f = \frac{X_{max}}{ \bar{X} }$

Frequency domain features were obtained via Welch's power spectral density estimation, which can reflect the energy distribution of signals across different frequency components and effectively identify frequency shifts and dispersion phenomena caused by defects. Thirteen frequency domain features were extracted in this study, with their definitions shown in Table 2. In the following formulas, $s(k)$ represents the spectrum of the signal $x(n)$, where $k=1,2,3, \dots, K$, and K is the number of spectral lines. The frequency value of the k -th spectral line is denoted by f_k . The characteristic parameter p_1 reflects the vibration energy in the frequency domain. Parameters p_2, p_3, p_4, p_6 and $p_{10}-p_{13}$ reflect the degree of dispersion or concentration of the spectrum, while p_5, p_7, p_8 and p_9 reflect the change in the position of the main frequency.

Table 2: Frequency domain features and their mathematical definitions.

Expressions	Expressions
$p_1 = \frac{\sum_{k=1}^K s(k)}{K}$	$p_8 = \frac{\sqrt{\frac{\sum_{k=1}^K f_k^4 s(k)}{\sum_{k=1}^K f_k^2 s(k)}}}{\sum_{k=1}^K f_k^2 s(k)}$
$p_2 = \frac{\sum_{k=1}^K (s(k) - p_1)^2}{K}$	$p_9 = \frac{1}{\sqrt{\frac{\sum_{k=1}^K s(k)}{\sum_{k=1}^K f_k^4 s(k)}}}$
$p_3 = \frac{\sum_{k=1}^K (s(k) - p_1)^3}{K(\sqrt{p_2})^3}$	$p_{10} = \frac{p_6}{p_5}$
$p_4 = \frac{\sum_{k=1}^K (s(k) - p_1)^4}{Kp_2^2}$	$p_{11} = \frac{\sum_{k=1}^K (f_k - p_5)^3 s(k)}{Kp_6^3}$
$p_5 = \frac{\sum_{k=1}^K f_k s(k)}{\sum_{k=1}^K s(k)}$	$p_{12} = \frac{\sum_{k=1}^K (f_k - p_5)^4 s(k)}{Kp_6^4}$
$p_6 = \sqrt{\frac{\sum_{k=1}^K (f_k - p_5)^2 s(k)}{K}}$	$p_{13} = \frac{\sum_{k=1}^K (f_k - p_5)^{0.5} s(k)}{Kp_6}$
$p_7 = \sqrt{\frac{\sum_{k=1}^K f_k^2 s(k)}{\sum_{k=1}^K s(k)}}$	

3. Multi-Branch 1D-CNN Model Architecture

A damage identification model based on a multi-branch one dimensional convolutional neural network (1D-CNN) was designed for the time frequency dual-domain feature characteristics of ultrasonic guided wave signals to achieve accurate classification of defects in composite plates, as illustrated in Figure 3. The model takes the time domain and frequency domain features as input, conducts targeted learning on features of each domain through a branched network structure, then completes defect classification via feature fusion and fully connected layers, and combines data augmentation strategies to improve model generalization ability. Its core design concept is domain-specific learning and fusion classification: independent 1D-CNN branches are built for the physical meaning and data distribution differences of time and frequency domain features to avoid information interference between them, the learning results of each branch are fused in the channel dimension to integrate discriminant information of the dual-domain features, and finally a fully connected network is used to realize high order mapping of features for classification and recognition of different defect positions.

The model consists of an input layer, a multi-branch feature learning layer, a feature fusion layer and a classification output layer: the input layer adapts feature dimensions and converts data formats for the extracted time frequency dual-domain features; the multi-branch feature learning layer includes two parallel 1D-CNN sub-networks, each composed of two 1D convolution layers, activation functions, batch normalization layers and Dropout layers, and unifies feature dimensions via global average pooling; the feature fusion layer splices the 64 dimensional feature vectors output by each branch in the channel dimension to form a 128 dimensional comprehensive feature vector; the classification output layer maps the fused features to defect category probabilities through a two layer fully connected network and the Softmax activation function. For model training, the Adam optimizer and cross entropy loss function are adopted, a learning rate decay strategy based on validation set loss is used, and reasonable hyperparameters are set with training conducted on a CUDA hardware environment to ensure training effect and convergence stability.

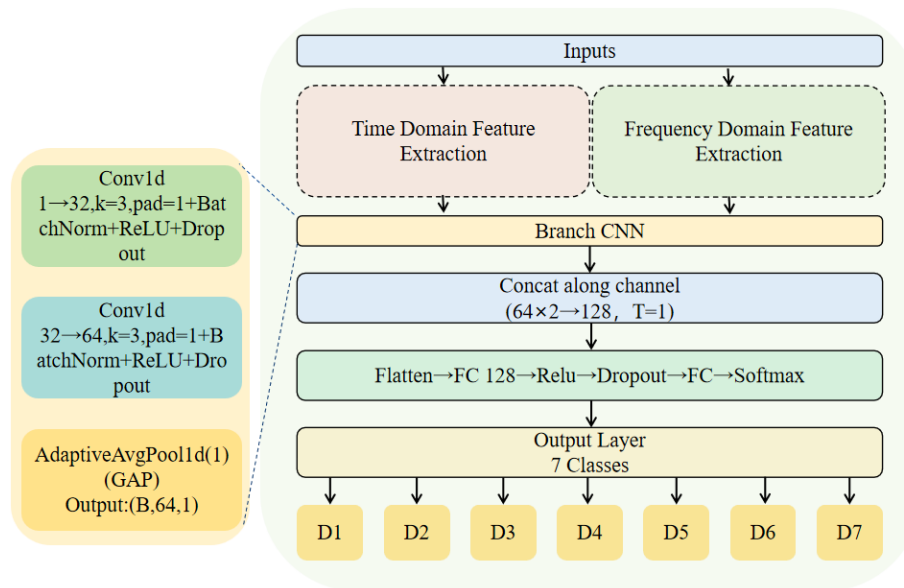


Figure 3: Overall architecture of the multi-branch 1D convolutional neural network for damage identification.

4. Experimental Results and Analysis

To verify the performance superiority of the proposed multi-branch 1D-CNN model, single-branch 1D-CNN, LSTM and Transformer were selected as benchmark models for comparative experiments. All models were trained and tested on the same dataset with consistent evaluation metrics, training hardware and optimized hyperparameters, ensuring the fairness and validity of the experiment, and the comprehensive performance comparison results are shown in Table 3.

Table 3: Comparison of defect identification performance of different models.

Model	Precision (%)		F1 (%)		Recall (%)		Accuracy (%)	
	max	mean	max	mean	max	mean	max	mean
1D CNN	91.62	91.35	91.58	91.49	91.47	91.33	91.54	91.28
LSTM	81.01	80.34	80.86	80.25	80.53	80.36	80.66	80.23
Transformer	90.84	90.73	90.92	90.77	90.79	90.68	90.96	90.74
Multi-1D CNN	94.10	93.60	93.97	93.58	94.12	93.72	94.06	93.62

Quantitative analysis of Table 3 shows that the multi-branch 1D-CNN model achieves an average classification accuracy of 93.62%, with all evaluation metrics including precision, recall and F1-score significantly outperforming the three benchmark models—surpassing single-branch 1D-CNN (91.28%), Transformer (90.74%) and LSTM (80.23%) by 2.34, 2.88 and 13.39 percentage points respectively. Single-branch 1D-CNN and Transformer yield similar performance but are inferior to the proposed model due to information interference in multi-feature learning and low dimensional feature overfitting risk, while LSTM performs poorest as it is unsuitable for low-dimensional handcrafted feature learning of guided wave signals.

Five repeated training experiments were conducted to test model stability, with classification accuracy variance as the evaluation index. The proposed model has an accuracy variance of only 0.10, much lower than single-branch 1D-CNN (0.15), Transformer (0.21) and LSTM (0.52), indicating its stable and high classification performance against training randomness. This advantage stems from its domain specific lightweight structure and effective regularization strategies (Dropout, batch normalization), which enhance generalization ability. The results confirm that the time-frequency dual-domain feature learning structure enables sufficient and targeted feature extraction, and multi-domain fusion realizes information complementarity, making the model more adaptive to composite plate defect classification than traditional models.

5. Model Interpretability Analysis Based on SHAP

To address the "black box" problem of the deep learning model and verify the core role of time-domain features in damage identification, this chapter adopts the SHapley Additive exPlanations (SHAP) method to quantitatively analyze the feature importance and decision-making mechanism of the proposed multi-branch 1D-CNN model. SHAP is a model-agnostic interpretability method based on game theory, which can assign a Shapley value to each input feature to quantify its contribution to the model's prediction results, thereby revealing the internal decision logic of the model. The SHAP summary plot of the top 10 important features is shown in Figure 4, where the horizontal axis represents the SHAP value (positive values indicate promotion of the model's prediction, negative values indicate inhibition), the vertical axis sorts features by average absolute SHAP value from high to low, and the color represents the magnitude of the feature value.

As shown in Figure 4, all the top 10 features with the highest contribution to the model's damage identification are time domain statistical features, including mean value, skewness index, waveform index, pulse index, skewness, kurtosis index, etc. This directly verifies that time-domain features are the core discriminant basis of the model, which is consistent with the physical mechanism that Lamb wave signals produce obvious time-domain waveform and amplitude changes after interacting with defects. Among them, the mean value has the highest average absolute SHAP value, which is the most critical feature for the model to distinguish different defect states, as it can directly reflect the overall energy change of the signal caused by defect reflection and scattering.

The SHAP analysis results further confirm the rationality of the time-frequency dual-domain feature system and the multi-branch network structure designed in this paper. The model's decision making process relies on the essential physical characteristics of Lamb wave signals related to defects, rather than spurious correlations, which endows the model with clear physical interpretability. This not only improves the reliability of the damage identification method, but also lays a foundation for its engineering application in the field of composite material non-destructive testing.

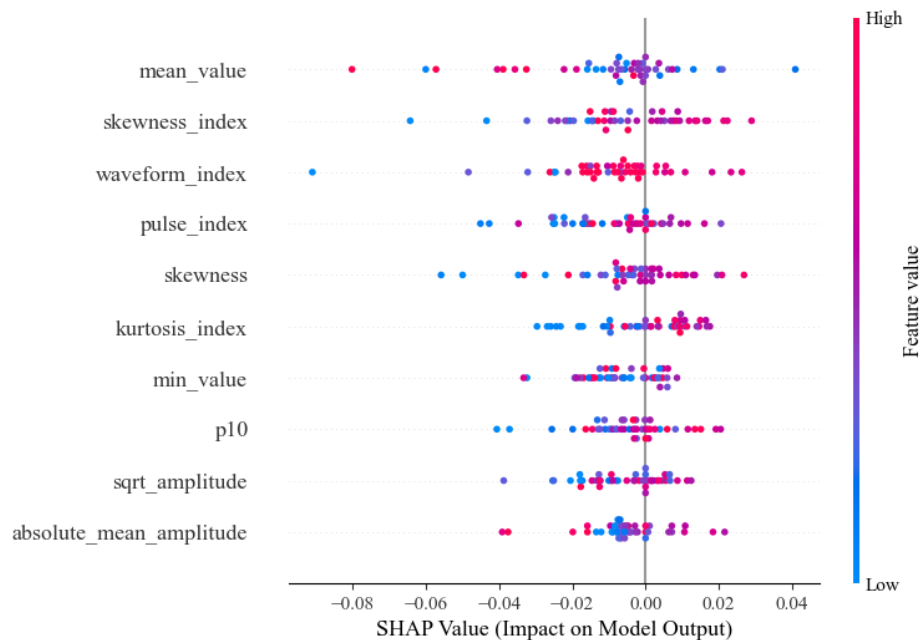


Figure 4: Summary plot of SHAP values for the top 10 important features of the model.

6. Conclusion

In response to the problems of insufficient feature representation and poor interpretability of deep learning models in Lamb wave damage identification of composite materials, this paper proposes a damage identification method based on time-domain core-frequency domain complementary dual-domain feature fusion and interpretable deep learning. A multi-branch 1D-CNN framework is constructed to realize targeted learning and efficient fusion of time domain and frequency domain features, with time domain features as the core discriminant basis. Data augmentation is integrated to improve the model's generalization ability, and the SHAP method is adopted to reveal the model's

decision making logic. Experimental results show that the proposed method achieves an average classification accuracy of 93.62% on the composite plate dataset, which is significantly superior to benchmark models such as single-branch 1D-CNN and LSTM. SHAP analysis verifies that time domain features are the core discriminant features of the model, and the decision-making process is highly consistent with the physical mechanism of Lamb waves, realizing the unification of high precision and physical interpretability. This method provides an effective technical solution for intelligent non-destructive testing of composite materials and has good engineering application potential.

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