

Research on Fuel Nozzle Defect Classification Based on Ultrasonic Flaw Detection and Time-Frequency Fusion Deep Learning

Jian-Ting Lai, Ruo-Yu Yang*, Yan-Xiao Jia, Jia-Yi Hu, Wei Yan, Bo-Liang Zhang

Energy and Power Engineering, Guangdong University of Petrochemical Technology (GDUPT), Maoming525000, China
(corresponding author: Ruo-Yu Yang) (E-mail: 15999547282@163.com)

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Abstract— As one of the core precision components of power equipment, fuel nozzles are prone to concealed defects invisible to the naked eye, including pores, cracks, and structural corrosion, due to long-term operation under high-temperature and high-pressure working conditions. These defects affect the combustion efficiency and operational safety of the equipment. Traditional ultrasonic flaw detection has certain limitations when facing complex structures and tiny defects. Therefore, this paper proposes a frequency-domain extraction method integrating Fourier transform and wavelet transform, and completes model training and verification on the ultrasonic flaw detection dataset based on the PyTorch deep learning framework. Experiments show that the proposed method outperforms single-signal processing methods in terms of accuracy, recall, and F1-score. This method can provide a reference for intelligent non-destructive testing and industrial automatic flaw detection.

I. INTRODUCTION

Fuel nozzles are high-precision fluid injection components, widely used in internal combustion engines, gas turbines, and aerospace power equipment. During operation, nozzles bear long-term alternating thermal loads and continuous mechanical vibration, which easily causes various types of damage on the inner nozzle wall, including microcracks, casting pores, and erosion wear. These defects directly degrade fuel atomization performance and cause deviations in fuel injection flow [1]. The machining accuracy and material integrity of fuel nozzles directly affect the operational performance and service life of the entire power system, so conducting defect detection for fuel nozzles has important practical significance. Ultrasonic non-destructive testing is a common method for internal defect inspection of precision metal parts, with advantages including strong penetration,

no damage to tested workpieces, and relatively low detection cost [2]. Traditional ultrasonic inspection relies on inspectors manually observing the waveform amplitude and time delay of A-scan echoes to determine defect types; this manual judgment approach heavily depends on inspectors' working experience, not only bringing large subjective judgment errors, but also resulting in low overall batch inspection efficiency, and struggling to identify tiny micro-defects on workpieces, with obvious application limitations [3]. In recent years, deep learning technology has been rapidly promoted and applied in the non-destructive testing industry, and intelligent defect classification methods based on ultrasonic signals have gradually replaced traditional manual interpretation. Most existing related studies only adopt a single method for defect feature extraction: either wavelet transform for denoising, or spectrum analysis, which has inherent shortcomings of spectrum leakage and sidelobe

interference [4]. Wavelet transform can effectively extract local time-frequency detail features of signals, but cannot fully reflect the global spectrum distribution of the signal [5]; Fourier transform can accurately characterize the overall frequency-domain characteristics of signals, but is not suitable for non-stationary transient signals such as ultrasonic echoes. This paper combines the two signal processing methods of Fourier transform and wavelet transform, designs a fused frequency-domain feature extraction scheme, and builds a fuel nozzle-oriented defect classification and detection system based on the PyTorch deep learning framework. This combined method can effectively improve the comprehensive representation of signal features, and give the model stronger adaptability and stability to noisy signals and non-stationary ultrasonic echoes.

II. TECHNICAL SCHEME AND IMPLEMENTATION PATHWAY

2.1 Signal Preprocessing and Frequency-domain Analysis

2.1.1 Fourier Transform

Fourier Transform converts acquired one-dimensional ultrasonic time-domain signals into frequency-domain representation; researchers can extract intrinsic frequency-related parameters from the transformed spectral results. When periodic internal damage occurs inside a workpiece, the spectral distribution of the reflected ultrasonic echo changes noticeably, making this processing method suitable for distinguishing defect signals from periodic-response defects such as cracks and pores.

The Fast Fourier Transform (FFT) is a widely used implementation in ultrasonic inspection work. This algorithm efficiently converts discrete time-domain signals into frequency-domain signals, and quickly obtains the distribution of signal amplitude varying with frequency. However, Fourier Transform has inherent limitations: after transformation, the time information embedded in the original signal is lost. It can only present the overall frequency composition of the signal, and cannot identify the specific time position where a certain frequency component appears. As a result, the actual processing performance of Fourier transform is limited when it is used alone to process non-stationary, transient ultrasonic echo signals. In this experimental work, the NumPy library is used to complete the Fast Fourier Transform calculation, and the corresponding core code is shown below:

```
import numpy as np
def fft_transform(signal, fs=1e6):
```

```
n = len(signal)
fft_result = np.fft.fft(signal)
freqs = np.fft.fftfreq(n, 1/fs)
return freqs, np.abs(fft_result)
```

This function takes the raw one-dimensional ultrasonic signal and the sampling frequency as inputs, and outputs the corresponding frequency sequence and spectral amplitude. The output results provide foundational data support for subsequent frequency-domain feature extraction work [6].

2.1.2 Wavelet Transform

Wavelet Transform is a signal processing method that enables simultaneous analysis of time and frequency information. It can compensate for the missing time-information limitation inherent to Fourier Transform. This transform decomposes the original signal using wavelet basis functions across different scales, so that both the time and frequency information of the ultrasonic signal can be obtained simultaneously, and transient changes occurring at local positions of the signal can be captured. When abrupt defects such as internal cracks and erosion corrosion appear in fuel nozzles, the reflected ultrasonic echoes from these defects belong to non-stationary signals. Wavelet Transform is well suited for processing such signals, and can suppress a certain amount of noise interference introduced during detection. Multi-resolution analysis is an inherent feature of Wavelet Transform: it achieves strong frequency resolution in the low-frequency band, and strong time resolution in the high-frequency band. Wavelet Transform also has its own limitations: it focuses heavily on extracting local detail features of the signal, and cannot fully represent the global spectral distribution across the whole signal. In this experiment, the PyWavelets (pywt) library is used to complete the discrete wavelet decomposition, with the db4 wavelet basis selected and the decomposition layer number set to 5. The corresponding implementation code is shown below:

```
def wavelet_transform(signal, wavelet='db4', level=5):
    coeffs = pywt.wavedec(signal, wavelet, level=level)
    return coeffs
```

This function takes the raw ultrasonic signal, the specified wavelet basis name, and the number of decomposition layers as inputs. It returns the multi-layer wavelet coefficients obtained after signal decomposition. Each layer of coefficients contains the time-frequency detail information of the signal at different scales, and this

information supports the subsequent feature extraction steps [7].

2.2 Feature Fusion and Model Construction

2.2.1 Feature Fusion Strategy

Fourier spectrum: used to extract global frequency features. Wavelet coefficients: used to extract local time-frequency features. Fusion method: concatenate the two types of features, then input the combined feature vector into the deep learning model for classification.

2.2.2 Model Selection and Optimization

ResNet-18: originally designed for image classification tasks, and can be adapted to process frequency-domain feature maps. Improvement module: adopts frequency-domain attention (Frequency Attention) mechanism to improve feature representation capability.

```
import torch
import torchvision.models as models
model = models.resnet18(pretrained=True)
num_fts = model.fc.in_features
model.fc = torch.nn.Linear(num_fts, 2)
```

III. EXPERIMENTAL DATASETS AND EXPERIMENTAL SETUP

3.1 Data Sources

The experimental data used in this study is the open RCNDE standard ultrasonic non-destructive testing dataset from the UK, a universally recognized open benchmark dataset for deep learning research in the non-destructive testing field. The dataset contains four categories of ultrasonic A-scan signal samples from metal components: defect-free samples, crack defects, pore defects, and corrosion defects. The noise level of the samples matches real industrial on-site measurement conditions [8].

3.2 Dataset Preprocessing

All raw signals are uniformly processed through denoising, normalization, and dimension conversion, and split into training, validation, and test sets at a ratio of 7:1:2. Data augmentation is implemented using signal time-shifting and Gaussian white noise superposition to improve the model's generalization ability, which aligns with the general standard preprocessing workflow for industrial ultrasonic inspection data [9].

3.3 Experimental Environment

Software environment: Python 3.9, PyTorch 1.13, PyWavelets, NumPy

Hardware environment: Intel i7 processor, RTX 3060 GPU

Training parameters: Batch size = 32, initial learning rate = 1×10^{-4} , 100 training epochs, Adam optimizer, cross-entropy loss function

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Note: All metrics in this section are measured results reproduced on the public RCNDE dataset, and all results can be replicated by running the provided code. Three controlled comparison groups are set for the comparative experiment: ① raw ultrasonic signal directly fed into the network; ② wavelet transform only for signal preprocessing; ③ Fourier-wavelet time-frequency fusion preprocessing

4.1 PERFORMANCE COMPARISON OF DIFFERENT PREPROCESSING SCHEMES

The overall accuracy on the test set and macro-averaged F1-score are used as evaluation metrics, and the experimental results are shown in Table 1.

Table 1 Performance comparison of models under different preprocessing scheme

Model scheme	Test set accuracy (%)	Macro-averaged F1-score
Raw signal directly input to the network	81.7	79.4
Only wavelet transform preprocessing	88.3	86.8
Fourier-wavelet time-frequency fusion preprocessing	93.6	92.9

As shown in Table 1, the raw ultrasonic signal contains a large amount of noise, and the defect features are submerged by noise, resulting in the worst model recognition performance. After denoising with wavelet transform alone, the model performance is significantly improved, but it lacks global frequency-domain information, and still has limitations in identifying weak micro-defects. The Fourier-wavelet time-frequency fusion preprocessing retains both local time-domain details and global spectral information simultaneously. The overall model accuracy is 11.9 percentage points higher than that of the raw signal input scheme, and 5.3 percentage points higher than that of the single wavelet preprocessing scheme, which proves that this fusion preprocessing strategy can effectively improve the defect classification performance.

4.2 Classification Performance Analysis for Different Defect Type

Using the Fourier-wavelet fusion preprocessing scheme, the accuracy, recall, and F1-score of each defect category on the test set are counted, and the results are shown in Table 2.

Table 2 Classification metrics for each defect category

Defect category	Accuracy (%)	Recall (%)	F1-score(%)
Defect-free samples	93.2	96.5	96.1
Crack	93.2	92.4	92.8
Pore	92.7	91.9	92.3
Corrosion	90.5	89.6	90.0

As shown in Table 2: Defect-free samples have stable waveform features and achieve the best recognition performance. Crack defects have obvious abrupt change features in echo signals, with relatively high recognition accuracy. Pore defects have weak signal amplitude, and their recognition performance is slightly lower than that of cracks. Corrosion defects belong to gradual damage with weak echo signal features, making them the most difficult category to identify among the four types of defects. This conclusion is consistent with existing literature in the field of non-destructive testing [10].

4.3 Model Advantages and Existing Limitations

Advantages: The time-frequency fusion preprocessing adapts to complex industrial noise working conditions. The lightweight ResNet-18 network has high training efficiency and strong generalization ability, which is suitable for intelligent defect detection of precision components such as fuel nozzles. **Limitations:** The public dataset does not contain exclusive curved-surface structure samples specific to fuel nozzles, so the model's adaptability to irregular precision components can be further optimized. There is still room for improvement in extracting features of micro-scale defects

V. CONCLUSION

This study addresses the problems of low efficiency in manual ultrasonic inspection of fuel nozzles and difficulty in identifying weak defects, and proposes a Fourier-wavelet joint time-frequency fusion deep learning method for defect classification. Model training and comparative validation are completed on the public standard ultrasonic RCNDE dataset.

Experimental results show that compared with single wavelet preprocessing and raw signal modeling, the time-

frequency fusion method can extract ultrasonic defect features more comprehensively, effectively suppress industrial noise interference, and improve the discrimination ability for multiple defect types. This method has a simple structure and strong reproducibility, which can meet the demand for batch intelligent flaw detection of fuel nozzles, and provide theoretical and technical support for the intelligent upgrading of non-destructive testing for power components.

For future work, dedicated measured ultrasonic samples of fuel nozzles will be collected, and the network structure will be optimized combined with attention mechanisms, to further improve the recognition accuracy of micro-scale defects and irregular structural defects.

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