ISSN: 2472-3703 DOI: 10.6911/WSRJ.202405_10(5).0005

Aircraft Electromechanical Equipment Fault Detection Method Combined with Big Data Model

Jinze Li*

AVIC Xi'AN AERONAUTICS COMPUTING TECHNIQUE RESEARCH INSTITUTE, Xi'an, Shaanxi, 710000, China

*Corresponding authors: Jinze Li

Abstract

Aiming at the problem that the vibration signals of rolling Electric Unmanned Aerial Vehicle equipments are easily disturbed by external noise, and the traditional fault diagnosis methods are difficult to extract fault features with low accuracy, a rolling Electric Unmanned Aerial Vehicle equipment fault diagnosis method based on communication clutter suppression wavelet transform (WT) mechanism and convolutional neural network combined with support vector machine (CNN-SVM) is proposed. Firstly, the extended Electric Unmanned Aerial Vehicle equipment vibration signal is transformed into a two-dimensional wavelet time-frequency map using the wavelet transform method. Secondly, an improved convolutional neural network model is used to train the segmented two-dimensional image set to extract the deep features of time-frequency images. Finally, the extracted feature vector is input into the SVM classification layer after the parameter optimization to realize the fault classification of rolling Electric Unmanned Aerial Vehicle equipments. The experimental results show that the recognition accuracy of the proposed method is higher than traditional method.

Keywords

Electric Unmanned Aerial Vehicle equipment; Convolutional neural network; Fault diagnosis.

1. INTRODUCTION

With the rapid development of science and technology, modern industrial productivity has been significantly improved, and the scale and complexity of rotating machinery and equipment are also increasing [1]. As the core part of rotating machinery, Electric Unmanned Aerial Vehicle equipments bear the important function of supporting and reducing the friction of the unit. Electric Unmanned Aerial Vehicle equipments are the core components of large rotating machinery such as steam turbine units. Due to high operating loads and harsh working environments, long-term operation can easily lead to deterioration of lubrication status, which in turn can cause a series of adverse reactions such as friction, biting, corrosion, cracks, etc., ultimately leading to oil film instability, disrupting normal lubrication status, and causing major safety accidents, Therefore, effective monitoring and early warning of the lubrication status of sliding Electric Unmanned Aerial Vehicle equipments is of great significance [2]. Electric Unmanned Aerial Vehicle equipments is of great significance to ensure the safety and economic benefits of industrial production.

However, because the Electric Unmanned Aerial Vehicle equipment is affected by many external factors and noise in the long-term work, the collected vibration signal becomes complicated and difficult to analyze, which makes the fault characteristics difficult to extract [3].

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In order to effectively extract fault characteristics in Electric Unmanned Aerial Vehicle equipments, we usually need to de-noise the signal first. Common signal processing methods include wavelet transform and empirical mode decomposition. Although Empirical Mode Decomposition (EMD) method has been widely used in processing rotating machinery fault signals, there are still problems of overlapping of different intrinsic mode functions and pseudo-modes on signal boundaries. For this reason, Ensemble Empirical Mode Decomposition (EEMD) is proposed [4]. Nasiri et al. [5] proposed three improved LeNet fault diagnosis models and compared the influence of different fine-tuning methods on transfer learning diagnosis results. Riba et al. [6] use the self-developed experimental device to transform the collected one-dimensional vibration signal through the characteristics of Continuous wavelet transform, CWT, to obtain the input time-frequency image. Input to CNN for fault classification, the highest classification accuracy can reach 100%. Berri et al. [7] combine Global Average Pooling (GAP) with the convolution layer to reduce the use of the full connection layer in the previous CNN model and solve the problem of long training time and many parameters in the traditional CNN model. Traditional convolutional neural networks usually use Softmax classifier to achieve fault classification in fault diagnosis, but SVM classifier is more powerful than Softmax classifier in the case of multiple classifications. In addition, traditional CNN uses full connection layer with many parameters and takes a long time, which is easy to cause overfitting [8].

Aiming at the problems existing in the traditional intelligent fault diagnosis methods, this paper will use the combination of CNN and SVM to achieve Electric Unmanned Aerial Vehicle equipment fault classification. Firstly, the Electric Unmanned Aerial Vehicle equipment vibration signal collected by the acceleration sensor is normalized, and the data is enhanced by 1/3 overlapping data acquisition. Secondly, the dimension conversion method is used to convert the two-dimensional time-frequency image into CNN to extract the deep features of the signal. Finally, the extracted feature vectors are normalized and divided and input into the SVM optimized to realize classification diagnosis.

2. METHOD

2.1. Wavelet scattering transform and CNN-SVM fault diagnosis model

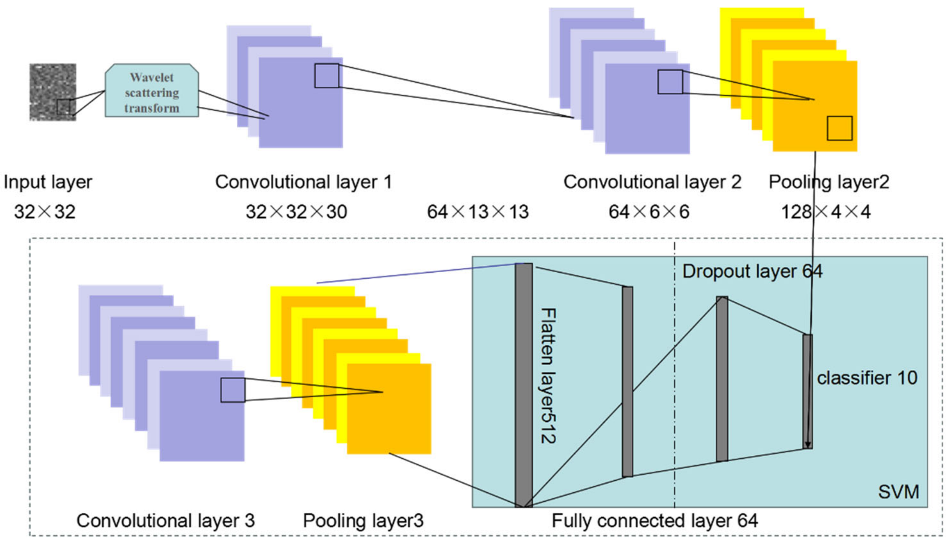

Figure 1. Wavelet scattering transform and CNN-SVM fault diagnosis model Structure

Aiming at the deficiency of traditional CNN (convolutional neural network, CNN) model diagnosis and recognition accuracy, this paper designed a three-layer stacked CNN-SVM (convolutional neural network combined with support vector machine, CNN-SVM) network.

Firstly, the extended Electric Unmanned Aerial Vehicle equipment vibration signal is transformed into a two-dimensional wavelet time-frequency map using the wavelet transform (WT) method. Secondly, an improved convolutional neural network model is used to train the segmented two-dimensional image set to extract the deep features of time-frequency images. Finally, the extracted feature vector is input into the SVM classification layer after the parameter optimization to realize the fault classification of rolling Electric Unmanned Aerial Vehicle equipments. Wavelet scattering transform and CNN-SVM fault diagnosis model as shown on figure 1.

2.2. Wavelet scattering transform

Because the acoustic emission signal of the Electric Unmanned Aerial Vehicle equipment collected in practice will be interfered by the noise of the surrounding working environment, it will affect the identification and analysis of the weak signal in the early fault stage. Therefore, a signal feature analysis and extraction method with translation invariance and local stability is needed. In this paper, wavelet scattering transform (WST) is used to extract the acoustic emission signals of sliding Electric Unmanned Aerial Vehicle equipment automatically. The wavelet scattering framework is shown in Figure 2. Firstly, wavelet scattering averages the input signal using the wavelet low-pass sweep filter to generate layer 0 scattering coefficient [9]. Then the high-pass wavelet filter ψ transforms the signal continuously to generate a set of scaling coefficients. The nonlinear operator (called modulus) is applied to the scaling coefficients, and the output is filtered by wavelet low-pass filter to generate the first layer scattering coefficients. The output of the upper layer becomes the input of the operation of the next layer: The lubrication state identification of plain Electric Unmanned Aerial Vehicle equipments based on acoustic emission and WST-CNN coordination is repeated in the same process to obtain the scattering coefficient of the second layer. In short, WST can be summarized as the convolutional calculation of the wavelet sign added with nonlinear operation to obtain the wavelet sign with translation invariance and local stability [10], and the wavelet scattering transformation formula is:

$$S_J(n)f = |f \cdot \psi_n(x)| \cdot \phi_J \tag{1}$$

Among: ψ is a pass filter; ϕ is a low-pass filter;

J is the maximum scale; $S_J(n)f$ Is the scattering coefficient, i.e. the wavelet scattering feature.

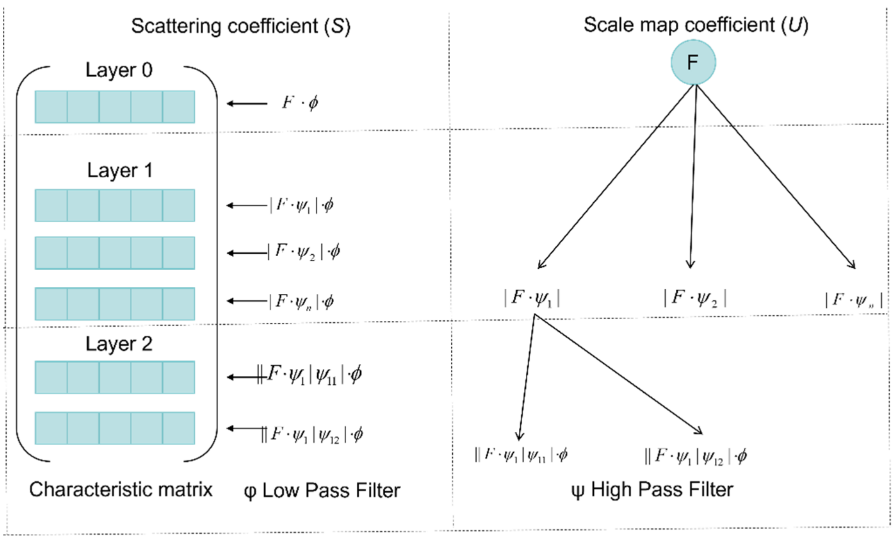

Figure 2. Wavelet scattering framework

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Since each iteration requires more computing power, for the acoustic emission signal of plain Electric Unmanned Aerial Vehicle equipment [11], three layers can satisfy the application: the first layer basically performs average operation, but the details of the signal are lost; Layer 2 captures detail, similar to scale-invariant transform function; Layer 3 provides additional information to improve classification.

The linear combination form of multi-kernel functions is

$$K(x_i, x) = \gamma K_1(x_i, x) + (1-\gamma) K_2(x_i, x), \\ 0 \le \gamma \le 1 \tag{2}$$

$K_1(x_i, x) = (x^T \cdot y + 1)^d, K_2(x_i, x) = \exp(-\frac{\| x - y \|^2}{2\sigma^2})$ is the weight coefficient. Combined with Lagrange duality, the hyperplane finding problem is transformed. To solve the duality problem, the objective function based on kernel function is:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x) \\ s.t. \sum_{i=1}^{n} \alpha_i y_i = 0, 0 \le \alpha_i \le c \tag{3}$$

The corresponding decision function is:

$$f(x) = sign(\sum_{i=1}^{n} a_i * y_i K(x_i \cdot x) + b*) \tag{4}$$

Gaussian kernel function parameter σ, and weight coefficient γ make the selection of MKLSVM parameters particularly complex. To choose the right one Parameters, using particle swarm optimization algorithm to optimize parameters.

3. EXPERIMENT

3.1. Wavelet Transform Scattering Coefficient Setting

In traditional or shallow machine learning techniques, a manual feature extraction step is usually required to learn differentiated information from data such as images. Features and classifiers must be designed and selected manually [12]. The wavelet scattering transformation of the data can not only reduce the dimension of the monitoring data, reduce redundant information and improve the computational efficiency, but also extract the essential characteristics of the data and extract the implicit signal characteristics. Figure 6 shows the structure of a wavelet scattering network, which is called a deep network because it performs three main tasks that make up a deep network: Convolution, nonlinear and pooling. Convolution is performed by wavelet, the modal operator [13] is used as linearization, and the filtering of low filters is similar to the pool wavelet scattering network, which can obtain low variance features from time series and image data with less configuration, and capture important information while reducing dimensionality [14]. For use in machine learning and deep learning.

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3.2. Comparison of fault diagnosis results

The actual test classification results completely match the predicted classification results, and there are no misidentified samples. As shown in Table 1, the average classification accuracy of the proposed model is 0.33% higher than that of the traditional CNN fault diagnosis results, achieving a high diagnostic accuracy.

Table 1. Average Diagnostic Accuracy Of The Model

Method	Classification accuracy%
CNN-Softmax	99.11
proposed method	99.83

In order to evaluate the anti-noise capability of the proposed method, the model trained in 3.2 is saved, and noise interference is added to the data of the verification set, and Gaussian white noise of -4dB, 0dB 4dB, 8dB and 12dB is added respectively. The model classification results are shown in Table 1.

In this paper, traditional CNN was selected to extract fault features and input them into fault diagnosis classification models of different classifiers. The input data were the same, and the diagnostic results were compared with the method in this paper, as shown in Figure 3.

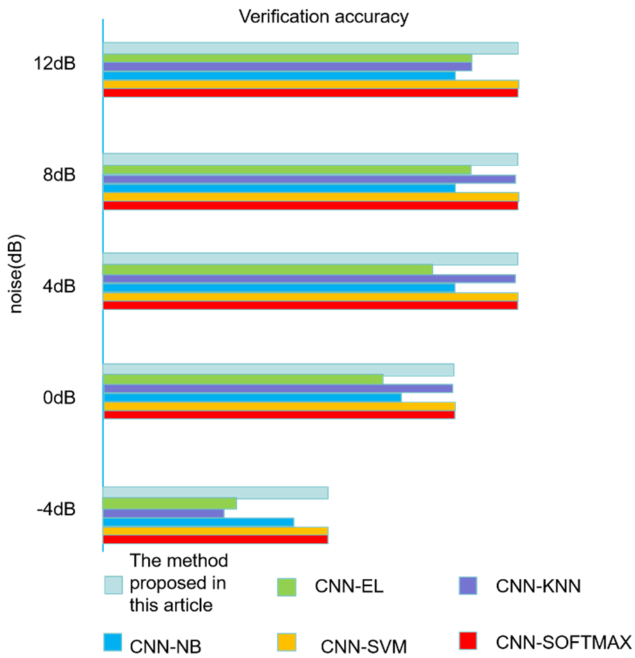

Figure 3. Diagnosis accuracy of each model under different noise conditions

It can be clearly seen from the above table that compared with other fault diagnosis methods that use CNN to extract features and input different classifiers for classification, the verification accuracy of the proposed method in this paper has obvious advantages. In order to verify that the model also has good fault classification results under variable load conditions, the Electric Unmanned Aerial Vehicle equipment fault data under two load conditions of motor speed of 1797r/min and 1772r/min are selected in the experiment, and the fault types are the same. Therefore, there are 14,000 wavelet time-frequency fault diagrams after WT conversion. Of these, 11,200 are the training set and the remaining 2,800 are the validation set. The average

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value removed from the five experimental results is taken as the final training result of the experiment. Figure 4 shows the column analysis diagram of each comparison method.

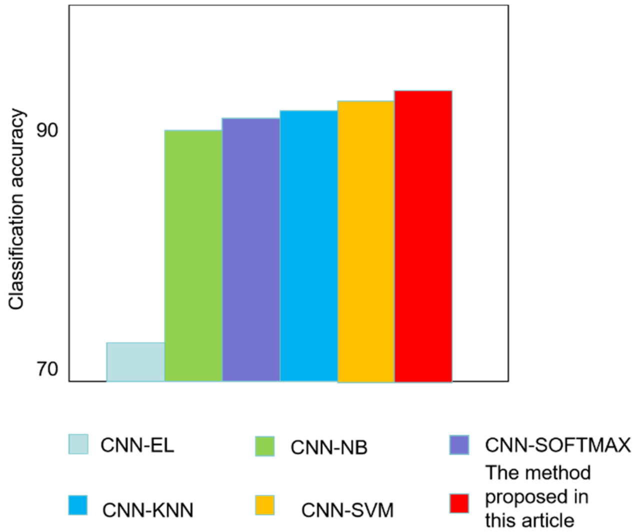

Figure 4. Diagnosis accuracy of each model under different working conditions

4. CONCLUSION

This paper presents a Electric Unmanned Aerial Vehicle equipment fault detection method based on communication clutter suppression technology combined with CNN-SVW. The wavelet scattering network is easy to set up, easy to understand and interpret the extracted feature matrix, and has both translation invariance and local stability, and the extracted feature matrix has stronger robustness. In practical application, the main parameters of wavelet scattering network are selected and compared.

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