A Fiber Vibration Signal Identification Method Based on the Combination of EWT-FE and LSTM

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Abstract. As the optical fiber perimeter security system is widely used in real life, how to identify the types of intrusion events in a timely and effective manner is becoming a major research hotspot. At present, in this field, various signal feature extraction algorithms are usually used to extract intrusion signal features to form feature vectors, and then machine learning algorithms are used to classify the feature vectors to achieve the role of identifying the types of intrusion events. As a common signal feature extraction algorithm, the EMD algorithm has been widely used in the feature extraction of various vibration signals, but it will have the problem of modal aliasing and affect the feature extraction effect of the signal. Therefore, EWT, VMD and other algorithms have been successively used to improve modal aliasing. On the basis of fully comparing the existing algorithms, this paper proposes a fiber vibration signal identification method that decomposes the signal through the empirical wavelet transform (EWT) algorithm and then extracts the fuzzy entropy (FE) of each component, and uses LSTM for classification. The final experiment shows that the method can identify four kinds of fiber intrusion signals in time and effectively, with an average recognition accuracy rate of 97.87%, especially for flap and knock recognition rate of 100%.

Keywords. Empirical wavelet transform, Fuzzy entropy, LSTM.

1. Introduction
At present, the optical fiber perimeter security system on the market mainly uses interferometer-based optical fiber distributed sensors such as Michelson interferometer, MZ interferometer, Sagnac interferometer, etc. The basic principle is to sense the light inside the optical fiber when an intrusion event occurs. Certain characteristics such as phase, intensity, wavelength, etc. will change, and then a series of modulation signals, namely fiber vibration signals, will be generated in the photodetector. Optical fiber vibration signal is a non-stationary signal. The feature extraction methods of this type of signal currently mainly include wavelet decomposition, other decomposition models such as EMD, VMD, etc., and intuitive feature extraction methods that use waveform statistical parameters. Some scholars use the wavelet transform multi-scale analysis method to extract the high-frequency coefficients of each scale of the signal decomposition, and then calculate the energy on each scale space, and select the scale space energy to form the feature vector for classification and recognition. In 1998, Huang [1] et al. used the EMD algorithm to adaptively empirically decompose the signal for non-stationary signals, and then perform the Hilbert transform to obtain the Hilbert spectrum and time-frequency energy spectrum to achieve the signal Time-frequency localized analysis. However, the EMD algorithm is prone to modal aliasing in signal feature extraction, which will greatly affect the
signal feature extraction effect. Mahmoud [2] et al. proposed the concept of zero-crossing rate of fiber vibration signals, using the zero-crossing rate of the signal and other statistical parameters to form a feature vector, and detecting or identifying intrusion signals by setting a threshold. However, due to the lack of signal pattern expression details, lack of adaptability, sensitive parameter characteristics, and false alarms, this method is only suitable for situations with obvious statistical characteristics.

In 2013, Gilles of France [3] proposed an empirical wavelet transform (EWT) algorithm based on adaptive empirical mode decomposition and wavelet analysis theory. This algorithm can effectively improve the modal aliasing problem in EMD and is aimed at non-stationary another breakthrough in signal processing. Now EWT has been widely used in the identification of many non-stationary signals. For example, Yu-xing Li [4] and others combined EWT with RDE (Reverse dispersion entropy) to identify four types of ship radiation signals, and achieved good results. Peng Yin and Xin Xiong [5] decomposed the fault signal of rolling bearing by EWT, compared the kurtosis value of each component of EWT and EMD, and provided a new idea for identifying fault signal of rolling bearing. Wu Deng [6] and others combined EWT and FE, decomposed four kinds of bearing signals and calculated fuzzy entropy respectively, and used SVM to classify and recognize different signals by setting thresholds. Experimental results show that EWT-FE has a higher accuracy rate than EMD-FE.

Fuzzy entropy (FE) is an improvement of sample entropy (SE). It aims at the defect of binary similarity judgment of distance and number in sample entropy. It proposes the use of membership function to judge similarity, so that fuzzy entropy can be a more precise description of the complexity of the time series. This paper combines EWT-FE and LSTM, proposes a fiber vibration signal identification method. As shown in figure 1, the original signal is preprocessed to denoise first, the vibration signal is intercepted from the original signal, and then the vibration signal is divided into M parts according to the time point. Perform EWT decomposition on each part of the signal, extract the fuzzy entropy of each component to form the feature vector of the part of the signal, and then arrange the feature vector of each part of the signal according to time points to form the characteristic matrix of the original signal, and finally use LSTM for classification and recognition.

2. Empirical Wavelet Transform
The empirical wavelet transform constructs a filter bank based on the wavelet frame theory, adaptively decomposes the signal into a series of AM-FM components arranged from high to low frequency, and then extracts the feature quantity. The specific implementation steps are as follows:

Step 1: Calculate the Fourier transform of the input signal f(n) to obtain the spectrogram.

Step 2: According to the spectrogram of the signal, find the local maximum points of f(w) and arrange them in descending order, and divide the signal according to the maximum points. Take the middle value of two adjacent maximum points as the frequency domain boundary point wn.

![Figure 1. Experiment process.](image-url)
Step 3: Construct scaling function $\hat{\phi}_n(\omega)$ and wavelet function $\hat{\varphi}_n(\omega)$.

$$
\hat{\phi}_n(\omega) = \begin{cases} 
1 & |\omega| \leq (1-\gamma)\omega_n \\
\cos \left( \frac{\pi}{2} \beta \left( \frac{1}{2\gamma\omega_n} \right) |\omega| - (1-\gamma)\omega_n \right) & (1-\gamma)\omega_n \leq |\omega| \leq (1+\gamma)\omega_n \\
0 & \text{otherwise}
\end{cases}
$$

$$
\hat{\varphi}_n(\omega) = \begin{cases} 
0 & x \leq 0 \\
\sin \left( \frac{\pi}{2} \beta \left( \frac{1}{2\gamma\omega_{n+1}} \right) |\omega| - (1-\gamma)\omega_n \right) & (1-\gamma)\omega_n \leq |\omega| \leq (1+\lambda)\omega_n \\
0 & \text{otherwise}
\end{cases}
$$

$$
\beta(x) = \begin{cases} 
x^4 \left( 35 - 84x + 70x^2 - 20x^3 \right) & x \leq 0 \\
1 & x \geq 1
\end{cases}
$$

$$
\gamma < \min_n \left( \frac{\omega_{n+1} - \omega_n}{\omega_{n+1} + \omega_n} \right)
$$

Step 4: Construct empirical wavelet transform, define the detail correlation coefficient $W_{f}^d(n, t)$ and approximate correlation coefficient $W_{f}^a(0, t)$.

$$
W_{f}^d(0, t) = \langle f, \phi_1 \rangle = \int f(t)\overline{\phi_1(t)} dt = F^{-1} \left( F(f) \overline{\phi_1(\omega)} \right)
$$

$$
W_{f}^d(n, t) = \langle f, \varphi_n \rangle = \int f(t)\overline{\varphi_n(t)} dt = F^{-1} \left( F(f) \overline{\varphi_n(\omega)} \right)
$$

Step 5: Perform signal reconstruction according to (7).

$$
f(t) = W_{f}^c(0, t) \ast \phi_1(t) + \sum_{n=1}^{N} W_{f}^c(n, t) \ast \varphi_n(t) = F^{-1} \left( F(f) \hat{\phi}_1(\omega) + \sum_{n=1}^{N} W_{f}^c(\omega) \hat{\varphi}_n(\omega) \right)
$$

3. Optical Fiber Vibration Signal Experiment

3.1. Feature Extraction and Classification Recognition

In this paper, a distributed optical fiber sensing system based on the Sagnac optical fiber interferometer collects 1280 optical fiber vibration signals of four types: throwing, flapping, knocking and walking, including 300 throwing, 288 flapping, 300 knocking, and 392 walking. After preprocessing the original signal by spectral subtraction, the vibration segment signal is intercepted by endpoint detection, as shown in figure 2.
Figure 3 shows the result of EWT decomposition of the vibration signal in 5 layers. It can be seen that there is no obvious modal aliasing phenomenon in each component. In [6], the author proposed a method of extracting fuzzy entropy of each component by EWT decomposition of bearing fault signal and then using SVM to classify. Although this method can effectively identify four kinds of bearing fault signals, it is used in fiber vibration signal identification, the average recognition accuracy of this method is less than 50%. This is because although the waveforms of the four optical fiber vibration signals have obvious differences, the fuzzy entropy of the flap type signals in all samples collected is concentrated between 0.9-2.4. The knock is 1.8-2.4, the throw is 0.6-1.6, and the walk is 0.4-2.5, which causes a large number of different signal samples to have similar fuzzy entropy. Therefore, only extracting the fuzzy entropy reflecting the complexity of the signal is difficult to effectively distinguish the four types of optical fiber vibration signals.

Figure 2. Four signals.
Therefore, in order to take full advantage of the obvious difference between the four fiber vibration signal waveforms, the signal is divided into M parts according to time points, and then the signal of each part is decomposed by EWT, and the fuzzy entropy of each component is extracted to form the characteristic matrix of the original signal. When calculating fuzzy entropy, it is necessary to set the embedding dimension m and the similarity tolerance r. m generally takes the value 2, and r generally takes 0.1-0.25 standard deviation of the original data.

Since different signals have different time lengths, the characteristic matrices of each signal have different dimensions, and traditional classification algorithms such as SVM will be difficult to process when dealing with such data. Therefore, this paper uses LSTM as a classifier. LSTM can not only process time series data in multiple dimensions, but also compared to traditional machine learning algorithms, LSTM can use the advantages of big data to learn more useful features, thereby ultimately improving the accuracy of classification or prediction. This article uses the LSTM toolkit in Matlab to realize the classification and recognition of the four signals, 60% of the 1280 samples are used for training and 40% are used for testing.

### 3.2. Result Analysis

The EMD algorithm cannot pre-set the number of decomposition layers. Even the same type of fiber signal has different decomposition layers. In [7], the author uses the correlation coefficient method to calculate the correlation coefficient between each component and the original signal, and selects the correlation coefficient $r_j \geq 0.3$ component, and then calculate its scale entropy as a feature vector for classification and recognition. Therefore, this paper also performs EMD decomposition on each part of the signal and selects the components with correlation coefficients greater than 0.3 to extract the fuzzy entropy to form a feature matrix. The number of decomposition layers of VMD and EWT is set to 5. Table 1 shows the classification accuracy of the three algorithms.

| Method Recognition | EMD-FE-LS TM | VMD-FE-LS TM | EWT-FE-LSTM |
|--------------------|-------------|-------------|-------------|
| throw              | 86.6%       | 91.23%      | 96.82%      |
| Flap               | 99.05%      | 98.35%      | 100%        |
| knock              | 98.5%       | 99.42%      | 100%        |
| walk               | 84.65%      | 91.57%      | 94.66%      |
| Average            | 92.2%       | 95.165%     | 97.87%      |
As shown in table 1, the overall recognition rate of EMD and VMD for the four fiber vibration signals is lower than EWT. After many experiments, the classification accuracy of EWT reached 97.87%, especially the accuracy of flap and knock reached 100%. It can be seen that a fiber vibration signal identification method based on EWT-FE-LSTM proposed in this paper can effectively identify the four signal types in the experiment.

4. Conclusion
The empirical wavelet transform (EWT) combines the adaptive characteristics of EMD on the basis of wavelet transform, and can adaptively set the number of signal modal decomposition layers. Compared with EMD, it has a complete theoretical basis. Experiments show that both EWT and VMD can effectively suppress the modal aliasing phenomenon that occurs in signal feature extraction, but the feature extraction effect of VMD depends on the parameter combination. Different parameter combinations have a greater impact on the ability to suppress modal aliasing, and currently there is still a lack of strict and effective theoretical basis on how to select the parameters of VMD. Compared with traditional machine learning algorithms, LSTM in deep learning can not only process time series data with various dimensions, but also use the advantages of independent learning features of big data to obtain higher classification accuracy. This paper proposes a fiber vibration signal recognition method that combines artificially extracted features with LSTM. The fuzzy entropy of the signal is extracted by EWT to form a feature vector, and then the ability of LSTM to automatically learn features is used to further extract effective features from the feature vector. Obtain a higher classification accuracy rate. Compared with traditional signal recognition methods, this method does not need to extract too many signal features, and at the same time it can better deal with different working conditions and has stronger model generalization ability.

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