An Energy Ratio Feature Extraction Method for Optical Fiber Vibration Signal

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Abstract: The intrusion events in the optical fiber pre-warning system (OFPS) are divided into two types which are harmful intrusion event and harmless interference event. At present, the signal feature extraction methods of these two types of events are usually designed from the view of the time domain. However, the differences of time-domain characteristics for different harmful intrusion events are not obvious, which cannot reflect the diversity of them in detail. We find that the spectrum distribution of different intrusion signals has obvious differences. For this reason, the intrusion signal is transformed into the frequency domain. In this paper, an energy ratio feature extraction method of harmful intrusion event is drawn on. Firstly, the intrusion signals are pre-processed and the power spectral density (PSD) is calculated. Then, the energy ratio of different frequency bands is calculated, and the corresponding feature vector of each type of intrusion event is further formed. The linear discriminant analysis (LDA) classifier is used to identify the harmful intrusion events in the paper. Experimental results show that the algorithm improves the recognition rate of the intrusion signal, and further verifies the feasibility and validity of the algorithm.

Keywords: OFPS; energy ratio; LDA classification

1. Introduction

The optical fiber pre-warning system utilizes the optical fiber sensor technology to realize the external intrusions pre-warning [1, 2], which is widely used in the perimeter security field such as border and military areas. At present, the acquisition of the intrusion signal in optical fiber pre-warning system (OFPS) is mainly based on Mach-Zehnder (M-Z) interferometer [3] and phase-sensitive optical time domain interferometer (Φ-OTDR) [4]. In practical applications, the number of fiber core in fiber-optic sensor based on the M-Z system is 3 or 5

[5, 6] which exceeds the number of remaining cores. Besides, for concurrent intrusions, the detection performance of the system based on M-Z interferometer will decline badly [7], which further limits the application of the system in the scene. References [7, 8] propose a method of signal acquisition for OFPS based on Φ-OTDR with single-core optical fiber, which can establish sufficient data samples for the conventional perimeter intrusion events and meet the majority of concurrent intrusions.

In this paper, the vibration signal is collected by

the system based on Φ-OTDR and is analyzed. At present, researches concerning optical fiber vibration mainly include measuring and collecting data, signal processing, and data analysis. There are various types of intrusion events in the actual scene. According to the detected vibration signal, accurately identifying the harmful intrusion event and harmless interference event is one of the key technologies of the OFPS. And it has important theoretical value and practical significance, which can forecast pipeline leakage and prevent serious loss occurring in the field of pipeline transport [9, 10]. In this paper, an energy ratio feature extraction method is drawn on in OFPS.

The feature extraction method based on time-domain analysis is widely used for its rapid calculation and applicable practical application. Reference [11] proposes a feature extraction method for optical fiber signal based on time-domain features, which performs well in distinguishing harmful intrusion event and harmless interference. But for different types of harmful intrusion events, this method shows badly. Reference [12] proposes an improved fast Fourier transform (FFT) filtering method based on energy-ratio pretreatment which can distinguish the harmful intrusion event and harmless interference event efficiently. Reference [13] proposes a robust method to identify the optical fiber intrusion, which extracts the time-domain characteristics of the signals as inputs into the neural network for training and recognition. However, the adaptive threshold is almost decided by experience without definite mathematical reasoning. In [14], the battlefield-acoustic signal is decomposed, and the energy ratio is taken as the characteristic vector for classification, where the performance of classifying the type of battlefield-acoustic signal is obvious. It is clear that the acoustic signal and the optical fiber signal are very similar that both are one-dimensional signal. Hence, the frequency domain analysis is used in this paper, and the extracted feature vectors in the frequency domain are input into the classifier. In this paper, this energy ratio feature extraction method is

drawn on, which can preserve the frequency band where exists intrusion signal, and the effective information is retained with low cost of calculation. The linear discriminant analysis (LDA) classifier [15] is adopted in order to illustrate the validity of the feature.

The organization of the paper is listed as follows. In Section 2, the whole process of the proposed algorithm is given, and the detailed flow of energy ratio feature extraction is described. The experiments with real data are performed in Section 3. Finally, conclusions are provided in Section 4.

2. Feature extraction and classification

The overall flow chart of the signal feature extraction and recognition algorithm is depicted in Fig. 1. The main steps are as follows: (1) pre-processing the signals and calculating the signals' power spectral density (PSD); (2) dividing the signals into n segments; (3) calculating the energy ratio of each frequency band; (4) classifying the signals by LDA classifier and obtaining the recognition ratio of different n; (5) feedback to the Step 2 to find the most suitable n. The parameter w of LDA classification model is obtained by training.
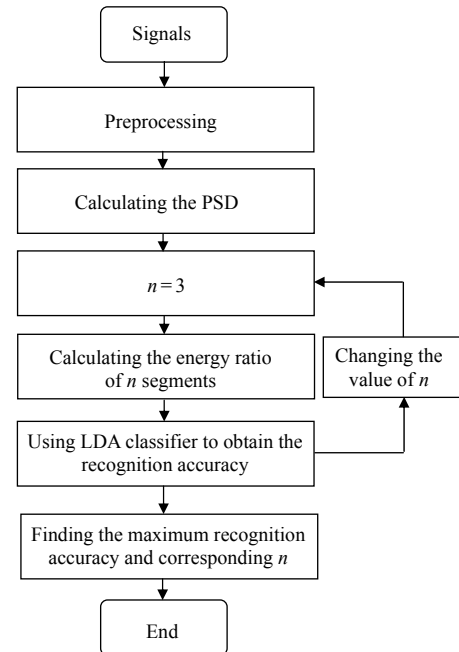

Fig. 1 Processing flow of intrusion signal recognition method of OFPS based on energy ratio.

In the process of training, the model parameter is obtained based on the above processes of the labeled samples.

2.1 Energy ratio extraction

The detailed flow of energy ratio extraction is shown in Fig. 2. Firstly, the signal is preprocessed, and the PSD is calculated. Then, the signals after PSD is divided into n segments, that is, the sum of energy is calculated in $1\text{Hz} - \dfrac{k}{n}\text{Hz}$, $\dfrac{k}{n}\text{Hz} - 2 \cdot \dfrac{k}{n}\text{Hz}$, $\cdots$, $(n-1)\dfrac{k}{n}\text{Hz} - k\text{Hz}$, and k is the length of the signals after PSD. Thus the total energy of the n frequency bands can be obtained. Finally, the energy ratios of the n frequency bands are calculated.
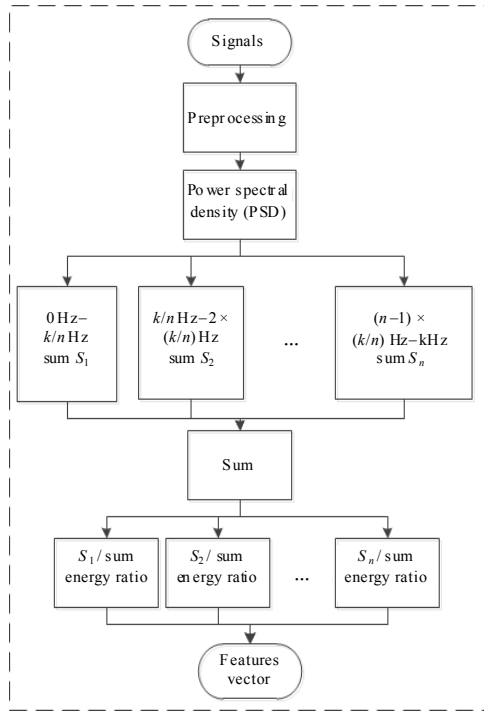

Fig. 2 Processing flow of energy ratio extraction.

Step 1: Through autocorrelation analysis and FFT, the PSD of the signal is obtained. The autocorrelation equation is defined as

$$R(k) = \frac{\sum\limits_{s=0}^{N-1-k}[X(1+s)v'(s)][X(1+s+k)v'(s+k)]}{\dfrac{1}{2}\left(\sum\limits_{s=0}^{N-1-k}[X(1+s)v'(s)]^2 + \sum\limits_{s=0}^{N-1-k}[X(1+s+k)v'(s+k)]^2\right)} \quad (1)$$

where X is the vibration signal, v denotes the window function, N is the length of the signal, and s is the position of signal sequence.

Step 2: Calculating the energy of n frequency bands, respectively.

Step 3: Obtaining the energy ratio of n frequency bands and normalizing them. The feature extraction of the vibration signal is accomplished.

2.2 LDA signal identification classification

In this paper, the vibration signal is classified by LDA classification algorithm, so as to realize the recognition of the event. LDA projects the high-dimensional sample data to the low-dimension best identification vector space by linear transformation which can guarantee the maximum interclass distance and minimum intra-class distance as much as possible.

According to the basic idea of LDA, the linear transformation is used to establish an objective function $J(w)$. We obtain w by the maximum value of $J(w)$ and then determine the threshold of the classification.

The objective (2) can be acquired by making the J_B bigger and the J_W smaller as

$$J(w) = \frac{J_B}{J_W} \quad (2)$$

where J_B is available as

$$J_B = w^T(\overline{x}_1 - \overline{x}_2)(\overline{x}_1 - \overline{x}_2)^T w \quad (3)$$

where w is an unknown vector, $\overline{x}_1$ is the center point coordinates of the first class of the sample, and $\overline{x}_2$ is the central point coordinates of the second class of the sample. S_B is expressed as

$$S_B = (\overline{x}_1 - \overline{x}_2)(\overline{x}_1 - \overline{x}_2)^T \quad (4)$$

$$J_B = w^T S_B w \quad (5)$$

$$J_W = \sum_{x \in X_1} w^T (x - \overline{x}_1)(x - \overline{x}_1)^T w + \sum_{x \in X_2} w^T (x - \overline{x}_2)(x - \overline{x}_2)^T w \quad (6)$$

where S_W is expressed as follows:

$$S_W = \sum_{x \in X_1} (x - \bar{x}_1)(x - \bar{x}_1)^{\mathrm{T}} +$$

$$\sum_{x \in X_2} (x - \bar{x}_2)(x - \bar{x}_2)^{\mathrm{T}}. \qquad (7)$$

Then (2) can be written as

$$J(w) = \frac{J_B}{J_W} = \frac{w^{\mathrm{T}} S_B w}{w^{\mathrm{T}} S_W w} \qquad (8)$$

where S_B and S_W represent the dispersion matrices of interclass and intra-class, respectively.

According to the Lagrange Multiplier, the constraint condition is taken as $w^{\mathrm{T}} S_W w = 1$,

$$w^{\mathrm{T}} S_B w = \lambda S_W w = S_W(\lambda w). \qquad (9)$$

Fisher discriminant analysis formula can be drawn from (9)

$$(S_W^{-1} S_B) w = \lambda w \qquad (10)$$

where w achieved by (10) is taken as the eigenvector which corresponds to the largest eigenvalue of $S_W^{-1} S_B$, so that the sample data has the best separation effect.

2.3 Method for obtaining the value of *n*

The signal after PSD is divided into n segments. Then, the energy ratio of different frequency bands corresponding n is calculated and further forms the feature vector space. And for different n, the recognition ratio can be obtained when the feature vectors are put into the LDA classifier. The value of the n corresponding to the maximum recognition ratio is what we need. The specific flow chart is shown as Fig. 3. Besides, Fig. 4 shows the energy ratio at $n = 4$.
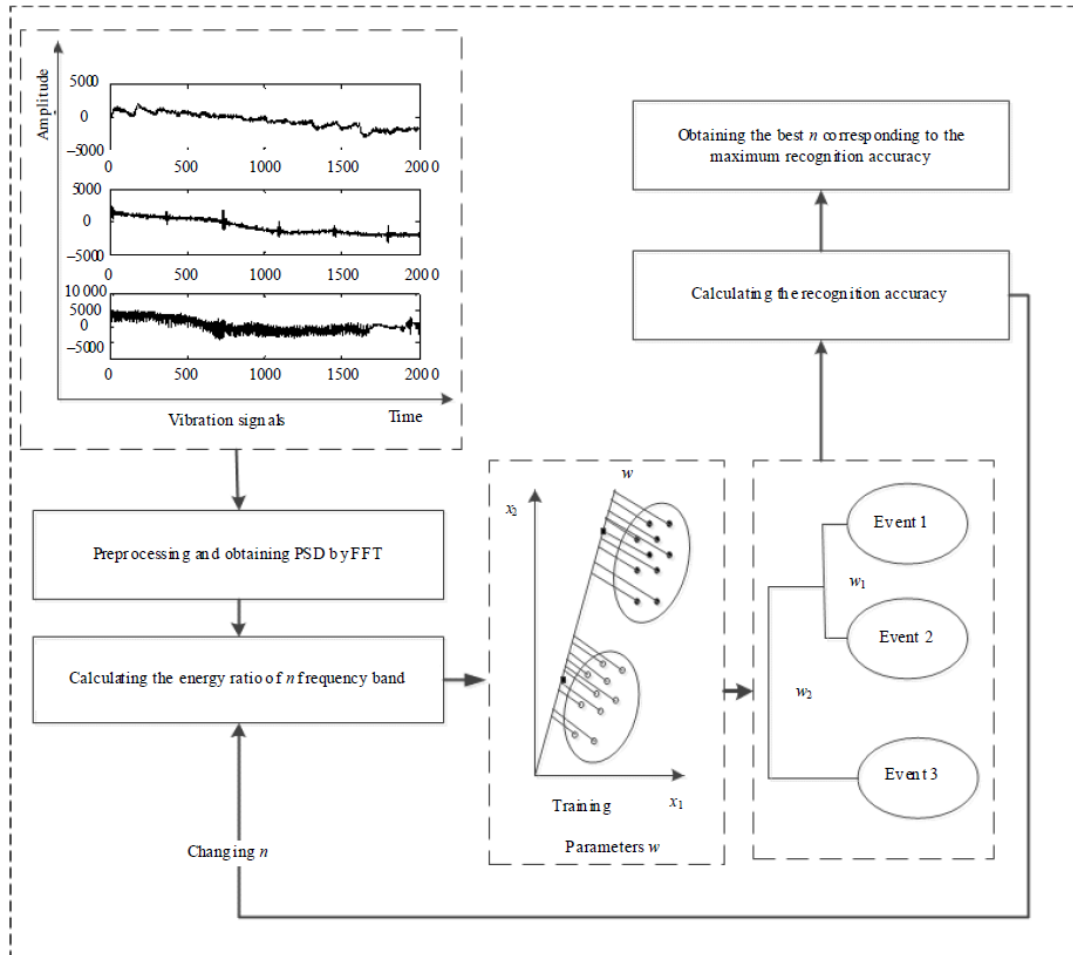

Fig. 3 Obtaining the best value of *n*.

In order to ensure the independence of the features, the energy ratios at $n-1$ frequency bands are taken as the final feature vector which is input into LDA classifier.
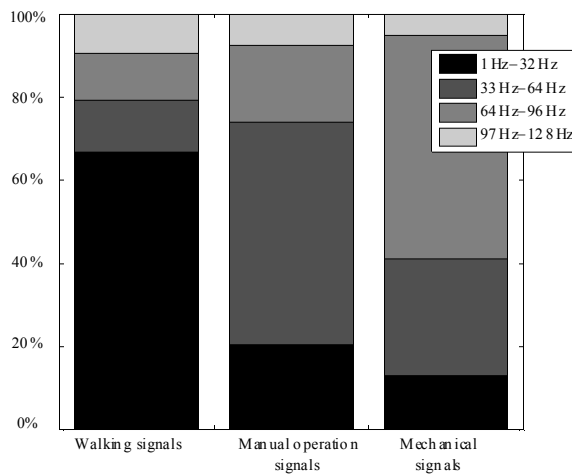
Fig. 4 Distribution of energy ratio in 4 frequency bands.

3. Experiment and analysis of measured data

3.1 Measured data

The measured data, collected in Mentougou, Beijing, China, are carefully analyzed. The obtained walking, mechanical, and manual vibration signals are the results of the waking, drilling, and picking by pickaxe. The resolutions in the time and spatial dimensions are 1 ms and 16 m. The vibration alarm points detected by the system are shown in Fig. 5, that is, the abscissa represents the position, and the ordinate represents the time in which the vibration can be shown as "•".
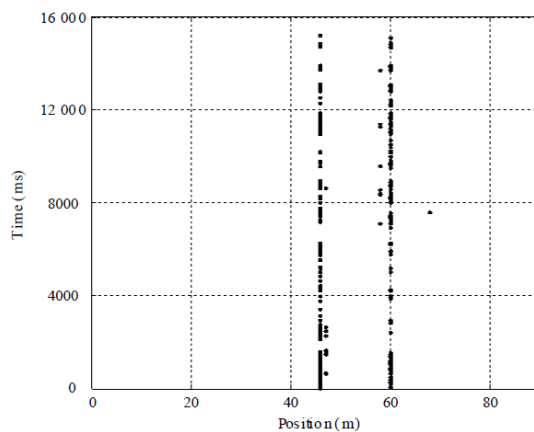

Fig.5 Detection result of optical vibration signal.

3.2 Feature extraction and recognition experiment based on energy ratio

The original waveforms of different types of vibration signal are shown in Fig. 6. According to the method described in Section 2.3, the recognition
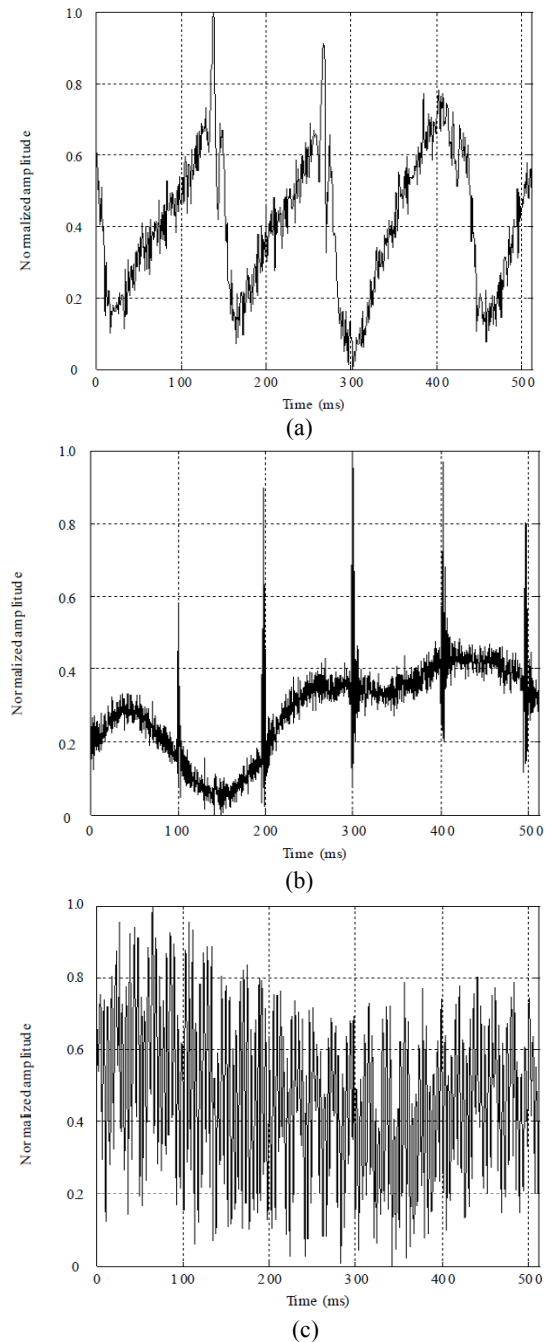
accuracy is shown in Table 1.

(a)

(b)

(c)

Fig. 6 Original vibration signal of system: (a) walking signals, (b) manual operation signals, and (c) mechanical signals.

As shown in Table 1, the best recognition accuracy appears when $n=4$. And then, the method mentioned in this paper is described next. According to Section 2.1, the signal spectrum is shown in Fig. 7. It can be seen from Fig. 7 that the frequency components of the walking signals, manual operation signals, and mechanical signals are mainly

distributed in ranges of 3 Hz–15 Hz, 30 Hz–50 Hz, and 55 Hz–70 Hz, respectively.

Table 1 Recognition accuracy of events at different *n*.

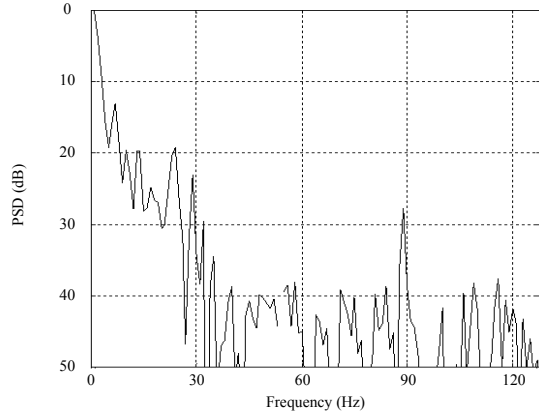| *n*	Recognition accuracy of different signals (%)		
	Walking signals	Manual operation signals	Mechanical signals
3	60	62	75
4	94	92	90
7	85	77	72

(a)

(b)

(c)
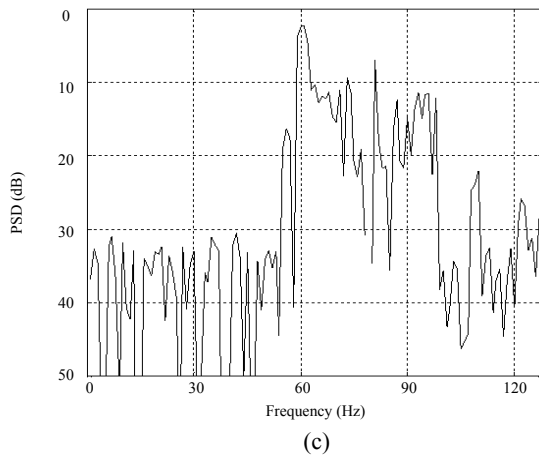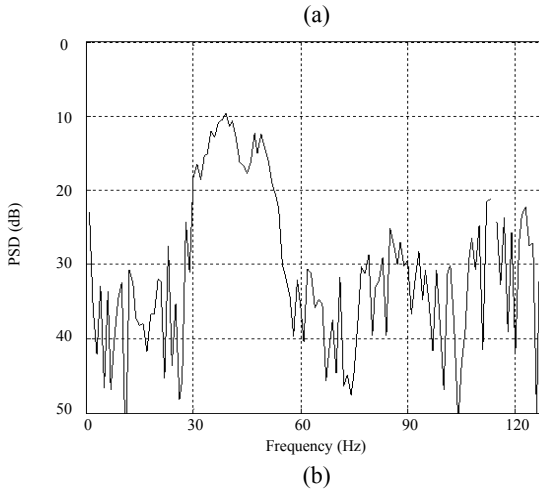
Fig. 7 Power spectral density of vibration signal: (a) walking signals, (b) manual operation signals, and (c) mechanical signals.

The features distribution figure of the three intrusion signals is shown in Fig. 8. As we can see from Fig. 8, there is a high dispersity between different intrusion signals, and points from each type of the signal are located closely together.
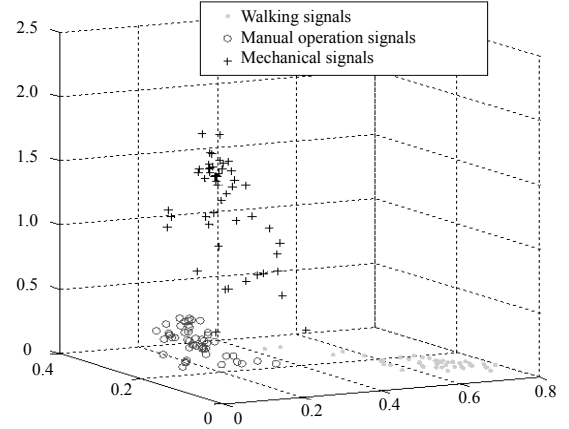

Fig. 8 Feature distribution of three signals.

Consequently, the concentration ranges of different signals are different. Therefore, the energy ratios of the three signals at 3 Hz–15 Hz, 30 Hz–50 Hz, and 55 Hz–70 Hz are calculated, whose results are shown in Fig. 9. It can be seen clearly from Fig. 9 that the energy of walking signal in the range of 3 Hz–15 Hz accounts for 79%, the energy of manual operation signal in the range of 30 Hz–50 Hz accounts for the highest, 58% and the energy of mechanical signal in the range of 55 Hz–70 Hz accounts for 62%.
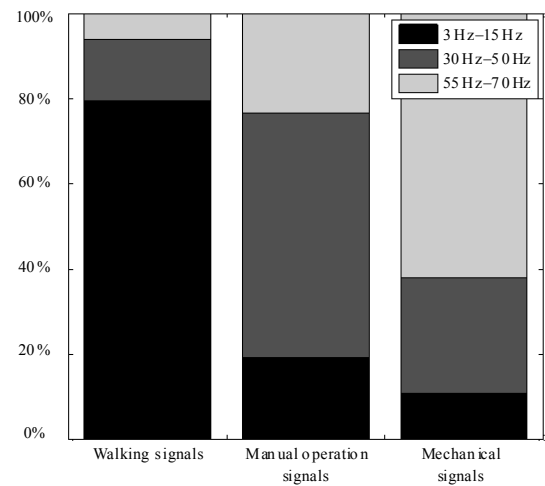

Fig. 9 Distribution of energy ratio.

The vibration signal is identified according to the method described in Section 2.2. According to

the class separability criteria in [16], J_1 represents that the bigger it is, the easier different classes can be classified. And J_1 between different signals are shown in Table 2.

Table 2 Separability criteria.

Signals	J_1
Walking signals and manual operation signals	3.2746
Walking signals and mechanical signals	3.1693
Mechanical signals and manual operation signals	1.7410

It can be seen from Table 2 that J_1 between walking signal and the other signals is bigger. Therefore, the walking signals are regarded as a class (Sample 1), while the manual operation signals and the mechanical signals are treated as another class (Sample 2). The LDA model parameters of training sample are used to train to find a suitable straight line *w* so that the two types of samples can be placed on both sides of the straight line.

The test samples are input into the LDA classification model obtained by training, and the test results are shown in Fig. 10. It can be clearly seen from Fig. 10 that after training, the LDA classification model can separate Sample 1 and Sample 2 as well as obtain the projection center point classification threshold *th* which is –0.1847. Thus the recognition of the walking signals is completed.
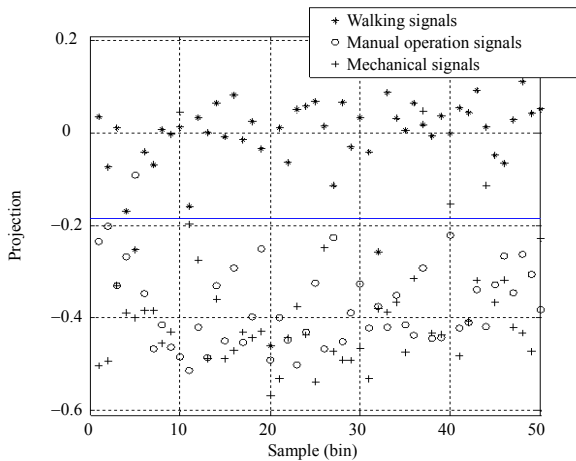

Fig. 10 Classification results of walking signals (Sample 1) and manual operation signals & mechanical signals (Sample 2).

Then, the manual operation signals (Sample 3) and mechanical signals are identified (Sample 4). Similarly, the LDA model parameters are trained by the training samples, and the test samples are input into the LDA classification model. The test results are shown in Fig. 11. According to Fig. 11, the manual operation signals and the mechanical signals can be separated, and the projection central point classification threshold *th* is –0.2847.
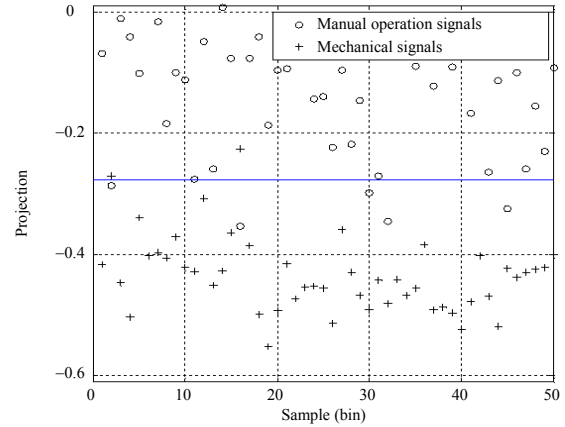

Fig. 11 Classification results of manual operation signals (Sample 3) and mechanical signals (Sample 4).

The LDA classification recognition rate of the test sample is calculated, and the trained optimal discriminant space is identified as the recognition criterion. The experimental results are shown in Table 3.

Table 3 Classification results of LDA.

Results Real signals	Walking signals	Manual operation signals	Mechanical signals	Recognition accuracy (%)
Walking signals	0.94	0.06	0	94
Manual operation signals	0.02	0.98	0	92
Mechanical signals	0.08	0.02	0.90	90

It can be seen from Table 3 that the method provided in this paper can effectively identify the walking signals, the manual signal, and the mechanical signals in the optical fiber in the OFPS, and achieves high recognition rate which is 94%, 92%, and 90%, respectively. Hence, we can draw the conclusion that the energy ratios extracted from fiber vibration signal are effective and reliable.

4. Conclusions

In this paper, the vibration signal of the OFPS is studied. According to the characteristics of different

vibration signals, the energy ratio feature extraction method is drawn on. The LDA model is used to reduce the size of the data and classify it. The projection parameters *w* are trained, and the projection central points are differentiated to different thresholds to realize the classification and recognition of the signals. After the experiments, and the distinction threshold *th* between walking signals and manual and mechanical signals is –0.1847, the distinction threshold *th* between the manual operation signals and the mechanical signals is –0.2947. The recognition rates of the walking signals, the manual signals, and the mechanical signals are 94%, 92%, and 90%, respectively. Therefore, it can be clearly seen that the algorithm can effectively recognize the fiber vibration and guarantee the reliability is high.

Acknowledgement

Reference

[1] Y. Yang, H. Feng, Z. H. Wang, Z. Sha, G. Q. Wang, Z. N. Jia, *et al.*, "Application and development of distributed optical fiber sensing technology in pipeline detection," *Electro-Optic Technology Application*, 2016, 31(6): 1–9.

[2] Z. G. Qu, "Study on the leakage detection and pre-warning techniques based on the distributed optical fiber for the long-distance oil and gas pipelines," Ph.D. dissertation, Tianjin University, Tianjin, China, 2007.

[3] J. M. Chen, "Research on fiber perimeter protection system based on Mach-Zehnder interferometer," M.S. thesis, Yanshan University, Qinhuangdao, China, 2012.

[4] F. Zhu, "Research on performance enhancement of phase sensitive time-domain reflection sensor system," Ph.D. dissertation, Nanjing University, Nanjing, China, 2015.

[5] Y. An, S. J. Jin, X. Feng, H. Feng, and Z. M. Zeng, "Optical fiber pipeline security pre warning system based on coherent Rayleigh scattering," *Journal of Tianjin University* (*Science and Technology*), 2015, 48(1): 70–75.

[6] L. P. Yin and G. Lei. "Joint stochastic distribution tracking control for multivariate descriptor systems with non-Gaussian variables," *International Journal of Systems Science*, 2012, 43(1): 192–200.

[7] H. Q. Qu, T. Zheng, F. K. Bi, and L. P. Pang, "Vibration detection method for optical fiber pre-warning system," *IET Signal Processing*, 2016, 10(6): 692–698.

[8] B. Yang, W. Gao, and G. Xi, "The key technologies for Φ-OTDR-based distributed fiber-optic sensing systems," *Study On Optical Communications*, 2012, 38(4): 19–22.

[9] H. Q. Qu, T. Zheng, L. P. Pang, and X. L. Li, "A new two-dimensional method to detect harmful intrusion vibrations for optical fiber pre-warning system," *Optik*, 2016, 127(10): 4461–4469.

[10] T. Zheng, "Theoretical basis research on detection and recognition method for Φ-OTDR optical fiber intrusion," M.S. thesis, North China University of Technology, Beijing, China, 2017.

[11] N. Lu, B. W. An, Y. L. Li, Y. L. Li, and X. J. Lu, "Signal recognition algorithm of fiber-optic security system based on time-domain features," *Transducer and Microsystem Technologies*, 2017, 36(4): 150–152.

[12] Y. Lu, Z. K. Han, and Y. Chen, "FFT narrow band filtering method based on energy-ratio pretreatment," *Journal of Southeast University* (*Natural Science Edition*), 2010, 40(5): 948–951.

[13] S. S. Mahmoud, Y. Visagathilagar, and J. Katsifolis, "Real-time distributed fiber optic sensor for security systems: performance, event classification and nuisance mitigation," *Photonic Sensors*, 2012, 2(3): 225–236.

[14] Y. X. Lv, S. X Sun, and X. H. Gu, "Battlefield acoustic target classification and recognition based on EMD and power ratio," *Journal of Vibration and Shock*, 2008, 27(11): 51–55.

[15] J. Y. Chen, "A K-MEANS and LDA based discriminative and compact dictionary learning method," M.S. thesis, South China University of Technology, Guangzhou, China, 2015.

[16] S. Theodoridis, and K. Koutroumbas, *Pattern recognition*. Beijing, China: Publishing House of Electronics Industry, 2010: 191–193.