IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 5, 2018, accepted December 19, 2018, date of publication January 1, 2019, date of current version January 16, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2889699

Pattern Recognition Using Relevant Vector Machine in Optical Fiber Vibration Sensing System

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This work was supported in part by the Foundation of Science and Technology on Near-Surface Detection Laboratory under Grant 614241402050417, in part by the National Natural Science Foundation of China under Grant 61501468, in part by the Key Research and Development (R&D) Projects of Shanxi Province under Grant 201803D121071, in part by the Social Development Project of the Shanxi Province Key Research Plan under Grant 201703D321037, in part by the Coal-Bed Methane Joint Research Fund of Shanxi Province under Grant 2016012011, in part by the Natural Science Foundation of Shanxi Province under Grant 201701D221115, and in part by the Research Project through the Shanxi Scholarship Council of China under Grant 2016-035.

ABSTRACT Invasion incident pattern recognition is crucial for a distributed optical fiber vibration sensing system based on a phase-sensitive time-domain reflectometer. Despite traditional pattern recognition identifying the vibration signal, the classification accuracy needs to be improved and the classifier requires probabilistic output, in order to ameliorate the performance of pattern recognition. A novel pattern recognition method is proposed in this paper. The characteristic vector is extracted from the original vibration signal by wavelet energy spectrum analysis. The probabilistic output is realized by the classification algorithm of a relevance vector machine. The optimal decomposition layer of the wavelet energy spectrum analysis is determined as six layers because of the compromise between the classification accuracy and the computational complexity. Taking into consideration the ground material and the weather, the experiments of three vibration patterns are carried out including walking through the fiber, striking on the fiber, and jogging along the fiber at 2, 5, and 8 km of the sensing fiber. With the help of 10-fold cross validation, the multi-classification confusion matrix is obtained in order to clarify the correct and incorrect classification results. Moreover, the performance measures, involving precision, recall rate, f-measure, and accuracy, are then analyzed. A classification macro-accuracy of 88.60% is finally obtained.

INDEX TERMS Distributed optical fiber sensor, Φ-OTDR, pattern recognition, relevance vector machine, wavelet energy spectrum.

I. INTRODUCTION

Distributed optical fiber vibration system based on phase-sensitive time-domain reflectometer (Φ-OTDR) has been used for the disturbance location [1]–[5], which was widely applied in the near-ground military target detection and recognition, perimeter security, energy transmission pipeline safety warning, engineering structural safety testing and many other fields due to its simple structure, strong anti-electromagnetic interference, high sensitivity and ability of long-range distributed detection of vibration signals [6]–[8].

Because the sensing fiber is susceptible to circumstances, such as the wind and rain, passerby walking or animals landing, these innocuous events maybe trigger the system alarming. In order to reduce the nuisance alarm rate (NAR), many studies have been realized by means of the algorithm improvement [9], [10], the system structure change [11], [12], and the pattern recognition method.

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Some researchers have done a lot on pattern recognition technology. Madsen (2007) [13] utilized the Short Time Fast Fourier Transform (ST-FFT) to compute spectrogram-based features. Qu *et al.* (2010) [14] utilized the energy in frequency bands computed from multi-scale wavelet packet decomposition as its characteristics vector. The machine learning method support vector machine (SVM) was used as classifier, the accuracy of which is 95%. Martins *et al.* (2015) [15] utilized ST-FFT to deal with its original signal and employ energy in frequency bands. And the Gaussian Mixture Model (GMM) was applied as the classifier. Wang *et al.* (2015) [16] used the Euclidean distance of Fast Fourier Transform (FFT) Frequency Spectrum (EDFS) to identify the four types of signals. Tejedor *et al.* (2016) [17] focused on the pipeline integrity threats, also utilized the combination of ST-FFT and GMM to monitor the pipeline. Zhang *et al.* (2017) [18] used the multi-feature parameter method to extract the signal characteristics, and the SVM was used as a classifier, the accuracy of which is 94%. Cao (2017) [19] used FFT to extract features and SVM was used as classifier. The accuracy is 92.62%.

It can be seen that the above researchers applied the pattern recognition technology in the vibration sensing system to get the vibration type and obtained a higher accuracy rate. However, in order to further improve the accuracy of classification in the actual situation, we will analyze the key parts of the pattern recognition process. Pattern recognition process mainly includes two parts: feature extraction and classifier design. Feature selection and extraction have a great impact on the accuracy of classification. Reasonable feature can greatly improve the classification accuracy and reduce NAR. The accurate feature extraction method can contain as much as possible the intrinsic information of the vibration signal. At the same time, the different types of vibration signals can be distinguished clearly in its characteristic space, and the classification accuracy can be greatly improved. As the vibration signal is often shock, abrupt, and its frequency components are complex, it shows non-stationary. Furthermore, the wavelet is often used to deal with non-stationary signals. By wavelet analysis, the vibration signals can be decomposed layer by layer according to the frequency characteristics, and then the vibration characteristics of the signals can be fully characterized. If the probability distribution of the classification result can be known, the supervisor can judge the type of the alarm effectively. Therefore, the pattern recognition and probabilistic output of unknown vibration can be realized simultaneously by relevance vector machine (RVM). The RVM has the advantages of the simple construction of kernel function and the strong generalization ability.

In this paper, the method of pattern recognition based on the wavelet energy spectrum analysis and the relevance vector machine will be expounded in the Φ-OTDR system. We will firstly describe the basic principles of wavelet energy spectrum and RVM based on the process of pattern recognition. Then the Φ-OTDR system structure which we used will be explained briefly. In order to contain the enough information of the vibration in a lower dimension, the feature space formed by wavelet energy spectrum is determined by the analysis and experiment. Finally, the RVM and one-to-one classification will be utilized to accomplish the purpose of the output of probability classification. In order to verify the effectiveness in the actual situation of the proposed pattern recognition algorithm which combines the wavelet energy spectrum and RVM, considering the condition of ground and weather the experiments would be established. Moreover, three patterns including walking through the fiber, striking on the fiber and jogging alone the fiber will be recognized in the simulation conditions. The model of classification will be evaluated overall by using confusion matrix and performance measures. Focusing on the generalization and comprehensiveness of the classification method, k-fold cross validation will be applied to analyze recognition results.

II. PATTERN RECOGNITION BASED ON RVM ALGORITHM

A. PATTERN RECOGNITION PROCESS

Generally, a complete pattern recognition process includes feature extraction, classifier selection and classifier design. A typical pattern recognition process is shown in Fig.1. It is primarily divided into two parts: classification of unknown patterns and classifier design. Firstly, the classification of unknown patterns contains four steps: the acquisition of vibration signal data, the pretreatment by de-noising, the feature extraction and the classification. Secondly, the most important classification needs a suitable and efficient classifier which is designed by the preprocessing, training and parameter determining of the training set.

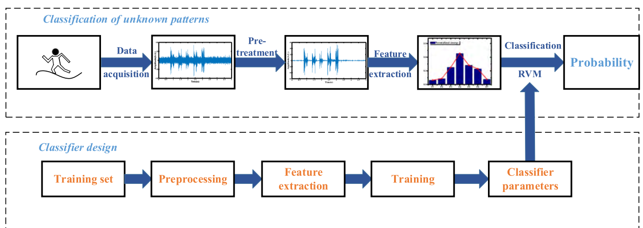

FIGURE 1. Typical pattern recognition process.

In this paper, the wavelet energy spectrum analysis is proposed to be used during the feature extraction step, taking into account characteristics of vibration signal. Moreover, the relevance vector machine (RVM) is chosen as the classifier in the Φ-OTDR vibration sensing system.

B. WAVELET ENERGY SPECTRUM

Theoretically, the feature extraction is the acquisition process of characteristic vector of signal. Based on the wavelet theory [20], the original collected signals need to be decomposed, and the energy of reconstructed coefficients should be calculated in order to obtain the wavelet energy spectrum.

Wavelet analysis has more advantages than traditional time domain or frequency domain analysis in dealing with non-stationary signals such as vibration signals, comparing with the traditional Fast Fourier Transform (FFT) analysis [21], [22]. At the same time, wavelet analysis itself has time-frequency characteristics, which is equivalent to mapping one-dimensional time signal to two-dimensional time-frequency scale. In this way, the change of frequency can be observed in a short time. The attributions of time and frequency of the original vibration signal can be represented by wavelet energy spectrum for the energy distributing among different frequency scales. In addition, according to these different frequency scales, reconstruction coefficients could be calculated by the wavelet decomposition and could be then used for the construction of characteristic vectors. Thus, the wavelet energy spectrum used as characteristic vector has the property of unity.

Hence, the multi-resolution analysis wavelet transform is used here to decompose the original signal [23]. The multi-resolution analysis of wavelet uses orthogonal wavelet basis to decompose the signal into different frequency scales, in order to make full use of the signal information at all frequency scales, which could more accurately reveal the inherent signal characteristics.

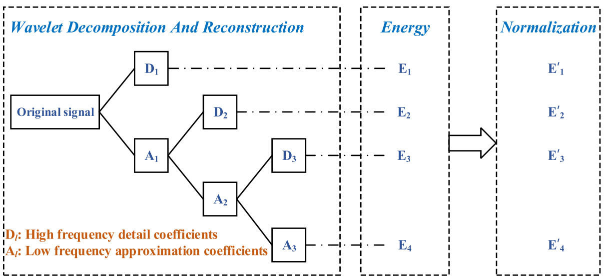

FIGURE 2. **The 3-layer decomposition process of the wavelet energy spectrum analysis.**

The Fig.2 shows the complete decomposition process of the wavelet energy spectrum analysis, for a 3-layer example. From the wavelet theory, the original discrete signal $x(n)$ will be decomposed by L-layer wavelet, which can be expressed as the sum of the reconstruction coefficients $D_l(n)$ and $A_l(n)$ under the l-th decomposition level:

$$x(n) = \sum_{l=1}^{L} D_l(n) + A_L(n) \tag{1}$$

where $D_l(n)$ is the high frequency detail coefficients, $A_l(n)$ is the low frequency approximation coefficients, l is the ordinal values of decomposition levels, and $L$is the total number of decomposition levels.

Supposing the length of reconstructed coefficients is N, the energy of reconstructed coefficients E_l under the l-th decomposition level and the last energy of reconstructed coefficients E_{L+1} can be calculated as:

$$E_l = \sum_{n=1}^{N} |D_l(n)|^2, \quad l = 1, 2, \ldots, L \tag{2}$$

$$E_{L+1} = \sum_{n=1}^{N} |A_L(n)|^2 \tag{3}$$

Thus, the wavelet energy spectrum $\boldsymbol{E}$ of the original signal $x(n)$ could be obtained as:

$$\boldsymbol{E} = [E_1, E_{2,} \ldots E_{L+1}] \tag{4}$$

In order to make the classifier's parameter converge, the result $\boldsymbol{E}$ should be normalized, and the normalized characteristic vector $\boldsymbol{E}'$ is obtained as:

$$\boldsymbol{E}' = \frac{\boldsymbol{E}}{\sqrt{\sum_{l=1}^{L+1} |E_l|^2}} \tag{5}$$

C. RELEVANCE VECTOR MACHINE

The selection and design of the classifier is the core of pattern recognition system. The efficient classifier can greatly improve the classification accuracy.

In this paper, the relevance vector machine (RVM) is used as a classifier for Φ-OTDR vibration system. The RVM is a learning machine based on the Bayesian framework.

In comparison with conventional support vector machine (SVM) which is proposed in 1995 [24], RVM is a sparse probability model proposed by Tipping in 2001, which has the advantages of high sparsity, probability output, and the kernel function does not need to satisfy the Mercer condition [25]. At present, RVM has been widely used to deal with regression and classification issues [26].

1) THE PRINCIPLE OF PROBABILITY OUTPUT

It is of great significant to obtain the probability value of vibration patterns. From the probability theory, unknown eventt_* can be predicted by the known events $\boldsymbol{t}$, and the probability is $p(t_*|\boldsymbol{t})$. Distribution function of t_* or $\boldsymbol{t}$ is usually decided by parameter θ. From the theory of Markov chain, the predictive function $p(t_*|\boldsymbol{t})$ is given:

$$\mathrm{p}\left(t_*|\boldsymbol{t}\right) = \int p\left(t_*|\theta\right) p\left(\theta|\boldsymbol{t}\right) d\theta \tag{6}$$

Because the equation (6) could not integral in most situation, thus the delta function is used to approximate the probability $p(\theta|\boldsymbol{t})$, that is $p(\theta|\boldsymbol{t}) = \delta(\theta - \hat{\theta})$. With the help of delta function, the equation (6) can be simplified as:

$$\mathrm{p}\left(t_*|\boldsymbol{t}\right) = p\left(t_*|\hat{\theta}\right) \tag{7}$$

The estimate value $\hat{\theta}$could be found from the process of maximize $p(\theta|\boldsymbol{t})$. According to the Bayesian theory, $p(\theta|\boldsymbol{t})$ is directly proportional to the $p(\boldsymbol{t}|\theta)$, so the value $\hat{\theta}$is given:

$$\hat{\theta} = \arg\max p\left(\boldsymbol{t}|\theta\right) \tag{8}$$

Therefore, through maximizing $p(\theta|\boldsymbol{t})$, the parameter $\hat{\theta}$can be found. And the predictive function could use to predict the probability of unknown events.

2) THE ESTABLISHMENT OF CLASSIFIER MODEL

The normalized characteristic vector $\boldsymbol{E}'$ of the original signal collected by the Φ-OTDR vibration system needs to be linked to any of the predetermined vibration types. These vibration types could constitute a set of classification targets, which are noted as $\{tn\}_{n=1}^{N}$, where t_{n} is the output vibration type that corresponds to input characteristic vector $\boldsymbol{E}'_{\mathrm{n}}$. So a set of input-output samples pairs $\{E'_n, tn\}_{n=1}^{N}$ could be obtained.

Thus, the RVM's kernel model y can be written as [27]:

$$y(E'_n; \boldsymbol{w}) = \sum_{i=1}^{N} \omega_i K(E'_n, E'_i) + \omega_0 = \boldsymbol{\Phi}(E'_n)\boldsymbol{w} \tag{9}$$

where $\boldsymbol{w} = (\omega_0, \omega_1 \ldots \omega_N)^T$ is weight vector for adjusting the classification model, $K(E', E'_i)$ is the kernel function for mapping characteristic vectors to kernel space, $\Phi(E'_{\mathrm{n}})$ is the $N \times (N+1)$ coefficient matrix of the linear equations. So the classification model can be gotten if $\boldsymbol{w}$ is given by the iterative computation.

Aiming at the classification problem, sigmoid function $\sigma(y)$ is generally used to map the result kernel model y to intervals [0, 1]. Considering the two-class situation, t_{n} follows two-point distribution. Thus, the known events are following the Bernoulli distribution, and the likelihood will be gotten.

$$P(\boldsymbol{t}|\boldsymbol{w}) = \prod_{n=1}^{N} \sigma\left\{y\left(E'_n; \boldsymbol{w}\right)\right\}^{t_{\mathrm{n}}} \left[1 - \sigma\left\{y\left(E'_n; \boldsymbol{w}\right)\right\}\right]^{1-t_n} \tag{10}$$

From the equation (7) and (8), the parameter $\boldsymbol{w}_{\mathrm{MP}}$ is obtained by maximizing the equation (10). In this way, the classifier model is established:

$$p\left(t_*|\boldsymbol{t}\right) = p\left(t_*|\boldsymbol{w}_{MP}\right) = \begin{cases} \sigma\left\{E'_n; \boldsymbol{w}_{MP}\right\} & t_* = 1 \\ 1 - \sigma\left\{E'_n; \boldsymbol{w}_{MP}\right\} & t_* = 0 \end{cases} \tag{11}$$

In order to avoid overfitting, some additional constraint often added on the weight vector by using Bayesian perspective method.

D. CLASSIFIER PERFORMANCE

To evaluate the generalization and effectiveness of classifier, it is essential to build performance measure. In this part, the concept of confusion matrix and several indexes of classifier will be discussed.

After the normalized characteristic vector $\boldsymbol{E}'$ is obtained, it can be used to train the classifier, and to test the classifier performance. Due to RVM is a supervised learning model, the result of the classifier can be described by confusion matrix. Fig.3 shows a binary classification confusion matrix.

Four performance measures derive from the confusion matrix including accuracy, precision, recall rate and F-measure, which could represent the classifier performance comprehensively in theory. The definition of these performance measures is shown in Fig.3.

The accuracy is the proportion of correct classification in total samples, which is the most often used classifier performance index. The precision and the recall rate are a pair of contradictory indexes in a certain pattern. The precision indicates a certain pattern's correct classification proportion and the recall rate indicates a certain pattern's actual classification amount in the percentage of predicted class. The F-measure is the harmonic mean of the precision and the recall rate.

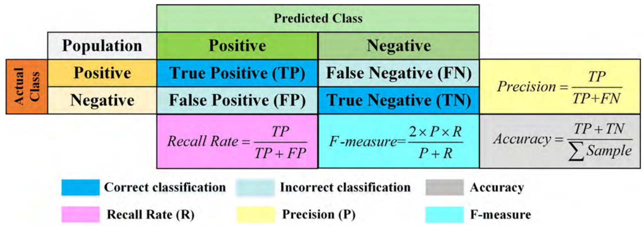

FIGURE 3. Binary classification confusion matrix and performance measure.

In the process of evaluating the pattern recognition performance, two separate data sets, which are the classifier training set and the classifier testing set, must be involved. The samples in the classifier training set should be as large as possible to cover all the pattern characteristics to ensure that the model library is stable and reliable.

However, the classifier training setwhich can't be used as testing set is not allowed to test the classifier performance. On the other hand, only one training set and one testing set cannot objectively evaluate the classifier learning and generalization ability. Therefore, due to the above reasons, the k-fold cross validation (CV) is utilized to test the classifier performance in this paper [28]. Moreover, this efficient method could comprehensively evaluate the recognition performance measure and generalization ability of the classifier.

According to the theory of k-fold CV, the collected data set is firstly divided into k subsets. Each subset contains all patterns to be recognized, and the numbers of samples in every pattern are equal.

Then, the i-th subset is selected as the testing set; the other k-1 subsets are selected as the training sets. In this way, the result of$i$-th fold is obtained. According the Fig.3, the$i$-th fold confusion matrix can be acquired and the measures of classifier performance can be calculated from the equations in Fig.3. Those are, the accuracy A_{i}, the precision P_{i}, the recall rate R_{i} and the F-measure $F1_{\mathrm{i}}$.

This process should be repeated k times in the same way. As a result, k-fold confusion matrix and performance measures can be acquired. And these measures can be described detailedly as the accuracy $A = (A_1, A_2, \ldots, A_{\mathrm{k}})$, the precision $P = (P_1, P_2, \ldots, P_{\mathrm{k}})$, the recall rate $R = (R_1, R_2, \ldots, R_{\mathrm{k}})$ and the F-measure $F1 = (F1_1, F1_2, \ldots, F1_{\mathrm{k}})$.

Therefore, the average measure could be calculated and used for the classifier performance evaluation. Moreover, the average measure is named as macro-measure, as shown in the following equations:

$$\text{macro-A} = \frac{\sum_{i=1}^{k} A_i}{k} \tag{12}$$

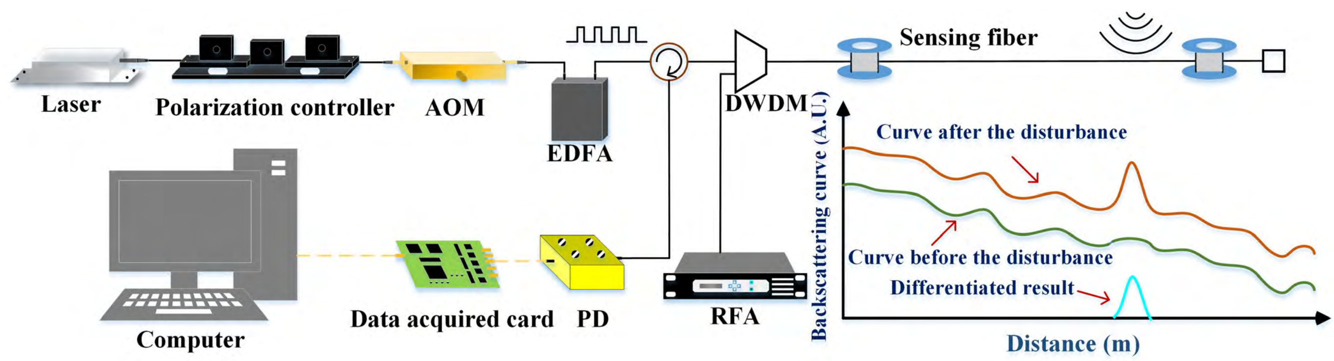

FIGURE 4. The structure of Φ-OTDR system.

$$\text{macro-P} = \frac{\sum_{i=1}^{k} P_i}{k} \tag{13}$$

$$\text{macro-R} = \frac{\sum_{i=1}^{k} R_i}{k} \tag{14}$$

$$\text{macro-F1} = \frac{2 \times \text{macro-P} \times \text{macro-R}}{\text{macro-P} + \text{macro-R}} \tag{15}$$

III. SYSTEM

A. EXPERIMENTAL SETUP

The Φ-OTDR vibration sensing system is based on the Rayleigh backscattered theory. When the optical fiber is affected by the external vibration, the refractive index of optical fiber changes and the light phase fluctuates, due to the non-homogeneity of the optical fiber. Then, the backscattered lights interfere in the sensing fiber and the vibration information is obtained by demodulating Rayleigh backscattered light intensity. With the help of the difference algorithm, the $(i+8)^{\text{th}}$ curve is chosen to subtract from the i^{th} curve to pre-process the original Rayleigh backscattered curve, the vibration location information can be also obtained.

The structure of Φ-OTDR vibration sensing system is shown in Fig.4 [29]. This system uses the ultra-narrow linewidth laser as the light source to generate the sensing light, which is then modulated by the acousto-optic modulator (AOM). The optical pulse is amplified by Erbium-doped Optical Fiber Amplifier (EDFA) and injected into the sensing fiber via the circulator. The pattern recognition needs the stable light intensity along the whole optical fiber to ensure the accuracy of identification. However, the Rayleigh backscattered light will be normally attenuated with the length of the fiber. So the Raman fiber amplifier (RFA) is used to compensate the degradation of the light intensity in the Φ-OTDR vibration sensing system. The backscattered interference light is detected by the photodetector and then transformed into the electrical signal. The data acquisition (DAQ) card whose sampling rate is 50MSa/s could collect the electrical signals and upload them to the host computer. The experiment is carried out with a total sensing length of 10 km, a repetition frequency of 8 kHz and a pulse width of 200 ns.

B. Experimental Design

Based on theΦ-OTDR vibration sensing system, experiments should be designed to verify the feasibility of pattern recognition method. Therefore, the experimental scheme is determined and experimental environments are simulated in the laboratory.

There are three common patterns including passing through the fiber (stepping once), striking on the fiber once, and jogging along the fiber (stepping more times) to be distinguished by the pattern recognition method in the Φ-OTDR system. The total length of the sensing fiber is set as 10km. Four individual persons participate in the experiment to generate these vibration patterns together. Each pattern repeats 40 times by four persons at 2 km, 5 km and 8 km of the sensing fiber, respectively. And the acquisition time of the vibration is set as 4 seconds.

In order to verify that the pattern recognition method could distinguish effectively the vibration sources in reality environment, the experimental environments are established considering the condition of ground and weather. Taking into consideration the ground material and the weather, the sensing fibers are installed on the marble ground and sandy soil, respectively. Then the moist soil is used to simulate the weather after raining. So three different conditions are built up. In summary, three patterns under three environments conditions at three different positions are chosen to carry out the experiments.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

In this section, the influence of wavelet layer would be discussed and a suitable decomposition layer would be selected. Based on the suitable layer, an experiment under simulation environment is realized. Moreover, the confusion matrix and the performance measure is applied to analyzing the classification results.

A. THE LAYER OF WAVELET ENERGY SPECTRUM

In order to determine the optimal decomposition layers in the wavelet energy spectrum analysis, theoretical analysis and experimental verification are carried out in this part.

According to the experiment design in section III.B, and considering only one experimental environment condition that the sensing fiber is installed on the marble ground, an experiment is established. Thus, 360 vibration samples (3 'patterns' $\times$ 3 'positions' $\times$ 1 'condition' $\times$ 40 'times' $=$ 360 samples) are obtained in total. Fig.5 shows temporal domain waveforms of three vibration patterns which are pretreated bythe wavelet de-noising method based on sym3.

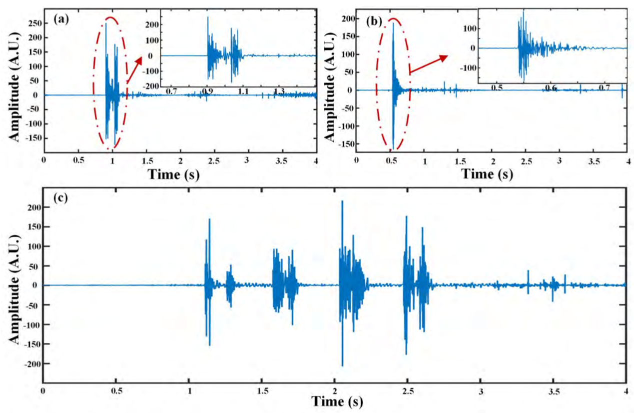

FIGURE 5. **Temporal domain waveforms of (a) stepping on the fiber, (b) striking on the fiber, and (c) jogging along the fiber.**

Fig.5 (a) and Fig.5 (b) indicates that stepping on the fiber and striking on the fiber is much more similar in temporal domain. So the conventional temporal feature extraction could not describe the vibration appropriately. Fig.5 (a) shows that the moment of stepping and leaving on the optical fiber contains high-frequency components, and the middle of the wave normally contains low-frequency components. Fig.5 (b) shows that the amplitude and frequency of striking signal is obviously changed after the moment of striking on the fiber.

So the analysis simultaneously balancing the temporal and frequency characteristic of vibration patterns is crucial for the Φ-OTDR system which can only detect vibration caused by dynamic strain. As a result, the wavelet energy spectrum analysis is applied in feature extraction.

The characteristics of 360 vibration samples could be extracted by the wavelet energy spectrum analysis with the wavelet base of Daubechies 3. It is necessary for the classification accuracy and computational load of the pattern recognition system to discuss the decomposition layers of the wavelet energy spectrum analysis. The vibration signals collected from the experiment are decomposed by wavelets, with different decomposition layers, then tested by the RVM for pattern recognition in order to obtain the classification accuracy.

Fig.6 shows the classification accuracy of the classifier with the help of 10-fold cross validation. The decomposition layer varies from 1-layer to 9-layer, the corresponding classification accuracy is marked by different colors. It can be seen that when the decomposition layers are lower, the classification accuracy is also lower and fluctuates more greatly.

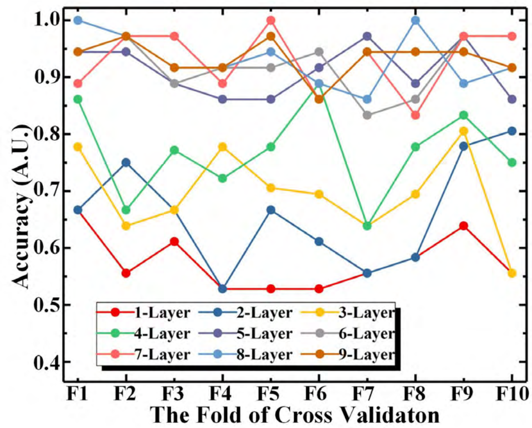

FIGURE 6. **10-fold cross validation of different decomposition layers.**

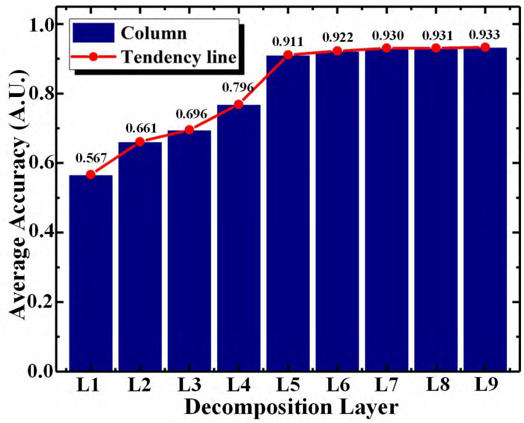

FIGURE 7. **Average classification accuracy of different decomposition layers.**

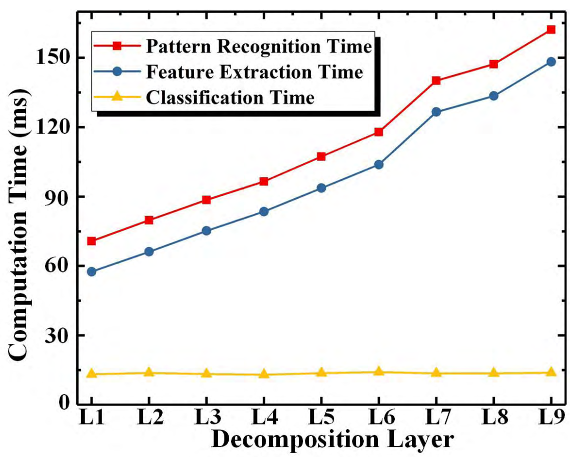

FIGURE 8. **Computation time of different decomposition layers.**

When the decomposition layers increase, the classification accuracy also increases and tends to be stable.

Fig.7 shows the average accuracy of the classifier that are obtained through 10-fold cross validation from the

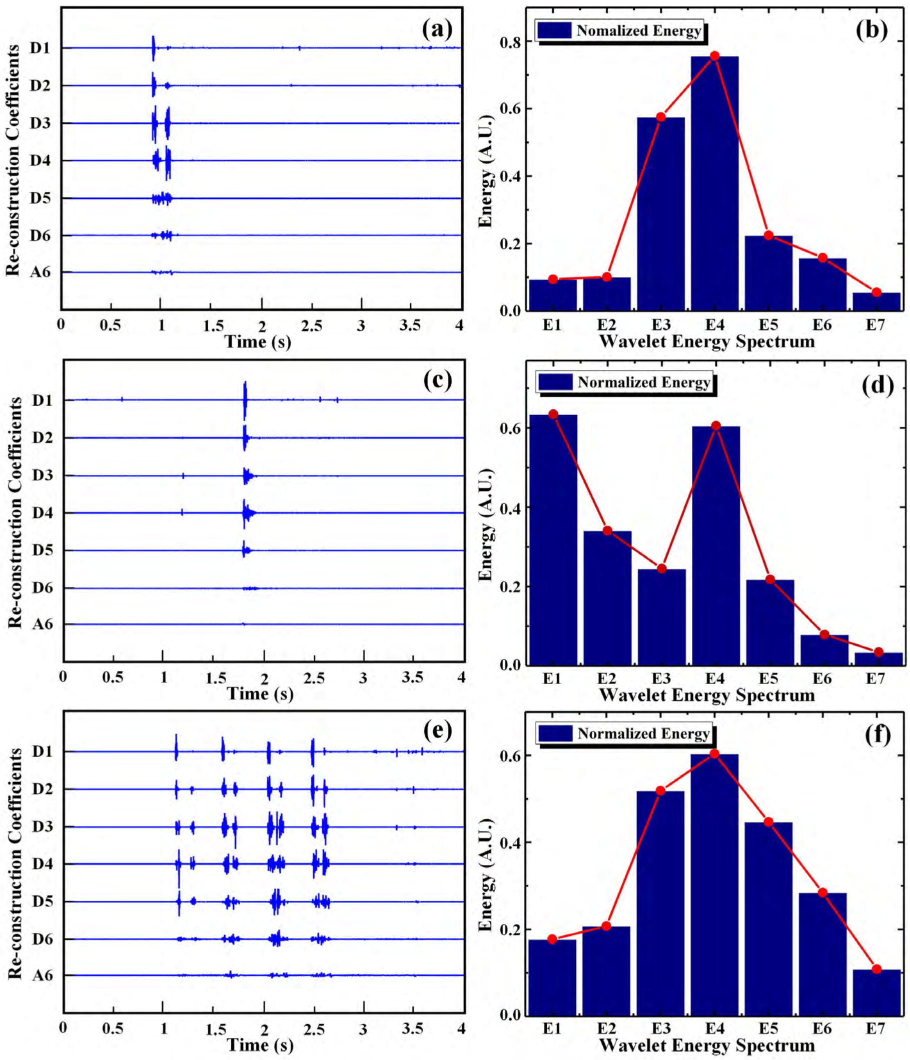

FIGURE 9. (a) The reconstruction coefficients and (b) the wavelet energy spectrum analysis of walking through the fiber. (c) The reconstruction coefficients and (d) the wavelet energy spectrum analysis of striking on the fiber. (e) The reconstruction coefficients and (f) the wavelet energy spectrum analysis of jogging alone the fiber.

equation (12). Obviously, when the number of decomposition layers is greater than 5, the classification accuracy could already be greater than 0.9. Therefore, the feature extraction require decomposition layer greater than 5.

Moreover, the increase of decomposition layers could not continuously improve the classification accuracy and gradually become saturate. Due to the increasing dimension of wavelet energy spectrum, it could increase the computational complexity and computing time of classification. Fig.8 shows the variation of computing time with the decomposition layers. The feature extraction time is increasing linearly with the decomposition layers. The classification time is constant and the average value is 13.544ms. So the total computing time of pattern recognition including the feature extraction and classification is gradually increasing with the decomposition layers and mainly spent on feature extraction.

As the compromise between the classification accuracy and the computational complexity, the energy of reconstructed coefficients of 6-layer wavelet decomposition will be used as the characteristic vector of the original signal in this paper. Moreover, the elapsed time of 6-layer wavelet decomposition is 117.9 ms.

Fig.9 shows the reconstruction coefficients and wavelet energy spectrum analysis of three different vibration patterns, that is, passing through the fiber (Fig.9 (a) and Fig.9 (b)), striking on the fiber (Fig.9 (c) and Fig.9 (d)), and jogging along the fiber (Fig.9 (e) and Fig.9 (f)). Take the case of passing through the fiber, Fig.9 (a) shows six high-frequency reconstruction coefficients (D_1, D_2, D_3, D_4, D_5, D_6) and a low-frequency reconstruction coefficient (A_6) which are obtained after the 6-layer decomposition from the equation (1). Fig.9 (b) shows the normalized energy spectrum $\boldsymbol{E}'$ of each reconstruction coefficients calculated from the equation (2) and (3), which are used as the characteristic vector of original motion signal.

Furthermore, from the normalized energy spectrums of Fig.9 (b), Fig.9 (d) and Fig.9 (f), we can see that there are obvious difference for the energy distribution. Therefore, the wavelet energy spectrum could be effectively used in pattern recognition.

B. PATTERN RECOGNITION IN REALITY CONDITION

Based on the suitable dimensions of wavelet energy spectrum and the experiment design in section III.B, considering three different environment conditions, an experiment is established to verify the effectiveness of the pattern recognition method in actual situation. Therefore, 1080 vibration samples (3 'patterns' $\times$ 3 'positions' $\times$ 3 'conditions' $\times$ 40 'times' = 1080 samples) are collected in total.

With the help of the wavelet energy spectrum analysis process in the section IV.A, Fig.10 summarizes the average normalized energy distribution of three different vibration patterns. It can be seen that the energy distributions of striking (marked in red) and walking (marked in black) are remarkably different in time-frequency domain after wavelet energy spectrum analysis. Moreover, the walking (marked in black) and the jogging (marked in blue) are very similar because they all include the motion of stepping.

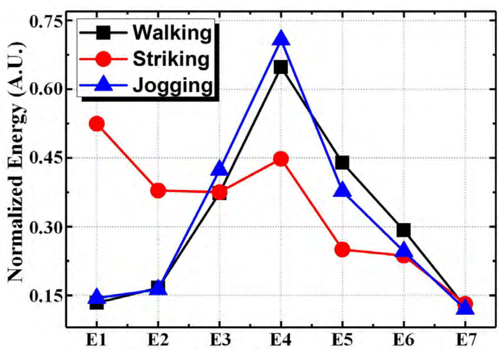

FIGURE 10. **Average normalized energy distribution of three different vibration patterns.**

The 1080 samples are then subjected to 10-fold cross validation to obtain the classification result of each fold. Taking the first-fold cross validation for example, the confusion matrix can be obtained, and the recall rate and precision can be therewith calculated. Fig.11 shows the confusion matrix of the first-fold cross validation.

Main diagonal of the confusion matrix is the correct classification, which is marked in blue. Other elements of the confusion matrix, which is marked in light blue, are incorrect classification results. The performance measure is calculated by the equations shown in Fig.3. It can be seen that the first-fold accuracy is 89.81% and F-measures of walking, striking and jogging are 83.58%, 98.63% and 86.84%, respectively.

		Predicted Class			
	Population	Walking	Striking	Jogging	Precision
Actual Class	Walking	28	1	7	77.78%
	Striking	0	36	0	100%
	Jogging	3	0	33	91.67%
	Recall	90.32%	97.30%	82.50%	89.81%
	F-measure	83.58%	98.63%	86.84%	

Correct classification   Incorrect classification   Accuracy

FIGURE 11. **Confusion matrix and performance measure of the first-fold cross validation.**

TABLE 1. **Macro performance measure.**

	Walking	Striking	Jogging
Precision	82.78%	97.50%	85.56%
Recall rate	86.01%	97.05%	83.91%
F-Measure	84.36%	97.27%	84.73 %
Accuracy		88.60%	

In the same way, through the 10-fold cross validation, we can get 10 confusion matrices and 10 groups of performance measures. Fig.12 shows performance measure changes with each fold. Fig.12 (a), (b), (c) show three patterns' performance measures of walking through the fiber, striking on the fiber and jogging along the fiber, which include the precision (marked in black), the recall rate (marked in red) and F-measure (marked in blue). The value of F-measure is between the precision and the recall rate. Fig.12 (d) summarizes the accuracy variation with folds, and it can be seen that the accuracy is maintained at more than 80%.

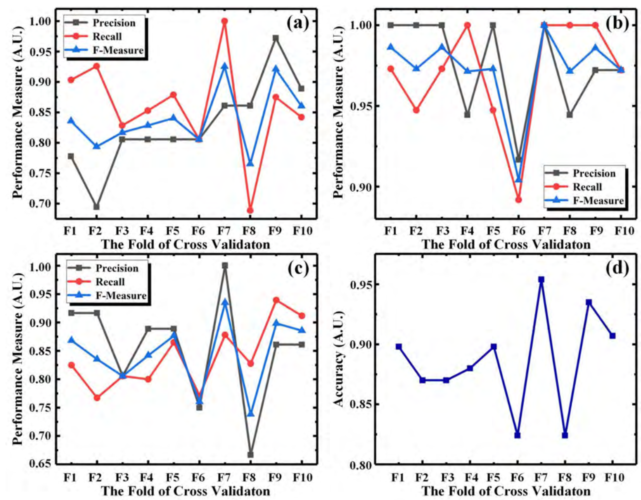

FIGURE 12. **Performance measures for (a) the walking through the fiber, (b) the striking on the fiber, and (c) the jogging alone the fiber. (d) The accuracy variation with folds.**

From the 10-fold cross validation, different macro performance measures of three vibration patterns are calculated by the equations (12), (13), (14) and (15), which are summarized in TABLE 1.

With the help of experiment results considering the condition of the ground material and the weather, it can be proved that, via the wavelet energy spectrum analysis and RVM, vibration signals can be successfully recognized and a classification macro-accuracy of 88.60% can be obtained. In addition, the F-measure of the pattern of striking is 97.27% in TABLE I, which means the striking is hardly to be confused with the other two patterns. Moreover, according to the confusion matrix in Fig.11 and performance measures in Fig.12, the patterns of walking and jogging are more likely to be confused with each other. The reason for this phenomenon is that those two patterns both include the behaviour of stepping.

V. CONCLUSION

In order to reduce the NAR of Φ-OTDR vibration sensing system, a pattern recognition method is presented in this paper. Considering the non-stationary of vibration signal, the wavelet energy spectrum analysis is used to extract characteristic of vibration signal. Relevance vector machine is used as classifier because it has the capacity of probability output without overfitting and its kernel function is easy to build. Due to the decomposition layers of wavelet has great influence on recognition result, we have carried out experiments and analysis on wavelet energy spectrum and 6-layer decomposition is selected. Taking into consideration the ground material and the weather, an experiment is carried out to verify that the classifier can distinguish three patterns including walking through the fiber, striking on the fiber and jogging along the fiber. With the help of 10-fold cross validation, the confusion matrix is obtained and performance measures including precision, recall rate, F-measure and accuracy are analyzed comprehensively. This method could thus provide a novel solution for the near-ground military target detection and recognition.

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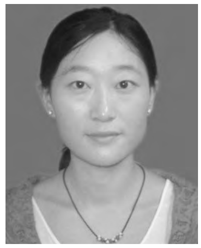

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