DOI: 10.3969/j.issn.1673-5188.2017.03.007
http://kns.cnki.net/kcms/detail/34.1294.tn.20170824.1424.004.html, published online August 24, 2017

Practical Pattern Recognition System for Distributed Optical Fiber Intrusion Monitoring Based on Φ-COTDR

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Abstract

At present, the demand for perimeter security system is increasing greatly, especially for such system based on distributed optical fiber sensing. This paper proposes a perimeter security monitoring system based on phase-sensitive coherent optical time domain reflectometry(Φ-COTDR) with the practical pattern recognition function. We use fast Fourier transform (FFT) to exact features from intrusion events and a multi-class classification algorithm derived from support vector machine (SVM) to work as a pattern recognition technique. Five different types of events are classified by using a classification algorithm based on SVM through a three-dimensional feature vector. Moreover, the identification results of the pattern recognition system show that an identification accurate rate of 92.62% on average can be achieved.

Keywords

fiber optics sensors; COTDR; distributed vibration sensing; SVM; pattern recognition

1 Introduction

Nowadays, phase-sensitive optical time domain reflectometry (Φ-OTDR) is widely used in optical fiber perimeter security monitoring system for its distinguished advantages over other technologies [1]. Nevertheless, Φ-OTDR has not been well performed in real applications. In Φ-OTDR system, the trace for analysis is an optical time domain signal, which results from coherent addition of amplitudes of lightwave backscattered from different positions of the fiber [2]. When disturbance occurs at a certain position, the change of the length and the refractive index of the fiber may happen, which will change the phase at that position. Accordingly, the trace mentioned above changes. However, in the real environment, the sensing signal trace is easily interfered by noise sources. Different disturbing events even have the same effect on the trace [3], causing false alarms frequently, which are intolerable for some practical applications. The most important challenge for us is to distinguish the events that we should prevent from all the disturbing ones.

For this purpose, we designed a practical pattern recognition system for distributed optical fiber intrusion system based on phase-sensitive coherent optical time domain reflectometry (Φ-COTDR). The reason for choosing Φ-COTDR is to get a higher Signal Noise Ratio (SNR) and longer monitoring distance [4]. There are two classification levels in the practical pattern recognition system. Along fiber intrusion monitoring channels, the first level classification identifies all intruded channels, while the intruded channels are further analyzed to get the types of intrusion events at the secondary classification level. The sensing signal for analysis is gathered by accumulating the varying trails at different moments at each channel [5]. In our experiment, Event A (a stable state), Event B (walking on the lawn while the fence is exposed to the wind), Event C (shaking the fence), Event D (walking on the lawn) and Event E (vibration exciter) are tested. Event A is used to verify the effectiveness of the intrusion detection (the first level classification). After careful signal analysis, some features are extracted and formed as a feature vector in support vector machine (SVM) for pattern recognition. The experiment results show that the pattern recognition system has a robust performance.

2 Pattern Recognition System for Optic-Fiber Fence Based on Φ-COTDR

The practical pattern recognition system consists of the classifier training and testing stages (**Fig. 1**). In the classifier training stage, the sensing signals we obtained averagely achieve 25 times improvement in SNR. After signal analysis, some features are selected and they are quite important for the subsequent event classification task. The intrusion learning is carried out firstly, which will trigger an alarm if intrusion happens. Meanwhile, the invaded channels are located and the system can preserve the channel information for event classification. This process relieves the data stress of calculating all channels. Then, some SVM classifier models are preserved for testing. In the testing stage, the system can realize intrusion detection and classify the events effectively.

2.1 Functional Requirements

For the optical fiber intrusion monitoring system based on Φ-COTDR, the sensing signal traces are easily interfered by environmental noise, temperature change and other disturbing

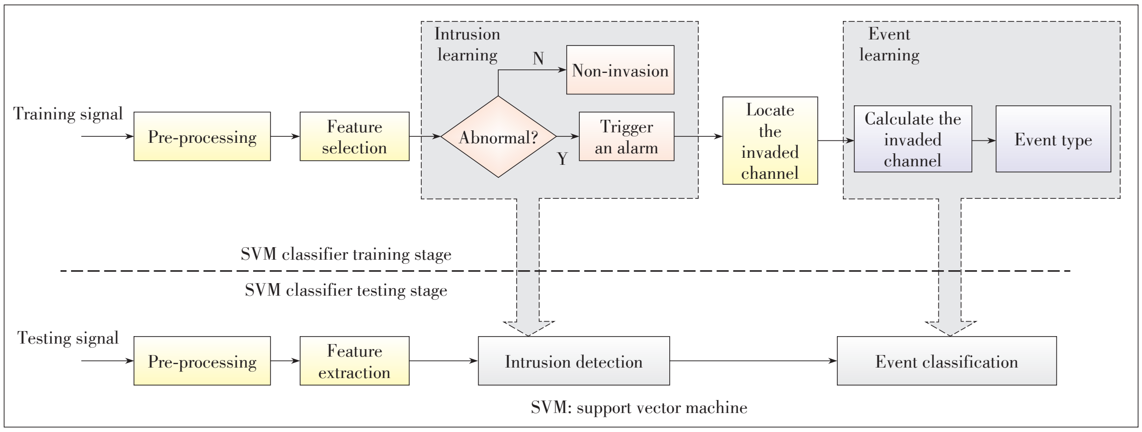


Figure 1. The algorithm flow of the pattern recognition system.

events [6]. In real applications, different events monitored by the system have the similar effect on the Φ-COTDR trace, so that the collected sensing signals show some similar characteristics. Therefore, it is hard for the system to detect the intrusion events and classify them correctly. Moreover, generalization ability is vital to the pattern recognition system, in other words, the system should perform well in the sensing signal for training the classifiers, as well as in testing the new sample. For the real application of the system, the surroundings differ greatly and the data set we collect may show different characteristics. Certain signal processing methods and classification algorithms are adopted depending on the actual features of the data. For the offline training and testing in this paper, depending on the characteristics of the data, we applied fast Fourier transform (FFT) and a classification algorithm derived from SVM to make the system more practical.

2.2 Signal Processing and Feature Selection

At each channel along the sensing fiber, we accumulated the Φ-COTDR traces gathered at different moments to construct a series of temporal signals. The sampling rate of the temporal signal is 400 Hz, the spatial Φ-COTDR traces are sampled at 250 MS/s. After averaging, we got a 400 × 5000 matrix for each sample. As we know, there are rich information in frequency domain of signals. For the time domain signals, we subtracted the average value and applied FFT to get the spectrum of each channel. The total energy, the energy of low frequency, the peak value and the mean value of the spectrum were all calculated for each position. After careful selection, Feature I (energy ratio of a low frequency to total energy), Feature II (total energy), Feature III (ratio of peak value to mean value) are formed as a feature vector in SVM. The normalized method is also applied on the feature vectors. We calculated the feature vectors of 20 samples for each events randomly, and the distributions of Feature I, Feature II and Feature III for 5 events are illustrated in **Fig. 2**. From Fig. 2 a , the vibration exciter is the least and the stable state takes the largest position, which is consistent with the fact and they can be classified effectively. Feature III makes a great contribution to the events classification, which can be seen from Fig. 2c . Certain samples of Event B and Event D are mixed, which means that the identification rate between them may not be so good.

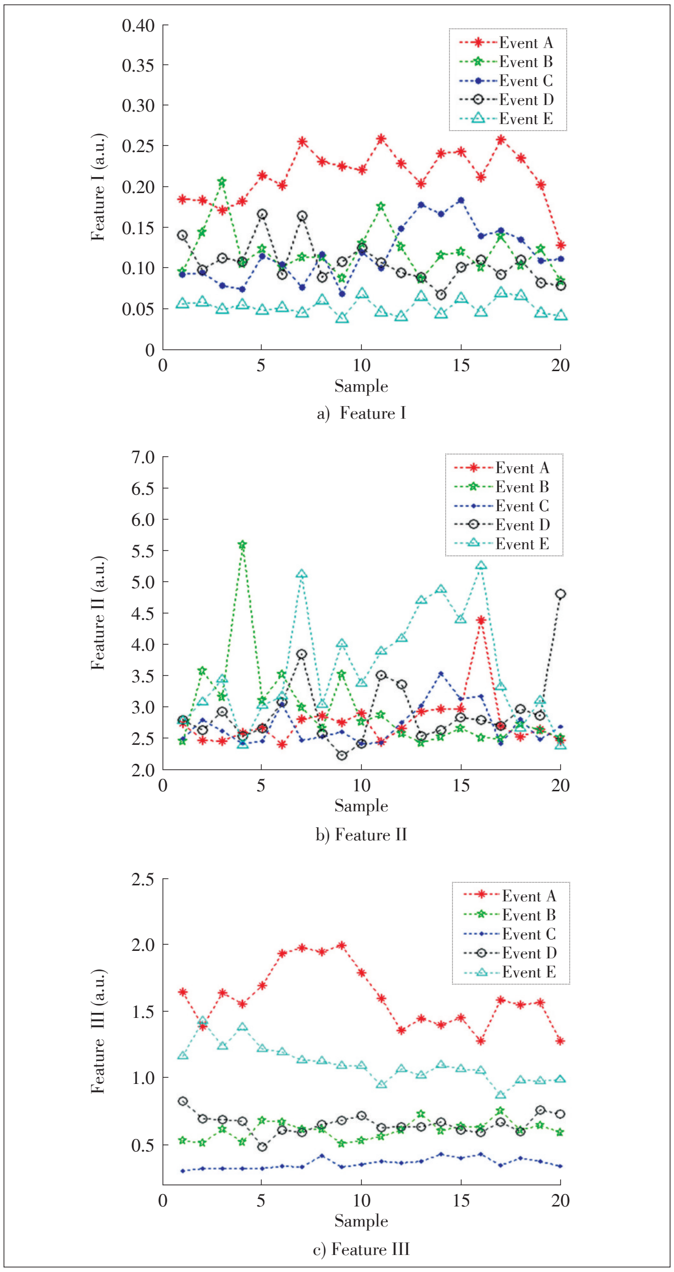
2.3 Support Vector Machine

Nowadays many pattern recognition techniques are applied to optical fiber sensors, especially in distributed vibration sensing [7]. SVM is a powerful and popular supervised learning method based on statistiacal learning theory in machine learning. As shown in Fig. 3, when linear decision hyper-planes are no longer feasible, by using a kernel function, the input space (x_1, x_2, x_3..., x_n) is mapped to a high-dimensional feature space and an optimal margin hyper-plane (OMHP) will be found in the mapped space. The rectangles in dark grey in **Fig. 3** work as a kernel function and stand for support vectors, and $K(x_i,x)$ means the inner product between the input space and the support vector. The output y is a linear combination of the inner products. The way to get the OMHP can be converted into a solution to a quadratic programming (QP) problem, so the solution to an SVM is global and unique [8]. The SVM classification algorithm has a robust generalization ability. On the contrary, artificial neural network (ANN) is a classification method based on empirical risk minimization. Its performance partly depends on the empirical knowledge and prior knowledge of the designer, which cannot ensure its generalization ability [9]. Generally, the back propagation (BP) ANN only converges to locally optimal solutions, while SVM always finds a global optimum value [10]. Neither ANN nor SVM is perfect. However, the SVM is more suitable for our requirements in the practical fiber fence monitoring system, especially in the real scenarios. Therefore, we choose a multi-class classification algorithm based on SVM as a learning method in this paper.

3 Experimental Results and Discussion

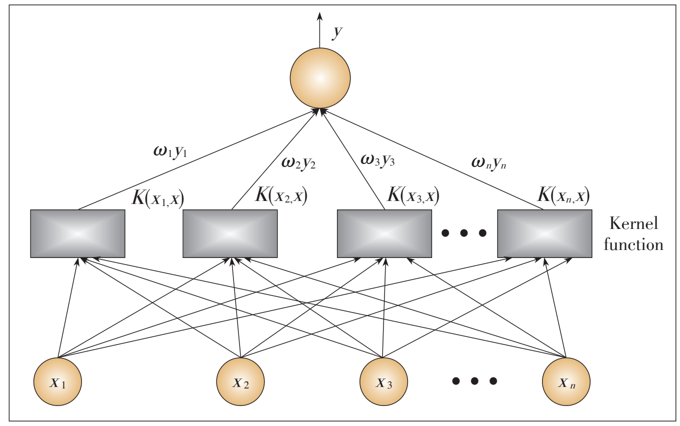
3.1 Overall Optic-Fiber System

The proposed configuration of Φ-COTDR system for evaluating the intrusion monitoring system is shown in **Fig. 4**. An ultra



▲ **Figure 2. The features distribution of the five events.**

-narrow linewidth (<0.1 KHZ) laser (UNLL) with maximum output power of 40 mW is used. The lightwave from the UNLL is split into two arms by using a coupler. The lightwave from one arm of the coupler is modulated by the acoustic-optical modulator (AOM) that is driven by a function generator. A series of modulated pulses generated from the AOM are amplified by the erbium-doped fiber amplifier (EDFA), and then launched into the 50 km sensing fiber through a circulator. The backscattered Rayleigh lightwave produced in the sensing fiber is amplified by using another EDFA. Another arm of the coupler is functioned as a local oscillator and interferes with the backscattered Rayleigh lightwave from the sensing fiber. We use a



▲ **Figure 3. The model of the SVM.**

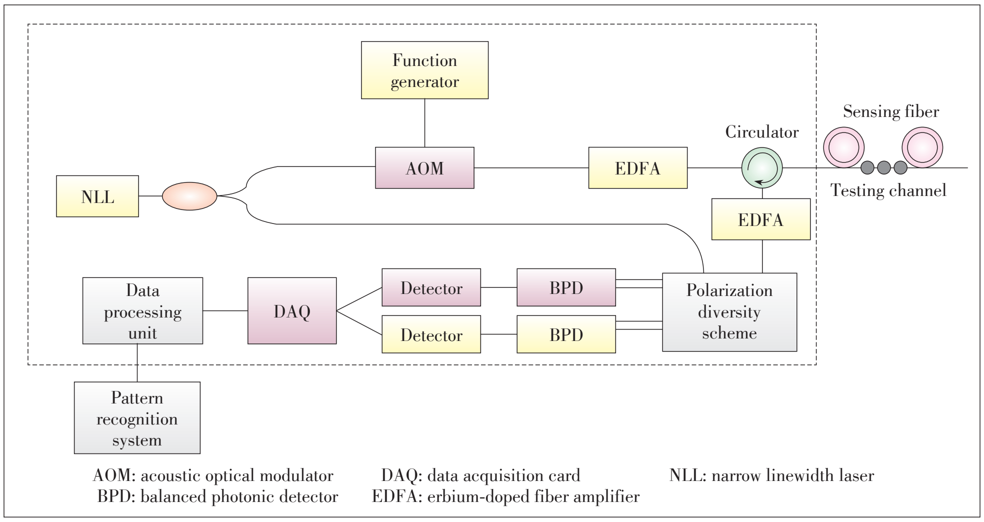
polarization-diversity scheme to avoid the effect of polarization-related problems on coherent detection. The raw Φ-COTDR signal traces are sampled by a data acquisition card (DAQ) (250 MS/s). The signal is processed further in the data processing unit and then transmitted to the pattern recognition system. The triggering pulse repetition rate is set at 400 Hz, which means that the vibration response range is 200 Hz. There are 5000 channels along the sensing fiber, the testing fence is set at the 2038th channel, the lawn is set at the 2035th channel, and the vibration exciter is set at the 2033th channel located at 20.38 km, 20.35 km, and 20.33 km respectively. Five events above are tested in these channels. Especially, each human intrusion event was conducted by different persons to increase the diversity of samples so as to improve the robustness of the pattern recognition system.

3.2 Intrusion Detection and Event Classification Results

To verify the performance of the pattern recognition system, 650 samples are used in the SVM training stage, including 150 Event A, 100 Event B, 150 Event C, 100 Event D, and 150 Event E samples. For the testing stage, a testing sample set that contains 150, 100, 150, 100, 150 for each event is constructed. After pre-processing and feature extraction, a series of feature vectors are put into the SVM. Radial basis function (RBF) is used as the kernel function. By cross validation, we can get some robust SVM classifier models to classify different events. The results are illustrated in **Table 1**. The average identification accurate rate (AIAR), intrusion detection rate (IDR), event classification rate (ECR) and the identification accurate rate for each type (IARE) are calculated for further analysis. The AIAR achieved for the five events is 92.62%. The IDR can be up to 98.6%, which is significant to real application. The ECR of the system is 91.2%. All in all, the test results strongly prove the robustness of the proposed system.

4 Conclusions

A practical pattern recognition system for distributed fiber-



▲**Figure 4. The experimental setup of Φ-COTDR system.**

▼**Table 1. The identification results of the pattern recognition system**

	Event A	Event B	Event C	Event D	Event E	IARE	AIAR	IDR	ECR
Event A	146	0	0	0	4	97.33%			
Event B	4	91	0	4	1	91%			
Event C	0	0	148	2	0	98.67%	92.62%	98.6%	91.2%
Event D	1	29	0	69	1	69%			
Event E	2	0	0	0	148	98.67%			

AIAR: average identification accurate rate
ECR: event classification rate
IARE: identification accurate rate for each type
IDR: intrusion detection rate

optical intrusion monitoring system based on Φ-COTDR is proposed. It is proved quite effective for intrusion detection, by classifying events accurately and reducing the nuisance alarm rate greatly. The experimental indoor test proves the system robustness. In the future, more features will be extracted to further improve the robustness of the SVM classifier, more events will be classified and more field tests in specific outside environments will be carried out. We plan to put more emphases on the function of self-adaption for the pattern recognition system, which is a more challenging work. We believe the Φ-COTDR will have a bright future with the help of the practical pattern recognition system.

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Manuscript received: 2016-01-01

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