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Intrusion recognition method based on echo state network for optical fiber perimeter security systems

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ABSTRACT

In order to accurately and efficiently identify different types of intrusion signals of optical fiber perimeter security systems, this paper proposes a novel intrusion signal recognition method based on an echo state network (ESN). A perimeter security system based on an in-line Sagnac interferometer is employed to simulate in lab two laying situations of the sensing fiber: attached to a physical fence or buried under ground and acquire various event signals. The preprocessed signals are input into a trained well ESN to identify different types of events. The final recognition result of an event signal segment is determined according to the most dominant classification label corresponding to the signal segment. As a result, the average identification rates are 98.75% and 100% for the two laying situations, respectively. The proposed method has no need of extracting signal features and a large number of samples to train the classifier model. Therefore, more accurate and more effective intrusion identification can be achieved by the method than by others. The method is expected to satisfy the requirements of the practical application in the security field.

1. Introduction

In recent years, distributed optical fiber sensing technology has been widely concerned due to the capacities of detecting and locating the vibration signals acting on the sensing fiber and the advantages of high sensitivity, anti-electromagnetic interference and low price et al. It can be used as perimeter defense in the security field [1–8]. Different types of signals obtained by an optical fiber perimeter security system need to be identified as non-intrusion events or specific types of intrusion events to reduce the false alarm rate. Intrusion recognition methods have received increasing attention and played an important role in perimeter security. Fang et al. [9] proposed a recognition method based on gait characteristics for walking intrusion signals. The method can only distinguish non-intrusion events and walking intrusion events. Moreover, when a person with abnormal gait intrudes, the rate of false alarm will increase. In addition, there are many methods of intrusion recognition based on machine learning algorithms. Such as employing supervised artificial neural networks together with a feature extraction algorithm based on level crossing features in the time domain [10], a K-nearest neighbor (KNN) classifier [11] or support vector machine (SVM) classifiers [12–14]. However, sometimes the feature extraction has deviation due to the selection of level threshold without accurate basis. KNN algorithm is computationally expensive and requires a lot of memory. SVM classifiers are time-consuming in the training phase for large training sets. In addition, two integrated schemes based on radial basis function (RBF) neural network classifier were applied to discriminate intrusion events, one involving signal preprocessing based on empirical mode decomposition (EMD) and kurtosis characteristics [15], another using endpoint detection and filter-bank-based feature extraction [16]. The former can discriminate four common intrusion events. The latter can not only distinguish two common intrusion events, but also discriminate non-intrusion events and intrusion events. However, the identification processes of the two schemes are complex and the identification rates (IRs) need to be improved. All the above methods are difficult to satisfy the requirement of practical application for high IRs and simple recognition process.

In this paper, focusing on the need for improving the IRs, simplifying the identification process and saving the training time of the classifier model, we propose a new recognition method based on an echo state network (ESN). ESNs have achieved good results in many fields, including the dynamical pattern recognition or the time series classification [17–19]. However, as far as we know, this is the first time that ESNs are used for recognizing optical fiber intrusion signals. The recognition method based on the ESN has no need of extracting the signal features. It is also fast and convenient to train the ESN classifier model because only one weight matrix needs to be trained using a few samples. By a suitable decision rule, the proposed method can obtain very high IRs. We used the method to identify the signals detected by a perimeter security experimental system based on an in-line Sagnac

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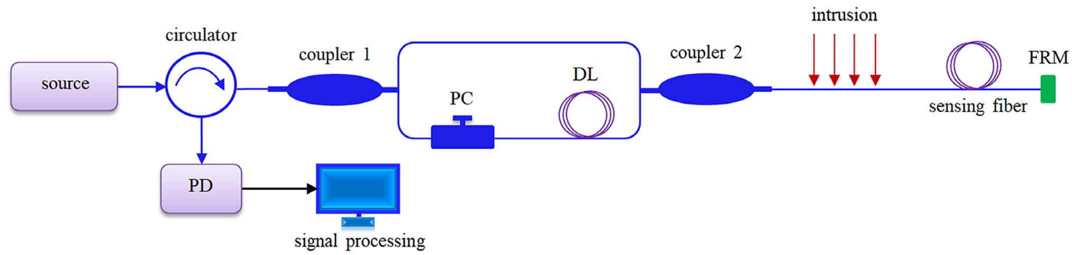

Fig. 1. Schematic diagram of optical fiber perimeter security system based on in-line Sagnac interferometer.

interferometer. The experimental results verify that the method can quickly identify the signals of the perimeter security system.

2. Optical fiber perimeter security system

Fig. 1 is the schematic diagram of the optical fiber perimeter security system based on in-line Sagnac interferometer [4,9]. The system is sensitive to the phase changes caused by external vibration signals and has no response to the slow change of the environment. It is easy to lay for the in-line structure. These characteristics make the system one of the most promising perimeter security systems.

In the system, the continuous waveform light from a broadband source is injected into the coupler 1 through a circulator. The light is split into two beams, one of which reaches the coupler 2 through the fiber pigtails of the two couplers. Then, the light is launched into a sensing fiber to the Faraday rotation mirror (FRM), the reflected light passes through the sensing fiber, coupler 2, delay loop (DL) and polarization controller (PC) to the coupler 1. The other beam comes back to the coupler 1 through PC, DL, coupler 2, sensing fiber, FRM and the fiber pigtails of the two couplers. The two beams have the same optical path and can produce interference in the coupler 1.

When an intrusion acts on the sensing fiber, the phase of the light in the fiber will change, which leads to the change of output light intensity to be revealed from the photodetector (PD). Finally, the signal processing unit processes the acquired data to obtain the recognition results of different events.

3. Echo state network

ESNs were presented by Herbert Jaeger in 2001 as a new designing and training approach for recurrent neural networks (RNNs) [20]. They simplify the training process of the networks without requiring a large number of training samples, and are easier to be determined in structure than traditional RNNs.

Fig. 2 shows the architecture of an ESN [20]. It can be seen that the ESN consists of an input layer, a reservoir and an output layer. In the input layer, there are K input nodes. The reservoir contains N sparsely connected internal nodes. N is called as the size of the ESN. In the output layer, there are L output nodes. W_{in}, W, W_{back} and W_{out} are the input weight matrix, the internal weight matrix, the feedback weight matrix and the output weight matrix, respectively. W_{in}, W and W_{back} are generated randomly and keep fixed. Only W_{out} is obtained through a linear regression algorithm in the training phase.

The state update equation of the internal node of the reservoir can be expressed as:

$$x(n+1) = f(Wx(n) + W_{in}u(n+1) + W_{back}y(n)) \quad (1)$$

Where f is the activation function of the internal node, $x(n)$ is the state of the node, $u(n)$ is the input signal and n is the discrete time.

The output signal $y(n)$ of the network is obtained as:

$$y(n+1) = f_{out}(W_{out}x(n+1)) \quad (2)$$

Where f_{out} represents the output function in output layer.

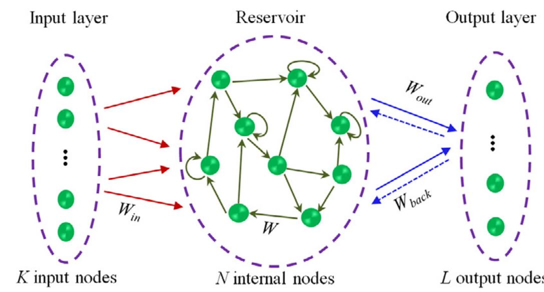

Fig. 2. The architecture of an ESN. The dashed arrows represent optional feedback connections.

4. Intrusion recognition method based on ESN

We employ the ESN model to recognize different event signals. ESNs belong to RNNs, which are good at resolving those time-related problems, such as the signals recognition of the optical fiber perimeter security system. Moreover, the high-dimensional characteristics of the reservoir can expand the input signals into the high-dimensional space, making the signals identification easier, and ESNs' consistency and separability are also conducive to the classification of signals [21]. Therefore, the ESN algorithm is suitable for the recognition of optical fiber intrusion signals. Since ESNs greatly simplify the training process of RNNs, a trained ESN can directly classify event signals, other than their features. In other words, the recognition method based on ESNs is no need of extracting features of signals, the input signals are just the event signals. In terms of signal recognition, ESN is superior to other RNNs. In the latter, failure to extract the main features of signals will lead to excessive training time and even dimensional disasters.

The recognizing process is as follows. First, the ESN is generated. Then, in the input layer, different types of raw event signals as input data are preprocessed for event discrimination. Next, the ESN is trained and the W_{out} is determined. Finally, the ESN is used to classify the preprocessed signals into different categories.

4.1. Generation of ESN

Generation of an ESN mainly includes determining the numbers of nodes in each layer, three weight matrices W_{in}, W, W_{back}, activation function f and output function f_{out}, as well as the spectral radius (SR), which is an important parameter of the ESN. Both the input and output layers consist of one node to input the preprocessed signal and obtain the output signal. In the reservoir layer, the size N of the reservoir is determined by experience. If N is too small, dynamic characteristics of the ESN are not rich enough; too big, computing time is too long, which affects the timeliness of processing. The W_{in} and the W are two matrices with sizes $N \times 1$ and $N \times N$, randomly generated according to certain rules, respectively. For the sake of simplicity, the W_{back} is set as 0, namely, no feedback from the output layer exists in the network. The common activation functions have sigmoid and linear functions [22]. The sigmoid functions make the internal nodes have nonlinearity abilities. The linear functions provide shorter memory capacities for the internal nodes. In most ESNs, linear functions are selected as the output functions, which enable the training of the network to obtain a global optimal solution. When the *SR* is less than 1, the echo state property of the reservoir can be guaranteed in most cases [22].

4.2. Signal preprocessing

In the actual application of the optical fiber perimeter security system, different types of event signals acquired have different durations. An event signal may be regarded as a signal segment, or a sample. Due to their different lengths, it is inconvenient to put various signal segments in a matrix as the input of the reservoir. Therefore, different kinds of event signal segments are combined freely and connected end to end to form a long one-dimensional time series as a sample set, namely, the samples are fed into the reservoir in a serial way. The selection of types of event signals is based on the consideration that the optical fiber perimeter security system is mostly in a non-intrusion state in reality. Therefore, no matter in training or testing phases, non-intrusion signals account for a greater proportion of the input data. The training sample set covers all kinds of event signals. However, the test sample set may include partial types of event signals.

Then, the time series is normalized to complete the preprocessing process of the signal. The *i*th data point of the preprocessed signal can be obtained according to the following equation:

$$y_i = (x_i - x_{\min})/(x_{\max} - x_{\min}) \tag{3}$$

Where x_i, x_{min} and x_{max} are the *i*th data point, the minimum and maximum values of the whole time series, respectively. The values of all the data points are mapped into the range between 0 and 1.

4.3. Training the ESN

Training the ESN is to seek the optimal output weight matrix W_{out} under appropriate parameters. Here, W_{out} is a matrix of size $1 \times N$, which is initialized to 0. For the fence-mounted type, the training sample set consists of non-intrusion events and one kind of intrusion event. For the ground-buried type, the training set has the same number of samples, including non-intrusion events and two kinds of intrusion events. The meanings of non-intrusion events for the two types of fiber laying ways are different, which are defined in Section 5.1, respectively. In addition, different types of events are labeled, namely, the output signals of non-intrusion event, intrusion event 1, intrusion event 2 and intrusion event 3 are designated as the labels of “0”, “1”, “2” and “3”, respectively.

The training sample set is preprocessed and input into the reservoir to train the ESN. The states of internal nodes are collected in matrix *B*. W_{out} can be obtained through Eq. (4).

$$W_{out} = pinv(B)T \tag{4}$$

Where *pinv* is pseudo inverse. *T* is the desired output signal.

4.4. Testing the ESN

The test sample set is preprocessed and drives the reservoir. The output signal $y(n)$ of the network is obtained according to Eq. (2). Since the test output is a continuous signal, and the desired output consists of four discrete labels of “0”, “1”, “2” and “3”, the output signal needs to be quantified according to the following rule. When the amplitudes of the output signals are greater than 2.5, between 1.5 and 2.5 or between 0.5 and 1.5, the corresponding output labels are “3”, “2” or “1”, respectively. The rest correspond to output labels “0”. Finally, the recognition result is to classify all the signal segments, according to the decision rule that the most dominant output labels corresponding to the signal segment is the final classification label. The IR is employed to evaluate the recognition results, which is shown as:

$$IR = \frac{N_c}{N_a} \times 100\% \tag{5}$$

Where N_c is the number of segments correctly identified, N_a is the total number of testing segments in the test sample set.

5. Recognition results

5.1. Raw event signals

We built the experimental system according to Fig. 1 to acquire the raw event signals in two simulated laying situations of the sensing fiber: attached to a physical fence and buried under ground. The source is a broadband light source with a central wavelength of 1550 nm and an output power of 2 mW. The DL and the sensing fiber are single-mode fiber with the length of 1.01 km and 3.1 km, respectively. The sampling rate of signals is 10 kS/s.

Because Sagnac fiber interfering systems are immune to slow environmental change, such as temperature fluctuation, the temperature non-uniformed effect in long distance optical fiber may be ignored. For the fence-based system, the vibrations caused by wind and rain need be considered. Therefore, we obtained the event signals of climbing the fence by shaking the fiber hung at the edge of the vibration-proof optic table many times under different simulated weather conditions, which are sunny, wind, light rain and wind, heavy rain and wind. Considering the actual application situation, shaking the fiber once or no artificial vibration of the fiber are considered the non-intrusion events. For the buried system, we acquired the event signals of pedestrian intrusion by walking across the sensing fiber and the human damage event signals to the system by knocking the cardboard, under which the fiber was laid, more than once. Knocking the fiber once or no vibration acting on the fiber is regarded as the non-intrusion events. Since the buried system is almost unaffected by the outside environment, it is unnecessary to collect signals from it in severe weather conditions. The experiments were repeated many times to obtain enough experimental data. The typical waveforms of various types of event signals are shown in Fig. 3. It can be seen that the signals of different events have different characteristics.

5.2. Recognition results of fence system

The size *N* of the reservoir is set as 200. The input weight matrix W_{in} is generated between −1 and 1 with equal probability. The internal weight matrix *W* is a random sparse matrix with uniform distribution. The activation function *f* is a nonlinear hyperbolic tangent function tanh. For the sake of simplicity function, the output function f_{out} is a linear identical function. The spectral radius *SR* of the reservoir is set as 0.4.

The training set consists of 240 event signal segments. Shaking event segments (twice and three times) under four different weather conditions of sunny day, wind, light rain and wind and heavy rain and wind account for 1/8 of the training data. The others are non-intrusion signals (shaking once and no artificial vibration) under the four kinds of weather conditions. The shaking event is treated as intrusion event 1. The training time is 10.23 s under the training set and the programming platform of Matlab software on an ordinary personal computer.

For four weather conditions, four test sets were constructed, respectively. Each test set is composed of 60 segments including 20 shaking events and 40 non-intrusion events. We took the test set under the sunny day condition as an example to show the test results. After the quantization and decision process of the test output, the final classification results were obtained. The test outputs before and after being quantified and decided are shown in Fig. 4. Before the test outputs are quantified, they are slightly disordered in the amplitudes, as shown in Fig. 4(a). Especially at the data point of about 4000, the fluctuation of the amplitude is relatively obvious, as shown in the inlet of local enlargement in Fig. 4(a). Even so, the test outputs are consistent with the desired labels corresponding to the test input, namely, “1” to shaking events and “0” to non-intrusion events, as shown in Fig. 4(a)

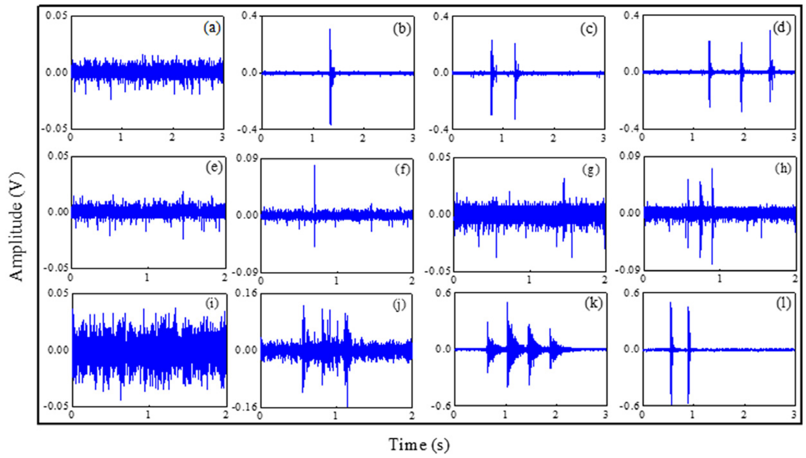

Fig. 3. The typical waveform of various types of events, (a) no artificial vibration in a sunny day, (b) shaking the fiber once in a sunny day, (c) shaking twice in a sunny day, (d) shaking three times in a sunny day, (e) no artificial vibration in a windy day, (f) shaking the fiber once in a windy day, (g) no artificial vibration in light rain and wind, (h) shaking three times in light rain and wind, (i) no artificial vibration in heavy rain and wind, (j) shaking three times in heavy rain and wind, (k) walking, (l) knocking the cardboard twice.

and Fig. 4(b). The disordered phenomenon disappears after the test outputs are quantified, as shown in Fig. 4(c). Fig. 4(d) presents the test outputs based on segments after being decided by the decision rule in Section 4.4. It is obvious that the shaking events can be identified from non-intrusion events without any mistake under the condition of sunny day. The *IRs* under the four different weather conditions are 100%, 100%, 98.33% and 96.67%, respectively. Therefore, the average *IR* is 98.75% for the fence-based system. The average time taken by the ESN classifier model to identify each segment is only 0.081 s under current conditions.

5.3. Recognition results of buried system

The size N of the reservoir, the input weight matrix W_{in}, the internal weight matrix W, the activation function f, the output function f_{out} and the *SR* of the reservoir are the same as Section 5.2.

The training set also has 100 signal segments, including 30 trials of artificial knocking (twice and three times), 30 trials of walking and 40 non-intrusion events (knocking once and no vibration). Knocking and walking events are intrusion event 2 and intrusion event 3, respectively. The time taken to train the ESN is only 7.58 s under the training set, the software and hardware conditions.

We take three test sets. Both the first and second test sets are composed of 60 segments. The first set includes 1/3 pedestrian (walking) intrusion segments. The rest are non-intrusion events. The second set consists of 20 knocking events and 40 non-intrusion events. The third set includes 20 pedestrian intrusion signals, 20 knocking and 46 non-intrusion events. For the non-intrusion events and the two kinds of intrusion events in the three test sets, all the *IRs* can reach 100%. In addition, the average time taken by the classifier to identify each segment for the three test sets is 0.157 s, 0.121 s and 0.131 s under current conditions, respectively. Therefore, the average identification time of each segment is 0.136 s for the buried system. The *IR* of 100% is achieved for each test set in a shorter time.

In order to intuitively present the recognition results, Fig. 5 shows a test output after being decided and a desired output. We can see that the two outputs are exactly same, no matter of the results based on segments in Fig. 5(a) and data points in Fig. 5(b).

To study the effect of training set size on identification rate and training time, we constructed two other smaller training sets. The first contains 90 signal segments consisting of 27 walking events, 27 knocking and 36 non-intrusion events. The second contains 30 segments, and the walking events, knocking events and non-intrusion events each account for 1/3 of the training set. The third test set above containing 86 signal segments is used to test the ESNs at different training sets. *IRs* under two kinds of training sets are 97.76% and 32.56%, and their training time is 7.02 s and 2.42 s, respectively. When the training set is small, the training speed is improved, however, the identification rate is reduced. In order to maintain high recognition performance, the training samples should not be too few, at least meet the required number of training the ESN classifier.

5.4. Comparison of identification performances between the proposed method and the method based on RFB neural network

To evaluate the recognition performances of the proposed method more objectively, taking the buried type as an example, we compared the identification performances between the proposed method and the method combined EMD, kurtosis characteristics with RBF neural network [15]. In the latter case, the event signals are decomposed into intrinsic mode function (IMF) components of 13 layers based on EMD at first. Then the kurtosis feature vectors are constructed with the first 11 IMFs and input into the RBF network to identify the categories of the signals. The identification rates and identification time are shown in Fig. 6. I, II and III represent the identification performances of three test sets in Section 5.3, respectively. IV is the average identification rate for the three test sets. V denotes the average identification time for each segment of the three test sets.

As shown in Fig. 6(a), for the three different test sets, the identification rates of the method based on RBF neural network are 96.67%, 68.33% and 76.74%, respectively. The average *IR* is 80.57%, which is obviously lower than 100%, the *IR* of the proposed method. From Fig. 6(b), we can see that the identification time for each segment of three different test sets based on RBF network is 0.097 s, 0.114 s and 0.1 s, respectively; each is slightly shorter than the corresponding time of the proposed method. The average identification time of the method is 0.104 s, only 0.032 s less than that of the proposed method under the same test set and the computing platform. However, the training time of the method is 5.05 s longer than that of the proposed method under the same training set and the computing platform.

6. Conclusion

In this paper, we propose a novel identification method for intrusion signals based on ESN. We use the method to identify the signals detected by an optical fiber perimeter security system based on the in-line Sagnac interferometer. By selecting suitable parameters of the network and the decision method for the final classification label,

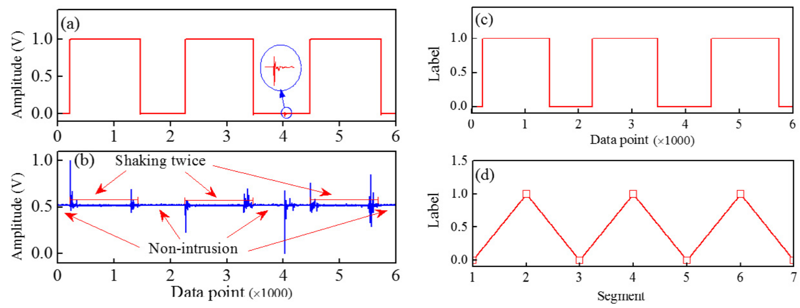

Fig. 4. The test outputs before and after being quantified and decided for the fence type, (a) test output before being quantified, (b) test input, (c) test outputs after being quantified, (d) test outputs after being decided.

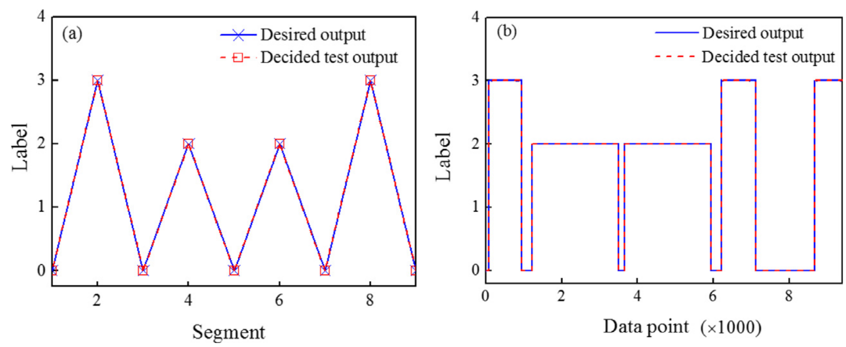

Fig. 5. Comparison between the test output after being decided and the desired output for the ground-buried type. (a) Based on segment, (b) Based on data points.

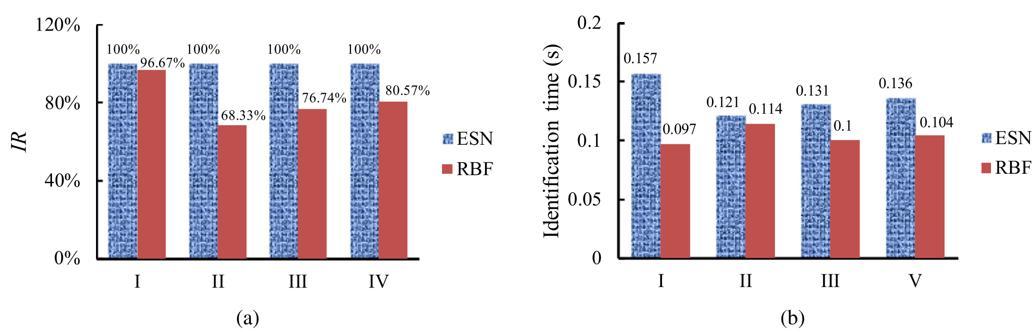

Fig. 6. Comparison of identification performances between the proposed method and the method based on RFB neural network. (a) Identification rate. (b) Identification time.

the average identification rates can achieve 98.75% and 100% for both simulated fence-based and buried fiber optic perimeter security systems, respectively. The proposed method has no need of extracting the signal features, hence, the recognition process is simple. In addition, there are no requirement for large numbers of signal segments to train the classifier model, therefore, the training time is shorter than other methods. Although the identification time is slightly longer, the time is tolerable for the practical use. To sum up, using the proposed method one can identify intrusion signals accurately and quickly, and the false alarm rates of optical fiber perimeter security systems can be reduced. The method is expected to meet the demand of the practical application in the security field.

Acknowledgments

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