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Fully modelling based intrusion discrimination in optical fiber perimeter security system

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ABSTRACT

In order to develop an efficient, accurate and richly functional intrusion discrimination scheme in the optical fiber perimeter security, this paper proposed a fully modelling based scheme for the DMZI vibration system. In this scheme, data modelling is applied in both the feature extraction stage and the pattern classification stage. By means of incorporating the coefficients of AR modelling into the feature vector, the intrusion characteristics are described in a brief, overall and essential way, which helps to recognize more intrusion types than the existing schemes. Moreover, owing to that the sigmoid modelling is applied in the classifier design, the proposed scheme is endowed with a particular function of estimating occurrence probabilities for all intrusion types. Besides, the adoption of AdaBoostSVM technique further enhances the classification rate. Experimental results showed that, with the above techniques incorporated, our proposed discrimination scheme can identify 6 intrusion types with the average classification rate 87.14% using only 4-length feature patterns, which presents vast potentials for DMZI applications.

1. Introduction

Recently, distributed optical-fiber vibration sensing techniques are widely applied in the perimeter security because of the advantages of immunity to electromagnetic interference and simple manipulation [1,2]. As a typical distributed optical-fiber vibration system, Dual Mach-Zehnder interferometry (DMZI) vibration system [3,4], which is attractive for the high sensitivity and fast response, receives increasing attention in a lot of fields such as submarine cable security [5], pipeline leakage detection [6] and airport guarding [7]. Generally, the perimeter security scheme in a DMZI system involves 3 steps: intrusion positioning [8–10], endpoint detection [11,12] and intrusion discrimination [13,14]. Up to now, the former two techniques have fully been developed, whereas the technique of intrusion discrimination remains immature. Specifically, a mature intrusion discrimination scheme should achieve improvements in 4 aspects: 1) The complexity of feature extraction should be low as possible; 2) The recognition system should not only yield the identification result of a particular intrusion, but also provide the occurrence probabilities for all intrusion categories. 3) The classification accuracy for various intrusions should be sufficiently high; 4) It is able to discriminate invasive events as many as possible.

However, the existing intrusion discrimination methods [15–18] cannot meet these 4 requirements. For example, Mahmoud et al. [15] proposed a classification scheme, which consists of a level crossing based feature extractor and a supervised neural network. However, limited by the fact that the features are only extracted in the time domain, this scheme can only discriminate 4 kinds of events. Moreover, the level crossing operation heavily relies on several thresholds which can hardly be properly specified in practical applications, thus the classification rate is not sufficiently high. Liu et al. [16] proposed a scheme based on wavelet decomposition and support vector machine (SVM) [19], in which the feature vector is structured with the detected signal energies over different frequency bands. However, due to the limitation that these frequency bands are rigidly segmented by wavelet decomposition in multiple levels, this not only reduces the efficiency but also degrades its classification performance (only 3 kinds of intrusions are discriminable). Liu et al. [17] proposed a high-accuracy scheme by combining empirical mode decomposition (EMD) with the RBF neural network, in which the feature extraction arises from the kurtosis of several intrinsic mode functions (IMFs) during EMD operation. This method is able to discriminate 4 kinds of intrusions. Nevertheless, as a data-driven signal decomposition method, EMD has to work in an iterative mode and thus consumes exhaustive complexity. Qu et al. [18] proposed an efficient multi-feature method, whose recognition result is obtained by simply judging these features' value

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ranges. However, this scheme can only discriminate 3 types of intrusions (vehicles, machine and human intrusions), which cannot meet the demand of further discriminating various human intrusions (such as knocking, cutting, crashing, waggling etc.).

In order to concurrently achieve the above 4 merits, this paper proposes a DMZI intrusion discrimination scheme integrating 3 aspects of technique improvements. Firstly, to lower the complexity of feature extraction, we construct a concise feature vector structured with autoregressive (AR) [20,21] modeling coefficients and the zero-crossing rate (ZCR); Secondly, we incorporate the sigmoid model fitting technique [22] into an SVM classifier, which endows the recognition system with the function of providing the occurrence probabilities for all intrusion categories (Note that, all the discrimination schemes involved in [15–18] do not possess this function); Thirdly, we adopt the AdaBoost technique [23] to organically synthesize the results of multiple SVM classifiers, which further enhance the classification accuracy. One remarkable characteristic of our scheme lies in that, data modelling technique is utilized in both the feature extraction stage and the pattern classification stage. Hence, our proposed system is called *fully modelling* based intrusion discrimination scheme. Field experiments verified that, this scheme can accurately identify 6 common intrusions (fence climbing, knocking the cable, waggling, crashing, kicking and fence cutting) with the average recognition rate about 87.14%.

This paper is organized as follows. Section 2 gives a brief description of the DMZI system. Section 3 presents the dataflow of the proposed scheme; Section 4 elaborates the construction principle of AR-modelling based feature vector; Section 5 mainly addresses the sigmoid modelling based classifier design, in which the improved classification technique based on AdaBoostSVM is also involved. Section 6 gives the performance comparison between the proposed intrusion discrimination scheme and the EMD-based scheme. Finally, Section 7 comes to conclusions.

2. DMZI vibration system

Fig. 1 illustrates the structure of DMZI vibration system: At coupler C1, a beam of laser with narrow linewidth is split equally through an isolator, and launched into a dual Mach-Zehnder Interferometer consisting of coupler C4 and coupler C5. Two light beams then propagate oppositely in clockwise (CW) and counter-clockwise (CCW) directions and interfere at their counterpart coupler (C5 or C4). The interference outputs are detected by PIN diodes PD1 and PD2 after circulators C2 and C3 respectively. Then, the output signals of the PIN diodes are collected by 2 Data Acquisition (DAQ) cards with different sampling frequencies. Specifically, the DAQ1 works in a low rate and is used for endpoint detection (i.e., determine the starting moment of the intrusions) and event discrimination [13,17], whereas the DAQ2 works in a high rate and is used for intrusion positioning. Finally, the sequences discretized by both DAQs are fed into the industrial personal computer (IPC) to implement the intrusion discrimination algorithms.

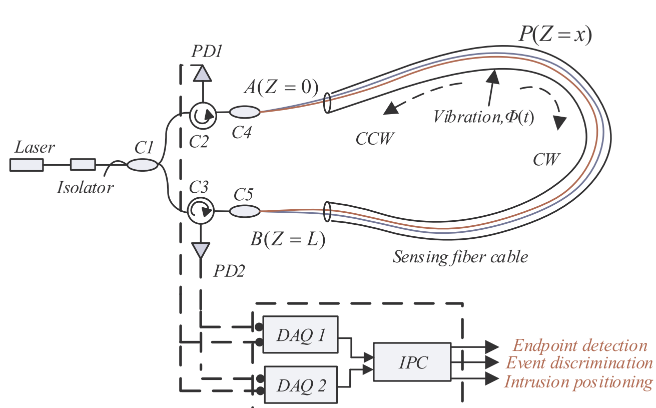

Fig. 1. Schematic diagram of DMZI vibration sensor. DAQ1: Data Acquisition Card for location; DAQ2: Data Acquisition Card for pattern recognition; IPC: Industrial Personal Computer; C1, C4, C5: 3 dB fiber coupler; C2, C3: Optical circulator; PD1, PD2: Photon-detector.

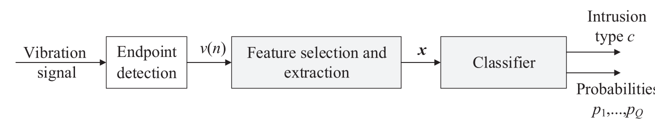

Fig. 2. Dataflow of intrusion event discrimination.

3. General description of the proposed scheme

As Fig. 2 shows, our proposed event discrimination scheme consists of 3 stages: Firstly, implement the endpoint detection algorithm on the input vibration signal to determinate the starting moment of an intrusive event [12,11]; Secondly, characterize the detected intrusion as a feature vector $\boldsymbol{x}$ from some proper perspective; Finally, use a classifier to identify the intrusion type c (assume Q kinds of intrusions are discriminable) and estimate the occurrence probabilities $p_1, \dots, p_Q$ of all intrusion categories. Note that, a functional distinction between our intrusion discrimination scheme and the existing schemes [15–18] lies in: our scheme can yield occurrence probabilities $p_1, \dots, p_Q$ whereas the existing schemes cannot.

In stage 1, the endpoint detection is realized by means of our previously proposed technique in [12]. To emphasize, this paper focuses on stage 2 (to construct the feature vector $\boldsymbol{x}$) and stage 3 (to design the classifier). Their dataflow is illustrated in Fig. 3, which includes the following operations.

Stage 2: Implement p-order AR modelling on the signal $v(n)$ and calculate its zero crossing rate ZCR. Then, combine the coefficients $a_1, \dots, a_p$ resulting from AR modelling with ZCR to construct a feature pattern $x = [a_1, \dots, a_p, ZCR]^{\mathrm{T}}$.

Stage 3: Use T multi-category SVM classifiers to process the pattern x in parallel to acquire M decision sets $\{f_{1,1}, \dots, f_{1,Q}\}, \dots, \{f_{M,1}, \dots, f_{M,Q}\}$. Further, by means of the sigmoid model fitting technique, these decision sets are translated into M occurrence probability sets $\{p_{1,1}, \dots, p_{1,Q}\}, \dots, \{p_{M,1}, \dots, p_{M,Q}\}$. Lastly, implement AdaBoost-based weighting sum on these probability sets to estimate Q occurrence probabilities $p_1, \dots, p_Q$. Accordingly, the final intrusion type c is decided by

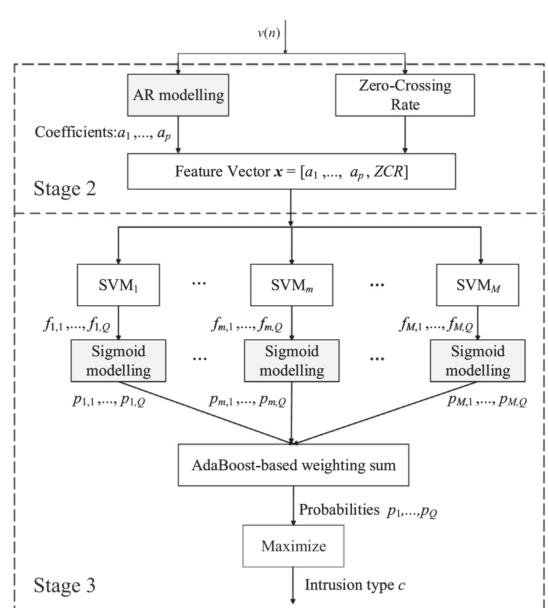

Fig. 3. Dataflow of feature extraction and pattern classification.