An optic-fiber fence intrusion recognition system using mixture Gaussian hidden Markov models

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Abstract: Since the development of optic-fiber interferometers and design of outstanding speech recognition models, the study on perimeter intrusion detection systems (PIDS) becomes a field of interest. In this paper, an optic-fiber based fence intrusion detection and recognition system that uses Sagnac interferometers and mixture Gaussian hidden Markov models (GMM-HMMs) is proposed. Experiments on real fence intrusions are performed, and comparisons are also carried out between our approach and the SVM based method, which prove our system more robust and accurate.

Keywords: fence intrusion, optic-fiber, recognition, Sagnac interferometer, Gaussian mixture model (GMM), hidden Markov model (HMM)

Classification: Optical systems

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1 Introduction

Perimeter intrusion detection systems (PIDS) have been widely applied on security protection regions, such as houses, jails, airports and gas pipelines. However, there are usually different kinds of intrusion patterns, some of which are even visually indistinguishable. In addition, the previous systems are restricted with sensors’ capabilities, the missing and false alarm rates are unsatisfactory in these days. Therefore, it is a challenge but of importance to design newly fence intrusion detection and recognition systems.

A detailed review on PIDS using the optical fiber sensors was conducted by Allwood et al. [1]. They separated the techniques into three categories: (1) interferometry, (2) scattering, and (3) fiber Bragg grating based detection [1]. Among them, the interferometry based PIDSs are widely used, especially for the systems using Sagnac interferometers [2, 3, 4, 5]. This is not only because their high efficiency, but also for their low cost. In this work, a $3 \times C_2^3$ coupler Sagnac interferometer based system is designed to detect the fence intrusion vibration signals.

With regard to recognition and classification on the intrusion patterns, different approaches were proposed. In Ali et al.’s work [2], the polarization controller was used to visually distinguish human walks and object falling events. In addition, works taking advantages of support vector machines (SVM) or neural networks (NN) as classifiers were also carried out [3, 5, 6, 7]. However, for the polarization controller based classifier, it is sensitive to the device. And for the SVM or NN based approaches, it is time consuming training the classifier models.

Since the vibrations are similar to speech signals, methods on speech recognition are considered, e.g., the perfect hidden Markov model (HMM). A PIDS using the non-homogeneous HMM (NHMM) was introduced in Yousefi et al.’s [8, 9] work. Though possessing good performance, it was restricted with sensors’ memories, and its intrusion patterns seemed easy to distinguish.

In our work, a mixture Gaussian hidden Markov model (GMM-HMM) based classifier is designed. We separate the vibration signals into two categories, harmful and harmless (See Fig. 1), which are more complicated and indistinguishable than Yousefi et al.’s. Besides, in order to improve alarm ability, we shorten the sampling time interval, directly enframe and extract features on the raw vibration signals, which is different from our works before [5, 3].

The rest of the paper is organized as follows. In Sec. 2, we describe the system, preprocessing of the signal and the MFCC features. After that, in Sec. 3, our
proposed GMM-HMM intrusion recognition model is explained in detail. Then in Sec. 4, experiments are carried out and comparison of our GMM-HMM model with the GA-SVM is also demonstrated. Finally, we conclude in Sec. 5 with some discussions and outlooks.

2 System and feature

In order to detect the fence intrusion signals, the Sagnac interferometers are taken advantaged to design the distributed optic-fiber sensing system. In this section, we firstly explain the sensing system, and then the preprocessing and extracting of features on the vibration signals.

2.1 Sensing system

Fig. 2 illustrates the framework of our intrusion detection system. It is designed with a $3 \times 3$ coupler Sagnac interferometer, which is composed of light source, photoelectric detector, coupler and fiber loop [3, 4]. The vibrations are then detected by photoelectric detector, gathered by signal acquisition card, preprocessed and recognized by the classification module.

2.2 Preprocessing and feature extraction

Before extraction of features, the raw vibration signals should be preprocessed. Firstly, the analog signals are sampled under the sampling frequency $f_s$, which is 15 kHz in our system. Then, the system noise is filtered using wavelet as well as our works before [3]. Finally, we separate the digital signal sequence into slices with a sampling time interval $t_s$, so as to generate the training and test samples for the classifier.
The Mel frequency cepstrum coefficients (MFCCs), described as representations of the short-term power spectrum of a speech-like signal, have been widely used in speech recognition areas [10, 11].

Since the vibrations are speech-like, in this work, the MFCCs are extracted as the features. We follow the descriptions in Ganchev et al.’s paper to calculate the MFCCs, and the first 12 coefficients are extracted as the features of one frame (See Sec. 2.2 in [10] for details). It should be noted that, the sliced vibrations are directly enframed without extracting the voice activity segments as the approaches in [3, 5], which decreases the algorithm’s complexity.

After enframing and feature extracting on the sliced vibration signals, the feature vectors can be formed and input as the observations in our GMM-HMM models, which are introduced in the next section.

3 Intrusion detection and recognition model

To recognize the intrusion patterns, a classifier is designed. In this section, the GMM-HMM model is firstly briefly described, and then we propose the fence intrusion recognition algorithm.

3.1 GMM-HMM

A hidden Markov model is a random sequence whose underlying Markov chain is not directly observable. The hidden states in the sequence can be observed only through a separate random function characterized by the observation probability distributions [11]. When the probability distribution obeys to multivariate mixture Gaussian functions, we generate the GMM-HMM model. In our fence intrusion recognition problem, a hidden Markov Model combined with GMM is designed (See Fig. 3).

There are three basic elements for a general hidden Markov sequence [11]. The first is the transition probability matrix of the hidden Markov states, $A = [a_{ij}]$, $i, j = 1, 2, \ldots, N$.

$$a_{ij} = P(q_t = j|q_{t-1} = i), \quad i, j = 1, 2, \ldots, N.$$ (1)

Here, $q_t$ is the Markov state at time $t$, and $N$ represents the amount of Markov states.
After that, the initial state-occupation probabilities of the hidden states are required and defined as follows,

\[ \pi = \{ \pi_i \}, \quad i = 1, 2, \ldots, N, \]  

(2)

where \( \pi_i = P(q_1 = i) \).

And the last element is the most important observation probability distribution, \( P(o_t|s_j), \ i = 1, 2, \ldots, N \), in which \( o_t \in \mathbb{R}^D \), and \( s_j \) is the \( j \)th state in the Markov chain. When it obeys to mixture Gaussian distributions, it is defined as,

\[ b_i(o_t) = P(o_t|s_j) = \sum_{m=1}^M c_m \frac{1}{(2\pi)^D/2|\Sigma_m|} \exp \left[ -\frac{1}{2} (o_t - \mu_m)^T \Sigma_m^{-1} (o_t - \mu_m) \right], \]  

(3)

where \( c_m, m = 1, 2, \ldots, M \) are the coefficients of the mixture single Gaussian functions, which are restricted to \( \sum_{m=1}^M c_m = 1 \), \( c_m > 0 \), and \( \mu_m, \Sigma_m \) are the \( m \)th expectation and covariance matrix of \( x \). And \( M \) here represents the amount of mixture Gaussian functions.

### 3.2 Intrusion pattern recognition

Since vibrations are separated into harmful and harmless categorizes, two single GMM-MHH models should be trained. Thus, likelihoods of the vibrations to each HMM can be calculated and compared, and the maximum respects to the potential intrusion pattern.

Let \( q_1^T = (q_1, q_2, \ldots, q_T) \) be the hidden state sequence in the GMM-HMM model, and the probability of \( q_1^T \) is as follows,

\[ P(q_1^T) = \pi q_1 \prod_{t=1}^{T-1} a_{q_t,q_{t+1}}, \]  

(4)

which is calculated with Eq. 1 and Eq. 2.

After that, we denote \( P(o_1^T|q_1^T) \) as the conditional probability of \( o_1^T \) sequence generated by \( q_1^T \), which is calculated with,

\[ P(o_1^T|q_1^T) = \prod_{t=1}^T b_t(o_t) = \prod_{t=1}^T \sum_{m=1}^M c_m \frac{1}{(2\pi)^D/2|\Sigma_m|} \exp \left[ -\frac{1}{2} (o_t - \mu_m)^T \Sigma_m^{-1} (o_t - \mu_m) \right]. \]  

(5)

Then, based on the Bayesian theorem, we have

\[ P(o_1^T, q_1^T) = P(o_1^T|q_1^T)P(q_1^T), \]  

(6)

where \( P(o_1^T, q_1^T) \) is the joint probability of the hidden and observed sequences.

Finally the total or cumulate likelihood of the observed sequence is calculated by summing the likelihoods in Eq. 6 over the hidden state sequence \( q_1^T \).

\[ P(o_1^T) = \sum_{q_1^T} P(o_1^T, q_1^T). \]  

(7)

To solve the GMM-HMM model, as well as the the total likelihood \( P(o_1^T) \), the celebrated algorithm namely forward-backward can be utilized [11, 12].
In our work, as for fence intrusions, we design three hidden states in the HMM, i.e. (1) quiet state, (2) harmonic falling state, and (3) high peak state. The amount of mixture Gaussian distributions is also set as three.

4 Experiments and results

Experiments on real fence intrusion vibrations were carried out to demonstrate the performance of our designed system and the GMM-HMM based classifier. And comparisons of our approach with our previous GA-SVM [3] were also performed, which has been applied commercially\(^1\).

4.1 Datasets and evaluation strategy

The fence intrusion detection system in our work was assembled as Fig. 2 illustrated. In addition, the maximum voltage of the photoelectronic detector, and the sampling frequency \((f_s)\) were also fixed in advance, which were 4 V and 15 kHz. With regard to intrusion signals, the harmful and harmless vibrations were generated by rattling and sweeping on the optic-fiber cables manually.

During real applications, we have found that recognition accuracy was affected by \(t_s\), i.e., the slice or sampling time interval. For instance, if we trained the classifier with signals sliced at a long \(t_s\), and tested it with signals from a shorter interval, the accuracy would be significantly decreased. However, the shorter \(t_s\) is, the more efficient or real-time the system is.

Since that, to test the robustness of our designed classifier, we sliced the vibrations under different time intervals. In this work, two time intervals, 1 and 2 seconds were set. And four pairwisely formed datasets, \(D_{i,j}\), \(i, j = 1, 2\), were obtained, in which suffix \(i\) was respect to the time interval of training data, and

\(^1\)Brightfiber: http://www.brightfiber.com.cn/en
to the test data. Besides, in each training or test subset, there were around 100 single samples.

The false alarm rate (FAR) and missing alarm rate (MAR) are defined as evaluation indices. In this work, the harmful intrusions are set as positive signals, while the harmless are set as negative. Thus, FAR and MAR are calculated by the false positive (FP) and false negative (FN) measurements over total samples, i.e. $\text{FAR} = \frac{\text{FP}}{N_s}$, and $\text{MAR} = \frac{\text{FN}}{N_s}$ [3].

### 4.2 Experiments and comparisons

The datasets above were applied to train and test the classification models introduced in Sec. 3.2, as well as the GA-SVM model in work [3]. After that, the FAR and MAR on each dataset were calculated and listed in Table I.

We can find that, the recognition accuracies of $D_{11}$ and $D_{22}$ were both better than $D_{12}$ and $D_{21}$, and $D_{21}$ was the worst. This proves our assumption that the slice time interval can affect the system. In our view, when the slice time interval was decreased, the main body of intrusion vibrations were probably truncated, which led to mis-classifications.

However, when compared with the GA-SVM model, our GMM-HMM classifier achieved significantly better performance in all the datasets, especially for $D_{21}$. This proves that our approach was with better robustness than the GA-SVM model. By means of this, we can shorten sampling time interval so as to improve alarm efficiency.

Besides, an example of estimated paths of the vibration samples were illustrated in Fig. 4 to display performance of the GMM-HMM classifiers. It can be found that the trained models matched well with the vibration patterns as our expectation.

| Approaches | Index | $D_{11}$ | $D_{12}$ | $D_{21}$ | $D_{22}$ |
|------------|-------|----------|----------|----------|----------|
| GA-SVM     | FAR (%) | 5.38 | 6.81 | 12.38 | 5.00 |
|            | MAR (%) | 5.41 | 3.66 | 4.64 | 4.55 |
| GMM-HMM    | FAR (%) | 1.92 | 4.08 | 4.64 | 1.96 |
|            | MAR (%) | 1.90 | 2.85 | 3.17 | 1.59 |

Table I. Comparisons on GA-SVM and GMM-HMM models. FAR and MAR represent the false alarm and missing alarm rates.
In this paper, we proposed a fence intrusion detection and recognition system that uses optic-fiber interferometers and mixture Gaussian hidden Markov models. The intrusion vibrations are detected and gathered by the systems, and then classified with the GMM-HMM based classifiers. After that, the harmful intrusions will be alerted. Experimental results showed that our approach not only can recognize intrusion patterns accurately, but also is robust at different sampling time intervals.

We also carried out comparisons of our approach to the GA-SVM models. It shows that our classifier achieved significantly lower FAR and MAR, which proves that the GMM-HMM model is suitable for recognizing intrusion patterns. The false and missing alarm rates of our approach are around 4% and 3%.

In the further work, we are planning to add more intrusion patterns so as to improve the flexibility of our system. Besides, the localization of intrusions is also our interested field, especially for the application on gas pipeline protection.

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