Open-set Events Identification Based on Deep Metric-learning for DMZI Perimeter System

Chengang Lyu, Member, IEEE, Jianying Jiang, and Ziqiang Huo

Abstract—Intrusion monitoring based on optical fiber distributed sensing is a pattern recognition problem of target events. Due to the addition of uncontrollable unknown events in practical applications, the open-set problem brought about greatly reduces the accuracy of traditional events recognition methods. In order to solve this problem, this paper design a deep metric-learning network, combined with Recurrent Plot (RP) coding to improve the accuracy of target events recognition in an open environment. In this paper, the RP algorithm is used to encode the intrusion signals into images that reflect the signal’s motion. The deep metric-learning network is used to project the image into the feature space. And feature centers of each class can be calculated rely on the training samples. So, the network identifies the intrusion event according to the distance between the test sample and the feature center. By setting the appropriate threshold, the samples whose distance exceeds the threshold are identified as unknown class to solve the open-set problem. In the experiments, the dual Mach-Zehnder interferometry (DMZI) distributed optical fiber perimeter system is built to collect event signals. For 7 known event classes the highest identification accuracy can reach 99.7%. After adding 3 unknown event classes, the accuracy rate can exceed 93.3% with appropriate threshold. And the total response time is only 0.4 s. This novel method guarantees the accuracy of target identification under the introduction of unknown events and improves the robustness of the distributed optical fiber perimeter security system.

Index Terms—Distributed optical fiber, intrusion identification, metric-learning, open-set.

I. Introduction

OPTICAL fiber sensing technology, such as fiber Bragg grating (FBG), Fabry-Perot interferometer (FPI), optical time domain reflectometer (OTDR), Mach-Zehnder interferometer (MZI), etc., with its high sensitivity, anti-electromagnetic interference, flexible and lightweight advantages, has excellent performance in various sensing applications [1]–[8]. Among these optical fiber sensing technologies, the dual Mach-Zehnder interferometry (DMZI) technology has been widely used in the field of distributed optical fiber perimeter security system (DFSS), such as airports, communities, and factories, due to its interference measurement accuracy and distributed measurement capability [9]–[12]. The DMZI optical fiber sensing structure has extremely high sensitivity to the environmental disturbance signals. Therefore, how to quickly and accurately identify the target intrusion events is one of the key research directions in this field. In recent years, the introduction of machine learning technologies makes the identification of intrusion events more and more accurate. Liu et al. used empirical mode decomposition (EMD) algorithm combined with radial basis function (RBF) network.

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The identification rate of four known intrusion events reached 85.75% [13]. Liang et al. analyzed the equivalent frequency distribution of the signal and classified it by the time-frequency envelope similarity. The identification rate of four known intrusion events reached 90% [14]. Jia et al. extracted 30 features and used near category support vector machines. The identification rate of four known intrusion events reached 94% [15]. Next year, they proposed a method combined the extreme learning machine (ELM) and fisher score feature selection. The identification rate of five known disturbance events exceeded 95% [16]. Wang et al. established a spatial time-frequency spectrum dataset and used DPN network for training and learning. In the experiments of seven known events, the f1-scores were all higher than 97% [17]. Although the above methods have achieved high identification accuracy of intrusion events, these identification accuracies are limited to the identification of fixed event classes. In other words, these methods assume that the testing event classes are within a range of known classes, which ensure the accuracy of identification. However, in practical applications, uncontrollable other events are frequent and inevitable, which generate the unknown class datasets and lead to an open-set problem in identification [18]. And these unknown events would be classified into the most similar known events based on the traditional identification methods, resulting in an extra error rate. Javier Tejedor et al. deployed the pipeline integrity detection system in a fully realistic scenario. In the classification of 8 hours of real-world recorded data, the
accuracy rate was 53.5% [19]. In the author's analysis, about 26.7% of the error rate is due to actual activities without training. And this extra error rate would continue to increase with the occurrence of unknown class events. Therefore, how to distinguish the unknown random events and ensure the accuracy rate of the known target events is an open-set problem that must be solved in practical applications.

According to above, this paper proposes an open-set event identification method based on deep metric-learning, which maps the events sample to the feature space and judges the relationship between the events according to the feature similarity [20]. Through the feature learning, different classes are separate by a certain margin and keep the same classes as close as possible. Therefore, it can identify the testing samples far away from all training classes as unknown events, and achieving the open-set identification. In experiments, the DMZI distributed optical fiber perimeter security system is built to collect event signals. In order to further improve the events’ feature discrimination, the Recurrent Plot (RP) algorithm is used to extract the motion characteristic, which is the amplitude of the signal fluctuates with time. Images encoded by RP can show the deeper time correlation of event motion, highlight the characteristics of each intrusion classes. RestNet18 is used to learn these characteristics and map them into the feature space. We calculate feature center of each class relies on the training samples, modify the identification part of the network, and set a threshold to identify the sample far from the feature center as an unknown event class. To the best of our knowledge, this is the first study to mix known and unknown event classes in the experiments. The field experiments results verify that the deep metric-learning with RP algorithm achieve high identification rate of 99.7% among 7 known event classes, and exceed 93.3% when adding 3 unknown event classes. In addition, the total response time 0.4s also guarantee the real-time requirement in practical security monitoring.

II. PRINCIPLES

The framework of open-set intrusion event identification consists of three parts, as shown in Fig. 1. The first part is to collect sensing signal by DMZI. The second part is the signal encoding base on RP algorithm. The third part is to use deep metric-learning to achieve open-set intrusion identification.

A. Sensing Signal Acquisition

The DFSS takes the optical fiber as the sensing and transmission component, and achieves long-distance monitoring along the optical fiber by detecting the changes of optical wave parameters. It is an integrated system with sensing and transmission, which can well serve the needs of various industries for intelligent and integrated environmental sensing and monitoring systems. Among them, DMZI has the characteristics of low cost, simple structure, high sensitivity, convenient installation and maintenance [21]–[23]. So, it has been extensively used in DFSS. Its structure is shown in Fig. 2.

The continuous narrow-band laser with a wavelength of 1550 nm is divided into two beams by C1 at a ratio of 1: 1. A beam propagates along the direction of clockwise (CW), interferes at coupler C3, and is finally collected by PD1. The other beam propagates along the direction of counterclockwise (CCW), interferes at coupler C2, and is finally collected by PD2. When the sensing area receives external intrusion disturbance, the light propagating along the CW and CCW will produce phase changes.

Assuming that the length of the fiber is L, the refractive index is n, and the diameter of optical fiber is D. When the external disturbance occurs, the phase change can be expressed as:

$$\Delta \varphi = \beta L \frac{\Delta L}{L} + L \frac{\Delta n}{n} + L \frac{\Delta D}{D}$$

where $\beta$ is the propagation constant. In this formula, the first term is the phase change caused by the change of fiber length. The second term is the phase change caused by the change of fiber refractive index. The third term is the phase change caused by the change of fiber diameter.

The interference of light converts the phase change into the intensity change:

$$I = I_n [1 + K \cos(\Delta \varphi + \varphi_0)]$$

where $I$ is the output light intensity, $I_n$ is the average light intensity, K is the influence coefficient, and $\varphi_0$ is the initial phase of the light.
Through PD acquisition and analysis, the interference light intensity signal is converted into a voltage signal, and the class of the intrusion event can be identified.

B. Time-series Signal Encoding

The intrusion signal collected by the sensor is a time-series signal, and the time-domain signal contains a large amount of characteristic information, such as the development trend and duration. However, intrusion time-series signals are often non-stationary and nonlinear, which greatly exacerbate the difficulty of signal processing. In this paper, we use the RP algorithm to extract the signal’s motion information, that is, the signal fluctuates up and down with time. RP can encode signals into images, and these images visualize the deeper temporal correlation of the signal's motion information [24], [25].

The main idea of RP algorithm is to extract the recursive motion state of the signal. The process is summarized as follows: firstly, reconstructing the phase space of the intrusion signal, and then generating the recurrent plot according to the distance between the phase points.

Fig. 3 shows the step-by-step instructions for calculating RP for a simple time-series signal. First reconstruct the phase space from the intrusion signal \( x = \{x_1, x_2, ..., x_n\} \) , where \( n \) is the number of sampling points. The points in the phase space represent the motion states of the signal. Each point in the space is a \( m \)-dimensional vector:

\[
S_i = (x_i, x_i + \tau, ..., x_i + (m-1)\tau), \quad i = 1, 2, ..., N
\]

(3)

where \( N = n - (m-1)\tau \), \( m \) is embedding dimension, and \( \tau \) is time delay. Then calculate the distance between each phase point to generate an \( N \times N \)-dimensional distance matrix:

\[
R_{ij} = \theta(e - ||S_i - S_j||), \quad i, j = 1, ..., N
\]

(4)

where \( N \) is the number of states S, \( e \) is a distance threshold, \( ||\cdot|| \) is a norm and \( \theta(\cdot) \) is the Heaviside function.

It can be seen from (4), the recurrent plot generated by the R-matrix contains only two values \{0, 1\}. In order to prevent the loss of features, we omit the distance threshold and use the gray-scale recurrent plot. The smaller the gray value in the recurrent plot, the closer the states between the phase points.

The recurrent plot visualizes the trajectory of signal motion state changes, and it contains abundant characteristic information [26]. Fig. 4 shows several typical state recursive characteristic diagrams, which can be divided into four types: periodic, homogeneous, drift, and disrupted. In the periodic structure, the state appears repeatedly and regularly, which indicates the periodic of the signal. The homogeneous structure indicates that the signal is relatively stationary and random. The drift structure is formed by the slowly changing signal. The disrupted structure is caused by a sudden change in the signal. A closer look at the recurrent plot also reveals some small-scale details, such as single points that represent short signal duration and vertical or horizontal lines that represent long-term signal stability.

RP can extract the effective features of the signal, eliminate a lot of redundant features, and visualize the signal. These are beneficial for signal analysis and identification.

C. Open-set Events identification

Recent years deep learning has achieved rapid development and progress, which achieves unparalleled performance in many areas such as real-time speech translation, object recognition, and natural language processing [27]–[29]. Deep learning combines feature extraction and intrusion identification to achieve end-to-end learning. It has the following advantages [30]:

1) Hand-crafted feature extraction is usually limited by human domain knowledge. It can only extract shallow information. Deep learning can adaptively extract features, and
deep neural networks can extract deeper meaningful features, which are beneficial to the identification of intrusion events.

2) Deep learning can better handle massive data. Through repeating training on the collected data to extract features. So, it can achieve high-precision testing requirements.

Class in the training set is called “known class”, and class that is not in the training set is called “unknown class”. As shown in the Fig.5 (a), the traditional classification problem is a close-set problem, assuming that test class and training class are exactly the same. However, as shown in the Fig.5 (b), in the real application, the test classes are often do not exist in the training set, which is called the open-set problem. The goal of open-set identification is to correctly divide known class and correctly identify the unknown class [31].

How does deep learning identify unknown class? One method is to add unknown class in the training set. Training an N+1 class classification network, where N is the number of known class. However, the problems of which samples should be included in the unknown class and how many different types of samples are needed cannot be solved. Another method is to construct multiple binary classifiers. According to the results of these classifiers, the test class is comprehensively judged. However, the training time of this method is longer. Moreover, if two or more classifiers judge the test sample belongs to its class, the final class cannot be determined.

The open-set problem is essentially feature similarity learning. No longer mechanically classify the test sample into one of N classes, but judge the sample class according to the similarity of the features with each class [32]. Taking face recognition as an example, this is an open-set problem. Humans can easily determine whether the person is known or not because humans identify face by learning and memorizing features, such as round face and single eyelid.

As shown in Fig. 6 (a), the original classification method only generates classification boundaries among different classes. So, when distinguishing unknown class, the classification algorithm will only assign it to similar known class. In practice application, the appearance of a large number of unknown class events will cause serious errors.

The method used in this paper is shown in Fig. 6 (b). We adopt deep metric-learning network to learn an embedding function, which projects the samples into the feature space. Through network training and learning, in the feature space, the distance between the same class is continuously reduced, while the distance between different classes is expanded. Then the class boundaries and feature centers of each class can be learned. Those within the boundary belong to this class, and those outside all the boundaries belong to the unknown class.

The network learns the class boundary through triplet loss [33]. As shown in Fig. 7, three samples are input each time, an anchor sample, a positive sample, and a negative sample. The anchor sample is the same type as the positive sample and different from the negative sample. Enter three samples into the same neural network. This paper selects RestNet18 network learning embedding function, which outputs 64-dimensional (64-D) feature vectors, and uses the triplet loss function to learn network parameters. Its expression is as follows:

\[
    \text{disp} = \| f(x^a) - f(x^p) \| \tag{5}
\]

\[
    \text{disn} = \| f(x^a) - f(x^n) \| \tag{6}
\]

\[
    \sum_i (\text{disn} - \text{disp} + \alpha) \tag{7}
\]
where \( N \) is the total number of samples, \( x_i^a \) is the anchor example, \( x_i^p \) is the positive example, and \( x_i^n \) is the negative example. \( disp \) is the feature distance between anchor and positive samples and \( disn \) is the feature distance between anchor and negative samples. \( \alpha \) is the margin, which is used to control the distance between positive and negative samples. \( ||·|| \) is the Euclidean distance. + means that when the distance between two vectors is greater than margin the loss is 0, otherwise loss is non-negative.

In order to reduce the distance between similar classes and facilitate the setting of threshold for identification, this paper adds the \( disp \) after the triplet loss function. And in order to prevent overfitting, regular term is added. The final loss function is:

\[
\sum_{i=1}^{N} (\text{disn} - \text{disp} + \alpha) + \text{disp} + \sum_{i=1}^{N} \lambda (f(x_i^a) + f(x_i^p) + f(x_i^n)) \tag{8}
\]

where \( \lambda = 0.01 \) is regularization parameter.

It makes the distance between similar classes be approximately zero, while the distance between different classes is approximately \( \alpha \).

We calculate feature centers of the known class through the trained network, and calculate the distance between the test sample and the feature centers. By setting a distance threshold, samples distances less than the threshold belong to corresponding known class and all samples whose distance exceeds the threshold are identified as unknown class. This method can solve the open-set identification problem.

### III. EXPERIMENTS AND DISCUSSION

The overall experimental process is shown in the Fig. 8, using the DMZI system to collect different man-made or natural intrusion signals. Then using the RP algorithm to encode signals and input them to the network for training, and calculating the feature centers of known classes for testing.

#### A. Dataset Construction

We used the DMZI system, as shown in the Fig. 2, to collect event signals. The experimental system was applied to the perimeter of the building to detect the intrusion events, and the optical fiber cable was placed on the iron fence in the wave shape. The intrusion events tested in this research are described as follows, heavy and light rain (spraying water on fence to simulate raining environment), wind blowing (collecting sensing signals in windy days), treading (stepping on optical fiber cable to simulate over fence intrusion), slapping (slapping the optical fiber cable by hand), impacting (impacting the fence by shoulder), knocking (knocking the fence by a stick to simulate destructive intrusion), Ambient noise (caused by normal ambient noise without intrusion), pressing (squeezing the optical fiber cable by hand), wagging (shaking the fence by hand).

This paper selected seven known class events for network training, verification and testing. Including treading, slapping, impacting, knocking, heavy rain, light rain, and wind blowing. Three other signals ambient noise, pressing and wagging as unknown classes for network testing and evaluation. Based on signal characteristics and system performance, we set the data sampling rate to 2 kHz and the sampling window to 1 s. The normalized signal is shown in the Fig. 9.

We choose embedding dimension \( m = 4 \) and time delay \( \tau = 5 \) for signal coding. A total of 9,000 feature images encoded by RP with a size of 1985 × 1985 were generated, including 4,800 man-made intrusion signals, 3600 natural interference signals, and 600 images as unknown. The encoding result is shown in the Fig. 10. Each class displays three RP-converted images. After RP conversion, it can display the unique characteristics of each class, further highlighting the difference between the classes.

In this paper, the data of the seven known classes were allocated to training set, verification set and the testing set according to the ratio of 6:2:2, and the three unknown classes data were all put into the testing set for testing.

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**Fig. 8.** Experimental process overview.

**Fig. 9.** Normalized signal waveform. (a) - (g) is known class and (h) - (j) is unknown class.

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In this paper, the data of the seven known classes were allocated to training set, verification set and the testing set according to the ratio of 6:2:2, and the three unknown classes data were all put into the testing set for testing.
B. Training Model

We choose Resnet18 network learning feature space mapping function. In order to reduce network parameters, the image size was adjusted to 299 × 299. Our training used stochastic gradient descent, fixed learning rate $1 \times 10^{-5}$ (decreasing the learning rate by 20% every 40 epochs). And the parameters were optimized by Adam algorithm ($\beta_1 = 0.9$, $\beta_2 = 0.99$). Running on an Intel(R) Xeon(R) CPU @ 2.30GHz, Tesla P100 with batch size 64 for 100 epochs.

We randomly selected a class of image from the training set as an anchor sample, another image from the same class as positive sample, and a class of image from the remaining classes as negative. Input these three images into the ResNet18 network and output the 64-D feature vector. The triplet loss function was used to optimize the network parameters, where margin $\alpha = 0.2$, so that the distance between the same class was close to zero, and the distance between different classes was close to 0.2.

In the verification set, the image group selection method was used as same as the training set. If the distance between the positive and negative groups was greater than $\alpha$ or the distance between positive samples was smaller than $\alpha$, the classification was correct. Through the verification, we continuously adjusted the appropriate hyperparameters and training time.

C. Testing results and Discussion

The feature center of the class was obtained by calculating the average of the feature vectors. Therefore, we input all training samples into the trained network and calculated the feature centers of seven known class. We input each testing sample into the network to obtain the feature vectors, and calculated the distance between them and each feature center. The distance less than the threshold verified that it belongs to this class, and if the distance from each feature center was greater than the threshold verifies that this sample belongs to an unknown class.

The choice of threshold is very important. It determines the accuracy of the final identification and its choice is related to the training parameters. During training, we choose the margin $\alpha = 0.2$, trying to make the distance between the boundaries of known classes was 0.2. So, we choose different thresholds between 0 and 0.2 for multiple experiments and the results show that 0.11 was the most suitable threshold. Here we show the comparison of the five thresholds of 0.01, 0.1, 0.11, 0.12, and 0.2, explain the importance of the threshold, and its influence on the whole experiments.

We defined UA as unknown class accuracy which is the percentage of correctly classified in unknown class. KA as known class accuracy which is the percentage of correctly classified in known class. AA as all class accuracy which is the percentage of correctly classified in all classes.

![Fig. 11](image_url)

**Fig. 11.** Visualize classification results without unknown classes. The class from 0 to 7: Heavy rain, Light rain, Wind blowing, Treading, Slapping, Impacting, Knocking, Unknown. The yellow dots (7) are known class samples that are mistakenly classified as unknown class.

Table I shows the classification results when there only seven known classes. If the threshold is close to zero, only the signal that is almost the same as the feature center is identified as the corresponding class. Therefore, when the threshold is 0.01, all samples are identified as unknown class. As the threshold increases, the class boundary expands, more and more test samples will be contained in the class boundary, and the classification accuracy of known classes will also increase. If the threshold is equal to the margin 0.2 selected during training, almost every known class can be correctly identified. And no samples are identified as unknown class, where 0.3% of the error is the misclassification between classes.

<table>
<thead>
<tr>
<th>Threshold</th>
<th>AA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>0.1</td>
<td>0.11</td>
</tr>
<tr>
<td>0.11</td>
<td>0.12</td>
</tr>
<tr>
<td>0.2</td>
<td>0.2</td>
</tr>
</tbody>
</table>

Table I shows the classification results when there only seven known classes.
the effect of adding only one of them. The results are shown in Table II. With the appropriate threshold, the model can identify different unknown classes, while correctly identify known classes.

Fig. 12 is a graph of the accuracy rate at different thresholds when the unknown class is pressing. It can be seen that UA and KA are negatively correlated. One increase will inevitably lead to another decrease and this is consistent with their actual relationship.

Through the analysis of Table I and Table II, we can see that all unknown classes can be identified when the threshold value close to zero. And when the threshold is equal to margin 0.2 selected during training, almost all known classes can be correctly identified. So, in order to ensure the accuracy of both known and unknown classes, an appropriate threshold should be selected. From the experimental results, for our dataset 0.11 is the most appropriate threshold.

To further validate the network performance, we tested the identification effect when adding two or more unknown classes and the results are shown in Table III. Selecting the most appropriate threshold value 0.11 obtained from the above experiment, the accuracy of the known and unknown classes is relatively balanced. No matter which unknown classes are added, the total accuracy exceeds 93.3%. As long as selecting the proper threshold, more unknown classes do not result in performance degradation. And this proper threshold is

![TABLE II](image)

<table>
<thead>
<tr>
<th>Unknown class</th>
<th>AA / KA / UA (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pressing</td>
<td>0.01 / 0.1 / 0.11/ 0.12 / 0.2</td>
</tr>
<tr>
<td>Ambient noise</td>
<td>10.6 / 90.1 / 93.3 / 95.3 / 90.4</td>
</tr>
<tr>
<td>Wagging</td>
<td>10.6 / 90.1 / 93.6 / 95.8 / 90.1</td>
</tr>
</tbody>
</table>

Fig. 12. Accuracy rate at different thresholds. The unknown class is pressing. When the threshold is 0.05, AA, KA, UA are 33.8%, 26.0%, 100%. When the threshold is 0.15, AA, KA, UA are 95.3%, 99.2%, 62.5%. As the threshold increases, KA keeps rising and UA keeps falling. Since the number of known class samples accounts for 89% (1680/1880) of the total, AA rises first and then falls.

Fig. 13. Visualize identification results with different unknown class.

0-6 are known classes, 7 is unknown class. The threshold is 0.11. (a) Adding pressing as unknown class. (b) Adding pressing and wagging as unknown class. (c) Adding pressing, wagging, and ambient noise as unknown class.
relatively stable.

Fig. 13 shows the identification results when adding unknown classes. Different classes of unknown class are mapped to different positions in the feature space, but they basically fall outside the class boundary of the known class. Therefore, selecting the appropriate threshold can distinguish the known class from the unknown class, so as to achieve open-set identification.

In order to clarify the advantages and better performance of the proposed method, we compare it with the methods discussed above and the results are shown in the Table IV. For the identification of only known classes, our method can achieve relatively high accuracy. As far as we know, in the direction of distributed optical fiber intrusion identification, there is currently no research literature on the identification of unknown classes. The method we proposed separately verified the identification effect of one, two and three unknown classes, and the accuracy rate can reach more than 93.3%.

In summary, the model can identify unknown class well and achieve open-set identification. The signal preprocessing time is 0.8 ms, the identification time is 0.39 s, and the total time is about 0.4 s. This method can also ensure real-time identification.

IV. CONCLUSION

This paper proposes a DFSS open-set intrusion event identification method, which based on deep metric-learning. It uses the RP algorithm encoding the signal while extracting the signal’s motion characteristics. The deep metric-learning network is used to map the encoded image into the feature space. And it completes the open-set events identification from the feature similarity.

In the experiments, the DMZI optical fiber perimeter security system is built to collect 10 classes event signals, including 7 as known classes and 3 as unknown classes. For the identification of 7 known event classes, the highest identification accuracy can reach 99.7%. After adding 3 unknown event classes, it can make the average accuracy rate all exceed 93.3% with appropriate threshold. And the total time spent of the algorithm is only 0.4 s. This method guarantees the identification accuracy of the known target events under an open environment, and also achieves the unknown class events division. It provides a new idea for the open-set DFSS intrusion event identification in practical applications.

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