

# Pattern recognition of gait signals using $\phi$ -OTDR

Fanran Meng<sup>a</sup>, Wenxiang Zhang<sup>a</sup>, Guo Zhu<sup>a</sup>, Xian Zhou<sup>a</sup>, Fei Liu<sup>a\*</sup>

<sup>a</sup>School of Computer and Communication Engineering, University of Science & Technology  
Beijing, Beijing 100083, China

## ABSTRACT

Gait recognition is of great significance in many fields such as human identity recognition, medical rehabilitation, remote monitoring, and so on. In this paper, the gait signal pattern recognition as well as the identity recognition is achieved through machine learning based on the data obtained by phase sensitive time-domain reflectometer ( $\phi$ -OTDR). The dynamic phase variation caused by the pedaling directly acting on the fiber was recorded. By extracting the temporal-spatial features of the recorded signal, the recognition accuracy of the two experimenters can be resolved as high as 90% via a convolutional neural network (CNN). It provides an effective solution for human identity identification in perimeter security applications using  $\phi$ -OTDR.

**Keywords:**  $\phi$ -OTDR, Gait recognition, CNN, temporal-spatial features

## 1. INTRODUCTION

As a new biometric recognition technology, gait recognition can not only realize the recognition of individual identity[1]-[3] according to people's walking posture but also can be used to detect people's physiological and pathological characteristics[4]-[6]. In the future, it can be expanded to the security inspection of banks, stations, and other places. Thus the investigation of gait pattern recognition is of great significance. Depending on the type of sensor, the gait recognition methods can be divided into the video method[7], the force sensor method[8], infrared method, and acoustic method. Alessandro Manzi et al.[9] described a clustering approach to gait recognition by extracting skeletal data from a depth camera that was unaffected by external problems. Zifeng Wu et al.[10] learned similarity by deep convolutional neural network(CNN). A deep neural network can be trained to recognize the most significant changes in a person's gait pattern from a small group of flagged multi-angle videos of pedestrians walking, and thus identify a person. Alharthi et al.[11] developed a biometric verification system to measure human gait and walking patterns. As long as an individual walks on a floor pressure mat, the system can analyze the 3D shape of the pedal steps and time-based perception data and successfully identify personal information. However, the structures of these two methods are complex and require a lot of calculation.

The  $\phi$ -OTDR system has advantages including simple structure, high sensitivity, low computing burden, long detection distance, and so on. It has been widely used in perimeter safety, pipeline safety alarm, and other fields to realize external environment monitoring such as strain, temperature, and vibration. Nian Fang et al.[12] proposed a recognition method of walking intrusion signals based on gait characteristics in  $\phi$ -OTDR. By using the special step period characteristic included in the vibration signal caused by a walking intruder, the signal of human intrusion is easily distinguished from animals or other random disturbances. Shi et al.[13] proposed a deep learning-based multi-radial distance event classification method. The method can distinguish both event types and radial distances by extracting the temporal-spatial data matrix.

This paper proposes a gait pattern recognition method based on the  $\phi$ -OTDR system. The phase space-time image is obtained by recording the phase change caused by the pedal signal of two people on the optical fiber. In this paper, the phase, amplitude, and temporal-spatial characteristic information in the phase temporal-spatial image are used to achieve 90% accuracy by the ResNet50 classification algorithm. The experimental results show that this method can effectively identify the identity information of different people, and preliminarily verify the feasibility of the gait recognition method based on  $\phi$ -OTDR system. This method provides a reliable approach for identity identification with high privacy.

## 2. EXPERIMENT AND DATASETS

### 2.1 Experimental setup and method

The structure of  $\phi$ -OTDR is shown in Figure 1(a). The prototype  $\phi$ -OTDR instrument in experiment is shown in Fig 1(b) with the detailed principle described in [14]-[16]. Ultra-narrow linewidth laser is used as light source. The position, amplitude, and phase of the disturbance signal can be obtained by the corresponding digital signal processing. We can extract the perturbation waveform applied on the whole sensing fiber with a specific spatial resolution. The optical fiber was arranged on the floor in U-shape. The dynamic phase variation caused by the pedaling directly acting around the fiber was recorded. The location of pedaling signal is determined by the difference of Raileigh-backscattering signal (RBS), and the waveform of pedaling is extracted by demodulating the phase variation of the RBS.

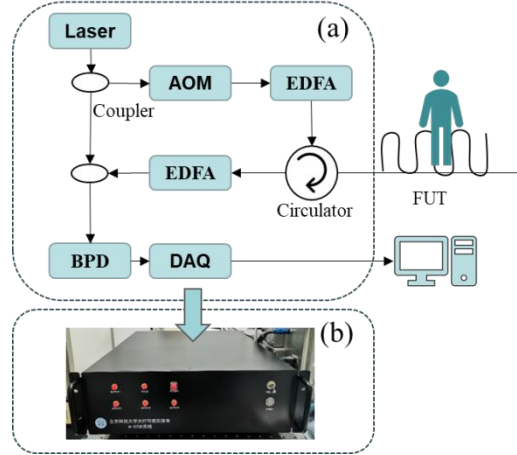


Figure 1. Experimental setup and  $\phi$ -OTDR miniaturization real-time monitoring system. (AOM, acoustic-optic modulator; EDFA, erbium-doped fiber amplifier; BPD, balanced photoelectric detector; DAQ, data acquisition card; FUT, fiber under test.)

### 2.2 Datasets

In the field test, the developed  $\phi$ -OTDR instrument was used, and the optical fiber length was 1km. The probe pulse width was 100 ns corresponding to a spatial resolution of 10 m, and the repetition period was 22  $\mu$ s. The frequency shift of AOM is 80 MHz and the sampling rate of DAQ is 200MS/s. The details of the two experimenters are shown in Table 1.

Table 1 Experimenters' information.

Item	Gender	Height (cm)	Weight (kg)
Walker 1	Women	158	53
Walker 2	man	180	70

The phase temporal-spatial image, obtained from the demodulated phase, can be used to locate the signal, select the interval of signal disturbance, and reduce the computation of data preprocessing. The time-domain waveforms of single step are presented in Figure 2. Figure 2(a), Figure 3(a) and Figure 4(a) demonstrate the pedaling waveform from the female experimenter, and (b) the male experimenter. Figure. 3 shows the temporal-spatial image of a single step waveform. The operation period of a pedal signal is about 0.8s. The continuous pedal phase temporal-spatial image is shown in Figure 4. The output signals have intermittent and periodic gait characteristics.

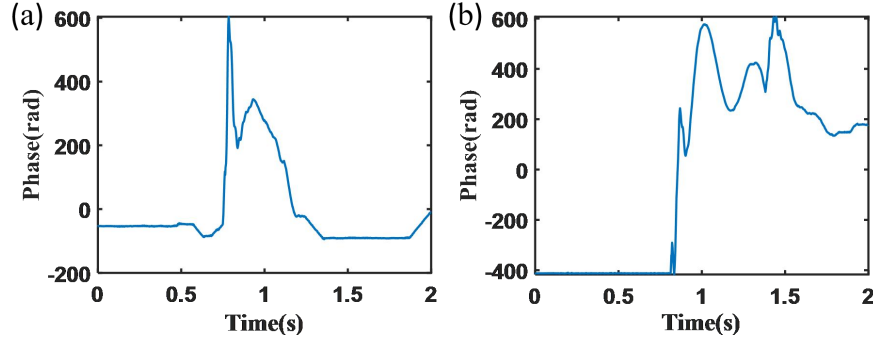


Figure 2. Single step time domain waveform.

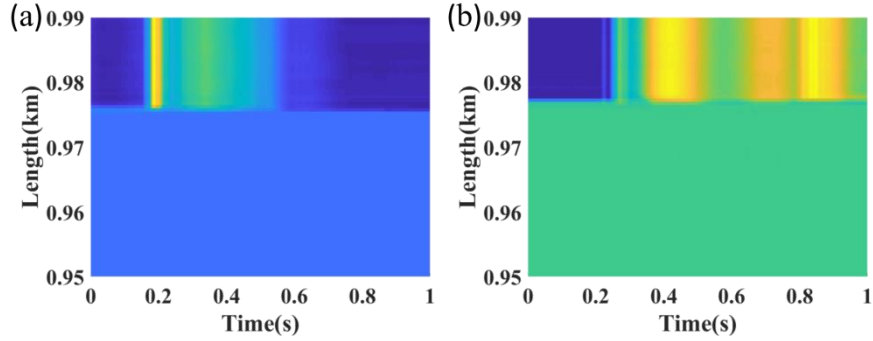


Figure3. Single step phase temporal-spatial image.

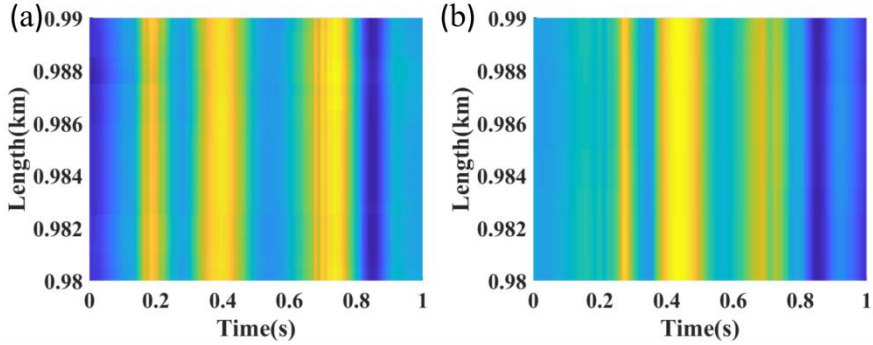


Figure4. Continuous pedal phase temporal-spatial image.

### 3. RESULTS AND ANALYSIS

Deep learning methods such as CNN can automatically learn the features of data sets and fit the optimal classification algorithm. Therefore, they are suitable for  $\phi$ -OTDR event classification. In this paper, ResNet50 network is used as the recognition classifier. The ResNet50 architecture consists of 4 blocks containing 50 conv2d. The learning rate is set at 0.003. The batch size can be understood as a batch processing parameter, and its limit value is the total number of training set samples. In deep learning, the principle of small-batch data processing is generally adopted. Each batch size is composed of 32 images randomly selected from the training data. The loss curve oscillation is significantly reduced and the convergence speed is accelerated. The model trained a total of 100 epochs. The ratio of training set to verification set is 7:3. In addition, we used the original temporal-spatial image to train the model to verify the effect of temporal-spatial on classification accuracy. The resultant validation accuracy curves are shown in Figure. 5. During the training on temporal-spatial images, the best test accuracy is 91%. The

training results are shown in Table 2. The recognition accuracy of the two experimenters can be resolved as high as 90% via a ResNet50. The recall rate and f1 score of the input temporal-spatial images are both above 90%, indicating that the model has a good recognition effect on the phase temporal-spatial characteristics of the pedaling signal. The experimental results show that the gait temporal-spatial characteristics based on the  $\phi$ -OTDR system can be effectively recognized.

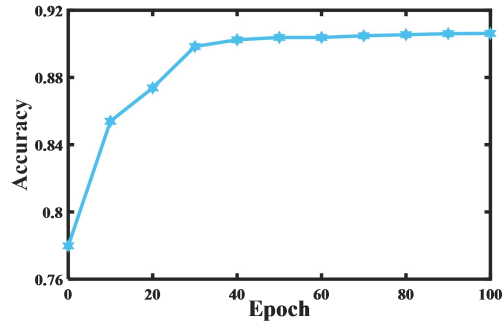


Figure5. Classification accuracy curve.

Table 2. The training results of pedaling.

	Precision	recall	f1-score
Walker 1	89.09%	91.21%	90.38%
Walker 2	90.12%	90.39%	91.56%

#### 4. CONCLUSION

In this work, a gait recognition method based on  $\phi$ -OTDR system is proposed. Different experimenters can be accurately identified by using the phase, amplitude, and temporal-spatial characteristics of the pedal signals. The feasibility of  $\phi$ -OTDR system in gait recognition is verified in this work. The method has the advantages of non-contact, long distance, and good privacy, which can be used in privacy-sensitive scenes such as identity identification and family health monitoring.

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