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A Method for Train Tracking Based on Distributed Acoustic Sensing

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Abstract. It is crucial to obtain the position information of the moving train for railway safety, such as Automatic Train Protection System, Train Interlocking System, Railway Section Occupation and son. Distributed Acoustic Sensing (DAS) is an optical instrument that use optical fibers as sensors for vibration signal perception. This technology can sensitively capture vibration signals around the optical fibers, and has the ability to work under humid and strong electromagnetic interference environments. In this paper, a train tracking method based on distributed acoustic sensing is proposed. This method can achieve the real-time measure of a running train on position, speed and direction parameters. In order to identify and track the vibrations of moving trains, we proposed a Convolutional neural network for recognizing the moving train. Compared with traditional machine learning methods, the deep learning can eliminate the need for laborious feature extraction. it is show bye the field test that our approach can achieve 98.61% correct tracking.

Keywords. Distributed acoustic sensing; Train tracking monitoring; Convolutional neural network

1. Introduction

Railway transportation plays a significant role on economic and social development of a nation. Railway safety is an increasingly serious issue. It is very important to measure the train moving status information, such as the train position, real-time speed and the direction, etc. The accurate position of a train on the track is sufficient to prevent the collisions of trains and increase traffic capacity. This is an important requirement for the decarburization of traffic. Furthermore, railway accidents could cause serious issue. A small abnormal event may lead to serious consequences, even cause human casualties or heavy losses of property. Traditionally, train tracking monitoring and protection is often performed by the methods such as track circuit, video monitoring, or other track-side equipment. These conventional approaches require far more monitoring installation and complex network for signal transmission. Distributed acoustic optical sensors used as an auxiliary approach (see Figure.1) that can continuously monitor and protect the railway safety.

Distributed acoustic optical sensors (DAS) system is an optical instrument that use single model fiber as a sensor for vibration sensing [1]. Non-coherent optical time

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domain reflectometry(OTDR) technology has been widely used for parameter measurement of optical fiber. Rayleigh backscattering is highly sensitive to stress effects, which can obtain the intensity and position of the stress on the optical fiber. Distributed acoustic optical sensors (DAS) technology utilizes this Rayleigh backscattering technique to sense the intensity and location of vibration signals. Unlike video surveillance needs an enormous amount of camera devices. Here, the single model fiber can continuously monitor vibration event and serve as a transmission medium to transmit signal simultaneously. Furthermore, the method realizes the sensing and spatial localization of vibration events. So, it is suitable for the long-distance and real-time sensing for vibration events [2,3].

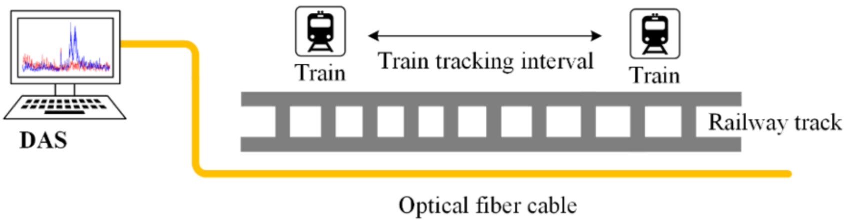

Figure 1. DAS for railway monitoring and protection.

In the on-site applications, the recognition of the event type from the DAS is a valuable research topic [4,5]. Based on the analysis and research of the document literature, these approaches mainly include traditional machine learning method such as support vector machines and random forests, as well as deep learning methods such as recurrent neural network, convolutional neural networks [6-9]. In this paper, we present a method directly use raw data generated by DAS that can measure the train position, real-time speed and the direction of a running train. Further, a compact CNN structure is argued for recognizing the moving train on the track. The experiment result confirmed that our approach is used to identify the position of the trains.

Our work is organized as follows: The Section 1 gives the background and the state of the art methods. The Section 2 introduces the data collection and data pre-processing. The Section 3 shows the network structure of the convolutional neural network we proposed. The Section 4 shows the experimental result and its comparison with traditional machine learning methods. Finally, the Section 5 gives the conclusion.

2. Data Collection and Data Pre-processing

Construct a data matrix based on the collected data. The row of the data matrix represents space domain (Length of the optical fiber along the track) and the column of the data matrix stands for time domain (time of the rain running along the railway). Due to the hight intensity of the Rayleigh backscattering from each positions are different, there are different direct current component intensity in the signal. Additionally, vibration installation track-side also leading to different noisy component in the signal. To remove the direct current component and the noise composition in the vibration signal [10]. Here, the signal filtering technique like signal smoothing and band-pass filtering are used for data pre-processing. The moving average technique refers to calculating the average of neighbouring points for each point in a signal. An example of the temporal-spatial for the train running along the railway track is shown in Figure 2.

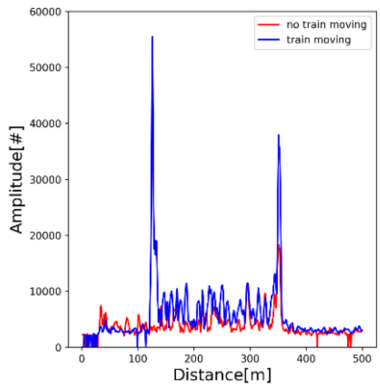

Figure 2. Different signal sources. Blue curve represents a train moving on the track, and the red curve represents no train on the track.

In Figure 2, the blue curve represents the train moving along the railway track, and the red indicates that there are no train running on the railway track. We can see that when the train running along the railway track, there are significant differences in signals. Compared to the signals without train running on railway tracks, the vibration signals show a larger amplitude when the train running on the track. We will also the larger amplitude lasting for a period of time. We also see the larger amplitude will continue for a period of time.

3. Convolutional Neural Network for Train Tracking

In general, when a train travels along the railway track, the optical fiber laid along the track would sense strong vibration. Then our DAS sensor unit receives and stores these vibration signals. We directly use these temporal-spatial data to produce an image of train movement trajectory. An illustration of the vibration detection can be found in Fig.3.

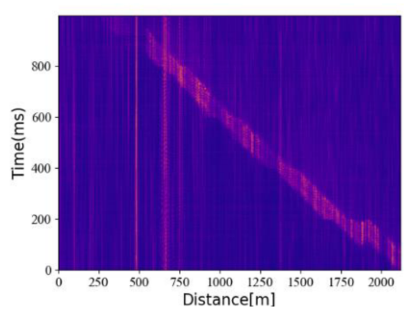

Figure. 3 Raw temporal-spatial data of a train moving on the track for visualization

Figure 3 depicts a train movement trajectory of a moving train. In the figure, the horizontal direction stands for space domain (Length of the optical fiber along the track) and the vertical direction stands for time domain. We can clearly know about the direction, speed, and the position of the moving train from the movement trajectory. For example, the slope of the inclining of the high brightness beam stands for the direction of a moving train. The reciprocal of the slope stands for speed. It should be noted that there are another two vertical high brightness beam, which can be explained by one of two factors: either there is natural vibration source continually working, or the position is the fiber fusion point of two optical fibers.

In order to recognize the train moving along the railway track, we convert raw temporal-spatial data first to a gray scale image (see Figure.4) and then a convolution neural network is used for recognizing the moving train.

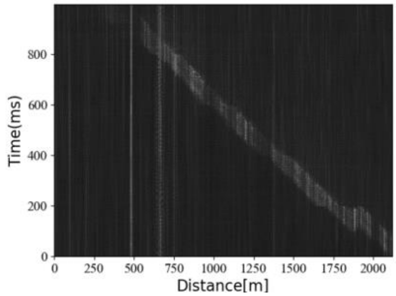

Figure 4. A gray scale image of the raw temporal-spatial data

Classic convolutional neural network such as AlexNet, GoogLeNet and VggNet can all achieve good classification results. However, due to their huge network architecture, all of them have relatively low training speed. As the high timeliness required for train tracking, a small, faster, but still maintain accuracy network is needed.

Based on the above analysis, a suitable convolutional neural network structure was designed. The network can direct recognize these gray images. Firstly, two convolutional layer and one pooling layer with a maximum operation are performed. In order to better extract features of gray images, we construct another two convolutional layers. As before, there is also a pooling layer for down sampling. Finally, the output layer is a fully connected neural network for classifying these gray images. Here, there is always a ReLU activation function behind each convolution layer. The structure of the CNN for recognize the position of the moving train as illustrated in Figure 5.

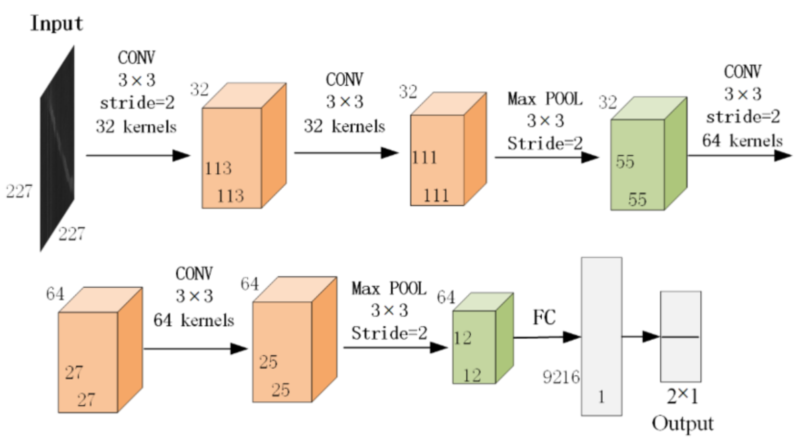

Figure 5. Structure of the CNN for recognize the position of the moving train

Generally, the classification ability of convolutional neural networks is proportional to their network depth. So far as we know, the deeper the depth, the higher the classification accuracy. However, the deep network architecture can lead to a serious decrease in training speed. Additionally, the deep network usually exhibits over fitting problem. On the other hand, there will be obvious characteristic of the vibration while the train moving on the track. Thus, a small network architecture will achieve a good classification result. And the experimental results demonstrate that our method can achieve good classification performance.

4. Experimental and Discussion

In the on-site applications, 2600m of communication fiber were installed in a cable trench close to the railway tracks. These optical fiber cables are all ordinary communication cables, and no special cables was done for this work. At one side, the fiber cable was located in the cable trench, and in the other side, the fiber cable was deployed to the lab where concatenated to DAS. Here, the DAS collects the vibration data and stores it in a data storage system. Due to the presence of distinct vibration features during the train moving on the train, here, we directly put the matrix data generated by DAS into the neural network.

To perform the train tracking, there are total 2872 gray images were used to train our convolution neural network for train recognition, and there 671 gray images were used to test the network. These images come from the data matrix generated by DAS. In our test experiment, we can observe all the tracks of the moving trains on the railway track. However, due to the external disturbance and the noise in the signal, there are several false positive results during the evaluation experiments. The experimental verification shows that our approach can achieve more than 98.61% correct tracks.

Using the same data as in the preceding, a classical machine learning approach(ML) was employ to perform the train tracking task. Here, we use support vector machine (SVM) as the classical machine algorithm. SVM is also a good classification method. It has been widely applied in pattern recognition problems such as image recognition and text classification. It should be noted that SVM algorithm use raw signal data instead of image data. In the test period, SVM can also observe all tracks of the moving trains compare to our approach. However, of the 421 total tracks, SVM found 347 correct tracks in the evaluation experiments. SVM only achieve 82.42% correct tracks. Here, SVM are difficult to handle large-scale datasets. It computational complexity increases with the increase of the sample data scale. When dealing with large-scale datasets, the training time and memory consumption of SVM may become very high, even difficult to accept. The experiment proves that our approach has a good massive data processing ability compared to the SVM algorithm.

5. Conclusions

In this paper, a recognition method for the position information of the moving train has been proposed. The method directly used raw data generated by DAS. Furthermore, the mothed intuitively revealed the information of positions, speed, and direction of a moving train. In order to identify and track the vibrations of moving trains, a small CNN structure is proposed with high recognition accuracy. The experimental results demonstrate that our method can achieve good classification performance.

For application in the ground truth scenes of railway, DAS shows great potential. DAS can also perform track disease monitoring tasks, such as track fracture, track rockfall, asymmetrical settlement of subgrade, etc. In the future research, we will evaluate more algorithms to increase the correctness, timeliness and robustness of the application of the DAS.

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References

[1] Sun M, Yu M, Lv P, et al. Man-made threat event recognition based on distributed optical fiber vibration sensing and SE-WaveNet [J]. IEEE Transactions on Instrumentation and Measurement, 2021, 70: 1-11.

[2] M. Lunglmayr and G. C. Amaral, "Linearized bregman iterations for automatic optical fifiber fault analysis," IEEE Trans. Instrum. Meas., vol. 68, no. 10, pp. 3699–3711, Oct. 2019.

[3] R. Sifta et al., "Distributed fiber-optic sensor for detection and localization of acoustic vibrations," Metrol. Meas. Syst., vol. 22, no. 1, pp. 111–118, Mar. 2015.

[4] Li, J.; Wang, Y.; Wang, P.; Bai, Q.; Gao, Y.; Zhang, H.; Jin, B. Pattern recognition for distributed optical fiber vibration sensing: A Review. IEEE Sens. J. 2021, 21, 11983–11998.

[5] Wu, H.; Zhou, B.; Zhu, K.; Shang, C.; Tam, H.Y.; Lu, C. Pattern recognition in distributed fiber-optic acoustic sensor using an intensity and phase stacked convolutional neural network with data augmentation. Opt. Express 2021, 29, 3269–3283.

[6] Wang, W.; Hu, W.; Wang, W.; Xu, X.; Wang, M.; Shi, Y.; Qiu, S.; Tutumluer, E. Automated Crack Severity Level Detection and Classification for Ballastless Track Slab Using Deep Convolutional Neural Network. Autom. Constr. 2021, 124, 103484.

[7] Yao, Z.; He, D.; Chen, Y.; Liu, B.; Miao, J.; Deng, J.; Shan, S. Inspection of exterior substance on high-speed train bottom based on improved deep learning method. Measurement 2020, 163, 108013.

[8] H. Xu, X. Zhang, Z. Zhang, and M. Li, "Study on pattern recognition method based on fiber optic perimeter system," Proc. SPIE, vol. 9679, 2015, Art. no. 96790Y.

[9] Q. Sun, H. Feng, X. Yan, and Z. Zeng, "Recognition of a phase-sensitivity OTDR sensing system based on morphologic feature extraction," Sensors, vol. 15, no. 7, pp. 15179–15197, 2015.

[10] Shi, Y.; Wang, Y.; Zhao, L.; Fan, Z. An Event Recognition Method for Φ-OTDR Sensing System Based on Deep Learning. Sensors 2019, 19, 3421. https://doi.org/10.3390/s19153421.