Tunnel disturbance events monitoring and recognition with distributed acoustic sensing (DAS)

Tai-Yin Zhang, Bin Shi*, Cheng-Cheng Zhang*, Tao Xie, Jun Yin and Jun-Peng Li

1School of Earth Sciences and Engineering, Nanjing University, Nanjing, Jiangsu 210023, China
2Yuxiu Postdoctoral Institute, Nanjing University, Nanjing, Jiangsu 210023, China

*Correspondence to: shibin@nju.edu.cn (B.S.), zhang@nju.edu.cn (C.-C.Z.)

Abstract. Accurately identifying disturbance events along tunnels is essential for their safe operation, which constitutes an important part of tunnel health monitoring and abnormality warning. In recent years, distributed acoustic sensing (DAS), a state-of-the-art fiber-optic sensing technology, has developed rapidly in the field of earth science and engineering. Based on the principle of phase-sensitive optical time-domain reflectometry, DAS allows detecting acoustic/vibration signals along a common fiber-optic cable up to tens of kilometers. This brings new opportunities for monitoring of long perimeters such as underground tunnels. In this paper, we propose a DAS-based method for the recognition of disturbance events along tunnels. The EMD denoising algorithm is employed to optimize vibration signals to better extract the time–frequency domain features of monitored events. Different events are then recognized via a machine learning-based multi-class classification approach. The Random Forest algorithm is applied to analyze the DAS data acquired with fiber-optic cables deployed along the tunnel lining, successfully recognizing a variety of vibration events during the construction of the tunnel including unexpected disasters such as rockfalls, with a recognition accuracy of 92.31%. This DAS-based disturbance identification method may provide a new opportunity for unmanned, real-time monitoring of tunnel abnormal events.

1. Introduction

Geological disasters often occur in the tunnel construction process, such as surrounding rock deformation, water leakage, gushing, and rock burst [1]. These events pose a serious threat to the health of tunnel structures. How to monitor geological disasters along the tunnel is one of the crucial topics in tunnel structural health monitoring [2]. In recent years, distributed acoustic sensing (DAS), a state-of-the-art fiber-optic sensing technology, has developed rapidly in the field of earth science and engineering. Based on the principle of phase-sensitive optical time-domain reflectometry, DAS detects seismo-acoustic signals along a common fiber-optic cable up to tens of kilometers [3]. With the advantages of long-distance, long-term, and distributed monitoring, DAS brings new opportunities for monitoring of long perimeters such as underground tunnels.

Recently, the DAS technology has been successfully applied for intrusion detection and railway health monitoring [3–7]. In the field of intrusion detection, several scholars have proposed advanced machine learning or deep learning algorithms; these algorithms allow to extract and distinguish the characteristics of various disturbance events such as vehicle driving, train driving, hammering, and
walking [5–7]. The resulting recognition accuracy was generally within the range of 85–98%. For railways, fiber-optic cables are commonly laid near rails. Using these accompanying cables, DAS can record the speed and position of running trains, railbed wear, deviation, etc. [3]. In addition, combining near-surface imaging techniques with coherent seismic waves generated by trains, Rodriguez Tribaldos et al. obtained the stratigraphic information within 500 m below a rail line [4].

In this paper, we develop a DAS-based approach for the recognition of disturbance events during the construction of tunnels. First, we use the EMD denoising method to remove high-frequency white noises of DAS signals. Then, we employ the Random Forest algorithm for event classification and recognition. Finally, we test the robustness of the proposed method using a DAS dataset of three types of vibration events recorded during the construction of a railway tunnel. The results show that our approach achieves a recognition accuracy of 92.31%.

2. Distributed Acoustic Sensing Measurement Principle

When a light pulse travels through a fiber core with impurities, a part of the light will deviate from the original propagation direction to generate scattered light. There are three types of scattering light: Rayleigh scattering, Raman scattering, and Brillouin scattering, and their scattering mechanisms differ from one another [8]. Rayleigh scattering can only change the propagation direction of the photon without changing its energy. The optical frequency of Rayleigh scattering is consistent with the incident light, so it is called elastic scattering; However, Brillouin scattering and Raman scattering belong to inelastic scattering due to their frequency drift phenomenon.

DAS system based on the principle of phase-sensitive optical time-domain reflectometry (Φ-OTDR) can detect the vibration events along an optical fiber cable by measuring the phase changes of Rayleigh backscattered (RBS) signals [3]. The disturbance events can impose dynamic strain on the nearby optical fiber. Then the length, core diameter, and refractive index of the fiber will change accordingly, which in turn causes the phase difference of the RBS. In general, the core diameter and refractive index only have little effect on the phase difference of the fiber. For simple analysis, we only consider the effect of the fiber length (axial strain). Therefore, the dynamic strain change process can be easily obtained by demodulating the phase difference of the fiber before and after the vibration event.

In our test, we use a DAS system based on digital heterodyne detection. Figure 1 shows the schematic of the DAS system. First, the continuous light output by one narrow linewidth laser (NLL) is divided into two paths by an optical coupler. One path forms high-power pulses, and the other path forms interfering pulses; second, the high-power pulses are modulated by an acoustic optical modulator (AOM) and amplified by an erbium-doped fiber amplifier (EDFA). Then, via a circulator, the modulated pulses can be launched into the optical fiber; Third, the returned RBS light and the reference light are coupled and then input to the balanced photodetector (BPD) to become electrical signals. Finally, the raw data is collected through the data acquisition card (DAQ) and stored in the computer.

![Figure 1. The schematic of the DAS system.](image-url)
3. Methodology

Various abnormal vibration events in the tunnel are usually sudden, complex, and hazardous. Their vibration signals often appear as non-linear and non-stationary time series. Therefore, it is necessary to analyze signals in both the time domain and the frequency domain simultaneously for better extracting the signal features. To begin with, the Empirical mode decomposition (EMD) method used can remove the high-frequency white noise. Next, we can obtain frequency by short-time Fourier transform (STFT). Then, via utilizing time-domain amplitude normalization and frequency-domain binarization, the signal eigenvalues can be standardized well. Afterward, we artificially select 10 main time-frequency domain features as the final identification signs. Finally, it is the random forest model that the feature information input into for pattern recognition.

3.1 Signal Denoising

The EMD denoising method is to obtain the inherent fluctuation pattern through the characteristic time scale of the data [8]. The basic idea of this method is to decompose the original signal into a series of Intrinsic Mode Functions (IMFs), then analyze the time domain and frequency domain of each IMF separately, and finally stack the processed IMFs to generate a reconstructed signal [9]. In practical processing, we first find the local maximum and minimum of the original signal $s(t)$. Besides, the upper and lower envelope lines are formed by the cubic spline interpolating function. What’s more, we can obtain $i_i(t)$ by subtracting the mean value of the upper and lower envelope lines from the original signal:

$$s(t) - a_i(t) = i_i(t)$$

In the second processing, $i_i(t)$ is taken as the original input signal, and the average value of envelope lines $a_i(t)$ and the difference value $i_i(t)$ are obtained by repeating the above operations:

$$i_i(t) - a_i(t) = t_i(t)$$

After several repeated operations, until the last processing result meets the following requirements:

- The number of extreme points and zero-crossing points of the signal is equal or differs by at most one;
- The mean of the envelope of the local maximum and the envelope of the local minimum is zero. It is worth noting that too many decompositions may destroy the signal structure. Therefore, the end condition needs to be constrained by the Cauchy convergence criterion [9].

3.2 Pattern Recognition Algorithm

How to achieve the randomness of sample data is a common problem faced by machine learning. Since random sampling is limited to a specific data set, no matter what kind of machine learning algorithm. Consequently, the training results are easily affected by randomness, especially when the sample size is small. To solve this problem, Leo Breiman and Adele Cutler proposed the Random Forest algorithm [10]. The structure of the algorithm is shown in Figure 2. This method builds a lot of decision trees, each tree will learn one kind of decision rule from the samples, and then these trees form a “forest” and finally make the decisions through multiple trees voting [11]. The steps of the random forest algorithm are as follows:

- Multiple sample sets are collected by bootstrap resampling. For each sampling, a fixed number of samples are selected from all training samples, including those that may be repeated.
- Each sample set can be regarded as a decision tree. In the process of building a decision tree, a subset containing part of features is randomly selected from all features. Next, the optimal feature needs to be selected from this subset.
The output of all trees is voted, and the class with the most votes is selected as the decision result of the random forest. 

The Random Forest algorithm can sample the training samples and features at the same time to ensure the independence between each decision tree and reduce the interference of sample randomness on the results. With the advantages of small computational cost and simplicity of operation, this method shows strong performance in tunnel vibration events recognition.

4. Field Test and Results

4.1 Project Overview

The tunnel is a single-hole double-track tunnel with a length of 7208 m and a height of 13.08 m. The arch crown is about 3 m from the ground surface. Figure 3 depicts the layout of the optical cable in the tunnel. The cables were arranged in series along the longitudinal direction at the vault and bottom of the tunnel, with the length of 2732 m at the vault and 4526 m at the bottom. The bottom end was connected to the DAS system on the earth’s surface through the tunnel shaft. In order to improve the sensitivity of the cable to tunnel vibration events, some methods were adopted to enhance the coupling between cable and tunnel structure. At the arch crown, the optical cable was fixed outside the concrete cover by cement mortar to prevent the cable from falling off. At the bottom of the tunnel, the optical cable was laid in the gutter way and poured with concrete.

![Figure 2. Structure of the Random Forest model.](image)

4.2 Event Detection

Many types of construction machinery inevitably produce strong mechanical vibrations during tunnel construction progress. Usually, we regard the vibrations (sounds) as engineering noise, because they make the originally quiet environment become a place with serious noise pollution. However, these noises can turn into serviceable information and provide significant support for the construction of tunnels employing machine learning.

During the two-day real-time field monitoring test, DAS captured the effective engineering vibration signals on the surface through the optical cable of the vault. The vibration amplitude, frequency, energy, and other features of vibration signals could be clearly obtained by drawing the time-domain and frequency-domain diagrams.

The events recorded in this test can be divided into three categories: excavating, drilling and rockfall. In the excavation event, the driver operated the excavator to excavate at different vertical
distances of 0, 3, 6, 9, and 15 m. Each group was repeated five times, and the single excavation depth was controlled at about 50 cm. In the end, DAS recorded 121 excavation events. The second type of event was drilling. We drilled holes in the places with vertical distances of 0, 3, 6, 9, and 15 m in turn. For better comparison with the excavation event, we artificially controlled the excavation depth to be about 50 cm and repeated it five times for each place. Finally, one hundred and thirty-nine drilling events were recorded by DAS during the test. Rockfall event was the third type of recorded events. To simulate the rockfall in the tunnel, we release stones with weights of 0.5, 1.0, 1.5, and 2.0 kg at different heights of the tunnel (1, 3, 6, and 9 m). Ten repeated rockfall tests were carried out at each height to reduce the errors. In the test, a total of 151 rockfall events occurred.

![Figure 3. Schematic diagram of optical cable laying in tunnel.](image)

### 4.3 Event Denoising

Figure 4 shows the EMD denoising process of a drilling rig event. The left side of the figure is the time domain information of each IMF, and the right side is the frequency domain corresponding to each IMF frequency domain information. It can be seen from the figure that the original signal lasts for 25 s, and the frequency domain is mainly below 100 Hz.

The spectrum width of IMF 1 is larger than that of the system, and the spectrum density remains almost constant. Therefore, IMF 1 is defined as the white noise of the surrounding environment in this test. IMF 2–5 which the time-frequency domain characteristics are similar to the original signal are considered to be vibration mode decompositions. From IMF 2 to IMF 5, there is a gradual transition from high frequency to low frequency, and the frequency bandwidth is narrowed rapidly in turn. For IMF 2, its frequency domain is 0–220 Hz, but mainly concentrated below 80 Hz; Compared with IMF 2, IMF 3 lacks the frequency information of 100–220 Hz, but amplifies the frequencies below 100 Hz; IMF 4 and IMF 5 only show the frequencies of 0–50 Hz; IMF 6–7 are the false components generated by EMD over-decomposition. Considering the component energy, IMF 3 has the most energy, accounting for 31.54% of the total energy; the energy ratio of IMF 4 is 1.79% lower than that of IMF 3; IMF 2’ energy and IMF 5’ energy are similar, which are 12.95% and 19.10%, respectively.

Via EMD denoising, we remove the IMF 1 component (white noise) while retaining the IMF 2–7 for reconstruction. Finally, the reconstructed signals are the original input signal for machine learning.

### 4.4 Feature Construction and Selection

Three types of vibration events (excavating, drilling, and rockfall) are selected to draw the oscillograms and STFT diagrams. When drawing the waveform, make different events comparable, we normalized the amplitude to make it unified within 0–1. In the short-time Fourier transform, we choose Hamming window and set the window width to 100.

The data processing results of three vibration events are shown in Figure 5. Three types of events can be clearly distinguished on the waveform graph. The duration of excavation is almost the same as that of the drilling event, but the excavation's amplitude signal varies with time; the amplitude of the drilling is relatively smooth and stable; rockfalls are sudden events with short duration and appear as sudden and steep peaks in the time series. In the STFT spectrum, we can see that the frequency ranges of drilling and excavating are similar, both below 80 Hz, which is difficult to distinguish by eyes; in
contrast, rockfall event’s frequency is wider, ranging from 0–500 Hz. In addition, we use the image binarization method to highlight signal frequency features and reduce the amount of data calculation. As shown in this figure, the binary image can remove the high-frequency noise and show the frequency characteristics of various events.

We select variance, root means square, standard deviation, mean square error, crest factor, and form factor as features in the time domain and choose the area, perimeter, compactness, and Euler number of the binary image in the frequency domain. Finally, each event has ten characteristic values.

![Figure 4. The EMD decomposition result of a drilling event.](image)

| Events     | Waveform | STFT       | Binary Image |
|------------|----------|------------|--------------|
| Excavating | ![Waveform](image) | ![STFT](image) | ![Binary Image](image) |
| Drilling   | ![Waveform](image) | ![STFT](image) | ![Binary Image](image) |
| Rockfall   | ![Waveform](image) | ![STFT](image) | ![Binary Image](image) |

![Figure 5. Schematic diagram of the time–frequency domain features of the three events.](image)

4.5 Classification Results
We input the denoised event features into the random forest algorithm mentioned in section 3.2, and train the model according to the ratio of training set: validation set = 7:3. The classification recognition result is 92.31% (accuracy), 92.31% (recall), and 93.48% (precision). We also used the BP Neural Network algorithm to identify these events, the accuracy rate was 90.11%, the recall rate was 90.11%, and the precision rate was 90.84%. As for the specific training steps of BP neural network, the number of neurons in the hidden layer is 4, and the number of neurons in the output layer is 2. The transfer function of the hidden layer neurons is the tansig function, and the transfer function of the output layer is the purelin function. The confusion matrices of the two methods are shown in Figure 6 and Figure 7, respectively.

**Figure 6.** Confusion matrix of Random Forest algorithm.

**Figure 7.** Confusion matrix of BP Neural Network algorithm.

5. Conclusions
In this article, based on the EMD and Random Forest algorithm, we propose a pattern recognition method for tunnel abnormal vibration events. First, the DAS system is employed to monitor real-time dynamic strains exerted on a fiber-optic cable deployed along the lining of a tunnel. Then, the recorded vibration signals are denoised by the EMD method to remove the high-frequency white noise and improve the signal-to-noise ratio. Ten key features extracted from original signals are considered as training samples to be input into the Random Forest model. The test results show that the accuracy of the recognition method based on Random Forest can be as high as 92.31% for three different types of vibration events. Compared with the traditional BP Neural Network algorithm, the recognition performance of our method has been significantly improved. In the future, we will focus on improving the coupling between fiber-optic cables and structures under testing and on optimizing machine learning algorithms. We anticipate that real-time monitoring and early warning of various vibration events along tunnel linings can be achieved by combining DAS and machine learning.

Acknowledgments
This work was jointly supported by the National Natural Science Foundation of China (grant 42030701), the Natural Science Foundation of Jiangsu Province (grant BK20200217), the China Postdoctoral Science Foundation (grant 2021M691498), the Fundamental Research Funds for the Central Universities (grant 020614380110), and the Yuxiu Young Scholars Program of Nanjing University.

References
[1] Huang L, Hao H, Li X and Li J 2018 Source identification of microseismic events in underground mines with interferometric imaging and cross wavelet transform Tunn. Undergr. Sp. Technol. 71 318–28
[2] Bhalla S, Yang Y W, Zhao J and Soh C K 2005 Structural health monitoring of underground facilities - Technological issues and challenges *Tunn. Undergr. Sp. Technol.* **20** 487–500

[3] Lindsey E, Lindsey N J and Martin E R 2021 Fiber-optic seismology *Annu. Rev. Earth Planet. Sci.* **47** 309–36

[4] Rodriguez Tribaldos V, Ajo-Franklin J, Dou S, Lindsey N, Ulrich C, Robertson M, Freifeld B, Daley T, Monga I and Tracy C 2019 Surface wave imaging using distributed acoustic sensing deployed on dark fiber: Moving beyond high frequency noise *Preprint at EarthArXiv: 10.31223/osf.io/jb2na*

[5] Dumont V, Tribaldos V R, Ajo-Franklin J and Wu K 2020 Deep learning on real geophysical data: A case study for distributed acoustic sensing research *Preprint at arXiv: 2010.07842*

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

[7] Wu H, Xiao S, Li X, Wang Z, Xu J and Rao Y 2015 Separation and determination of the disturbing signals in phase-sensitive optical time domain reflectometry (Φ-OTDR) *J. Light. Technol.* **33** 3156–62

[8] Masoudi A and Newson T P 2016 Contributed Review: Distributed optical fibre dynamic strain sensing *Rev. Sci. Instrum.* **87** 011501

[9] Boudraa A O and Cexus J C 2007 EMD-based signal filtering *IEEE Trans. Instrum. Meas.* **56** 2196–202

[10] Leo Breiman 2001 Random forests *Mach. Learn.* **45** 5–32

[11] Angelo P, Resende A and Drummond A C 2018 A survey of random forest based methods for intrusion detection systems *ACM Comput.Surv.* **51** 1–36