Exploiting CNN-BiLSTM Model for Distributed Acoustic Sensing Event Recognition

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Abstract. Distributed acoustic sensing (DAS) can provide high sensitivity and spatial resolution remote positioning and monitoring capabilities, making it widely used by researchers for peripheral security applications. However, in daily use, complex environments can lead to low accuracy and poor real-time performance in event recognition. At present, research on DAS event recognition mainly focuses on the classification accuracy of different events, with limited discussion on noise interference. Even with a high event recognition rate of 95%, thousands of events occurring every day can still lead to hundreds of false positives, significantly reducing system availability. This study aims to improve the practicality of DAS by combining Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (LSTM), building on traditional artificial intelligence (AI) recognition models. By statistically analyzing and summarizing the recent events that occurred at adjacent points, this work proposes a secondary analysis method to reduce the frequency of false positives, effectively reducing potential daily false positives from hundreds to every 2-3 days, thereby improving the practicality of the model.

Keywords: Distributed Acoustic Sensing, Artificial Intelligence, Signal Recognition.

1 Introduction

With the continuous development of technology, communication fiber optic cables are one of the infrastructures of modern communication. They are the main medium connecting various communication nodes and are of great significance for ensuring the stable operation of communication networks [1,2]. Due to the long-term underground or underwater exposure of optical cable lines to various environmental and external factors, their maintenance is particularly important. Traditional protection measures include regular inspections and maintenance, setting up fences, installing monitoring equipment, etc., to prevent unauthorized personnel from approaching the line for construction. However, due to the possibility of unauthorized construction by relevant personnel and the untimely detection of manual inspections, serious fiber optic damage incidents cannot be avoided in many cases.

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Distributed fiber optic sensing technology is a technology that uses light waves as the sensing carrier and optical fibers as the transmission medium [3]. It utilizes the sensitive characteristics of light to detect changes in external parameters. In this technology, light waves are captured and transmitted to the receiving end, which detects changes in the state of light such as intensity, wavelength, frequency, phase, and amplitude, and demodulates the measured values of physical quantities. Compared with other monitoring equipment and sensors, distributed fiber optic sensing technology has the advantages of strong resistance to electromagnetic interference, good stability, strong corrosion resistance, low long-distance transmission loss, no need for electricity, strong real-time performance, small size and easy burial. It is now widely used in various application scenarios such as building structural health detection, perimeter security in the field of national defense, oil and gas pipeline monitoring in the field of energy, shape detection in the aerospace industry, railway safety monitoring and protection, and ocean monitoring. Distributed fiber optic sensing systems also have characteristics such as high spatial resolution, high detection sensitivity, wide monitoring range, and short response time. They are one of the main research and development directions for future intelligent perimeter security and intelligent scene monitoring [4,5].

With the development of deep learning, researchers combine the collected single channel or spatiotemporal data with deep learning methods to achieve end-to-end event recognition. The dataset of deep learning is mainly divided into collected digital signal data and data obtained through short-time Fourier transform, digital signals are converted into event images using grayscale images and combined with image classification algorithms or object detection algorithms for event classification. However, although traditional recognition models have good classification performance for different events, there is less discussion on the interference of noise, and frequent false alarms in practical applications can lead to low device availability. On the basis of traditional Artificial Intelligence (AI) recognition models [6], this article proposes a Convolutional Neural Network with Bidirectional Long Short-Term Memory (CNN-BiLSTM) model, which effectively reduces the frequency of false alarms and makes the model more feasible by statistically analyzing and summarizing recent events of neighboring points for secondary analysis.

2 Method

2.1 Background of Distributed Fiber Optic Sensing Technology

At present, the anti-external damage detection of long-distance optical fibers mainly relies on the collection of data and pattern recognition through distributed fiber acoustic sensing (DAS) systems. Its working principle is to use a narrow linewidth laser as the light source to emit probe light. When external vibration events affect a specific position of the sensing fiber, the electro-optical and thermal optical effects in the sensing fiber will cause changes in the length and refractive index of the scattering unit, thereby affecting the phase of the backward Rayleigh scattering light. This change will propagate to the phase difference of Rayleigh scattering light in the detector, allowing for the detection of vibration events within the fiber optic [7]. When the optical fiber is disturbed by external vibrations, its phase difference can be expressed as

$$\Delta\varphi = (4\pi n/\lambda)\Delta L \tag{1}$$

, where λ is the wavelength of the incident light; ΔL is the optical path change caused by vibration; n is the refractive index of the fiber core. According to equation (1), There is a linear relationship between ΔL and the phase difference $\Delta\varphi$ between the two reference regions. Therefore, by demodulating the phase change of the scattered signal, Δ phi can be obtained, enabling quantitative measurement of vibration and achieving distributed fiber optic sound field sensing function.

2.2 Data Preprocessing

The data is first accumulated on the original data, and then judged and filtered based on the root mean square value set by the threshold and condition of empirical values over a period of time, as shown in Fig.1. The spatial resolution of the original data is 10m/point, the sampling frequency is 2Khz, and the single collection period is 10s. Therefore, the size of the single collection of 2D data is 3K * 20K. Due to the large amount of data, a preset threshold screening is required before analysis.

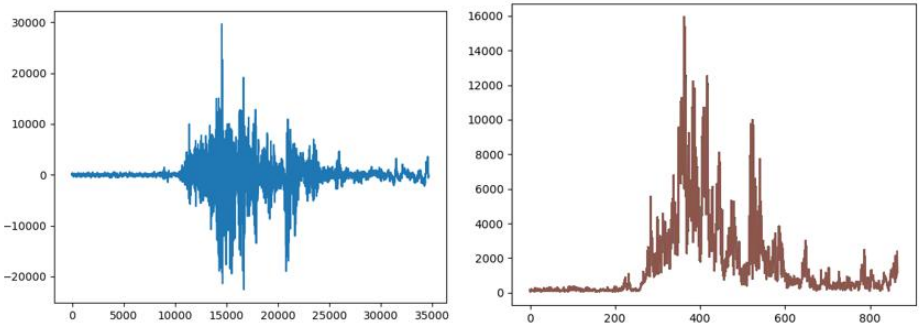

Fig. 1. Example of the original data (left), and the preprocessed data (right) after summing up 40 frames and calculating the root mean square (Figure Credit: Original).

If the number of frames exceeding the specified threshold within a single collection cycle (10 seconds) exceeds the specified number of times, the event is recorded as a possible abnormal event, thus avoiding the computational recognition difficulties caused by massive raw data.

After the above filtering, the input format for a single event is a one-dimensional data with a length of 20K. This work splits it into 10 individual data with a length of 2K (1s) and performed 1DCNN and FFT analysis on them.

2.3 AI-based Recognition Model

Although the vibration information data could be obtained at corresponding positions through the above system, there are still many difficulties in practical application due to low data accuracy, large noise interference, and complex data features. Although there are many papers on using artificial intelligence for pattern recognition, there are still many difficulties. The data accuracy is mainly limited by the equipment, and as the measurement distance increases, the errors caused by the equipment will be exponentially amplified, which is particularly evident in optical fibers with high losses due to poor quality. Noise interference includes a large number of false alarms caused by external interference such as vehicles and subways that may have a pathway due to the complex environment near the fiber optic cable on site. The complexity of data characteristics is also caused by the on-site environment. For example, the ground of different media may cause significant differences in the vibration frequency information monitored by the same equipment, and the different burial depths of optical fibers and the straight-line distance from the construction point to the optical fiber will also greatly affect the amplitude of vibration. Traditional research focuses more on how to distinguish different types of vibrations, and there is less research on eliminating noise interference [8]. Its testing environment is relatively single, and it will encounter many difficulties in practical field applications. This article uses the neural network structure of CNN-BiLSTM network, and based on this, combines some manually set preselection conditions and a CNN neural network that references event information from the past period of time, thus achieving better anti-interference results in complex noise environments [9,10].

Table 1. Structure of the proposed CNN-BiLSTM.

Layer	Type	Setting	Step	Activation	Dimension
1	Input	2000x1	-	-	2000 x 1
2	ConvIDI	1500x 5	2	Relu	1500 x 2000
3	MaxPool+BN	2	2	-	1500 x 1500
4	Conv1D2	1024x 5	2	Relu	1024 x 1500
5	MaxPool+BN	2	2	-	1024 x 750
6	Conv1D3	512x5	2	Relu	512 x 750
7	MaxPool+BN	2	2	-	512 x 375
8	Conv1D4	256x5	2	Relu	256 x 375
9	MaxPool+BN	2	2	-	256 x 187
10	Conv1D5	128x5	2	Relu	128 x 187
11	MaxPool+BN	2	2	-	128 x 93
12	BiLSTM1	256	4	-	-
13	BiLSTM2	128	4	-	-
14	FC	128	-	Relu	128
15	FC	32	-	Relu	32
16	Softmax	6	-	-	6

Due to the characteristics of abrupt changes and instability in fiber optic sensing signals. The network structure for identifying events needs to be determined based on the characteristics of the collected event data and the performance of different hyperparameters during the training process. In the feature extraction module, there are several sets of convolutional modules and BiLSTM modules. The convolution module consists of Conv1D, which slides the convolution kernel along the time dimension of the sequence, MaxPool, which reduces the size of the input feature map, and BatchNormalization, which accelerates model training and enhances model generalization ability. The BiLSTM module consists of forward LSTM cells and reverse LSTM cells. The first 15 layers in the specific feature extraction module are convolutional modules, and the last two layers are BiLSTM modules. The network settings are as follows: Conv1D1 uses a convolution operation with 1500 kernel sizes of 5 and a stride of 2, uses a hot path activation function to increase the nonlinearity of the model, and generates 1500 feature maps with dimensions of 2000. Secondly, a Max Pool with a stride of 2 is used for pooling operations, extracting the maximum value from each 2D neighborhood and generating 1500 feature maps with dimensions of 1500. Normalization (BN) is added after convolution and pooling to accelerate network training and convergence, control gradient explosion, and prevent overfitting. The following layers of Conv1D use a similar structure. The architecture is demonstrated in Table 1.

To balance feature extraction and computation speed, The number of nodes for BiLSTM1 and BiLSTM2 is set to 256 and 128, respectively, with a time step of 4. In order to enhance the non-linear expression ability of the network and alleviate the problem of vanishing gradients when reverse error gradients are transmitted back, the Relu activation function is used after each convolution operation, which also helps to improve training accuracy.

In the event classification module, the softmax function is used as the classifier to calculate the probability scores of six event types, where each element has a value between 0 and 1, and the sum of all elements is 1. The category with the highest probability score is used as the classification result of the event. Within the event classification module, it mainly consists of two fully connected layers (FC) and a Sofmax layer. The number of neurons in FC1 layer is set to 128, connected to the feature layer generated by BiLSTM2 layer. The number of neurons in FC2 layer is set to 32, which is used to fully connect the feature data with the output of FC1 layer. Finally, the Sofmax layer is used to classify it, which consists of six neurons used to divide the input feature data into six different event categories.

Subsequently, use the aforementioned neural network to make event judgments on the filtered events. Due to the complexity of the on-site situation, the accuracy of individual event judgment is not high enough and there are often false alarms. After analysis, the concentration of most false alarm events is very low, and frequent false alarms are rarely seen in the same location in adjacent time periods. However, actual construction will frequently generate events of the same type. Therefore, based on the above classification, this work extracts the event types, vibration intensity, and vibration time from the event information, and count all events in the past 15 minutes near the location. If the number of events of the same type is greater than 2, it is organized into 2 * 900 two-dimensional data, where the i-th row corresponds to the event judgment information of the i-th second in the past, the first column is the judgment type of the event (if there are no events, it is recorded as 0), and the second column is the intensity information of the event (determined by the average value of the corresponding event).

This work used a 1D CNN network again for training classification, and due to the integration of information for a period of time, the false alarm rate significantly decreased.

3 Results

This work choses a testing fiber optic to collect signal data from excavator excavation, drilling machine construction, and human impact at distances of 5, 10, and 20 kilometers. Moreover another fiber optic is used to collect signals from vehicles passing by and subway passing through the entire process as interference information. This article categorizes the data into 6 different signals, including drilling machine events, excavator events, crusher events, manual excavation, vehicle passing, and other noise. The collected raw data format is to generate 2K x 3k two-dimensional data per second, where 3K corresponds to a total range of 30KM, with one sampling point every 10m, and 2K is the sampling frequency of the raw data. This article collects 15000 classic events of different types as a database, of which 50% are noise events.

After preliminary screening and testing, taking the data of fiber optic deployed on site with an actual range of 30KM as an example, a total of more than 27000 events were reported in three days, with an average of no more than 5 event locations reported every 10 seconds, effectively reducing the amount of data.

After training with the data, the confusion matrix obtained by the CNN-BiLSTM model on the event validation set can be obtained, as shown in Fig. 2. The rows represent the label probability of the predicted event, and the columns represent the true label probability of each event. From the analysis of the confusion matrix, it can be seen that the CNN-BiLSTM model has high event classification performance, with drilling machine events achieving a recognition rate of 100%, and the recognition rate of other events is also above 94.5%.

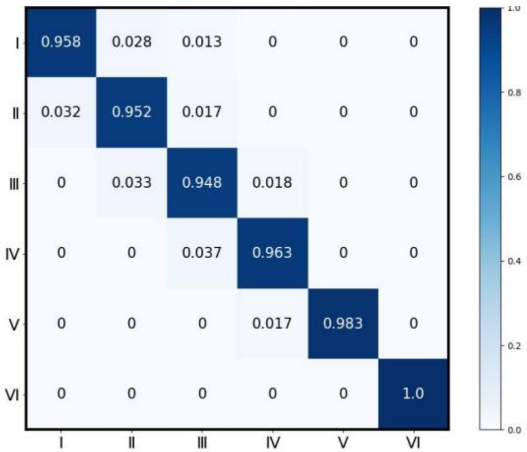

Fig. 2. Confusion matrix results of the proposed CNN-BiLSTM model (Figure Credit: original).

The first type is noise events. Although the recognition rate has reached 95% at this time, due to the possibility of generating thousands of interferences signals every day, there are still hundreds of false alarms in practical applications, which brings great interference to maintenance personnel. It can be seen that it is necessary to introduce a secondary classification network that integrates a segment of events. This work used the previously collected data again and generated their corresponding two-dimensional data in chronological order. It can be seen that due to the manual setting of requiring more than two reporting events within 15 minutes before proceeding to the next analysis, this preset condition has effectively filtered out over 80% of scattered false alarm events. After training, its filtering ability for previously misreported events reached over 95%,In actual on-site testing, false alarms occur approximately every 2-3 days, and their accuracy is significantly improved.

4 Discussion

After the previous analysis, it can be seen that the introduced deep learning classification network and comprehensive event network effectively reduce the false alarm frequency of the system and ensure its usability in practice. However, the current algorithm still has some shortcomings, such as in practical applications, differences in the surrounding media of the fiber and the vertical distance between the construction position and the fiber may lead to some special differences; For example, due to the need to analyze events over a period of time, it takes 3-4 minutes to complete event reporting after actual construction. Part of these issues can be achieved through expanding the sample size to achieve better universality. For example, the current event library has a sample size of approximately 15000 various events, and collecting more samples can effectively increase network parameters and further improve accuracy. On the other hand, the advancement of technological equipment can reduce the background noise of the equipment and increase the credibility of event classification.

5 Conclusion

Distributed fiber optic sensing systems have various characteristics such as long-distance monitoring, high sensitivity, and strong anti-interference ability, and are widely used in various scene fields. However, at present, there are shortcomings in distributed fiber optic sensing event recognition, such as poor event recognition ability and cumbersome and complex event image recognition algorithms. This study takes deep learning methods as the starting point from digital signal data and image data, and has made some progress. A distributed fiber optic acoustic sensing system is built, and the collection of six types of event data, including manual mining, crusher, drilling machine, excavator, vehicle passing, and other noise, is completed.

A small event database was collected for six types of events, and deep learning algorithms were used for event analysis to generate preliminary event classification. After synthesizing data for a period of time, secondary classification was carried out.

A distributed fiber optic sensing event data recognition method based on 1DCNN BiLSTM has been proposed. The IDCNN BiLSTM proposed successfully addresses the issues of low event recognition accuracy, difficulty in processing large amounts of data, and the need for manual feature extraction in traditional statistical and machine learning methods in distributed fiber optic sensing events. This model directly inputs the collected digital signal data into 1DCNN for automatic feature selection and extraction, and utilizes the memory module of BiLSTM to fully mine the hidden temporal relationships within the data, thereby completing event recognition.

In addition, to address the issue of insufficient accuracy in identifying individual events and the inability to effectively eliminate noise interference, this work introduced a comprehensive secondary CNN event analysis system over a period of time. By collecting 15 minutes of events for comprehensive analysis, this work successfully avoided the problem of a large number of false alarms of noise events, making it suitable for practical application.

However, the introduction of a comprehensive time analysis system will lead to a longer actual response time, and there may be a delay of 3-4 molecules from construction to actual reporting. In response to this, there may be better models and larger samples in the future to make the response time shorter.

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