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PIPELINE SAFETY EARLY WARNING METHOD FOR DISTRIBUTED SIGNAL USING BILINEAR CNN AND LIGHTGBM

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ABSTRACT

Oil and gas pipelines are known as the backbone of global energy, and securing their safety is crucial for energy supply. In this study, we utilized a novel machine learning method based on the spatiotemporal features of distributed optical fiber sensor signals to monitor the safety of oil and gas pipelines in real time. Encouraging empirical results on a large amount of data collected from real sites confirmed that our model could accurately locate and identify the damage events of a pipeline in real time under strong noise and various hardware conditions, and could effectively handle the signal drift problem. Furthermore, as a generalized tool, the proposed solution could be applied to other industrial inspection fields. Our codes and video demos are available at https://github.com/yyysjz1997/B-CNN_LGBM-PSEW.

Index Terms— energy pipeline safety early warning, industrial distributed time–space signal processing, action recognition, bilinear convolutional neural network, lightgbm

1. INTRODUCTION

Oil and gas pipelines are widely used in the field of energy transportation because of their low cost, fast construction speed, and high safety. According to the latest statistics from Central Intelligence Agency (CIA), the total length of the global oil and gas pipelines is already 3.55×10^6 km, but at the same time, the accident rate in the United States, for example, has reached 0.5 times per year per 1,000 km, and incidents may cause considerable indirect economic loss, environmental pollutions, energy crises, and personnel safety issues [1]. Unfortunately, the current approach to monitoring pipeline safety still focuses on inefficient and costly manual inspections. Consequently, the use of intelligent early warning algorithms to replace traditional manual monitoring is a technical issue that needs to be addressed in the oil and gas pipeline transmission industry.

Most pipelines are buried underground to reduce their floor space, which makes it difficult to observe their safety directly. Moreover, the complex environment along the pipelines, most of which are laid through farmland, desert, hills, and other remote areas, is highly unsuitable for manual inspection. Therefore, researchers have attempted to use a redundant optical fiber, which is in the cable and uses for the company's internal communication and equipment data transmission, to achieve a distributed pipeline safety early warning (PSEW) function through the coherent optical time domain reflectometer (COTDR) technology without increasing the operating cost [2, 3]. Although it has the advantages of good real-time performance and easy installation [4], its internal signal is susceptible to fluctuations due to environmental influences. Concretely, it has strong noise, weak signals, signal jitter, and the problem of signal drift over time [5], which places higher demands on recognition algorithms based on optical fiber sensor signals.

In this study, we attempted to fuse a bilinear convolutional neural network (B-CNN) and a light gradient boosting machine (LightGBM) for PSEW based on distributed optical fiber sensor signal data from real sites. The contributions of this paper include the following:

(a) We propose an approach that reanalyzes industrial distributed signals in both spatial and temporal domains and obtains excellent location and identification performance.

(b) We have collected a large amount of signal data from long-distance pipelines that are already in service and built a database for model construction and evaluation.

(c) We prove that our model is more adaptable to complex environments and more scalable to hardware than other baselines under the premise of good real-time performance.

2. RELATED WORKS

PSEW based on distributed optical fiber remains largely unexplored. Previous studies primarily focused on the use of traditional signal processing and analog speech recognition algorithms to analyze signals. For example, Fouda *et al.* [6] presented an estimation method based on a frequency-domain power spectrum, and Zhang *et al.* [7] applied mel-frequency cepstral coefficients (MFCC) to extract features. Similarly, machine learning (ML) is also suitable for PSEW systems [8–13]. More specifically, Wu *et al.* [14] used hidden Markov models (HMMs) to judge the events. In addition, Yang *et al.* [15] and Shi *et al.* [16] proposed modified convolutional neural networks, and Kong *et al.* [17] applied a probabilistic neural network to solve this problem.

However, most of them only extract the features in the time domain and do not fuse the information of the spatiotemporal dimensions. Furthermore, most of the work has not been verified for long-distance pipelines already in service, which makes them less convincing in the cases of real site data with strong noise, weak signals, and drift problems.

3. METHODS

Our method merges two ML models for the spatiotemporal localization and identification of invasive events. In detail, B-CNN is applied for spatiotemporal feature extraction, and LightGBM is used for precise classification and localization.

3.1. B-CNN for action recognition

B-CNN contains two feature extractors, whose outputs are multiplied using the outer product and pooled to obtain the bilinear vector [18, 19], thus making two different features, e.g., global features and local features, work together to improve the classification of fine-grained images.

In addition, 3DCNNs, as a widely used method in action recognition, can effectively fuse the information of the targets in both the space domain and the time domain [20]. Similarly, the distributed signal has a space–time correlation, which is not a common two-dimensional image [21] but a one-dimensional vibration signal in the time domain. Consequently, we used B-2DCNN to extract the space–time features of distributed signals in detail.

3.2. LightGBM

LightGBM is a gradient boosting decision tree proposed by Microsoft in 2017 [22], whose advantages such as efficient training process, distributed support, and low memory overhead can be used to make systems better and faster in industrial practice. Concretely, LightGBM uses the gradient-based one-side sampling (GOSS) to exclude most of the samples with small gradients and calculates the information gain with other data. Furthermore, LightGBM applies exclusive feature bundling (EFB) to transform many high-dimensional mutually exclusive features into low-dimensional dense features, thereby avoiding the computation of redundant and unnecessary zero-valued features. Therefore, to obtain more accurate and robust results, we applied LightGBM for precise classification and localization.

4. DATASET

Our data were collected at a China National Petroleum Corporation in-service pipeline in Suzhou, China, along which there are complex areas such as railways, factories, and villages. Different from ideal conditions, our data had the features of strong noise, weak signal, and signal drift that were unique to long-distance pipelines at real sites.

More specifically, we used a redundant optical fiber installed beneath the pipeline as a signal carrier, which could monitor a length of 48 km with 2,400 uniformly distributed observation points. These points were 20 m apart; i.e., the spatial resolution was 20 m. Moreover, to verify the universality of the hardware and the adaptability to signal drift, we gathered 494-GB data in 2016 continuously from May 10 to June 2 and from November 19 to December 17 and used 100-Hz and 500-Hz signals, respectively. The signal categories included background noise (no damaging events), manual excavation (might have been oil theft by drilling), mechanical excavation (third-party construction damaging the pipe), and vehicle driving (potential threat of heavy vehicles rolling over the pipe). We labeled the precise categories and the spatiotemporal coordinates of each event.

In particular, note that our data collection was a very manpower-consuming and time-consuming process, which required professionally skilled technicians to spend up to two months traveling along the pipeline in harsh environments and repeatedly simulating different intrusion events at dozens of observation points.

5. EXPERIMENTS

The architecture developed is illustrated in Fig. 1, and the specific training process of the model is as follows:

(a) Fix the spatial domain, and slide a window in the time domain to generate samples of size $2{,}000 \times 7$. Here, 2,000 is the number of data items in the time domain, which corresponds to the length of 4 s in the case of the 500-Hz signals or 20 s in the case of the 100-Hz signals, and 7 is the number of spatial observation points, i.e., 120 m of the pipe.

(b) Standardize the above samples separately.

(c) Input the pre-processed samples into the B-CNN to pre-train and obtain all the parameters of the convolutional and fully connected layers.

(d) Freeze the parameters of the convolutional layer in B-CNN, and the results from the flattened layer are input to the LightGBM model and retrain to obtain the optimal LightGBM model parameters.

(e) The prediction value represents the result of its central observation point in 4 s in the case of the 500-Hz signals or 20 s in the case of the 100-Hz signals.

Moreover, to verify the generalizability of the method for the signal drift problem, we divided all the data into training and validation sets consisting of the data from May and June and the testing set containing the data from November and December. In addition, we adopted the Adam optimizer [23] with a learning rate of 0.001 and a batch size of 128. We used an Intel Core i7-8700 CPU at 3.2 GHz, a GTX1080ti GPU, and 32 GB of RAM for training and verification.

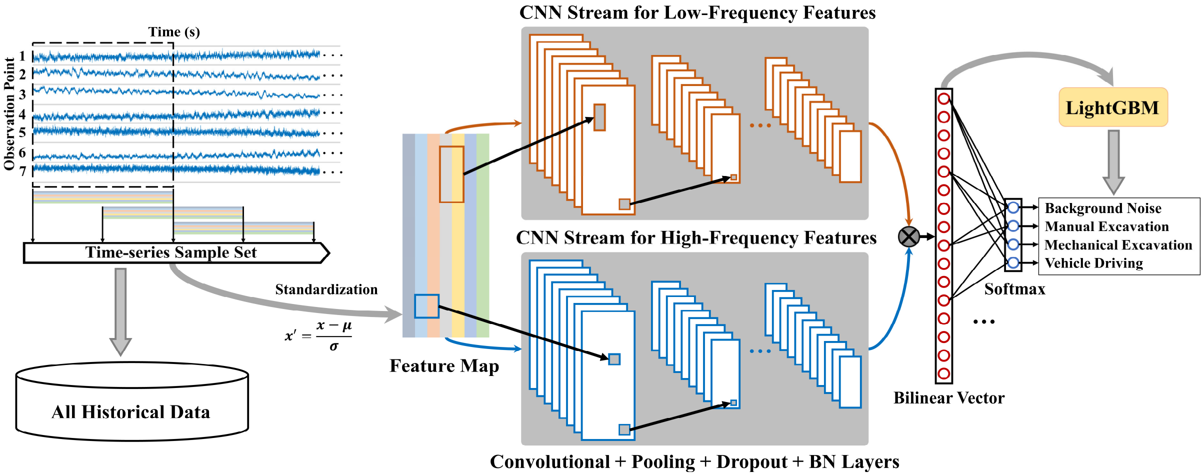

Fig. 1. Data pre-processing and structure of the proposed B-CNN and LightGBM model. More specifically, we changed the size of the input and the output matrix to allow our data to be trained, and we adjusted the size and the initial weights of the convolutional kernels and added the pooling and the batch normalization strategies in the two CNN streams of the original B-CNN [18,19], intending to better fit our distributed data.

6. RESULTS AND DISCUSSIONS

In this section, we describe the evaluation of our algorithm against other baselines in terms of identification and localization performance, time cost, and model size. Further, we present the test results for the pipelines already in service.

Table 1. Performance comparison of different algorithms on 500-Hz/100-Hz testing sets

	DNN	1DCNN	2DCNN	B-CNN	B-CNN_LGBM
Background noise					
Precision (%)	87.20/85.33	95.26/96.26	**100.0/100.0**	99.88/**100.0**	**100.0/100.0**
Recall (%)	87.20/86.29	96.58/98.83	**100.0/100.0**	**100.0/100.0**	**100.0/100.0**
F1-score (%)	87.20/85.81	95.92/97.53	**100.0/100.0**	99.94/**100.0**	**100.0/100.0**
AUC	0.873/0.867	0.978/0.989	**1.00/1.00**	0.999/**1.00**	**1.00/1.00**
Manual excavation					
Precision (%)	91.32/89.26	97.75/94.38	**100.0/100.0**	98.98/99.25	**100.0/100.0**
Recall (%)	92.24/90.68	94.83/95.33	91.38/98.06	93.26/98.50	**96.98/99.75**
F1-score (%)	91.78/89.96	96.27/94.85	95.50/99.02	96.03/98.87	**98.47/99.87**
AUC	0.928/0.908	0.972/0.956	0.957/0.990	0.975/0.991	**0.989/0.999**
Mechanical excavation					
Precision (%)	72.66/69.78	81.37/73.59	83.51/75.19	93.57/82.86	**97.25/85.03**
Recall (%)	74.36/75.67	84.32/78.67	95.29/**100.0**	92.88/98.68	**98.67/100.0**
F1-score (%)	73.50/72.61	82.82/76.05	89.01/85.84	93.22/90.08	**97.95/91.91**
AUC	0.753/0.763	0.855/0.808	0.959/0.973	0.967/0.982	**0.988/0.985**
Vehicle driving					
Precision (%)	93.76/82.37	95.23/91.79	97.70/**100.0**	98.33/**100.0**	**98.67/100.0**
Recall (%)	95.28/83.56	97.88/**90.67**	**99.42**/80.05	98.33/85.37	99.12/88.86
F1-score (%)	94.51/82.96	96.54/91.23	98.55/88.92	98.33/92.11	**98.89/94.10**
AUC	0.955/0.848	0.980/0.925	0.992/0.900	0.992/0.950	**0.994/0.968**
Total					
Accuracy (%)	87.02/82.86	92.91/89.87	95.72/93.49	96.89/95.27	**98.83/96.47**

The performances of B-CNN_LightGBM and the other models in the testing set under the same conditions and with the average of 10 repeated experiments are presented in Table 1, and Figs. 2 and 3 show the AUC of each model for the four intrusion events for the 100-Hz and 500-Hz testing sets, respectively. First, the CNNs had better metric values in all the four events than the DNN, which proved that the convolution could perform more effective feature extraction for distributed signals with a front-to-back frame dependency and a constant correlation length. Moreover, most of the results of the 1DCNN, which extracts features only in the time domain, were significantly worse than those of the 2DCNN, which computes the features in both spatial and temporal dimensions. The difference between these was particularly obvious in the case of mechanical excavation, which fully demonstrated the existence of a strong space–time correlation of our distributed signals. Furthermore, B-CNN could better dig the features. The two feature extractors that we chose used different convolution kernels to extract the high-frequency and the low-frequency features separately, and the comparison in Table 1 shows that the two features were highly complementary. Moreover, LightGBM could further fit the features obtained from B-CNN and obtain better recognition results than the fully connected layer.

Next, as we attempted to solve a practical engineering problem, the real-time performance and the model size determined the applicability of the hardware and the practical application effects. Therefore, we tested a 4-min data sample from a 48-km pipe and repeated the test 10 times, averaging the results shown in Table 2. Our method could accurately identify and locate the damage events within an extremely short period of time. In particular, the total recognition time was 19.37 s for 500 Hz and 7.987 s for 100 Hz, which fully met the requirements of industrial-level real-time performance. Furthermore, the model size was only 25.68 MB, allowing it to be deployed in most embedded systems.

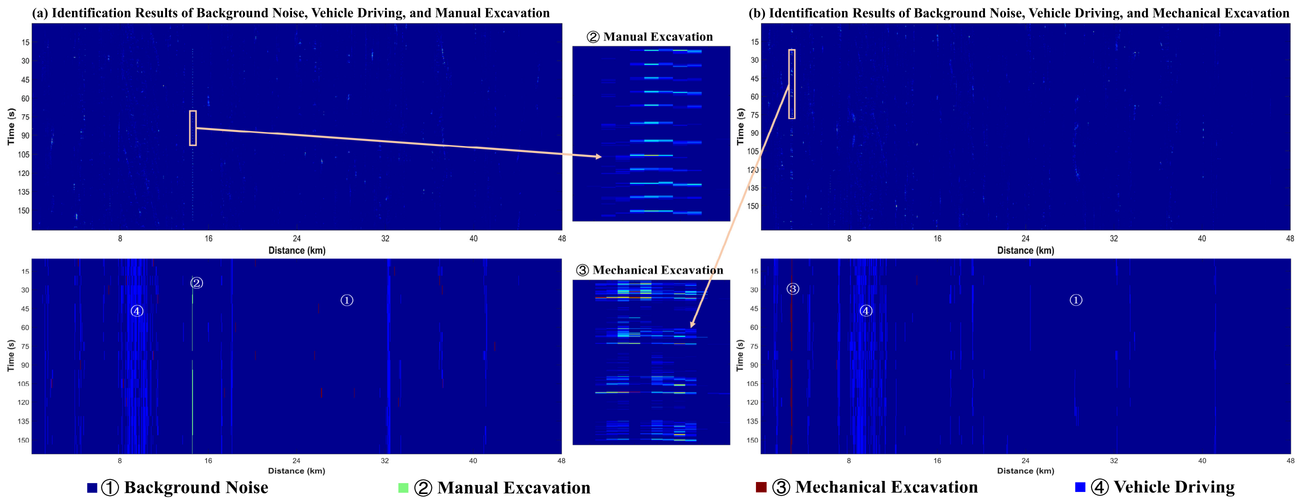

Fig. 4. Feature maps and identification results from a 48-km pipe of 500-Hz data. The upper portion shows the fusion features extracted from B-CNN, and the lower portion presents the corresponding identification results. (a) Manual excavations appear at approximately 14 km and last for nearly 120 s. (b) Mechanical excavations appear at 2 km and last for approximately 160 s. There are also continuous vehicle driving events from 8 to 10 km.

Table 2. Model size and time cost of a 4-min data sample from a 48-km in-service pipeline

	Model time	Total time	Model size
100 Hz	5.569 s	7.987 s	25.68 MB
500 Hz	15.36 s	19.37 s	

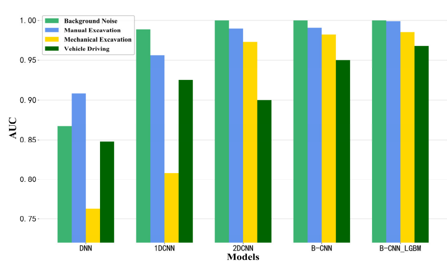

Fig. 2. AUC dependency on different models of 100-Hz data

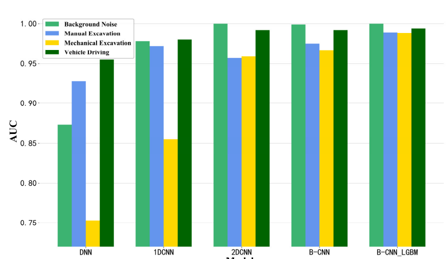

Fig. 3. AUC dependency on different models of 500-Hz data

Finally, Fig. 4 shows the identification results of a complete pipeline using 500-Hz data. Fig. 4a shows that the accuracy of our model for manual excavation (②) was 98.57% for the spatiotemporal localization and identification. There were false alarms for the mechanical excavation (③), with a rate of approximately 5.62%, but such samples were almost discrete and we could constrain the minimum time of the intrusion events to filter them. As for Fig. 4b, the model could adequately locate and identify the mechanical excavation (③) with 98.33% accuracy in the time–space domain.

7. CONCLUSIONS

In this paper, we proposed a novel real-time PSEW technology combining B-CNN and LightGBM based on the spatiotemporal features of distributed optical fiber sensors. According to the experimental results from real pipelines, the described algorithm could identify and locate damage events under the conditions of strong noise, weak signals, and signal drift with accuracies of 96.47% (100 Hz) and 98.83% (500 Hz) in testing sets. In addition, by comparing B-CNN with other models, we demonstrated that the industrial distributed signals were strongly correlated with both spatial and temporal information and that B-CNN could effectively acquire various complementary industrial distributed signal features. Furthermore, LightGBM could summarize features better and improve the robustness of the model as compared to the fully connected layer. Moreover, our model fully met the industry standards in terms of model size, real-time performance, and easy deployment.

The limitation of this paper is that the algorithm is not fully robust to abnormal and error data, which requires more field tests and long-time applications to verify. Fortunately, the verification has already begun, and we will improve the fault tolerance with online learning based on the field feedback, which will be presented in our follow-up work.

In the future, we plan to explore the applications of distributed signal early warning in other areas, such as national border security technology, earthquake early warning, and bridge safety monitoring.

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