2020 19th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES)

Convolutional Neural Network based Diagnosis of Electric Rotating Machines using Field Sensor Signals

Mengsheng Wang, Yanbin Zhang, Xin Wang, Kuilin Fu
Wuhai UHV Power Supply Bureau of Inner Mongolia Power (Group) Co., Ltd
E-mail: 308960499@qq.com

Yuhan Zhang
Huanan Industrial Technology Research Institute of Zhejiang University, Guangzhou, China
Email: zhangyh@zjuhn.com.cn

***Abstract*—The safe operation of power substation equipment is fundamental for guaranteeing the performance and reliability of the power systems. However, the electric equipment and devices are confirmed prone to component failure and breakdown that may directly lead to the power outage. In this paper, a cost-effective solution based on the convolutional neural network is presented for the analysis of faults of electric rotating machines. To reinforce the robustness under a noisy environment, a linear discriminant criterion based metric learning technique is also employed to improve the loss function during the training process. The developed approach can automatically extract self-learned fault features and conduct fault diagnosis. The developed solution has been carefully evaluated through simulation and experiments to quantify the performance. The experimental results demonstrated the effectiveness of the proposed solution for fault diagnosis.**

Keywords- power substation equipment; Acoustic signal; Condition monitoring; Diagnosis.

I. INTRODUCTION

In recent years, the emerging technologies, e.g., Internet of things, big data and artificial intelligence technology, has shown great potential for different application domains. The intelligent diagnosis method based on data-driven shows full feasibility and superiority in fault diagnosis. In the era of electromechanical big data, how to effectively use mass production data and play the value of data has become a research hotspot in the field of the power system. The early fault detection and analysis of electrical equipment in the substation, also known as fault diagnosis, condition monitoring and predictive maintenance Maintenance), which is one of the most important and extensive applications in modern industry, is to evaluate the system status and predict the possible faults in advance through sensor data and advanced signal processing and analysis technology, to give timely maintenance suggestions. Due to the importance of this issue of abnormal state detection, this paper exploits the fault diagnosis for the electric rotating machines using field sensor signals. The data-driven and artificial intelligence based methods adopt the machine learning methods to learn the pattern features from available historical data and carries out pattern recognition and decision-making.

At present, conventional methods for fault diagnosis of substation equipment, e.g., the vibration signal, acoustic emission signal, strain signal, temperature signal, oil parameters and electrical signal Signals. In particular, supervisory control and data acquisition (SCADA) systems are widely used in the power systems for data acquisition and condition monitoring and management [1]. The vibration signal often contains inherent fault characteristics. Previous practice showed that through a variety of signal processing technology, many forms of features and characteristics can be extracted from the collected field vibration signal. The analysis of these signals can accurately and effectively identify the fault type, fault location, fault severity and so on according to these feature information [2]. It is worth noting that a variety of signal sensors, including vibration signals, are intrusive and need to be embedded in the equipment, which increases the complexity and failure probability of the equipment. The non-intrusive sound signal detection is also very promising in fault diagnosis.

The original vibration signal obtained by the acceleration sensor is a one-dimensional time-domain signal, and the commonly used methods are mainly divided into the time-domain analysis, frequency-domain analysis and time-frequency-domain analysis (e.g., [3] [4]). In most recent years, the intelligent diagnosis and analysis solutions are investigated.

In fact, the fault detection and diagnosis can be considered as a pattern recognition problem, normal operation state and various fault states can be regarded as a specific pattern, which can be classified and identified according to the extracted features, and the fault diagnosis method based on pattern recognition is intelligent diagnosis technology. For pattern recognition, the vibration signal processing method can be used as a feature extraction method. Once sufficient feature information is obtained, the machine learning model can be trained for recognition. It is worth mentioning that high-dimensional features are often redundant, and some features may be repetitive or even invalid, which increases the training difficulty of classifier and affects the accuracy of classification. Therefore, feature dimension reduction and feature selection are also very important in practical application. Principal component analysis (PCA) and independent component analysis (ICA) are often adopted for feature selection [5], and some classifiers can also automatically select features in the training process, such as decision tree (DT). At present, the statistical learning classification methods are widely used in intelligent diagnosis methods, that is, machine learning method, including the k-NN algorithm [6], random forest algorithm [7], support vector machine (SVM) [8] and artificial neural network (ANN) [9], which can achieve good results in rotating machinery fault detection and analysis. However, it should be noted that the machine

2473-3636/20/$31.00 ©2020 IEEE
DOI 10.1109/DCABES50732.2020.00028

learning-based algorithmic solution also has some disadvantages. Firstly, feature extraction needs a very complex signal processing method, and it is very dependent on expert knowledge and diagnosis experience. It can be a time-consuming process, and feature extraction does not have a fixed approach. Every new fault diagnosis task needs to redesign the feature extraction process In fact, most of the work of fault diagnosis is to extract features; secondly, machine learning models are some shallow classifiers, which have limited learning ability and many limitations in dealing with complex pattern recognition problems. To better solve the above problems, more advanced intelligent methods are urgently needed, and deep learning method provides a new solution for fault diagnosis due to its ability of automatic learning features. In this work, we presented fault detection and diagnosis solution based on the convolutional neural network for electric rotating machines using field sensor signals. To enhance the robustness under a noisy environment, a linear discriminant criterion-based metric learning technique is also employed to improve the loss function during the training process. The developed approach can automatically extract self-learned fault features and conduct a gearbox fault diagnosis.

This paper has the following sections: Section II presents the proposed diagnosis algorithmic solution in detail based on the collected field sensor vibration signals and the developed CNN based model. The proposed solution is evaluated through simulations and the numerical results are provided and discussed in Section III. Finally, Section V gives the conclusive remarks.

II. Proposed Diagnosis Solution Using Vibration Signals

This section proposes the intelligent fault diagnosis framework, as illustrated in Fig. 1. Firstly, data argumentation is used to increase the sample numbers by sampling the raw signals with overlap. Then, the LDCNN is designed based on one dimensional CNN combining the improved loss function to exact and obtain the high abstract features from the input signals. Finally, the feature classification is carried out through the adoption of a softmax classifier to determine the operational condition of electric equipment.

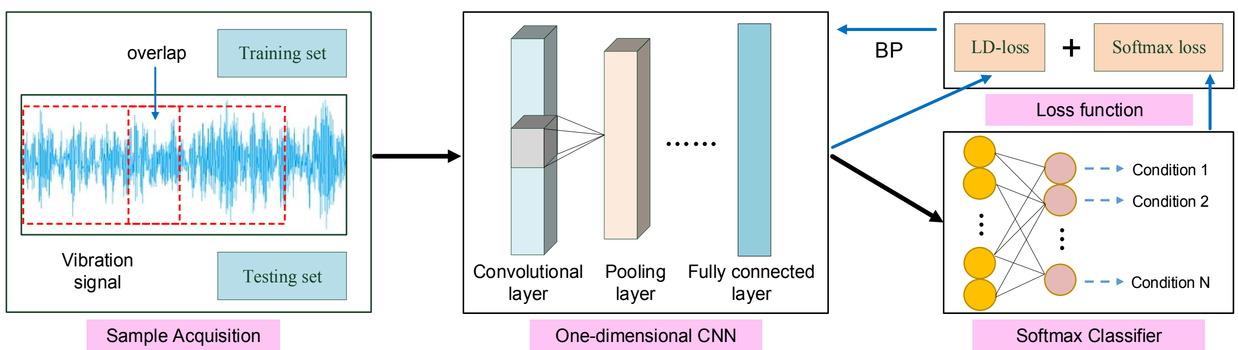

Figure 1: Flowchart of the proposed method

A. Sample Acquisition

The raw vibration signals are collected by accelerometers, and then the overlap sampling is used for obtaining data segments for model training. For the deep learning task, sufficient data is essential to prevent the model from overfitting and enhance generalization ability. For fault diagnosis, sometimes the measurement is limited, so slicing the original data with overlap is convenient to acquire a large number of training samples. In this work, the segment length is 1024, and the overlapping rate is set to 0.3.

B. The architecture of the proposed Model

TABLE I. The structure of the basic CNN model

Layer	Kernel size	Stride	Kernel depth	Padding
C1	1×32	8	16	same
P1	1×4	4	16	valid
C2	1×5	1	32	same
P2	1×2	2	32	valid
C3	1×3	1	64	same
P3	1×2	2	64	valid

To reduce the complexity of the network and improve the execution efficiency, we build the network as concise as possible through experiments in this work. Our designed model architecture consists of three pairs of one-dimensional convolution and pooling layers and two fully connected layers for feature extraction as well as a softmax classifier for classification. In the first convolutional layer, the wide kernels are applied. And max pooling is adopted for pooling layers. Afterward, two fully connected layers are followed for further feature extraction. The nodes of the fully connected layers are set as 512 and 128, respectively. The overall structural parameters of convolution-pooling kernels are detailed in Table I.

C. Loss Function Design

The Softmax loss is adopted in this study and is defined as cross-entropy between the estimated output probability distribution and the target class probability distribution.

In deep neural networks, the high-level features of the top layer determine the classification result. Based on the distance metric mentioned in section II, for minimizing and maximizing the intra-class variations and the inter-class variations of the extracted features simultaneously, a linear discriminant loss function is adopted in this work as follows:

$$L_{ld} = \frac{D_w}{D_b} \tag{1}$$

It's defined as the ratio of intra-class variations and inter-class variations, where the metric of intra-class and inter-class variations are defined as the following equations:

$$D_w = \frac{1}{2}\sum_{i=1}^{m}\left\|x_i - c_{yi}\right\|_2^2 \tag{2}$$

$$D_b = \frac{1}{2}\sum_{i=1}^{m}\left\|c_{yi} - c\right\|_2^2 \tag{3}$$

where x_i denotes the features generated from the top layer, c denotes the center of feature space for all samples and c_{yi} denotes the center of samples belong to class y_i in feature space. In this way, the weights of top layer can be regarded as a linear transformation matrix, and optimized in training. Then, the final improved loss function can be written as the following equation:

$$L = L_s + \alpha \cdot L_c \tag{6}$$

where L_s represents the softmax loss, L_c denotes the linear discriminant loss for each epoch, α is a hyper-parameter used for balancing the two parts of the loss function.

III. Simulation Experiments and Numerical Results

The proposed solution is evaluated through numerical experiments using simulated signals. In simulations, the vibration signals are adopted. Fig. 2 shows the simulated fault impulses excited by outer-race and inner-race fault, respectively.

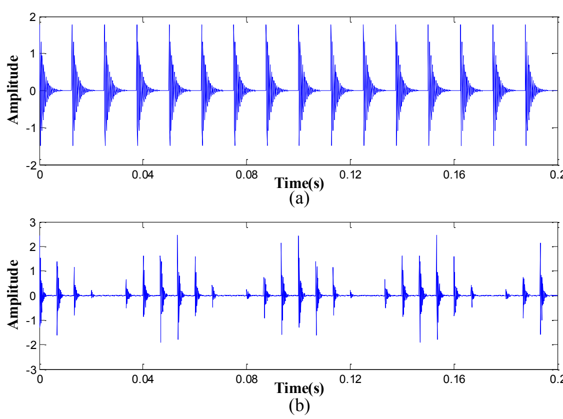

Fig. 2: Simulated vibration signals: (a) outer race signal; (b) inner race signal.

The simulated vibration signals can be constructed based on these source signals. After that, four forms of vibration signals are collected. As presented in Fig. 3, it can be seen that it is hardly to distingue the fault impulses due to the gear mesh vibrations and heavy noise. In a model-driven method, a complex signal processing technique is needed while in the data-driven method things become more intelligent. To employ an intelligent data-driven method, a complete dataset is essential. In this case, the dataset is constructed based on simulation signals of 4 classes of health conditions. In this work, 70% of them are used for training and the remainder is used for testing. To assess the performance of the proposed solution, this work conducted the experiments with several kinds of intelligent methods including 1-D CNN using raw vibration signal, traditional 2-D CNN using vibration image, WDCNN with a wide kernel of the first layer and two machine learning models with fifteen extracted time-domain statistical features. Fig. 4 shows the experimental comparison results.

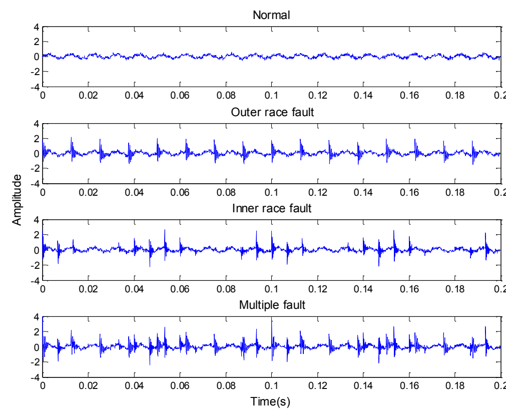

Fig. 3: Simulated vibration signals of different conditions.

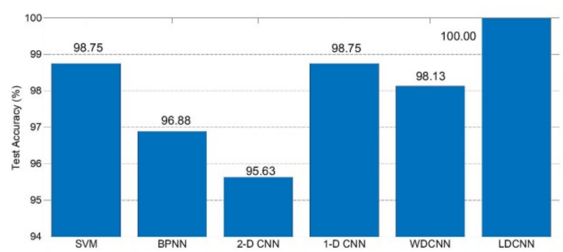

Fig. 4: Mean accuracy of testing methods.

The results above have shown that data-driven intelligent methods are capable of detecting and diagnosing both single and multiple faults. Among those methods, our proposed method achieved the highest accuracy without any feature extraction or signal processing. In particular, compared with the result of WDCNN, the improvement of accuracy by the proposed method verified the effectiveness of improved loss function. Besides, the results also demonstrate that machine learning algorithms such as support vector machines can also achieve high performance with valid features in some cases.

IV. Conclusion and Remarks

The proposed solution is extensively evaluated and the results confirmed that the proposed solution can accurately identify various forms of mechanical faults. In addition, it is demonstrated that the diagnosis performance is enhanced through the adopted convolutional neural network approach under the high noise-to-signal condition. Through the reasonable design of convolution neural network structure, the improvement of the cost function, the ingenious processing of vibration signal and the amplification of training samples, some preliminary results have been achieved. However, there are still many aspects need to be further improved:

(1) Model design and parameter selection

Because the current deep convolution neural network structure design mainly depends on experience and many experiments, there is no unified and feasible method, especially for fault detection and diagnosis. In the literature, many deep learning models have been widely used in research, but most of the researchers draw on the classic network structure or get a better design after repeated experiments, including the number of network layers, training parameters and input size. In addition, the selection of sample length also needs to be considered according to the sampling frequency and model input size, which is difficult to be compatible between different systems and tasks. Therefore, how to build a more reliable model design criteria in the field of fault diagnosis in the future, which can be compatible with the input of different time scales and signal lengths, automatically optimize the model training parameters, is very worthy of attention and further research and exploration.

(2) Diagnosis under different conditions

Because the historical fault data are often obtained under specific conditions and the actual model used for fault detection and diagnosis needs to face the fault signal detection task under various working conditions such as variable speed and variable load and non-stationary conditions. Therefore, how to learn the insensitive characteristics of working conditions from vibration signals is the key to improve the model performance in terms of the generalization ability. The Advanced signal analysis methods, such as wavelet transform and order analysis, are helping to solve the problem of off design condition, but there are some shortcomings such as the high requirement of knowledge and technology and difficulty in realizing automatic intelligent diagnosis. Thus, fault diagnosis methods under variable working conditions need to be further exploited. The research methods that can be tried include multidimensional data fusion mining, migration feature learning, multimodal learning, generative confrontation learning and model integration.

(3) Detection of compound faults

The research of composite fault diagnosis is still in the immature stage, especially the contradiction between the complexity of the method and the accuracy of diagnosis. Most signal decoupling methods need to go through complex time-frequency analysis to judge the various fault components contained in the fault characteristic frequency band. Therefore, further research on how to effectively extract the discriminative features of a single fault signal and enhance the sensitivity of the machine learning model to the coexistence of multiple fault features is of paramount importance for the accurate identification of composite faults.

ACKNOWLEDGMENT

This work is funded by the Science and Technology Project of Inner Mongolia Power (Group) Co., Ltd ([2020] No. 29).

REFERENCES

[1] W. Qiao and D. Lu, "A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis—Part II: Signals and Signal Processing Methods," in IEEE Transactions on Industrial Electronics, vol. 62, no. 10, pp. 6546-6557, Oct. 2015.

[2] J. Zarei, M. A Tajeddini, H. R Karimi. Vibration analysis for bearing fault detection and classification using an intelligent filter. Mechatronics, 2014, 24(2):151-157.

[3] A K S Jardine, et al, A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 2006, 20(7):1483-1510.

[4] Z. Chen and W. Li, "Multisensor Feature Fusion for Bearing Fault Diagnosis Using Sparse Autoencoder and Deep Belief Network," in *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 7, pp. 1693-1702, July 2017.

[5] D. T Hoang, H J Kang, A survey on Deep Learning based bearing fault diagnosis. Neurocomputing, 2019, 335:327-335.

[6] Z. Hu, L. Duan, L. Zhang, Application of improved KNNC method in fault pattern recognition of rolling bearings. Journal of Vibration and Shock, 2013

[7] D. Cabrera, et al. Fault diagnosis of spur gearbox based on random forest and wavelet packet decomposition, Frontiers Mechanical Engineering, 2015, 10(3):277-286.

[8] A. Widodo, B. Yang, Support vector machine in machine condition monitoring and fault diagnosis, Mechanical Systems and Signal Processing, 2007, 21(6):2560-2574.

[9] Y. Yu, D. Yu, J. Cheng, A roller bearing fault diagnosis method based on EMD energy entropy and ANN, Journal of Vibration and Shock, 2006, 294(1):269-277