Mechanical Fault Diagnosis Methods Based on Convolutional Neural Network: a Review

Tianzhe Zhang¹, Jun Dai²a

¹ College of Naval Architecture and Ocean Engineering, Dalian Maritime University, Dalian, China
² State Grid Xiangyang Power Supply Company, Xianyang, China
a daij36@hb.sgcc.com.cn

Abstract—Deep learning is good at abstract features from massive data and has good generalization ability, which has attracted more and more researchers’ attention. The Convolutional Neural Network (CNN) is a classic structure of deep learning and which is being widely and successfully used in the fields of computer vision, target detection, natural language processing, and speech recognition. Based on a detailed analysis of the current status and needs of mechanical system fault diagnosis, this paper introduces the structure of CNN and summarizes the application of CNN in the field of mechanical faults from the aspects of input data type, network structure design, and migration learning. The problems of deep feature extraction and visualization are also discussed, and finally, the difficulties in mechanical fault diagnosis are analyzed and several problems to be solved in the field of mechanical fault diagnosis based on CNN prospect.

1. Introduction

The Mechanical fault diagnosis technology is a science and technology that monitors, diagnoses, and predicts the status and failures of continuously operating mechanical equipment and guarantees the safe operation of mechanical equipment. It is of great significance for ensuring the safe operation of equipment [1]. Once the mechanical equipment fails, it will cause huge economic losses. Real-time condition monitoring of the equipment can ensure the safe operation of the equipment, reduce maintenance costs and prevent the occurrence of major accidents [2].

Many scholars have carried out numerous method researches on electro-hydraulic system fault detection and diagnosis, which can be summarized into three categories: model-based methods, knowledge-based inference methods, and data-driven methods [3-10]. The model-based method explores the operation law of the object by constructing a mathematical model and obtains the related information of normal and abnormal operation by studying the internal relationship between dynamic parameters and response signs under fault conditions. It is suitable for quantitative mathematical models with process accuracy. The knowledge-based reasoning method does not need to establish an accurate system model. It performs calculation reasoning and diagnosis based on system principle knowledge, people's long-term practical experience, and accumulated fault information, such as fault tree-based reasoning, expert systems, etc. However, as equipment becomes more and more complex, it becomes very difficult to establish accurate mathematical models. Data-driven diagnostic methods use only measurable condition monitoring signals or combine history without needing to understand the learning
and physical models of the system. The data is analyzed and characteristic information is extracted, to realize the fault diagnosis and performance evaluation of the system. Data-driven methods do not need to establish precise and complex system models, nor do they need a large amount of domain expert knowledge and knowledge expression reasoning mechanism, but usually require a large amount of accurate data.

Modern condition monitoring technology has been able to realize multi-point and full-life data collection of complex equipment, and then obtain massive amounts of data, leading to the era of "big data" for machinery health monitoring [11]. The research and use of advanced theories and methods, mining information from mechanical equipment big data, and efficiently and accurately identifying the health status of equipment have become a new problem facing mechanical equipment big data health monitoring. In essence, fault diagnosis and performance degradation assessment is a process of cognition of system failure modes and state evolution. The quality of cognitive ability directly affects the effect of diagnosis and assessment. In terms of data processing, in 2006, HINTON GE et al. published an article in "Science" and proposed the concept of deep learning for the first time [12], which set off a new wave of research on artificial intelligence and its application. Deep learning theory was rated as 2013 Top ten breakthrough technologies of the year. Well-known institutions such as Microsoft, Google, and Baidu intend to successfully apply it in image processing, speech recognition, target detection, information retrieval, natural language processing and other fields and have made breakthrough progress [13]. Deep learning aims at simulating the learning process of the brain, expressing hierarchical information and combining massive training data, extracting the information of higher-order essential features, and transferring the features layer by layer to realize the cognitive computing of information. Condition monitoring and diagnosis based on deep learning use big data to learn features, thereby portraying data-rich internal information and ultimately improving classification or prediction accuracy.

In the field of machinery health monitoring, the research and application of deep learning are still in its infancy. Compared with traditional machine learning fault diagnosis methods, deep learning can use the original signal as input to realize end-to-end fault diagnosis through the deep model established by deep learning, which overcomes the following shortcomings of traditional methods: (1) In terms of feature extraction, complex Signal processing technology and field expert experience often extract shallow fault features, which are greatly affected by human factors; (2) In terms of model training, feature extraction and diagnosis are not considered comprehensively, and model training has not been optimized; (3) Traditional methods are oriented With limited data samples, under the background of big data, the learning ability and generalization performance of the model is insufficient, and it is difficult to meet the needs.

CNN is a typical network in deep learning. It is widely used in vision and speech processing. Classic networks such as LeNet-5, AlexNet, VGG, ResNet, GoogleNet, etc. have appeared [14][15], especially using CNN as the core technology The "Human-Machine Go War" --- Google AlphaGo's success story is impressive. The successful use of CNN in the above-mentioned fields mainly stems from its advantages in model structure and training methods [16] [17] (1) The multi-level structure with multi-layer convolution transformation as the core has stronger nonlinear feature extraction capabilities; (2) "Feature learning" is directly oriented to pattern recognition, and realizes that feature extraction, selection and classifier are jointly optimized; (3) During training, CNN utilizes large samples for "layer-by-layer unsupervised greedy learning", data-driven adaptive adjustment of parameters, and then uses small samples for "overall supervised fine-tuning" to realize the overall correction of human cognition to network learning.

Based on introducing the basic framework and working principle of CNN, this article analyzes the characteristics and advantages of the CNN network, summarizes the network structure design and network training skills, and from the three perspectives of model data input, migration learning, and information fusion Summarizes the current research status and application of CNN network in mechanical fault diagnosis, and further discusses the realization of deep-level feature extraction and
visualization problems of CNN network, and discusses the difficulties of CNN network in realizing mechanical system fault diagnosis in the future And challenges, and look forward to the future direction of this field worthy of further research.

2. CNN's network structure and design

2.1. CNN basic network structure
CNN is a typical deep feedforward artificial neural network, inspired by biological perception mechanisms, and generally consists of convolutional layers, pooling layers, and fully connected layers. The essence is to construct multiple filters that can extract the features of the input data. Through these filters, the input data is convolved and pooled layer by layer, and the topological structure features hidden in the data are extracted step by step. Deeper, the extracted features gradually become abstract, and finally the translation, rotation, and scaling of the input data are unchanged. Its main feature is the combination of sparse connections, weight sharing, and spatial or temporal downsampling. Sparse connections reduce the number of training parameters by establishing non-fully connected spatial relationships between layers through topological structure; weight sharing can effectively avoid algorithm overfitting; sub-sampling makes full use of the locality and other characteristics of the data itself to reduce data Dimension, optimize the network structure, and ensure a certain degree of displacement invariance. Therefore, it is very suitable for the processing and learning of massive data.

2.2. CNN structure design
The construction of the CNN network model can be formed by cross stacking the convolutional layer, the activation layer, the pooling layer, and the fully connected layer to form different diagnostic models. Increasing the depth (number of layers) of the model or its width (number of convolution kernels or number of neurons) can improve the performance of the network, but the following problems are prone to occur:

(1) Under the limited training data set, too many parameters can easily lead to over-fitting.
(2) The larger the network, the more parameters, and the greater the amount of calculation and complexity, which makes the model difficult to apply; The deeper the network, the problem of gradient disappearance is likely to occur and the model is difficult to optimize.

However, there is no mature method for how to construct the network and how to optimize the network. Researchers can only construct it through experience or experiment. It has the following characteristics:

(1) The use of convolutional layer. Although the convolutional layer significantly reduces the number of connections in the network, the number of neurons in the output feature map is not significantly reduced. If the fully connected layer is directly connected, the number of parameters is still very large, and overfitting is prone to occur; The more the number of product cores, the more feature maps are generated, and the greater the amount of calculation.

(2) The use of the activation layer. The activation layer is generally placed after the convolutional layer, and the output of the convolutional layer is subjected to non-linear mapping. At present, the rule function is mainly used, which largely solves the problem of gradient dissipation when optimizing the neural network.

(3) The use of the pooling layer. After the pooling layer is usually added to a convolutional layer, it is used to reduce the feature dimension. Pooling down-samples each local area of the feature map. As a generalization of this area, it reduces the parameters and improves the local invariance.

(4) Use smaller convolution kernels, such as 3 × 3 or 1 × 1 convolution kernels commonly used in image processing. CNN develops to a deeper level (L>50), that is, increase the number of layers instead of increasing the convolution kernel quantity.

(5) The operation of convolution is becoming more and more flexible. At the same time, combined with the use of convolution step size, the role of pooling becomes smaller and smaller, the proportion of pooling layers in convolutional networks decreases, and even full convolutional networks appear.
3. Mechanical fault diagnosis method based on CNN

CNN was originally used to process two-dimensional images. Because of its powerful cognitive computing capabilities, scholars began to introduce it into the field of mechanical fault diagnosis, which can well characterize the complex mapping relationship between signals and mechanical health, and improve diversity, non-linearity, high ability to diagnose and analyze health monitoring data [18-21].

3.1. CNN data input type

(1) The integration of one-dimensional signals into a two-dimensional matrix. For mechanical fault diagnosis, the collection is mainly one-dimensional vibration signals, etc. How to convert one-dimensional signals into two-dimensional signals and then use CNN to diagnose is a study by many scholars The problem. WEN L et al. [8] intercepted a data sample with a length of 1 × M2 through a sliding window from the collected one-dimensional vibration signals and then arranged them in order into an M × M two-dimensional matrix.

This data preprocessing method is simple and the amount of calculation is small. The peak value of the vibration signal is converted into the gray value of each line, which makes the converted images closer and difficult to distinguish. When using CNN for training, it requires a long training time and classification recognition. The accuracy is limited.

(2) Signal transformation to realize the conversion of two-dimensional images. To study the conversion of mechanical vibration signals into two-dimensional images, scholars have studied the use of different signal processing methods to decompose or transform one-dimensional mechanical vibration signals. For mechanical fault diagnosis, the most commonly used analysis method is time-frequency distribution. The two-dimensional time-frequency distribution image of the vibration signal can be obtained through the method of time-frequency transformation. Commonly used time-frequency analysis methods include short-time Fourier transform and continuous wavelet transform, S transform, Hibert-Huang transformation, Wigner distribution, etc. For example, GUO S et al. [17] proposed a mechanical fault diagnosis method based on CWT and CNN. First, continuous wavelet time-frequency distribution of the vibration signal is performed, the complete cycle time-frequency image is extracted, and then multiple CNNs are trained to perform classification and identification. Verstraete D et al. [5] used short-time Fourier transform STFT, HHT, and wavelet analysis to obtain time-frequency distribution images, and integrated the time-frequency distribution images into two formats of 32×32 and 96×96. The diagnostic accuracy of the two inputs was tested separately.

Among the above-mentioned methods for converting one-dimensional signals to two-dimensional images through signal conversion, time-frequency distribution is undoubtedly the most commonly used and effective method. The time-frequency distribution can provide joint distribution information in the time domain and the frequency domain, and can better highlight the relationship between signal representation and mechanical health, which is conducive to the training and recognition of CNN. However, the time-frequency distribution is computationally intensive and the image resolution is high. The amount of data input to CNN has also increased greatly, and the amount of calculation is large. When using wavelet transform, VMD, etc. to process the original signal, although the fault components can be separated and the fault characteristics can be highlighted, there is a certain frequency aliasing phenomenon in the decomposition process. The intermediate processing process will inevitably cause the loss of information. It has a certain impact on the accuracy of diagnosis.

3.2. Multi-sensor information fusion fault diagnosis based on CNN

As the monitoring objects become more and more complex, the condition monitoring signal presents the characteristics of nonlinearity, time-varying, uncertainty, etc. When the system fails, it often shows multiple signs. It is difficult to detect the failure by relying on a single theoretical method and information Make precise judgments and appear unacceptably high probability of false alarms and underreports.

Multi-Source Information Fusion (Multi-Source Information Fusion, MSIF) technology is to use computer technology to automatically analyze and synthesize information from multiple sensor
observations from multiple information sources under certain criteria to obtain valuable comprehensive information processing that cannot be obtained by a single or single type of information source Technology [22-23]. The research goal of multi-source information fusion technology is to use the advantages of multiple sensors to improve the accuracy of system fault diagnosis, generally including data-level fusion, feature-level fusion, and decision level fusion. Multi-sensor information fusion requires the collected signals to be collected synchronously, and these signals have relevance to the diagnosed faults.

4. Difficulties and challenges faced by CNN-based mechanical fault diagnosis

4.1. Difficulties in mechanical fault diagnosis
As one of the most important and typical networks in deep learning, CNN has been introduced into the field of mechanical fault diagnosis. Although it is in its infancy, its research and application have achieved initial results. However, the field of mechanical fault diagnosis has its characteristics and difficulties: (1) The mechanical system is large-scale and complicated and is generally composed of multiple subsystems, components, and parts, forming functions, failures, and symptoms with different levels; (2) The failure status is diverse, single failure and compound failure coexist, one failure may correspond to multiple symptoms, one symptom may correspond to multiple faults; (3) The fault signal is complex, due to the complex transmission path, the signal is nonlinear, non-stationary, and the fault characteristics are weak; (4) The normal operating condition data is massive and the fault data is lacking. Coexist with problems such as incomplete failure modes; (5) The failure data is uncertain. The test data is easily affected by the test environment and background noise, which makes the system faults and symptoms have the characteristics of randomness, ambiguity, and uncertainty. Based on the abovementioned difficult problems in the field of mechanical fault diagnosis, researchers need to continue to study the mechanism of mechanical system failure and explore the adaptability of CNN in the field of mechanical fault diagnosis.

4.2. Prospect of mechanical fault diagnosis based on CNN
With the development of information technology, condition monitoring systems have been able to achieve multi-point, high-sampling frequency full-life data collection for large-scale complex mechanical systems, and recently obtain massive condition monitoring data. It is unrealistic to rely solely on professional technicians and diagnostic experts for manual analysis. Intelligent methods need to be studied for automatic analysis. There are still many problems in mechanical system fault diagnosis based on CNN that need to be studied and solved urgently.

(1) CNN fault diagnosis based on the data imbalance problem. Deep learning is based on "big data", to realize the ability of "informed and informed". Having "massive" condition monitoring data is the prerequisite for studying the fault diagnosis of mechanical systems based on CNN [24]. At present, in the field of fault diagnosis research, there are many test data based on test benches, but few measured data based on industrial systems; there are many fault data simulated in the laboratory, but few fault data are occurring; such a problem is common in mechanical condition monitoring. When the mechanical system is performing condition monitoring, a large amount of normal working condition monitoring data can be easily obtained, but it is difficult to obtain and capture fault condition data, which leads to extremely unbalanced data samples and brings difficulties to mechanical system fault diagnosis. Therefore, it is necessary to study the fault diagnosis model based on CNN to solve the fault diagnosis of the mechanical system under the condition of unbalanced fault data based on the above-mentioned reality. The CNN network also requires a large number of training samples. With the seemingly irreconcilable contradiction between the two, the author believes that two methods can be used to solve the problem. One is to study abnormal monitoring of mechanical systems based on the CNN network, that is, to achieve detection in two steps. With the abnormal operation status, after accumulating a certain amount of fault data, the incremental learning method is used to improve the
CNN diagnosis system to realize the recognition of the fault mode; the second is to use the reinforcement learning method to perform reinforcement learning on the current small amount of fault data.

(2) CNN fault diagnosis network based on semi-supervised learning. Under the conditions of modern testing technology, massive state monitoring data is easy to obtain, but data labeling requires expert knowledge, which is time-consuming, laborious, and costly. Therefore, it is often very difficult to obtain high-quality labeled data. Limited and easily available impure data sets are usually mixed with a large amount of normal data and a small amount of abnormal data. Therefore, how to improve fault diagnosis performance under impure data sets has become an urgent problem in this field. How to use a large number of unidentified samples to improve the performance of the classifier is one of the most concerning issues in current machine learning research. Semi-supervised learning is a learning model between supervised learning and unsupervised learning. It can use a small number of labeled samples and a large number of unlabeled samples at the same time to obtain better classification performance. Therefore, under existing conditions, making full use of unlabeled data samples to study a semi-supervised CNN fault diagnosis method is a direction for future research on CNN-based mechanical fault diagnosis.

5. Conclusion
As a typical deep learning network, CNN is a method of studying advanced cognition from the information processing mechanism of the human brain represented by deep learning theory. The research and application in the field of mechanical fault diagnosis are getting more and more attention. Multiple convolution kernels implement filtering and feature extraction of the input signal. Multiple convolution kernels increase the diversity of features. The multi-layer convolution method improves the depth and stability of feature extraction, combined with weight sharing. The simplification of operations and the non-linear processing ability of activation functions can handle 2-D images and 1-D time-series signals well.

The fault diagnosis field of the mechanical system has a good application prospect. However, even though CNN has many advantages, it is based on the training and learning of massive data. The problem is that the feature dimension and the amount of calculation increase sharply. Because of the characteristics of mechanical system fault diagnosis, there are still many problems in mechanical fault diagnosis based on CNN Research and solve, and then improve its adaptability in the field of mechanical fault diagnosis.

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