Design of Fault Diagnosis Algorithm for Electromechanical System Based on Artificial Intelligence

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Abstract: A relatively perfect system for the fault diagnosis of mechanical and electrical products has been formed through decades of development. Nevertheless, the traditional fault diagnosis methods fail to cope with the gradual huge mechanical and electrical system. As a result, the advantages of fault diagnosis mode driven by data are increasingly prominent. Meanwhile, the effect of fault diagnosis has exceeded the traditional fault diagnosis methods in many fields. Through the use of the deep learning technology based on artificial intelligence, it carries out mapping and fitting. By fully taking advantages of neural network, it can effectively obtain the accurate classification of fault data. A fault diagnosis method based on the fault data of mechanical and electrical system is designed in this thesis. When it comes to the basic process, it is to take data sets for different mechanical and electrical products. Through the use of feature engineering method, it extracts the fault features of data. Through the use of deep learning technology, it carries out the intelligent diagnosis. According to the experimental results, it indicates that the fault diagnosis method based on deep learning technology can distinguish a variety of fault modes in mechanical and electrical system in an effective way. What’s more, good classification results in fault recognition have been achieved by a variety of deep convolutional neural network structures, so the feasibility of the method is further verified.

1. Introduction

With the gradual improvement of the level of automation of mechanical and electrical systems, the scale of expansion, the increasing complexity of the system, in bringing great benefits at the same time to mechanical and electrical systems, especially in the aerospace field of mechanical and electrical systems, etc. have brought a large number of safety problems[1]. In the face of increasingly complex electromechanical systems, safety reliability and diagnostic repair are becoming increasingly important. In the aerospace field, electromechanical systems such as power systems, power systems, and life support systems are directly related to the performance and operating status of aircraft[2]. In the field of spaceflight, the development of spacecraft fault diagnosis technology is also very important, however, due to the complexity of the spacecraft itself, its fault diagnosis is difficult to rely on a single method, the need for a combination of multiple technologies to make up for the shortcomings of a single method[3]. At present, there are three main categories of methods used in the field of space: model-based method, signal processing method and artificial intelligence-based method[4].

According to the traditional fault diagnosis method, it is necessary to have a comprehensive understanding of mechanical and electrical system equipment, including various components: combination forms and working environment, and then analyze the source of the fault by layer analysis
based on fault performance information[5]. Compared with model-based fault diagnosis method, the more applicable data-driven fault diagnosis method has been developed under the background of higher complexity of computing and modeling in the big data age[6]. Its greatest advantage is that it does not need the prior knowledge of the system and the accurate mathematical physics model structure, but rather the statistics of the big data generated by the system operation test, which provides a new way of thinking for data mining.

In recent years, the fault diagnosis algorithm based on deep learning can solve the problem by introducing more powerful mathematical tools, can deal with more complex data sets with larger data volume, realize deep-level feature extraction and fault diagnosis, and show unique advantages and potential in feature extraction and pattern recognition[7]. The construction of deep neural network provides a powerful help for extracting the hidden characteristics of data and mining abstract information. Since the deep neural network itself is more like a "black box", it is difficult to explain specifically the characteristics extracted, and specific failure patterns still need to be combined with expertise to be used[8]. In the field of data-driven fault diagnosis, Wan Peng proposes a diagnostic model of nonlinear fluid learning and support vector machine, which uses characteristic parameters such as the time domain and frequency domain of mechanical and electrical system to construct high-dimensional feature space, and its fault diagnosis accuracy has achieved more than 95%[9]. Li Heng proposes a troubleshooting method that uses a combination of short-term Fourier transformations and convolutional neural networks, which can also achieve fault pattern recognition from input to intelligent diagnosis, and which can also be improved with the increase of the type and number of faults[10]. Ge Qiangqiang uses a probability-generated model depth confidence network stacked by multiple limits on Boltzmann machines for better diagnostic results[11]. In the field of deep learning application, convolutional neural network is one of the most widely used and popular network structures, and its local connection, weight sharing and pooling operation make it effective in reducing network complexity and enhancing robustness[12]. The application of deep learning technology makes fault diagnosis develop rapidly in the field of data drive, provides a new development idea for mechanical and electrical system fault diagnosis, has a unique advantage in the face of large-scale aerospace equipment mechanical and electrical system, is a more promising research method[13].

In this paper, a data-driven fault diagnosis method is proposed for the increasingly complex mechanical and electrical systems, and by making full use of the powerful data processing power of deep learning technology, the original data is characterized, multi-dimensional feature maps are extracted and entered into the next layer of neural network structure, so as to achieve intelligent diagnosis of faults. The main structure of the thesis is as follows: First, the first section tells the background of the study, the second section tells the construction of the model, the third section is about the selection of data, and finally the experimental and summary part.

2.Model construction
This section focuses on the troubleshooting process algorithms and some necessary additional knowledge that are constructed in this article.

2.1 All processes
As shown in Figure 1, the specific process of fault diagnosis model algorithm designed in this paper is divided into four parts: (1) Mechanical and electrical system data acquisition and simple classification; (2) Fault feature engineering; (3) Characteristic identification; (4) diagnostic methods. The data acquisition part should meet the various fault problems that can reflect the mechanical and electrical system, and the representation of each fault can be characterized by data. Fault feature engineering and fault feature recognition methods can be used using the same neural network structure, or they can be used separately, according to the fault data type to choose the appropriate method. Finally, the display map is selected by the appropriate method to achieve troubleshooting.
2.2 Feature engineering
In the case of feature engineering, wavelet transformations were chosen. There are several advantages to using wavelet transformation: first, wavelet transformation can carry out time frequency analysis, the original data can be combined with neural network, and second, wavelet transformation itself has a certain denoise effect, through the characteristic energy concentration and noise signal dispersion method of filtering. Wavelet transformation:

Where $b$ is the translation parameter, slide on the timeline; and $a$ is the telescopic parameter, slide on the scale axis.

![Feature engineering diagram](image1)

Figure 1. Our model

As shown in Figure 2, feature engineering uses wavelet transformations and neural network structures to extract the original collected data into a feature diagram in the same format and enter it into the next layer.

2.3 Deep convolutional neural network
During the deep learning phase, the raw data is featured to obtain a dimension-consistent Feature Map, entered into the neural network, gets recognition, and selects the maximum pooling to further noise. The specific parameters of convolutional neural network structure are shown in Table 1:

![Feature engineering diagram](image2)
Table 1 Convolutional neural network parameters

| Layer          | Output size | Parameter |
|----------------|-------------|-----------|
| Input          | 2×32×32     | /         |
| Feature 1      | 32×32×32    | 96        |
| Feature 2      | 64×32×32    | 2112      |
| Convolution 1  | 32×30×30    | 18464     |
| Convolution 2  | 32×28×28    | 18496     |
| Max pooling    | 32×14×14    | /         |
| Convolution 3  | 64×12×12    | 36928     |
| Convolution 4  | 128×10×10   | 36928     |
| Max pooling    | 128×5×5     | /         |
| Convolution 5  | 64×3×3      | 18464     |
| Fully connected 1 | 128×1       | 36992     |
| Fully connected 2 | 6×1        | 774       |
| All            |             | 169254    |

3. Data set
The experimental data used in this paper are derived from the fault data of the rolling bearing experimental data center of Western Reserve University in the United States. The sample of the dataset is shown in Table 2.

Table 2. Samples of fault data

| Name      | Train | Test | All  | Labels |
|-----------|-------|------|------|--------|
| Normal    | 1000  | 100  | 1100 | 0      |
| OR007     | 1000  | 100  | 1100 | 1      |
| IR007     | 1000  | 100  | 1100 | 2      |
| IR014     | 1000  | 100  | 1100 | 3      |
| IR021     | 1000  | 100  | 1100 | 4      |
| B007      | 1000  | 100  | 1100 | 5      |

4. Experiment
The mechanical and electrical system fault diagnosis algorithm design test based on artificial intelligence is selected and reprocessed by a set of raw time domain signal data, the input time frequency analysis module after wavelet transformation, the convolutional neural network is entered after wavelet transformation, after the training of 32 batch sample sizes at a time, the network gradually approaches the optimal solution, and finally obtains the complete convolutional neural network model parameters. Finally, the test data is fed into the entire system network, and the test output results are used as the result of troubleshooting. The data accuracy list after convolutional neural networks and improved convolutional neural network processing is first made as Table 3:
Table 3. Test accuracy

| Neural Networks | epoch | accuracy | epoch | accuracy |
|-----------------|-------|----------|-------|----------|
| CNN             | 10    | 94.92%   | 50    | 98.62%   |
| VGG             | 10    | 97.83%   | 50    | 99.34%   |

The test results are shown in the table, compared with the traditional fault recognition algorithm based on machine learning, and the fault diagnosis algorithm based on deep learning technology has achieved good results. CNN and VGG network structure in the iteration of about 10 times the accuracy and average accuracy of more than 95%, 50 iterations of the accuracy of more than 98% of the results. As can be seen from Table 3, in the process of increasing the number of training iterations, the accuracy of convergence of both methods is higher than 98%, of which the convergence speed of VGG neural network structure is faster, and its final accuracy is higher than that of traditional neural networks.

As can be seen from Figure 3, in the process of fault data identification, iteration about 10 times, the accuracy has been trained to a higher level, both methods have been more than 90% accuracy. In the subsequent iteration process, the accuracy of the traditional convolutional neural network structure fluctuates greatly, and the fluctuation is obvious. Improving convolutional neural network structure is smaller up and down, and the overall stability does not affect the improvement of accuracy. As shown in Figure 4, convolutional neural network structure in the identification of different faults in the inner ring of the identification of a large error rate, in the number of iterations to eliminate this error, improve
5. Conclusion
In this paper, a method is designed to combine the characteristic engineering of processing data with the deep convolutional neural network, by using wavelet transformation and feature engineering based on deep learning technology, and then connecting the convolutional neural network structure and realizing the classification. At the same time, in order to better control the propagation of feature information in the model, prevent feature disappearance and gradient dispersion affect the training effect, a smaller convolution module is introduced. The results show that the model can effectively extract a variety of fault characteristic information and classify it, and achieves good classification effect, and can effectively identify fault mode and complete fault diagnosis. In the face of more complex, more types of faults of mechanical and electrical system structure, the method used in this paper can quickly expand the application, but also by combining other deep learning technology, to build a better fault diagnosis system, with a good application prospects.

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