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Engineering Ship Power Machinery Serialized Monitoring System Integrated with Deep Learning

Mateev Rafael*
Natl Inst Technol Goa Ponda, Ponda 403401, Goa, India
**corresponding author*

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Abstract: The monitoring cloud platform of the ship power system can provide an important guarantee for the autonomous navigation of intelligent ships, and it can process, store and analyze the data generated in the navigation process. The change of its running state will affect the effective evaluation of intelligent equipment, navigation environment and driving behavior of ships by technicians. This paper mainly studies the design of engineering ship power machinery serialized monitoring system integrated with deep learning. This paper mainly uses NI data acquisition equipment to collect multi-dimensional vibration signals of shafting, gear box and bearing, and uses vibration method to monitor and diagnose the running state of shafting, and develops a ship shafting condition monitoring and fault diagnosis system based on LabVIEW. In order to improve the efficiency and accuracy of ship shafting fault identification and diagnosis, a ship shafting fault diagnosis method based on deep learning was proposed. The deep belief network (DBN) method is applied to shafting fault diagnosis.

1. Introduction

Along with the continuous development of science and technology, the diesel engine has become more sophisticated, automation degree is also rising, this kind of development trend, make the system structure and increasing the complexity of diesel engine, such as diesel engine air intake system, fuel supply system, cooling system, etc., and each system has many small systems and components, The four working processes of intake, compression, work and exhaust of diesel engine involve the knowledge of dynamics, thermodynamics and chemistry, and most Marine diesel engines operate in a poor environment, so the probability of failure in the operation process is high [1-2]. When the ship is in operation, it is necessary to collect and analyze relevant parameters for monitoring and fault diagnosis of diesel engine physical parameters. But, due to the complex structure of diesel engine, and there are many different kinds of fault, even if the observed parameters or the abnormal data changes, in the absence of a large number of fault cases, on the basis can only rely on the personnel working on the ship, with limited experience, for diesel engine state judgment, and fault diagnosis. In this case, misjudgment or missed judgment will often occur, so relying on manual experience for fault diagnosis will not only lack sufficient reliability, but also have great labor intensity for the staff [3-4]. Fault diagnosis of artificial experience cycle is long, often requires repeated downtime, and to tear open outfit of diesel engine, then to determine the cause of the problem, and this method is to the fault of diesel engine have been developed to the human eye can see, or diesel engine problems arise to judge function, greatly increases the maintenance costs of the diesel engine and its personnel's workload, It reduces the safety and reliability of the ship system [5-6].

The international research on ship monitoring cloud platform starts from ship-to-shore communication. The European Union has completed the deployment of "RIS system", which can effectively integrate ship information in the basin and effectively coordinate the compatibility of different ship information systems [7]. The International Maritime Organization (IMO) has launched the Remote Identification and Tracking System (LRIT), which can effectively identify and transmit the location, transportation and navigation information of ships in real time, enabling the remote and safe management of ships. On the basis of the Internet of things, Hyundai Heavy Industries and Electronics and Communication Research Institute of Korea has developed the ship network to increase the information communication ability between people and ships, between ships and ships, and between ships and banks, and incorporated enterprises, shipyards and goods into the management system, forming the prototype of the monitoring cloud platform [8]. Japanese shipping companies and shipbuilding enterprises jointly established IOS-OP (Internet of Ships Open Platform), a ship information sharing Platform, which was used to collect and share various data in the sailing process of Ships, and relevant staff could evaluate the sailing status of Ships based on the data [9]. Although the research on ship monitoring cloud platform started late in China, thanks to the efforts of domestic ship industry and scientific research personnel, breakthroughs have been made in many key fields, and a good ship industry system has been formed. The development level of ship monitoring cloud platform in China has been among the top international ranks [10].

Improving the reliability evaluation system of the monitoring platform and establishing the reliability evaluation model can effectively reduce the impact caused by faults, ensure the healthy operation of the system and reduce the difficulty of technical personnel, which is of great significance to the safe navigation, control decision-making and efficient management of intelligent ships.

2. Ship Dynamic Monitoring and Fault Detection System Based on Deep Learning

2.1. The System Design

The system design is roughly divided into several parts: complete multi-channel signal synchronous acquisition, and support the display of test signal time domain waveform, spectrum, axis trajectory and a number of related characteristic parameters; Real-time data processing, various forms of display processing results, for the ship shafting operation state and fault diagnosis to provide a basis; Waveform data is stored and played back to realize offline data analysis; Real-time monitoring of shafting state, over-limit alarm can be timely, to avoid the occurrence of "false alarm" or "false alarm"; According to the analysis results, the fault alarm, specific to the measurement points and characteristic parameters, and appropriate maintenance suggestions; The database matching with this monitoring system is established to facilitate the query, display, statistics, storage and export of data, achieve good management of data, and realize trend analysis and display [11-12]. Therefore, the system should contain five modules: vibration analysis and processing, vibration signal display, diagnosis and alarm, trend analysis, storage and playback [13].

The vibration analysis and processing module is a module for analyzing and processing the signals collected by the sensor. The vibration signals are transmitted to the host computer through the acquisition card and the chassis. The sensitivity conversion, filtering and time-frequency analysis of the signals are carried out in the monitoring program to obtain the waveforms in the time domain and frequency domain, and each characteristic parameter of each signal is extracted [14].

Display module display system processing vibration signal after figure and characteristic parameters of the figure includes all monitoring channel signal time domain, frequency spectrum diagram and axis path diagram, characteristic parameters in two forms, according to one is a form of form, the other is on the shafting structure, according to the corresponding points of the two forms are to be carried out in real time display [15].

The diagnosis and alarm module is divided into two sub-modules: fault alarm and fault diagnosis. The analysis and judgment results of collected signals are displayed in a table. The fault alarm and fault diagnosis tables are divided into three parts: serial number, time and details. The fault alarm details show the situation that the feature parameter exceeds the threshold, and the fault diagnosis details show the possible fault status and cause of the current shafting. The update time of the information in the two tables can be set, and the default value is 1min. At the same time, in order to prevent "false alarm" and "false alarm", when the system detects abnormal shafting state, a delay time is set, and the alarm will start when the state is abnormal within this period [16].

The trend analysis module displays the running trend of characteristic parameters, which is divided into historical trend and future trend. In the process of system operation, the feature parameters of all measuring points are stored in the database at a certain time interval. During trend analysis, the feature parameters stored in the database are extracted into LabVIEW, and the channel selection button, feature parameter selection button, time axis, average mode selection, etc., are set. The trend of different characteristic parameters of different channels is displayed based on the user's selection.

Storage playback module into the storage and playback, storage including the waveform data storage and database storage, data playback module for playback waveform before storage, system operation process, the storage characteristic parameters to the database on a regular basis, not only can be manually and automatically store all channels of the original waveform, the waveform file named after the time, when the offline analysis, The playback file name and channel can be selected through the data playback module to process the waveform.

The monitoring system program structure is designed well, so that the system can complete the required functions, and then the front panel of the system should be designed and optimized. The design of the program is related to function, and the design of the front panel is related to operability, which makes the whole front panel easy to understand, cover rich content and easy to operate. Therefore, the front panel of the ship shafting condition monitoring system is divided into five parts: overall monitoring, signal characteristic analysis, fault alarm and diagnosis, trend analysis and data playback [17-18].

2.2. DBN Fault Diagnosis

Deep confidence networks (DBNS) are stacked with multiple layers of restricted Boltzmann machines, each of which can simply be viewed as independent

In the classification of one-dimensional vibration signals, when the dimension of input data is less than or equal to 1000 and there are few categories (2-4 categories), the three-layer or four-layer network structure can be adopted. When the dimension of the input data is greater than 1 000 but less than 5 000 and there are many categories (4-6 categories), a four-layer or five-layer network structure can be adopted.

The number of nodes in the input layer is selected according to the length of the input signal. For example, when the input signal is an N-dimensional vector, the number of nodes in the input layer should be N.

After all RBM training, a classifier model will be set at the end for fitting or classification. The classifier model generally chooses the logistic function or softmax function.

logistic function is also known as sigmoid function, and its function formula is:

$$f(x)=\frac{L}{1+e^{-l(x-x_0)}} \tag{1}$$

Where: x0 is the center of the function curve; k is the slope of the curve.

The essence of the softmax function is data mapping: mapping one k-dimensional data into another k-dimensional data with elements in the data ranging from (0,1). The formula of softmax function is:

$$S_i = soft\max(g) = \frac{e^{gi}}{\sum_{i=1}^{d} e^{gi}} \tag{2}$$

Type: j = 1, 2,... , K.

DBN classification of ship axis coefficient data is a multi-class problem, so softmax function is selected as the final classifier model.

Deep learning is a process of abstracting and extracting low-level features to form high-level features. It is a learning network based on data features. When the original signal directly as a low-level input, deep learning can through the network learning to the characteristics of the original signal itself, do not need artificial feature extraction and selection process, avoiding the traditional feature extraction method of complexity and uncertainty, makes could improve the maneuverability of machine learning, machine learning intelligent got enhanced.

The shafting fault diagnosis method based on DBN is shown in Figure 1.

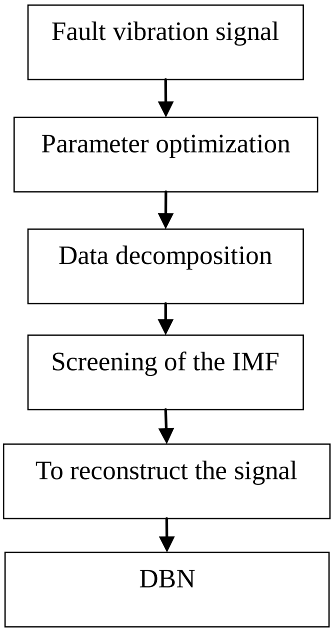

Figure 1. Fault diagnosis method of shafting based on DBN

3. Fault Diagnosis Test Experiments

This section will be carried out comparative experiments of different diagnosis network, the first in a simulated data sets will be traditional DBN diagnosis and comparison between the network and improve the DBN diagnosis analysis of the performance before and after improvement, followed by a further sign of effectiveness, case western reserve university in the United States public data sets will be improved DBN diagnosis network compared with other diagnosis network, Analyze the performance differences among different diagnostic networks.

The variable noise experiment needs to simulate the bearing vibration signal polluted by noise. To this end, the bearing vibration signal to be tested is first processed with noise in the time domain. The added noise is Gaussian white noise with different signal-to-noise ratio (SNR), and then the original vibration signal is taken as the input signal of the diagnosis network. The anti-noise ability of the network model is judged by the final recognition accuracy. In order to analyze the anti-noise capability of the improved DBN diagnostic network, the SNR range is set as -5dB to 5dB in this section, and then the diagnosis effect on the added noise test set is compared. Also to avoid randomness, the experiments were repeated 10 times for each model.

The variable working condition experiment needs to simulate bearing vibration signals under different working conditions, so the bearing vibration signals under different load conditions are used for combination verification. Considering in a simulated data set contains three kinds of load conditions, so the cross validation, in which some load conditions of bearing vibration signals as the training set, the other two load conditions of bearing vibration signals as the test set, the recognition accuracy of judgment on the test set network operation mode adaptive ability of the model.

4. Experimental Results

4.1. Comparison of Diagnosis Results

Table 1. Diagnostic results before and after improvement

Model	Test set	Average accuracy rate	Average number of training rounds
Traditional DBN	0% simulated data set	93.7%	20
Improve DBN	0% simulated data set	95.2%	14

As can be seen from the data in table 1, improve the effects of DBN diagnosis network model of the two is more outstanding, not only the training of the network on the training set speed significantly increased by 30%, but also improve the accuracy in test set was 1.5%, this indicates that the improved DBN diagnosis network can be trained more efficiently, more good recognition effect.

4.2. Variable Noise Experiment

Table 2. Experimental results of variable noise

	-5	-3	-1	0	1	3	5
Traditional DBN	52%	67%	68%	79%	87%	91%	92%
Improve DBN	92%	93%	93%	93%	93%	94%	94%

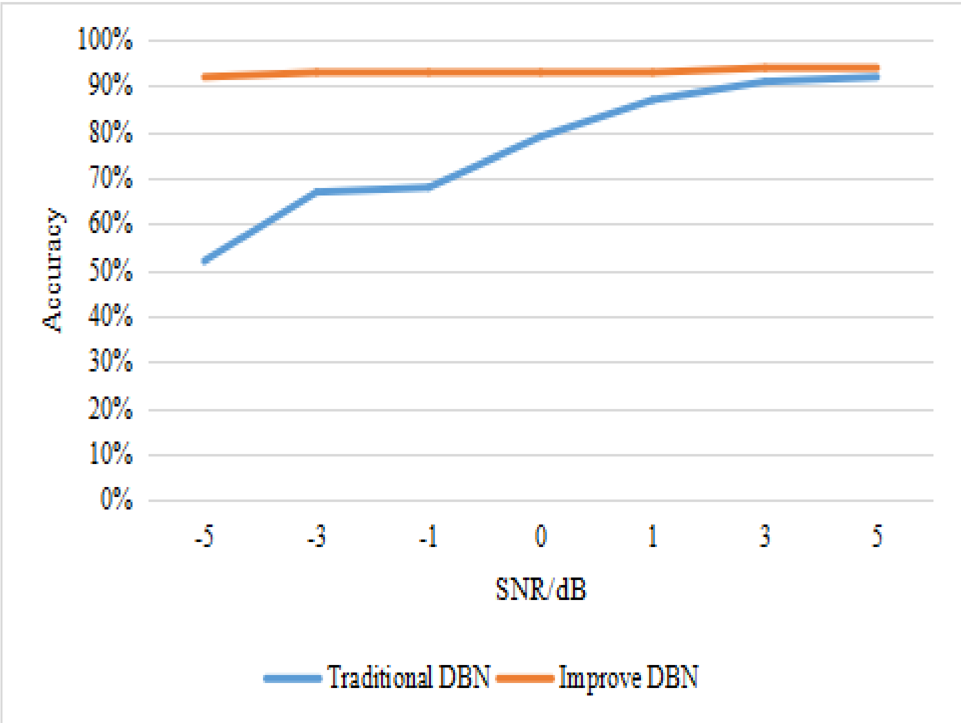

Figure 2. Statistical results of variable noise experiment

As shown in Table 2 and Figure 2, by observing the final experimental results, it can be found that when SNR exceeds 3dB, both diagnostic models can maintain an accuracy of more than 90%. However, when SNR is lower than 3dB, the performance of traditional DBN diagnostic network decreases rapidly, and when SNR=-5dB, the accuracy rate is only about 52%. This is because at this time, the test set signal has been seriously contaminated, so the diagnosis network may not learn the key features for fault diagnosis from the training set, and finally reduce the classification performance on the test set.

4.3. Variable Condition Experiment

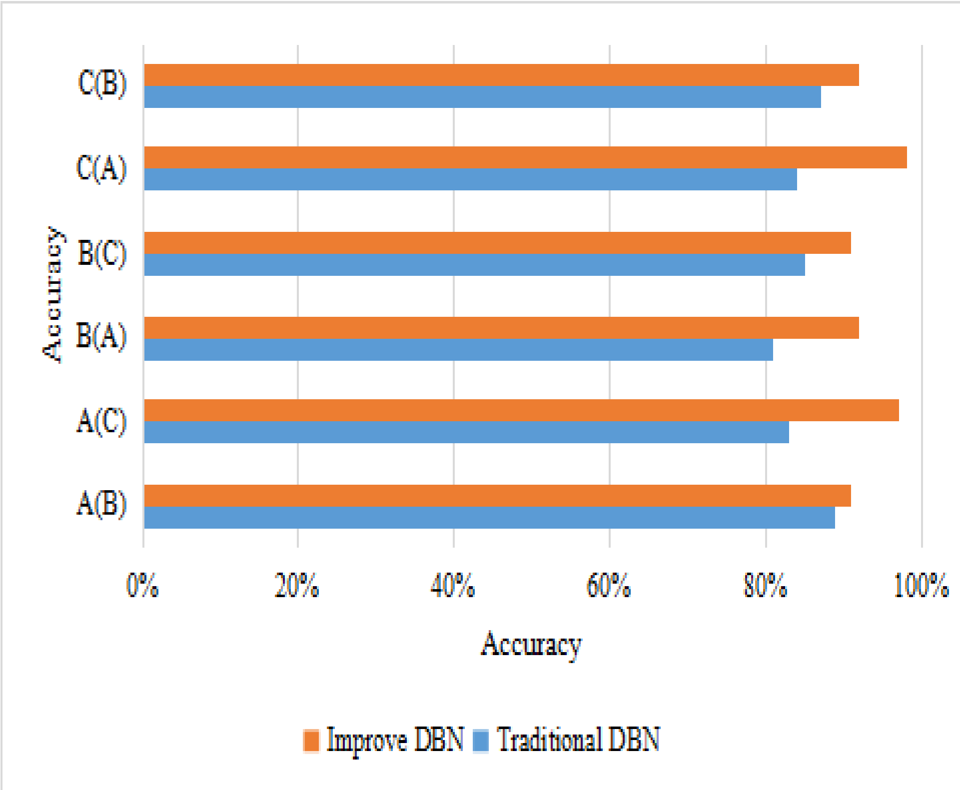

Figure 3. Experimental results of variable working conditions

As shown in Figure 3, the traditional DBN diagnostic network has poor domain adaptive ability, and the diagnosis rate in the cross-validation experiment is as low as 81%, while the improved DBN diagnostic network can achieve more than 90% recognition accuracy in any condition.

5. Conclusion

In today's increasing technology reform, our country for the ocean is also continuously exploring in depth, ships as the most important means of transportation, how to ensure the safe navigation of ships in today's big data-driven becomes a key research question. As an important branch of machine learning, deep learning can effectively use huge data sets to mine the deep internal characteristics of data, which can surely serve as a solid bridge in the connection between big data and health status monitoring. In order to improve the efficiency and accuracy of ship shafting fault identification and diagnosis, a ship shafting fault diagnosis method based on deep learning is proposed.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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