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Ship Lock Electromagnetically Remote Fault Diagnosis Mode Based on Machine Learning

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Abstract: The traditional electromechanical fault diagnosis mode of the ship lock adopts the wired connection control intelligent control system, which cannot be remotely and wirelessly controlled through the control field and more strict control mode. The design of ship lock electromechanical remote fault diagnosis mode based on machine learning is proposed. The concept of machine learning and the characteristics of neural network are summarized. The fault diagnosis mode and fault diagnosis technology of electrical communication system are proposed. The experimental comparison of fault diagnosis accuracy of CNN SVM GA-SVM model shows that the deep learning bearing fault diagnosis model based on CNN network model has better performance.

1. Introduction

With the rapid development of network information technology, remote fault diagnosis of ship lock electromechanical system has become a feasible technology. The ship lock electromechanical remote fault diagnosis method combines computer technology, machine learning and fault diagnosis technology.

With the continuous progress of science and technology, many experts have studied electromechanical remote fault diagnosis. For example, Ge Y proposed a fault modeling and reasoning method for electromechanical systems based on fuzzy Petri nets (FPN) [1]. Clark Stallkamp R, Lockee B B used FPN's forward matrix reasoning to analyze the reliability of the electromechanical system subsystem, and obtained the probability importance of the target database. They studied the application of the visual monitoring and fault diagnosis system in the management of mine electromechanical equipment [2]. Ng M C, Farhani G, Farhani N monitor and analyze potential failures, formulate failure maintenance strategies, provide technical support, and lay a foundation for improving the safety and reliability of overall equipment operation in coal mines.

Combined with the actual situation of the Coal Mine Co., Ltd., this paper analyzes the causes of the faults of the electromechanical equipment in the coal mine, and probes into the fault diagnosis technology of the electromechanical equipment in the coal mine [3]. Although the research results of electromechanical remote fault diagnosis are rich, the research on electromechanical remote fault detection mode of ship locks based on machine learning is still insufficient.

In order to study the electromechanical remote fault diagnosis mode of ship lock based on machine learning, this paper studies the machine learning and electromechanical remote fault detection mode of ship lock, and finds out the vibration monitoring method. The results show that machine learning is beneficial to the development of electromechanical remote fault diagnosis mode for ship locks.

2. Method

2.1. Machine Learning

(1) The concept of machine learning

Machine learning is a branch of artificial intelligence, which enables computers to learn by imitating human learning behavior and constantly improve themselves. The main process of machine learning is to acquire data, preprocess data, extract and select features, and finally diagnose and predict. Feature extraction is very important for machine learning. Traditional machine learning needs artificial feature extraction, and with the increase of the size and complexity of data samples, traditional machine learning feature extraction is insufficient, so deep learning has developed and solved many problems. Machine learning can be divided into two stages according to the development stage [4]. The first stage is shallow learning. With the emergence of BP neural network, shallow learning began to be concerned and applied, followed by perceptual machine, decision tree, support vector machine and other algorithms. Through traditional machine learning, rules can be learned and predicted from data samples. Machine learning drives the next neuron of the previous neuron. It can be transmitted even if it is far away. But in practice, it is found that machine learning can not deal with these problems even in this way, because with the transmission of information, there will always be some information slowly ignored. A common solution to the above problem is to find a processing unit to store the past information, which can be directly extracted when useful, discarded when not in use, and modified when necessary. Since information is easily lost when it is transmitted to neurons one by one, a processing unit can be found to store past information [5]. Therefore, the establishment of long-term and short-term memory networks is to solve this problem. The shallow learning model is better, but it relies on manual feature extraction based on expert knowledge; However, artificial feature extraction may filter out the fault data. Samples with large data volume are more suitable for deep learning modeling, and can adaptively extract depth features with strong representation ability.

(2) Characteristics of neural network

The most basic characteristic of neural network is parallel distributed processing mode. Its unique knowledge representation structure and information processing principle have made remarkable progress in many fields; Therefore, neural network is considered as the most promising general model of intelligent computer system. The learning rule of neural network is an algorithm to modify the weight, which aims to obtain appropriate mapping function or other system performance. Teachers' free learning rules use adaptive learning methods to enable nodes to selectively accept different features in the input space, showing their unique performance [6]. For a multilayer feedforward network with at least one hidden layer, as long as there are enough hidden layer neurons, it can achieve any approximation of any function of interest with any accuracy; In other words, it can save almost all the information in the sample as knowledge to the trained network. BP neural network is widely used in function approximation, classification learning and pattern recognition. The feature extraction method mainly solves the problems of large amount of information and high dimension in the monitoring data. After extracting fault information features, it is necessary to select appropriate algorithms for data classification. Echo network constructs a random network structure by randomly arranging large-scale sparsely connected analog neurons to form an efficient circular neural network, also known as reserve pool computing [7].

2.2. Ship Lock Electromechanical Remote Fault Diagnosis Mode

(1) Electrical service system

The management of the signal system on the turnout related equipment is mainly to master the change trend of its current value through the centralized signal monitoring system (CSM for short), and maintain or repair the equipment during the sunroof maintenance. The on-site personnel need to test and debug the switch machine at the skylight point according to the operation plan, and the workload is very heavy. During the non skylight period, the operation of the equipment can only be analyzed by viewing the current curve collected in real time. At the ship lock hub station, technical experts need to read various turnout action curves every day. The task of reading is meticulous and arduous [8]. He needs to carefully check the fixed and reverse action status of the turnout and master the subtle changes in the action process, which requires high vision and technical quality of technicians. Once the staff misunderstood the actual operation status of the switch switching equipment and failed to find the abnormal situation of the switch switching equipment, the possible safety consequences would be unimaginable. It is urgent to conduct performance analysis and intelligent fault diagnosis on the switch machine equipment, reduce the workload of the commissioner, and improve the existing monitoring and diagnosis methods to meet the requirements of the leap forward development of the ship lock. Hard faults are usually caused by sudden changes in the circuit, such as open circuit and short circuit in the circuit, which lead to changes in the circuit structure and generally make electronic equipment unable to work; Soft fault is different from hard fault. It changes gradually and will not cause sudden changes in the circuit as hard faults do [9]. The main reason is that the parameter value of the part changes gradually with the influence of time and environmental conditions, and exceeds the tolerance range of the part. Compared with hard fault, soft fault will not cause complete failure of electronic equipment, but will cause performance degradation of electronic equipment. The process of fault diagnosis can be understood as the process of finding component or system faults. By reproducing the fault scenario or deeply studying the changes of key parameters and component operating conditions during the fault process, we can grasp the rules [10]. Before the failure occurs, we can predict and warn the possible problems of the equipment according to this rule. After the failure occurs, judge the cause, point and extent of the failure, and assist the decision-maker in making maintenance decisions.

(2) Fault diagnosis technology

In the practical application of field unit diagnosis, fault diagnosis can be divided into simple diagnosis and accurate diagnosis. Simple diagnosis is to use a simple vibration instrument to measure the vibration data obtained by the equipment, and judge by listening to the sound and touching experience. Generally, it can judge whether the equipment operates normally, the severity of the fault, and predict the development trend of the fault. Accurate diagnosis is a further step on the basis of simple diagnosis. After obtaining the vibration measurement data, analyze the waveform, spectrum and other characteristics, compare them with the vibration characteristics of typical faults, and diagnose equipment faults in combination with mechanical knowledge and previous experience [11]. Generally, it is possible to determine the location, nature, extent and cause of the failure and propose more reasonable maintenance measures. At present, there are two main methods for accurate diagnosis of equipment vibration: knowledge-based method and numerical method. The common methods of knowledge-based precise diagnosis include data model analysis, fault tree analysis, neural network based diagnosis and expert system diagnosis. Data model analysis method uses the changes of data model structure and parameters to study the state of equipment during operation, and essentially studies the dynamic change process of vibration signal. This method uses the designed mathematical model to directly simulate and analyze without accumulating the previous operating conditions of the system. The fault tree analysis method takes the maximum fault of the diagnosis object as the main objective of analysis, finds out all factors that cause the fault, and expands level by level according to the event level [12].

(3) Fault Diagnosis Method for Rolling Bearing of Unit

It is a common method to use the vibration signals of rolling bearings for condition monitoring and fault diagnosis. Vibration data usually have nonlinear and non-stationary characteristics, which are more difficult to process than linear and smooth signals. Especially when the wind power system enters the era of big data and small samples, the typical fault diagnosis samples are insufficient [13]. Compared with neural network, support vector machine (SVM) can effectively obtain the global optimal solution and avoid the local minimum problem. At the same time, SVM can not only handle high-dimensional data, but also have a good learning ability for small samples, and the computational complexity of the algorithm itself is not high. Support vector machine is a machine learning method based on statistical learning theory, which is widely used in data classification and pattern recognition [14].

2.3. Vibration Monitoring

In order to obtain more information in the vibration signal, it is usually necessary to use some mathematical methods to extract feature information from the original signal. The average value reflects the size of the static component in the vibration signal. In the continuous signal, calculate the average value as shown in equation (1):

$$\overline{\chi} = \frac{1}{T}\int_0^T \chi(t)dt \tag{1}$$

Where x (t) is a continuous signal; T is the signal period, S, as shown in Formula (2):

$$\overline{\chi} = \frac{1}{N}\sum_{n=1}^{N} \chi(n) \tag{2}$$

Where $\chi(n)$ is discrete signal and N is sampling point number.

For continuous signal x (t), there is Fourier transform, as shown in equation (3):

$$\chi(f) = \int_{-00}^{00} \chi(t)e^{-2\pi jft}dt \tag{3}$$

Where, f is the frequency, Hz [15].

3. Experience

3.1. Object Extraction

In the process of system development, the system needs to be debugged in order to timely analyze and correct the remote system. Due to the limitation of laboratory environment, field equipment cannot be used for system debugging, so a set of CNN model simulation control system needs to be developed. To build a CNN model simulation control system, you need to purchase switches, buttons, relays, indicator lights and other components, and carry out extremely complex circuit wiring. It is not convenient to modify the circuit later [16]. Therefore, this paper constructs a PC based CNN model simulation control system with LabVIEW platform, realizes communication with PLC through OPCservice, connects PC and PLC, and conducts PLC program debugging and remote system testing. The system creates PLC variables through OPC protocol and binds them to the switch elements on the front panel of LabVIEW software to control PLC [17]. When modifying, you only need to change the binding variables and the addresses of the daemons. Compared with the development of the CNN model simulation control system, the development cycle of the CNN model simulation control system software is shorter, and the later maintenance is more convenient.

3.2. Experimental Analysis

Before connecting LabVIEW and PLC, first analyze the model PLC program of CNN to determine the PLC variable type to be created by OPC. There are many types of CNN model equipment, and different types of CNN models occupy different PLC points. On the basis of analyzing various CNN models, our laboratory reasonably arranged the distribution of input and output points of equipment, designed a general PLC program for CNN models, which is applicable to any CNN model. The model information of the device is stored in the VW storage area, and different action programs are executed by judging the data in the VW storage area [18]. The methods of fault feature extraction mainly include principal component analysis, wavelet transform, etc. Among many feature extraction technologies, wavelet transform is a typical MRA analysis technology and time-frequency analysis method. It converts the time signal to be measured from the time domain to the frequency domain, and decomposes the complex signal into multiple simple signals. Therefore, the time-domain and frequency-domain characteristics of the signal can be observed to extract the characteristics representing the essence of the signal. Principal component analysis is mainly used to reduce dimensions, so wavelet transform is selected to extract fault features.

4. Discussion

4.1. Comparison of Model Results

In terms of accuracy, under the same data set, there is still a certain gap between the SVM based model and the CNN based model, but the effect of the GA optimized SVM model is close to that of the CNN model. Table 1 lists the test accuracy of different models. Due to the randomness of training set extraction, multiple verifications are required.

Table 1. Test accuracy of different models

Number of verifications	SVM(%)	GA-SVM(%)	CNN(%)
1	8.5	8.7	9.4
2	5.7	7.9	8.5
3	5.6	7.4	7.5
4	7.5	6.8	8.5

It can be seen from the above that the test accuracy of the SVM network model in the first test is 8.5%, the second test accuracy is 5.7, the third test accuracy is 5.6, and the fourth test accuracy is 7.5%; The test accuracy of GA-SVM network model in the first test is 8.7%, the second test accuracy is 7.9, the third test accuracy is 7.4, and the fourth test accuracy is 6.8%; The test accuracy of the CNN network model in the first test is 9.4%, the second test accuracy is 8.5, the third test accuracy is 7.5, and the fourth test accuracy is 8.5%. The specific results are shown in Figure 1.

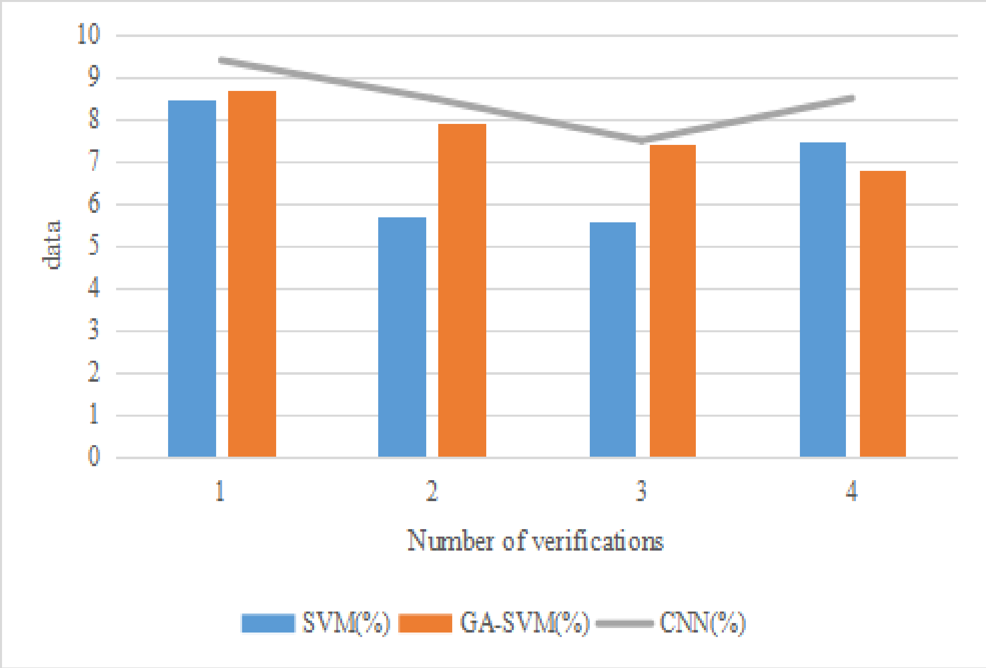

Figure 1. Test accuracy of different models

It can be seen from the above figure that the accuracy of the SVM network model optimized by GA algorithm is indeed improved by comparing it with the SVM model optimized by GA algorithm. Although the deep learning model based on CNN network only uses raw data and does not construct artificial features, its comprehensive accuracy is almost the same as or even higher than that of GA-SVM model, which shows that the deep learning bearing fault diagnosis model based on CNN has better performance. Although the classification accuracy of CNN network cannot reach 10%, it does not need feature extraction and filtering, which avoids the problem of parameter optimization in SVM. Therefore, it has a good effect in the field of bearing fault diagnosis, and can realize real-time online monitoring of bearing status.

4.2. Reliability Test

One of the stress testing scenarios: stress testing using a fault alarm. If the analog equipment fails and there is an early warning or alarm, the hardware system will generate a large number of files at this time, which can effectively test the system reliability. See Table 2 below for test results.

Table 2. Fault alarm pressure test results

Type	Duration(s)	Data generation interval(s)
A	3	1
B	3	2
C	4	1

It can be seen from the above that the duration of hardware system A is 3s and the data interval is 1s; B Hardware system duration is 3s, and data interval is 2s. The duration of hardware system C is 4s, and the data interval is 1s. The specific presentation results are shown in Figure 2.

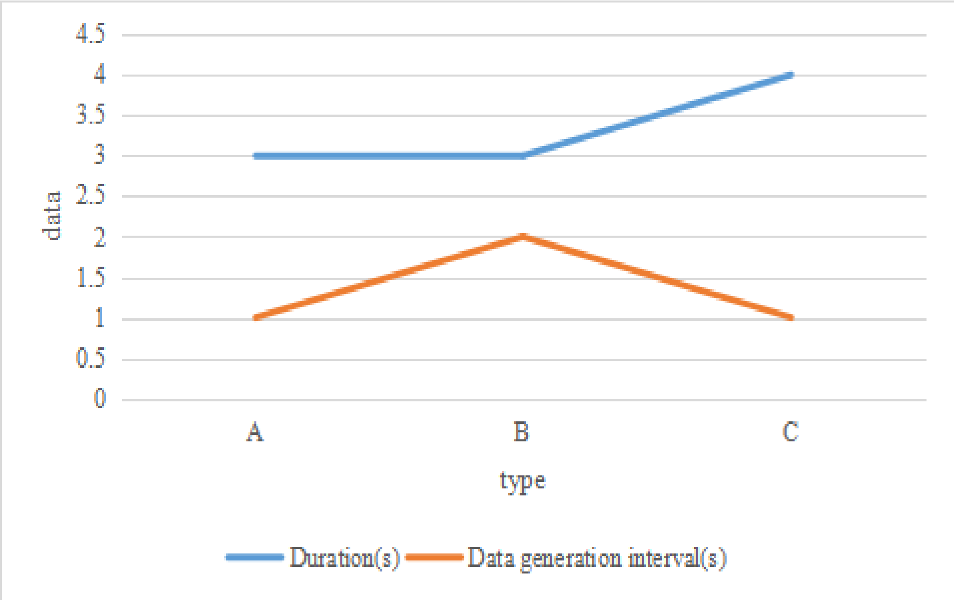

Figure 2. Fault alarm pressure test results

The frequency of file generation for hardware system design shall be at least 1 minute. In the actual wind farm, in order to reduce the data storage pressure, the file generation frequency is generally set to not less than 20 minutes, while the file generation frequency selected by the test is 5 seconds. The test file contains all data types and is the largest file generated by the system. This scenario test has the effect of stress testing. During the scenario test, the monitoring log shows that there is no data loss, data communication, storage module and database work normally, and system resource consumption is normal.

4.3. Determination of Chaotic Characteristics of Wind Turbine Operating State Characteristics

The time series of discrete wavelet transform coefficients of the vibration monitoring signal of the front bearing of the main shaft of the wind turbine, the delay time obtained by the mutual information method and the change curve of mutual information are shown in Table 3.

Table 3. Delay time curve of measuring points of shaft front bearing

Information relevance	Delay (sampling interval)
0.34	0.556
0.35	0.546
0.36	0.435
0.37	0.431

Table 3 above shows the mutual information curve of the time series of offline wavelet transform coefficients of the vibration signal of the front bearing of the wind turbine main shaft under different delay times. The horizontal axis represents different delay times, and the vertical axis represents mutual information between time series of discrete wavelet transform coefficients under different delay times. It can be seen that when the delay time is 0.37, the mutual information reaches the first minimum value, indicating that the phase space coordinates have the best independence in this case. 0.37 is selected for phase space reconstruction.

5. Conclusion

With the integration of large electromechanical system and control system, the reliability of the system becomes more and more important, and various new fault diagnosis technologies and methods are emerging. In today's information age, the rapid development and good application prospects of Internet and LAN technology make them become the media of various information. In this paper, the chaotic characteristics of fan operating state characteristics are determined. The results show that mutual information reaches the first minimum value, indicating that the independence of phase space coordinates is the best in this case. 0.37 is selected for phase space reconstruction.

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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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