World Scientific Research Journal (WSRJ) ISSN: 2472-3703
www.wsr-j.org

Research on Automatic Machine Fault Diagnosis Technology

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Abstract: To improve the efficiency of equipment maintenance, military development requires the transformation of weapons and equipment from post-fault maintenance and regular maintenance systems to condition-based maintenance and preventive maintenance systems. Research on mechanical fault diagnosis techniques is the fundamental guarantee for achieving this change. Applying modern fault detection and diagnosis technology to the fault diagnosis of automatic machines has important practical application value for establishing equipment maintenance system that meets military construction requirements. This paper introduces the measurement and preprocessing of fault signals, and expounds the research status of fault feature extraction technology, the research status of fault pattern recognition and the research status of automata fault diagnosis, and proposes further research directions of mechanical fault diagnosis technology. The development of diagnostic techniques provides research ideas.
Keywords: fault diagnosis; mechanical fault diagnosis technology; fault signal extraction.

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1. INTRODUCTION

A self-propelled anti-aircraft gun is a new type of high-altitude gun that is independently developed by China and meets the requirements of digitalization. It is the main battle equipment for low-altitude defense in China. As the core part of its fire turret, the automatic machine belongs to the typical complex mechanical system [1]. During the shooting of the anti-aircraft gun, the automaton performs the functions of unlocking and locking, unlatching and latching, pumping and throwing, firing, etc. under the action of high temperature and high pressure gunpowder gas, plus high temperature during actual use. The impact of harsh working conditions such as high pressure and strong impact makes the automatic machine one of the highest failure rates of the anti-aircraft weapon system [2]. Due to the short time of the self-propelled artillery installation, the common faults and their causes and other related information and experience are relatively scarce. Maintenance personnel often adopt the methods of “looking, touching or listening” and dismantling and unloading the box. Carrying out [3].

2. RESEARCH STATUS OF MECHANICAL FAULT DIAGNOSIS TECHNOLOGY

2.1 Fault signal measurement and preprocessing

Engineering practice shows that different types of mechanical faults will exhibit different characteristic waveforms in dynamic signals [5]. The vibration signals directly reflect the main information of the operating state of the equipment. In the existing mechanical fault diagnosis technology, based on vibration signal measurement and analysis the application of vibration diagnostic methods is particularly common [6]. The acquisition of the vibration signal has the advantages of easy acquisition, no need to disassemble the mechanical equipment, and the like, and covers a wide range without affecting the normal operation of the equipment. With the development of sensor technology, signal processing technology and pattern recognition technology, the accuracy of fault diagnosis has been greatly improved. Therefore, whether it is a relatively simple mechanical equipment such as bearings, gear boxes, hydraulic pumps, or in the diagnosis of large and complex mechanical equipment such as diesel engines, reciprocating compressors, generator sets, etc., diagnosis methods based on vibration signal analysis and processing Be the most important way.

2.2 Research status of fault feature extraction technology

The traditional signal processing method based on Fourier transform is only suitable for processing stationary signals. It can only obtain the calculation result of signal history averaging when dealing with non-stationary signals [7]. Simply analyzing the stationary signal from the time domain, the frequency domain or a single scale can no longer meet the requirements of signal processing, and the method of analyzing the non-stationary signal from the time-frequency domain has emerged one after another. The analysis methods for non-stationary or time-varying signals are collectively referred to as time-frequency analysis [8], which mainly includes short-time Fourier transform (STFT), wavelet transform (WT), Wigner-Ville time-frequency analysis (WVD), and adaptive time. Frequency analysis method.

1) Short-time Fourier transform. The basic idea is to achieve localization in the time domain, multiply a time-limited window function before the signal Fourier transform, and assume that the non-stationary signal is stationary in the short-term interval of the analysis window, with one in time The time-sliding window can achieve better locality in both the time domain and the frequency domain. STFT has been widely used in the analysis of slowly varying signals, but its resolution in the time domain and frequency domain remains the same as the window is determined.

2) Wavelet transform. Wavelet transform is a time-frequency analysis method in which both time window and frequency window can change with scale. It can not only locate short-time high-frequency components in non-stationary signals, but also analyze low-frequency components [9]. The field of fault diagnosis has been widely used [10]. Feng et al. [11] proposed a normalized wavelet packet decomposition method, and used the wavelet packet relative energy, wavelet packet global entropy and wavelet packet node entropy to characterize the signal. Wu [12] and so on based on discrete wavelet transform to extract the energy spectrum as the feature vector, the adaptive neural fuzzy inference system is used to determine

the location of the fault bearing and distinguish the fault state. Zhao [13] extracted the wavelet packet energy value of the rolling bearing vibration signal, and trained the decision tree fault model for fault diagnosis, and achieved high diagnostic accuracy.

3) Wigner-Ville time-frequency analysis. WVD solves the problem of short-time Fourier transform to a certain extent, and can refine the different frequencies of the signal, and has good time-frequency resolution. However, it uses a bilinear transformation, which is subject to cross-interference suppression when analyzing multi-component signals [14].

After the idea of fractal dimension and fractal geometry was proposed by the famous scientist Mandelbrot, after decades of development, it has gradually become a new discipline popular in the scientific community today, and has been extended to all branches of social science and natural science. 44]. Fractal theory is a theory that studies the overall and local self-similarity. The concept of Fractal Dimension is introduced into fractal theory as an important parameter to quantitatively describe the degree and complexity of self-similarity of fractals. It is fractal geometry. The most core part of the theory. Mechanical vibration signals are often typical non-stationary and nonlinear signals. They have fractal characteristics in a certain scale range. It is feasible to quantify their structural features as characteristic parameters for fault diagnosis. The feature extraction of fractal dimension in nonlinear dynamic systems and Fault diagnosis and other aspects have been widely used.

Many scholars use single fractal dimension to extract vibration signals and use them for fault diagnosis. However, single fractal analysis can only reflect the overall information of vibration time series, and it is insufficient to describe the local characteristics of signals. Multifractal can reflect the proportion and unevenness of the probability measure distribution on the whole fractal structure. The generalized fractal dimension and multifractal spectrum are used to describe the overall characteristics well, and improve the fineness of signal geometric features and local scale behavior. Denisse [15] used multifractal theory for earthquake case analysis to study the spatial distribution of seismic activity. Zhao Haiyang [16] performed multifractal analysis on multi-sensor signals to form the initial feature matrix of generalized fractal dimension, applied singular value decomposition method for data compression, and extracted matrix eigenvalues as fault feature vectors. Qi Qingqing et al. used multifractal spectrum energy and generalized fractal dimension spectrum energy as two-dimensional feature vectors. The input probabilistic neural network classifies the gear faults and verifies that the correlation dimension is higher than the extracted feature dimension as the feature vector.

2.3 Research status of fault pattern recognition

(1) Fault pattern recognition based on neural network

The neural network is a mathematical neuron model based on the physiological structure of the human brain. Because neural network has parallel distributed processing, associative memory, self-organization and self-learning ability and strong nonlinear mapping characteristics, it can identify and classify complex information, thus providing new pattern recognition for fault diagnosis and condition monitoring. Means, with great application potential. Li Jiangang et al used the Elman neural network to classify and diagnose the fault types of coal mine main fans.

Bangalore et al. [17] used artificial neural networks for data detection and acquisition systems, and achieved good results in early fault diagnosis of gearbox bearings. Dou Wei [18] extracted the vibration state parameter graph of rotating machinery through image processing technology, and used the feature information for RBF network for fault diagnosis. In recent years, hybrid diagnostic methods that use intelligent algorithms to optimize the network structure and parameters of neural networks have developed rapidly.

(2) Fault pattern recognition based on multi-core support vector machine

Support Vector Machine (SVM) is a machine learning method based on the principle of structural risk minimization in modern statistical theory [18]. It shows many unique advantages in solving small sample, nonlinear and high dimensional pattern recognition problems. It is widely used in the field of mechanical fault diagnosis. Widodo [19] reviewed the application of mechanical condition monitoring and fault diagnosis in the 10 years after SVM was proposed. Tang [20] combined SVM with the dimension reduction method of manifold learning to realize the fault diagnosis of wind turbine gearbox. Wang [21] extracted features from the angles of energy, HHT spectrum and related frequencies, and used SVM to identify various fault states of the engine. The kernel function parameters of SVM play an important role in classification performance. Therefore, many optimization algorithms and optimization algorithms are applied to SVM.

The SVM uses a single-core mapping method that uniformly processes all samples. Different kernel functions have different characteristics. When the application changes, its performance will show great differences. Therefore, how to select and construct the nuclear function is a major difficulty, and there is still no perfect theoretical basis. In response to these problems, a large number of studies have been conducted on the Kernel combination method, which can utilize the characteristics of each basic kernel function to make up for the deficiency of a single kernel function. In 2002, Chapelle et al. first proposed the concept of Multi-Kernel Learning (MKL) method. Later, the multi-core SVM proposed by Lanckriet et al. was able to map different features with different kernel functions. To construct a multi-core learning model, we must first consider the multi-core combination method. There are linear combination methods, extended synthesis methods, non-stationary combination methods and local multi-core learning methods, etc., where linear convex combinations Multi-core learning is the most common one. The use of multi-core models instead of single-core models can enhance the interpretability of decision functions and achieve better performance than single-core models. Multi-core learning translates the problem of how to represent a sample into a feature space into a question of how to select the basic kernel and weight coefficients, which solves the problem of the construction and selection of kernel functions to some extent. Therefore, after establishing the model framework of multi-core learning, effectively determining the weight coefficient of the basic kernel is the key to solving the MKL problem. In response to this problem, a variety of effective multi-core learning theories and methods have emerged, such as the Boosting multi-core combination model learning method , and the multi-core learning method based on Semidefinite Programming (SDP).

3. RESEARCH STATUS OF AUTOMATIC MACHINE FAULT DIAGNOSIS

In recent years, with the development of mechanical fault diagnosis technology, a large number of modern signal feature extraction and pattern recognition methods have been discovered and promoted to the field of automatic machine fault diagnosis, and achieved certain results. By reviewing relevant literatures at home and abroad, it is known that there are many studies on the reliability of automatic weapons in foreign countries, but there are few studies on the fault diagnosis of automatic machines. In China, mainly the research team of North University of China has carried out a lot of research work under the support of the National Natural Science Foundation of China (No. 51175480). Pan Mingzhi et al. extracted the wavelet energy spectrum entropy, wavelet singular spectral entropy and wavelet time entropy as fault characteristic parameters, and verified the effectiveness of the proposed model by simulation analysis. Du Heng et al. used the local wave with adaptive characteristics to decompose the signal to obtain the IMF component, extracted the local wave feature spatial spectral entropy, marginal spectral entropy and time-frequency entropy as fault features, and input the genetic algorithm optimized support vector machine. Fault classification identification. Pan Hongxia introduced the chaos theory into the fault diagnosis of the automaton. The chaotic parameters such as Lyapunov dimension, correlation dimension and K entropy were used to extract the characteristics of the measured signals, and the Elman neural network was trained to identify the fault pattern.

4. DEVELOPMENT OF FAULT DIAGNOSIS TECHNOLOGY

(1) In terms of feature extraction, firstly, according to the characteristics of non-linear and non-stationary characteristics of the typical fault vibration signal of the automaton, the advantage of using local feature scale decomposition is fast, the component contains more information, and the time-frequency spectrum analysis and time Methods such as sequence analysis are combined. Secondly, the application of multifractal theory in fault feature extraction is further studied, and the characteristic parameters that can reflect the fault state of the automaton are extracted.

(2) In terms of fault pattern recognition, the performance of traditional single-core SVM depends largely on the type of kernel function, parameters and the defects of existing optimization methods. It is proposed to use multi-core support vector machine for intelligent pattern recognition and in the core. The selection of functions, the optimization of their weight coefficients, and the design of multi-classification models are studied to improve the pattern recognition effect of multi-core SVM.

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