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Machine Tool Fault Diagnosis Based on Support Vector Machine

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Abstract: Fault diagnosis of machine tools and other mechanical equipment is essentially a process of pattern recognition, i.e. the process of classifying the operational data of the equipment under fault from the normal operational data. However, traditional support vector machine based fault diagnosis is performed under the condition of sample balancing, i.e. the number of samples contained in faulty data and normal data is approximately equal, although SVM classifiers have shown good results for such data sets and have gained wide application. The aim of this paper is to investigate machine tool fault diagnosis based on support vector machines. The necessity of machine tool spindle bearing fault diagnosis is analysed, and an improved support vector machine rolling bearing fault diagnosis method based on wavelet packet decomposition is proposed. Wavelet packet decomposition is performed for feature extraction and then the extracted feature vectors are imported into three optimised bearing fault diagnosis models, Gs-Pca-Lssvm, Ga-Pca-Lssvm and Pso-Pca-Lssvm, and the experimental results show that The accuracy of all three models is 95% and above.

1. Introduction

The machine tool is mainly used to complete the machining process through the user's pre-set machining program, after issuing a travel command, which is then converted into an action signal by the servo system. During the work of a CNC machine tool, its subsystems must maintain a high degree of coordination and stability [1-2]. Considering the realistic working conditions, due to the ageing and wear of components, as well as the accumulation of fatigue in some machining processes, the performance indicators of CNC machine tools will become lower and lower over time, until failure occurs [3]. By the above process decomposition, China's CNC machine tool

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performance and the gap between the developed countries are mainly in, the domestic machine tool failure rate is high, the product production process processing quality is not stable enough, the service life and aging speed is too fast, repair and maintenance costs are not low and other reliability problems [4].

The above problems have brought great trouble to domestic consumers of CNC machine tools, and because of the low value-added industry in the low-end profits, further caused the low market competitiveness of China's CNC machine tools, no financial resources to research and development and a series of problems [5]. m. Z. Naser to CAK6150 CNC lathe as an example, the study of CNC machine tool control system, proposed a Fanuc system-based CNC machine control diagnosis scheme. To achieve this process, he used the CNC/PMC structure to control the parameters and signals of the control system. Also, in order to improve the intelligence of the CNC machine tool, a neural network model based on fuzzy theory is presented, which determines the type of machine tool fault by completing fault classification with fuzzy inference rules. Finally the previous program was checked. The results show that the program not only determines faults but also improves the machine tool machining efficiency [6].Naira Firdous uses CNC machine tool troubleshooting as a research object and proposes an appropriate knowledge representation structure that helps to improve retrieval efficiency and subsequent similar reasoning. The development of an expert system for machine tool fault diagnosis based on the Siemens 808d CNC was carried out [7]. Gabrielle Gauthier Melançon designed a support vector machine based fault model for naval engines. A multi-classifier for ship engine fault diagnosis was built using the support vector machine. Finally, the ship was tested through simulation experiments. The support vector machine can accurately identify the performance of the ship engine fault diagnosis model [8]. In summary, it is essential to carry out research on fault diagnosis of CNC machine tools.

In this paper, an analytical study of the electric spindle is carried out; the bearing in the electric spindle is the component with the highest number of failures, and the deterioration of the bearing failure easily leads to the deterioration of other components. For this reason this paper starts with a data-driven approach to machine tool fault diagnosis. Through experiments, it is verified that the method and the system developed in this paper for rolling bearing faults in CNC machine tool feed systems is correct, effective and feasible.

2. A Study of Machine Tool Fault Diagnosis Based on Support Vector Machines

2.1. Machine Tool Spindle Bearings

To CNC machine tools, for example, common failures generally include electrical system failure or component system failure. Nowadays, although most CNC systems have self-diagnostic functions, which can be used for common electrical system faults as well as fault diagnosis of simple components connected to the system, the system cannot diagnose the faults caused by mechanical faults of the components and the decline in processing quality [9-10].

The spindle system is one of the most important components of the CNC machine tool, which mainly includes the spindle, bearings and spindle housing. The main role of the spindle system is to transmit motion and power to the workpiece or tool and drive the tool or workpiece movement, and then complete the surface machining of the workpiece. Bearings, as a necessary rolling body, are an important part of the spindle assembly, but also one of the important sources of failure of the spindle assembly, whose operating condition directly affects the performance of the entire spindle or machine tool system and can effectively prevent major accidents from occurring [11-12].

2.2. Data-driven Machine Tool Fault Diagnosis

(1) The basic principle of statistical (multivariate) analysis and diagnosis is that the method of extracting statistical features based on the data already collected takes into account the intrinsic connection between all variables at the same time [13]. This is because it is possible to monitor and diagnose fluctuations in the data in real time by extracting the characteristic statistical values of the measurement data (e.g. values with invariance such as mean and variance) and then setting a gap value.

(2) The basic principle of the signal processing method is: first collect the variable signal values containing a large amount of information in actual production and life, then extract the characteristics of the use of these signal values, and finally use the relevant processing techniques to solve the time-frequency problem. As different fault signals may cause different spectral features, common methods based on signal processing include wavelet transform and spectral analysis [14-15].

(3) The basic principle of quantitative artificial intelligence methods is: by simulating the human thinking and decision-making methods used to achieve artificial intelligence diagnosis, the approach generally does not require a defined mathematical model can use the computer to apply human decision-making behavior to fault diagnosis, the current application of such methods are more widely used: SVM, artificial neural network and Hidden Markov Model (Hidden Markov Model (HMM)), etc. [16].

2.3. Advantages of Support Vector Machines

According to the analysis of the principle of SVM and the process of constructing the classification decision function, it is understood that SVM has the following characteristics:

(1) SVMs are based on statistical learning theory, the principle of structural risk minimisation, and seek learning machines to minimise the experimental risk and trust domain. In terms of sample size, support vector machines are better suited to small samples than traditional learning machines based on empirical risk minimisation, with the aim of obtaining the best solution under existing conditions, not just when samples are often unconstrained [17-18].

(2) The algorithm simplifies the quadratic optimisation problem.

(3) For non-linear problems, the non-linear transformation is assigned to a high-dimensional feature space and a linear discriminant function is constructed to implement the non-linear discriminant function.

(4) The complexity of the algorithm does not depend on the dimensionality of the sample, effectively avoiding the "dimensional disaster" irrelevance.

(5) From the classification decision function, it can be seen that the SVM classifier focuses on the key samples with more feature vectors, which can effectively eliminate the sunken redundant sample data and has good robustness.

(6) The number of support vectors is used to characterise the complexity of the SVM classifier and to suppress the occurrence of overfitting.

3. Investigation and Study of Support Vector Machine Based Machine Tool Fault Diagnosis

3.1. Construction of the Bearing Test Platform

The bearing test platform uses the hp engine to measure its acceleration data independently of the engine bearings and the vicinity of the engine bearings. Engine bearing faults are imported using EDM to artificially create corresponding faults in a variety of different locations such as rolling bodies, inner rings of rolling bearings as well as outer rings.

3.2. Experimental Data Acquisition for Bearing Fault Diagnosis

In order to carry out the research experiments, the fault test data of 40 rolling bearings were obtained from the official website of the Bearing Research Centre. In this experiment 12 rolling element failure experiments, 12 inner ring failure experiments, 12 outer ring failure experiments and 4 normal cases were covered. Because of the presence of three sensors, 40 sets of 3 types of sample tasks were taken from the raw data respectively.

3.3. Improved Support Vector Machine Rolling Bearing Fault Diagnosis Based on Wavelet Packet Decomposition

The wavelet packet decomposition algorithm can be represented as follows:

$$B_j^{2j-1}(t) = HB_{j-1}^{i}(t), B_j^{2j}(t) = GB_{j-1}^{i}(t) \tag{1}$$

Bij is set to be the first wavelet packet in layer j. B10 is a digital signal to be decomposed. As the number of decomposition layers increases, the wavelet packet band splitting becomes more refined, making the original signal clearer. The signal obtained in the decomposition factor reconstruction is not redundant and the perturbed data is eliminated. The characteristic fault types of the self-vector parameters are constructed from the decomposition factors and the reconstruction formula:

$$B_j^{i}(t) = H^* B_{j+1}^{2i-1}(t) = GB_{j+1}^{2i}(t) \tag{2}$$

In this paper, the fourth order Daubechies wavelet basis (denoted as db4 in Matlab) is chosen because firstly, Daubechies wavelets are highly adaptive and reconstruct the signal more smoothly. At the same time, the smoothness of the signal reconstruction is related to the order of the vanishing moments of the dbN wavelet basis function, which increases with the order N. The effect of band localization is influenced by the smoothness of the signal, which in turn affects the ability to divide the frequency bands.

4. Analysis and Research of Machine Tool Fault Diagnosis Based on Support Vector Machines

In this paper, a 4-layer decomposition of the vibration signal is carried out, so that 8 wavelet packets can be obtained at layer 4, as shown in Table 1. The distribution of the amplitude of the reconstruction coefficients of the wavelet packets varies under different types of faults, so the energy characteristic parameter should be chosen whichever is the sum of the squared reconstruction coefficients (wavelet packets of each frequency band). The four energy spectra of the bearings are shown in Figure 1.

A vector construction method for extracting energy-valued failure characteristics using 12kHZ sampling frequency wavelet packet decomposition was used to extract reconstructed vibration signals under four bearing conditions (bearing failure, normal, inner ring failure, outer ring failure). The number of sampling points is 3012 and the power values are normalised for each frequency band. The number of arbitrarily extracted fault vectors was 10 groups per display, constituting a set of 100 fault features.

The feature vectors from the wavelet packet decomposition were divided into a training set and a test set, with a ratio of 9:1 (90/10) between the training and test sets. After being trained in the Gs-Pca-LSSVM, Ga-Pca-LSSVM and Pso-Pca-LSSVM models respectively, they were imported into the test set for validation. In the Ga-Pca-LSSVM, Pso-Pca-LSSVM models, the initial population was 100 and the number of iterations was 100, and a five-fold cross-validation was performed. The results of the three types of experiments and the optimisation parameters are shown in Table 3. Table 2 shows the coding of rolling bearing faults.

Table 1. Signal energy spectrum

Frequency band serial number	Inner ring fault signal energy spectrum	Rolling body fault signal energy spectrum	Normal signal energy spectrum	Outer ring fault signal energy spectrum
1	0.02	0.34	0.55	0.03
2	0.04	0.02	0.41	0.01
3	0.34	0.32	0.08	0.39
4	0.44	0.05	0.09	0.02
5	0.03	0.01	0.04	0.03
6	0.05	0.03	0.01	0.22
7	0.53	0.21	0.03	0.01
8	0.23	0.12	0.03	0.02

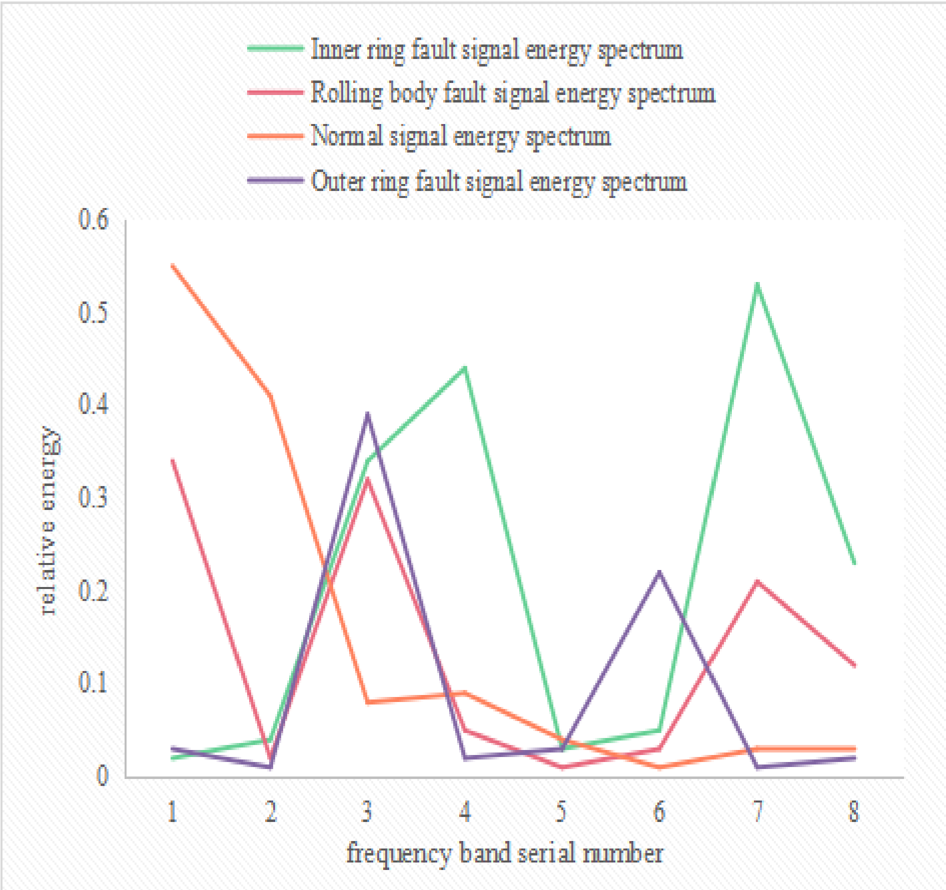

Figure 1. Four energy spectra of bearings

Table 2. Fault codes for rolling bearings

Fault category	Fault Code	Category Tags
Rolling body failure	2000	one
Normal	0200	two
Outer ring failure	0020	three
Inner ring failure	0002	four

Table 3. Results of the three types of experiments

Models	Diagnosis rate (%)	Time consuming (s)	Best c	Best g
Gs-Pca-LSSVM	98	11	72	25
Ga-Pca-LSSVM	96	15	6	18
Pso-Pca-LSSVM	97	13	12	33

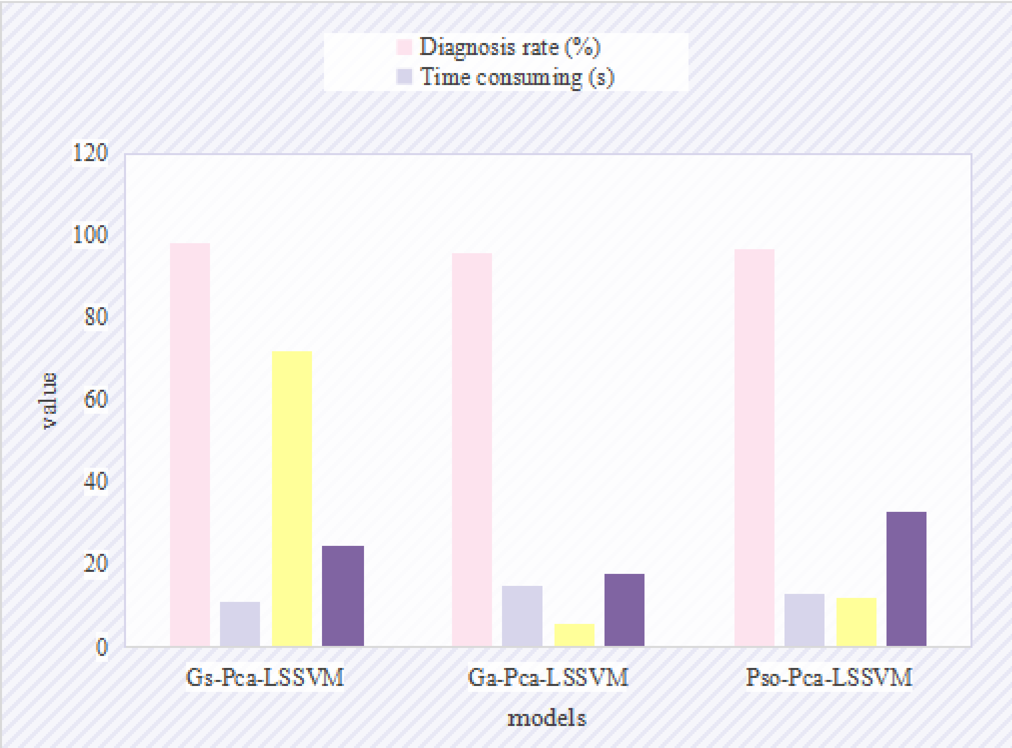

Figure 2. Comparison of the three models

From Figure 2, it can be concluded that the diagnostic rates of all three models are above 96%, indicating that feature extraction plays a key role in the improvement of diagnostic accuracy. Among the three models, the Gs-Pca-LSSVM model took the shortest time. From (c, g), it can be seen that the Gs-Pca-LSSVM model is less likely to fall into a local optimum.

5. Conclusion

When a bearing failure occurs in a machine tool, it can affect the processing accuracy and quality, or cause a production stoppage or even a safety accident. Therefore, it is of great significance to carry out research on online monitoring and diagnosis of rolling bearing faults in CNC machine tools. This paper elaborates the concept, classification principle, main parameters and advantages of support vector machine; optimizes the construction of support vector machine by using wavelet packet decomposition and verifies its superiority with experimental data; analyzes and compares the diagnostic accuracy of different models. The study has some shortcomings and needs further improvement. The selection of wavelet bases and the number of decomposition layers for wavelet noise reduction in the paper are based on experience and several experiments, and further research is needed; the method of parameter optimisation of the support vector machine still needs to be studied to ensure high efficiency while avoiding falling into local extremes as far as possible; the influence of the selection of the support vector machine kernel function on the diagnostic model is not considered in the paper, and this part needs to be carried out in the next work.

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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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