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Vibration Response Characteristics of Engineering Ship Power Machinery Based on Machine Learning

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Abstract: In recent years, machine learning algorithms have flourished, and with superior performance, a new generation of information technology represented by machine learning algorithms has been widely used in the field of fault diagnosis. Researchers have proposed a large number of dynamics modelling and control algorithms based on machine learning, and these algorithms have achieved good results in the study of mechanical vibration signal response. Therefore, this paper takes the mechanical dynamics of engineering ships as the research object and adopts a machine learning-based approach to carry out research on mechanical fault diagnosis models. The paper focuses on the mechanical vibration signal fault model to capture the uncertainty of the mechanical dynamics system and the use of a model predictive control algorithm based on the machine learning model to determine the mechanical faults.

1. Introduction

With the deep integration of information technology and marine engineering, it is necessary to use advanced intelligent technology to diagnose mechanical power failures in a timely manner [1-2]. In the field of fault diagnosis, since different signals have different sensitivities to specific types of faults, multi-sensor acquisition systems can be built to detect faults in components or mechanical systems in a comprehensive manner [3]. Gaussian processes have a strong ability to process data dynamically and can be used to solve prediction problems over a certain time series [4-5]. The rapid development of signal processing algorithms and machine learning algorithms has also provided solid technical support for accurate identification of mechanical faults [6]. The basic idea is to use various algorithms to perform a series of processes on the data acquired by the sensors and thus assess the operational status of the equipment and determine the type of fault occurring [7].

In recent years, with the development of machine learning information technology, a large number of scholars have carried out in-depth research on machine learning and engineering ship power machinery fault diagnosis. For example, Kinoshita F and other researchers have studied the extraction of characteristic parameters of low-frequency vibration signals in conjunction with vibration monitoring principles, detailed the sample processing and data normalisation process of vibration signals, and validated the model using the comparison of parameter samples and calculation groups, and this research has provided theoretical support for GIL machinery fault diagnosis [8]. experts such as Keita have used computer signal processing techniques to monitor and record the vibration signals of mechanical dynamics online, collecting test data using an intelligent data processing system and processing the data [9]. The study of machine learning has revealed that machine learning-based machinery fault diagnosis models are a direction worthy of further research.

The vibration signals are often characterised differently for different faults occurring in the equipment, and therefore vibration signals are widely used in the fault diagnosis of power mechanical equipment. This paper discusses the power machinery fault diagnosis model for ships based on machine learning. The structure of this paper can be roughly divided into three parts: the first part is the basic overview part, which includes the modelling of vibration signal fault diagnosis and power system uncertainty; the second part is the construction of the mechanical power fault diagnosis model, which is constructed by vibration signal feature extraction and parameter model; the third part is the model analysis part, which mainly includes fault diagnosis experimental analysis and alternative The third part is the model analysis, which mainly includes the experimental analysis of fault diagnosis and the analysis of the influence of the number of alternative action sequences.

2. Basic Overview

2.1. Vibration Signals

For fault diagnosis of vibration signals, statistical features are usually needed to reflect the changes in the signal and characterise the fault information of the vibration signal [10]. Generally speaking, statistical features contain statistical features in the time domain and statistical features in the frequency domain, and each statistical feature has some physical significance [11]. The modelling process for distinguishing the feature selection fault diagnosis model for smooth non-smooth signals is shown in Figure 1.

The specific modelling process is as follows.

Step 1: Signal pre-processing:The vibration signal is pre-processed using a pre-processing method combining empirical modal decomposition and wavelet decomposition, while the obtained sub-signal set is signal filtered using screening conditions.

Step 2: Smoothness differentiation: The ADF test is used to discriminate the smoothness of the sub-signal set, and the sub-signal set is divided into two parts: smooth and non-smooth.

Step 3: Feature extraction:Multiple time-frequency statistical features are computed for the smooth and non-smooth sub-signals separately.

Step 4: Refinement of feature selection:The features extracted from the smooth part and the features extracted from the non-smooth part are selected using a recursive feature elimination algorithm to select the smooth key features and non-smooth key features that contain fault information.

Step 5: Establish the fault diagnosis model:Use the selected smooth part key features and non-smooth part key features in step 4 to model together to obtain the fault diagnosis model.

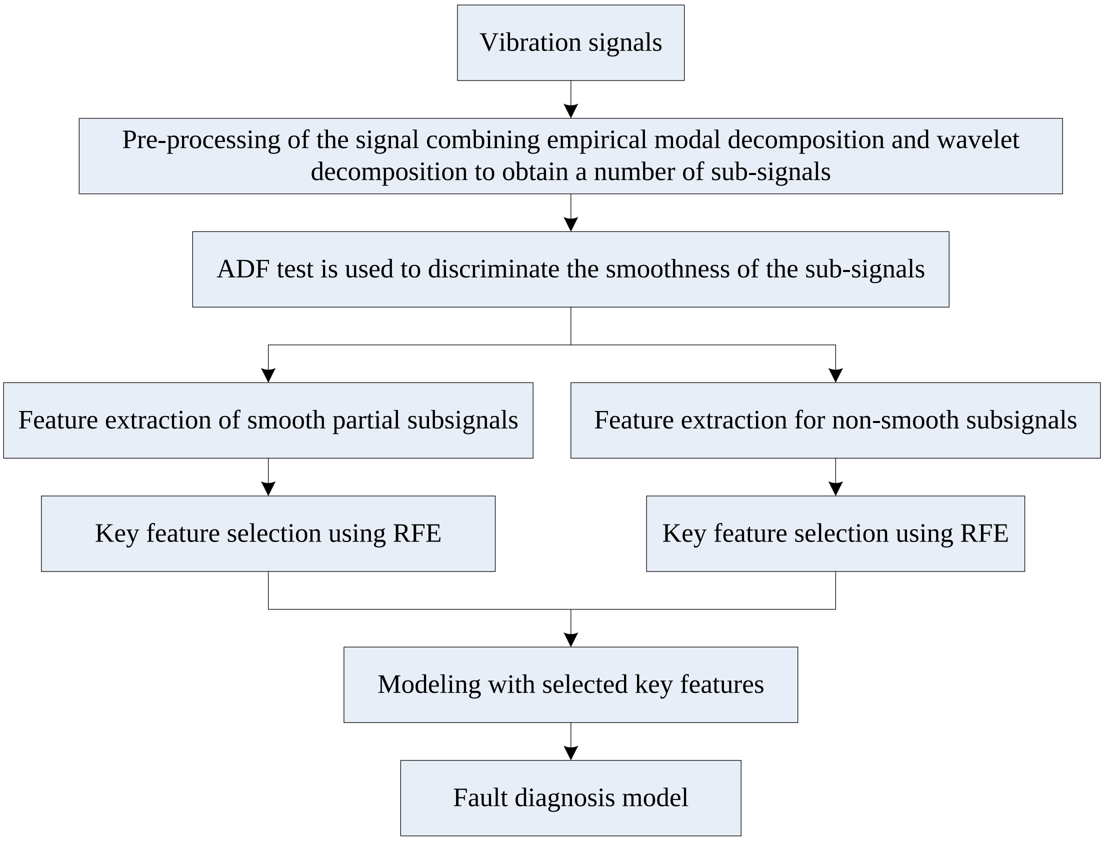

Figure 1. Modeling flow chart

2.2. Uncertainty of the Dynamical System

The uncertainty of the dynamical system is characterised by two ways, namely stochastic uncertainty and cognitive uncertainty [12]. Stochastic uncertainty is mainly caused by causes such as observation noise and process noise, and is an inherent characteristic of the system [13]. Stochastic uncertainty can be represented by the parameters of the parameterised distribution of the output. Cognitive uncertainty arises from uncertainty in the subjective perception of the dynamical system. The main reason for the existence of cognitive uncertainty is the limitation of the data describing the dynamical system, which is a given on data sets of definite size, and only with infinite data does cognitive uncertainty disappear [14-15]. Bayesian inference methods are often used to reduce the impact of cognitive uncertainty [16].

3. Model Construction

3.1. Vibration Signal Feature Extraction

In order to quantitatively establish the optimal number of segments, the M- SE eigenvalues of each sub-node were calculated by different segmentation modes and the SD of the corresponding M-SE eigenvalues between the sub-nodes were obtained for quantitative analysis, and the results are shown in Table 1.

Table 1. M-SE values of each node under different segmentation patterns

M	(2,0)	(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)	SD
4	2.81	2.21	2.34	2.48	2.56	2.42	2.79	0.316
5	2.84	2.43	2.47	2.53	2.61	2.56	2.63	0.258
6	2.87	2.54	2.64	2.59	2.68	2.69	2.78	0.227
7	3.14	2.58	2.67	2.64	2.74	2.73	2.87	0.324
8	3.26	2.79	2.83	2.72	2.93	2.86	3.02	0.276

It can be seen from Table 1 that the M-SE feature values of individual nodes are larger when the number of segments is higher. This means that as the number of segments increases, the uncertainty of the feature information obtained by each node becomes larger, but it does not mean that the smaller the uncertainty of the feature information obtained by the nodes is better, because with too few segments, small offsets and mutations within the segment interval appear insignificant compared to the whole segment interval, and valid feature information is not easily detected. At the same time, the SD value of the MSE eigenvalues between the nodes is found to be the largest when M=7, and the optimal number of segments is determined to be seven. Therefore, the M-SE eigenvalues extracted by the seven-segment method are finally chosen as the input features for subsequent fault identification, and the convergence of the amount of feature information extracted from different sub-signals can be effectively avoided.

3.2. Parametric Model

The principle of the parametric model is that the predicted values are calculated directly from the actual physical and mathematical relationships, with the form of the function predetermined in advance [17]. The advantage of parametric models is that they have actual physical meaning and derivation process, can effectively grasp the characteristics of the whole system, and in most cases, the form of the parametric model has been fixed, with high accuracy and ease of use [18]. The general mathematical form of the parametric model is as follows.

$$M = AP + Y \tag{1}$$

Where M is the value to be calculated, A is the pre-designed model matrix, P is the observation point and Y is the observation error. The kinetic model is derived from the energy equations of the system. The parameter matrices in the equations have a strict physical meaning and when the model parameters are accurate, the deviations from the parametric model are minimal, whereas when the model presets are not the same as the actual situation, the results are often incorrect. However, in practice, it is difficult to match the predetermined model parameters exactly with the actual model parameters.

$$S = R^{-1}(u)[\tau - G(u,\dot{u})\dot{u}] \tag{2}$$

4. Model Analysis

4.1. Experimental Analysis of Fault Diagnosis

The validity of the machine learning based stochastic intuitive fuzzy set was first verified using individual sensor data. Firstly, at the 1st point, 50 consecutive observations were made for a total of 6 sets. Afterwards, the frequencies of the 1st, 2nd and 3rd amplitude points were used as the fault characteristic frequencies for 1X, 2X and 3X respectively, and the high frequency component after 3X was ignored, i.e. p=3, to obtain a total of 300 data sets. Finally, the 300 data sets were inverse analysed using the established fuzzy database. Table 2 shows the validation results of the inverse analysis diagnosis method.

Table 2. Validation of the inverse analysis diagnosis method

Type of fault	Accuracy	Number of errors	Number of uncertainties	Accuracy rate
Fault type 1	297	1	2	99.0%
Fault type 2	299	0	1	99.7%
Fault type 3	298	0	2	99.3%

As can be seen in Table 2, for different fault types, the accuracy of the inverse analysis diagnostic method reaches 99.0% and above, which indicates that the use of fuzzy set theory in the field of mechanical fault diagnosis is feasible and can achieve good results. Most of the current fault diagnosis work is carried out in the same operating environment, i.e. the same experimental platform and the same background temperature, n data sets are measured and then divided into two groups, one containing n-m data sets and the other containing the remaining m data sets. Due to the same operating environment, there is a high degree of consistency and similarity between the n-m data sets and the m data sets, which are considered to be inherently consistent. This is the fundamental reason for the high diagnostic accuracy and poor generalisation of traditional methods, and is the focus of controversy in the field. The inverse analysis diagnostic method validates the robustness and generalisation capability of the mechanical fault diagnosis model.

4.2. Analysis of the Influence of the Number of Alternative Action Sequences

The number of alternative action sequences in the machine learning-based MPC method is an important influencing factor on the control of mechanical vibration response for a certain number of prediction steps T The control effect is mainly evaluated in terms of control time and cumulative error, where the error is a two-parameter cumulative error, and the faster the desired position is reached in the control process, the smaller the two-parameter cumulative error is. The more the angle of the three joints in the control process is close to the desired position, the closer the two-parameter error between the actual position and the desired position is to 0. The natural logarithm can amplify this proximity, thus evaluating the stability of the final convergence.

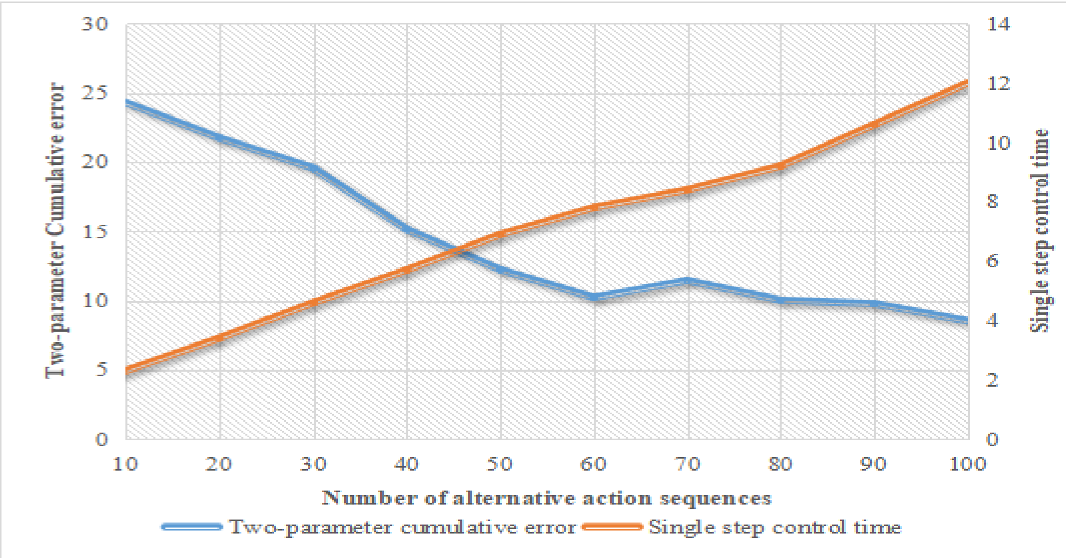

Figure 2. Two-parameter cumulative error and single-step control time results

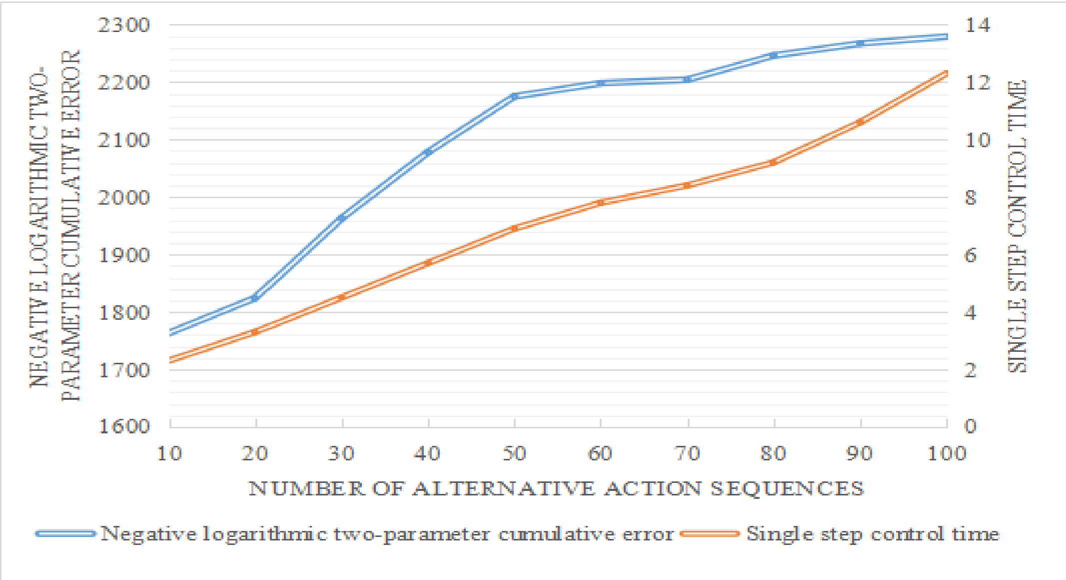

Figure 3. Negative logarithmic two-parameter cumulative error and single-step control time results

The simulation results can be seen in Figures 2 and 3, where the solid line represents the mean value of 20 iterations of the simulation. From Figure 2, it can be found that the control time of a single step increases linearly with the number of alternative action sequences, while the cumulative two-parameter error decreases more significantly when the number of alternative action sequences increases from 10 to 60, and the decrease after the number of alternative action sequences is greater than 60 is small and almost negligible, indicating that an appropriate increase in the number of alternative action sequences can improve the comprehensive control effect, but after a certain level of increase, the time However, after a certain degree of increase, the time cost increases linearly and the comprehensive control effect does not improve significantly. As can be seen from Figure 3, the negative logarithmic two-parameter cumulative error rises significantly when the number of alternative action sequences is from 10 to 50, and rises slowly after the number of alternative action sequences is higher than 50, indicating that increasing the number of alternative action sequences within a certain range can significantly improve the stability, but beyond the range the stability increases slowly and the single-step control time still increases linearly. Therefore, it is important to weigh the control effect and single-step control time when selecting alternative action sequences.

5. Conclusion

In the vibration response of engineering ship power machinery, the vibration signal is not only easy to collect, but also when the equipment fails, there will be immediate response on the vibration signal collected by the equipment, and the characterization of the vibration signal will often be different for different failures of the equipment, so the vibration signal is widely used in the fault diagnosis of mechanical power systems. This paper conducts fault diagnosis experiments based on machine learning for vibration feature representation and mechanical fault diagnosis methods. It is found that the inverse analysis diagnosis method has robustness and generalisation capability for mechanical fault diagnosis models. The MPC algorithm based on machine learning yields good control results, and the number of alternative action columns can be increased within a certain range to improve the control effect. The modelling and control methods used in this paper can also be applied to other space robot modelling and control tasks to verify the data efficiency and robustness of the algorithm.

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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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