Data Acquisition and Management Strategy for Motorized Spindle Test

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***Abstract*—Motorized spindle is the critical component in the CNC machine tool, and it is of considerable significance to obtain its overall performance and expose its weak link via conducting reliability test. Multi-dimensional signals with high sampling frequency and long storage period pose a great challenge to data collection and management process. This paper is devoted to proposing an efficient and systematic method for data acquisition, feature extraction, and data management methods. The redundancy of the original signal is removed by similarity analysis of feature matrixes, after which the most typical sample during the test is preserved as a data sample for data mining and data analysis. The proposed strategy can not only be applied in the motorized spindle but also be a guide for the test of similar mechanical system.**

***Index Terms*—condition monitoring, motorized spindle, data mining, data analysis**

I. Introduction

With the increasing demand for long-durable and less-downtime in manufacturing, the performance and reliability of motorized spindle are undergoing a wide range of improvement [1]. As the core component of machine tools, the performance and reliability of motorized spindle directly affect machining quality and opening rate [2]. Thus, it has been studied extensively by researchers and engineers in recent years [3-4].

Performing specific test for the motorized spindle is a useful approach to evaluate the overall performance and expose the weak link of tested motorized spindle [5]. However, the tests are sophisticated, where acquired signals are not necessarily the same. The variety of spindle types, the complexity of work condition, diversified of fault modes, as well as long test period lead to abundant of mixed information which is hard to be analyzed [6]. The organization of test data is conducive to establishing the connection among data and fully carrying out data mining [7].

The data management approach should allow deploying information flow and extract useful process information [8]. For example, the data arrangement and optimization approach are designed by model [9] and embedded information tracking technologies to trace and optimize components' performances through life cycles. Several procedures have been suggested to improve data collection for extracting useful indicators [10]. However, the representative of extracted indicators requires a clear understanding of raw data.

In this paper, multi-dimensional data acquisition and management strategy are designed for the test of motorized spindle, and the redundancy of the original signal is removed by similarity analysis of the feature matrixes. The signal fragments with typical characteristics are reserved into the sample database, which lays a foundation for further data analysis. The utilization of the proposed data management strategy is applied in the test platform of the motorized spindle, where several kinds of experimental data are arranged regularly.

The structure of this paper is as follows. Section 2 introduces the basic structure and function of motorized spindle together with its test system where the abundant type of data is produced. Section 3 proposes a data management strategy of multi-dimensional signal and illustrate the feature extraction and similarity comparison method for different feature matrixes. Section 4 presents the application of the proposed method, and Section 5 draws the conclusion.

II. Test System of Motorized Spindle

A. Motorized Spindle

The motorized spindle is the core component in machine tools that directly cut off workpiece with extremely high rotating speed. There are plenty of cutter types which are function-oriented according to manufacture process type, as shown in Fig. 1. The workload of motorized spindle varies a lot according to cutting tools and cutting types, which leave it abundant time to simulate and test the performance of motorized spindle under all kind of manufacturing type in real machine tools.

The motorized spindle is a coupled product of the high-speed motor system and mechanical spindle, which composes of spindle-bearing system, motor system, tool changer system, electric system, lubrication system, cooling system, spindle housing, and other components. Electric power is converted into alternating magnetic fields of rotor and stator when the motorized spindle

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starts to work, and subsequently drive the rotating of the main shaft. The tool holder, which is attached with the taper interface of the spindle, is rotating together with the shaft that under the support of front and rear bearings (Fig. 2).

Figure 1. The application of motorized spindle

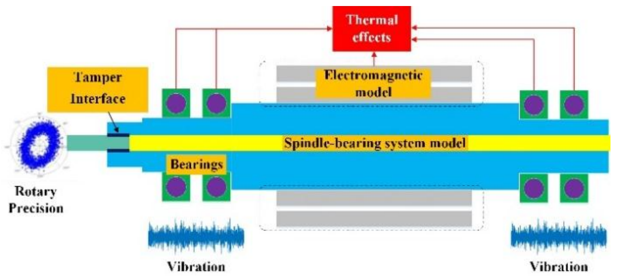

Figure 2. Structure of motorized spindle

B. Load Simulation for Motorized Spindle

Load simulation serves as an indispensable part to accurately verify the reliability and performance of motorized spindle. Although the exact approach is the actual processing of the workpiece, the factors that affect machining performance varies a lot and are not easy to control in actual cutting. It can be a better solution to establish a test system which can simulate the processing load of the spindle in an all-round way. In this way, the performance of the spindle under different load can be inspected, and the failure of the spindle are easy to be activated without actual cutting.

According to cutting dynamic, it can be concluded that the processing is affected by three significant loads: axial cutting force, radial cutting force, and cutting torque [11]. In the case of different types of processing, the size, direction, and frequency of these three kinds of loads equip with different combinations. Therefore, it is necessary to design a test system which can simulate the real working conditions and simultaneously exert dynamic axial force, radial force and torque on the front end of the spindle, as the schematic diagram in Fig. 3. Load spectrum is designed and embedded into the control system so that the load simulation system can automatically undergo all required workload situation as closely as actual cutting.

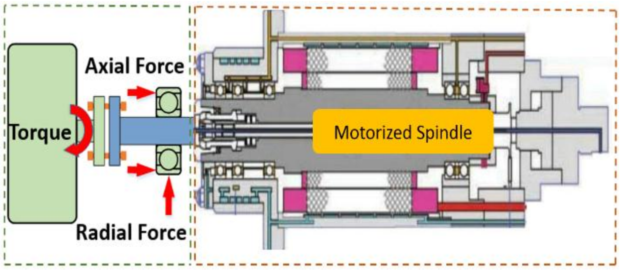

Figure 3. The loading mechanism of motorized spindle

C. Data Acquisition

Plenty of data belonging to different dimensions and different physical meanings are acquired during the test. It is necessary to arrange and management these data in a reasonable way so that all possible information of the tested system can be utilized. According to the life cycle of motorized spindle pictured in Fig. 4, these data can be classified into four major stages, namely, basic information, quality test data, prognosis and health management data, and reliability analysis data.

The basic information includes technical and operation log, which are useful in data analysis. Quality test data are acquired for evaluating the performance of the tested spindle. Mainly include factory test sheet, the result of lab test index, precision index, and performance during loading.

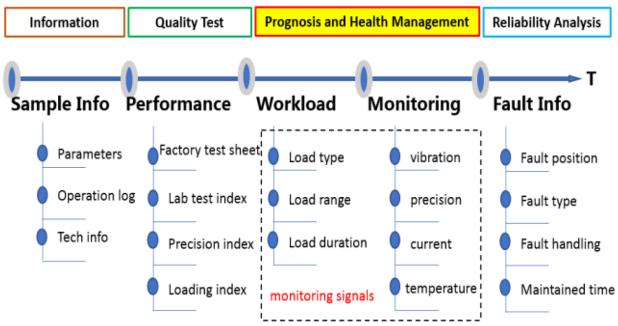

Figure 4. Data type of lifecycle

Prognostics and health management (PHM) is an emerging discipline to scientifically manage the health condition of engineering systems and their critical components [12]. Based on the information provided by PHM, the reasonable system maintenance schedule can be arranged. PHM reveals the condition monitoring signals of spindle under different load situation, which is a date-driven way for fault diagnosis and prognosis. The condition monitoring system is designed and set up for data acquisition of all useful signals, which is the most essential part of data management.

The heat generation and transformation status of the motorized spindle can be revealed by temperature signal (T). The overall dynamic character of the motorized spindle is shown by vibration signals, especially by bearing vibration signals. The rotating orbit is the key factor which determines the precision of workpiece. Therefore, the rotating orbit should be clearly recorded. The rotation of motor is driven by electricity; thus, the three phases' current of the motorized spindle is also included in the condition monitoring system. All the above signals are accumulated and arranged as shown in Fig.5, which fill in the database for date mining and data processing of the motorized spindle test platform.

When the test is interrupted by fault, fault diagnosis and reliability analysis need to be carried out through both the operation time, signal and fault position, which provides precious test sample for optimized designing and improvement of the tested motorized spindle.

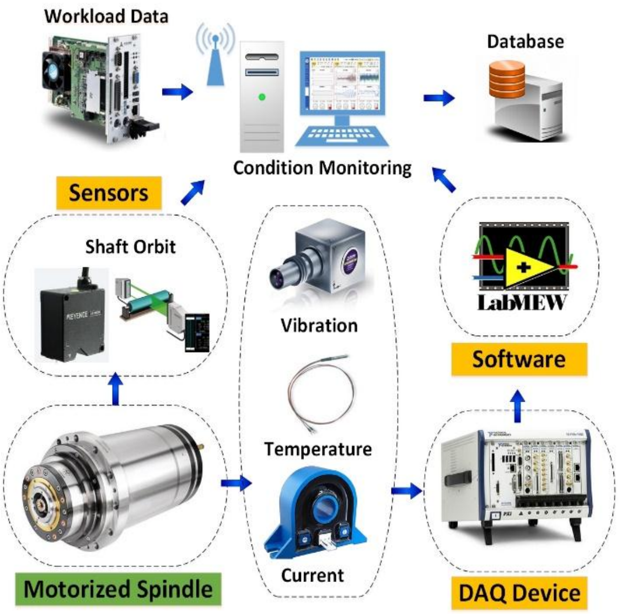

Figure 5. The loading mechanism of motorized spindle

III. Data Processing and Arrangement

The data acquired during the motorized spindle test has multiple dimensions and high sampling frequency. Besides, long-term continuous data collection leaves a heavy burden for data storage. These properties of test data pose a great challenge to data collection and management. In this chapter, the data types of spindle test are correlated to provide useful labels for future analysis. Then, according to the defined feature extraction method, the feature matrix of each time segment is established, and an automatic recognition method is proposed to rank the similarity of the feature matrix, and finally, the representative signal segments are selected for further analysis.

The establishment of a dynamic database can effectively manage and analyze test data of different types, to accurately and conveniently conduct data mining for test data. The database designed in this paper is composed of three parts. The database of condition monitoring signal stores the condition monitoring information including three-direction vibration, three phases' current, rotating orbit of the shaft, dynamic loading force and temperature during the spindle test. The operation state database stores the information includes test operator, test begin and end time, load condition, sensor and DAQ cards configuration, environmental factors, and other information. The fault information database stores the fault occurs time, fault position, and fault phenomenon of the motorized spindle when a failure occurs. This section focuses on the first two types of data, which is the signal of motorized spindle under different load and test condition.

Motorized spindle test is carried out under different loading plans, so signals need to be labeled by its loading plan. For the vibration, current, rotating orbit, loading force, and temperature signals under a specific loading plan, different features are extracted. As for vibration signals, time-domain and frequency-domain eigenvalues are extracted respectively according to the descriptions in Table 1. Where root mean square (V) is the most important index for overall evaluation in industry, while other features are useful in further fault analysis.

TABLE I. Feature Extraction For Vibration Signals

Features	Indication
Root mean square	Current amplitude and energy
Peak	Maximum amplitude
Skewness	Incipient faults
Kurtosis	Early faults rather than a severe fault
Average frequency	Energy in current signal
Standard deviation	The concentration of the frequency spectrum

A simple and widely used method for motor current diagnosis [13] is to calculate the root mean square of three-phase' currents (I) for the conversion of the AC current to the equivalent DC current.

$$I = \sqrt{\frac{1}{3}(I_U^2 + I_V^2 + I_W^2)} \tag{1}$$

The rotating performance of motorized spindle can be express by its rotating orbit by two-direction displacement sensors [14], the center of the spindle motion is defined by least square circle fitting. Arbitrary point set is assumed as $\{M_i\} = \{(x_i, y_i)\}$, the center of minimum envelop circle of which is (a, b), radius of which is r, according to the definition, the minimum envelop circle satisfies the formula given by:

$$\begin{cases} (x_i - a)^2 + (y_i - b)^2 \le r^2 \\ r \to min \end{cases} \tag{2}$$

The radius r in the object function can be defined as:

$$r = \max_{1 \le n \le i}\left(\sqrt{(x_i - a)^2 + (y_i - b)^2}\right) \tag{3}$$

As for cutting force, the root mean square is obtained:

$$F = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f_i^2}, i = 1,2,\cdots,N \tag{4}$$

By combining all the feature character, the status matrix of a specific loading scheme can be defined as

$$M = [V\ I\ r\ F\ T] \tag{5}$$

The monitoring signals of the system are determined both by the condition of motorized spindle and loading system. The cutting force is a reference parameter which indicates the state of the simulating load system instead of the motorized spindle itself. There, F should be separated analyzed to be the abnormal detection of the test system. Temperature is a rather slow-changing index, compared with vibration, current and rotating orbit. As for short time monitoring, a simplified feature matrix can be formed as

$$M_x = [V\ I\ r] \tag{6}$$

The condition of Similarity level is wildly used in many data mining techniques, such as clustering, nearest neighbor classification, and anomaly detection. The similarity between different groups of samples is a numerical measure of the degree of difference between samples. Distances and correlation coefficients are usually used as measure index of similarity of two status matrixes.

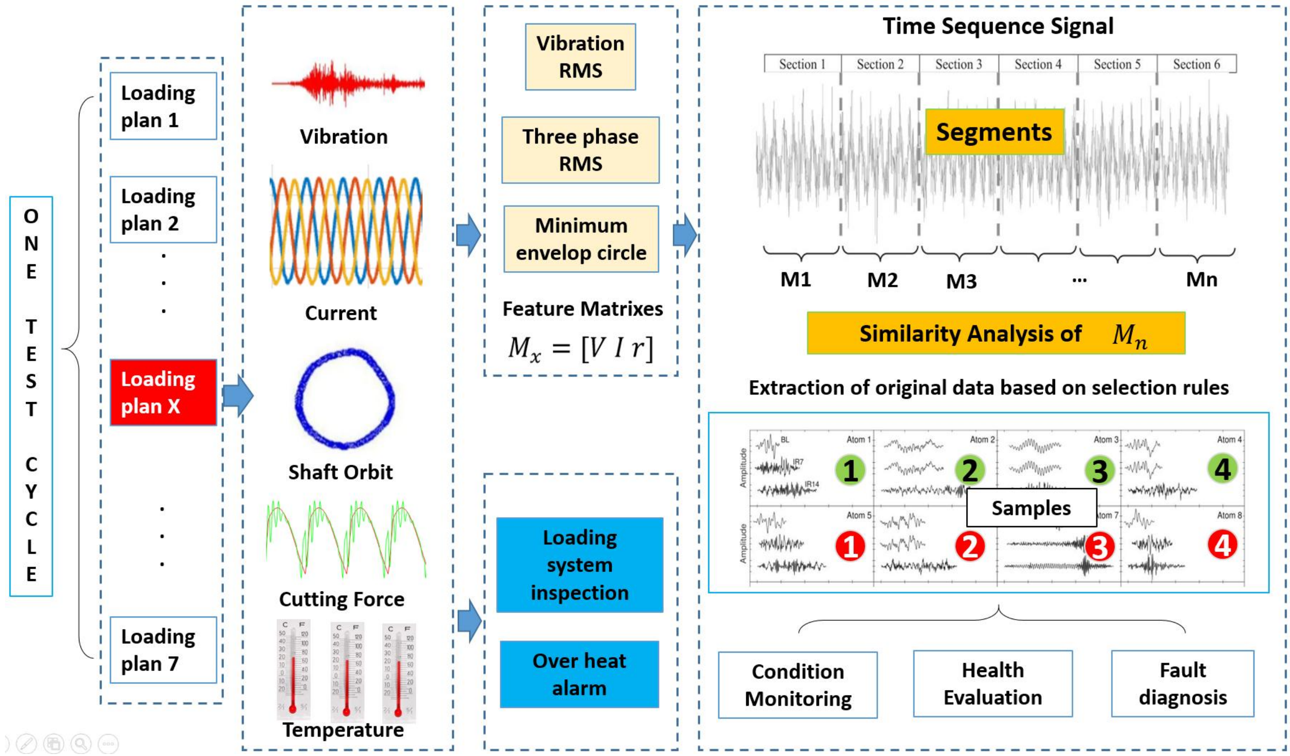

Figure 6. Scheme for data arrangement

The similarity is usually calculated based on Euclidean distance, but it does not consider the scale factor of each dimension and treats the difference between each index or the dimension of each variable as the same. Therefore, in this paper, the Euclidean distance is modified to calculate the similarity by using standardized Euclidean distance, and each component is standardized to mean and variance.

Convert feature matrix M_x to a normalized status matrix A_x,

$$\mathrm{H} = \frac{M_x - M}{S} \tag{7}$$

M is the mean of the sample set, S is the standard deviation of the sample set.

According to the Euclidean distance formula, the similarity can be obtained by:

$$d = \sqrt{\sum_{k=1}^{n}(H_1 - H_2)^2} \tag{8}$$

Where H_1 and H_2 are two condition sample set and n is the dimension of sample, in this case, $n = 3$.

The original signal is split into several segments arranged by time sequence. In order to manage a large amount of data, several pre-defined rules are proposed:

1) The condition of loading system should be monitored independently, and the system needs to be repaired or adjust if loading force or torque is far away from the set value.

2) The length of each signal segment can be set as one second initially, which means feature matrixes M_x are acquired once a second.

3) State of the tested motorized spindle is classified into a healthy zone, stable zone, and unstable zone. Healthy zone means motorized spindle is in the same condition as the historical healthy state; Stable zone means the feature matrixes keep stabilization for over 10 seconds. Unstable zone refers to matrix alters significantly whose variance is higher than set value α.

The similarity calculation method is used to judge the similarity between the data fragments and the similarity values d are the function of the monitored time period as $d(t)$. This function acts as a tool for condition monitoring and extracting meaningful data fragments. In the stable zone, the distribution of $d(t)$ with a 95% believe interval are divided into four segments as shown in Fig. 7, where 4 values in the separation linesd_1, d_2, d_3 and d_4 are obtained. The originals data fragments of the corresponding d of t_{s1}, t_{s2}, t_{s3} and t_{s4}can be preserved as data samples of this stable zone. As for the d outside the 95% believe interval, 4 most distinguished samples are preserved. Because the data in unstable zone is of great importance with fault character, all signals from t_{u11} to t_{u12} need to be restored as samples.

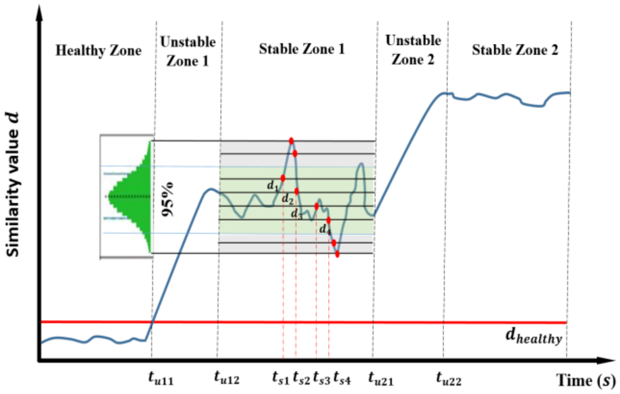

Figure 7. Data selection method based on similarity

Based on the above description, we propose the data management process, as shown in the flow chart in Fig. 6. During the condition monitoring process, loading plans are strictly labeled. In a specific load plan, abundant signals of the motorized spindle are obtained, and above feature extraction methods can be used to acquire feature matrix M_x which express the health condition of the test sample. Feature matrixes of different time period are compared used standardized Euclidean distance method to evaluate the similarity of test signals and the most representative data are selected as the sample while redundant data are deleted. These well-chosen samples are useful for condition monitoring, health evaluation and fault diagnosis, which belongs to data analysis and data mining of experiment.

IV. Application

To verified and applied the proposed data management strategy, test platform shown in Fig. 8 is used to provide load simulating ability for the motorized spindle, including axial force, radial force, and torque. The test system includes three subsystems: multi-dimensional dynamic loading system, control system, and condition monitoring system. By simulating the load plan according to statistics pattern of manufacturing factories (Fig. 9), the multi-dimensional dynamic loading system can reproduce the load condition of the motorized spindle in actual work. The condition monitoring system collects the physical signals of the tested motorized spindle and conduct similarity analysis. The data management and analysis can be conducted by using the acquired data from all these three platforms.

As for the fact that the proposed strategy is the same for any of the loading plan, here we use one of the load plan (plan No. 1) for description. The healthy zone of the motorized spindle can be determined after the spindle is checked to be in an excellent performance. Here we use data in a healthy zone and bolt looseness fault which belongs to a stable zone. Test result and the selected sample are shown in Fig. 10. It can be seen from the result that the proposed method clearly distinguished different status and preserved the most typical signals of each status while leaving typical signal samples for future analysis.

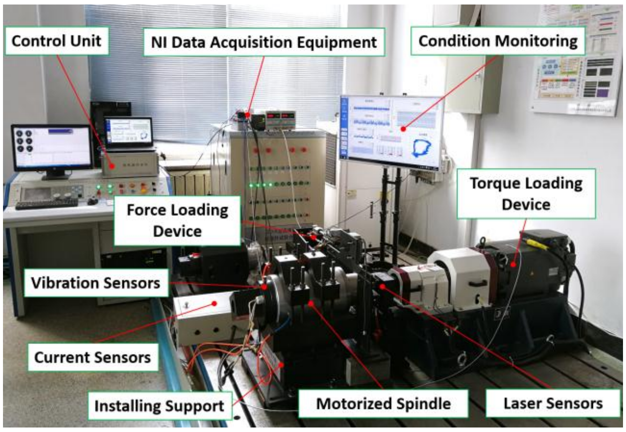

Figure 8. Loading mechanism of motorized spindle

Basic Information				Force		Torque
Plan No.	Time (s)	Speed (r/min)	Freq (Hz)	Basic Value(N)	Amplitude (N)	Value (N.M)
1	2906	595	10	646	220	12.9
2	2707	595	10	1293	474	25.8
3	814	950	16	485	132	9.7
4	2318	950	16	970	244	19.4
5	864	1600	27	460	175	9.2
6	648	1900	32	340	144	6.8
7	540	3000	50	282	103	5.6

Figure 9. Loading plan of motorized spindle

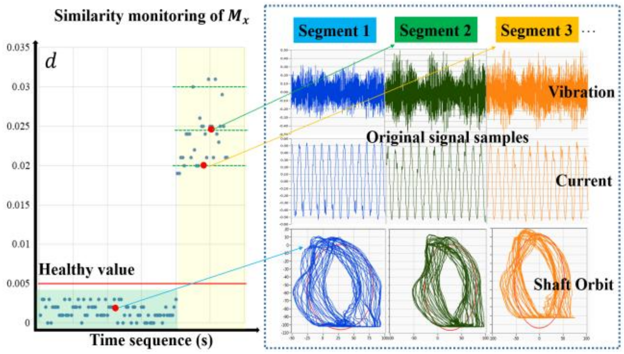

Figure 10. Data selection result of motorized spindle test

V. Conclusion

Authors propose in this work, a strategy of the test data collection and effective data management for the test of the motorized spindle. Based on a complete load simulating test platform of the motorized spindle, continuous reliability test is carried out with abundant physical signals and load information. These data are rearranged according to the proposed load-signal scheme, which simplified important information into the feature matrix. Moreover, sample selection method for reducing redundancy of data based on similarity analysis is used on feature matrix to eliminate the repeatability and obtain a less complicated data sample for future analysis. The proposed framework is conductive and guides extensive scale test data collection.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Weizheng Chen conducted the research and wrote the paper; Zhicheng Zhang analyzed the data; Binbin Xu and Fei Chen revised the paper; all authors had approved the final version.

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