

Development of a Machine Tool Diagnostic System Using Micro-Electromechanical System Sensors: A Case Study

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(Received December 25, 2014; accepted May 15, 2015)

Key words: MEMS sensor, back propagation neural network, machine tool diagnostic system

In this study, micro-electromechanicals (MEMS) system sensors were used to extract physical signals from a machine tool. A performance assessment was carried out using fuzzy logic theory. This, in turn, was used to judge the ownership of various signals. It then defined the level that each ownership group belonged to in order to determine whether the performance was broken or not. If normal, the system determined specified rules for such normality. During the process of extracting the vibration and noise signals, the system used Fourier transform to analyze any changes made to each signal in the frequency field, and then principal component analysis was used to decrease the data dimensions. We then evaluated the work status of the machine tool on the basis of the signal features. Furthermore, we built a feature math model from the recorded signals using a back propagation neural network and further determined the abnormal items using an error function. Finally, we obtained a diagnostic feature for the performance of the machine tool using physical signals through diagnostic reports from a human-machine interface. The machine tool diagnostic system is able to provide maintenance personnel with a proper way of responding quickly to any reduction in the output from the machine tool so as to avoid further damage.

1. Introduction

1.1 Background

With industry changes and increased market demands, in addition to the development of high-efficiency and high-precision machine tool hardware in recent years, the developmental focus of machine tool providers has moved towards intelligent machine tools. The development of intelligent software is the most critical technology for machine tool diagnostic among all that is currently available provided by software

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vendors. The most significant development in intelligent machine tools is the monitoring of machine performance. For example, the prediction of the failure of components or performance aging leads to early precautionary maintenance processes, which reduces additional costs or loss of credit caused by such failures. When a machine is operating, it vibrates, and such vibration under normal operation tends to be minimal. With aging, the degree of vibration may increase up to the point of failure. Determining the amount of physical signals for an excellent or extraordinary feature is carried out using the machine's collection of physical signals, followed by an analysis conducted by professionals, so as to judge the reason(s) for the abnormality behind the amount of mechanical physical signals. As a result of the various levels of knowledge, experience, and methods of analysis adopted by each expert, there may be a huge gap among assessment results, thereby affecting any timely intervention on the machines involved.

1.2 *Motives*

Generally speaking, the ideal machine tool has no vibrations, noise or increase in temperature during operation. Its energy will be applied to processing and operating entirely without loss. However, such a condition is not applicable in practical use owing to wear on parts and components during operation. This leads to partial dissipation in the form of vibration, noise, and thermal energy inside the machine tool. Such conditions might worsen with increased operational time, thereby causing damage and the ultimate failure of the machine, even potentially achieving a state in which the machine is irreparable. Thus far, the primary methods used for machine diagnostic are categorized as: (1) artificial tests, where engineers judge each part of a machine through visual, auditory, and tactile perception. Such a method is highly subjective and might lead to mistaken judgment due to inexperience on the part of the examiner; and (2) instrumental diagnostic, such as the use of a spectrum analyzer. Such instruments are expensive because of operator costs and may not be applicable or appropriate for the long-term monitoring of a single machine. To help processing firms obtain greater efficiency, resulting from less labor in the maintenance process, the lowering of service costs due to damage, and the prevention of declines in productivity due to accidental damage, performance diagnostic of machine tools will likely become a focus of study in the future. For this reason, in this study, a machine tool diagnostic system (MTDS) was developed.

This system was used to analyze physical phenomena that caused a reduction in performance through the use of a signal processing method where current performance was evaluated. In addition, the current state of the machine was evaluated, and a health feature function model was developed through statistical and artificial intelligence analyses of current channels for potential failure so that necessary measures could be taken to further improve the reliability and productivity of the machines under consideration.

1.3 *Literature review*

In signal processing, Whittaker proposed the Nyquist sampling theorem in 1915 to avoid signal aliasing, which occurs frequently in signal sampling and leads to signal

distortion. These effective principles related to sampling guidelines have been effective for many years and will likely remain so.⁽¹⁾ In 1965, Cooley and Tukey published a fast algorithm in the discrete Fourier in the “Mathematics of Computation”, which is called the fast Fourier.⁽²⁾ Its value lies in butterfly computing architectures that reduce the amount of multiplication required to meet immediate processing requirements for many engineering tasks. The study of the fast Fourier applies to the analysis for the stationary signal collected by MEMS sensors, which is mainly because the fast Fourier expresses overall intensity wherein the frequency of the stationary signal will not vary with time. In previous studies, some scholars used spectral analysis methods on a fixed-speed motor and considered the peak of a specific frequency as a feature. In 1986, Jolliffe proposed principal component analysis (PCA) where eigenvalues and eigenvectors were used to reduce the data dimension and were applied in a variety of mathematical models successfully.⁽³⁾

In performance evaluation and diagnostic theory, Luo and Zeng studied the diagnostic method for vibration signals in bearing damage in 2008. They predicted that bearing damage occurred at different points. They then used the bearing vibration signals emitted during operation to analyze and determine the operating condition of the ball bearings by signal measurement and processing techniques; however, the findings only suggested an upward trend of the amplitude of each frequency.⁽⁴⁾

In 2009, Wu and Kuo used discrete wavelet conversion (DWC) and artificial neural network to distinguish and compare the types of fault occurring in vehicle engines.⁽⁵⁾ Discrete wavelet analysis was used to reduce the complexity of the eigenvectors, and then the artificial neural network technique was used to differentiate between them. The results demonstrated that fault diagnostic is effective and can be used on various automotive engines, further confirming that an artificial neural network can be an effective tool for fault classification.⁽³⁾

In 2003, Li *et al.* used PCA to reduce the data dimensions and neural network to complete the classification of information, further applying them in the current data of drilling processes successfully.⁽⁶⁾ The experimental data showed that PCA can reduce the data dimensions effectively, and that the recognition rate behind such neural network is up to 93%. Some other researchers applied Fourier and neural network based methods for machine diagnosis and prediction based on historical data matrix.⁽⁷⁻¹⁰⁾

2. Back Propagation Neural Network for MTDS

The neural network is a combination of a large number of simple arithmetic units connecting to a network. It has the basic ability to learn, memorize, and generalize.⁽¹¹⁻¹⁶⁾ Among the many types of neural network, the back propagation neural network is the core of all the others and has the following four advantages: (1) function approximation: train the input vector and correspondent output vector to a model and establish function approximation; (2) model identification: link an undetermined output vector with an input vector, thereby achieving the effect of discrimination; (3) classification: define and classify the type of input vector; and (4) data compression: reduce the dimension of the input vector for convenient transfer and storage.

Given all the features and advantages above, our study adopted the back propagation neural network as the structure. The framework of the back propagation neural network is multilayer perception (MLP). The learning algorithm that is commonly used is error back propagation (EBP). Thus, they were combined as a back propagation neural network. Figure 1 shows a framework of the back propagation network in this study.^(5,6)

3. System Structure of MTDS

3.1 System structure

In order to solve the common problems that occur in machines, more than one sensor should be installed on it, with consideration of convenience as well as cost. In this study, we used micro-electromechanical systems (MEMS), a MEMS triaxial accelerometer, a temperature sensor, and a MEMS microphone as the sensors to measure vibration, temperature, and noise, respectively. The connection of MEMS sensors is shown in Fig. 2.

3.2 Spindle design and position of sensor

The driving means was divided into four categories, namely, (1) gear, (2) belt, (3) direct link, and (4) a link built into the motor. A traditional miniature machine, based on a gear and belt that computerized numerical control (CNC) machines currently use in the market, is based on a direct link and a link is built into the motor. Among which, the direct link constitutes the primary driving manner. Therefore, it is discussed here.

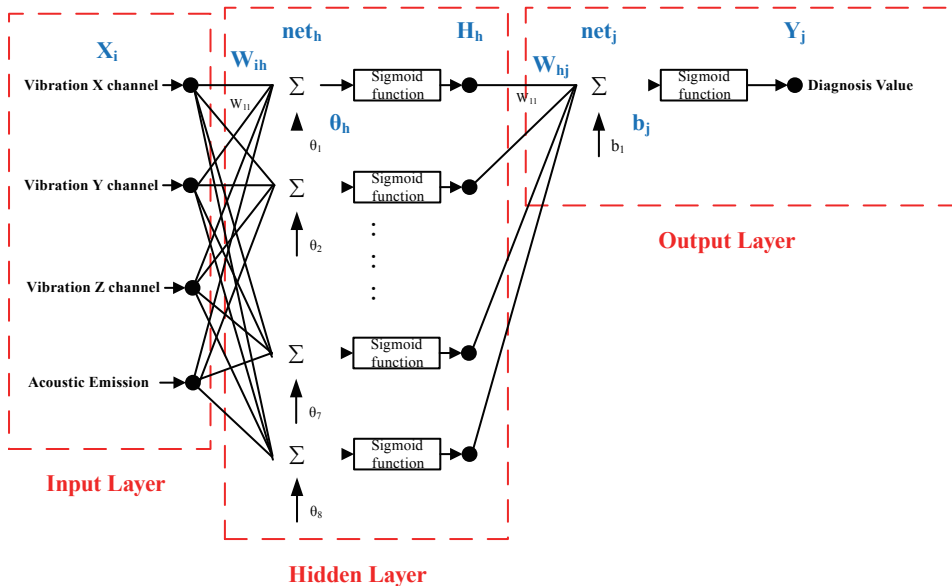


Fig. 1. (Color online) Framework of back propagation neural network in this study.

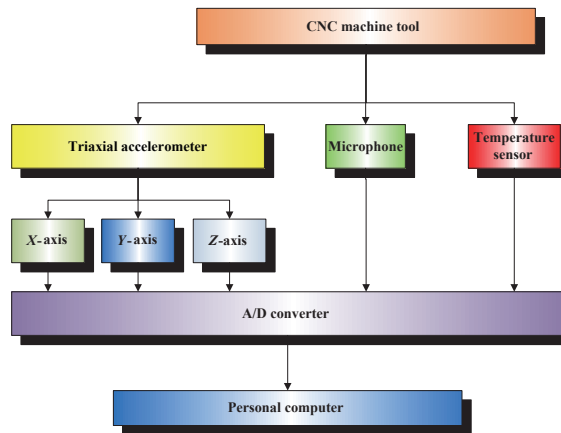


Fig. 2. (Color online) Connection of MEMS sensors.

Take a spindle as an example. In order to obtain real-time monitoring and a variety of physical signal data from a spindle, under the ideal condition of this study, three grooves were designed to erect physical signal sensors such as an accelerometer, a temperature sensor, and a microphone.

4. Experimental Results and Discussion

4.1 Hardware specification of the experiment

In this experiment, a miniature integrated processing machine was the example in the laboratory. A MEMS triaxial accelerometer, a MEMS microphone, and a MEMS temperature sensor were installed on the spindle sleeve as in the structure shown in Fig. 3. Then, the data from the connected battery and extract card were transferred to a computer through the signal data extract card. Finally, the analysis and diagnosis of health were provided by the machine diagnostic system. Table 1 shows the specifications of the spindle motor. Table 2 shows the specifications of the servo motor.

4.2 Experiment: interposed performance test of spindle tool

A common problem occurred on the machine shown in Table 3. The tool that is interposed on the spindle side often caused excessive vibration of the machine owing to motor failure of the turret or sensing error of the extreme switch, resulting in an extraordinary quality of processing. For this reason, this experiment categorized the spindle in terms of the tool's interposing manner, where the normal interposed tool and extraordinary interposed tool were classified as abnormal performance. Figure 4 shows a comparison of the normal interposed and extraordinary interposed tools. Table 3 shows the setting of category of abnormal performance in experiment No. 1.

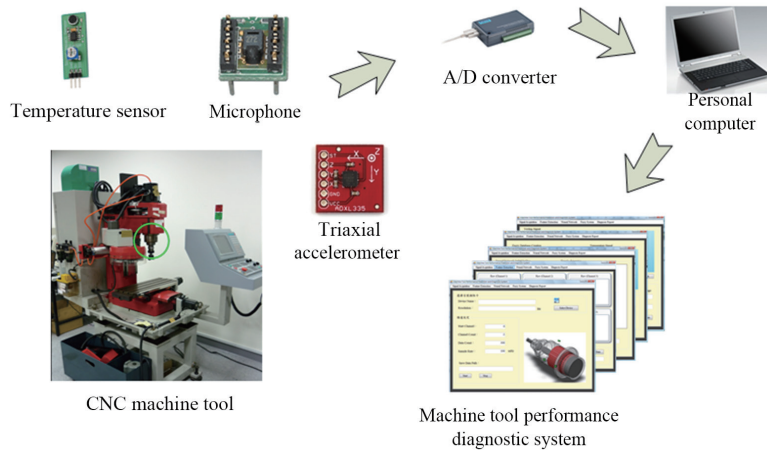


Fig. 3. (Color online) Structure of machine diagnostic system.

Table 1
Specification of spindle motor.

Brand	YASKAWA
Model No.	SGMAV-10A
Rated rotation speed	3000 rpm
Maximum instant speed of rotation	6000 rpm
Rated torque	3.18 N·m
Instant maximum torque	9.55 N·m

Table 2
Specification of servo axle motor.

Brand	YASKAWA
Model No.	SGMJV-04A
Rated rotation speed	3000 rpm
Maximum instant speed of rotation	6000 rpm
Rated torque	1.27 N·m
Instant maximum torque	4.46 N·m

Table 3
Setting of category of abnormal performance in experiment No. 1.

Status setting	Category setting of performance abnormality.
Normal	The tool is adhered to the head of the spindle.
General	The tool is distanced from the head of the spindle by 3 cm.
Extraordinary	The tool is distanced from the head of the spindle by 5 cm.

4.3 Performance evaluation of interposing status of spindle tool

We set the normally interposed tool and the loosened interposed tool at the spindle motor IDLE at 1000 RPM. Then, we set the sampling frequency in the extracting program as 100 Hz and the sampling value as 1024 points. Finally, the attribution function model was built by extracting the *XYZ* triaxial physical signal of vibration, sound wave, and temperature. In order to validate the effect of the performance of the system designed for machine tools in this study, both categories of performance were extracted thrice, and the physical signal was extracted once at random between normal and abnormal performances, according to the sample of fuzzy logic theory. The mean of the physical signal sample with normal performance served as the standard value, whereas that with abnormal performance served as the critical value. Table 4 shows the experimental environment setting of performance evaluation for the interposed spindle tool.

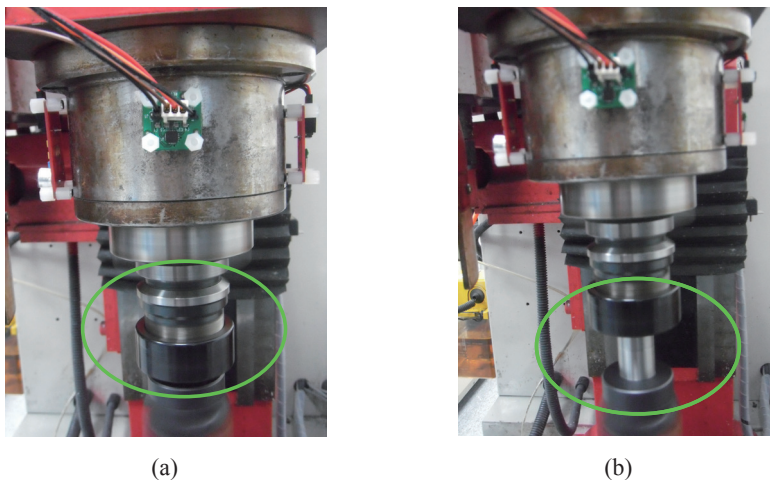


Fig. 4. (Color online) Comparative result of (a) normal interposed tool and (b) extraordinary interposed tool.

Table 4

Experimental environment setting of performance evaluation for interposed spindle tool.

Rotation speed of spindle motor	1000 rpm
Sampling frequency	100 Hz
Sampling point	1024 samples
Category of extracting signal	<i>XYZ</i> triaxial vibration, sound wave, temperature
Number of extracted groups of normal signal	3 groups
Number of extracted groups of abnormal signal	3 groups
Fuzzy logic sample	Each per normal and abnormal signals
Waiting test	Two groups of normal and abnormal signals

Table 5
Example of performance evaluation for interposed spindle tool.

Measured item		Standard value	Critical value
	<i>X</i>	0.244448	0.24433
Vibration	<i>Y</i>	0.240111	0.242042
	<i>Z</i>	0.244897	0.246669
Acoustic		0.105008	0.10129
Temperature		0.098707	0.09886

Table 6
Performance evaluation level classification of interposed spindle tool.

Level	Degree of membership	Vibration			Acoustic	Temperature
		<i>X</i>	<i>Y</i>	<i>Z</i>		
1	1	0.244448	0.240111	0.244897	0.105008	0.098707
2	0.75	0.244419	0.240594	0.24534	0.104079	0.098745
3	0.5	0.244389	0.241077	0.245783	0.103149	0.098784
4	0.5	0.24436	0.241559	0.246226	0.10222	0.098822
5	0	0.24433	0.242042	0.246669	0.10129	0.09886

Table 7
Performance evaluation and test result of interposed spindle tool.

Performance No.	Performance	Attribution	Level	Success/Fail
Test #1	Normal	0.97	1–2	○
Test #2	Normal	0.92	1–2	○
Test #3	Extraordinary	0.18	4–5	○
Test #4	Extraordinary	0.24	4–5	○

The classification of attribution function and level was completed by fuzzy logic theoretical computation. Table 5 shows the example of performance evaluation for the interposed spindle tool. Table 6 shows the performance evaluation level classification of the interposed spindle tool.

We applied another four groups of physical feature signals to the built attribution function and level classification table to realize the performance of these four groups of signals that were awaiting evaluation. Such a mechanism will be helpful to the unit operator's evaluation of the current state of the machine. Table 7 shows the performance evaluation and test result of the interposed spindle tool.

4.4 Success rate of healthy evaluation experiment

For the experiment, we set up the triaxial accelerometer on the spindle. Three models of sensors were deployed for testing. The experiment was separated into three channels using 2400 models for training out the framework and then evaluating the status of

Table 8
Success rate of healthy evaluation experiment.

Channel	Test number	Performance status	Test times	Success times	Success
#1	Testing #1	Normal	200	200	100%
	Testing #2	Fault	200	200	100%
	Testing #3	Fault	200	200	100%
	Testing #4	Fault	200	200	100%
#2	Testing #1	Normal	200	200	100%
	Testing #2	Fault	200	200	100%
	Testing #3	Fault	200	200	100%
	Testing #4	Fault	200	200	100%
#3	Testing #1	Normal	200	200	100%
	Testing #2	Fault	200	200	100%
	Testing #3	Fault	200	200	100%
	Testing #4	Fault	200	200	100%

Note: Success rate = (Success times) / (Test times)

the running spindle. Three types of fault were tested in this experiment, including the increase of spindle speed with twofold and threefold position bias. When the fault signal is revealed, the diagnostic function will enable the root cause of the fault to be determined immediately. As shown in Table 8, the diagnostic success rate is determined on the basis of the amount of testing signals. The average diagnostic time of this framework proposed in this research is 1.11 s.

5. Conclusions

In this study, a MEMS sensor was used to extract physical signals from a machine tool. A performance assessment was carried out using fuzzy logic theory. It showed the ownership of the verified signals and then defined the level that each group of ownership belonged to and also showed whether the performance was normal or not. If normal, the system determined specified rules for such normality. In the process of extracting signals of vibration and noise, the system used Fourier transform to analyze any changes made on each signal in the frequency field. Then, PCA was used to decrease the data dimensions; we evaluated the work status of the machine tool from the features of the signals. Furthermore, we built a feature math model from recorded signals using fuzzy logic theory, determining any abnormal item. Lastly, we accomplished the diagnostic of the performance of the machine tool using physical signals through diagnostic reports from a human-machine interface. The MTDS was able to provide maintenance personnel with the proper way to respond to diagnostic results in order to avoid any damage leading to the reduction in the output from the machine tool.

Acknowledgements

We are grateful to the Ministry of Science and Technology for providing funding and technical support for this study under Grant No. 103-2221-E-006-085, and because of which, this study was conducted smoothly.

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