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Classification of operating conditions of machinery combined with transmissibility function method

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ABSTRACT

Condition monitoring of machinery is concerned for the purpose of maintenance, productivity and avoiding potential downtime. In the trend of smart factory, the virtual representation of machining process can be built by measuring the vibration. Different working conditions and fault conditions should be identified. Different working conditions have different characteristics with the general signal processing parameters in time and frequency domain. The dimension reduction method like PCA, and the cluster method like k-means can be used for further classification. In order to accurately classify different operating conditions, the feature extracted from the measured signal should be distinct enough. In this case, multiple vibration sensors have to be implemented, and transmissibility function between different sensors of the dynamic system can be considered as the characteristic parameters. This paper combines transmissibility function and signal processing parameters for classification of different operating conditions to extract more information about operating process.

Keywords: Operating condition, Transmissibility function, Machine learning

1. INTRODUCTION

In the trend of smart factory, the manufacture process is monitored by various kinds of sensors for the purpose of maintenance, optimization and productivity. As for machining process, states of the machine tool are represented by vibration sensors. The vibration signal of operating condition can be simply characterized by signal processing features, such as mean, standard deviation, variance in time domain, and spectrum, resonance frequency, central frequency, wavelet(1, 2), cepstrum(3, 4) and so on.

The modern machine learning technique is implemented in the field of condition monitoring(5), which does not require sufficient diagnostic knowledge on the characteristics of vibration signals. However, there are many working conditions during the machining process, the features extract from the vibration signals should be distinct enough.

In a complex mechanical system, not only the characteristics of the source but also the transfer path should be analyzed. Transfer path analysis is commonly used in the automotive industry, where the each source's contribution to the overall noise(6) are analyzed. In different machining process, modal parameters should be analyzed as well, and these modal parameters are time-variant during the process. Another technique is invented which is called operational modal parameter estimation(7). In case the exact input source, the excitation force, and the transfer function cannot be measured, modal parameter data can be estimated by operating data.

The relationship between the sensor signals at the desired location and measured location can be expressed as the transmissibility function by the methodology of operational transfer path

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analysis(8). As the state of machining changes, the cutting force and the stress of the structure vary consequently. This kind of difference can be represented in the transmissibility matrix.

This paper demonstrates a novel method which uses the transmissibility function to monitor the machining process. This feature is distinct for different operating conditions, and the experimental work is shown.

2. METHOD

2.1 Classification

The purpose of condition monitoring is to classify the data. If the label is available, the classifier such as KNN(9), random forest(10), CNN(11) can be used for classification. If the label is unavailable, the k-means(12), DBSCAN(13), Graph Community Detection(14) is used to clustering the data.

Before the classification can be implemented, the high dimensional data should be reduced to the low dimensional data, and PCA(15) is commonly used, and the charactistics has to be carefully chosen when performing PCA.

2.2 Transmissibility Function

Assuming that the transfer function of the system is linear and time invariant, the vibration signal at the one location can be derived by the signal from other locations, which can be denote as **Y=AX**, where **A** is the transmissibility function from the sensors X to the sensor Y.

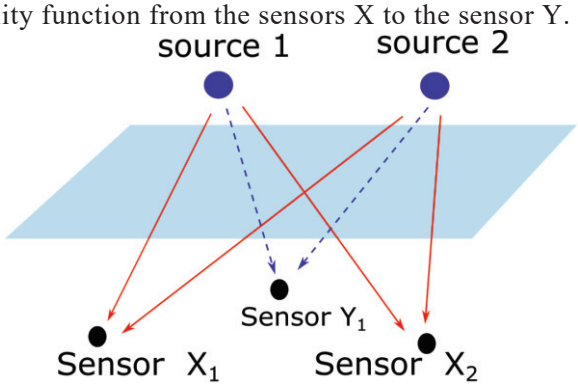


Figure 1 Diagram of the transmissibility function

The transmissibility function can be obtained by the operational condition $\mathbf{A} = \mathbf{Y}\mathbf{X}^*(\mathbf{X}\mathbf{X}^*)^{-1}$ in case the system is time-invariant. Then the signal at locations Y, can be estimated by the reference sensors at location X

$$\mathbf{Y}_{predict} = \mathbf{A}\mathbf{X}_{new} \tag{1}$$

If the system is time-invariant, the predicted data $\mathbf{Y}_{predict}$ should be exactly the same as the measured data $\mathbf{Y}_{new}$. In case the system is time-variant, matrix **A** changes continually and the predicted data $\mathbf{Y}_{predict}$ is different from the measured data $\mathbf{Y}_{new}$. Therefore the error between $\mathbf{Y}_{predict}$ and $\mathbf{Y}_{new}$ ($error = \mathbf{Y}_{predict} - \mathbf{Y}_{new}$) points to the variance of the transmissibility functions. This gives a way to monitor the variance of the system.

3. EXPERIMENTAL RESULTS

3.1 Experimental set-up

The experiment was implemented on a 3-axis milling machine. One accelerometer was mounted on the spindle, while the other two were mounted on bench clamp and workbench. A rectangular aluminum work piece with the length of 60 cm, was cut by different depth of cutting, feed rate and spindle speed, as shown in Table 1.

Table 1 – Different machining parameters

Operating Condition	Cutting depth, mm	Feed rate,mm/min	Spindle speed,RPM
1	1	500	1500
2	1	500	2500
3	3	500	1500

The work piece was rigidly fixed in the middle, while the left-hand side and right-hand side were left free. The milling cutter was moving from left side to right side as shown in Figure 2. As the cutter was moving, excitation point was moving, thus the transfer function and modal response were changing.

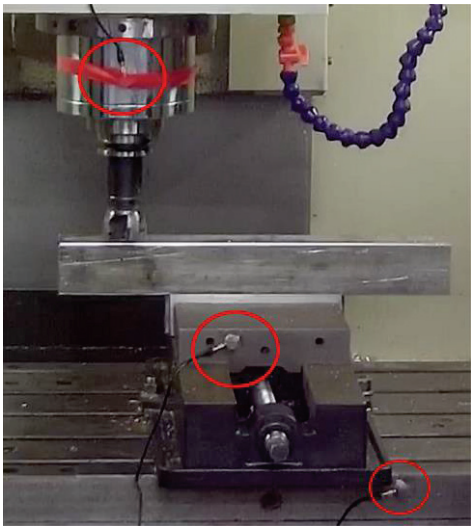


Figure 2 Test rig

3.2 Classification using the one accelerometer

For the huge amount of data, manually observing the data in time and frequency domain is tedious. Principal Component Analysis(PCA) is a commonly-used approach to extract unknown underlying features. As shown in Figure 3, different working conditions, different cutting depth, feed rate and spindle speed can be grouped into different clusters.

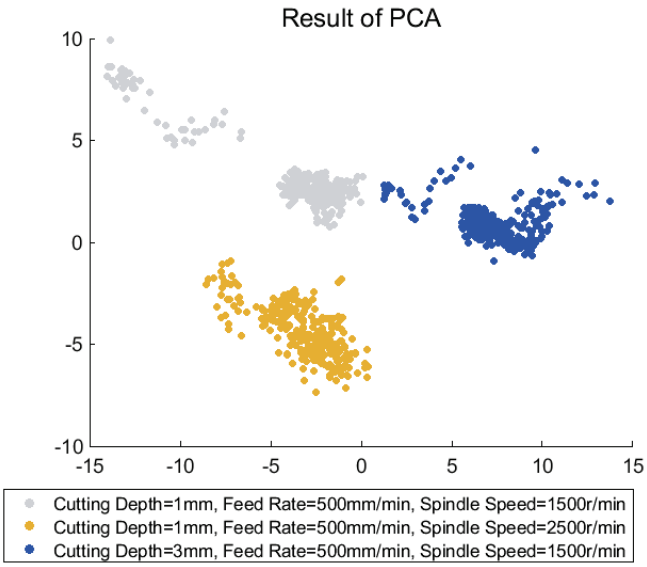


Figure 3 Scatter plot by PCA, the vibration is picked up on bench clamp

3.3 The transmissibility matrix variance during the process

In order to distinguish different characteristics at different cutting positions, the transmissibility function is considered. Calculated with the operational data, a spectrogram-like figure is drawn in Figure 4, which is the transmissibility from the spindle to workbench. It shows the time-variance of the transmissibility from the spindle to the workbench when the cutter moves from left to right. At the left-most side and right-most side, there are resonance responses between 1k-2kHz, and since the middle part is fixed, the magnitude is smaller. This figure illustrates variance of the transmissibility and gives additional information for condition monitoring.

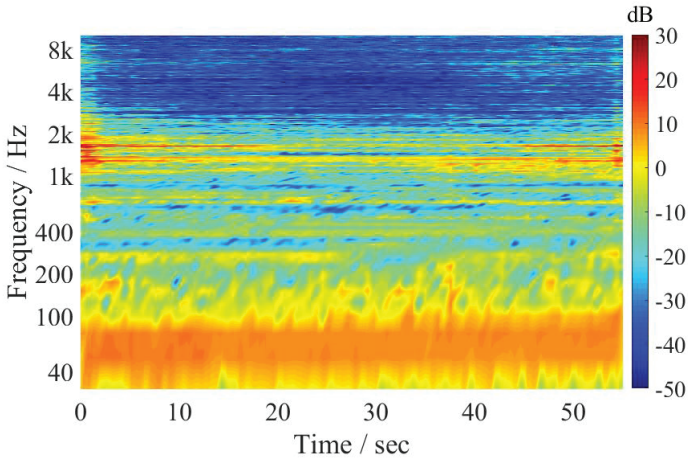


Figure 4 Transmissibility function from the spindle to the workbench

3.4 Classification of different operating conditions

Performing PCA on the time-variant transmissibility function calculated by one-third octave SPL of different operating conditions, the data is distinct in the scatter plot, as shown in Figure 5. Therefore, this feature can be used for the further classification algorithm like KNN.

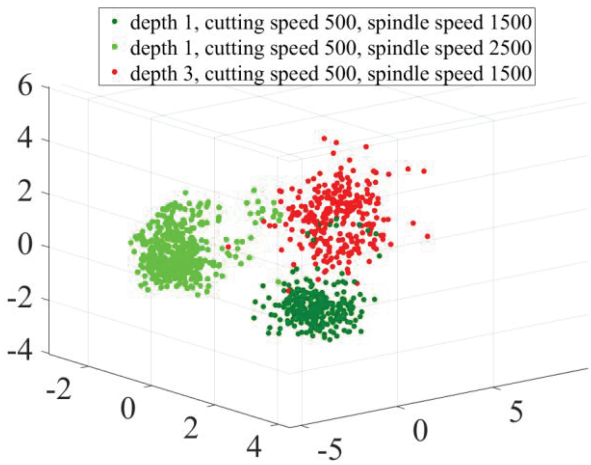


Figure 5 Scatter plot of different operating conditions

3.5 Classification of different cutting positions

During the process when the tool moves from the free-vibrating side to the rigid-fixed side, the modal response is changed, and variance should be monitored as well. According to Equation 1, a simple way is to compare the difference. For example, the measured signal at the leftmost-10cm is used to estimate transmissibility matrix **A**, then estimated signal is calculated when the tool is cutting the middle position. Since the transmissibility function is changed, error could be large at certain frequencies. Figure 6 compares the measured and the estimated spectrum from different training condition. If the matrix **A** changes too much, the estimation error increases. Training Condition 2 means the cutter processes at center position of the work piece. The Condition 1 and

Condition 3 means the position of leftmost 10 cm and rightmost 10 cm respectively. The measured condition is real measured data when the tool is cutting the middle rigidly fixed part of the work piece.

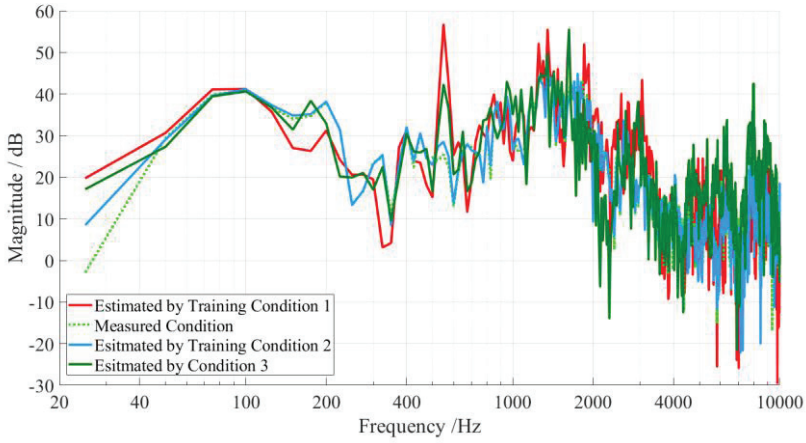
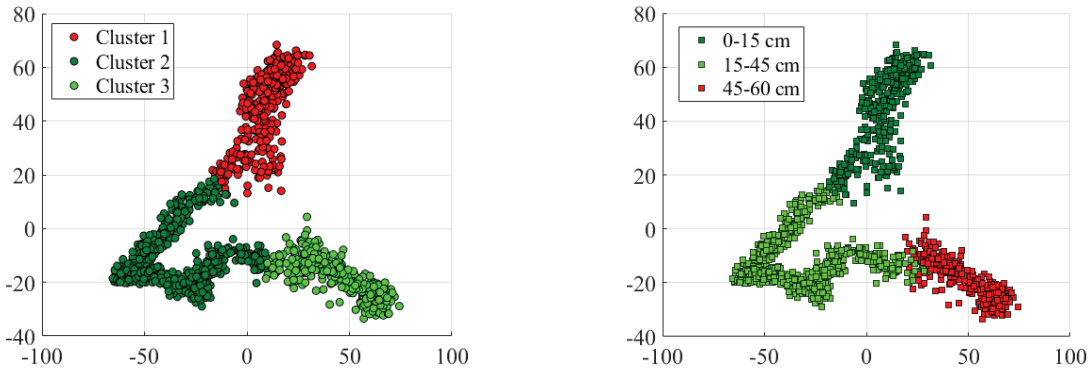


Figure 6 Estimation error corresponding to the reference sensor

Furthermore, PCA is implement on the estimation error, the difference caused by the change of transmissibility function is distinct.

During the experiment, the tool is continuously moving from the leftmost side to the rightmost side. Figure 7a shows the scatter plot when performing k-means clustering algorithms to divide the data into three groups. Figure 7b shows, the manually-divided groups by the position 15 cm and 45 cm. The mismatches between the groups are only 3.9%, 3.8%, 11.7% respectively, and this means that the transmissibility function at the left and right free-vibrating side are different from that at the rigidly-fixed position. This gives a way to automatically classify the different operating conditions.



a) b)

Figure 7 Scatter plot by PCA of estimation error

4. CONCLUSIONS

This paper presents the transmissibility function as the feature to represent different operating conditions of machining process. The transmissibility gives a distinct feature which helps to classify not only the different feed rate, spindle speed and cutting depth, but also the different cutting position. The further work should research on different classification methods which can classify the working conditions of machining process automatically.

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