Novel On-line Monitoring Method of Cutting Chatter Based on Neural Network Pattern Recognition Technique

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Abstract

A novel cutting chatter monitoring method is presented by investigating the characteristics of probability density of the cutting system vibration response. When the cutting is stable, the vibration response can be regarded as random noise and the corresponding probability density function is normal distributed. However, sinusoidal components dominate the vibration response and its probability density function is U-shaped distributed when the cutting process experiences chatter. Thus the probability density of the vibration response is sensitive to cutting chatter and is employed as the monitoring parameter in this study. Neural network pattern recognition technique is introduced to recognize cutting chatter considering its excellent capability of classification. Experiments conducted on an engine lathe confirm that the probability density of the vibration response a suitable monitoring parameter and cutting chatter can be successfully detected by the proposed method.

1. Introduction

Cutting chatter is a dynamic unstable phenomenon in cutting system, which degrades the workpiece surface quality, reduces cutting tool and machine lives, and even worse causes the failure of machine tool. Chatter monitoring depends heavily on the selection of sensors, as well as on the data processing techniques employed. Excellent reviews on the sensors in machining process can be found in [1]. Generally, sensing techniques can be classified into direct measurement, where the information is obtained via signal processing and indirect measurement, where the attribute is obtained directly from the signals. Typical indirect sensing techniques, such as dynamic force [2, 3], acceleration [4, 5], ultrasound waves [6] and drive current [7] can be utilized in cutting chatter monitoring.

The purpose of cutting chatter monitoring is to detect the chatter and send alarm in the early stage of chatter development in order to ensure timely chatter control mechanism can be triggered. Thus the selection of monitoring parameter is of great importance to achieve this goal. The monitoring parameter must be sensitive to cutting chatter and its processing time must be short. In general, statistical parameters including mean value and standard variance, spectrum analysis based frequency domain parameters and wavelet analysis based time-frequency domain parameters can be employed as the monitoring parameters. In this paper, the probability density function of the vibration response, a new monitoring parameter, is introduced. The calculation of monitoring parameter can be conducted just in time domain and only very simple algorithm is involved, therefore the processing time is very short.

2. Determination of monitoring parameter

In this study, probability density of the vibration response is utilized as the monitoring parameter as it varies greatly when the cutting process is stable and experiences chatter. In stable cutting, the vibration response $a_r(t)$ can be regarded as random noise and its probability density

$$p(a_r) = \frac{1}{\sqrt{2\pi}\,\sigma_r} \exp\left(-\frac{a_r{}^2}{2\sigma_r{}^2}\right) \tag{1}$$

where $a_r(t)$ is the vibration response in stable cutting, $p(a_r)$ and σ_r are probability density and standard deviation of $a_r(t)$. But if the cutting process becomes unstable, sinusoidal components dominate the vibration response, which might be described as:

$$a_s(t) = A_{ns} \sin(\omega_{ns} t + \phi_s) \tag{2}$$

where $a_s(t)$ is the vibration response in unstable cutting, $p_s(t)$ is the probability density of $a_s(t)$, A_{ns}

is the amplitude of $a_s(t)$, ω_{ns} is the circular frequency of $a_s(t)$, ϕ is the phase of $a_s(t)$ .The probability density function $p(a_s)$ can be expressed as[13]:

$$p(a_s) = \frac{1}{\pi\sqrt{A_{ns}^2 - a_s^2}} \tag{3}$$

It is certain that there is a transitional cutting process from stable state to unstable one. During the transitional cutting process, the vibration response can be expressed as the superposition of sine signal and the random signal, that is

$$a(t) = a_r(t) + a_s(t) \tag{4}$$

where $a(t)$ is the vibration response in transition process. Assuming $a_r(t)$ and $a_s(t)$ are independent of each other, the probability density function $p(a)$ of $a(t)$ is the convolution of p_r and $p_s(a)$, i.e.

$$p(a) = p(a_r) * p(a_s)$$
$$= \frac{1}{\sigma_r \pi \sqrt{2\pi}} \int_0^{\pi} \exp\left(- \frac{(a - A_{ns}\cos\phi)^2}{2\sigma_r^2} \right) d\varphi \tag{5}$$

On the basis of Equation (5), standardized probability density function for different values of $R = \sigma_s^2 / \sigma_r^2$, where σ_s is the standard deviation $a_s(t)$, can be plotted, as shown in Figure 1.

It can be found from the curves in Figure 1 that shapes of the probability density function curves varies significantly corresponding to different value of R . When the cutting is stable, the vibration response contains random noise only (R =0) and its probability density shows normal distribution. When R increases gradually from zero to infinite, the sine components increase gradually and the cutting process is in the transition process from stable cutting to unstable one. As R approaches infinite, the probability density of the vibration response presents a U-shaped distribution, which means the sine component dominates the vibration response and cutting process experiences strong chatter.

To conclude the above results, the probability density function of the cutting system vibration response is sensitive to the cutting states and it can be utilized as the parameter to monitor the cutting chatter online. At the same time, the calculation of this monitoring parameter is in time domain and very simple algorithm is required. Therefore, it is confident that the cutting chatter can be detected in time and reliable chatter control can be achieved if an appropriate control mechanism is employed.

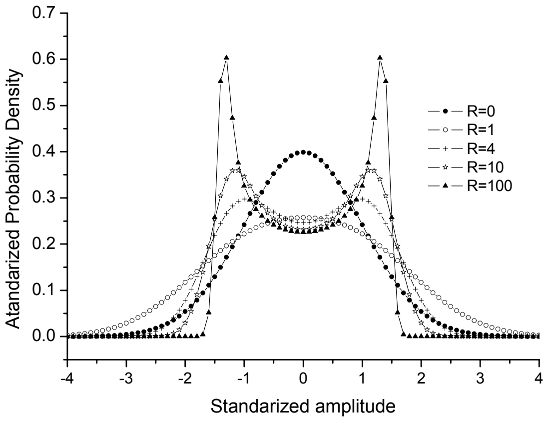

Fig. 1 Typical probability density function

3. Chatter monitoring scheme

Cutting chatter monitoring can be regarded as a typical pattern recognition problem, and then it can be conducted by utilizing an effective pattern recognition method. Pattern recognition is the process of identifying objects according to certain features. A whole patter recognition process can be divided into the following three critical steps:

1) Sensing—to pick up the information of the object by some kind of a transducer.
2) Features extraction—to characterize an object to be recognized by measurements whose values are very similar for objects in the same category and very different for objects in different category.
3) Classification—to assign the object into a category based on the extracted features.

The most classical pattern recognition problem is the statistical one. Bayesian decision theory is a fundamental statistical approach. This approach is based on quantifying the tradeoffs between various classification decisions using probability and the costs that accompany such decisions.

However, with the development of artificial intelligence in recent years, new pattern recognition methods based on artificial intelligent techniques, such as neural networks, fuzzy logic, genetic algorithms and expert systems, are successfully employed in many fields. Especially, the neural network pattern recognition methods have been verified as a powerful tool to solve the complicated classification problem. It has been proven that any continuous function can be implemented in a three-layer neural network. At the same time, pattern classification is considered as perhaps the most important application of artificial neural networks as a majority of neural networks applications can be categorized as solving complex pattern classification problems.

So a MLP neural network is employed in this paper to detect the cutting chatter. Then the next key problem is how to extract the representative features from the monitoring parameter. As shown in Figure 1, the probability density function of the vibration response takes different looks corresponding to different cutting states. Thus the frequency numbers of standardized vibration amplitude falls in a certain range should vary obviously in different cutting states. In this study, the ranges for frequency numbers calculation are set as: [-2.4 -2], [-1.4 -1], [-0.8 0.8], [1 1.4] and [2 2.4]. Then five values of frequency number are fed into a neural network with 20 hidden nodes and one output node for chatter monitoring. The network is a multilayer type consisting of an assemblage of neurons that are arranged into layers. The input layer contains 5 nodes and each node is connected to all the 20 neurons in the adjacent hidden layer. Similarly, each of the neurons in the hidden layer is connected to the neuron in the output layer.

To conclude the above discussions, the novel chatter monitoring scheme as shown in Figure 2 can be achieved. The vibration response collected from the cutting system is processed first to calculate the frequency numbers of standardized vibration amplitude falls in the five predetermined ranges. Then the values of frequency numbers are input to the neural network classifier. Finally, the chatter can be monitored by investigating the neural network output.

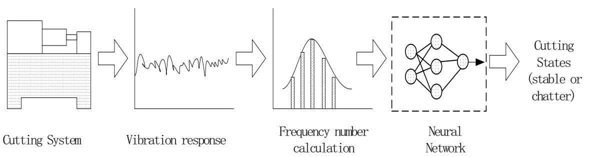

Fig. 2 Chatter monitoring scheme

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4. Experimental verifications

The experiments are carried out on a general engine lathe and a cylinder workpiece is machined, as shown in Figure 3. The tool holder is specially designed with low rigidity in order to introduce the cutting chatter easily. The acceleration response signal is picked up by an accelerometer mounted on the end of the cutter. Then the acceleration response signal is amplified by the charge amplifier and fed into A/D converter for digitalization. The calculation of the monitoring parameter and pattern recognition are processed in a computer.

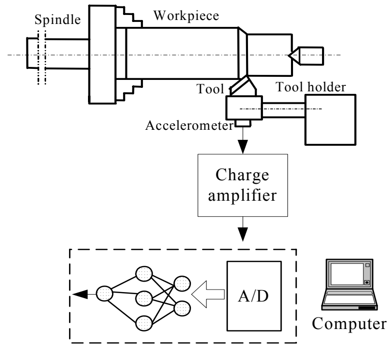

Fig.3 Cutting chatter monitoring system

The first part of experimental verification is conducted to confirm the probability density of vibration response is sensitive to the cutting chatter. One group of probability density functions are displayed in Figure 4. Among these curves, curves (a) and (b) are obtained when the cutting is stable and curves (c) and (d) are obtained when chatter is early and fully developed respectively. It can be found from Figures 4 that the probability density of the acceleration response transits from normal distribution to U-shaped distribution when cutting process transits from stable to unstable states. Therefore, the probability density function of vibration response is sensitive to cutting chatter. These results are coincident with the analysis results in Section 1.

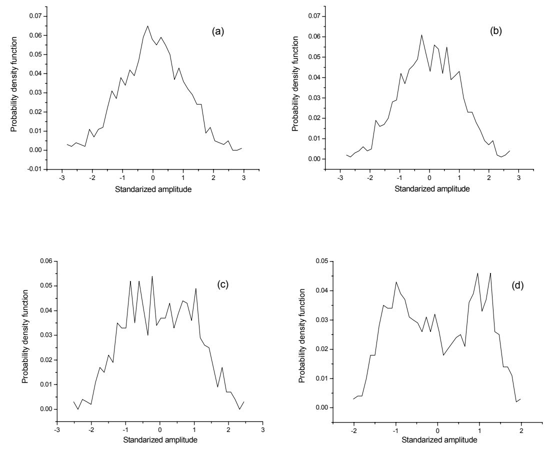

Fig. 4 Probability density of vibration responses

Then the proposed neural network based chatter monitoring scheme is examined. The neural network is trained first by utilizing the data of vibration response collected in the cutting process. In the training process, the learning rate is set to 0.1 and the moment constant is set to 0.85. The output of the neural network is set to 1 when cutting process experiences chatter and 0 for stable cutting. The weights are initialized to random value with uniformly distribution. After the successful training of neural network, it can be used to recognize the cutting state and indicate whether the cutting chatter occurs or not.

The typical results of many tests are shown in Figures 5 and 6 and let us look at Figure 5 first. In this figure, the time domain vibration response is displayed. At the beginning of cutting, the cutting process is stable and no chatter can be observed. But the cutting chatter gradually develops around 10s and very strong chatter occurs after 15s. The corresponding output of the neural network is depicted in Figure 6. It can be easily found the neural network outputs values close to 0 when the cutting is stable. But the output values increase gradually and values are close to 1 when the chatter is fully developed. If we set the threshold for alarming as 0.5, the monitoring system can detect the cutting chatter at 10s in this example, i.e. the cutting chatter is detected at the early stage of chatter development.

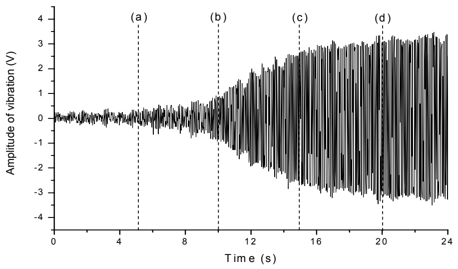

Fig. 5 Vibration response in chatter development process

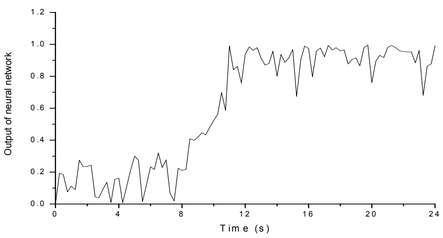

Fig.6 Output of neural network

Considering the successful rate of the proposed method for chatter monitoring, this method can be combined with a chatter control system as a monitoring module to achieve stable cutting with high machining efficiency. If the chatter is detected, chatter control mechanisms, for example, varying spindle speed cutting [8], can be triggered to suppress the chatter under development.

5. Conclusions

The probability density function of vibration response transits from normal distribution to U-shaped distribution when the cutting process changes from stable state to unstable one. To reflect this changing process, the frequency numbers of standardized vibration amplitude falls in the predetermined ranges are employed as the inputs of neural network classifier. The verification experiments demonstrate that the probability density function of vibration response is sensitive to the cutting chatter. Moreover, the proposed neural network pattern recognition based chatter monitoring method is proved to be a potential chatter detection technique with high accuracy and reliability.

References

[1] J. Tlusty, G. C. Andrews, “A critical review of sensors for unmanned machining”, *Annals of the CIRP,* 1983, 32 (2), pp. 611-622.

[2] Y. S. Tarng, T. C. Li, “Detection and suppression of drilling chatter”, *ASME J. of Dynamics Systems, Measurement, and Control,* 1994, 116(4), pp. 729-734.

[3] C. Su, J. Hino, and T. Yoshimura, “Prediction of chatter in high-speed milling by means of fuzzy neural networks”, *Int. J. of Systems Science*, 2000, 31 (10), pp. 1323-1330.

[4] X. Q. Li, Y. S. Wong, and A. Y. C. Nee, “Tool wear and chatter detection using the coherence function of two crossed accelerations”, *Int. J. Machine Tools & Manufacture*, 1997, 37 (4), pp. 425-435.

[5] T. Bailey, Y. Ruget, A. Spence, and M. A. Elbestawi, “Open-architecture controller for die and mold machining.”, *American Control Conference*, Seattle, Washington, June 1995, pp. 21-23.

[6] N. H. Abu-Zahra and J. H. Lange. Tool chatter monitoring in turning operations using wavelet analysis of ultrasound waves. *International Journal of Advanced Manufacturing Technology*, 2002, 20 (4), 248-254.

[7] E Soliman, F.Ismail. Chatter detection by monitoring spindle drive current. *International Journal of Advanced Manufacturing Technology*, 1997, 13 (1), 27-34.

[8] K. Jemielniak, A. Widota, “Suppression of self–excited vibration by the spindle speed variation method”, *Int. J. Mach. tool Design and Research, Publisher,* 1984, 24 (3), pp. 207–214.