# **Correlation Analysis of Tool Wear and Cutting Sound Signal**

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**Abstract**: With the classic signal analysis and processing method, the cutting of the audio signal in time domain and frequency domain analysis. We reached the following conclusions: in the time domain analysis, cutting audio signals mean and the variance associated with tool wear state change occurred did not change significantly, and tool wear is not high degree of correlation, and the mean-square value of the audio signal changes in the size and tool wear the state has a good relationship.

Key words: Signal analysis; Frequency domain analysis; Time domain analysis; Tool wear; the audio signal.

## I. Introduction

A large amount of signal information collected by the sensor can only be used to characterize the cutting state to a certain extent, but it can not be directly used to establish the mathematical model between the tool wear and the tool wear state. Only through the appropriate means of signal processing, a small amount of tool wear and the state of the large correlation between the characteristics of the information analysis and extraction, in order to ensure the reliability of the tool state identification. In the dynamic system of metal cutting, the signal of the sensor is the performance of the whole system. In this system, the workpiece, the cutter, the cutting parameter and the change of the tool wear degree and so on, all can make the characteristic of the signal of the sensor to have the corresponding change<sup>[1]</sup>.

Therefore, the tool wear process is essentially a non-stationary random process, then the output signal of the sensor also showed the characteristics of non-stationary random process. In practical applications, due to the test to get the analysis of finite length signal samples, so it can be similar to that of the output signal belongs to the stationary random process, and obey normal distribution, can be through time domain analysis, frequency domain analysis and time domain analysis method for monitoring signal analysis.

# II. The introduce of Signal Analysis

(1) time-domain analysis and time domain features

It refers to the time domain signal to the time axis of the signal amplitude of the waveform representation<sup>[2]</sup>. Let the test sample collected data  $x_i(t)$ , i = 1, 2, ..., N, then the sample data can be

time-domain characteristics analysis by the following method.

1) the mean  $\mu$  x, the expression is:

$$E[x(t)] = \lim_{T \to \infty} \frac{1}{T} \int_{0}^{T} \mathbf{x}(t) dt$$
(3-1)

Mean represents the mean value within a range of random data, the signal changes in the expression of central tendency. Different sensor signals with the tool wear degree of change corresponding changes occur in varying degrees, and therefore mean that some signals may be used to monitor tool wear, such as mean cutting force signal<sup>[3]</sup>.

2) variance  $\sigma x2$ , the expression is:

$$E[(x-\mu_x)^2] = \lim_{T \to \infty} \frac{1}{T} \int_0^T [x(t)-\mu_x]^2 dt$$
(3-2)

Variance also called standard deviation, the size of the performance of its volatility random signals. As for the cutting force signal, the use of the mean to represent static cutting force, but with variance represents the dynamic cutting force.

3) energy XRMS, the expression is:

$$X_{RMS} = \sum_{i=1}^{N} x_i^2$$
(3-3)

Energy is used to represent the signal energy varied within certain period of time.

4) The mean square value  $\varphi x2$ , the expression is<sup>[4]</sup>:

$$\varphi x^{2} = \lim_{T \to \infty} \frac{1}{T} \int_{0}^{T} x^{2}(t) dt$$
(3-4)

Mean square value represents the average power of random signals. The total energy sensor signal acquisition will with increasing degree of tool wear increases. Therefore, all changes square value can characterize the state of the tool<sup>[5]</sup>.

From monitoring features described above to obtain the time-domain signal it can often be used as a monitoring tool wear characteristics of the state vector. For the selection of monitoring features typically require different signal characteristics through careful analysis, to determine the relationship of mutual correspondence between states and tool wear.

#### (2) frequency domain analysis and frequency domain characteristics

Frequency domain analysis is the representation of signal in the frequency domain by means of mathematical transformation. Spectrum analysis is the most common method of signal analysis. According to the nature of the signal and the difference of the transformation method, the specific method includes the spectrum analysis, power spectrum analysis, etc.. In the practical application, the characteristics of the tool wear state can be extracted by the spectral structure of the signal<sup>[6]</sup>.

1) spectrum and phase spectrum

If the time domain signal satisfies the following conditions:  $\int_{1}^{\infty} |x(t)| dt$ , the existence of the function is

only limited to the extreme point, continuous or only a finite number of first class discontinuity, then the Fu Liye transform exists, the spectral function of the signal is expressed as:

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt = \left| X(\omega) \right|^{e^{j\phi(\omega)}}$$
(3-5)

The real part of X (s) is expressed as:

$$\left|X(\omega)\right| = \sqrt{\operatorname{Re}^{2}[X(\omega)] + \operatorname{Im}^{2}[X(\omega)]}$$
(3-6)

The imaginary part of X (s) is expressed as:

$$\varphi(\omega) = \arctan \frac{\operatorname{Im}[X(\omega)]}{\operatorname{Re}[X(\omega)]}$$
(3-7)

The amplitude and phase of the signal are respectively corresponding to amplitude spectrum and phase spectrum<sup>[7]</sup>.

2) power spectrum

Power spectrum analysis is used to describe the frequency structure of the signal. The power spectrum is divided into two different forms: the self power spectrum density and the cross power spectrum density. The energy distribution of the signal is determined by the power spectral density function:

$$S_{x}(\omega) = \left|F(\omega)\right|^{2} = \int_{-\infty}^{\infty} R_{x}(\tau) e^{-j\omega t} dt$$
(3-8)

The different signals of the same frequency are distinguished by the mutual power spectrum density function:

$$S_{xy}(\omega) = \int_{-\infty}^{\infty} R_{xy}(\tau) e^{-j\omega t} dt$$
(3-9)

#### III. Time domain characteristics analysis

According to the Nyquist sampling theorem, only the sampling frequency is greater than twice the highest frequency of the signal, in order to ensure after the conversion of analog and digital signal process, digital signal sampling completely retained the information in the original signal. Cutting the audio signal in audible range of frequency is 20-20kHz. In this paper, the audio signal sampling parameters are set as follows: sampling frequency 48kHz, quantization precision 16bit. 200mm of the single cutting length of the audio data to record, taking into account the amount of computation, select one second of the cutting audio signal as the original data to be processed.

Signal acquisition process in fact is the microphones to collect continuous state of random cutting audio signal sampling transformation for discrete digital voltage signal in time and amplitude. The main work of this paper is to analyze the difference between the signals, and the time domain waveform of the characteristic wear is analyzed and compared. Fixed cutting parameters for 1211r, by cutting depth is 0.3mm, the feed rate is 0.1mm/r. Cutting experiment with single factor variables with tool wear. Tool wear for the 0mm, 0.2mm, 0.5mm cutting audio signal in a second time domain waveform, as shown in figure 3-9.



(a) the time domain waveform of the audio signal when the tool wear is 0mm



(b) the time domain waveform of the audio signal when the tool wear is 0.2mm



(c) tool wear for 0.5mm audio signal time domain waveform Fig.3-9 time domain waveform of audio signal under different wear of 3-9 tool

From 3-9 can be seen from the figure, cutting the audio signal in the time domain waveform, with the increase of wear, cutting the amplitude of the audio signal has increased a certain increase. Tool wear 0.2mm waveform, as shown in Figure 3-9 (b), audio signal amplitude and wear volume of MM little change, indicating that the cutter is wear the steady state, the cutting process of the audio signal to remain stable. Tool wear to achieve 0.5mm waveform, as shown in Figure 3-9 (c), the amplitude of the audio signal changes, the signal component is more complex, cutting tool into the severe wear phase. As can be seen, there is a certain relationship with the audio signal and the cutting tool wear state .

Random selection of orthogonal experimental design table in the combination of arbitrary cutting parameters test, can be obtained by time-domain signal analysis method similar to figure 3-9 audio signal time-domain waveform. Considering the features all of the statistics of repeatability and complexity throughout the experiment in the time domain analysis, in order to facilitate the analysis and selects only with all cutting parameters under different degree of wear of the six groups of audio signal in the stable cutting the second time domain waveform statistics. Through the LabVIEW analysis of the signal, the 6 signal of the time domain characteristic value.

## **IV.** Conclusion

After a large number of experimental data comparison and analysis, cutting audio signal of the mean and variance of the change regularity is not strong, and the tool wear state dependence is not great and mean square value changes in the size of the tool wear rate showed a positive correlation between can be as time-domain characteristics of monitoring characteristic value. Time domain mean square value and tool wear amount of the relationship between the histogram and line diagram, respectively, as shown in Figure 3-10.





3-10 The volume Figure histogram of relationship between mean square value and amount of tool wear

Figure 3-10 and figure 3-11 analysis shows that, under the conditions of the selected six kinds of tool condition test, cutting audio signals mean square value and tool wear are accompanied by relationship, you can select cutting audio signal in time domain, mean square value as the tool wear condition monitoring of a parameter.

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