Tool Wear Feature Extraction Based on Hilbert Marginal Spectrum

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Abstract. In the metal cutting process, the signal contains a wealth of tool wear state information. A tool wear signal’s analysis and feature extraction method based on Hilbert marginal spectrum is proposed. Firstly, the tool wear signal was decomposed by empirical mode decomposition algorithm and the intrinsic mode functions including the main information were screened out by the correlation coefficient and the variance contribution rate. Secondly, Hilbert transform was performed on the main intrinsic mode functions. Hilbert time-frequency spectrum and Hilbert marginal spectrum were obtained by Hilbert transform. Finally, Amplitude domain indexes were extracted on the basis of the Hilbert marginal spectrum and they structured recognition feature vector of tool wear state. The research results show that the extracted features can effectively characterize the different wear state of the tool, which provides a basis for monitoring tool wear condition.

1. Introduction
In the metal cutting process, the tool wear state has great influence on machining quality of the workpiece. Therefore, it is of great significance to grasp the tool wear condition in time to improve the machining quality of the workpiece and control the machining cost of the parts. Tool wear is a complex phenomenon in the metal cutting process with different variety of the way, such as flank, rake, boundary wear [1]. It is related to the characteristics of the cutting tool, workpiece material, cutting parameters and so on. Acoustic emission (AE) signal is one of the most effective methods to monitor tool wear. AE signal is a kind of instantaneous elastic wave phenomenon, which is generated by the internal or local fast release of the material and directly derived from the tool. So it contains a wealth of tool wear state information.

In this paper, the author collected the acoustic emission signals of different wear stages in the cutting process and used the Hilbert Huang transform (HHT) and Hilbert marginal spectrum to analyze the acoustic emission signals. Present method extracted amplitude domain index on the basis of Hilbert marginal spectrum and used statistical method and the two-dimensional scatterplot to screen five indicators including: skewness, kurtosis, crest factor, margin index, pulse index. They form a feature vector which describes the tool wear state and provides some basis for tool wear condition monitoring and identification.

2. The experiment system and experimental method
The experimental program is shown in figure 1. Experiments were carried out on a C616 lathe. The workpiece material is T10 Carbon Tool Steel. The cutting tool is YT15 Carbide Tool. The experimental used R15-ALPHA resonant acoustic emission sensor which center frequency is 150kHz and preamplifier which bandwidth is 20kHz ~ 1.2MHz as well as Gain is 40dB. The Experiment select PXI - 6366 acoustic emission acquisition card. The Sampling frequency is 2MHz.
In the process of tool wear, the tool wear condition is judged according to the wear of tool flank (VB) [2]. Wear loss in 0.15mm to 0 mm is defined as the initial wear. Wear loss in 0.15 mm to 0.3 mm is defined as medium wear. Wear loss greater than 0.3mm is defined as severe wear which is considered to be invalid.

In the cutting process, the cutting parameters which affect the cutting tool wear state are: cutting speed, feed rate and cutting depth. In order to collect a comprehensive and accurate tool wear acoustic emission signal, the orthogonal test method is used to carry out a comprehensive combination of the three main cutting parameters, and a total of 27 different combinations of cutting parameters. The experimental method is shown in figure 2.

![Experimental system design](image)

**Figure 1.** Experimental system design

![Experimental flow chart](image)

**Figure 2.** Experimental flow chart

![Signal timing diagram of different wear](image)

**Figure 3.** Signal timing diagram of different wear
During the experiment, only the last 5 seconds of data for each tool were collected. Figure 3 shows the time sequence diagram of the signal with different tool wear, the cutting condition is the cutting speed of 520 r/min, feed rate which is 0.176 mm/r, cutting depth which is 0.4 mm. The wear loss from top to bottom is 0.05 mm, 0.13 mm, 0.16 mm, 0.20 mm, 0.27 mm, 0.35 mm.

3. Signal preprocessing

3.1. Empirical mode decomposition principle

Empirical mode decomposition (EMD) is adaptive. The signal is decomposed by empirical mode decomposition and a number of intrinsic mode functions (IMF) are obtained.Each IMF components includes local features of different time scales of the original signal. The IMF components must satisfy two conditions: (1) the number of extreme points and the number of zero crossing is the same or the maximum difference of one. (2) the upper and lower envelope lines are about the local symmetry of the time axis. So that the signal can be decomposed into a finite number of IMF components and a residual function. The original signal \( S(t) \) is decomposed by EMD, which is expressed as:

\[
S(t) = \sum_{i=1}^{n} c_i(t) + r_n(t)
\]

where the average trend of the signal is represented by the residual function \( r_n(t) \). And each IMF component is \( c_1(t), c_2(t) \ldots c_n(t) \), respectively including different frequency segment composition of the signal from high frequency to low frequency.

![Figure 4](image)

Figure 4. EMD decomposition results of different wear state signals

Figure 4 is the EMD decomposition results of the signal in different wear states, the wear loss from left to right is 0.05 mm, 0.20 mm, 0.35 mm. As can be seen from the graph, the signal is adaptively decomposed into a number of IMF components, and the final IMF component is a residual function. The IMF component obtained by the decomposition of AE signals with different wear loss is different.

3.2. Principal component analysis

The IMF component obtained by the decomposition of AE signals with different wear amounts is different. The IMF components include mechanical noise, electromagnetic noise, spurious components, and so on, which make the Hilbert time-frequency spectrum aliasing and affect the main frequency of the signal. Xiren M employed the variance contribution rate to analyze the principal component of the signal and the magnitude of variance contribution rate of IMF component is used as a measure of the principal component [3]. The IMF component with large variance contribution rate contains the main information of the signal. The formula for calculating the variance contribution rate of IMF component is:
\[ M_i = \frac{D_i}{\sum_{i=1}^{n} D_i} \quad (2) \]

\[ D_i = \frac{1}{N} \sum_{k=1}^{N} [c_i(k\Delta t)]^2 - \left[ \frac{1}{N} \sum_{k=1}^{N} c_i(k\Delta t) \right]^2 \quad (3) \]

where \( D_i \) is the variance of the \( i \)-th IMF components; \( \Delta t \) is the time interval of the sampling point.

Gang L used the principle of mutual relation to filter the signal, and the main components of the signal were obtained [4]. He measured the true or false of the IMF component by the size of the correlation of the IMF component and the original signal. The correlation coefficient among the false component and the noise component and the original signal is very small. The related formula is:

\[ \rho_{xy} = \frac{\text{cov}(X,Y)}{\sqrt{\text{D}(X)\text{D}(Y)}} \quad (4) \]

where \( \text{cov}(X,Y) \) is the covariance of the two signal, \( \text{D}(X) \) and \( \text{D}(Y) \) is the variance of the signal X and the signal Y.

In this paper, the variance contribution rate and the correlation coefficient method are used to analyze the signal [5]. The combination of the two methods is used to select the main components that are sensitive to tool wear and remove the unwanted components, so that the extracted signal features are more and more accurate. Figure 5 is Principal component analysis of IMF component.

![Figure 5. Principal component analysis of IMF component](image)

From Figure 5, we can see that the correlation coefficient of the IMF component and the original signal and the variance contribution rate of each IMF component gradually increased to a certain extent. But after reaching a certain degree, it will decrease dramatically. Through the study, it was found that correlation coefficient is large between IMF1 to 4 and the original signal. After IMF5, the correlation coefficient is almost close to zero, and the variance contribution rate is less than 2\%. By combining the correlation coefficient and variance contribution rate, we can know that the main components of the signal are concentrated in the first 4 order IMF components, and the residual IMF component can be eliminated.

4. Signal feature extraction based on Hilbert marginal spectrum

Hilbert marginal spectrum is obtained by Hilbert Huang transform. Hilbert Huang transform is a new nonlinear and non-stationary signal analysis method proposed by N.E.Huang et al. [6,7], which is widely used in the field of fault diagnosis [8]. Hilbert Huang transform (HHT) consists of two parts: Empirical Mode Decomposition and Hilbert transform. First the signal is through the empirical mode
decomposition to get a series of intrinsic mode functions; then the intrinsic mode function is used to carry out Hilbert transform to get the Hilbert time spectrum which contains the time, frequency, amplitude (energy). Hilbert marginal spectrum is obtained by integrating the Hilbert time-frequency spectrum.

4.1. Hilbert time spectrum

Every IMF component obtained from the EMD decomposition can be carried out by Hilbert transform, the instantaneous amplitude, instantaneous phase and instantaneous frequency of each IMF component with the time variation can be obtained. The IMF component $c_i(t)$ of the signal $S(t)$ is transformed by the Hilbert transform, then its complex analytic signal is:

$$ H(c_i(t)) = c_i(t) + j\tilde{c}_i(t) = a_i(t)e^{j\phi_i(t)} $$  

(5)

where $a_i(t)$ is the amplitude function of the $i$-th IMF component, and $\phi_i(t)$ is the phase function of the $i$-th IMF component.

After EMD decomposition and Hilbert transform, the original signal $S(t)$ can be expressed as:

$$ S(t) = \text{Re}\sum_{i=1}^{n} a_i(t)e^{j\phi_i(t)dt} $$  

(6)

$$ H(\omega,t) = \text{Re}\sum_{i=1}^{n} a_i(t)e^{j\phi_i(t)dt} $$  

(7)

where the $\omega_i(t)$ is instantaneous frequency and the Hilbert time spectrum of the original signal is called the $H(\omega,t)$.

Figure 6 is the Hilbert time-frequency spectrum of the original signal and after principal component analysis. The results show that the Hilbert time-frequency spectrum of the principal component analysis can eliminate the influence of false component and the residual frequency of low frequency part, so that the main frequency curve of the signal is more clear and accurate.

Figure 7 is the Hilbert time-frequency spectrum of AE signal under different tool wear condition. The Hilbert time-frequency spectrum of different tool wear state is more obvious difference, the change can be clear in time-frequency space. In figure 7 (a), tool is in the initial stage of wear. From the time-frequency chart, we can see that the signal frequency is relatively single, the frequency is mainly concentrated in the following 50 kHz, the frequency is evenly distributed over time. In figure 7 (b), tool is in the middle stage of wear, tool in continuous cutting process is accompanied by the rebound of the high temperature and high pressure, material on tool flank extrusion effect, the inner cutter began to trend micro cracks, acoustic emission signal began to become more and more complex,
frequency began to appear in more than 50 kHz, the high frequency information mainly concentrate between 50 kHz to 200kHz, frequency curve appear mixed phenomenon. In figure 7 (c), tool is in the stage of severe wear, the internal crack of the cutting tool is extended to form a serious wear, and a large number of high frequency information appears in the signal. High frequency information can be clearly seen from the time-frequency spectrum between 50 kHz and 400 kHz. The Hilbert time-frequency spectrum has obvious change in different tool wear condition, therefore the Hilbert time-frequency spectrum can be used as an auxiliary feature to monitor and identify the tool wear condition.

![Image of time-frequency spectrum](image)

**Figure 7.** Hilbert time-frequency spectrum of tool under different wear condition

### 4.2. Hilbert marginal spectrum

Hilbert marginal spectrum is different from the Fourier spectrum, it can handle the non-stationary signal. On the basis of the spectrum of Hilbert, it will be the time for integration. we can get the corresponding Hilbert marginal spectrum ($h(\omega)$):

$$h(\omega) = \int_0^T H(\omega,t)dt$$  \hspace{1cm} (8)

where $T$ is the signal length in the formula.

Hilbert marginal spectrum can more accurately reflect the signal actual frequency components. With the change of tool wear condition, the frequency components of the AE signal can be changed correspondingly, so the Hilbert marginal spectrum can be used as the basis for identifying the tool wear condition. From figure 8 (a), we can see that the main frequency of the signal concentrate 0 kHz to 100 kHz when the tool in the initial stage of wear. The figure 8 (b) and (c) are the Hilbert marginal spectrum of the signal when the tool is in the stage of medium wear and severe wear. The signal's main frequency is still concentrated in 0 kHz to 100 kHz, but with the tool wear signal, frequency components change gradually. Between 100 kHz to 200 kHz, we can see high frequency information compared to the initial wear stage.
4.3. Amplitude index

Signal's Hilbert marginal spectrum contains a wealth of tool wear information. But through directly observing the signal Hilbert marginal spectrum, we are difficult to accurately distinguish corresponding changes. By extracting amplitude characteristic index of the Hilbert marginal spectrum, the author used the amplitude index to distinguish different tool wear Hilbert marginal spectrum and then identify the different tool wear condition [9]. Amplitude domain indexes which include: mean absolute, peak, rms, root mean square amplitude, variance, peak to peak, skewness, kurtosis, crest factor, waveform index, pulse index and margin index is a total of 12 indicators.

The two-dimensional scatterplot helps analysis and select feature index [10]. By visual observation, we can know the characteristic distribution of the tool wear state is dense and the degree of dispersion is low, and the degree of dispersion between the different states is large and the distance is far, such features can be more accurate classification of tool wear condition. In this paper, the author used statistical methods to combine the 12 characteristic indexes and observed the clustering of the samples by two-dimensional scattered point diagram and compared different feature combination classification results and selected from the features of good classification effect including: skewness, kurtosis, crest factor, margin index and pulse index. Study found that with the tool wear, this five amplitude domain characteristic index can better distinguish different wear conditions and the size of the eigenvalues has a clear trend with tool wear, as shown in figure 9. Therefore, they can be used as indicators of tool wear condition identification.
Figure 10. Two dimensional scatter diagram of the combination of different characteristic indexes

Five kinds of extracted amplitude domain index were combined with each other and found a total of 10 kinds of combinations, here only lists the four combinations, figure 10 is 2D scatter plot of 48 samples of different wear stages of different feature combinations. By observing the scattered point diagram we can find different combinations of features classification results, the feature combination classification effect of figure a, b and d is relatively good, and feature combination of figure c did not distinguish the mid wear and severe wear. The feature combined with each other to identify the tool wear state. In different wear stage there are varying degrees of mixed phenomenon. Therefore, the five feature together described different tool wear states, this method is more completeness, its information is more comprehensive and can be better for tool wear state recognition and provide a basis for prediction.

5. Conclusions
By using the correlation coefficient and the variance contribution rate, the author analyzes the principal component of the IMF component of EMD decomposition. The results show that this method can effectively remove the interference in the Hilbert time-frequency spectrum. With the change of tool wear, the Hilbert time-frequency spectrum can clearly reflect the changes of the tool wear acoustic emission signal in time-frequency space. Hilbert marginal spectrum can more accurately reflect the signal frequency components. Its five amplitude domain index that include: skewness, kurtosis, crest factor, pulse index and margin index can distinguish Hilbert marginal spectrum of different wear state and different tool wear state. Therefore it can provide a certain basis for tool wear condition monitoring and identification.

6. References
[1] Yousheng L, Jianxin D, Hui Z, et al. J. Tribology, 28(5): 443-447. (2008)
[2] shan G. J. Journal of Northeast Dian li University, 33(3): 5. (2013)
[3] Xiren M, Xiaomei W, Dunyi S, et al. J. Transactions of China Electrometrical Society, 29(11): 154-161. (2014)
[4] Gang L, Chuang L, Xiangyang X, et al. J. Journal of Vibration and Shock, 34(12): 212-218. (2015)
[5] Feng X, Yunfei L. J. Journal of Basic Science and Engineering, 22(6): 1238-1247. (2014)
[6] Huang N E, Shen Z, Long S R, et al. Huang, N.E. et al. The Empirical Mode Decomposition and the Hilbert Spectrum for Nonlinear and Non-stationary Time Series Analysis. Proc. R. Soc. Lond. A 454, 903-995 J. Proceedings of the Royal Society A Mathematical Physical & Engineering Sciences, 454(1971):903-995. (1998)
[7] Huang N E, Shen Z, Long S R. A new view of nonlinear water waves J. Annual review of fluid mechanics, 31(1): 417-457. (1999)
[8] Moufa G, Lilan X, Xiren L, et al. J. Proceedings of the CSEE, 34(28): 4990-4997. (2014)
[9] Xiaohan C, Aiming W, Ruxiang H, et al. J. Journal of Vibration, Measurement & Diagnosis, 36(2): 351-358+406. (2016)

[10] Nantian H, Dianguo X, Xiaosheng L. J. Transactions of China Electro technical Society, 26(10): 23-30. (2011)