TELKOMNIKA, Vol. 11, No. 10, October 2013, pp. 5911 ~ 5916
ISSN: 2302-4046

Feature Extraction of Turing Tool Wear Based on J-EEMD

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Abstract

In the monitoring of cutting tool state, a large number of redundant information is contained in the sensor signal. Therefore, it is obviously not conducive to pattern recognition, and difficult to classify the tool wear state correctly from the available sensors. The test platform that had real-time information collection of the vibration and acoustic emission signals in turning was built. Observed signals were adaptively processed using the method of ensemble empirical mode decomposition introduced joint approximate diagonalization of eigenmatrices (J-EEMD). This method is based on the characteristics of the signal itself decomposed into several intrinsic mode functions (IMF), and then transforms the energy ratio between the IMF. The white noise of each IMF component has been eliminated by introducing JADE algorithm during the signal decomposition. Compared with the EEMD algorithm, the decomposition efficiency is significantly improved. The experiments showed that the method could identify the different states of tool wear, if applied to feature extraction of vibration and acoustic emission signal in the cutting process.

Keywords*: Ensemble empirical mode decomposition; Tool wear; Feature extraction; Turing*

1. Introduction

The empirical mode decomposition (EMD) proposed by Huang et al. (1998) is a time-frequency analysis method [1-2]. It is based on the time scale of the local signal characteristics, and the signal is decomposed into the superposition of a number of intrinsic mode functions (IMF). Certain significance band information is contained in each IMF exploded. EMD method has been widely used in many fields, but when jumping changes exist in the time scale of the signal, this case there will be an IMF component contains different time scales characteristic components, when the EMD decomposition is carried out on the signal. The major drawbacks of the original EMD are the mode mixing problem which is the conseconce of signal intermittence [3]. Because of this, so its application has been limited.

In order to solve the mode mixing problem in the process of traditional EMD decomposition method, the collection of empirical mode decomposition (EEMD) method proposed by Huang et al, based on numerous studies statistical properties of the EMD of white noise results. Gaussian white noise is added in the decomposition process in EEMD, and the combination of the signal and the noise as a whole. Time-frequency space is divided into different scales ingredient by filter bank, when the additional white noise is uniformly distributed in the entire time-frequency space. Different scale signal area is automatically mapped to the appropriate scale background white noise. At this time, White noise of zero mean is added to each imf, and the noise will cancel each other after many times the average calculation processing. Therefore, the integrated average times are more, the result which obtains is closer the primary signal [4].

Modal aliasing problems of traditional EMD is solved through EEMD, but in order to eliminate the influence of white noise added in the decomposition process of the original signal, the integrated average at least 100 times is required. The computational efficiency is clearly reduced, so that it is not conducive to online monitoring of tool wear. To solve this problem, J-EEMD decomposition algorithm has been proposed. Joint approximate diagonalization of eigenmatrices (JADE) algorithm is introduced in order to eliminate the impact of white noise in IMF components, thus weakening the impact caused by the lack of an integrated average number [5], [6].

Received April 23, 2013; Revised July 6, 2013; Accepted July 18, 2013

2. Test Platform and Program

2.1. Test Platform

In this study, tool wear condition monitoring system was built, which was capable of monitoring cutting force, vibration and acoustic emission signal of CNC turning process in real-time. As shown in Fig.1, the test equipment and instruments included: CK6143/100 CNC lathe, Kistler9257B dynamometer, 8702B50M1 K-Shear ceramic accelerometer, 8152B12SP acoustic emission sensors, DEWE-3021 digital acquisition system, and so on. The blank material and blade were respectively the austenitic stainless steel 304L and Kenna KC5010 turning insert. In particular, three types of blades included CNMG120404FP, CNMG120408FP and CNMG120412FP were used.

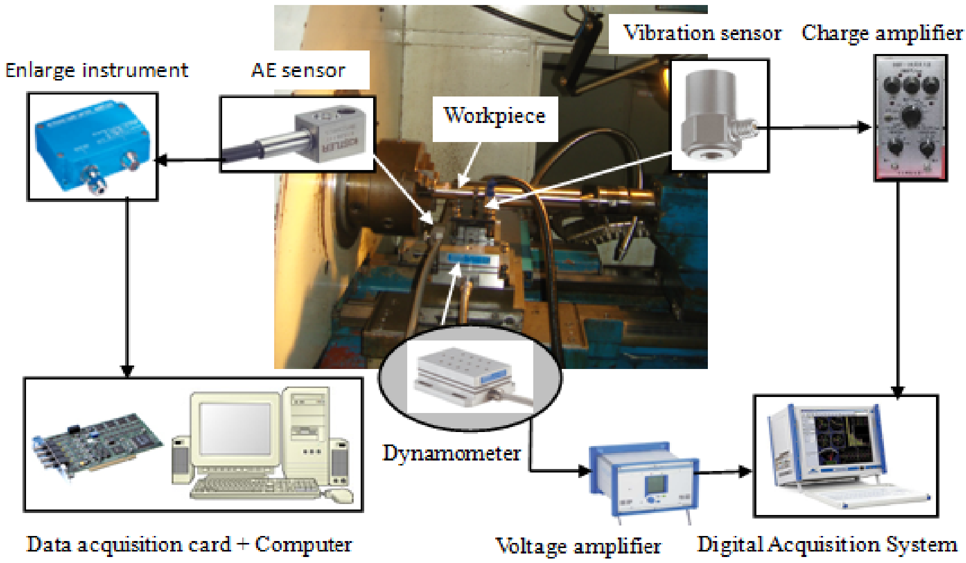


Figure 1. Test platform

2.2. Test Program

The uniform design is one of space filling designs and it seeks experimental points to be uniformly scattered on the domain. This method was proposed by Fang and wang in 1978 and had been popularly used since 1980 [7]. Test of cutting conditions were designed according to the uniform design method, as shown in table 1.

Table 1. CNC Turning Test Cutting Conditions

Group number	Cutting Speed (m/min)	Cutting depth (mm)	Feed rate (mm/r)	Edge radius (mm)
1	190	2	0.13	0.8
2	170	1.2	0.25	0.4
3	200	1	0.21	1.2
4	250	2	0.25	0.8
5	180	1.6	0.29	1.2
6	210	1.8	0.33	0.4
7	270	1.8	0.21	1.2
8	240	1.4	0.13	1.2
9	220	1.6	0.17	0.4
10	260	1.2	0.17	0.4
11	230	1	0.33	0.8
12	280	1.4	0.29	0.8

3. The JADE algorithm

JADE is an algorithm that uses significant eigenpairs of the cumulant tensor to find out the estimated values of independent components. In this algorithm the tensor eigenvalue decomposition is considered as more of a preprocessing step. Eigenvalue decomposition can be viewed as diagonalization. This can find a separating matrix suited to blind source separation.

Blind separation of mixed model can be expressed as:

$$x = As \tag{1}$$

Where:

x : observation matrix, $x = [x_1, x_2, \cdots, x_n]^T$

A : $n \times n$ unknown nonsingular mixing matrix

s : n unknown, statistically independent source signals, $s = [s_1, s_2, \cdots, s_n]^T$

The gole of the Blind Source Separation (BSS) is consists of recovering the set of source signals S solely from the observed (instantaneous and linear) ixtures X, by estimating either the mixing matrix A or its inverse $V = A^{-1}$ (silently assuming that A is invertible).

The essence of the BSS is to find a separating matrix W, making the observed signal x by the W transform, the output y as the estimate of the source signals.

$$y = Wx \tag{2}$$

Where each component of the x and y are mutually independent.

First, a whitening matrix should be computed according to the observation matrix.

$$z = Vx = VAs \tag{3}$$

Where:

z : whitened signal matrix, $z = [z_1, z_2, \cdots, z_n]^T$

V : whitening matrix

The JADE algorithm is based on the usage of the forth order cumulant tensor; it tries to maximize [6], [8].

$$J(A) = \sum_i \left\| diag(AF(M_i)A^T \right\|^2 \tag{4}$$

where A is the whitened mixing matrix and M_i are the eigenmatrices of the fourth order cumulant tensor (the eigenvalues of those eigenmatrices are the kurtosis values of the independent component, which can be calculated in this way). The starting point of the JADE algorithm is that the requirement of the most BSS algorithms to calculate the distributions of the independent components, can be fulfilled by optimizing the cumulant approximations of data [9]. The main advantage of the fourth order cumulants is that they can be optimized by means of the iterative Jacobi algorithm [10].

In summary, J-EEMD algorithm process is as follows:

(1) White noise of 0.4 standard deviation is added to the original signal $x(t)$.

(2) Two signals added White noise signal and White noise signal are Processed respectively by EMD algorithm, the results are recorded as IMF1 and IMF2.

(3) The observational matrix is composed of the corresponding component with IMF1 and IMF2, using JADE algorithm to blind source separation, thus, IMF0 is obtained signal component extracted from the results.

(4) Each row of components of IMF0 is scaled in accordance with each row of components of IMF1, obtaining the new IMF component.

(5) Added a new sequence of white noise each time, repeating the above four steps, the final decomposition result is each IMF decomposition integration average.

4. Feature Extraction Based on J-EEMD

4.1. Feature-Value Determination

As we all know that redundant information is contained in the original signal collected by the sensor. And having a strong randomness, so it is difficult to find a variation of the tool wear state directly from the raw data. Therefore, it is necessary to analyze the raw data using signal processing techniques, and to extract more reactive characteristics of tool wear. This test extract the signal energy and gravity frequency as a signal characteristic value.

Signal energy characterize the degree of signal strength. And reflec the sum of the signal energy in each frequency. Set p_i the spectral amplitude sequence of original signal by fast fourier transform (FFT), then the signal energy p can be calculated as follows:

$$p = \sum_{i}^{n} p_i^2 \tag{5}$$

The gravity frequency f_c response of a change of position of the spectral centroid. Different tool wear state caused changes in the vibration amplitude of some frequency, thus the position of spectral center of gravity are affected to a large extent. The calculation formula is as follows:

$$f_c = \frac{\sum_{i=1}^{n} f_i p_i}{\sum_{i=1}^{n} p_i} \tag{6}$$

4.2. Feature Data Extraction

The process of J-EEMD algorithm to extract the signal characteristics are as follows:

(1) Introduce a white noise with 0.4 variance, take the number of integrated average with10, and signals of vibration and acoustic emission are processed with J-EEMD.

(2) FFT is applied on the original vibration signals and acoustic emission signals, as well as decomposition of each IMF, putting the experiment data into Eq.(5) to calculate the energy.

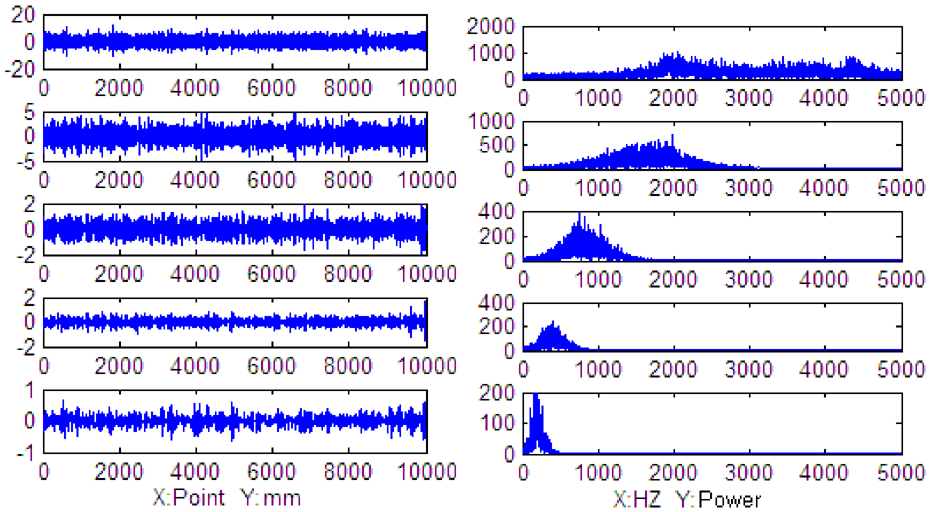
(3) set the original signal energy value as p_x, energy value of the ith IMF is p_{imfi}, thus get the energy ratio of each IMF as $Pp_i = p_x / p_{imfi}$.

(4) Calculate the gravity frequency to each IMF according to Eq.(6).

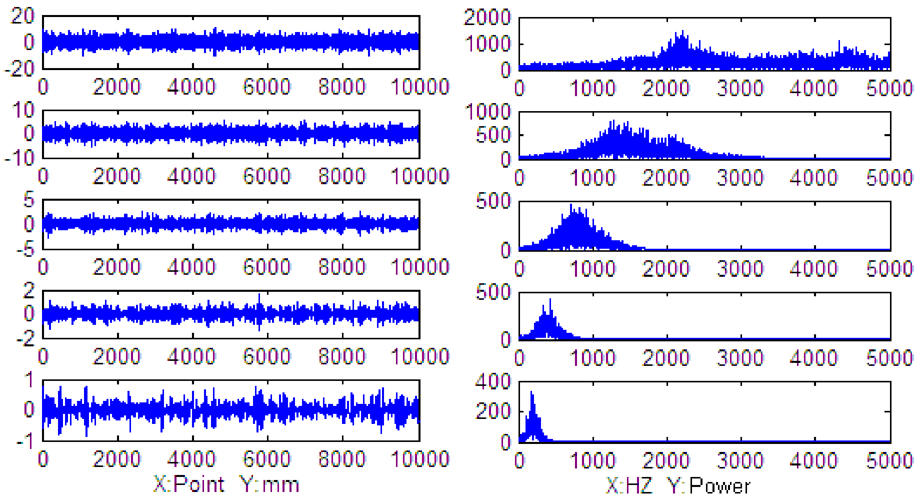
In our test, tool wear state was divided according to the the amount of flank wear. That is which state 1 indicates the tool flank wear as 0mm to 0.05mm, state 2 as 0.05mm to 0.1mm and state 3 as 0.1mm to 0.15mm. J-EEMD decomposition were completed under different tool wear state of vibration signals and acoustic emission signals in turning. Figure 1 shows a J-EEMD decomposition results of vibration signal obtained under the above three different states.

As can be seen from Fig. 2, the ranges of the frequency domain are not equal. Such as the first component, the energy is concentrated in the above 2000Hz, the second component, in the 1000Hz to 2000Hz, the third component, in the 500Hz to 1000Hz. That is to say, the more the tool wear is, the narrower the frequency range of IMF corresponding is.

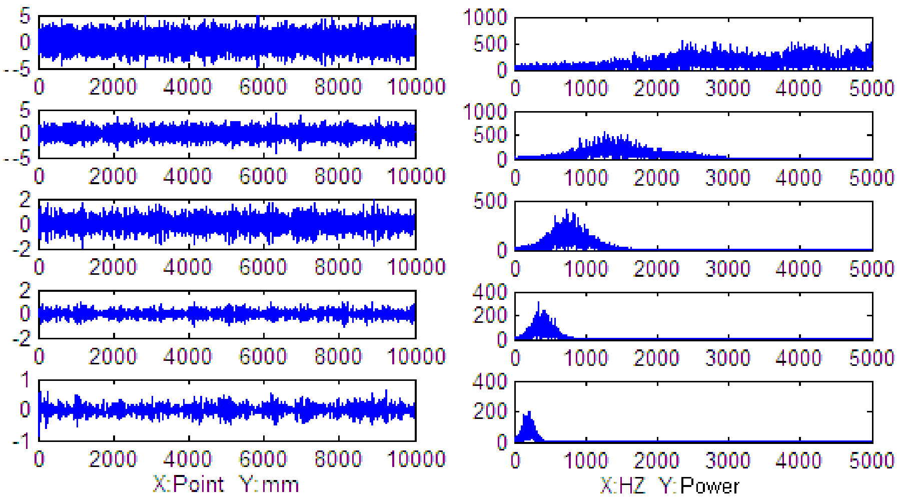
It also can be learned from the test analysis, that the signal energy is concentrated in the first three of IMF. At the same time, there are significant changes in the three IMF spectrum Spectrum of this three IMF changes with the degree of tool wear. Therefore, it is desirable that energy ratio after treatment of the J-EEMD first three IMF, as well as the gravity frequency were selectedas the characteristic values of the vibration signal measured experimentally. It is similarly to select the characteristic values of the acoustic emission signals.



a) Decomposition results of state 1



b) Decomposition results of state 2



c) Decomposition results of state 3

Figure 2. J-EEMD decomposition results of vibration signal

5. Conclusion

EEMD algorithm has solved the problem of mode mixing problem existing in traditional EMD, but has the lower computational efficiency, not conducive to online monitoring tool state. The blind source separation JADE algorithm is introduced into EEMD decomposition process, that can eliminate the white noise in the IMF components. The decomposition efficiency is significantly improved compared with EEMD algorithm. Experimental results show that the eigenvalue extracted through J-EEMD algorithm can be well identified the different states of the tool wear, on the basis of the feature extraction to cutting vibration and acoustic emission signals.

Acknowledgment

This study is supported by the Fundamental Research Funds for the Central Universities, China (SWJTU12CX039).

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