Wavelet packet transforms of acoustic emission signals for tool wear monitoring

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Abstract

In the tool wear monitoring systems, one of the most important issues is to extract signal features from signal detected under given cutting conditions. This paper uses wavelet packet transforms method to extract features from acoustic emission (AE) signal. Wavelet packet transforms can decompose AE signal into different frequency bands in time domain, the root means square (RMS) values computed from the decomposed signal of each frequency band are taken as features. Analyzing above features, the features are direct relation to tool wear. The experimental results indicate that it is an effective method to extract the features of tool wear monitoring using the wavelet packet transforms of AE signals.

1. Introduction

In flexible manufacturing systems (FMS), tool wear monitoring plays a critical role in dictating the dimensional accuracy of the workpiece and guaranteeing automatic cutting process. It is therefore essential to develop simple, reliable and cost-effective tool wear condition monitoring strategies in this vitally important area. Various methods for tool wear monitoring have been proposed in the past, these methods have been classified into direct (optical, radioactive and electrical resistance, etc.) and indirect (acoustic emission (AE), spindle motor current, cutting force, vibration, etc.) sensing methods according to used sensors [1-2]. Recent attempts have been concentrated on development of the indirect methods. Among indirect methods, AE is the most effective mean of sensing tool wear. The major advantage of using AE to monitor tool condition is that frequency range of the AE signal is much higher than of the machine vibrations and environmental noises and not interfere with the cutting operation. But AE signals often have to be treated with additional signal processing schemes to extract the most useful features from signals [3-5]. If AE signal can effectively be analyzed, tool wear may be detected using AE signals. Among various approaches have been taken to analyze AE signals, spectral analysis has been found to be the most informative for monitoring tool wear [6-7]. Spectral analysis such as fast Fourier transform (FFT) is the most commonly used signal processing techniques in tool wear monitoring. A disadvantage of FFT method is that it has a good solution only in frequency domain and a very bad solution in time domain.

Recently, wavelet packet transform proposed is a significant new tool in signal analysis and processing. Wavelet transform has a good solution in frequency and time domain synchronously can extract more information in time domain at different frequency bands. It has been to analyze tool failure monitoring signal [8-10]. The wavelet packet transform has been used for on-line monitoring of machining process. It can capture important features of the sensor signal that are sensitive to the change of process condition (such as tool wear) but is in sensitive to the variation of process working condition and various noises [11]. The wavelet packet transform can decompose sensor signal into different components in different time windows and frequency bands, the components, hence, can be considered as the features of the original signal.

The objective of this paper is to extract features from acoustic emission (AE) signal using wavelet packet transform method. A wavelet packet transform can decompose AE signal into different frequency bands in time domain, the root means square (RMS) values computed from the decomposed signal for each frequency band are used as features. Analyzing above features, the features that are direct relation to tool wear are used as final monitoring features. The experimental results indicate that the monitoring features had a low sensitivity to changes of the cutting conditions so that wavelet packer transform is shown to be an effective method to extract the features of the AE signals for tool wear monitoring.

2. Wavelet packet transform

Given a time varying signal f (t); wavelet transforms (WT) consist of computing coefficient that inner products of the signal and a family of wavelets, namely

$$w_f(a,b) = \int f(t)\psi^*_{a,b}(t)dt \tag{1}$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \qquad a,b \in R,\ a \neq 0;\ a$$

and b are the dilation and translation parameters, respectively; "*"denotes the complex conjugation.

When $a=2^j$, $b=k2^j$, j, k 0Z, wavelet are in this case

$$\psi_{j,k} = 2^{-\frac{j}{2}}\psi\left(2^{-j}t-k\right) \tag{2}$$

The discrete wavelet transform (DWT) is defined

$$c_{j,k} = \int f(t)\psi^*_{j,k}(t) \tag{3}$$

where $c_{j,k}$ is defined as wavelet coefficient, it may be though of as a time frequency map of the original signal $f(t)$. Here, a multi-resolution analysis approach is used in which a discrete scaling function

$$\phi_{j,k} = 2^{-\frac{j}{2}}\phi\left(\frac{t-2^jk}{2^j}\right) \tag{4}$$

set

$$d_{j,k} = \int f(t)\phi^*_{j,k}(t)dt \tag{5}$$

where $d_{j,k}$ is called as scaling coefficients, it is the sampled version of original signal, when j =0, it is the sampled version of the original. Wavelet coefficients $c_{j,k}$ (j=1,⌡,J) and scaling coefficients $d_{j,k}$ given by

$$c_{j,k} = \sum_n x[n]h_j[n-2^jk] \tag{6}$$

and

$$d_{j,k} = \sum_n x[n]g_j[n-2^jk] \tag{7}$$

where $x[n]$ are discrete-time signals, $h_j[n-2^jk]$ is the analysis discrete wavelets, the discrete equivalents to $2^{-j/2}$*symbol 121 \f "Symbol" \s 10* (2^{-j}(t-2^jk)), $g_j[n-2^jk]$ are called scaling sequence. At each resolution j>0, the scaling coefficients and the wavelet coefficients

$$c_{j+1,k} = \sum_n g[n-2k]d_{j,k} \tag{8}$$

$$d_{j+1,k} = \sum_n h[n-2k]d_{j,k} \tag{9}$$

In fact, it is well known that the structure of computations in a DWT is exactly an octave - band filter band[12]. The terms g and h are high-pass and low-pass filters derived from the analysis wavelet ψ(t) and the scaling function $\phi(t)$.

Wavelet packets are particular linear combinations of wavelets. They form bases that retain many of the orthogorality, smoothness and location properties of their parent wavelets [13]. The coefficients in the linear combinations are computed by recursive algorithm, with the results that expansions in wavelet packet bases have low computational complexity.

The discrete wavelet transform can be rewritten as follows:

$$
\begin{aligned}
c_j[f(t)] &= h(t) * c_{j-1}[f(t)] \\
d_j[f(t)] &= g(t) * c_{j-1}[f[t]] \\
c_0[f(t)] &= f(t)
\end{aligned}
$$

(10)

Set

$$
\begin{aligned}
H\{\cdot\} &= \sum_k h(k-2t) \\
G\{\cdot\} &= \sum_k g(k-2t)
\end{aligned}
$$

(11)

then equation can been written below

$$
\begin{aligned}
c_j[f(t)] &= H\{c_{j-1}[f(t)]\} \\
d_j[f(t)] &= G\{c_{j-1}[f(t)]\}
\end{aligned}
$$

(12)

Clearly, DWT only is the approximation $c_{j-1}[f(t)]$ but not the detail signal $d_{j-1}[f(t)]$, Wavelet packet transform do not omit the detail signal, therefore, wavelet packet transform is

$$
\begin{aligned}
c_j[f(t)] &= H\{c_{j-1}[f(t)]\} + G\{d_{j-1}[f(t)]\} \\
d_j[f(t)] &= G\{c_{j-1}[f(t)]\} + H\{d_{j-1}[f(t)]\}
\end{aligned}
$$

(13)

let $Q_j^i(t)$ is the ith packet on jth resolution, then, the recursive algorithm can also compute the wavelet packet transform, and it is below:

$$
\begin{aligned}
Q_0^1(t) &= f(t) \\
Q_j^{2i-1}(t) &= HQ_{j-1}^i(t) \\
Q_j^{2i}(t) &= GQ_{j-1}^i(t)
\end{aligned}
$$

(14)

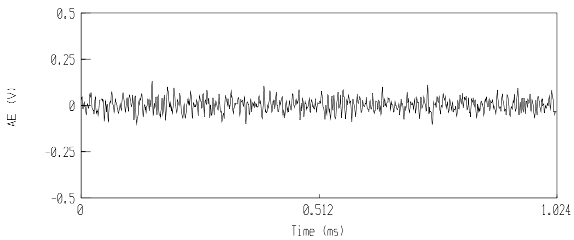
Where t=1,2, ..., 2^{J-i}, i=1,2,...,2^j, j=1,2,..., J, J=$\log_2 N$, N is data length.

3. Signal analysis and Features extraction

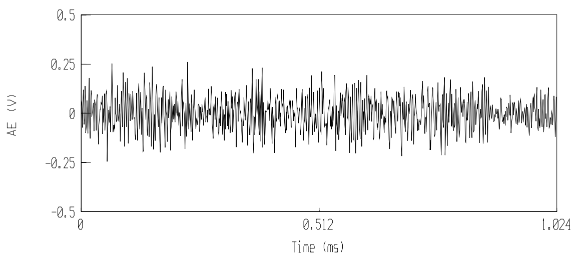
3.1. Signal analysis

In monitoring of tool wear, monitoring signals acoustic emission contains complicated information on the cutting processing. To ensure the accuracy and reliability of monitoring, it is important to extract the features of the signals that describe the relationship between tool condition. From a mathematical point of view, the features extraction can be considered as signal compression. Wavelet packet transform is represented as a compressed signal method. Therefore, it is ideal to use the wavelet packets as the extracted features [14,15]. According to above pointed, each wavelet packet transform represents certain information on the signal is a specific time-frequency window.

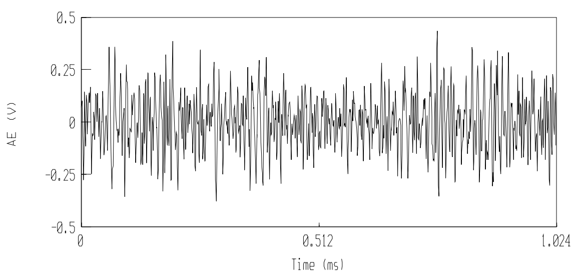
Fig. 1 shows a typical cutting process experiment in boring. The AE signal in time domain is presented. At the beginning of the cutting process, signal affected by tool wear is smaller because the tool is fresh, the magnitude of the AE is small, and cutting process is stable. As the tool wear increases progressing, the magnitudes of the AE have increased.



a)



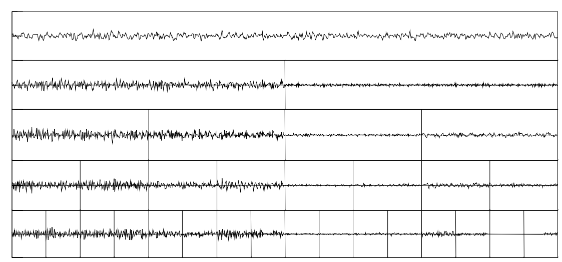
b)



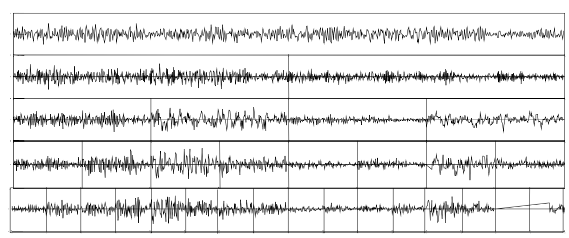
c)

Fig.1 The AE signal in a typical tool wear cutting process, cutting speed: 30m/min, feed rate: 0.2mm/rev, the depth of cut: 0.5mm; work material: 40Cr steel, tool material: high-speed-steel, without coolant. (a) VB=0.06 mm; (b) VB=0.26 mm; (c) VB=0.62 mm.

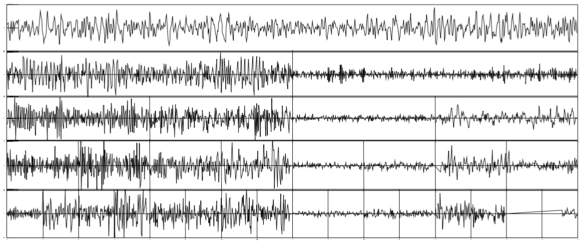
Fig.2 shows the decomposing results of AE signal for the experiment shown in Fig.1 through the wavelet packet decomposition. Fig.2 represent the constituent parts of the AE signal at frequency band [0, 62.5], [62.5, 125], ..., [937.5, 1000] kHz, respectively. Obviously, these decomposing results of AE signal not only keep the same features which are discussed above, but also provide more information such as the time domains constituent part of the AE signal at the frequency band. The mean values of the constituent parts of the AE at very frequency band can represented the energy level of the AE in the frequency band.



a)



b)



c)

Fig.2 The composing results of AE by wavelet packet transformation

3.2 Feature extraction

In tool wear monitoring, the feature selection and feature number are very important. The selected features must be independent and the number of features must be large enough. For the tool wear monitoring, the cutting conditions (cutting speed, feed rate and cutting depth) are also the features related to wear, when signal features extracted from AE signal corresponding to different cutting conditions, these cutting condition were also represented by the features. In practice, the cutting condition was not dependent on features. So we hope that the selected features should show a low sensitivity to change of the cutting conditions, namely, tool wear monitoring system could be suitable for a wide range of machining conditions.

According to discuss above, the RMS of in each frequency band was used to describe the features of different tool condition. As wavelet packet transform processing, the distribution of the wavelet packet transform is in disorder [16], the distributions of above wavelet packet transform results is as follows in order:

Decomposed order	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8
Frequency order	1	2	4	3	7	7	5	6

Decomposed order	n_9	n_{10}	n_{11}	n_{12}	n_{13}	n_{14}	n_{15}	n_{16}
Frequency order	16	15	13	14	9	10	12	9

But above features all are not sensitive to tool wear. According to a large mounts of data analysis, we found that n_4, n_3 , n_7 , n_8, n_6, n_5 , n_{13} are sensitive to tool wear. Fig.3 and Fig.4 show two typical examples, above features are replaced by q_1, q_2, q_3, q_4, q_5, q_6, q_7, respectively, those will be used to classify tool wear satiates.

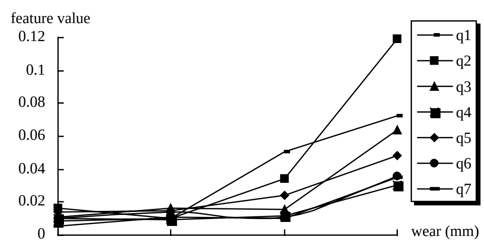


Fig.3 The relationship between features extracted and tool wear, cutting speed: 30m/min, feed rate: 0.2mm/rev, the depth of cut: 0.5mm; work material: 40Cr steel, tool material: high-speed-steel, without coolant

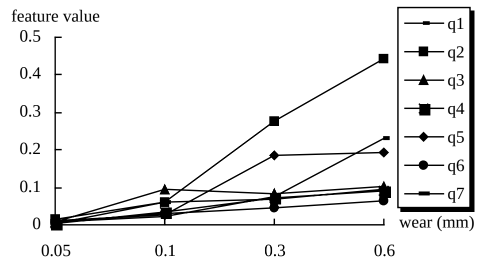


Fig.4 The relationship between features extracted and tool wear, cutting speed: 40m/min, feed rate: 0.3mm/rev, the depth of cut: 1mm; work material: 40Cr steel, tool material: high-speed-steel, without coolant

The selected features were summarized as follows:

q_1=RMS of wavelet coefficient in the frequency band [125, 1875.]KHz

q_2=RMS of wavelet coefficient in the frequency band [187.5, 250]KHz

⋮ ⋮

⋮

q_7=RMS of wavelet coefficient in the frequency band [500, 562.5]KHz

It is known that RMS of continuous AE is proportional to v_c a_p, tool flank wear VB, but it is independent on feed rate. For the purpose of elimination of the effects of cutting conditions on features, divided $v_c a_p$ into q_i (i=1, 2, ... , 7) and get new q_i value, the new q_i value are final monitoring features.

4. Conclusions

One of the most complex problems for tool wear condition monitoring system is that of extracting the signal features and describing the relationship between the tool wear condition and the signal features under a given cutting condition as accurately as possible. In this paper, a method has been developed for monitoring tool wear in boring operations using acoustic emission information. Several features were derived from wavelet packet transform, and the optimal features sensitive to tool flank wear selected. Moreover, the feature extraction with wavelet packet transform can be implemented real time since wavelet packet transform requires only a small amount of computation.

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