Wavelet analysis of acoustic emission signals in boring

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Abstract: Using acoustic emission (AE) signals to monitor tool wear states is one of the most effective methods used in metal cutting processes. As AE signals contain information on cutting processes, the problem of how to extract the features related to tool wear states from these signals needs to be solved. In this paper, a wavelet packet transform (WPT) method is used to decompose continuous AE signals during cutting; then the features related to tool wear states are extracted from decomposed AE signals. Experimental results verified the feasibility of using the WPT method to extract features related to tool wear states in boring.

Keywords: acoustic emission, tool wear, wavelet packet transforms

1 INTRODUCTION

Tool wear monitoring plays a critical role in the automatic cutting process, in order to avoid damaging the workpiece, cutting tool and machine tools. Therefore, it is necessary to develop a simple, reliable and cost effective method for monitoring tool wear states [**1**]. Various methods used to monitor tool wear states have been proposed, but the acoustic emission (AE)-based method is one of the most effective. The major advantage of using AE signals to monitor the tool wear states is that the frequency range is much higher than that of the machining vibrations and environmental noises; moreover, the installation of the AE sensor does not interfere with the cutting operation. However, the main problem is how to effectively extract the features related to tool wear states from AE signals [**2**].

In the cutting processes, the AE signals are usually sensed by the transducers, are amplified and transmitted, and then sent to the computer via the analogue-to-digital (A/D) converter. The key to the problem is how to analyse AE signals using an effective tool. Various approaches have been used to analyse AE signals [**3**, **4**], such as the Fast Fourier transform (FFT) method. A disadvantage of the FFT method is that it provides a solution only in the frequency domain; it cannot be used in the time domain. Recently, the wavelet transform method has been proposed which is a significant new tool in signal analysis and processing. The wavelet transform method can be used in both the frequency and time domains. It can extract a large amount of information from the time domain at different frequency bands. Wavelet packets are particular linear combinations of wavelets, which form bases that retain many of the orthogonality, smoothness and location properties of parent wavelets. The wavelet packet transform (WPT) method can be used to decompose signals into different components in different time windows and frequency bands; these components can then be considered as features of the original signals. Wu and Du [**5**] have used the WPT method to process cutting force signals and extract some important features from the decomposed cutting force signals.

The objective of this paper is to use the WPT method to decompose AE signals and extract the features related to tool wear states from decomposed AE signals.

2 WAVELET PACKET TRANSFORMS

Given the signal $f(t)$, the discrete wavelet transform can be written as follows:

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

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where $h(t)$ and $g(t)$ are high-pass and low-pass filters derived from the wavelet function $\psi(t)$ and the scaling function $\phi(t)$ respectively, c_j and d_j are the wavelet coefficients and the scaling coefficients respectively and c_0 is the original signal.

Set

$$H\{\cdot\} = \sum_k h(k-2t)$$
$$G\{\cdot\} = \sum_k g(k-2t) \tag{2}$$

Combining both equations yields

$$c_j[f(t)] = H\{c_{j-1}[f(t)]\}$$
$$d_j[f(t)] = G\{c_{j-1}[f(t)]\} \tag{3}$$

Clearly, the detail signal $d_{j-1}[f(t)]$ is omitted in the discrete wavelet transform. Wavelet packet transforms retain these detail signals $d_{j-1}[f(t)]$; therefore, the wavelet packet transform is

$$c_j[f(t)] = H\{c_{j-1}[f(t)]\} + G\{d_{j-1}[f(t)]\}$$
$$d_j[f(t)] = G\{c_{j-1}[f(t)]\} + H\{d_{j-1}[f(t)]\} \tag{4}$$

Let $Q_j^i(t)$ is the ith packet on the jth resolution. The wavelet packet transform can then be computed using the following recursive algorithm:

$$Q_0^1(t) = f(t)$$
$$Q_j^{2i-1}(t) = HQ_{j-1}^i(t)$$
$$Q_j^{2i}(t) = GQ_{j-1}^i(t) \tag{5}$$

where $t = 1, 2, \ldots, 2^{J-I}$, $i = 1, 2, \ldots, 2^j$, $j = 1, 2, \ldots, J$; $J = \log_2 N$ and N is the data length.

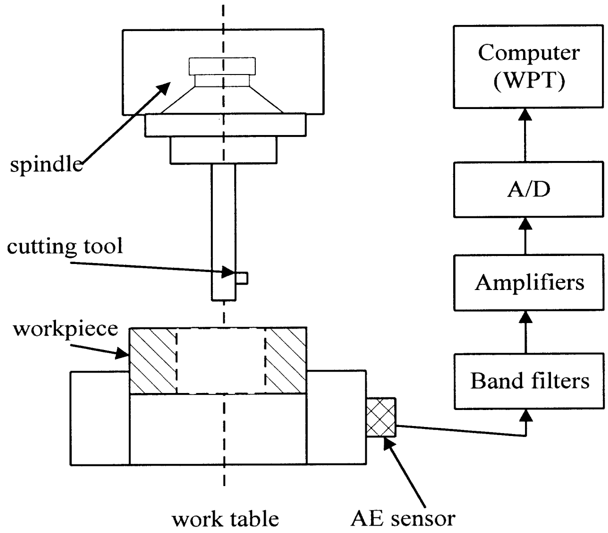

Fig. 1 Schematic diagram of the experimental set-up

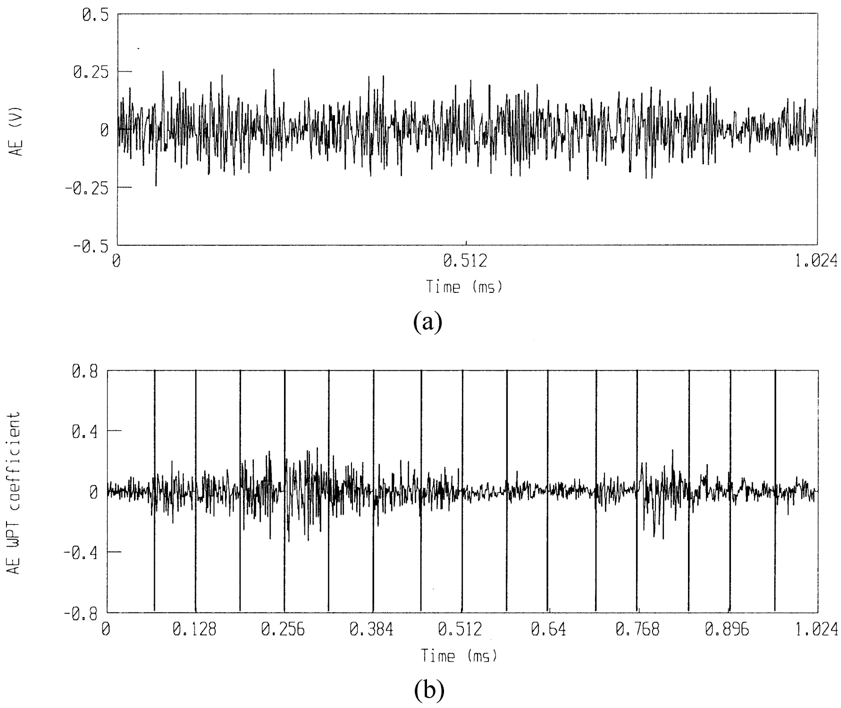

Fig. 2 (a) The continuous AE signals. (b) The decomposed results of continuous AE signals using WPT. Cutting speed, 30 m/min; feed rate, 0.2 mm/rev; depth of cut, 0.5 mm; workpiece material, 40Cr steel; tool material; high-speed steel, without coolant; tool wear, 0.26 mm

3 SIGNAL ANALYSIS AND FEATURES EXTRACTION

3.1 Experimental set-up

A schematic diagram of the experimental set-up is shown in Fig. 1. Cutting tests were performed on Machining Center Makino-FNC74-A20, a commercial piezoelectric AE transducer mounted on the worktable of the machine tools. During the experiments, the measured AE signals were amplified and passed through a band filter (high-pass at 50 kHz, low-pass at 1 MHz), before being sent to a personal computer via an A/D converter.

3.2 Signal analysis and features extraction

While analysing AE signals, it has been found that they contain some burst signals with high peak amplitudes. These burst signals are mainly related to chip breakage

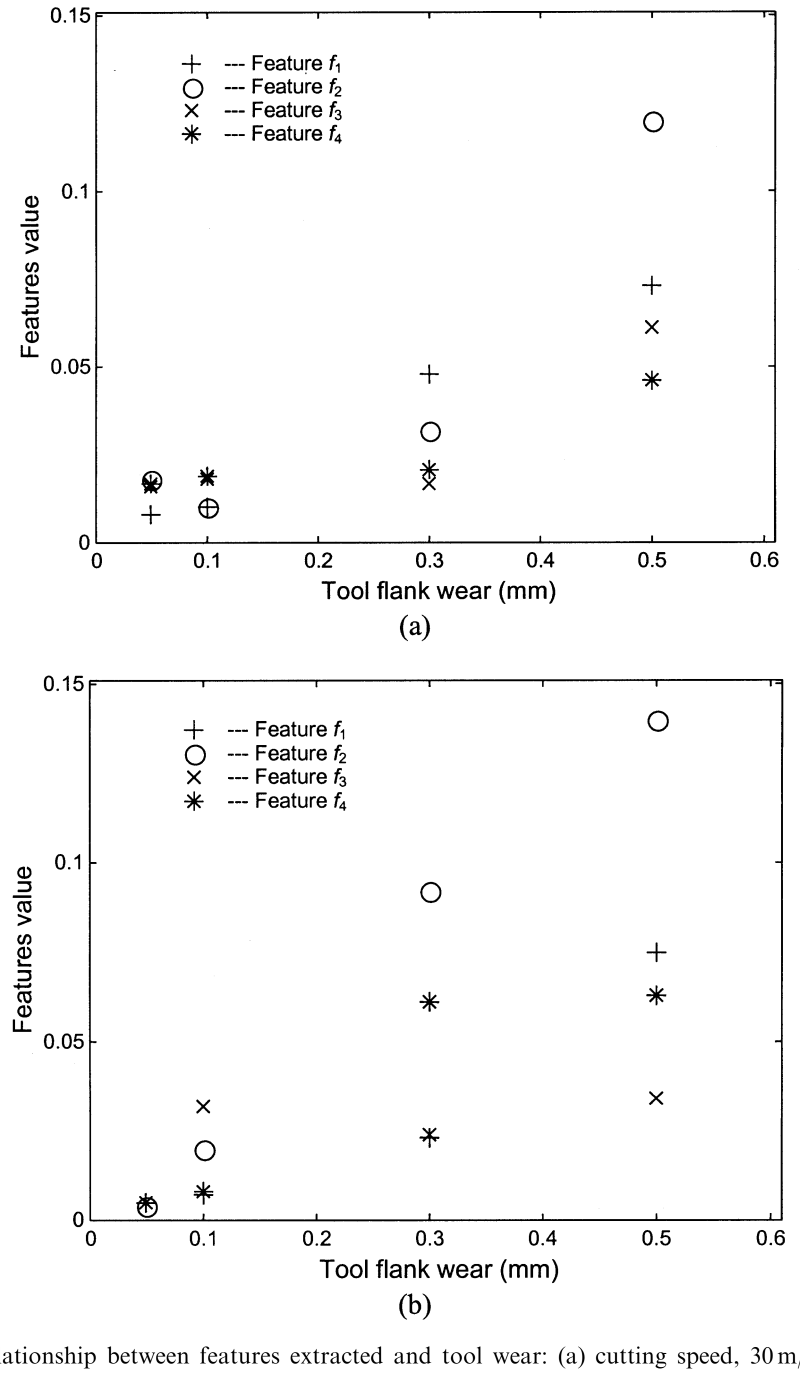

Fig. 3 The relationship between features extracted and tool wear: (a) cutting speed, 30 m/min; feed rate, 0.2 mm/rev; depth of cut, 0.5 mm; (b) cutting speed, 40 m/min; feed rate, 0.3 mm/rev; depth of cut, 1 mm; workpiece material, 40Cr steel; tool material, high-speed steel, without coolant

and so can be filtered out from the AE signals. The floating threshold method [6] has been shown to be effective in filtering these burst signals from the AE signals. The remaining AE signals are called continuous AE signals and are sensitive to tool wear states.

Friction between the workpiece and the cutting tool generates continuous AE signals, and is regarded as the most important source of continuous AE signals. According to experimental results [6], the r.m.s. of continuous AE signals is related to the cutting parameters (v, d) and tool flank wear, and can be expressed as follows:

$$AE_{\text{r.m.s.}} = F(K, v, d, w) \tag{6}$$

where K is the area density of contact points, v is the cutting speed, d is the depth of cut and w is the maximum flank wear.

The continuous AE signals contain complicated information on the cutting processes, which is important when considering how to extract the features of tool wear states from continuous AE signals. Figure 2a shows AE signals during boring at the maximum flank wear value of 0.26 mm. Figure 2b shows the decomposed results of AE signals for Fig. 2a using a wavelet packet transform. These decomposed results of the continuous AE signals provide information on the time domain constituent parts of the AE signals at the frequency bands. The r.m.s. values of the constituent parts of the AE signals in each frequency band represent the energy levels of the AE signals in the frequency bands. In Fig. 2b, the continuous AE signals are decomposed into 16 parts, the r.m.s. of each part R_i $(i = 1, 2, \ldots, 16)$ being regarded as a feature of the tool wear states. However, not all of these features are sensitive to tool wear states. According to the analysis of large amounts of data, only R_3, R_4, R_5 and R_7 are sensitive to the tool wear states. For the purpose of eliminating the effects of the cutting parameters v and f, vf is divided into the features above; the results are f_i $(i = 1, 2, \ldots, 4)$. In this paper, f_i values are taken as the final features used to monitor tool wear states. In order to verify whether the features above are sensitive to the tool wear states, some continuous AE signals were obtained in the given tool wear and the WPT method was used to analyse these signals in order to extract the features related to the tool wear states. Figure 3 shows the relationship between the features and the tool wear states under the different cutting conditions. From Fig. 3, it can be seen that the features are sensitive to the tool wear states. The tool wear states can be monitored using the above features extracted from the continuous AE signals using the WPT.

4 CONCLUSIONS

One of the most complex problems for AE-based monitoring of tool wear states is extraction of the signal features. In this paper, wavelet packet transforms are used to extract the features related to tool wear states from continuous AE signals in boring.

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