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Tool wear monitoring with wavelet packet transform–fuzzy clustering method

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Abstract

In the manufacturing systems such as flexible manufacturing system (FMS), one of the most important issues is to detect tool wear under given cutting conditions as accurately as possible. This paper develops a device for detecting acoustic emission (AE) signal form rotating tool with magnetofluid and presents a method of tool wear monitoring, the method consists of wavelet packet transform preprocessor for generating features from AE signal, followed by fuzzy clustering method (FCM) for associating the preprocessor outputs with the appropriate decisions. A wavelet packet transform is used to decompose AE signal into different frequency bands in time domain, the root mean square (RMS) values extracted from the decomposed signal of each frequency band were used as feature. Analyzing the above features, the features that are directly relation to tool wear are used as final monitoring features. According to boring tool wear grades, the tool wear states were divided into 'A','B','C' and 'D' classifications, the state 'D' is proposed to be used as the prediction of tool replacement. FCM was proposed to classify monitoring features automatically so as to recognize tool wear statutes. The experimental results indicate that the monitoring features had a low sensitivity to changes of the cutting conditions and FCM has a high monitoring success rate in a wide range of cutting conditions.

Keywords: Tool wear monitoring; Wavelet packet transform; Fuzzy clustering method; Acoustic emission; Tool replacement; Boring

1. Introduction

Flexible manufacturing systems (FMS) which employ automated machine tools for cutting operations require reliable process monitoring systems to overlook the machining operations. Among machine process variables monitored, tool wear 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 on-line tool wear condition monitoring strategies in this vitally important area. Due to the complexity of the metal cutting mechanism, a reliable commercial tool wear monitoring system is yet to be developed [1].

Various methods for tool wear monitoring have been proposed in the past, even though none of these methods were universally successful due to the complex nature of the machining processes. 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 [2]. Recent attempts have been concentrated on the development of methods which monitored the cutting process indirectly. Among indirect methods, AE is the most effective mean of sensing tool wear. The major advantage of using AE to monitor the tool condition is that frequency range of the AE signal is much higher than that of the machine vibrations and environmental noises and not interfere with the cutting operation. However, AE signals often have to be treated with additional signal processing schemes to extract the most useful information [3–5]. In the metal cutting process, AE is attributable to many course, such as elastic and plastic deformations, tool wear, tool breakage, friction, etc. If AE signal can effectively be analyzed, tool wear can be detected using AE signal. The AE signal is usually detected by transducers, then amplified and transmitted to counter, RMS voltmeter, spectrum analysis, etc. Among various

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approaches 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 resolution only in frequency domain and a very bad resolution in time domain so that it lose some signal information in time domain, it is only fitted to deal with stochastic stable signals. Recently, wavelet transform (WT) was proposed as a significant new tool in signal analysis and processing. It has been used to analyze tool failure monitoring signal [8–10]. WT has a good resolution in frequency and time domain synchronously, it can extract more information in time domain at different frequency bands. Wavelet packets are particular linear combinations of wavelets. They form bases which retain many of the orthogonal, smooth and locate properties of their parent wavelets. 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 are insensitive to the variation of process working condition and various noises [11]. The wavelet packet transform can decompose a 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 application of fuzzy logic pattern classification in tool condition monitoring has been reported [12,13]. Fuzzy clustering is the most important method in the application of the fuzzy pattern classification. Cluster analysis is the art of finding groups within data. Conventional clustering methods assign each object with a crisp border to a single cluster. Because of the vagueness of objects in many cases, data will be difficult for the conventional cluster methods to deal with them. This paper used fuzzy clustering method (FCM) to classify tool wear condition. The FCM, used in the individual clustering method called 'fuzzy ISODATA', which is one of the unsupervised classification methods, was first presented by Bezdek. It is also called the fuzzy c-means clustering algorithm. The use of fuzzy clustering for monitoring tool wear can identify the difference in wear states more realistically [14].

The objective of this paper is to introduce a method of online tool wear condition monitoring using wavelet packet and FCM. Wavelet packet transform of AE signal are used to obtain a set of monitoring features. Fuzzy clustering identifies the difference of tool wear states. This method eliminates the effect of cutting conditions in the result while making the classification. The experimental results show that the system with wavelet packet and FCM is feasible. The paper is structured as follows: Section 2 is a theoretical background of wavelet packet and FCM, Section 3 is AE signal source and the relationship between AE and tool wear, Section 4 is signal analysis and features extraction, Section 5 is experimental setup Section 6 is experimental results and tool replacement control and Section 7 contains conclusions.

2. Wavelet packet transform and fuzzy clustering method

2.1. Wavelet transform

An energy limited signal $f(t)$ can be decomposed by its Fourier transform $F(w)$, namely

$$f(t)=\frac{1}{2\pi}\int_{-\infty}^{+\infty}F(w)e^{iwt}\mathrm{d}t \tag{1}$$

where

$$F(w)=\int_{-\infty}^{+\infty}f(t)e^{-iwt}\mathrm{d}t \tag{2}$$

$f(t)$ and $F(w)$ are called as a pair of Fourier transform. Eq. (1) implies that $f(t)$ signal can be decomposed into a family that the harmonics e^{iwt} and the weighting coefficient $F(w)$ represent the amplitudes of the harmonics in $f(t)$. $F(w)$ is independent of time, it represents the frequency composition of a random process which is assumed to be stationary so that its statistics do not change with time. However, many random processes are essentially nonstationary such as vibration, AE, sound, and so on. If we calculate the frequency composition of a nonstationary in the usual way, the results are the frequency composition averaged over the duration of the signal so that it does not describe adequately the characteristics of the transient signal in the lower frequency.

In general, short-time Fourier transform (STFT) method is used in dealing with nonstationary. STFT has a short data window centered at time τ, (see Fig. 1). Spectral coefficients are calculated for this short length of data, the window is then moved to a new position and the calculation repeated. Assuming that an energy limited signal $f(t)$ can be decomposed by STFT, namely

$$G(w,\tau)=\int_{R}f(t)g(t-\tau)e^{-iwt}\,\mathrm{d}t \tag{3}$$

where $g(t-\tau)$ is called window function. If the length of the window is represented by time duration T, its frequency bandwidth is approximately $1/T$. Using a short data window means that the bandwidth of each spectral coefficient is of the order $1/T$ and is, therefore, wide. A feature of the STFT is that all spectral estimates have the same bandwidth. Clearly, STFT cannot obtain a high resolution in both the time and the frequency domains.

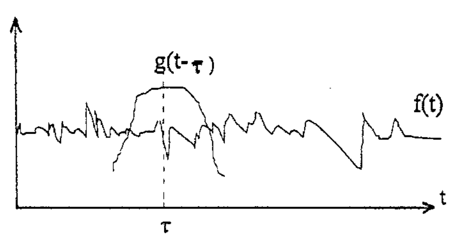

Fig. 1. An illustration of the STFT.

WT involves a fundamentally different approach. Instead of seeking to break down a signal into its harmonics, which are global functions that go on forever, the signal is broken down into a series of local basis functions called wavelets. Each wavelet is located at a different position on the time axis and is local in the sense that it decays to zero when sufficiently from its center. At the finest scale, wavelets may be very long. Any particular local features of a signal can be identified from the scale and position of the wavelets into which it is decomposed. The structure of a nonstationary signal can be analyzed in this way with local feature represented by close-packet wavelet of short length.

Given a time varying signal $f(t)$; WT consists of computing coefficient that is inner products of the signal and a family of wavelets. In a continuous wavelet transform (CWT), the wavelet corresponding to scale a and time location b is

$$\psi_{a,b}=\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right) \qquad a,b\in R,\ a\neq 0 \tag{4}$$

where a and b are the dilation and translation parameters, respectively.

The CWT was defined as follows

$$w_f(a,b)=\int x(t)\psi^*_{a,b}(t)\mathrm{d}t \tag{5}$$

where '*' denotes the complex conjugation.

With respect to $w_f(a,b)$ a signal $f(t)$ can be decomposed into

$$f(t)=\frac{1}{c_\psi}\int_{-\infty}^{+\infty}\int_{0}^{+\infty} w_f(a,b)\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)\mathrm{d}a\mathrm{d}b \tag{6}$$

where c_ψ is a constant depending on the base function. Similar to the Fourier transform, $w_f(a,b)$ and $f(t)$ constitute a pair of WT. Eq. (6) implies that WT can be considered to $f(t)$ signal decomposition. Compared to the STFT, the WT is a time–frequency function which describes the information of $f(t)$ in various time windows and frequency bands. when $a=2^j$, $b=k2^j$, j, $k\in Z$, the wavelet are in this case.

$$\psi_{j,k}=2^{-\frac{j}{2}}\psi(2^{-j}t-k) \tag{7}$$

The discrete wavelet transform (DWT) is defined

$$c_{j,k}=\int f(t)\psi^*_{j,k}(t) \tag{8}$$

where $c_{j,k}$ is defined as wavelet coefficient, it may be considered 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

$$\phi_{j,k}=2^{-\frac{j}{2}}\phi\left(\frac{t-2^jk}{2^j}\right) \tag{9}$$

set

$$d_{j,k}=\int f(t)\phi^*_{j,k}(t)\mathrm{d}t \tag{10}$$

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 $c_{j,k}$ ($j=1,\ldots,J.$) and scaling coefficients $d_{j,k}$ given by

$$c_{j,k}=\sum_n x[n]h_j[n-2^jk] \tag{11}$$

and

$$d_{j,k}=\sum_0 x[n]g_j[n-2^jk] \tag{12}$$

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

$$c_{j+1,k}=\sum_n g[n-2k]d_{j,k} \tag{13}$$

$$d_{j+1,k}=\sum_n h[n-2k]d_{j,k} \tag{14}$$

In fact, it is well known that the structure of computations in a DWT is exactly an octave-band filter [13]. The terms g and h are high-pass and low-pass filters derived from the analysis wavelet $\psi(t)$ and the scaling function $\phi(t)$.

2.2. Wavelet packet transform

Wavelet packets are particular linear combinations of wavelets. They form bases which retain many of the orthogonality, smoothness and location properties of their parent wavelets [14]. The coefficients in the linear combinations are computed by a factored or recursive algorithm, with the result that expansions in wavelet packet bases have low computational complexity.

The DWT can be rewritten as follows.

$$\begin{aligned} &c_j[f(t)]=h(t)^*c_{j-1}[f(t)]\\ &d_j[f(t)]=g(t)^*c_{j-1}[f(t)]\\ &c_0[f(t)]=f(t)\end{aligned} \tag{15}$$

Set

$$H\{\cdot\}=\sum_k h(k-2t) \tag{16}$$

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

then equation can been written as follows.

$$\begin{aligned} &c_j[f(t)]=H\{c_{j-1}[f(t)]\}\\ &d_j[f(t)]=G\{c_{j-1}[f(t)]\}\end{aligned} \tag{17}$$

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

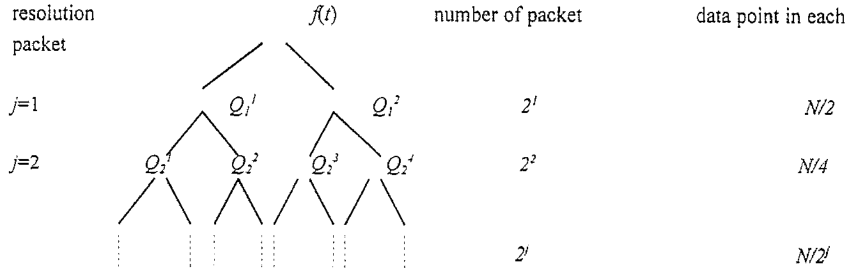

Fig. 2. The wavelet packet transform tree.

$$c_j[f(t)]=H\{c_{j-1}[f(t)]\}+G\{d_{j-1}[f[(t)]]\} \tag{18}$$
$$d_j[f(t)]=G\{c_{j-1}[f[(t)]]\}+H\{d_{j-1}[f(t)]\}$$

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

$$Q_0^1(t)=f(t)$$
$$Q_j^{2i-1}(t)=HQ_{j-1}^i(t) \tag{19}$$
$$Q_j^{2i}(t)=GQ_{j-1}^i(t)$$

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

The wavelet packet transform can be presented as Fig. 2.

2.3. Fuzzy clustering method

In general, there are two FCMs used in tool wear monitoring. One is the technique based on the fuzzy relationship between patterns and the other is the fuzzy c-means (fuzzy ISODATA) algorithm. In the paper, we will focus on the fuzzy c-means method. In the approach, the aim in clustering is to determine the cluster centers, which are representative values of features corresponding to the classified categories. Once clustering centers are determined at the learning stage, the classification is made by the comparison of the incoming pattern and each clustering center.

Let $X=\{X_1,X_2,\ldots,X_n\}\subset R$, where each $X_i=(x_{i1},x_{i2},\ldots,x_{is})\in R$ is a feature vector; x_{ij} is the jth feature of individual x_i. For each integer c, $2\le c<n$, let V_{cn} be the vector space of $\mathbf{c}\times\mathbf{n}$ matrices with entries in $[0,1]$, and let u_{ij} denote the ijth element of any $U\in V_{cn}$. The function $u_i{:}X\to[0,1]$ becomes a membership function and is called a fuzzy subset in X. Here $u_{ij}=u_i(x_j)$ is called the grade of membership of x_j in the fuzzy set u_i. In the space of samples, we suppose that there are n samples, which can be divided into c classes. Consider the following subset of V_{cn}.

$$M_{fc}=\left\{U\in V_{cn}\left|u_{ij}\in[0,1]\forall i,j;\ \sum_{i=1}^{c}u_{ij}=1\forall j;\sum_{i=1}^{c}u_{ij}>0\forall i\right.\right\} \tag{20}$$

Each $U\in M_{fc}$ is called a fuzzy c-partition of X; M_{fc} is the fuzzy c-partition space associated with X. For any real number $m\in[1,5]$, define the real-valued functional $J{:}M_{fc}\times L_c\to R$ by

$$J(\mathbf{U},\boldsymbol{V})=\sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m\|x_k-v_i\|^2 \tag{21}$$

$1\le m<\infty$, and usually $m=2$ where $\mathbf{U}=\{u_{ik}\}$ is the membership function, with $u_{ik}\in[0,1]$, which denotes the degree of membership of the kth pattern and ith cluster centers; $\boldsymbol{V}=\{v_1,v_2,\ldots,v_c\}$ is a vector of c cluster. These v_i are interpreted as clusters defined by their companion $\mathbf{U}$ matrix, and play a fundamental role in our development. The functional J is a weighted, least squares objective function. In order to obtain the optimum fuzzy partition, this objective function must be minimized, i.e.,

$$\text{minimize } \{J(\mathbf{U},\boldsymbol{V})\} \tag{22}$$

above equation optimal solution are that

$$u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\|X_k-V_i\|}{\|X_k-V_j\|}\right)^{2/(m-1)}},\forall i,k \tag{23}$$

$$V_i=\frac{\sum_{k=1}^{n}\left(u_{ik}\right)^m X_k}{\sum_{k=1}^{n}\left(u_{ik}\right)^m},\forall i \tag{24}$$

The following algorithms were used: (1) guess $\mathbf{U}$; (2) set c and m; (3) calculate cluster centers V_i; (4) calculate U_{ik}, update bU to U^*; (5) if $\max_{i,k}\{u_{ik}{}^*-u_{ik}\}=\le\varepsilon$, stop, otherwise, reliable $U^*\to\mathbf{U}$ and return to (3). Suppose that under a given cutting condition, a clustering center was determined by the features of training data sets. Then all subsequent observations can be classified by using Eq. (23). That is

$$u_{k0}=\frac{1}{\sum_{j=1}^{c}\left(\frac{\|X_0-V_i\|}{\|X_0-V_j\|}\right)^{2/(m-1)}},\forall i,k \tag{25}$$

where u_{k0} is the fuzzy grade of the current observation being assigned to kth wear state category and X_0 is the current observation.

The above method has been applied to monitor drilling wear [15]. The application results show that the fuzzy c-means method is more direct and easier to implement than the clustering technique discussed previously. With the integration of fuzzy sets, FCMs become very powerful for the classification of the pattern situated between clusters. They are particularly suitable for handling the clustering of wear states, which can be regarded as linguistic variables. But, the above method is effective only when the cutting conditions are kept constant, which limit the application of the method at the workshop level.

3. Acoustic emission signal and tool wear

3.1. Sources of acoustic emission

Research has shown that AE, which refers to stress waves generated by the sudden release of energy in deforming materials, has been successfully used in laboratory test to detect tool wear and fracture in single point turning operations [16]. Dornfeld [17] pointed out the possible sources of the AE in metal cutting: (a) plastic deformation during the cutting process in the workpiece; (b) plastic deformation in the chip; (c) friction contact between the tool flank face and the workpiece resulting in flank wear; (d) friction contact between the tool rank face and the chip resulting in crater wear; (e) collisions between chip and tool; (f) chip breakage; (g) tool edge chipping. AE sources in boring are shown as Fig. 3.

Research results have shown that friction and plastic deformation have comparable importance with regard to the generation of the continuous AE. Because the amplitude of the signals from the workpiece is reduced during wave transfer from workpiece to tool possibly by reflection at the interface, the friction between workpiece and tool can be regarded as the most important source of the continuous AE [18]. In the present investigation, we verified above results, therefore, we can consider the friction between workpiece and tool as the essential source of the AE.

3.2. The relationship between AE and cutting condition

The relationship between the RMS of continuous AE and the cutting parameters and tool wear can be established by experiment method. Results have shown that RMS is proportional to v_c a_p, tool flank wear VB, respectively, but it is independent on feed rate. The results are presented in Figs. 4–7.

According to above results, the RMS of AE can be calculated from the machining and tool wear parameters:

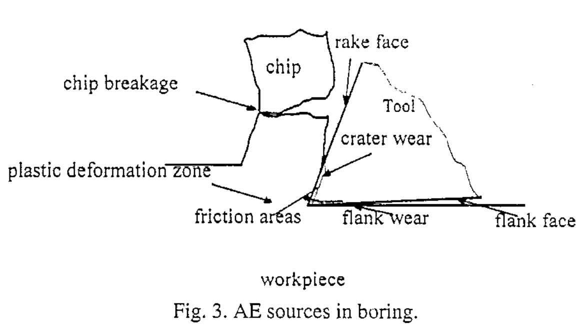

Fig. 3. AE sources in boring.

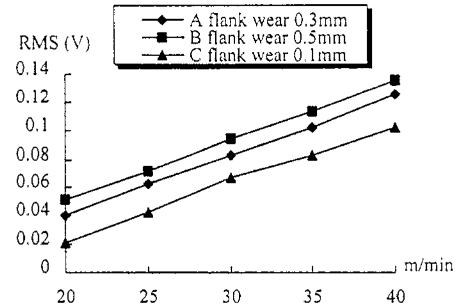

Fig. 4. The relationship of the RMS of AE and cutting speed, feed rate: 0.2 mm/rev, depth of cut: 0.5 mm.

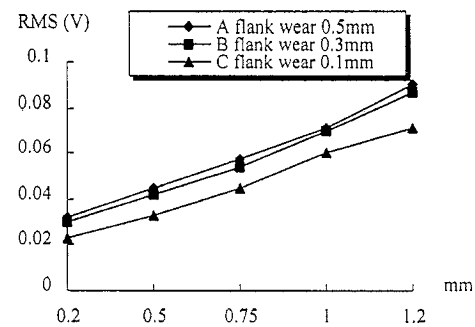

Fig. 5. The relationship of the RMS of AE and the depth of cut, cutting feed: 25 m/min, feed rate: 0.2 mm/rev.

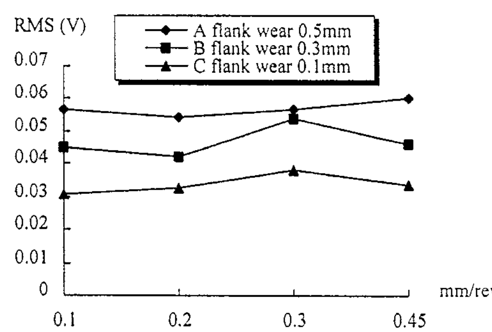

Fig. 6. The relationship of the RMS of AE and feed rate, cutting feed: 25 m/min, depth of cut: 0.75 mm.

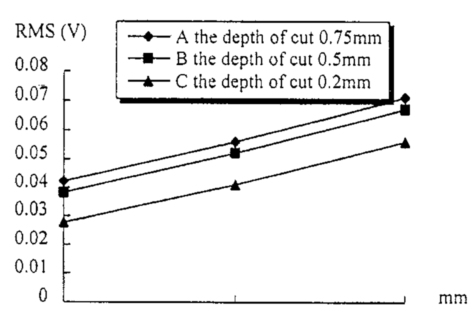

Fig. 7. The relationship of the RMS of AE and tool flank wear, cutting feed: 25 m/min, feed rate: 0.2 mm/rev.

$$\mathrm{RMS} = K v_c a_p \mathrm{VB} \qquad (26)$$

where K is the area density of contact points, v_c the cutting speed, a_p the depth of cut, VB the wear land. K depends on the structure of the surface, which remains nearly constant with increasing wear.

3.3. AE signal pretreatment

During the experiment, the friction between workpiece and tool generates a continuous AE signal, it gives information on tool wear. However, the experimental results show that sometimes burst-signals with high peak amplitudes interfere with the continuous AE signal. In fact, these burst signals relate to the chip breakage and give information on the chip behavior, but not on tool wear. Therefore, it is essential to filter out these bursts from the continuous AE signal for a reliable tool wear monitoring before further analysis is performed. The floating threshold value is defined, which is higher than the mean signal level. The constituents are due to chip impact and breakage exceeding this threshold are not considered as the determination of the mean signal level are filtered out from the continuous AE signal. The signal constituents below the threshold represent the continuous AE, which will be analyzed by follow signal processing method.

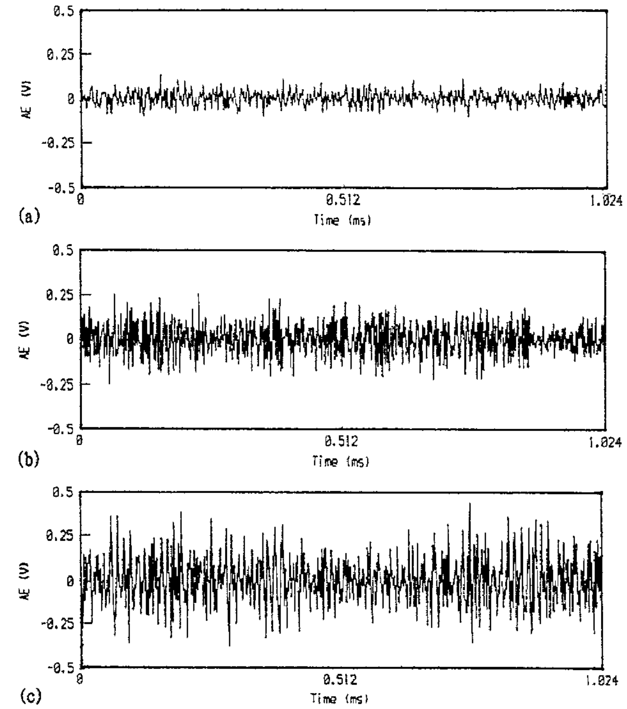

Fig. 8. The AE signal in a typical tool wear cutting process, cutting speed: 30 m/min, feed rate: 0.2 mm/rev, depth of cut: 0.5 mm, work material: 40 Cr steel, tool material: high-speed-steel, without coolant. (a) VB = 0.06 mm; (b) VB = 0.26 mm; (c) VB = 0.62 mm.

4. Signal analysis and features extraction

4.1. Signal analysis

In monitoring of tool wear, AE signals monitored contain complicated information on the cutting processing. To ensure the reliability of tool monitoring system, 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 signals methods. Therefore, it is ideal to use the wavelet packets as the extracted features [19,20].

Fig. 8 shows a typical cutting process experiment in boring. The AE signal in time domain are 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, cutting process is stable. As the tool wear increases progressing, the magnitudes of the AE increase.

Fig. 9 shows the AE signal in frequency domain for experiment shown in Fig. 8. It can be seen that the magnitude of AE in frequency domain are sensitive to the change of tool states.

Fig. 10 shows the decomposing results of AE signal for the experiment shown in Fig. 8 through the wavelet packet decomposition. Fig. 10 represents 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

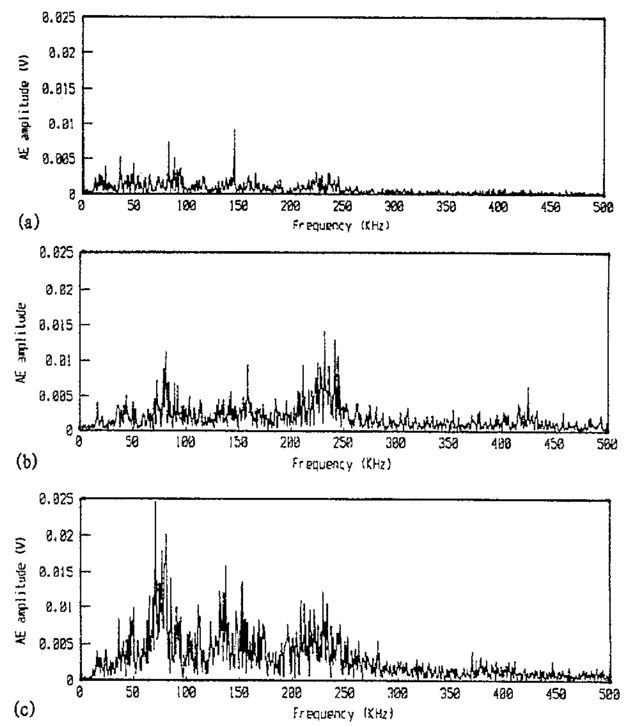

Fig. 9. The power spectral density of AE signal in a typical tool wear cutting process.

such as the time domains constituent part of the AE signalat the frequency band. The mean values of the constituent parts of the AE of each frequency band can represented the energy level of the AE in the frequency band.

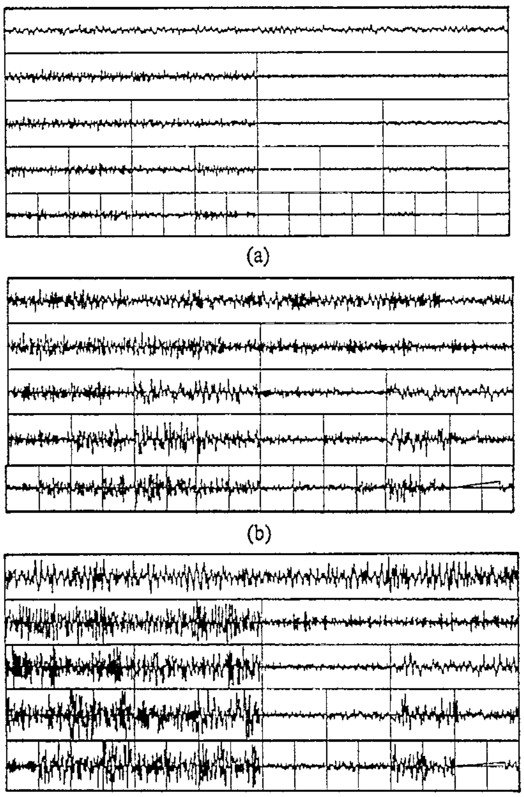

Fig. 10. The composing results of AE by wavelet packet transformation.

4.2. Feature extraction

In fuzzy c-mean method applications, 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 were not dependent on features. So we hope that the selected features should show a low sensitivity to change of the cutting conditions, such as tool wear monitoring system could be suitable for a wide range of machining conditions.

According to the above discussion, the RMS in each frequency band was used to describe the features of different tool condition. The selected features were summarized as follows.

n_1 = RMS of wavelet coefficient in the frequency band [0, 62.5] KHz
n_2 = RMS of wavelet coefficient in the frequency band [62.5, 125] KHz
⋮
n_{16} = RMS of wavelet coefficient in the frequency band [937.5, 1000] KHz

But above all of features are insensitive to tool wear. According to a large mounts of data analysis, we found that n_3, n_4, n_5, n_6, n_7, n_8, n_{13} are sensitive to tool wear, Figs. 11 and 12 showed two typical examples, and the above features are

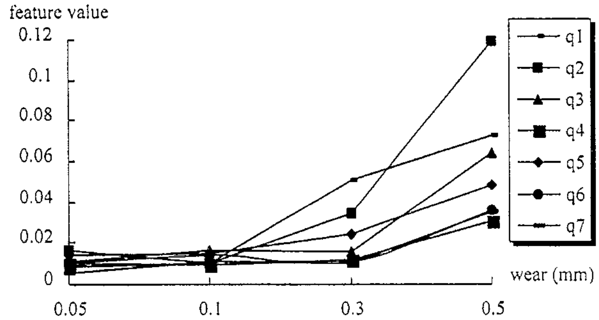

Fig. 11. The relationship between features extracted and tool wear, cutting speed: 30 m/min, feed rate: 0.2 mm/rev, depth of cut: 0.5 mm, work material: 40 Cr steel, tool material: high-speed-steel, without coolant.

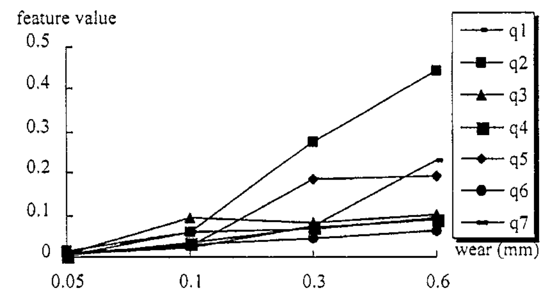

Fig. 12. The relationship between features extracted and tool wear, cutting speed: 40 m/min, feed rate: 0.3 mm/rev, the depth of cut: 1 mm, work material: 40 Cr steel, tool material: high-speed-steel, without coolant.

replaced by q_1, q_2, q_3, q_4, q_5, q_6, q_7, respectively, and those will be used to classify tool wear states.

According to Eq. (26), it shows 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 ($i = 1,2,\ldots,7$) and get new q_i value, the new q_i value are final monitoring features.

5. Experimental set-up

5.1. AE signal transmission

It is known that AE is considered as one of the most method for tool monitoring. One of the main obstacles in its application is how to detect the AE signals from rotating tool, such as Machining Center for boring and milling. Recently, transmitting AE signals of rotating tool to the AE sensor by liquid medium is one of the most effective method, which do not affect the machining process. The authors have studied the transmitted property for several liquids [21]. The results show that AE wave attenuation through magnetofluid with magnetic field is the smallest. Based on the above discussions, the authors had developed a device for detecting AE signal from rotating tool with magnetofluid. The device has been applied to FNC 74-A20 machining center. Its structure is shown as Fig. 13. The experiment results show that above structure can approve AE signal tool monitoring sensitivity.

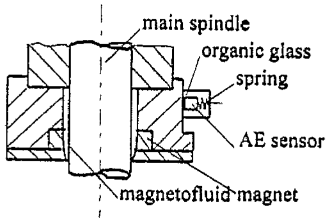

Fig. 13. Apparatus for detecting AE though magnetofluid.

The reason is that this structure has many advantages: firstly, it is able to obtain high signal/noise ratio for tool monitoring; secondly, the magnetofluid can be kept at a suitable place in machining tool spindle without disturbing the cutting process; thirdly, it can lengthen the signal exiting time to make the signal sampling and processing simple.

5.2. Experimental set-up

The schematic diagram of the experimental set-up is shown in Fig. 14. Cutting tests were performed on Machining Center Makino-FNC74-A20. In the experiments, a commercial piezoelectric AE transducer was mounted on spindle. AE signals were transducer by magnetic fluid between spindle and tool. During the experiments, the monitored AE signals were amplified, high-passed at 50 KHz, low-passed at 1 MHz, and then were sent via an A/D converter to a personal computer (AST/486).

A successful tool wear detecting method must be sensitive to tool wear change and insensitive to the variation of cutting conditions. Hence, cutting tests were conducted at different conditions to evaluate the performance of the proposed method. The tool parameters and cutting conditions were listed in Table 1.

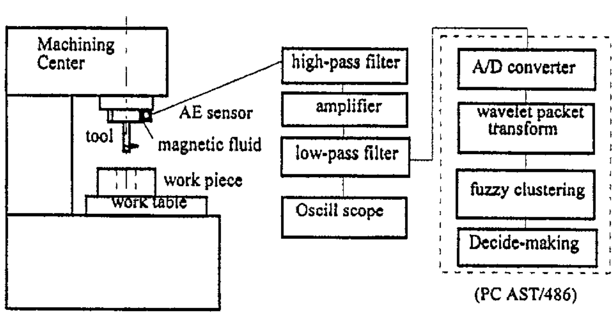

Fig. 14. Schematic diagram of the experimental set-up.

Table 1
Experimental conditions for the boring example

Tool	bore tool material: high-speed steel
	tool geometry: $\gamma=10°$, $\alpha=8°$, $\lambda=-2°$, $\chi=90°$, $\kappa=12°$, and $r=0.3$ mm
Cutting Condition:	cutting speed: 20 ~ 40 (m/min)
	feed rate: 0.1, 0.2, 0.3 (mm/rev)
	depth of cutting: 0.1, 0.2, 0.5, 0.75, 1.0, 1.25 (mm) without coolant
Workpiece	45# quenching-and-tempering steel

6. Experimental results and tool replacement

6.1. Experimental results

For above feature sets, clustering centers were calculated by successively applying Eqs. (23) and (24) with the optimization procedure using weighting exponent $m=2$. Another parameter to be decided is the cluster number c. The number of clusters c, should be determined according to process mechanism as well as one's needs. That is, understanding how many clusters are present in the unlabeled data sets should be done beforehand. In this research, tool wear state was classified into four classifications including: initial wear, normal wear, acceptable wear, severe wear, i.e., A, B, C and D. Based on tool flank wear, these wear states are summarized in Table 2. The resulting cluster centers of training data sets were calculated and listed in Table 3.

Before doing any classification, one must first find the grades of membership corresponding to each individual wear states. In the following example, Eq. (25) is used to calculate the grades of membership of test data, based on the above clustering centers, Table 4 shows the fuzzy membership grade of part test data, cutting conditions: cutting speed: 30 m/min, feed rate: 0.2 mm, depth of cutting: 0.5 mm. Fig. 15 shows the grades of membership for four different boring states A, B, C and D.

A total of 50 cutting tests corresponding to variable cutting states were collected. Thirty samples were randomly picked as learning samples; the remaining samples were used as the test samples in the classification phase. The classification results are listed in Table 5. From Table 5, overall performance is over 90%, tool wear condition monitoring system have a high success rate. Thus, the features selection is successful. It is shows that the tool wear condition monitoring system meets the need of application.

Table 2
Tool wear states classification

Tool condition	Flank wear	Classification
Initial wear	$0<$ wear <0.2mm	A
Normal wear	$0.2<$ wear <0.4mm	B
Acceptable wear	$0.4<$ wear <0.6mm	C
Severe wear	$0.6<$ wear	D

Table 3
Normalized cluster center centers of training features

	A	B	C	D
q_1	0.1506	0.1809	0.2074	0.2682
q_2	0.0367	0.0406	0.0431	0.0487
q_3	0.0935	0.1043	0.1096	0.1139
q_4	0.0599	0.0672	0.0767	0.0871
q_5	0.1715	0.2115	0.2402	0.2605
q_6	0.1038	0.1362	0.1612	0.1744
q_7	0.0573	0.0860	0.0987	0.1154

Table 4
The grades of membership of test data

Test number	μ_1 (A)	μ_2 (B)	μ_3 (C)	μ_4 (D)
1	0.9701	0.0276	0.0012	0.0011
2	0.7832	0.2012	0.0123	0.0033
3	0.0256	0.8341	0.1202	0.0201
4	0.0201	0.8014	0.1567	0.0218
5	0.0192	0.5217	0.2437	0.1962
6	0.0164	0.4413	0.3674	0.1749
7	0.0152	0.3432	0.4672	0.1744
8	0.0123	0.2023	0.5631	0.2223
9	0.0113	0.1089	0.6192	0.2606
10	0.0101	0.0962	0.6452	0.2485
11	0.0092	0.0812	0.6812	0.2284
12	0.0073	0.0715	0.4725	0.4508
13	0.0052	0.0478	0.4127	0.5343
14	0.0037	0.0545	0.3671	0.5747
15	0.0010	0.0278	0.3123	0.6589
16	0.0009	0.0178	0.2561	0.7257
17	0.0005	0.0081	0.1754	0.8160
18	0.0003	0.0016	0.1103	0.8878
19	0.0002	0.0007	0.0023	0.9936

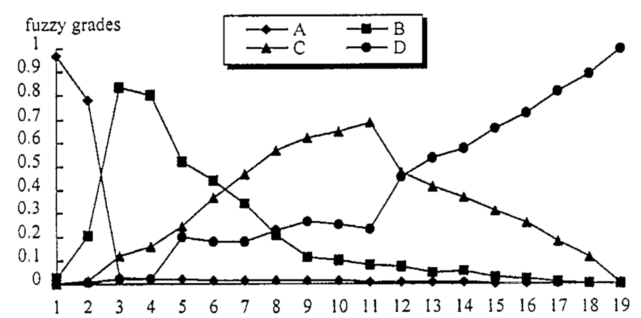

Fig. 15. Grades of membership for different boring states.

Table 5
Classification results of test samples

Tool wear performance condition	Recognizable rate (%)	Overall (%)
A	82	
B	89	90.25
C	92	
D	98	

6.2. Tool replacement control

It is known that one of the main objectives of detecting tool wear states is to provide the criterion for replacing tools. During practical application, we are interested only in noticeable changes of the tool wear states. According to detected tool wear states, we are able to decide if tool should be replaced. The above method can detect tool wear states according to previous data and results. For boring operation, on-line monitoring can be conducted by calculating the fuzzy grade of the current observation, the tool replacement decision is made when the fuzzy grade of 'D' of the current observation is close to 1.

In general, the rule for replacing is suggested as follows: if grade of membership of 'D' > 0.8 then replace the bore. Such as Table 4, test number 17 as the example, the grades of membership of test data is as follows: 'A' = 0.0005, 'B' = 0.0081, 'C' = 0.1754, 'D' = 0.8160. The high grade of membership of 'D' implies severe wear of the bore and the tool should be replaced.

7. 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 AE information. Several features were derived from wavelet packet transform, and the optimal features selected were sensitive to tool flank wear. Fuzzy ISODATA method provides more realistic classification for tool wear states.

The results can be summarized as follows.

(1) One of the main obstacles in AE application is how to detect the AE signals from rotating tool. Transmitting AE signals of rotating tool to the AE sensor by liquid medium is one of the most effective methods. The authors have studied the transmitted property for several liquids. The results showed that AE wave attenuation through magnetofluid with magnetic field is the smallest. Based on the above result, a device for detecting AE signal from rotating tool with magnetofluid has been developed. The experimental result showed that the above structure can approve AE signal tool monitoring sensitivity.

(2) The wavelet packet transform is a powerful tool for on-line monitoring of tool wear. It can capture improvement features of the sensor signal, namely, features are sensitive to the change of tool wear condition, but are insensitive to the variation of process working conditions and various noises. The wavelet packet transform decomposes AE signal into components in different time windows and frequency bands. The components which contain the principle components of the original signal are defined as objection of feature selected.

(3) The RMS of wavelet coefficient of the components selected can be considered as the monitoring features, the pretreated monitoring features have low sensitivity to changes in the process variables. The feature extracted with wavelet packet transform can be implemented real time since wavelet packet transform requires only a small amount of computation.

(4) Pattern recognition using the fuzzy ISODATA algorithm has been successfully incorporated into monitoring of the wear states of bore. The detection of the membership grade of the wear state 'D' was proposed as a control variable of bore replacement.

In short, the integrated wavelet packet transform and fuzzy c-mean analysis can enable tool wear condition monitoring system to have a high monitoring success rate over a wide range of cutting condition.

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