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On-line tool condition monitoring system with wavelet fuzzy neural network

LI XIAOLI, YAO YINGXUE and YUAN ZHEJUN

PO Box 422. Mechanical Engineering Department, Harbin Institute of Technology, Harbin, 150001, Peoples Republic of China

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In manufacturing systems such as flexible manufacturing systems (FMS), one of the most important issues is accurate detection of the tool conditions under given cutting conditions. An investigation is presented of a tool condition monitoring system (TCMS), which consists of a wavelet transform preprocessor for generating features from acoustic emission (AE) signals, followed by a high speed neural network with fuzzy inference for associating the preprocessor outputs with the appropriate decisions. A wavelet transform can decompose AE signals into different frequency bands in the time domain. The root mean square (RMS) values extracted from the decomposed signal for each frequency band were used as the monitoring feature. A fuzzy neural network (FNN) is proposed to describe the relationship between the tool conditions and the monitoring features; this requires less computation than a back propagation neural network (BPNN). The experimental results indicate the monitoring features have a low sensitivity to changes of the cutting conditions and FNN has a high monitoring success rate in a wide range of cutting conditions; TCMS with a wavelet fuzzy neural network is feasible.

Keywords: Tool condition monitoring, wavelet transform, fuzzy neural network, AE signal, drilling

1. Introduction

In recent years, one of the most important developments has been the trend towards cost-savings in the automated manufacturing environment; an effective method is to improve product quality and to reduce production time. Thus, a challenging question is posed in relation to the reliability and applicability of tool condition monitoring systems such that high availability levels of the sophisticated manufacturing systems in conjunction with high quality levels of manufactured components can be achieved.

From a process automation viewpoint, a sensing system must therefore be devised to detect the progress of tool condition during cutting operation so that tool failures can be identified and replaced in time (Li Dan and Mathew, 1990). A fair amount of research has been devoted to the detection of tool failure. The techniques reported include the use of optics, electrics, force, torque, power and current. The most common techniques in the industrial machining environment are acoustic emission (AE) and current (Byrne *et al*., 1995). In recent years AE sensors designed for detecting tool failure have been very successful. The major advantage of using AE to monitor the tool condition is the frequency range of the AE signal is much higher than the frequency of machine vibrations and environmental noises, so it does 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 (Iwata and Moriwaki, 1977; Souquet *et al*., 1987; Liang and Dornfeld, 1989).

Spectral analysis such as the fast Fourier transform (FFT) is the most commonly used signal processing techniques in tool condition monitoring systems. A disadvantage is that it has a good solution only in the frequency domain and a very bad solution in the time domain, so it loses some signal information in the time domain; it is only fitted to process stable stochastic signals. Wavelet transforms have recently been proposed as a significant new tool in signal analysis and processing. It has been used to analyse tool failure monitoring signals (Tansel *et al*., 1993; Kasashima *et al*., 1995; Tansel *et al*., 1995). The wavelet transform has a good solution in the frequency domain and in the time domain; synchronously it can extract more information in the time domain at different frequency bands.

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Moreover, wavelet transformations require less computation than FFTs (Daubechies, 1988, 1990; Cody, 1992). Hence wavelet transforms are fitted to process AE signal with an unstable stochastic signal so as to extract the signal features in relation to tool conditions.

Neural networks have recently been applied to tool condition monitoring. Neural networks are composed of simple processing elements, richly interconnected. These networks can be trained to recognize arbitrary relations between sets of input–output pairs by adjusting the weight of the interconnections. Generally, the most commonly used neural network in manufacturing-related research is the back propagation neural network (BPNN). However, BPNN needs to train for a long time, so its application is limited. We investigate the neural network with fuzzy inference; it can meet the needs of the actual application (i.e. real time) because of its fast learning capability (Dornfeld, 1990; Burke and Rangwala, 1991; Blanco *et al.*, 1995).

We propose a new drilling condition monitoring method based on the wavelet transform and a fuzzy neural network. Wavelet transformation of the AE signal is used to obtain a set of monitoring features. The fuzzy neural network is developed in order to describe the relationship between the tool condition and the monitoring features. The experimental results show the feasibility of a tool condition monitoring system (TCMS) with wavelet fuzzy neural network. Section 2 provides theoretical background on the wavelet transform and fuzzy neural networks. Section 3 describes the experimental set-up and results. Section 4 is the conclusions.

2. Wavelet transform and fuzzy neural network

2.1. *Wavelet transform*

We define a square integral function $\psi(t)$ (namely $\psi(t) \in L^2(R)$) as a family of functions, which satisfy the following equation:

$$\int_{-\infty}^{\infty} \frac{|\psi(w)|^2}{|w|} \mathrm{d}w < \infty \tag{1}$$

Assuming

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \qquad a, b \in R,\ a \neq 0 \tag{2}$$

$\psi_{a,b}(t)$ is defined as a continuous wavelet; $\psi_{a,b}(t)$ represents the family of wavelet obtained from the single $\psi(t)$ function by dilations and translations, where a and b are the dilation and translation parameters, respectively. The parameter a is related to the frequency. For small absolute values of a, the expression gives narrow versions of the original function and corresponds to a high frequency range; for large absolute values of a, the expression becomes large and corresponds to low frequencies. The parameter corresponds to the position of the family of functions (Tansel *et al.,* 1993). According to this discussion, the wavelet transform is essentially different from the Gobor transform.

If $f(t) \in L^2(R)$, define the continuous wavelet transform as below:

$$w_f(a, b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\ \overline{\psi\left(\frac{t-b}{a}\right)} \mathrm{d}t \tag{3}$$

where $\langle \cdot, \cdot \rangle$ is the inner product and $\overline{\psi\left(\frac{t-b}{a}\right)}$ is the complex conjugation of $\psi\left(\frac{t-b}{a}\right)$. To work with discrete signals, the discrete wavelet transform is often used. The discrete wavelet transform is defined as follows:

$$C_{j,k} = \int_{-\infty}^{\infty} f(t)\ \overline{\psi_{j,k}(t)} \mathrm{d}t \qquad j, k \in Z \tag{4}$$

where

$$\psi_{j,k}(t) = \frac{1}{\sqrt{2^j}} \psi\left(\frac{t - 2^j k}{2^j}\right) \tag{5}$$

the wavelet coefficients $c_{j,k}$ are thought of as a time–frequency map of the original signal $f(t)$.

In terms of the relationship between the wavelet function $\psi(t)$ and the scaling function $\phi(t)$, namely:

$$|\hat{\phi}(w)|^2 = \sum_{j=-\infty}^{\infty} |\hat{\psi}(2^j w)| \tag{6}$$

the discrete scaling function corresponding to the discrete wavelet function is as follows:

$$\phi_{j,k}(t) = \frac{1}{\sqrt{2^j}} \phi\left(\frac{t - 2^j k}{2^j}\right) \tag{7}$$

It is used to discretize the signal; the sampled values are defined as the scaling coefficients $d_{j,k}$:

$$d_{j,k} = \int_{-\infty}^{\infty} f(t) \overline{\phi_{j,k}(t)} \mathrm{d}t \tag{8}$$

when the resolution $j > 1$; the scaling coefficients and the wavelet coefficients are obtained as follows:

$$d_{j+1,k} = \sum_{-\infty}^{\infty} h(i - 2k) d_{j,k} \tag{9}$$

$$c_{j+1,k} = \sum_{-\infty}^{\infty} g(1 - 2k) d_{j,k} \tag{10}$$

where the terms g and h are high pass and low pass filters derived from the wavelet function $\psi(t)$ and the scaling function $\phi(t)$, the coefficients $d_{j+1,k}$ and $c_{j+1,k}$ represents a decomposition of the $(j-1)$th scaling coefficient into high frequency and low frequency terms. Thus, this algorithm decomposes the original signal $f(t)$ into different frequency bands in the time domain. We employ the orthogonal Daubechies filters of length 4.

2.2. *Fuzzy neural network*

2.2.1. *Fuzzy neural network (FNN) net topology*

Suppose the input and output pairs are $\mathbf{X} = (x_1, x_2 \ldots, x_n)$ and $\mathbf{Y} = (y_1, y_2 \ldots, y_m)$, respectively. $\mathbf{Y}$ is determined by $\mathbf{X}$ and $\mathbf{W}$, based on fuzzy inference it is defined as follows:

$$\mathbf{Y} = \mathbf{X} \circ \mathbf{W} \tag{11}$$

and

$$y_j = \max\big(\min(x_j, w_{ij})\big) \ (i = 1, 2, \ldots, n; \ j = 1, 2, \ldots, m) \tag{12}$$

where $\mathbf{X} \in [0, 1]$, $\mathbf{Y} \in [0, 1]$. w_{ij} are the elements of the weight matrix $\mathbf{W}$. Based on this set-up, the FNN net topology is as shown in Fig.1.

2.2.2. *Learning algorithm*

Assuming the desired FNN output values is T_j, the actual values is O_j, the minimizing square of the difference between them is E:

$$E = \frac{1}{2}\left(T_j - O_j\right)^2 \tag{13}$$

where $O_j = \max(\min(x_i, w_{ij}))$,

It is well known that

$$\frac{\partial O_j}{\partial w_{ij}} = \left(\frac{\partial E}{\partial O_j}\right)\left(\frac{\partial O_j}{\partial w_{ij}}\right) \tag{14}$$

where

$$\frac{\partial O_j}{\partial w_{ij}} = \frac{\partial \vee (\wedge(x_i, w_{ij}))}{\partial \wedge (x_s, w_{sj})} \ \frac{\partial \wedge (x_s, w_{sj})}{\partial w_{sj}} \tag{15}$$

set

$$a_1 = \frac{\partial \vee (\wedge(x_i, w_{ij}))}{\partial \wedge (x_s, w_{sj})} = \frac{\partial \vee (\wedge(x_s, w_{sj})), \bigvee_{i \neq s}(\wedge(x_i, w_{ij})))}{\partial \wedge (x_s, w_{sj})}$$
$$a_2 = \frac{\partial \wedge (x_s, w_{sj})}{\partial w_{sj}} \tag{16}$$

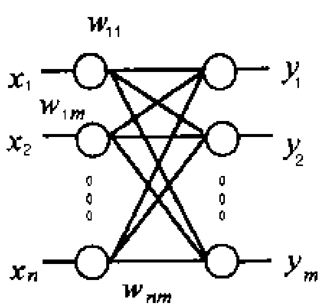

Fig. 1. FNN net topology.

In response, values are defined as follows:

when $\quad \wedge (x_s, w_{sj}) \geq \bigvee_{i \neq s}(\wedge(x_i, w_{ij})), \quad a_1 = 1,$

otherwise $\quad a_1 = \wedge(x_s, w_{sj})$

when $\quad x_s \geq w_{sj}, \quad a_2 = 1, \quad$ otherwise $\quad a_2 = x_s$

Assuming:

$$\frac{\partial O_j}{\partial w_{sj}} = \Delta \tag{17}$$

According to fuzzy minmax inference and smooth derivative ideas, a fuzzy ruler is constructed as follows:

$$\begin{aligned}
&\text{if } x_s < w_{sj} \text{ and } x_s \geq \bigvee_{i \neq s}(\wedge(x_i, w_{ij})) \text{ then } \Delta = x_s \\
&\text{if } x_s < w_{sj} \text{ and } x_s < \bigvee_{i \neq s}(\wedge(x_i, w_{ij})) \text{ and } \Delta = x_s^2 \\
&\text{if } x_s \geq w_{sj} \text{ and } w_{sj} \geq \bigvee_{i \neq s}(\wedge(x_i, w_{ij})) \text{ then } \Delta = 1 \\
&\text{if } x_s \geq w_{sj} \text{ and } w_{sj} < \bigvee_{i \neq s}(\wedge(x_i, w_{ij})) \text{ then } \Delta = w_{sj}
\end{aligned} \tag{18}$$

and

$$\frac{\partial E}{\partial O_j} = -(T_j - O_j) \tag{19}$$

Set

$$\delta = -\frac{\partial E}{\partial O_i} \tag{20}$$

then

$$\frac{\partial E}{\partial w_{ij}} = \delta_j \Delta \tag{21}$$

The changes for the weight will be obtained from a δ-rule with the expression:

$$\Delta w_{ij} = \mu \delta_j \Delta \tag{22}$$

where μ is the learning rate, $\mu \in [0, 1]$.

In order to test the FNN training speed, under the same condition (training sample) structure (5×5), learning rate ($\mu = 0.8$), convergence error ($e = 0.001$), FNN and BPNN training iteration are 8 and 427, respectively. Hence FNN is a highly effective neural network compared with BPNN. Figure 2(a and b) shows the behaviour of the training process.

3. Experimental set-up and results

3.1. *Experimental set-up*

The schematic diagram of the experimental set-up is shown in Fig. 3. Cutting tests were performed on a Machining Center Makino-FNC74-A20. In the experiments, a commercial piezoelectric AE transducer was mounted on a spindle. AE signals were transduced by a magnetic fluid between the spindle and the tool. During the experiments, the monitored AE signals were amplified, high passed at 50

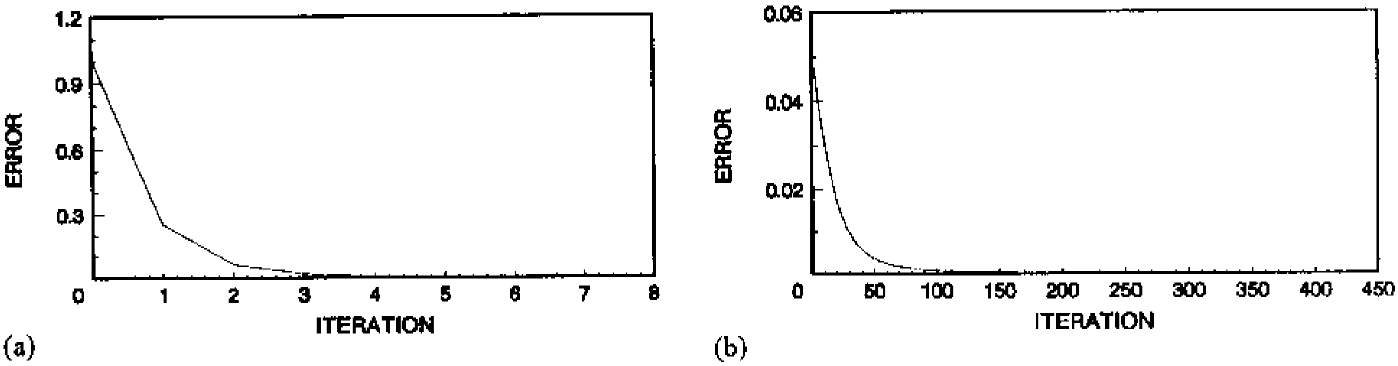

Fig. 2. Training process: (a) FNN, (b) BPNN.

kHz, low passed at 1 MHz, then sent via an analogue-to-digital (A/D) converter to a personal computer (AST/486).

A successful method for detecting tool failure must be sensitive to tool 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 was a high speed steel (HSS) drill with diameters of 2, 3, 9 and 12 mm. The spindle speed was 300 and 450 r.p.m.; the feed rate was 20, 25, 30 and 45 mm min^{-1}; there was no coolant. The workpiece was 45# quench steel.

3.2. *Tool states*

Tool condition was divided into five states: initial wear, normal wear, acceptable wear, severe wear and failure. In order to improve the FNN training speed, the tool condition was coded as follows: initial $(1,0,0,0,0)$, normal $(0,1,0,0,0)$, acceptable $(0,0,1,0,0)$, severe $(0,0,0,1,0)$ and failure $(0,0,0,0,1)$. Based on flank wear of the tool, these conditions are summarized in Table 1.

3.3. *Monitoring features*

It is well known that the energy level of the AE signal in the high frequency band gradually increases with increased tool wear. Figure 4(a–f) shows the decomposed results of the AE signal through wavelet decomposition in Fig. 4(a–f). represent the energy distribution of the AE signal in the following frequency bands: 0–62.5, 62.5–125, 125–250, 250–500 kHz and 0.5–1.0 MHz. They indirectly provided some information about the features of the frequency domain. The RMS values of the decomposed results for the AE signal in each frequency band can represent the signal features. In the neural network application, it is very important for feature selection and feature number. The selected features must be independent and their number must be large enough. The RMS value in each frequency band was used to describe the features of different tool conditions. The selected features were summarized as follows:

n_1 = RMS of wavelet coefficient in the frequency band $[500, 1000]$ kHz;

n_2 = RMS of wavelet coefficient in the frequency band [250, 500] kHz;

n_3 = RMS of wavelet coefficient in the frequency band $[125, 250]$ kHz;

n_4 = RMS of wavelet coefficient in the frequency band $[62.5, 125]$ kHz;

n_5 = RMS of wavelet coefficient in the frequency band $[0, 62.5]$ kHz.

In order to eliminate the effects of signal amplitude and to meet the needs of the FNN input, the features were treated using the equation:

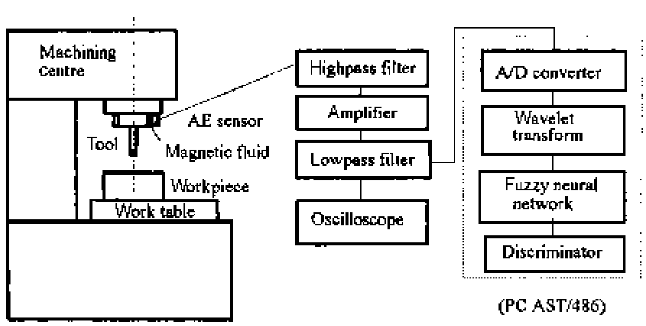

Fig. 3. Experimental set-up.

Table 1. Tool condition classification

Tool condition	*Flank wear*	*Code (FNN output)*
Initial wear	$0 < \text{wear} \leqslant 0.1$ mm	(1,0,0,0,0)
Normal wear	$0.1 < \text{wear} \leqslant 0.3$ mm	(0,1,0,0,0)
Acceptable wear	$0.3 < \text{wear} \leqslant 0.5$ mm	(0,0,1,0,0)
Severe wear	$0.5 < \text{wear} \leqslant 0.6$ mm	(0,0,0,1,0)
Failure	$0.6 < \text{wear}$	(0,0,0,0,1)

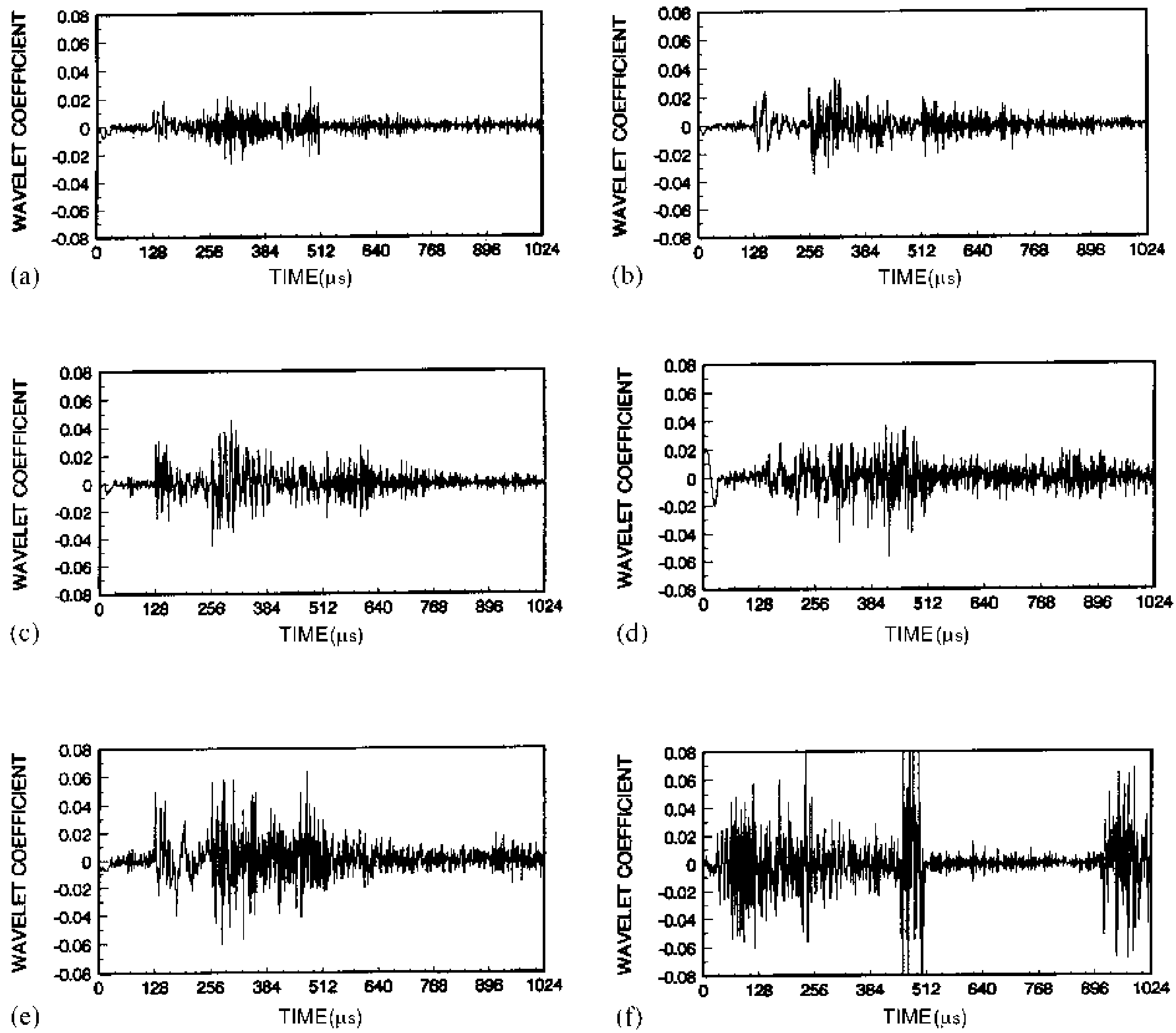

Fig. 4. Decomposed results for the AE signal at different flank wear by wavelet transformation. Tool diameter 4.7 mm, cutting speed 380 r.p.m., feed rate 20 mm min^{-1}, work material 40Cr steel; the tool was a high speed steel (HSS) twist drill, without coolant. (a) VB = 0.125 mm; (b) VB = 0.20 mm; (c) VB = 0.27 mm; (d) VB = 0.36 mm; (e) VB = 0.52 mm; (f) failure.

$$n_i = \frac{n_i}{\sum_{j=1}^{5} n_j} \qquad j = 1, 2, \ldots, 5 \tag{23}$$

3.4. *Experimental results*

A total of 80 cutting tests corresponding to variable cutting states were collected. Fifty samples were randomly picked as learning samples; the remaining samples were used as the test samples in the classification phase. The learning rate of the FNN is 0.8; the weights were initialized to random values between −0.5 and 0.5. The FNN is a layer perception with an architecture of 5 × 5. The five input nodes of the FNN correspond to the five feature components of the extracted feature vector. The final decision on tool condition is made according to:

$$\text{tool condition} = \max(y_j) \ (i = 1, 2, 3, 4, 5) \tag{24}$$

where y_i is the tool condition value of the FNN output. The test results are shown in Table 2, which indicates a high success rate. Thus, feature selection is successful. This result also shows that features extracted from the AE signal

Table 2. Test results

Tool condition	*Recognition rate* (%)
Air cutting	100
Initial	86
Normal	89
Acceptable	90
Severe	95
Failure	100

by wavelet decomposition has a low sensitivity to any change of the cutting condition. The results meet the needs of the application.

4. Conclusions

In a manufacturing system, machining efficiency is easily influenced by the tool condition in the cutting process. Among the most complex problems for a tool condition monitoring system is the extraction of the signal features and, as accurately as possible, to describe the relationship between the tool condition and the signal features under a given cutting condition. We have introduced a wavelet transform and a new FNN for tool condition monitoring in drilling. After conducting an investigation it became clear that the wavelet technique was used to decompose the AE signal, allowed more independent features to be obtained. These features were the RMS of the wavelet coefficient in the frequency band which had a low sensitivity to changes in the process variables. It also became clear that the fuzzy relationship between the tool condition and the monitoring features may be identified by using a fuzzy neural network, the training speed of the FNN is faster than that for a BPNN. In short, the integrated wavelet transform and the FNN enable a tool condition monitoring system to have a high monitoring success rate and fast training feed over a wide range of cutting conditions.

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