Journal of Materials Processing Technology 139 (2003) 237–242

Journal of Materials Processing Technology

www.elsevier.com/locate/jmatprotec

On-line tool breakage monitoring in turning

Wang Haili*, Shao Hua, Chen Ming, Hu Dejin

School of Mechanical Engineering, Shanghai Jiao Tong University, 1954 Hua Shan Road, 200030 Shanghai, PR China

Abstract

Acoustic emission (AE) and motor power sensors were used to detect the tool breakage in turning. Time–frequency analysis was used to process different AE signals emitted from the cutting process (normal cutting condition, tool breakage, chip fracture, etc.). Four types of power signal variation were observed in experiments when tool breakage occurred, which suggest that the change of power signals in the time domain was stochastic. Delayed variance is proposed to extract features from the power signals. The tool condition can be recognized through a neural network based on adaptive resonance theory (ART2).

Keywords: Tool breakage monitoring; Motor power; Acoustic emission

1. Introduction

The automatic in-process detection of cutting tool breakage is very important in achieving advanced manufacturing. To prevent possible damage to the workpiece and machine tool, a reliable and effective sensing technique is required for providing a rapid response to an unexpected tool failure.

Several methods that include monitoring the cutting force [1], motor power [2], and acoustic emission (AE) [3] have been investigated for this purpose. Sensing AE signals from the cutting process is one of the most promising methods. Because of its sensitivity, quick-response and the high frequency of AE signal to avoid ambient noise, this method is quite suitable to monitor tool breakage. AE in the turning process originates from several sources, such as tool breakage and chipping, chip fracture, friction between the tool and workpiece, plastic deformation, etc. Therefore, how to extract the tool breakage features from the various AE sources becomes the key problem to be solved. Research over the past few years has analyzed AE signals in various methods, such as count-rate, RMS voltage, spectral density, and so on. However, due to many AE sources during the cutting process, AE signals are mixed together in both the time and frequency domain. It is difficult to separate the different AE signals only in time domain or in frequency domain. Time–frequency analysis has been used to process the AE signals in this paper.

Detecting cutting force is another effective method to monitor tool breakage. Cutting force sensors, such as dynamometers are more suited to the laboratory and are difficult to use on production machine tools. As an alternative cutting force sensor, a motor power transducer can be installed conveniently on the machine tools, and motor power signals can also be easily obtained. Experimental work [4] shows that the tangential force is sensitive to tool breakage. This force increases suddenly when a broken tool nose is jammed between the tool and workpiece, then drops to zero due to the gap between the tool and the workpiece as the broken part of the tool insert was released. As the tool continued to move, it approached the workpiece again closing the gap and forces started to increase beyond their original values. However, more change in the nature of motor power signals were observed during the turning experiments presented in this paper. At the moment of tool breakage, one situation is that it first increases, then decreases to a relatively steady level, whilst another is that it decreases quickly to a low level, keep this level, and increases quickly to a new high level. These situations suggest that the change of power signal in the time domain is stochastic. To extract the tool breakage features from the above four change types of motor power, an improved signal processing method named delayed variance is proposed.

An unsupervised network based on the adaptive resonance theory (ART2) [5] has been used for the tool condition identification because of its excellent characteristics, such as fast learning, flexibility, and self-organizing ability. Features extracted from the motor power signals processed

* Corresponding author.
E-mail address: hlwang@mail.sjtu.edu.cn (W. Haili).

0924-0136/03/$ – see front matter
doi:10.1016/S0924-0136(03)00227-9

by the delayed variance method and AE signals processed by time–frequency analysis are combined into a vector input into ART2 to realize the recognition of tool breakage. Extensive cutting experiments have been carried out to evaluate the performance of this approach.

2. Signal processing

2.1. Time–frequency analysis

AE signals emitted from the cutting process can be divided into two types: continuous AE signal and burst AE signals. The magnitude of burst AE signals is often much larger than that of continuous AE signals. Burst AE signals originate from several sources, such as tool breakage, extension of micro-cracks in tool inserts, chip fracture, collision between the chip and the workpiece, etc. It is difficult to recognize the AE signals emitted at tool breakage from other AE sources in the time domain. Frequency analysis using fast Fourier transformation (FFT) has been employed by some researchers to process AE signals. The theoretical hypothesis of FFT is that signals are stationary or time invariant. However, burst AE signals are non-stationary because they are often related to extension of material cracking and breakage. Thereby, a more reasonable method to process AE signals is to adopt time–frequency analysis.

In 1966, Cohen generalized time–frequency distributions (TFDs) to an uniform expression as follows:

$$C_x(t,\omega,\phi)=\frac{1}{2\pi}\iiint \mathrm{e}^{\mathrm{j}(\xi\mu-\tau\omega-\xi t)}\phi(\xi,\tau) \times x\left(\mu+\frac{\tau}{2}\right)x^*\left(\mu-\frac{\tau}{2}\right)\,\mathrm{d}\mu\,\mathrm{d}\tau\,\mathrm{d}\xi \quad (1)$$

where $x(\mu)$ is the time signal, $x^*(\mu)$ is its complex conjugate, and $\phi(\xi,\tau)$ is a kernel function, representative of the particular distribution function. The bilinear structure of the TFD of Cohen class leads to the intersection of cross terms of multi-component signals. The exponential distribution (ED) proposed by Choi and Williams [6] solved this problem effectively. The kernel function of ED is

$$\phi(\xi,\tau)=\mathrm{e}^{-\xi^2\tau^2/\sigma} \quad (2)$$

Cross terms can be suppressed by adjusting the constant σ.

2.2. Delayed variance method

According to the following experiments introduced, the magnitude of the motor power signal in the time domain changes stochastically at the moment of tool breakage. Therefore, it is unreliable to detect the tool condition by preset threshold. The motor power of machine tools change in various ways due to tool breakage, which means that the motor power signal deviates from the mean under normal cutting conditions. Based on this fact, the delayed variance method is proposed to select the tool breakage features from the motor power signals.

In a short period of time, the tool condition can be considered unchanged under normal cutting conditions. As a result, the signal is stationary. Variance of the motor power signal is calculated based on the mean of an earlier short interval of time. In the real cutting process, normally the signal mean is calculated recursively based on the latest sampled data, so is the variance of the signal. Tool breakage signals are homogenized into the mean based on which variance is calculated that is relatively small after tool breakage. However, the calculated variance based on the earlier mean increases as compared with the traditional calculating method. Therefore, delayed variance can reflect the change of tool condition more definitely. The algorithm is shown in Ref. [7].

3. Experiments

Fig. 1 shows the experimental set-up and data acquisition system. Turning experiments were performed on a J1-MAZAK530 × 1000 horizontal lathe. The workpiece material used was 45 carbon steel round bar (hardness HB175). The variable-position carbide chips used were YT15. Several tiny high-speed steel bits were hammered into the bar to increase tool breakage.

AE signals were measured by a piezoelectric AE sensor, which was mounted at the side of the tool shank. Signals were amplified, filtered (band pass between 20 kHz and 1 MHz) and fed to a THS720 high-speed oscillograph. The signals were sampled at the sampling frequency of 2.5 MHz. The time domain record length is 2500. Motor power signals were transmitted to an A/D board through a power transducer. Motor power signals were sampled at the sampling frequency of 4 kHz. The time domain record length is 8000. Different cutting conditions (variable revolutionary speed,

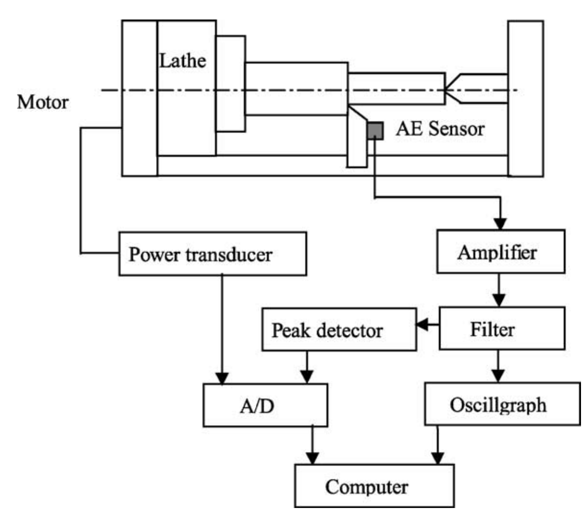

Fig. 1. Experimental set-up.

feed velocity, cutting depth) were explored to obtain variable tool broken area.

4. Data analysis and results

Four types of AE signals were observed during the cutting process in the experiments (see Fig. 2). The figure shows that the RMS of the AE signals under normal cutting conditions is between 25 and 200 mV. The RMS of the AE signals at the moment of tool breakage increases suddenly to above 300 mV normally, and the magnitude of the RMS is related to the area of tool breakage. Fig. 2(c) shows that the RMS of the AE signals also increases suddenly to 200–500 mV at chip fracture. Therefore, it is difficult to recognize tool breakage (from chip fracture only by RMS of AE signals). Time–frequency analysis is employed to process the AE signals. The TFD of the corresponding signals are shown in Fig. 3. The difference between various TFD of signals is obvious. TFD of AE signal is divided into many areas, and the energy contained in each area can be obtained. Tool breakage features can be extracted easily from the TFD as a normalized vector.

Experiment shows that the change of motor power signal in time domain is uncertain at tool breakage. Four typical changes were detected in experiments (shown in Fig. 4). (1) As shown in (a), magnitude of motor power signal increases quickly due to tool breakage. This case may be caused by the increase of the rake angle. (2) As shown in (b), the power increases suddenly when a broken tool nose jammed between the tool and workpiece, then drops due to the diminished cutting depth. (3) As shown in (c), power decreases quickly to a low level. This situation has two possible causes. One reason is that cutting depth diminishes too much because of large tool broken area. The other is that rake or flank face flaking off introduces the increment of the effective cutting angles, which reduce the consuming of motor power. (4) As shown in (d), power drops first and then increases. In all above cases, the most often situation occurred is case (1). Signal processing results of above signals by delayed variance method are shown in Fig. 5. Delayed variance of signals has much increase because of tool breakage, which demonstrates that the method proposed is effective. Therefore, the normalized delayed variance can be selected as tool breakage feature.

To detect tool breakage automatically, a neural network ART2 is employed. The principle and architecture of ART2 were described in detail by Carpenter and Grossberg [5]. Two delayed variance features of the motor power signal and

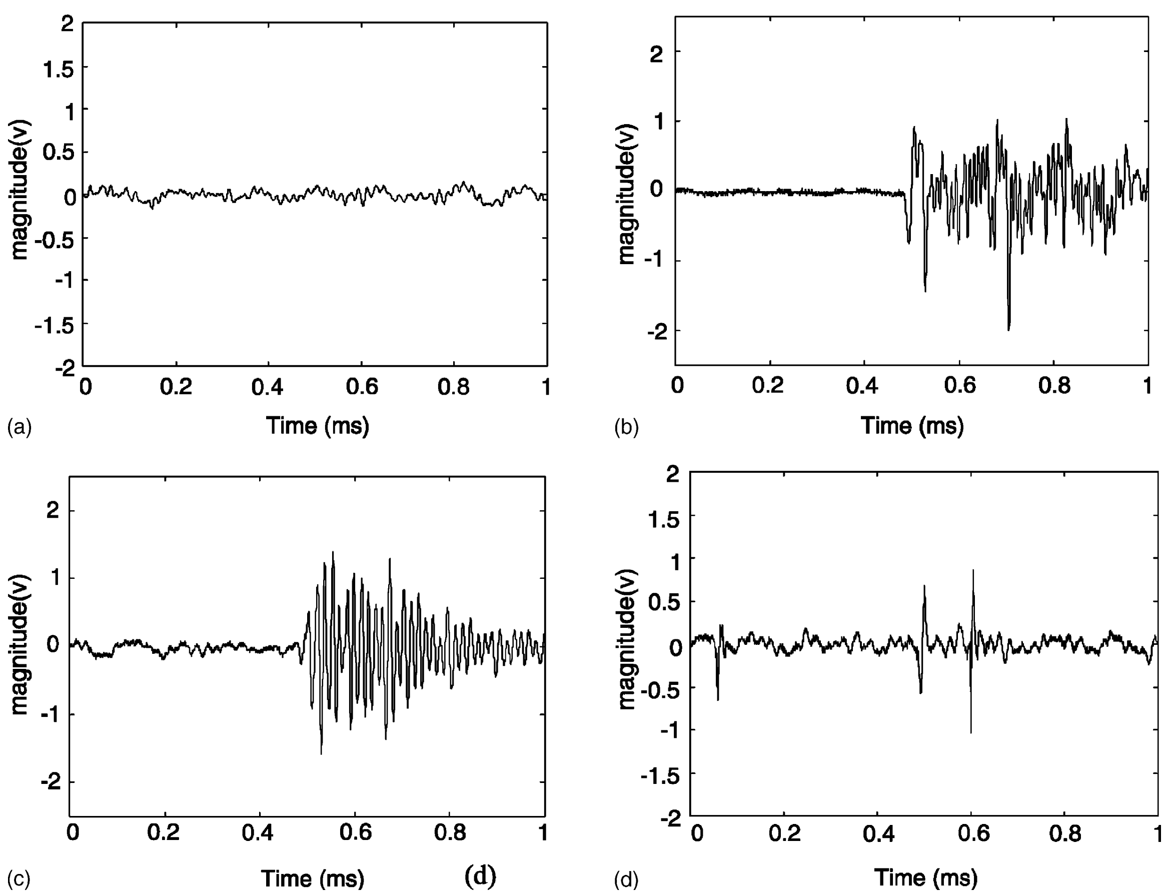

Fig. 2. Various AE signals: (a) under normal cutting conditions; (b) tool breakage; (c) chip fracture; (d) by stochastic factors.

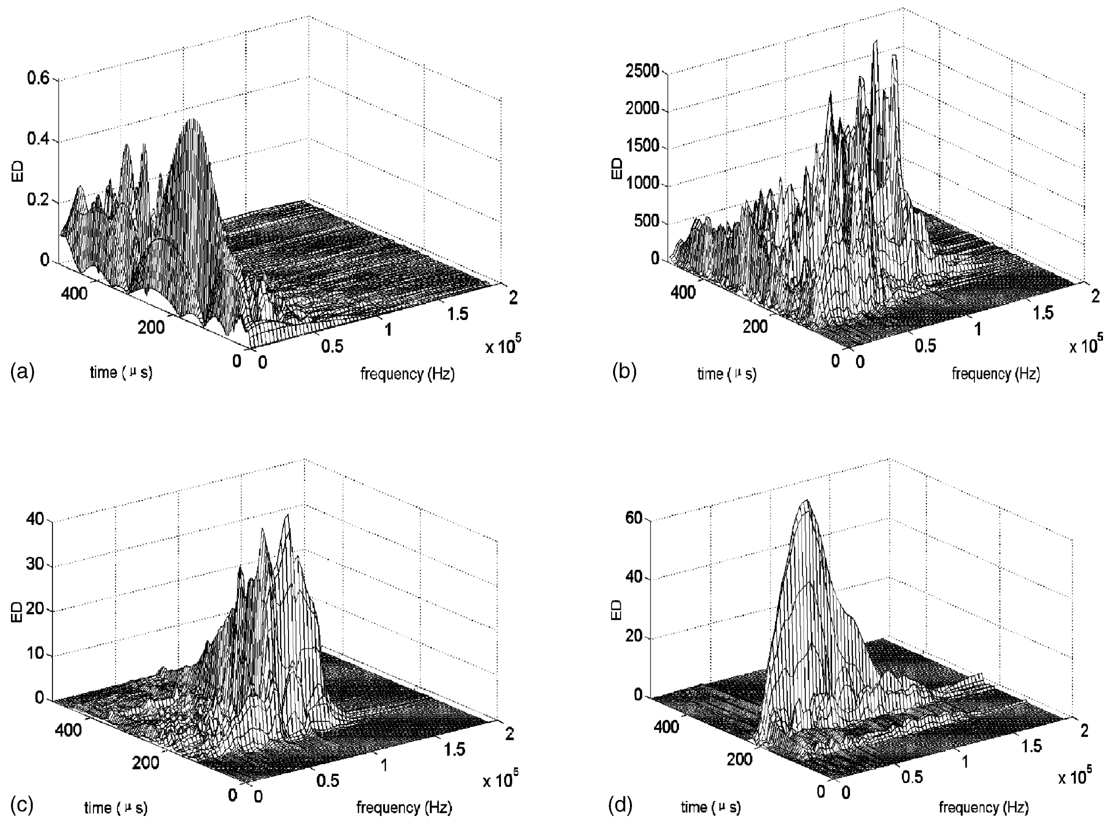

Fig. 3. TFD of AE signals: (a) under normal cutting condition; (b) tool breakage; (c) chip fracture; (d) by stochastic factors.

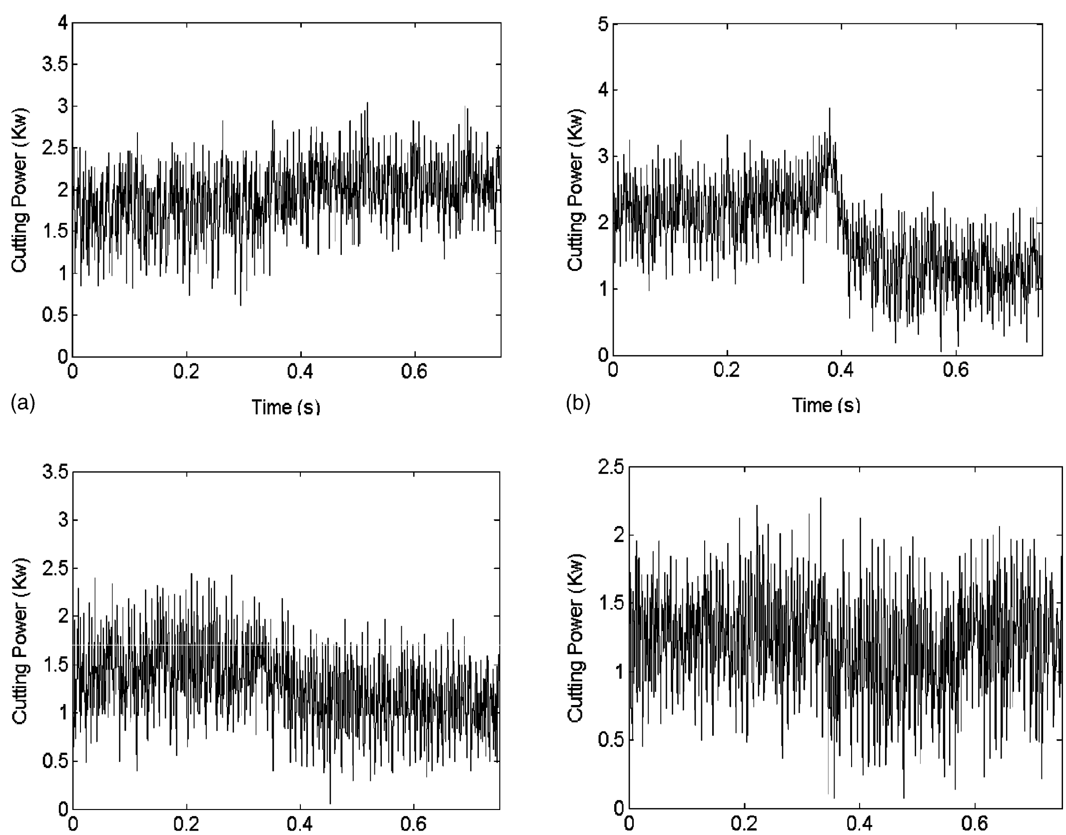

Fig. 4. Various motor power signals of tool breakage.

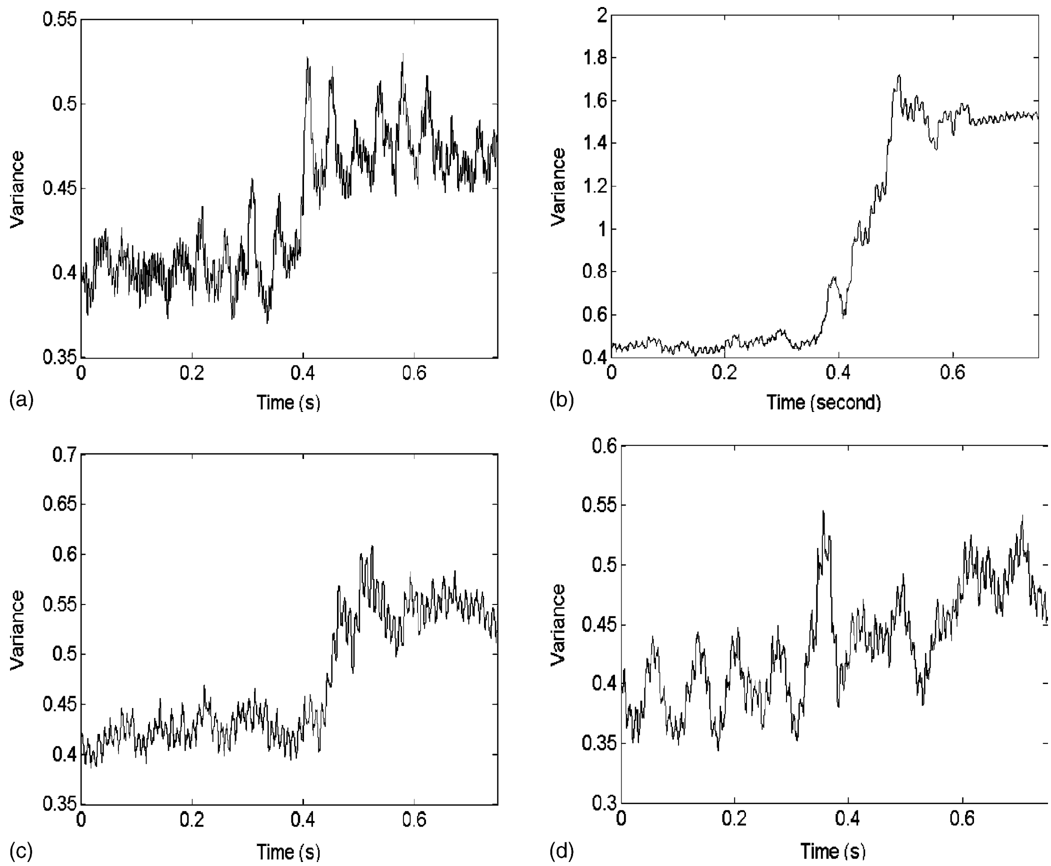

Fig. 5. Variance of various motor power signals.

the TFD feature vectors of the AE signal are combined into an input vector of ART2. ART2 has the ability to self-scale the input vector. Because the dimension of the TFD feature vector is much larger than that of the delayed variance feature, it is necessary to increase the number of delayed variance features. Otherwise, the delayed variance feature will be considered as noise of the input vector of ART2. Each input vector of ART2 is a sample mentioned below. The network have been trained by 20 learning samples under three conditions, as follow: (1) samples consist of TFD feature only; (2) samples consist of delayed variance feature only; (3) samples consist of both of the above combined features.

In the first case, vigilance parameter is set between 0.93 and 0.98, and the ART2 classify samples into four classes as shown in Fig. 2, where the second class represents a broken tool. In the second case, the vigilance parameter is set between 0.97 and 0.98, and the samples are classified into two classes of normal and broken tool condition. In the third case, the vigilance parameter selected is 0.93, and the samples are classified into two classes of normal and broken tool condition. When the vigilance parameter selected increases to 0.98, the number of class increases to 4, the same as in the first case. As a result, the classification of ART2 is more stable and effective in the recognition of tool breakage using the combined features. When the training process is finished, 20 testing samples consisting of combined features were input to the ART2 neural network. The correct recognition rate of tool breakage is a constant 95% when the vigilance parameter is 0.97.

5. Conclusions

Motor power and AE sensors were used to monitor tool breakage. Due to the difficulty of distinguishing various AE signals emitted from the cutting conditions (normal cutting condition, tool breakage, chip fracture, etc.), time–frequency analysis is adopted to extract features from the signals. Four types of power signal variation were detected in experiments when tool is broken, which suggest that the change of the power signals in the time domain was stochastic. An improved signal processing method, named delayed variance, is proposed to extract features from the power signals. The tool condition can be recognized through an ART2 neural network effectively.

References

[1] A. Novak, H. Wiklund, On-line prediction of tool life, Ann. CIRP 45 (1) (1996) 93–96.

[2] D. Cuppini, G. Errico, Tool wear monitoring based on cutting power measurement, Wear 132 (2) (1990) 303–311.
[3] J.A. Rice, S.M. Wu, On the feasibility of catastrophic cutting tool fracture prediction via acoustic emission analysis, Trans. ASME J. Eng. Ind. 114 (1992) 400–403.
[4] Li. Dan, J. Mathew, Tool wear and failure monitoring techniques for turning—a review, Int. J. Mach. Tool. Manuf. 30 (4) (1990) 579–598.
[5] G.A. Carpenter, S. Grossberg, ART2: self-organization of stable category recognition codes for analog input patterns, Appl. Opt. 26 (23) (1987) 4919–4930.
[6] H.-I. Choi, W.J. Williams, Improved time–frequency representation of multi-component signals using exponential kernels, IEEE Trans. ASSP 37 (6) (1989) 862–871.
[7] W. Haili, Study on strategy of multi-sensor tool condition monitoring, Ph.D. Dissertation, Shanghai Jiao Tong University, Shanghai, 1999.