Monitoring Vibration and Tool Wear by Pattern Recognition of Variance of Dynamic Force

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Abstract：In the automation of monitoring the status of cutting process, it is very important to monitor cutting vibration and tool failure. It has been found that the variance,autocorrelation function and autoregressive coefficient of dynamic cutting force are most sensitive to the status variation in the cutting process and closely related with the cutting vibration or tool wear, and can effectively be used in the pattern recognition of monitoring the cutting vibration or tool wear.

Keywords: *tool wear; monitoring; cutting force*

I. INTRODUCTION

In metal cutting process cutting vibration & tool wear or breakage will result in the reductions in the quality of machined surface, dimensional accuracy of workpiece, or even in the damage of worepiece or machining system. A lot of work offered on the mechanisms and their occurrence. A number of direct or indirect measurements have been proposed to detect the tool failure. It looks better to detect the tool breakage and wear simultaneously in a same way. But it is not reasonable to mix up the detections of the wear and tool breakage, since there are unnegligible differences between them in mechanism of formation, abruptness of occurrence, influence on machining process and system, urgency of detection and corresponding variation in measured signals. Due to the complexity and random of the cutting process, few of the proposed methods are successful on shop floor. There are some methods of prediction or dete- ction of cutting vibration too. As it is, both need to do more and shed a light on the mechanisms and measurements[1].

It is though that cutting force is one of the most important variables in the cutting process which affects the stability of the cutting process, consumption of cutting power, genera- tion of cutting heat, tool wear, quality of machined surface, deformation of machining system,…etc. Especially the dy- namic cutting force is most sensitive to the variation in the status of the cutting process. Some works tried to use its magnitude or power spectra for the detection of tool failure, which it is not good enough to be used directly for the de- tection, as it is very difficult to set the detection threshold.

One of the important problems for the pattern recognition is to decide the pattern modes. And more details of feature extraction, mapping, minimum distance classifier etc are discussed below.

II. THEORETICAL ANALYSIS AND DISCUSSION

In order to study the variation and mechanism of dynamic cutting force, its relationship to the tool wear, and cutting vibration, and the use in the detection of them, all experiments were made on an engine lathe with a stepless variable drive. Workpiece material was medium carbon steel C45(similar to AISI 1045), the insert of cutting tool YT15(similar to P10). Dynamic cutting force was measured by a piezoelectric dynamometer, cutting vibration was measured by a piezoelectric accelerometer, both were mounted on the tool holder, data were recorded on the tape by a nine channel tape recorder in the cutting process, and later input to the computer through the A/D converter, or processed by the CF920 FFT analyzer. The flank wear VB of cutting tool was measured with a microscope on the lathe to keep the status of the machining system as consistent as possible.

III. THEROTICAL ANALYSIS AND DISCUSSION

Feature extraction is very important considering that it is the key to the patter recognition. In fact, the number of the features with affects the feasibility and accuracy of the patter recognition has to be chosen carefully. Of course each of the features must have a close relationship with the samples, and be able to represent the major properties of the samples. According to the theory of random process and time series analysis, variance σ^2 (or standard deviation σ), autocorrelation function Rc, and autoregressive coeffi- cient Φ_i are some of the crucial variables to depict the stochastic process[2].(随即过程)

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_n X_{t-n} + a_t$$

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It can be seen obviously that variance σ_F^2 (for the sake of comparison, the standard deviation σ_F instead) of dynamic cutting force in the direction of cutting speed is closely related with the tool wear or cutting vibration by the experimental results in Fig.1, and Fig.2, can be calculated as

$$\sigma_F = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(F_i - \overline{F})^2} \tag{1}$$

Where

F_i the real value of the ith sample of dynamic cutting force

N the number of sampled data of the dynamic cutting force

$$\overline{F} = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{2}$$

In order to eliminate the influence of the variance σ_F^2 on the autocorrelation function $R(\tau)$, divide R(τ) by the variance $\sigma_F^2 = R(0)$. Then it can be computed as follows:

$$R(\tau) = \lim_{T\to\infty}\frac{1}{T}\int_0^T F(t)F(t+\tau)dt = E[F(t)F(t+\tau)] \tag{3}$$

$$R_c(\tau) = \frac{R(\tau)}{R(0)} = \frac{R(\tau)}{\sigma_F^2} \tag{4}$$

In fact $R_c(\tau)$ is similar to $R(\tau)$ in their waves, except for the magnitudes. Then for the simplicity, $R_c(\tau)$ is still called as the autocorrelation function, and for more sensitive, assume τ = 0.4 msec.

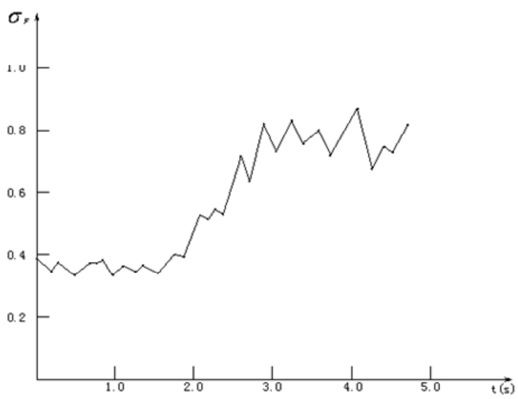

Fig.1 Relation curve of σ_F and cutting vibration (v=0.1m/s, f=0.08mm/r, a_p=0.3mm)

As for the flank wear of cutting tool, besides the variance of dynamic cutting force, the autoregressive coefficient ϕ_1 and cutting time are also closely related with it.

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_n X_{t-n} + a_t \tag{5}$$

The digitized data X_t of dynamic cutting force were used to develop the autoregressive model AR(n)

Or in a vector form

$$X_t = X^T(t)\phi + a_t \tag{6}$$

The parameters ϕ_i which show the dependence of X_t to X_{t-1} (here i=1,2,…,n) in the model were determined by the least squares estimates. The a_t is a white noise, or residual error[3].

The order number n of AR(n) model of the dynamic cutting force was decided by AIC criterion, if the tool wear VB is medium, order number n is 3,as the tool wear VB increases, the order number n rises up to 4 or 5.

It is found that along with the tool wear the absolute value of the autoregressive coefficient ϕ_1 in the AR(n) model of dynamic cutting force goes up obviously as Fig.3 shows.

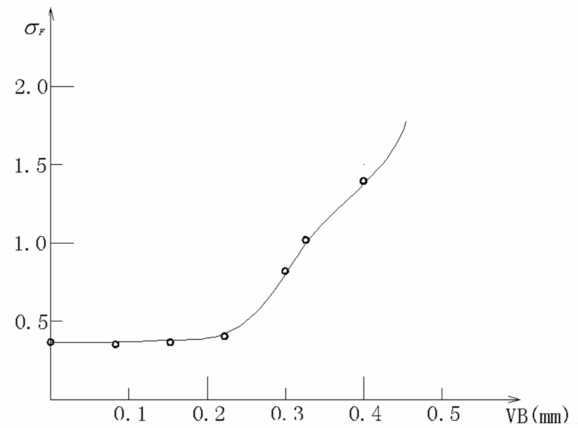

Fig.2 Relation curve of σ_F & tool wear VB(v = 2.1m/s, f = 0.18mm/rev,ap=0.5mm)

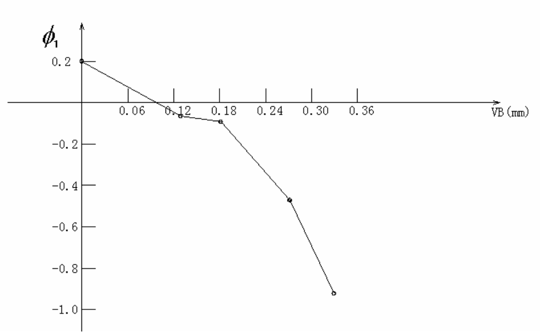

Fig.3 Relation curve of autoregressive coefficient Φ_1 tool wear VB(v=2.1m/s, f=0.18mm/rev,ap=0.5mm)

Moreover, despite with some scatter, at a certain extent, the cutting time can show the status of tool wear, and is helpful to the identification of initial period of tool wear, and some noises, …etc.

Assuming that there are three modes for the chatter detection:

W1 normal status of cutting process
W2 chatter begins to develop
W3 chatter exists constantly

And there are two modes for the tool wear identification:

W1 tool is normal below the wear criterion
W2 tool is over worn beyond the wear criterion

Based on the analysis discussed above, the pattern vector for the identification of chatter (X_V), or cutting tool wear (X_W) are

$$X_V = (\sigma_F, R_c)^T \tag{7}$$

Or

$$X_W = (\sigma_F, \varphi_1, t)^T \tag{8}$$

In order to improve the calculation of the patter classifier, and get the useful information from the original signal as much as possible, map the pattern vector (X_W) into a feat- ure space by using a linear transformation matrix A and reducing the dimensionality of the feature space as follows:

$$Y = AX_W \tag{9}$$

How to get the transformation matrix A is discussed below. According to the clustering criterion, it is best that in a same pattern mode the intraset distance of eigen vectors is the least which could be calculated as:

$$\overline{D^2} = 2\sum_{K=1}^{n} \sigma_K^2 \tag{10}$$

Where

$\overline{D^2}$ ——intraset distance of eigen vectors in a same pattern mode。

σ_K^2 ——the variance of the kth feature.

If the covariance matrix of a set of pattern vectors is C, then, there in

$$\overline{D^2} = 2trC \tag{11}$$

The covariance matrix C has eigen values $\lambda_1,\ldots,\lambda_n$, (n is the number of features in the pattern mode, here n=3), who- se eigen vectors are $e_1, e_2,\ldots, e_n$.

By the theory of pattern recognition, the transformation matrix A should be composed of m pieces of the smallest eigen vectors is the least. On account of the experimental data, eigen values of the covariance matrix C can be got, the two smallest of them are

$$\lambda_1 = 1.90,\ \lambda_3 = 0.73$$

And their eigen vectors are

$$e_2 = \begin{vmatrix} -0.707 \\ 0 \\ 0.707 \end{vmatrix} \tag{12}$$

$$e_3 = \begin{vmatrix} 0.628 \\ -0.461 \\ 0.628 \end{vmatrix} \tag{13}$$

The dimensionality of precise features of the pattern mo- de is designated as 2, then the transformation matrix A is

$$A = \begin{vmatrix} 0.628 & -0.461 & 0.628 \\ -0.707 & 0 & 0.707 \end{vmatrix}^T \tag{14}$$

The samples of the pattern vectors Y_W^T for the identify- cation of tool wear have been computed and listed in Tab.1

Tab.1. Samples of pattern vectors Y_W^T

In mode W1		in mode W2	
0.37,-0.12	0.31,-0.21	1.19,0.50	1.10, 0.19
0.68, 0.09	0.56, 0.12	0.94, 0.20	0.90, 0.33
0.62, 0.15	0.83, 0.19	1.02, 0.26	0.96, 0.39
0.81, 0.09	0.91, 0.29	1.10, 0.30	1.2, 0.38
0.95, 0.28	0.73, 0.22	1.07, 0.32	1.18, 0.16
0.43, 0.12	0.87, 0.20	1.23, 0.40	0.98, 0.29

And the three classes of trained samples Y_v^T have been got from the experimental data and shown in Tab.2. After ca- refully study, we selected three sets of standard samples from each of the two pattern W1 or W2 for the detection of chatter:

W1: (0.37, 0.24), (0.35, 0.35), (0.38, 0.21)

W2: (0.41, 0.35), (0.42, 0.40), (0.44, 0.33)

With the minimum distance classifier, any given pattern (σ, R_c) can be identified by a discrimination function as follows:

If

$$\min\left\{\sqrt{(\sigma-0.37)^2+(R_c-0.24)^2},\quad \sqrt{(\sigma-0.35)^2+(R_c-0.35)^2},\quad \sqrt{(\sigma-0.38)^2+(R_c-0.21)^2}\right\} >$$

$$\min\left\{\sqrt{(\sigma-0.41)^2+(R_c-0.35)^2},\quad \sqrt{(\sigma-0.42)^2+(R_c-0.40)^2},\quad \sqrt{(\sigma-0.44)^2+(R_c-0.33)^2}\right\}$$

Then (σ, R_c) ∈ W2. Therefore, it can be concluded that the occurrence of chatter is imminent, and the urgent remedy method must be taken as soon as possible.

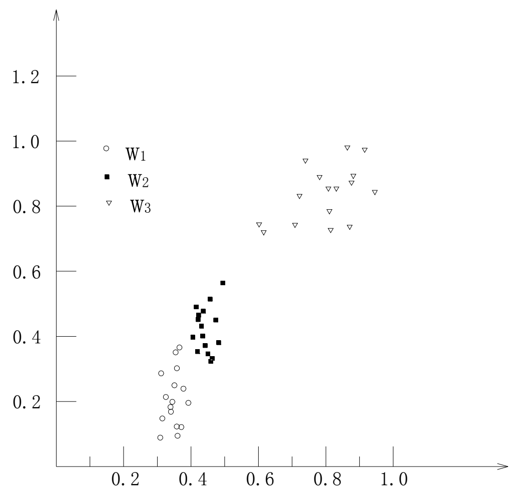

Fig.4 Pattern recognition of chatter in cutting process by σ_F and R_c

As shown in Fig.4 in identification there is no any confo- unding. And there is enough time to take an urgent remedy to avoid the danger.

Tab.2 Three classes of trained samples for the detection of chatter

W1			
0.36, 0.13	0.33,0.20	0.29,0.23	0.32,0.22
0.35, 0.13	0.31, 0.15	0.36, 0.37	0.38, 0.21
0.35, 0.10	0.37, 0.24	0.33, 0.19	0.34, 0.25
0.30, 0.09	0.35, 0.30	0.35, 0.35	0.33, 0.18
W2			
0.45, 0.31	0.42, 0.47	0.46, 0.44	0.42, 0.43
0.44, 0.50	0.42, 0.40	0.47, 0.38	0.43, 0.56
0.44, 0.33	0.41, 0.44	0.41, 0.48	0.41, 0.46
0.41, 0.35	0.45, 0.33	0.39, 0.39	0.43, 0.37
W3			
0.59,0.70	0.75,0.86	0.83,0.95	0.79,0.83
0.84,0.85	0.88,0.94	0.68,0.73	0.84,0.72
0.71,0.91	0.75,0.76	0.85,0.87	0.69,0.80
0.78,0.71	0.58,0.73	0.91,0.82	0.78,0.83

The minimum distance classifier has also been used to identify the status of tool wear. In the Euclidean space, the distance function of samples in the recognized pattern to the samples of standard pattern $W_1(Y_{1i})$, and $W_2(Y_{2j})$ are individually:

$$D_1 = \min\|Y - Y_{1i}\| = \min\left\{\sqrt{(Y - Y_{1i})^T (Y - Y_{2i})}\right\} \qquad (15)$$

And

$$D_2 = \min\|Y - Y_{2i}\| = \min\left\{\sqrt{(Y - Y_{2i})^T (Y - Y_{2i})}\right\} \qquad (16)$$

Where

i=1,2,…, N_1

j=1,2,… N_2

If $D_1 > D_2$,then there is Y ∈ W_2 .

All experiments show that the minimum distance classifier is relatively simple, it works effectively and reliably. It is sure to say that it is able to predict or monitor the status of cutting process (i.e. chatter, or tool wear) in this method.

Experiments also reveal that the influences of cutting conditions on those features are regular, approximately linear, and easier to be taken account of. In fact it can be imagined that it would be impossible to find a variable which is not only closely related with, and able to depict the cutting process, but not related with cutting conditions, or its thr- eshold is never influenced by them as well.

IV. CONCLUSIONS

A. In the light of the unnegligible differences between to- ol breakage and tool wear, the requirements for detection, and time-sharing function of a computer, it is better and re- asonable to detect the tool wear and tool breakage separate- ely.

B. Based on the theory of random process, and time series analysis, variance σ2 autocorrelation function R_c , and autoregressive coefficient ϕ_1 etc reveal the major features of a random process.

All of the experiments demonstrate that these variables of the dynamic cutting force are closely related with the cu- tting vibration, or tool wear, and very sensitive to its vari- ation. Because the influences of cutting conditions are reg- ular, and approximately linear, it is pretty easy to set or mo- dify the threshold of identification if necessary.

C. Pattern recognition with minimum distance classifier and patter vectors $X_V(\sigma_F, R_c)$ or $X_W(\sigma_F, \phi_1, t)$ can be used to predict chatter, or identify tool wear promptly and effectively.

This work is presented here not only to throw light on the dynamics of cutting process, but to offer a powerful base and method for monitoring the cutting process as well.

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