Strojniški vestnik - Journal of Mechanical Engineering 55(2009)1, 15-25
UDC 621.914.2

Paper received: 20.10.2006
Paper accepted: 09.02.2009

Condition Monitoring of Milling Tool Wear Based on Fractal Dimension of Vibration Signals

Chuangwen Xu[1,*] - Hualing Chen[2] - Zhe Liu[1] - Zhongwen Cheng[1]
[1] Lanzhou Polytechnic College, Lanzhou, Gansu, China
[2] School of Mechanical Engineering, Xi'an Jiaotong University, Xi'an, Shanxi, China

The development of flexible automation in the manufacturing industry is concerned with production activities performed by unmanned machining systems. A major topic relevant to metal-cutting operations is monitoring tool wear, which affects process efficiency and product quality, and implementing automatic tool replacements. In this paper, pattern recognition is described for the milling tool wear conditions by means of chaotic theory. Factors influencing the consistency of the calculated fractal dimension based on fractal dimension of vibration signals are analyzed. Angle domain tracing method is adopted during acquisition of vibration signals to minimize the effect from spindle speed. A new method for calculating the fractal unscale range is proposed in determining fractal dimension. The experiment results show that the fractal theory is leaded into monitoring field for milling tool wear to be practicable.

Keywords: tool wear, milling, fractal dimension

0 INTRODUCTION

In the past 20 years there has been great achievement on the research of monitoring tool breakage, especially, on the occurrence, development and evolvement of the tool breakage, and some significant conclusions are also drawn. But the tool wear monitoring is being researched now. Some methods are applied to the specific aspect, others are in the testing phase. Compared with other machining, the milling tool wear mechanism is more complicated and the accurate model of the milling tool wear cannot set up at all because there are many factors affecting the milling tool wear and these factors are influenced each other. To analyze the tool wear in the theory, it is a highly non-linear in the whole cutting process, including the tool material deformation from elasticity to plasticity, the slip region of the rake face and sticking region deformation and geometry shape of the swarf changes. The non-linearity in the cutting process includes non-linear geometry, material non-linearity and non-linear state. These factors make the change of tool wear very complicated, and thus the evolution process of the tool wear possesses the very strong uncertainty [1] to [8]. Generally, the evolution process of the tool wear is regarded as the random behavior or random variable because of its complexity. Therefore, the statistics theory can be used to research its distribution function and set up its modal forecasting. However, the certain law and the order are hided behind the stochastic semblance of such systems as the stock price, the price index, the traffic flow as well as the machine diagnosis system which are as complicated as tool wear system in recent years. This law or order can be a kind of chaotic behavior, but not a random behavior. Therefore, depending on the chaotic theory, we can analyze and forecast the evolution process [9] to [11] . Suppose the evolution process of the tool wear has the chaotic characteristic, it can be insufficiently accurate to research tool wear by using the probability statistics theory. As a result, we must consider the chaotic characteristic in the evolution process of the tool wear to discover its inherent law, and then the more accurate and reasonable analyzing result and modal forecasting can be obtained.

Fractal theory was found by Mandelbrot, an American scientist in Mid-70s. It provides strong tool for explaining complex dynamics system behavior and forecasting as well as other research and is widely applied to the fields of physics, chemistry, geology and aerographs and so on. It can be used to describe the geometry shape of similar structures [12]. A system self-comparability phenomena means the characteristic of a structure or process is similar

*Corr. Author's Address: Lanzhou Polytechnic College, Qilihequ,gongjiawan 1, Lanzhou, Gansu, China,730050, xuchuangwen@126.com

in different space and time domain. That is, the self-comparability phenomena is not only restricted to the body aspect but also same feature in function and information aspects and so on. It reflects universal being of the generalized hologram phenomenon. The fractal characteristic is described by fractal dimension which is different from the general integral dimension and is fine parameter to describe the complicated objects' characteristic in nature. It is shown in the research concerned that the change process of the complicated machinery moving state has fractal dimension characteristic. The tool wear is an outcome of the machine tool running [13]. Up to now, few researches analyzed the tool wear fractal dimension from the point of view of the time series. In this paper, the fractal characteristic of the tool wear conditions is discussed through applying the reconstruction phase space technology based on the fractal theory and calculating the fractal dimension of the time series of the tool vibration signals. Therefore, the chaotic characteristic in the evolutionary process of the tool wear vibration is testified. According to observed data of the acceleration signals of the tool wear vibration, the phase space of the topology structure of the unchanged attractor is reconstructed by the single variable. In the phase space, the important characteristic values, fractal dimension which describe the attractor are extracted. It is shown that the evolution process of the tool wear has the chaotic characteristic. This provides the theoretical foundation for forecasting the tool wear with the aid of the chaotic theory.

1 FRACTAL DIMENSION THEORY

1.1 The Phase Space Reconstruction

A method to reconstruct the phase space was proposed by Packard based on single variable time series [14]. Supposed the time series of a dimension $x_i = x(t_i)$, $t_i = t_0 + i\Delta t$, $i = 1, 2, \ldots, N$. m dimensional phase space is constructed in terms of sampling with equal space length and time delay τ, where τ is integral times of Δt. The m dimension phase space is defined as follows

$$X_i(m,\tau) = \{x_i, x_{i+\tau}, x_{i+2\tau}, \cdots, x_{i+(m-1)\tau}\}$$
$$i = 1,2,\cdots, N-(m-1)\tau \tag{1}$$

where m is embedding dimension, τ is time delay and $\tau = K\Delta t$, where Δt is interval time between sampling data and K is random integer. According to Tankens' embedding theory, method obtaining condition vector X_i from time series x_i is called time delay embedding method. Embedding dimension m and time delay τ must be selected carefully in order to give really expression to the dynamical characteristic from the measuring signal based on time delay embedding method [15] to [17]. Tankens' embedding theory fails to show the principle of selecting the time delay, but only consider that as long as embedding dimension fills with $m \geq 2D + 1$, reconstruction phase space and the system phase space are differential coefficient homeomorphism, that is, topology equivalence, their dynamical characteristic is completely similar in the qualitative sense. When D dimension attractor can be embed in $m \geq 2D + 1$ dimension phase space, the geometry characteristic of the initial attractor can be reappeared, and the evolvement law of the system can be researched. When the phase space is reconstructed, the selection of time delay τ must assure that every component is relative independence. That is, the relativity of the phase space ordinate is as less as possible. Autocorrelation correlation function and mutual information method are very common methods in selecting the time delay. In this paper mutual information method is used to select the time delay because it is more advanced [18]. Mutual information principle: supposed the states of the discrete variable X and Y are m and n, their entropy function is defined as follows

$$H(X) = -\sum_{i=1}^{m} p_i \ln p_i \tag{2}$$

where p_i is probability of which variable X appears in the i state. The combination entropy of the variable X and Y is defined

$$H(X,Y) = -\sum_{i=1}^{m}\sum_{j=1}^{n} p_{ij} \ln p_{ij} \tag{3}$$

where p_{ij} is probability that variable X appears in the i state and variable Y appears in the j state. According to the definition of the entropy of X and Y and combination entropy of X and Y, the mutual information can be derived as follows

$$I(X,Y) = H(X) + H(Y) - H(X,Y). \tag{4}$$

The total dependency of two variables can be measured by the mutual information function. Because the mutual information value of the first minimum is less and the two-double inception is differentiated more clearly, the dynamic characteristic of the attractor can be analyzed qualitatively and qualitatively through reconstructing the phase space. It is a better method to select time delay. Therefore, the optimum value is ascertained by using the average mutual information method, that is, selecting time delay when the mutual information function reaches the minimum firstly as time delay τ reconstructing the phase space.

1.2 Fractal Dimension

The fractal dimension includes many calculation methods such as capacity, correlation, box, self-similitude , information dimensions and correlation dimension and so on. They all describe the fractal characteristic of the fractal set from different aspects. And the correlation dimension can be directly calculated according to reconstruction the phase space by using a dimension time series. In other words, this is a method of calculating the attractor correlation dimension of relative dynamical system by using a dimension time series. Grassberger and Procaccia introduced a method for calculating correlation dimension, which is widely used today for characterizing strange attractors. In the paper, the fractal dimension for analysis is used with correlation dimension method.

In order to calculate the fractal dimension, the correlation function *C(r, m)* should be calculated firstly

$$C(r,m) = \frac{1}{N_R^2} \sum_{i=1}^{N_R} \sum_{j=1}^{N_R} H\left(r - \left\|X_i - X_j\right\|\right), \ i \neq j \tag{5}$$

where N_R is the total of the embedding space $\{X_i\}$ and shows the orbit length of the reconstruction system, $N_R = N - (m-1)\tau$. Here r is m dimension sphere radius and the distance scale of the phase space R^m. $\left\|X_i - X_j\right\|$ is Euclide n distance between two phase points. H is Heaviside function and defined as follows

$$H\left(r - \left\|X_i - X_j\right\|\right) = \begin{cases} 1 & r - \left\|X_i - X_j\right\| \geq 0 \\ 0 & r - \left\|X_i - X_j\right\| < 0. \end{cases} \tag{6}$$

According to the distance equation among points of Euclidspace R^m, the distance between X_i and X_j is

$$d_{ij} = \left\|X_i - X_j\right\| = \sqrt{\left(x_i - x_j\right)^2 + \cdots + \left(x_{i+(m-1)\tau} - x_{j+(m-1)\tau}\right)^2}. \tag{7}$$

The fractal dimension *D(r, m)* of the reconstructing phase space is

$$D(r,m) = \lim_{r \to 0} \frac{\ln C\ (r,m)}{\ln r}. \tag{8}$$

It is very clear that each pair of phase points is correlative, *C(r, m)* = 1 if r is very large; the dimension calculated from the correlation dimension formula is not the actual fractal dimension but an embedding dimension if r is too less than the vector difference between circumstance noise and measured error. (8) is a limit process and changes with the variety of the phase space dimension m. When m is more than the upper bound of the space dimension of the embedding attractor, D won't change with m variety and approach to saturation value D_∞ which is called saturation dimension. If the saturation dimension is not integer, it is a fractal dimension of the attractor to be calculated, thus, the system may be identified as chaos or random.

2 EXPERIMENTS

2.1 The Experiment Method

The milling experimental condition is shown in Table 1. In order to monitor milling tool wear conditions, tool wear conditions should be divided into 3 conditions: initial condition (tool wear value VB < 0.1mm), normal condition (tool wear value 0.1mm ≤ VB ≤ 0.35mm) and acute wear condition (tool wear value 0.35mm ≤ VB). 384 groups' typical acceleration signals of tool wear were obtained as primitive data of the time series analysis from different tool wear conditions, which are obtained through cutting experiment with the orthogonal experiment method according to experimental conditions for milling listed in Table 2. Figure 1 is recognition process for monitoring tool wear. Figure 2 is a sets of vibration acceleration signals.

Table1. *Cutting experiment condition*

Cutting tool	Material: High-speed steel. Type: End milling cutter. Diameter(mm): 14 to 20.
Milling method	Climb milling
Workspace material	Thermal refining 45 steel
Cutting speed /(m/min)	8.792 to 26.376
Feed speed /(mm/min)	20 to 35
Cutting depth /(mm)	2 to 5

Table 2. *Cutting Experiment group*

Level	Group 1			Group 2			Group 3		
	v	f	a_p	v	f	a_p	v	f	a_p
1	8.792	30	5	9.671	30	4	13.19	30	4
2	9.671	25	4.5	11.43	25	3.75	15.38	25	3.75
3	11.43	20	3.5	13.19	20	3	21.96	20	3
4	13.19	30	3	15.38	30	2.75	26.376	30	2.75

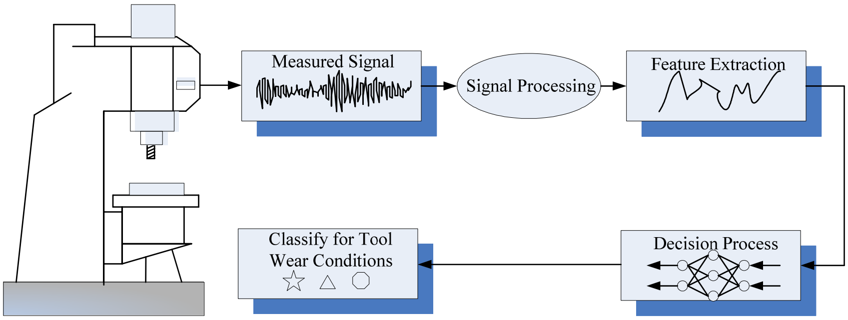
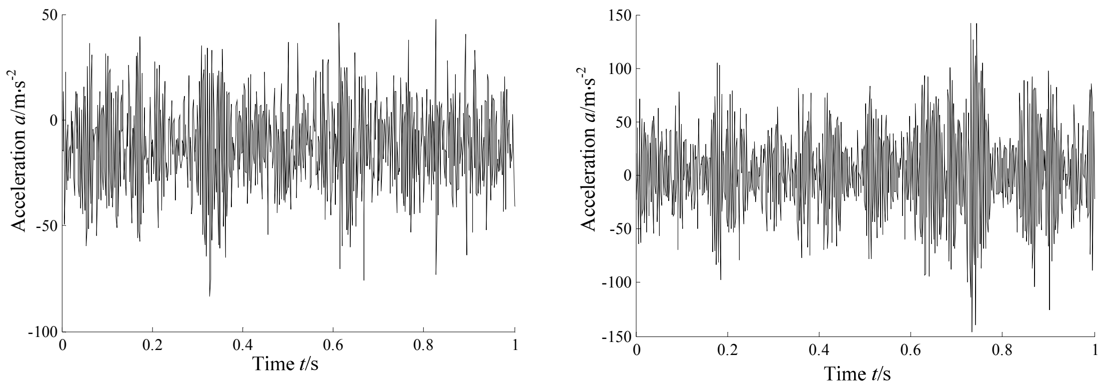
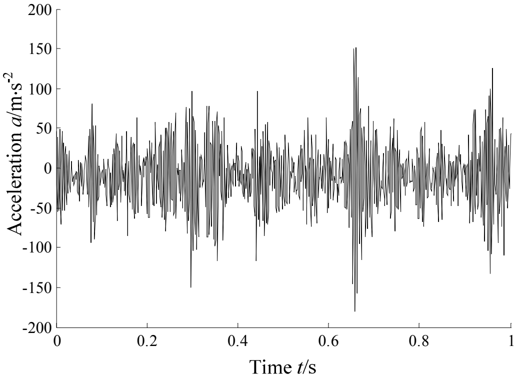


Fig. 1. *Recognition process for monitoring tool wear*



(a) The tool wear initial stage

(b) The tool wear normal stage



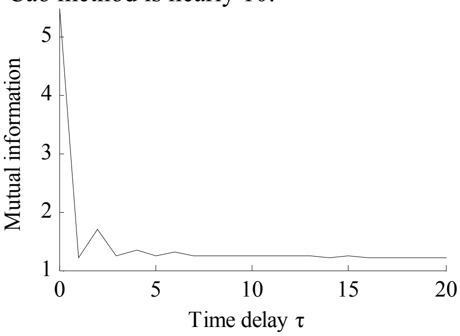
(c) The tool wear acute stage

Fig. 2. *The time domain shape of tool wear acceleration signals*

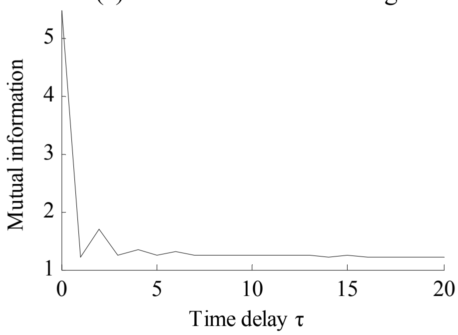
2.2 Parameters τ and m

To obtain fractal dimension about these informations during tool wear, parameters τ and m is developed. How to select the time delay τ and embedding dimension m, it is taken as the key point of the time delay phase space reconstruction. The time delay τ is adopted the mutual info method according to Eq. (2) to Eq. (4), The relation between mutual information and the time delay τ is shown in Figure 3. Here $\tau = 1$ is obtained.

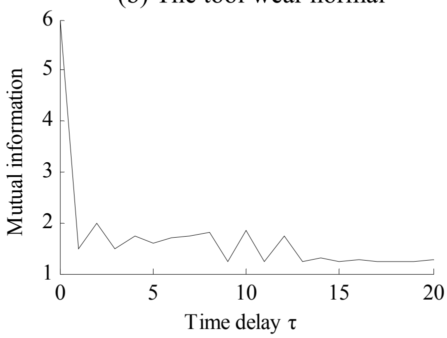
Embedding dimension is usually obtained from time series phase space reconstruction according to formula $m \geq 2D+1$. But such embedding dimension is not sure of minimum embedding dimension. Although much large embedding dimension can reconstruct the phase space such calculation easily increases other statistic complexity (such as Lyapunov exponent) and is easily disturbed by outside noise. So it is necessary to search a minimum embedding dimension to reconstruct completely the phase space. Selection of common embedding dimension has system saturation method, false neighboring method and optimization improving method based on false neighboring and so on. The later method of selecting the embedding dimension was proposed by Liangyue Cao in 1997. The method is defined two parameters $E_1(m)$ and $E_2(m)$, among them, the minimum embedding dimension m was decided by $E_1(m)$ and pointed out when $E_1(m)$ tends to be steadily in along with the evolution, the corresponds value m is the minimum embedding dimension. At the same time, $E_2(m)$ cannot be used to obtain the minimum embedding dimension, but it has a very good function, that is, it can be used to distinguishing random series or chaotic series from time series. It is random series if $E_2(m)$ is equal to 1 or is near to 1 to any m. Therefore, to real chaotic series, $E_2(m)$ cannot be equal to 1 to any m. Generally, $E_2(m)$ tends to 1 to a real chaotic series. Thus, it is a direct and simple method to decide whether the time series has fractal characteristic of the chaos series. In Figure 4, the minimum embedding dimension extracted by Cao method is nearly 10.



(a) The tool wear initial stage

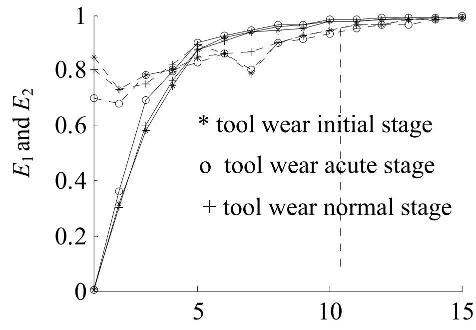


(b) The tool wear normal



(c) The tool wear acute stage

Fig. 3. *The relation curve between mutual information*

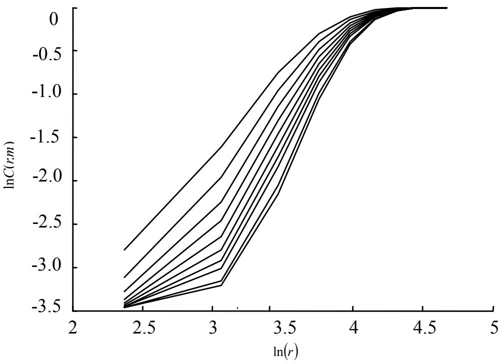


Full line indicates $E_1(m)$.
Dotted line indicates $E_2(m)$.

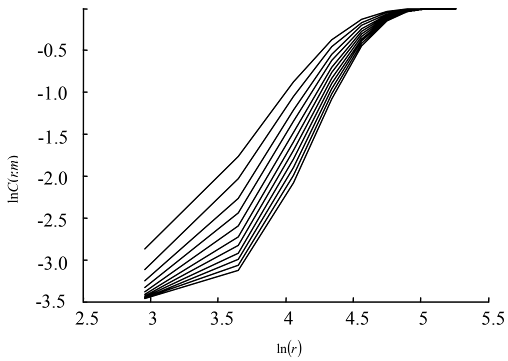
Fig. 4. *The minimum embedding dimension on Gao method*

2.3 Fractal Dimension Calculation

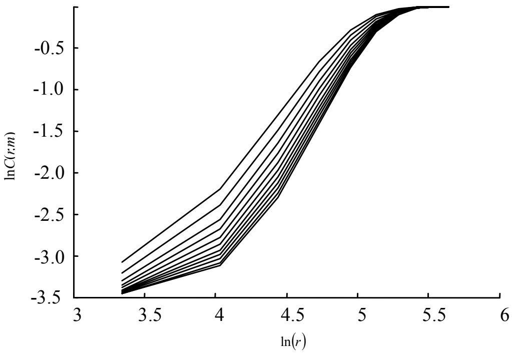
The ln$C(r,m)$ was calculated according to Eq. (5). Assigning different values to r, r_i: r_1, $r_2,\ldots,r_T$. The different correlation value $C(r_i,m)$: $C(r_1, m)$, $C(r_2, m,\ldots, C(r_T, m)$ is obtained correspondingly through calculating ln$C(r,m)$, T is the different value number of r . In order to decide r, firstly, Euclidean distance between all the phase points must be calculated. Secondly, initial value of r should be found out to be the distance of the minimum phase points. Finally, the step-size of r is ratio on the difference of the maximum and minimum phase points with T. Appling computer program , the relation between ln$C(r,m)$ and ln$r$ of the tool wear series signal is shown in Figure 5.



(a) The tool wear initial stage



(b) The tool wear normal stage



(c) The tool wear acute stage

Fig. 5. *The relation between* ln$C(r,m)$ *and* ln$r$

A bunch of curves with embedding dimension m = 2 to 12 can be seen in Figure 5 from left to right. It can be shown that the value of fractal dimension D increases gradually with the embedding dimension increasing to limited long series. In different embedding dimension there is no scale region or linear section existing on ln$C(r,m)$ and ln$r$. So the fractal dimension $D(m)$ is the calculation mean value of all D_p which is near the max 30% D_p when the linear slope D_p of 5 point minimum mean-square value is calculated. With the embedding dimension m increasing, m is the saturation embedding dimension m_s if $(D(m) - D(m\text{-}1))/D(m) \leq 10\%$ and $D(m)$ is thecorresponding fractal dimension D.

256 groups time-domain signals are collected in three different conditions at every 1024 sampling points as a calculation cycle according to groups 1 and 2 in Table 2. The fractal dimension is calculated in three different periods, then calculated average result as the

fractal dimension of the condition . The results of the fractal dimension are shown in Table 3.

Table3. *Experiment results with the noise signal*

Tool wear conditions	Initial wear	Normal wear	Acute wear
The fractal dimension	2.986 to 3.918	3.421 to 5.765	4.783 to 6.345

As it is shown in Table 3, fractal dimension in three different conditions is from low to high. The experiment results show that fractal dimension is different in three different conditions. We may use the characteristics to achieve tool wear condition monitoring. Value in Table 3 is non-integer, it is shown that the evolution process of tool wear conditions has the characteristics of chaos, at the same time, tool wear conditions can be recognize by using fractal dimension.

2.4 Factors Effecting Fractal Dimension

Measurable tool wear signals typically have very low signal-to-noise ratio (< 3dB) because of the variety of noise sources on the milling machine. However, relatively little research has been done on tool wear signal enhancement and noise reduction. For tool wear classification, most monitoring systems either use the noisy signals directly without preprocessing, or simply lowpass filter the signal to average out the corrupting noise sources. While it is relatively easy to implement, these techniques have proven to be generally ineffective at reducing the noise and tend to remove information necessary for appropriate tool wear classification. To choose more effective signal enhancement and noise reduction algorithms, we first need to examine the tool wear signal and noise generating processes. The original tool wear signal (without noise) consists of two main components: a slowly varying response of the workpiece material to quasi-periodic excitations, and randomly occurring transients. The interfering noise results from three main sources: mechanical noise, electrical noise, and fluid noise.

In Table 3, fractal dimension appears overlapping phenomena between different tool wear conditions so that recognition rate of tool wear is effected. Experimental results show that recognition rate can reach up to 57%. Research shows that calculation about fractal dimension not only depends on the characteristics of system itself, but also has something to do with system in noise and dimension of reconstruction the phase space. It can result in the different fractal dimensions for reasons in different noise level. So it is still difficult to describe accurately that a system is chaotic or random in high noise level, at the time same, in the same noise level because of different embedding dimensions calculation results about fractal dimension can be some differences. As a rule, it can contain noise to actual measured time series signal and in many conditions it can be very low signal-to-noise ratio [19]. In this way, it is difficult to describe accurately activities of system by means of fractal dimension. Therefore, it should also be one of the concerned problems in fractal dimension application to improve signal-to-noise ratio and decrease effect calculation results about fractal dimension. A threshold filtering algorithm based on SVD (The singular value decomposition) is used to process the raw data and to reduce the noise of the original measurement signals. Calculation results about fractal dimension of not de-noised and de-noised time series are shown in Table 4. From Table 4, in different tool wear conditions range of fractal dimension decreases and overlapping phenomena between different tool wear conditions disappears. So the identification accuracy is improved. The experiment results show that identification accuracy for tool wear can reach up to 71%.

Table 4. *Experiment results of the signal noise reduction*

Tool wear conditions	Initial wear	Normal wear	Acute Wear
The not de-noised fractal dimension	2.986 to 3.918	3.421 to 5.765	4.783 to 6.345
The de-noised fractal dimension	2.986 to 3.918	3.421 to 5.765	4.783 to 6.345

The effect of the sampling time on the fractal dimensions was also discussed in this paper. In Table 5, the fractal dimensions are described by sampling signal for tool wear at different time in normal wear condition

(VB=0.25mm). Where sampling frequency of vibration signals is 10 kHz, calculation data length N is 1024, embedding dimension m is 10, time delay τ is 1.

Table 5 . *Fractal dimensions at different sampling time*

Fractal dimensions	Data 1	Data 2	Data 3	Data 4	Data 5
D	3.725	3.201	3.388	3.516	3.269

As it is shown in Table 5, the fractal dimensions are different in same cutting condition, that is, it has been found that the fractal dimensions calculated by vibration signals have characteristics of low repeatability. The main reason from these data is presented below: there are some different excitation sources, which the tool spindle vibration response is overlaid according to the working order and the phase relationship in angle domain. Because of uncertain transfer paths from tool to measured place in some point, measured vibration signals, excitation response can be different in the degree of deterioration of measured place. At the same time, acceleration of vibration response can also be different in a fix measured place. To milling tool, if measured signal is sampled at a 10 kHz frequency and this signal was obtained at a spindle speed of 1000 r/min, 1024 data points can correspond with 1.7 working cycle of milling tool. So 1024 data points of random measured signal at different time can correspond with different working cycle and the fractal dimensions. In order to verify above analysis, Table 6 gives the fractal dimensions of measured signals in same spindle speed. When spindle speed is 1000 r/min, there is 5.4 working cycle. At different time, to compare difference about data in 0.4 working cycle with 6 working cycle, data in 0.4 working cycle only occupy 5.7%. The fractal dimension fluctuations are relatively small; 768 data points can correspond with 1.28 working cycle of milling tool, to compare difference about data in 0.28 working cycle with 1.0 working cycle, data in 0.28 working cycle occupy 28%. The fractal dimension fluctuations is relatively large; 600 data points can correspond with 1 working cycle of milling tool, it can accurately obtain data in 1.0 working cycle so that difference between data can be eliminated and the fractal dimension has very steady state. So data length should correspond with integer times of milling tool working cycle in calculation the fractal dimension. Sampling data length for angle domain tracking technique can eliminate data change of sampling 1 working cycle for speed undulate. Thus it is very necessary to improve consistency of the fractal dimension deeply.

The effect of the curve fitting data on the fractal dimensions was also discussed in this paper. Applying unscale range to determine above the fractal dimensions calculation method ,it is under the least square fitting residue minimum conditions based on of middle section of ln$C(r,m)$ and ln$r$ curve. It is necessary to determine the best similar fractal dimensions in ln$C(r,m)$ and ln$r$ curve. Little change of measured data can result in that fitting line rake ratio (fractal dimensions) can be changed. Therefore, a new method for calculating the fractal unscale range is proposed in determining the fractal dimension. This method is based on multi-segments average and threshold, which can extend the scope of the fractal unscale range. Approximate line section of both ends in ln$C(r, m)$ and ln$r$ curve is caused by less and more section of measured data from Figure 5. The data mainly lead to random noise and occupy within 15% to 20%. This is not obvious to change of tool wear conditions. Middle data section is main source for vibration information of tool wear conditions and it is also shown that there is linear relationship in middle data section. So the best information of tool wear condition can be applied and improved the fractal dimension accuracy using determining both ends and transition data section.

Table 6. *The fractal dimensions of measured signals in same spindle speed*

Data length	Data1	Data 2	Data 3	Data 4	Data 5	Data 6	Data 7	Data 8
3240	3.630	3.764	3.544	3.530	3.561	3.702	3.873	3.574
768	3.156	3.021	3.001	3.981	3.229	3.832	3.833	5.135
600	3.626	3.622	3.617	3.598	3.602	3.683	3.610	3.592

2.5 The Fractal Dimension Calculation After Improving

Applying above methods are presented, the results are satisfactory through analyzing 128 vibration signals of group 3 in Table 2 under three conditions.

The fractal dimension calculation before improving. A new sample data is composed of sampling 128 groups vibration signals according to milling experiment condition of group 3 in Table 2. Calculation results of the fractal dimension are shown in Table 7. Fractal dimensions appear overlapping phenomena between different tool wear conditions so that difference of fractal dimensions is not obvious. So it is difficult to recognize milling tool wear conditions based on fractal dimensions of original signals. The result can analyze basically with Table 3.

Table7. *Fractal dimensions of 128 groups of original signals (embedding dimension m=10)*

Experiment number	Actual condition	Fractal dimension	Recognition condition	Experiment number	Actual condition	Fractal dimension	Recognition condition
1	1	3.923	2	12	3	5.550	3
2	2	3.527	2	13	1	3.904	2
3	3	4.885	3	14	2	4.675	2
4	1	3.567	2	15	3	4.771	3
5	2	3.516	2				
6	3	4.785	3	123	1	4.669	2
7	1	3.856	1	124	2	4.948	2
8	2	3.854	2	125	3	4.882	3
9	3	6.308	3	126	1	2.997	1
10	1	3.875	1	127	2	5.665	3
11	2	5.553	2	128	3	4.881	2

Note: 1,2,3 in Table 7 indicate respectively initial wear, normal wear and acute wear.

Table 8. *Fractal dimensions of 128 groups of improving signals (embedding dimension m=10)*

Experiment number	Actual condition	Fractal dimension	Recognition condition	Experiment number	Actual condition	Fractal dimension	Recognition condition
1	1	2.667	1	12	3	5.001	3
2	2	3.789	2	13	1	2.678	1
3	3	5.023	3	14	2	3.994	2
4	1	2.823	1	15	3	4.038	2
5	2	3.398	2				
6	3	5.003	3	123	2	2.912	1
7	1	3.384	2	124	2	3.339	2
8	2	3.335	2	125	3	3.954	2
9	3	4.541	3	126	1	2.780	1
10	1	4.045	2	127	2	3.469	2
11	2	3.356	2	128	3	5.118	3

The fractal dimension calculation after improving. The fractal dimension calculation results are shown in Table 8 based on noise reduction as well as multi-segments average and threshold, which can extend the scope of the fractal unscale range. As it is shown in Table 8, the fractal dimensions are extremely obvious in different tool wear conditions, especially in initial tool wear it expresses powerful superiority. The experiment results show that identification accuracy for tool wear can reach to 82%.

3 CONCLUSIONS

A measurement method for the milling tool wear has been described. Extensive experiments have shown that the system developed in this paper is operational. The experiment results show that the fractal theory is leaded into monitoring field for milling tool wear to be practicable. In paper, parameters τ and m is developed in the fractal dimension calculation process and algorithm of the fractal dimension is given. The above analysis shows the fractal dimension change of vibration signals of the milling tool wear is consistent with the wear, at the same time, it can obviously present the change trend with wear increasing. The evolution process of the tool wear has the chaotic characteristic, thus provides theoretic basis for milling tool wear prediction by means of chaotic theory from it. build on past achievements. Factors effecting fractal dimension are explored. Finally, through method based on noise reduction as well as multi-segments average and threshold, which can extend the scope of the fractal unscale range, it is found that to distinguish the degree of tool wear condition is extremely obvious to a great extent, especially in initial tool wear it expresses powerful superiority. However, there are some limitations in fractal dimension techniques: 1) when for the embedding dimension with different value, fractal dimensions are influenced by the embedding dimension so that recognize results for tool wear are influenced; 2) effecting fractal dimensions about noise and sampling data length is very large. When Measurable tool wear signals typically have very low SNR, identification accuracy for tool wear is very low. 3) in milling tool wear monitoring, whole average identification rate is still in a low position to some extent, this will remain to be solved to propose new pattern techniques in order to overcome these limitations.

4 REFERENCES

[1] Xu, C.W., Chen, H. L. (2007) A Research of Tool Wear Recognizing Based on Wavelet Packet Pretreated and Neural Network, *System Design and Dynamics,* The Japan Society of Mechanical Engineers, 1(4), p.760-712.

[2] Prickett, P.W. , Johns, C. (1999) An Overview of Approaches to End Milling Tool Monitoring, *Machine Tools & Manufacture*, 39(1), p. 105-122.

[3] Dimla, E., Dimla, Snr. (2000) Sensor Signals for Tool Wear Monitoring in Metal Cutting Operations, *Machine Tools & Manufacture*, 40(8), p.1073-1098.

[4] O'Donnell, G., Young, P., Kelly, K. (2001) Towards the Improvement of Tool Condition Monitoring Systems in the Manufacturing Environment, *Materials Processing Technology*, 119(1), p.133-139.

[5] Erkki, J. (2002) Asummary of Methods Applied to Tool Condition Monitoring in Drilling, *Machine Tools & Manufacture*, 42(7), p.997-1010.

[6] Kopač, J., Šali, S. (2001) Tool Wear Monitoring During the Turning Process, *Materials Processing Technology*, 113(1), p.312-316.

[7] Axinte, D. A. (2003) Tool Condition Monitoring in Broaching, *Wear*, 254(3), p.370-382.

[8] Wang, H. L. (2003) On-line Tool Breakage Monitoring in Turning, *Materials Processing Technology*, 139(1), p. 237-242.

[9] O'Neill-Carrillo, E. , Heydt, G. T., Kostelich, E. J. (1999) Nonlinear Deterministic Modeling of Highly Varying Loads,*IEEE Transon Power Delivery*, 14(2), p. 537-542.

[10] Harrison, R. G. (1999) Non-linear Noise Reduction and Detecting Chaos: Some Evidence from the S&P Composite Price Index, *Mathematics and Computers in Simulation*, 48(6), p. 497- 502.

[11] Shao, H., Zhao, Q. X. (2006) Study and Application of Correlation Dimension in

Fault Diagnosis of Machine, *China Safety Science Journal*,16(3), p. 129-134.

[12] Mandelbrot, B. B. (1982) The Fractal Geometry of Nature, San Francisco: *Freeman*.

[13] Xu, Y. X., Yuan, P. X., Yang, W. P. (2003) Fractal and Wavelet Method on Complicated Machine Fault Diagnose, *Machine Industry Press*.

[14] Packard, N. H . (1980) Geometry from a Time Series, *Phys Rev*, 45(1), p. 712-716.

[15] Kantz, H. (1997) Thomas, S., Nonlinear Time Series Analysis, Cambridge : *Cambridge University Press* .

[16] Luo, F. (2000) Chip Study Based on Noise Reduction, *Xi'an Electronic University Journal*, 27(5), p. 664-667.

[17] Jin, W. Y. (2002) A Method for Estimating the Optimal Embedding Dimension and Delay Time, *2002 International Symposium on Information Theory and Its Applications* , *Xi'an* .

[18] Fraser, A. M. (1986) Independent Coordinates for Strange Attractors from Mutual Info rmation, *Physical Review*, 33(1), p. 1134-1140.

[19] Xu, C. W., Chen, H. L. (2008) The Fractal Characteristic of Vibration Signals in Different Milling Tool Wear Periods ,*the 7th International Symposium on Instumentation and Control Technology, Applied Mechanics and Materials*, 7128, p.1-6.