A NOVEL ONLINE METHOD OF MONITORING THE ROUGHNESS AND DAMAGE OF WORKPIECE DURING CUTTING

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Theories related to grayscale image self-affine dimension were presented in this study to describe roughness and damage in a workpiece. A novel technique was also proposed to monitor the surface quality of a workpiece online by using the grayscale image self-affine dimension and damage. A MEMRECAM HX-3E high-speed camera was used to capture the surface of cylinder cast iron workpieces during cutting and to verify the theoretical and actual online monitoring of workpiece surface roughness and damage. The proposed online monitoring technique was then compared with traditional monitoring techniques. Results revealed: (1) clear and small cut marks and textures on the workpiece surface. The corresponding calculated grayscale image self-affine dimension was also small, and thus grayscale image self-affine dimension satisfied the definition of fractal. (2) In the initial stage when cutting was unstable, the self-affine dimension and damage calculated using workpiece grayscale images were relatively larger than those obtained in other moments when cutting was stable. It was indicated that these parameters were sensitive to changes in workpiece surface stage. (3) The grayscale image self-affine dimension and damage increased as back cutting depth increased, and these findings were consistent with those observed on traditional workpiece quality tests performed while the machines were shut down. These phenomena indicated that, (1) the calculation theories on grayscale image self-affine dimension and damage were correct, and damage was also an important parameter to assess the workpiece quality. (2) Our proposed approach was a novel and effective technique for the online monitoring of workpiece quality. Therefore, this technique could be applied to monitor workpiece quality online and provide relatively higher sensitivity to changes in the workpiece surface stage than those of other traditional techniques.

Keywords: Online monitoring; Grayscale image self-affine dimension; Damage; Cutting; High-speed camera.

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1. Introduction

Modern high-end equipment manufacturing requires precision numeric control machine tools for automated processing and production throughout the entire cutting process without artificial intervention. This ensures workpiece quality and improves production and processing efficiency. However, traditional testing techniques for workpiece quality fail to provide real-time online monitoring of the workpiece cutting process. Hence, machines must be shut down to detect workpiece quality. This method not only reduces production efficiency but also increases the defect rate. Large amounts of resources are spent unproductively [1]. Therefore, the development of new online workpiece quality testing technique has become an important part of production and processing, as well as a key prerequisite to implement automated production.

Surface roughness and damage are important quantitative indicators of workpiece quality, which not only directly affects properties such as wear resistance, corrosion resistance, fatigue resistance, and contact stiffness, but also influences the coordination stability and airtightness of parts in a product [2]. Visual inspection and various instruments are used as the main methods to monitor these workpiece quality parameters and to determine the surface topography and related mechanical parameters [3], such as cutting force, temperature, surface three-dimensional (3D) coordinates, and acoustic emission signals. Relevant theories and approaches are applied to calculate surface roughness or damage variables. However, traditional monitoring methods require shutting down of machines. A cutting parameter is estimated on the basis of experience, and various parameters, such as roughness and temperature, affecting workpiece quality could be observed only after cutting is completed. The disadvantage of this method is the need to shut down machines. In the absence of automated production conditions, this method complies with production requirements. With the implementation of automated manufacturing, downtime inspection decreases production efficiency and quality and sometimes creates batch defects [1]. Therefore, online monitoring techniques should be developed to adhere to high requirements of precision machining production. Xu conducted this technical research in a rather early stage [4]. Based on the requirements of fast response and simplicity of underlying algorithms in engineering applications, as well as surface roughness formation theory, linear regression is applied to construct a mapping model between vibration intensity and surface roughness. Thus, a monitoring acquisition system is established to develop an online surface roughness alarm function. The proposed method [4] requires the development of a mapping model between vibration intensity and surface roughness through regression analysis. This model is possibly affected by empiricism, and therefore the predicted surface roughness is much more likely to be biased. Acoustic emission has also been applied [5,6,7,8]. In this technique, real-time workpiece surface roughness is indirectly measured after acoustic emission signals sent during workpiece cutting are post-processed. Acoustic emission signals are then used as an intermediate medium to obtain workpiece surface roughness indirectly, and this procedure contributes to improving measurement techniques. However, acoustic emission signals are severely disturbed by high-frequency signals of mechanical shock. Consequently, measurements become inaccurate, and the calculated workpiece roughness is remarkably different from the actual value.

In general, existing studies have evolved from traditional downtime inspection to online monitoring technique. Although this monitoring technique has been considerably improved, there are still several disadvantages to indirect online monitoring of workpiece surface quality parameters, namely, roughness, through intermediate parameters (such as temperature, cutting force, and acoustic emission signals): (1) The relationship between intermediate parameters and the parameter characterizing workpiece quality is affected by empiricism, and hence deviations and errors in the final measurements of workpiece quality parameters occur. (2) Intermediate parameter measurement is severely influenced by external interference, which reduces measurement accuracy and hence affects the accuracy of final workpiece quality parameters.

Thus, we used a high-speed camera to observe the real-time cutting process of high-speed rotating workpieces and then proposed relevant online monitoring methods to measure surface roughness and damage directly. Our investigation consists of two parts. First, we presented a calculation method of grayscale image self-affine dimensions and damage based on the interdisciplinary theory of mechanics, graphics, fractal geometry, and damage mechanics. Second, we proposed a novel online approach of monitoring workpiece roughness and damage. Using a high-speed camera and post-processing method, we obtained the 3D coordinates of grayscale image surfaces to calculate the real-time grayscale image self-affine dimension and damage.

2. Relevant methods regarding online monitoring

2.1 Calculation method of grayscale image self-affine dimension

Pentland [9] pioneered the study of fractal geometric characteristics of grayscale images. He explored the dimensions of various images of natural beauty, such as mountains, rivers, and leaves, and demarcated the images according to the grayscale image dimension. Studies have been conducted to examine the calculation method of grayscale image dimensions [10], and the dimensional theory of grayscale images has been applied to various fields, such as the description of tool surface topography after cutting damage [11, 12], geological joint surface topography descriptions [13], and computer graphics and image processing. These image dimensions were generally limited to self-similar dimensions. However, Mandelbrot [14] found that the surface fractal geometry of various materials was more characterized by the self-affine property. Hence, fractal Brownian function was used to calculate self-affine dimensions of grayscale images.

1) Construction of grayscale surface

Grayscale images were obtained by image conversion or capturing. Matlab 2015 programming language was applied to prepare relevant calculation software to extract the grayscale value of grayscale images. The point $(x, y, I_H(x, y))$ in the 3D Euclidean space was constructed by taking the pixel position coordinates as the horizontal and vertical coordinates, x, y, and taking the equivalent grayscale value $I_H(x, y)$, of the pixel calculated based on the actual material size, as the height value [9]. Likewise, 3D points were constructed in every corresponding pixel. Afterwards, these points were successively connected to construct a spatial curved surface named the grayscale surface.

2) Self-affine dimension calculation

The fractal Brownian function was a powerful tool to describe various types of surface self-affine fractal features and was set as $F_H(x, y)$. According to its definition, the Hurst exponent was given as $0 < H < 1$, $x, y \in R^2$. The random function was set as $F_H(x, y)$ on the probability space (Ψ, A, P), which satisfied the following conditions:

(1) $F_H(x, y)$ was continuous and (2) $F_H(0, 0) = 0$.

Variables $\Delta x, \Delta y \in R^2$, and the increment $F_H(x + \Delta x, y + \Delta y) - F_H(x, y)$ followed a Gaussian distribution with mathematical expectation of 0 and variance of $\sigma^2(\Delta x^2 + \Delta y^2)^H$. The probability density function could be expressed as follows:

$$f(r) = \frac{1}{\sqrt{2\pi\sigma^2\left(\Delta x^2 + \Delta y^2\right)^H}} \exp\left(-\frac{r^2}{2\sigma^2\left(\Delta x^2 + \Delta y^2\right)^H}\right) \tag{1}$$

Solving the mathematical expectation of incremental absolute value was as follows:

$$E\left(\left|F_H(x + \Delta x, y + \Delta y) - F_H(x, y)\right|\right) \propto \left(\sqrt{\Delta x^2 + \Delta y^2}\right)^H \tag{2}$$

Finally, the proportional coefficient K was selected and common logarithms of both sides were calculated as follows:

$$\log\left[E\left(\left|F_H(x + \Delta x, y + \Delta y) - F_H(x, y)\right|\right)\right] = H \log\left(\sqrt{\Delta x^2 + \Delta y^2}\right) + \log K \tag{3}$$

Considering that the specific study object was a grayscale image of a workpiece during cutting, the grayscale conversion value $I_H(x, y)$ of the pixel was the fractal Brownian function $F_H(x, y)$. The Hurst exponent H of the grayscale image was calculated using Eq. (3). The specific procedures were as follows: 10 groups of points (1/2log ($\Delta x^2 + \Delta y^2$), log [E ($|I_H$ ($x+\Delta x$, $y + \Delta y$) − I_H (x, y)$|$)]) were constructed in the coordinate system. The least squares method was used in the linear fitting of these 10 points. The Hurst exponent H was the fitting slope. According to the research results of Mandelbrot and Ness [14] and considering that the gray curved surface was in a 3D Euclidean space, n was taken as 3. Therefore, the Hurst exponent and fractal dimension had the following relation:

$$D = 3 - H \tag{4}$$

The Hurst exponent H was substituted to obtain the grayscale image self-affine dimension D applied to describe the workpiece surface roughness.

2.2 Damage calculation method to describe the workpiece damage degree

In 1958, Kachanov [8] argued that the main mechanism of material deterioration was the reduction in effective load-bearing area caused by micro-defects, and thus proposed a definition of damage variables. He recommended that the value of damage variables should be calculated by the ratio between the actual area and nominal area of material, that is,

$$D_a = 1 - \frac{S}{S_0} \tag{5}$$

where S represents the actual area of material and S_0 is the nominal area; And the measurement units of S and S_0 are both square millimeter. D_a is a dimensionless variable.

However, in this paper, what we studied were surface morphology changes and overall damage evolution of workpieces during cutting. Apparently, the ratio of its surface area failed to reflect the contribution of surface micropore depth to damage. Therefore, considering the actual situation of workpieces and learning from existing research methods, we used the ratio of actual volume and nominal volume of the workpiece to calculate damage variables.

In addition, in our experiment, the high-speed camera could only take photos of half of the side of the cylindrical workpiece. The reflective interference caused by the upper part of the side should be also excluded. Thus, the lower quarter of the cylinder was taken as the study object in the calculation of damage variables and dimensions (see Fig.3). The nominal volume of the cylindrical workpiece was expressed as follows:

$$V_0 = \frac{1}{4}\pi(R - h)^2 L \tag{6}$$

where V_0 represented 1/4 nominal volume with the measurement unit of cubic millimeter, R was set as the cylinder radius, h was the feed amount, and L represented the length of the calculated domain cylinder, which could be expressed as

$$L = {}^{46.6}\!/_{39.9} \times 53.45 = 62.425\mathrm{mm} \tag{7}$$

And the measurement units of R、h and L are millimeter.

The actual volume of the workpiece after damage was expressed as follows:

$$V_i = \delta_i \delta_j E(I_{ij}) \tag{9}$$

where V_i was the volume of the ith micro unit, δ_i represented the horizontal pixel interval, δ_j was taken as the pixel interval in the vertical direction, I_{ij} represented the converted pixel grayscale value in the four vertexes of the micro unit, and E was the mathematical expectation sign. The measurement units of δ_i、 δ_j and I_{ij} are millimeter. The measurement unit of the variable V_i is cubic millimeter.

Therefore, the actual volume of the workpiece after damage could be expressed as follows:

$$V = \sum_{i=1}^{m}\sum_{j=1}^{n} \frac{(x_{i+1} - x_i)^2 (I_{i,j} + I_{i+1,j} + I_{i+1,j+1} + I_{i,j+1})}{4} \tag{10}$$

and the damage variable value as

$$D_a = 1 - \frac{V}{V_0} = 1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} \frac{(x_{i+1} - x_i)^2 (I_{i,j} + I_{i+1,j} + I_{i+1,j+1} + I_{i,j+1})}{4}}{\pi (R - h)^2} \tag{11}$$

Where the measurement units of V and are cubic millimeter; the measurement units of $I_{i,j}$ 、$I_{i+1,j}$ 、$I_{i+1,,j+1}$、$I_{i,,j+1}$、x_i、x_{i+1} are millimeter.

3. Online monitoring test of workpiece roughness and damage

To verify the correctness of the theoretical method on which the monitoring technique was based and to demonstrate the actual operation method of online monitoring, we provided an example of online monitoring the roughness and damage of the workpiece. Based on the proposed method, a high-speed camera captures the cutting process of the workpiece surface. Real-time images were acquired. Then the grayscale image self-affine dimensions and damages were calculated to assess the workpiece roughness and damage degree.

3.1 Online monitoring equipment and test parameters selection

A MEMRECAM HX-3E high-speed camera (see Fig.1) used was manufactured by NAC. The maximum shooting speed of the camera was 220,000 fps. At full resolution of 2560 × 1920, the maximum speed was 2,000 fps, and the shutter speed could reach 1.1 μs. The memory card capacity was 32 GB. During the experiment, the workpiece rotation speed was set to 180 r/min. Because the rotation speed was not fast, a clear image of the workpiece cutting texture and marks during rotation could be guaranteed. Under the premise, we selected a smaller shooting frame rate, higher pixel resolution, and longer shooting time. Therefore, the shooting frame rate was set to 2,000 fps and image resolution to 1024 × 640. Previous studies[15] revealed that in the traditional method of testing workpiece quality during downtime, the back cutting depth had an effect on roughness within a certain range, but the influence was not significant. Thus, to determine the effectiveness and sensitivity of the proposed online monitoring method, we chose back cutting depth as research parameter, which was set to 0.5 mm and 1 mm. The workpiece feed rate was set to 30 mm/min.

3.2 Process of monitoring online roughness and damage of workpiece during the cutting

Cast iron was used as a raw material for cutting. Because there existed a layer of dark gray oxidation film on its surface, which negatively affects on the grayscale image data post-processing, the oxidation film was removed before the experiment until the surface was smooth and clean and pure. In this case, a cylindrical workpiece with a 54.45 mm diameter was obtained.

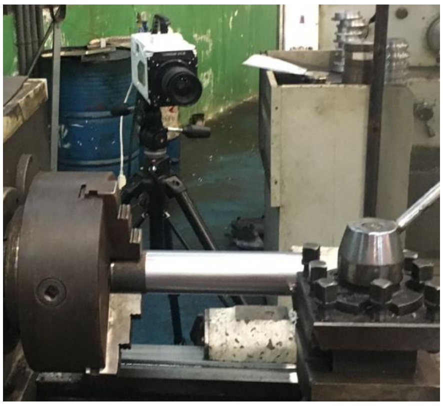

Fig. 1. Experiment on work piece cutting shot by high-speed camera

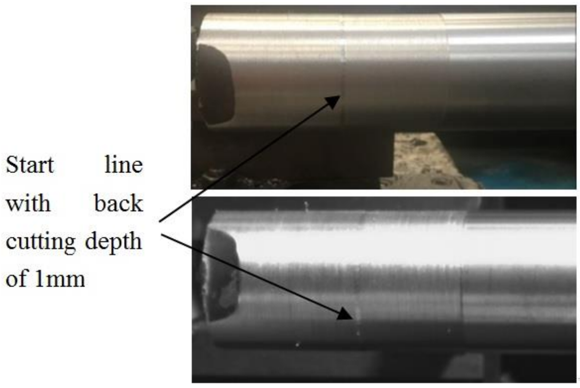

Fig. 2. True color image shot by a digital camera and grayscale images shot by a high-speed camera

Next, the high-speed camera was set up and adjusted so that the camera line of sight was perpendicular to the workpiece surface. In low light conditions, we were required to adjust the focus until a clear and high-resolution image was obtained. The shooting frame rate was set to 2,000 fps. Afterwards, the shooting range was adjusted to ensure the best image clarity. After setting the lathe speed, feed rate, and back cutting depth of 0.5 mm, the lathe was started and the workpiece began to rotate. When the speed reached a stable 180 r/min, the high-speed camera started to shoot images and stopped when storage (32GB) is full. Moreover, to acquire clearer static color images of the workpiece surface, a digital camera was used to take surface photos after the lathe was shut down (Fig. 2). To avoid the effect of cutting temperature on subsequent tests, the lathe was shut down for more than half an hour to cool the workpiece to room temperature. In the meantime, video data was exported to the computer. Cutting was then conducted for the same experimental workpiece after the back cutting depth was increased to 1 mm. In contrast to the previous test, the high-speed camera started shooting simultaneously with the cutting process to test the sensitivity of parameters describing workpiece quality. After the shooting, the video file (Fig. 2) was exported to the computer for data processing.

3.3 Analysis of online monitoring test and comparison study with traditional conclusions

Video files were converted into grayscale images to explore surface topography and damage changes during cutting. Since the workpiece was rotating at 180 r/min, the images shot by the camera did not belong to the same side, making the study object incomparable. To avoid this situation, groups of images were extracted, with intervals of 4 s, from the total 40,000 pictures so that the images taken by the camera were of the same side. Considering unpredictable occasional errors in the test, each group contained three grayscale images, and the extraction times were, respectively, t, $t + 0.002$, and $t + 0.004$ ($t = 0$ s, 4 s, 8 s, 12 s, 16 s, and 20 s). Eighteen images were extracted. Since we used 2 different back cutting depths, 0.5 mm and 1 mm, a total of 36 images were extracted. Fig.3 shows the surface grayscale images at time t with back cutting depths 0.5 mm and 1 mm, respectively.

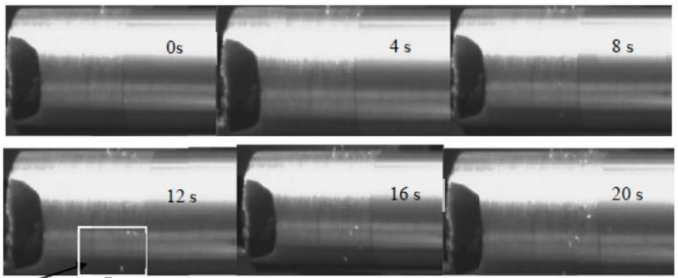

Fig.3.1a workpiece grayscale images with the back cutting depth of 0.5mm

intercepted image fileds:46.6*39.9mm

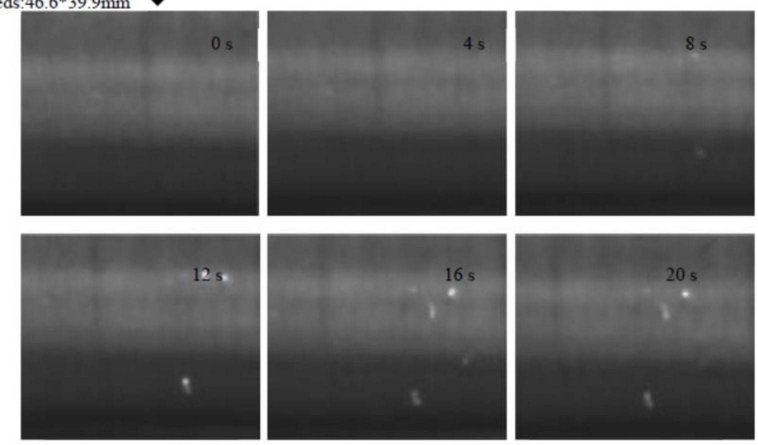

Fig.3.1b the intercepted images with the back cutting depth of 0.5mm

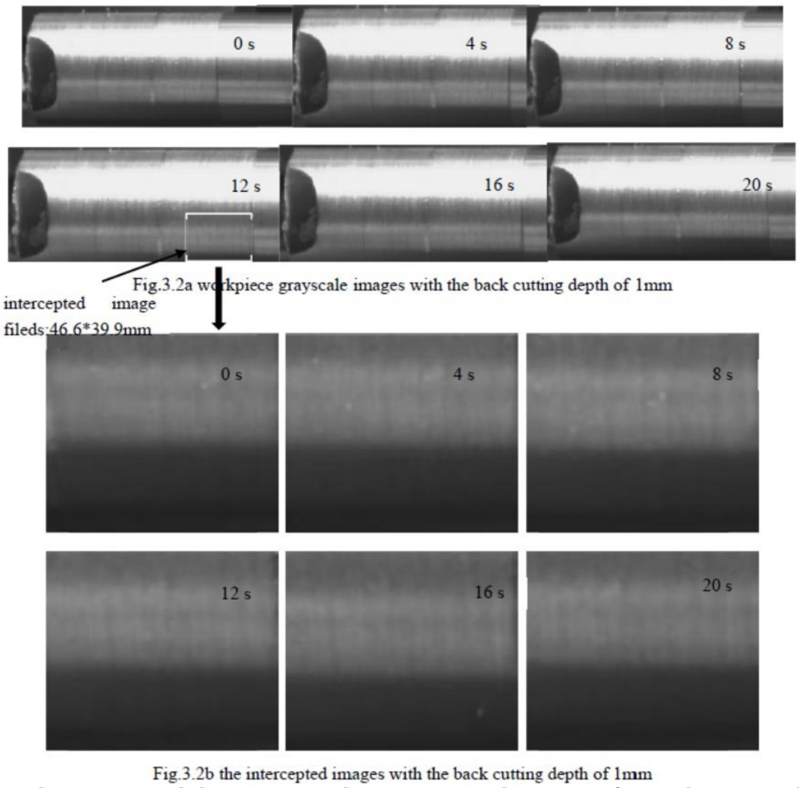

Fig.3. Grayscale images and the corresponding intercepted images of a workpiece with back cutting depths of 0.5 and 1 mm

In the high-speed shooting conditions with high frame rate, a halogen tungsten lamp was applied for supplementary lighting. However, this strong light exposure led to a reflective phenomenon. Thus, the lower half of the workpiece side was taken as the study object for data processing to avoid problems caused by reflection. This method would not affect the monitoring of different parts of the workpiece, because only pictures of different moments were needed to be extracted if we need to study the cutting quality of different sides or parts of the workpiece. The right end of the cutting surface when the image was shot was taken as the right baseline, while the bottom of the workpiece was the bottom baseline. Subsequently, a 46.6 × 39.9 mm rectangular area was reversely selected in the side grayscale image (Fig. 3.1.a and Fig. 3.2.a) and saved in .jpg format (Fig. 3.1.b and Fig. 3.2.b) for analysis and processing.

Based on the calculation theory of self-affine dimensions and damage of grayscale images, Matlab was applied to compile the calculation program of grayscale image self-affine dimensions and damage. Thirty-six processed images were input into the calculation program to calculate the corresponding dimension and damage (Table 1). Based on the statistical table of dimension and damage, the graphs show the dimension–time and damage–time relations with the back cutting depths of 0.5 mm and 1 mm, and the trend lines of these two parameters are shown in Fig. 4 and Fig. 5. The triangle point represents the self-affine dimension and the damage when the back cutting depth was 1 mm, and the dot corresponds to the value with a back cutting depth of 0.5 mm. The solid line shows the trend line when the back cutting depth was 1 mm, whereas the dashed line is that of a back cutting depth of 0.5 mm. The following discoveries were based on the analysis of Table 1, Fig. 4, and Fig. 5:

Table 1

Grayscale image self-affine dimension and damage

Time (s)	Parameters at a back cutting depth of 0.5 mm		Parameters at a back Cutting depth of 1 mm	
	Grayscale image self-affine dimension	Damage	Grayscale image self-affine dimension	Damage
0.000	2.058	0.102	2.117	0.217
0.002	2.079	0.105	2.12	0.229
0.004	2.086	0.107	2.136	0.212
4.000	2.053	0.097	2.106	0.192
4.002	2.069	0.095	2.105	0.193
4.004	2.076	0.095	2.117	0.19
8.000	2.056	0.105	2.114	0.188
8.002	2.082	0.096	2.102	0.183
8.004	2.063	0.104	2.11	0.196
12.000	2.075	0.095	2.109	0.194
12.002	2.07	0.094	2.118	0.189
12.004	2.06	0.095	2.115	0.194
16.000	2.059	0.108	2.123	0.192
16.002	2.076	0.109	2.101	0.191
16.004	2.053	0.109	2.114	0.192
20.000	2.053	0.11	2.097	0.19
20.002	2.079	0.11	2.102	0.197
20.004	2.051	0.102	2.108	0.194

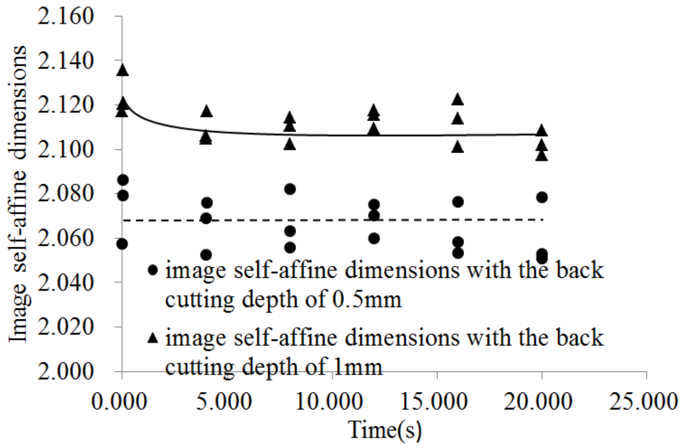

Fig.4. Grayscale image self-affine dimension trend

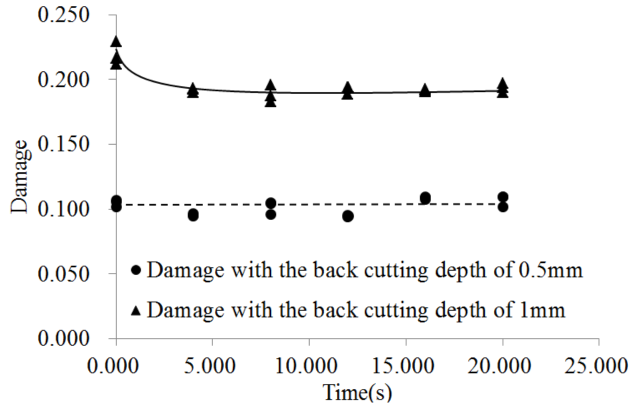

Fig.5. Damage trend observed in grayscale images

(1) Fig. 4 and Table 1 show that the calculated self-affine dimension was within the interval [2.051, 2.136] in all selected workpiece surface images. They were relatively small. In addition, the maximum self-affine dimension did not exceed 2.136, suggesting that all cutting surfaces were relatively flat with low roughness, regardless of the back cutting depth. Furthermore, the surface images after cutting showed that in addition to cutting texture and marks, additional uneven features were not observed (Fig. 2). The grayscale image dimension was relatively small if the workpiece surface roughness was comparatively low and vice versa, satisfying the fractal definition that its dimension was bigger if the surface is rougher, which means that the grayscale image dimensions were able to correctly reveal roughness of workpiece surfaces. These results further proved that the proposed image dimension was an accurate and feasible self-affine fractal dimension to characterize workpiece surface roughness.

Moreover, by the above theories and cutting tests, changing trend on the grayscale image dimensions at different times, i.e., workpiece surface roughness change with the change of time, was proposed to realize the aim of online monitoring of workpiece surface roughness. The principle shows that the presented approach is a novel effective way of real-time monitoring of workpiece surface roughness. The approach also avoided the low efficiency of the traditional detection method including complex procedures, such as stopping, loading, and unloading workpieces. This new method has laid a solid technical foundation for lowering defect rate.

From the relation between damage and time shown in Fig. 5 and Table 1, the damage value was in the interval [0.094, 0.229], suggesting a small workpiece damage value, which was consistent with the actual workpiece processing situation. In the video recordings shot by the high-speed camera and static photos taken by the digital camera, no large marks or grooves on the workpiece surface were observed. Such findings showed that the quantitative results of damage well reflect the degree of damage in workpieces during processing. Damage was also a great parameter for the online monitoring of workpiece quality.

(2) The trend lines of damage and the self-affine dimension (Fig. 4 and Fig. 5) show that when the back cutting depth was 1 mm, the grayscale image self-affine dimensions at time near 0 s (0.000 s, 0.002 s, and 0.004 s) were relatively large compared to other moments. Thereafter, the dimension and damage continued to drop, and then generally maintained a constant value. In contrast, when the back cutting depth was 0.5 mm, the dimensions and damages remained almost unchanged. This was because to test the response sensitivity of the self-affine dimension and damage to cutting state changing, the following shooting condition was set: when the back cutting depth was 0.5 mm, the recoding didn’t start until the cutting was stable, while when the back cutting depth was 1 mm, cutting and recording began simultaneously. At the beginning of cutting, the workpiece rotation speed increased constantly from 0 to 180 r/min. The cutting force between the tool tip and the workpiece was also constantly changing with the variation of rotation speed. The changes in cutting force led to uneven marks and texture on the workpiece surface, indicating a large self-affine dimension and damage. Such phenomenon did not exist with a 0.5 mm back cutting depth, because shooting did not start until the rotation speed reached 180 r/min. These findings suggested that the grayscale image self-affine dimension and damage were sensitive to changes in the surface cutting state, and thus performed good online monitoring of the roughness and damage changes of workpiece during machining.

(3) Fig. 4 demonstrates that the grayscale image self-affine dimension was larger when the back cutting depth was 1 mm than when the back cutting depth was 0.5 mm. Furthermore, the damage changes suggested a similar pattern in Fig. 5 when the back cutting depth increased from 0.5 mm to 1 mm. As the back cutting depth increased, the cutting force on the workpiece surface increased, resulting in greater squeeze between chips and the front face of the tool. Materials were likely to cohere, and the roughness and damage degree also increased. Therefore, the grayscale image self-affine dimension and damage when the back cutting depth was 1 mm were larger, which was consistent with the conclusion drawn by the traditional method of measuring surface roughness during downtime. In other words, as back cutting depth increased, the surface roughness of the workpiece increased. It is indicated that real-time online monitoring of workpiece roughness and damage was correct and feasible compared with the traditional research conclusions.

In conclusion, the calculated grayscale image self-affine dimension of workpiece surfaces was small, which was consistent with the low surface roughness revealed by static and dynamic images. The instability in the preliminary stage of cutting resulted in an increase of the grayscale image self-affine dimension and damage. In addition, these two parameters grew up with an increasing back cutting depth, which was consistent with the results in the traditional method. These findings showed that our proposed online monitoring method was correct and feasible. The technique can conduct real-time online monitoring of workpiece roughness and damage compared with the traditional techniques.

4. Conclusions

On the basis of interdisciplinary theories, such as fractal geometry, damage mechanics, mechanics, and iconography, we proposed a novel method to calculate the grayscale image self-affine dimension and damage. A high-speed camera was used to capture the cutting process. The variation rules of surface topography and damage were explored. A new technique for online monitoring of workpiece roughness and damage was presented. This study provided a technical basis for the improvement of the efficiency of workpiece machining and smooth implementation of automated production. Our main conclusions were as follows:

(1) A calculation method of grayscale image self-affine dimension was proposed to describe workpiece surface roughness during cutting. The calculation theory of damage during the cutting process was also discussed. And thus, a novel technique was proposed to monitor the surface quality of a workpiece online by using the grayscale image self-affine dimension and damage.

(2) Static images recorded by digital camera and video data shot by high speed camera revealed texture and marks on the workpiece surface during cutting, but overall surface roughness was insignificant. Moreover, the calculated grayscale image self-affine dimension and damage was small. This just satisfied the fractal definition that its dimension was the smaller if the surface is the smoother, and vice versa. It further suggested that these two parameters were able to effectively quantify surface roughness characteristics and the degree of damage. Moreover, by theories of grayscale image self-affine dimension and damage proposed in the paper, it was able to effectively realize the objective of online monitoring of workpiece surface roughness and damage.

(3) An experimental procedure was performed to test the sensitivity of the grayscale image self-affine dimension and damage to changes in status during cutting process. When the back-cutting depth was 1 mm, cutting and shooting were conducted simultaneously. When the workpiece rotation speed increased from 0 r/min to 180 r/min, the self-affine dimension and damage calculated from the grayscale images decreased until a constant value was reached. This finding indicated that these two parameters were sensitive to changes in the cutting process. Therefore, our techniques were effective.

(4) The increase in back cutting depth resulted in the increase of the grayscale image self-affine dimension that was used to describe surface roughness

during cutting. This was consistent with the conclusion drawn by traditional downtime detection methods that increasing back cutting depth leads to an increase in surface roughness. It also indicated that the proposed online monitoring method was theoretically correct and feasible. The technique can conduct real-time online monitoring of workpiece roughness and damage comparing with the traditional techniques. And thus it had its own advantages.

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R E F E R E N C E S

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