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Multi-dimension Tool Wear State Assessment Criterion on the Spiral Edge of Milling Cutter

Ying Tian¹, Liming Yang¹

Abstract

In the assessment of the tool wear state for the spiral edge of milling cutter based on machine vision, the traditional assessment criterion is often inaccurate due to the problem of information missing or incomplete especially near the tip area. In order to deal with this problem, different lighting-condition setting and additional non-image information compensation techniques are needed. In view of this, an integration tool wear detection method combined line laser edge detection and machine vision is proposed. Subsequently, the combined data acquirement experimental system is designed and built, which can simultaneously acquires two types of parameters: diameter and images under the same detection condition. Then, based on the above information, a multi-dimension series assessment criterion is proposed consisting of three dimensions index: The one-dimensional assessment index gives the average wear value of the spiral side, which mainly used as data ordination and characterizes the rule of tool wear degradation; the two-dimensional assessment index describes the contour of the wear region and calculates the area value, which can predict the change of the tool wear stage more precisely; the three-dimensional assessment index gives the 3D morphology by adding depth information within the wear region and quantified the volume of the worn-off part, which provides clues for early warning of the deterioration caused by the tool worn. Experiments proved that the multi-dimension series assessment criterion is helpful to reflect the trend of tool life and give a more accurate assessment of the tool wear state for the spiral edge of milling cutter.

Keywords: Tool wear detection Spiral edge of milling cutter Line laser edge detection Machine vision
Assessment criterion

1. Introduction

The judgment of the spiral edge wear state of the milling cutter occurs usually in milling processing. According to statistics, the detection process causes about 23% of downtime [1]. Therefore, the rapid, accurate and intelligent detection of tool wear state has a huge impact on the surface quality and machining accuracy of the workpiece. However, for the spiral edge of milling cutter, due to its complicated spatial spiral structure, it is difficult for the sensor to obtain surface wear data, resulting in serious lack of tool tip and internal information. At the same time, the current evaluation algorithms for milling cutters by single sensor information still have problems such as low calculation accuracy and insufficient evaluation [2,3,4]. So it is difficult to meet the requirements for rapid, accurate and comprehensive evaluation of the wear state of milling

cutters in automated production.

At present, the detection methods to evaluate the wear state of tools include indirect detection methods and direct detection methods. The indirect detection method is the method that use indirect signals such as current [5], cutting force [6,7], vibration [8,9], and acoustic emission [10,11] to evaluate tool wear state. These methods are mostly used for online monitoring. By establishing the qualitative or quantitative relationship between the indirect signal and the tool wear index value, the overall state of tool wear in the machining process can be judged. Due to indirect detection does not directly obtain evaluation parameters, interference in signal acquisition and inaccuracy of modeling calculation methods make it difficult to directly and reliably analyze tool wear state.

The other is the direct detection method: it refers to the method that directly measure the morphology and wear index of the tool wear region through the sensor, such as contact detection, machine vision and laser detection. Among them, the contact detection method has high detection quality, but it is inefficient and the equipment is expensive. Based on machine vision and laser measurement methods, the above problems can be avoided, and the flexibility of the system is increased due to their non-contact measurement characteristics. At the same time, with the further maturity of these two technologies, they can become supporting technologies for automated quantitative analysis of tool wear state.

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The tool wear detection method based on machine vision is not affected by cutting conditions and workpiece materials, and has high accuracy and reliability [12,13]. Image feature extraction methods based on machine vision include: statistical analysis methods and frequency domain analysis methods. The main statistical methods for analyzing the gray value characteristics of the wear region image include: gray-level threshold method [14], edge detection [15,16,17], and histogram method [18]; analysis methods based on spatial frequency domain feature extraction include: Fourier transform [19], wavelet transform [20] [21] and homomorphic filtering [22]. Statistical analysis methods are widely used basic methods. The spatial frequency domain feature extraction methods are less sensitive to noise and intensity changes, but requires higher periodicity, and is usually applied to materials with relatively uniform surfaces.

Researches show that the current researches on tool wear state are mostly based on machine vision methods. However, due to the complicated spatial morphology of the spiral edge of milling cutter, the uneven illumination in the obtained pictures result in the lack of the morphology on the part of the tool structure, such as the tool tip area; at the same time, relying only on a single machine vision detection method will cause the lack of internal depth information in the wear region, such as the scar area of the uniform wear region. The above problems make it difficult to study the spiral edge wear of milling cutter based on a single machine vision.

Among other high-precision non-contact measurement methods, the laser detection method has the characteristics of high efficiency, high precision, high sensitivity, and good real-time performance. At the same time, it can obtain size information such as the depth inside the wear region, which makes up for the lack of information obtained by machine vision in space. Therefore, laser technology has broad application potential in the field of tool wear detection. Matsumura et al. [23] proposed a method to detect the side edge wear of milling cutters by measuring the changes in diameter and height of milling cutters by line laser technology. Devillez et al. [24] used white light interferometry to restore the wear pits on the tool surface, and realized the measurement of the depth and width of the wear pits. It can be seen that laser detection technology has the advantages of strong robustness and reliable detection in the field of tool wear detection.

Therefore, in order to ensure the completeness of the information on the spiral edge wear region of milling cutter, and to achieve a comprehensive evaluation of the tool wear state, this paper combines machine vision technology and laser technology as the data source for tool wear detection.

Many scholars have conducted exploratory research on the indexes of evaluating tool wear status. Some used the texture of the wear region [25,26,27,28] to

characterize the wear region and use it as an index to predict tool wear state. Some scholars used evaluation indexes such as the width of the wear region [20], the average wear value [29], and the maximum wear value [15] to judge the wear state of the milling cutter. These evaluation indexes can only determine the degree of wear. However, the working load of the cutting edge at different positions in milling varies greatly, so the wear rate in different areas is different. At the same time, because the tool wear region is generated in a complex mechanical and thermal environment, it has strong irregularities. Therefore, more comprehensive geometric characteristics are needed as important bases for judging the degree of tool wear, such as wear region and wear volume.

Yu et al.[30] and Zhu et al.[31] proved that the width and area of the wear region of the milling cutter gradually increased over time. It is pointed out that the contour evaluation index of the wear region contains more tool wear information, which is more accurate in evaluating the degree of tool wear than the wear width index. Kuttolamadomet al. [32] established a method for measuring tool wear volume, and found that the volume tool wear rate is closely related to the material removal rate of milling tools [33].

In summary, many scholars believe that only using VB value as a tool wear evaluation index has limitations at this stage; some studies have shown that the evaluation index of wear area and the evaluation index of wear volume are more sufficient in evaluating the degree of tool wear. However, the application of 3D morphology restoration technology to tool wear detection is still in infancy. Therefore, it is important to study the multi-dimension series assessment criterion on the spiral edge wear of milling cutters at this stage for better evaluation of tool wear state.

In response to the above problems, an integration tool wear detection method combined line laser edge detection and machine vision is proposed. Subsequently, the combined data acquirement experimental system is designed and built, which can simultaneously acquires two types of parameters: diameter and images under the same detection condition. Then, based on the above information, a multi-dimension series assessment criterion is proposed consisting of three dimensions index: The one-dimensional assessment index gives the average wear value of the spiral side, which mainly used as data ordination and characterizes the rule of tool wear degradation; the two-dimensional assessment index describes the contour of the wear region and calculates the area value, which can predict the change of the tool wear stage more precisely; the three-dimensional assessment index gives the 3D morphology by introducing of the Shape from Shading (SFS) algorithm [20] to add depth information within the wear region and quantified the volume of the worn-off part, which provides clues for early warning of the deterioration caused by the tool worn. The multi-dimension series

assessment criterion can give more wear state information at the same position, which helps to give a more accurate evaluation of the tool wear state.

The rest of this paper is arranged as follows: Section 2 introduces the composition and working principle of the wear detection system for the spiral edge of milling cutter. Section 3 describes in detail the specific method of creating the multi-dimension series assessment criterion for the spiral edge wear of milling cutter. Section 4 analyzes examples of typical experimental samples of milling cutter. The method and process of using the multi-dimension series assessment criterion to evaluate the wear state are verified, and the evaluation effect is discussed. Section 5 is the conclusion of the whole research work.

2. The double-sensor integration tool wear detection system

2.1 Analysis of spiral milling process and wear regions

The surface wear inspection of milling cutter usually includes two regions: the end edge region and the spiral edge region. According to the international standard ISO 8688, in the side milling process of the milling cutter ($a_a > a_r$), the spiral edge is mainly used for working, as shown in Fig. 1.

Fig. 1. Diagram of side milling process

where (a_a is the back engagement, and a_r is the working engagement)

In the side milling process, the wear of the spiral edge is usually used as an indicator to evaluate the tool wear. Therefore, this article chooses the evaluation of the spiral edge wear region as the research object.

The wear region on the spiral edge of milling cutter is mainly concentrated on the flank surface, and it is not suitable to use the general VB detection method. In addition, the spiral edge of milling cutter has a complex spatial shape, and only relying on machine vision detection methods is sensitive to changes in light, which can easily lead to lack of information. In order to overcome the above shortcomings and consider the sensor fusion method, an detection system that integrates line laser edge detection and machine vision is proposed to achieve the integrity of information acquisition.

2.2 Tool wear detection system setup

The detection system for the spiral edge wear of milling cutter that integrates line laser technology and machine vision is designed. As shown in Fig. 2. The whole system is mainly composed of machine vision module, line laser sensor, three-axis motion controller, chuck, electric rotating platform and computer.

(a) Schematic diagram

(b) Physical diagram

Fig. 2. Schematic diagram and physical diagram of the detection system

The detection system can simultaneously collect two images under high and low light intensity, and the diameter data of the four-blade milling cutter.

The wear images of the milling cutter r are mainly obtained through the machine vision module in the system—an industrial camera with a high-frequency zoom lens and a ring light source for auxiliary camera illumination. The camera's internal software is perfect, allowing real-time transmission of images to be displayed on the computer screen. The brightness of the ring light source is controllable. So it can provide shooting conditions with different light intensity. The installation position of the industrial camera is perpendicular to the axis of the milling cutter. The height of the target captured by the industrial camera is $1.5 \sim 2\text{mm}$, the field of view range is $2.5\text{mm} \times 2\text{mm}$, the electronic magnification is 135, the working distance of the camera is 85mm, the image resolution is 1920×1080 , and each pixel σ represents $1.4206\mu\text{m}$.

The wear edge diameter of the milling cutter is

mainly realized by the line laser sensor in the system, as shown in Fig. 2(b). The model of line laser sensor is AMG-LSG-1030S, and the measurement accuracy is $\pm 0.5\mu\text{m}$. The sensor is installed on the fixed end of the Z axis of the three-axis motion controller, which can measure the diameter of the milling cutter accurately. The electric rotating platform provides rotation power for the main shaft, and can adjust the angle position required by the industrial camera to detect the spiral edge of milling cutter.

2.3 Procedures

The above system is used to carry out inspection experiments on the milled milling cutter, and collect the diameter data and image data at the same time. The specific acquirement procedure can be described as follows:

Step 1: Calibration work. First, use a three-jaw chuck to fix the milled milling cutter, and the tool rotates with the rotating platform for 30 s/r. Then, control the line laser sensor on the Z axis to locate the initial position measured at the tool tip. Finally, adjust the angle of the camera whose field of view is parallel to the axis of the milling cutter, and calibrate the axis of the milling cutter to coincide with the vertical line of the center of the camera's field of view.

Step 2: Line laser edge detection. The line laser sensor measures the diameter of the milling cutter with a displacement of $20\mu\text{m}$ several times along the axis of the milling cutter. The scanning range is 1.25 times the axial cutting depth. The collection frequency of the line laser sensor is 800times/s. The collected data is shown in Fig. 3.

Fig. 3. Display diagram of original data measured by line laser

Step 3: Machine vision inspection. After the diameter data measurement is completed, adjust the angle of the milling cutter through the rotating platform until the spiral edge wear region is parallel to the camera field of view. Then, the camera is used to capture the images of the tool wear under the high light (the strongest brightness of the light source) and the low light (turn off the light source) on the spiral edge of milling cutter at the same position. The images are shown in Fig. 4. Repeat the above process to obtain tool wear images of the four cutting edges.

Fig. 4. Spiral edge wear images under high and low light

Step 4: Save. Save the detected diameter data and image data at the same time to provide a data source for obtaining the multi-dimension series assessment criterion.

2.4 Tool wear detection method

To describe the real morphology of the tool wear region, a hierarchical multi-dimension series assessment criterion is proposed based on the fused data obtained from the detection system. The one-dimensional assessment index refers to the average wear value, which is calculated using the of diameter data and image data respectively. The result is used to verify the consistency of the two data results (line laser and machine vision). At the same time, the diameter data can be used as the calibration parameter of the three-dimensional assessment index to supplement the 3D information.

The two-dimensional assessment index mainly uses the image data. It can be used to obtain the accurate wear region contour and wear area value through image stitching method and combined threshold segmentation algorithm. This assessment index can predict the tool wear stage more accurately.

Based on the two-dimensional accurate contour results, the depth information and one-dimensional calibration information are supplemented by the SFS algorithm to obtain the 3D morphology and the volume of the worn-off part. Then use them as the three-dimensional assessment index that can provide early warning of deterioration of processing quality.

The multi-dimension series assessment criterion is constructed based on the results of the above three dimensions. Its visual display is shown in Fig. 5. The average wear value VB_{ave} is displayed as the one-dimensional assessment index, the contour of the wear region is displayed as the two-dimensional assessment index, and the 3D morphology of the wear region is displayed as the three-dimensional assessment index.

Fig. 5. Visual display of multi-dimension series assessment criterion

3. Multi-dimension series assessment criterion

Here is the multi-dimension series assessment criterion for tool wear state. The flow chart is shown in Fig. 6.

Fig. 6. The flow chart of the multi-dimension series assessment criterion

3.1 One-dimensional assessment index

At present, the average wear value VB_{ave} is still the most popular criterion for assessment the tool wear state, which is defined as the wear width of the flank face. It can represent the linear wear degree of the cutting edge, so it is called the one-dimensional assessment index, in this paper. Through the tool wear detection system mentioned above, a series of diameter data within the wear region can be captured by the line laser devices and be used to calculate the value of VB_{ave} .

According to the previous studies[7]: the principle of cutting edge wear in machining process and the calculation formula of VB are shown in Fig. 7

Fig. 7. Schematic diagram of the turning tool wear

$$VB = \left(\frac{1}{\tan \alpha} - \tan \gamma \right) NB \quad (1)$$

Where, VB is the wear value of the flank surface of the turning tool; γ is the rake angle of the turning tool; α is the relief angle of the turning tool; NB is the radial wear value.

However, this formula is inadaptatable for a milling cutter, due to the existence of the spiral structure. Here, an improved VB formula especially using in calculating the spiral edge with a helical angle is proposed, based on the diameter data set captured by the line laser sensor. The improved principle and the VB formula for a spiral edge cutter are shown in Fig. 8.

Fig. 8. Schematic diagram of the spiral edge wear of milling cutter

In Fig. 8, shows a cross section perpendicular to the cutter axis of a worn spiral milling cutter. The data of the cutter diameters can be directly captured by the line laser sensor both in initial state and current state respectively. Here R refers to the initial radius value; and R' refers to the maximum radius value in current state. Therefore, the ΔR , which means the amount of change along the radius direction in the cutter edge, which can represent the spiral edge wear degree in the current section. The accurate expression of VB_i is shown as follows:

$$\frac{R' \sin \theta}{\cos \alpha} = R \sin \alpha - R' \sin(\alpha - \theta) \quad (2)$$

$$NB_i = R' \sin \theta \tan(\alpha) \quad (3)$$

$$D_i = R' \sin \theta \tan(\alpha) \tan(\gamma) \quad (4)$$

$$VB_i = R' \sin \theta (1 - \tan(\alpha) \tan(\gamma)) \quad (5)$$

Where, D_i is the circumferential wear of the spiral edge; VB_i is the wear value of each section on the flank face of the spiral edge after the wear; γ is the rake angle of the spiral edge; α is the relief angle of the spiral edge; R is the initial radius value of the spiral edge of the current section; R' is the maximum radius value of the current section after wear; θ is the intermediate unknown quantity that needs to be solved. But θ is determined by the γ , the α , R and R' , so θ is the dependent variable that changes with. However, due to the complexity of solving the formula, θ needs to be solved by computer. So, the relationship between θ and R' is given here.

According to the function (5), R' is the only variable parameter, where the angle α and γ are given in the function. Therefore, the line laser sensor can be used to measure the maximum radius of the current

cross-section R' under the current state. According to the line laser sensor detection principle, each cross-section VB_i value was obtained after continuous diameter measurement for one circle of the milling cutter, it belongs to the discrete data. Therefore, it is necessary to feed multiple times within the cutting depth range along the axial direction of the milling cutter. After scanning the whole region of the edge processed are, a series of VB_i data can gained based on the function (5) of the different sections. Finally, the average wear value VB_i of the spiral edge is calculated using the function (6), which is the one-dimensional assessment index result in the spiral edge wear evaluation of milling cutter. The specific formula of VB_i is shown as follows:

$$VB_{ave} = \frac{1}{n} \sum_{i=1}^n VB_i \quad (6)$$

In order to prove the VB_{ave} index consistency of the two kinds of sensor data, another VB_{ave} is calculated based on the machine vision at the same experimental condition. The results comparison between machine vision and line laser measurement is shown in Fig. 9.

Fig. 9. Machine vision and line laser measurement results

It shows the average wear value by the line laser data is 0.1490mm, the standard deviation is 0.0485, while the standard deviation of the machine vision results is 0.0374 at the same VB_{ave} level. The two measurement results are basically close, indicating that the line laser measurement results are highly reliable.

At the same time, the measurement results of the line laser can also provide data support for the depth of cut calibration. Fig. 10 is a partial enlarged view of the milling cutter when the spiral edge is worn. After the spiral edge is worn, the position of the cutting edge moves, and there are two components in the direction, one is the circumferential wear amount D , and the other is the radial wear amount NB . The image data is collected by the camera radially shooting the milling cutter. Therefore, NB can be used to represent the depth information in the image data. Then, the NB_i obtained by the line laser sensor can provide scalable support for the depth information calibration of the following three-dimensional assessment index. Shows as section 3.3.

Fig. 10. Schematic diagram of the position of the cutting edge before and after the spiral edge is worn

In summary, the one-dimensional assessment index has high reliability. And its edge detection data provides the possibility for the fusion of line laser technology and machine vision technology.

3.2 Two-dimensional assessment index

The two-dimensional assessment index mainly refers to the contour and the accurate area value of the wear region. Aiming at the difficulty of acquiring tool tip information, image stitching method and combined threshold segmentation algorithm are used to capture complete tool tip information.

Although the one-dimensional assessment index can reflect the rule of wear degradation, there is a certain amount of tool tip information missing, and the information inside the contour of the wear region cannot be obtained. In order to evaluate the tool wear state more comprehensively, the two-dimensional assessment index is added here. That is, the wear region image including the complete tool tip is obtained, and a quantitative result is given: the area value of the wear region A_{VB} . The two-dimensional assessment index can predict the change

of the tool wear stage, which is more intuitive and comprehensive.

There are some prominent features in the spiral edge wear region of milling cutter, such as the contour of the tool tip is not clear and shadow areas. If the whole area is used for threshold segmentation, a lot of tool tip information will be lost. In this regard, image stitching and combined threshold segmentation algorithm are proposed to extract the contour of the tool wear region. The overall flow chart is shown in Fig. 11. The specific steps are as follows:

Step 1: Data source. Capture the original images of the tool in the same wear region under different light conditions; then cut each image into two parts: the tool tip region and the uniform wear strip region. Select the tool tip region under low light and the uniform wear strip region under strong light as the data source. The two perform subsequent image processing simultaneously.

Step 2: Pretreatment. Perform grayscale processing on them and take appropriate filtering methods to denoise. The purpose is to reduce the impact of noise on subsequent processing.

Step 3: Combined threshold segmentation algorithm. The method includes an improved histogram method and the local threshold segmentation algorithm. The improved histogram method can remove more band noise as a whole. The local threshold segmentation algorithm realizes the removal of fine noise near the contour of the wear region. The results of the two methods are superimposed to eliminate noise outside the wear region.

Step 4: Contour extraction. First, splice to obtain a complete tool wear region. Then, accurate edge detection is performed on the wear region. Finally, a complete tool wear region image with gray information is extracted.

Fig. 11. The flow chart of the method of extracting the spiral edge wear region of milling cutter

The method for extracting the tool wear region has two main characteristics. One is to propose a cutting strategy to preprocess the original images. The second is to propose a combined threshold segmentation algorithm

for the wear region images. The tool wear region can be clearly segmented from the image. In order to verify the effectiveness of this method, it is compared with the OTSU image segmentation method [35]. The OTSU

method is the most effective and widely used global threshold segmentation method. In the following, the effect images segmented by these two methods are compared, as shown in Fig. 12:

By comparing the segmentation effect, it is found that the OTSU method has insufficient ability to remove complex noise. For example, for the tool wear image Fig. 12(1-1) and its OTSU segmentation results in Fig. 12(1-3), the green box represents the uniform wear strip region. Strip reflections around it are recognized as worn regions. For the tool wear image Fig. 12(2-1) and its OTSU segmentation result in Fig. 12(2-3), the blue box represents the tool tip region. The shadow part of the tool tip region is directly deleted as a background; in addition, although the segmentation effect of the 2-3 uniform wear strip region is better, the fine noise around the contour boundary cannot be removed. In this regard, the above method highlights the following advantages:

- (1) Effectively remove the strong strip reflective noise around the uniform wear strip region;
- (2) The tool tip region with shadows and more complex wear can be fully obtained;
- (3) Realize the effective removal of fine noise around the boundary of the wear contour.

Fig. 12. Comparison of the segmentation effect between the proposed method and the OTSU method: the first row represents the original image; the second and third rows represent the segmentation effect of the proposed method and the OTSU method

After the complete wear region is extracted, the area value A_{VB} of the wear region can be calculated. The specific formula is as follows:

$$A_{VB} = \sum_{i=1}^m \sum_{j=1}^n P(i, j) \times \sigma^2 \quad (7)$$

Where, $P(i, j)$ represents each pixel in the wear contour, and σ represents the actual width of each pixel.

In this way, the two-dimensional assessment index can make up for the lack of one-dimensional assessment index that only has a VB_{ave} representing the rule of wear degradation. It can visually observe the contour and the internal wear condition of the wear region, and also obtain the wear area value A_{VB} . Even if the average wear value VB_{ave} is basically the same, the shape and contour of the wear region may be different. As shown in Fig. 13, the average wear value of the wear regions in Fig. 13 (a) and Fig. 13 (b) in the figure are 0.1466 and 0.1442, and the area values are 0.1747 and 0.1467. It can be found that the area value and the shape of the wear contour are quite different. Fig. 13 (a) wear region is uniform as a whole, in the normal wear stage, while Fig. 13 (b) the tool tip is about to enter the sharp wear stage. It shows that the two-dimensional assessment index can predict the change of the tool wear stage, which is helpful to further evaluate the wear state of the milling cutter.

Fig. 13. Two tool wear images with basically the same

3.3 Three-dimensional assessment index

Although the two-dimensional assessment index can better express the contour of the wear region and the internal gray information, but it can't express well the internal topography features such as pits, bumps, breakages and so on in the wear region. So, the three-dimensional assessment index containing the internal depth information of the wear region is needed to evaluate the tool wear state.

By introducing the Shape from Shading (SFS) algorithm, a single gray image of the spiral edge wear region is added with depth information through the change of gray value. In this way, the 3D morphology of the wear region and a quantitative result: the volume value V_{VB} of the worn-off part are obtained. In this way, the three-dimensional assessment data can provide early warning of the deterioration caused by the tool worn. The specific process of the SFS algorithm is as follows:

Fig. 14. The reflection diagram of the Lambertian model

Assuming that the image is in the xy plane, the camera is perpendicular to the image plane and coincides with the Z axis. The camera imaging model is shown in Fig. 14, which is the Lambertian reflection model. The reflection image of the Lambertian model can be expressed as: $E(x, y) = R(p, q)$. The height of the surface of the object represents $Z(x, y)$, the incident direction vector of the light source $S = [p_0, q_0, -1]^T$, and the normal vector of the surface of the object $N = [p, q, -1]^T$. In the Lambertian reflection model, for a diffuse reflection object with uniform surface reflection, the image gray level $E(x, y)$ at the normal vector N satisfies the following reflection equation:

$$E(x, y) = R(p, q) = \frac{1 + pp_0 + qq_0}{\sqrt{1 + p^2 + q^2} \sqrt{1 + p_0^2 + q_0^2}} \quad (8)$$

Where, $E(x, y)$ is the grayscale image of the image at the pixel point (x, y) ; $R(p, q)$ is the reflection image corresponding to the normal vector direction (p, q) of the surface of the object.

$$\begin{cases} p(x, y) = \frac{\partial z(x, y)}{\partial x} \\ q(x, y) = \frac{\partial z(x, y)}{\partial y} \end{cases} \quad (9)$$

In order to obtain the height of the surface of the object, a linearization method is adopted [34]. First, use the finite difference method to discretely approximate the surface gradients p and q , and then perform linearization in the height Z direction.

$$\begin{cases} p = \frac{\partial Z}{\partial x} = Z(x, y) - Z(x - 1, y) \\ q = \frac{\partial Z}{\partial y} = Z(x, y) - Z(x, y - 1) \end{cases} \quad (10)$$

For a certain pixel (x, y) and gray level $E(x, y)$ of the image, the linear approximation of the function f with respect to the height Z^{n-1} in the following formula can be expanded by Taylor series. Then use Jacobi iteration to solve. After simplifying, we can get:

$$0 = f(Z(x, y)) \approx f(Z^{n-1}(x, y)) + (Z(x, y) - Z^{n-1}(x, y)) \frac{df(Z^{n-1}(x, y))}{dZ(x, y)} \quad (11)$$

Then, for $Z(x, y) = Z^n(x, y)$, the height image of the n th iteration can be solved directly as follows:

$$Z^n(x, y) = (Z^{n-1}(x, y) - Z^{n-1}(x, y)) \frac{df(Z^{n-1}(x, y))}{dZ(x, y)} \quad (12)$$

Wherein:

$$\frac{df(Z^{n-1}(x, y))}{dZ(x, y)} = \frac{(p + q)(1 + pp_0 + qq_0)}{\sqrt{1 + p^2 + q^2} \sqrt{1 + p_0^2 + q_0^2} (p_0 + q_0)} - \frac{1}{\sqrt{1 + p^2 + q^2} \sqrt{1 + p_0^2 + q_0^2}} \quad (13)$$

Now, assuming that the initial estimated value of all pixels is $Z^0(x, y) = 0$, the height Z can be obtained by iteration through $Z^n(x, y)$.

Fig. 15. The 3D morphology of the wear region after adding depth information

Fig. 15(b) shows the 3D morphology of the wear region recovered after adding depth information to the wear region (a). Wherein, the gray area is the plane where the supplementary initial cutting edge is located; the red to blue height area is the 3D morphology of the wear region; the boundary line surrounding the wear region on the outside, which enhances the visual expression of the worn-off part.

The 3D morphology recovered by the SFS method is similar to the real surface shape and contains the detailed information of the reconstructed area. However, because the SFS method lacks strong external physical or geometric constraints, it generally obtains an approximate solution of the equation. An external physical condition needs to be added to make the method obtain accurate results. In this regard, this paper uses the radial wear value NB_i to calibrate the depth information of the cutting edge, and further calibrate the depth of the surface of the entire wear region. The specific calibration formula is as follows:

1. Calibrate the height value $h(x, y)$ of the 3D morphology

$$h(x, y) = \frac{\text{mean}(NB_i - \min(NB_i))}{\text{mean}(Z_i(x, y))} Z(x, y) \quad (14)$$

Where, $h(x, y)$ is the calibrated height value of (x, y) obtained by SFS method; $Z(x, y)$ is the uncalibrated original height value of (x, y) point obtained by SFS method; $\text{mean}(Z_i(x, y))$ is the average height of the cutting edge in the height image obtained by the SFS method.

2. Calibrate the depth value $H(x, y)$ of the 3D morphology relative to the height of the initial cutting edge

$$H(x, y) = \max(NB_i) - h(x, y) \quad (15)$$

Finally, after calibrating the depth value of the 3D morphology relative to the height of the initial cutting edge, the volume value V_{VB} of the worn-off part on the spiral edge of milling cutter can be calculated. The specific formula is as follows:

$$V_{VB} = \sum_{x=1}^m \sum_{y=1}^n \frac{(P(x, y) \times \sigma^2 \times (H))}{2} \quad (16)$$

In this way, the three-dimensional assessment index can make up for the lack of expression of the internal topography on the wear region by the two-dimensional assessment index. As shown in 4.2 (3). The restoration of the 3D morphology on the wear region is not only conducive to more intuitively get the internal wear, such as pits, bumps, etc., but also specific depth information and the volume value V_{VB} of the worn-off part during the milling process. Therefore, the three-dimensional assessment index can provide early warning of the deterioration of machining quality caused by the tool, and help to further analyze the wear mechanism of the spiral edge of milling cutter and evaluate the wear state of the milling cutter.

4. Results and discussions

This section discusses the effect of multi-dimension series assessment criterion using the integrated data consists of diameter data and image data. Section 4.1 shows the results of the worn state assessment based on the proposed multi-dimension series criterion. Section 4.2 has a discussion about the experimental results.

4.1 Results of multi-dimension series assessment criterion

After the milling cutter finishes processing the plane of the workpiece, use the equipment and process in Part 2 to acquire the required data. As shown in Fig. 16, ten test samples of typical tool wear state are selected to verify the multi-dimension series assessment criterion proposed. The quantitative results of the multi-dimension series assessment criterion obtained are shown in Table 1.

Fig. 16. Ten typical samples of typical tool wear state acquired

Tab. 1. Statistical table of quantitative results of multi-dimension series assessment criterion

Num	1	2	3	4	5	6	7	8	9	10
Average wear value (mm)	0.0796	0.1151	0.1754	0.2575	0.3109	0.1385	0.1391	0.2096	0.2137	0.2684
Wear area value (mm ²)	0.1004	0.1198	0.1836	0.2389	0.3604	0.1474	0.1663	0.2013	0.2286	0.2455
Wear volume value (mm ³)	0.0016	0.0030	0.0060	0.0110	0.0199	0.0031	0.0027	0.0078	0.0064	0.0145

4.2 Discussion

By observing the quantitative results of the multi-dimension series assessment criterion of ten samples, it can be found that:

(1) One-dimensional assessment index can characterize the rule of tool wear degradation. According to the average wear value in Table 1, it can be judged that sample 1 is in the initial stage of wear; samples 2 and 3 are in the mid-term normal wear stage; sample 4 is in the mid-term wear and enters the rapid wear stage; sample 5 is in the severe wear stage.

(2) Compared with the average wear value of the one-dimensional assessment index, the wear region contour in the two-dimensional assessment index can show the detailed information of the tool wear region and predict the change of the tool wear stage. Because in the case of basically the same VB_{ave} , the shape and contour of the wear region may be different. For example, in samples 6 and 7, the VB_{ave} of the two samples is basically the same, but the shape and area value of the wear region are quite different. The wear region of sample 6 is relatively uniform as a whole and belongs to a normal wear state, but the tool tip of sample 7 has been severely worn and is in a sharp wear stage. Samples 8 and 9 have similar situations. The wear of sample 8 is uniform throughout, but the wear of the tool tip region and bottom area of sample 9 is more serious. At the same time, it can be observed that there is a large built-up edge on the tool tip of sample 9.

(3) The 3D morphology of the wear region expressed by the three-dimensional assessment index increases the depth information in the tool wear region. It can provide early warning of the deterioration of machining quality caused by the tool. In the case where the area value and contour shape of the wear region are basically the same, the depth information in the wear region may not be the same. There will be different degrees of pits or bumps inside the area. For example, samples 4 and 10 have basically the same area value of the wear region, but the volume value of the wear region and the depth information in the wear region are quite different. It can be seen that there is a large pit in the wear region of sample 10, which causes the volume of the worn-off part is larger than the former. At the same time, it is always difficult to obtain accurate data on the tool tip region. However, the restoration of the 3D morphology is also more conducive to visually observing the depression of the tool tip after wear.

Therefore, the multi-dimensional quantitative results and visual display on the spiral edge wear state of milling cutter provide a more adequate and comprehensive

assessment index for the evaluation of the wear state of the tool. At the same time, it is helpful to further analyze the wear mechanism of the spiral edge of milling cutter.

5. Conclusions

This paper introduces an integration tool wear detection and assessment method combined line laser edge detection and machine vision techniques, and then a multi-dimension series assessment criterion for tool wear state is proposed. Here follows a summary of this work:

- According to the integration data detection principle, a double sensor detection device consisting of line laser and machine vision techniques has been setup and data capturing procedure and double sensor data calibration method have been proposed. The formula of the VB under the line laser detection is calculated by the modified compensation algorithm. It has a stronger robustness under the premise of ensuring reliability.

- A multi-dimension tool wear state assessment criterion is established an assessment criterion for tool wear with multiple dimensions. The multi-dimensional quantitative results and visual display on the spiral edge wear state of milling cutter provide a more adequate and comprehensive assessment index for the tool wear state assessment.

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Declarations

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• Conflicts of interest

The authors have no relevant financial or non-financial interests to disclose.

• Availability of data and material

The data sets supporting the results of this article are included within the article and its additional files.

• Code availability

Not applicable

• Ethics approval

Not applicable

• Consent to participate

Not applicable

• Consent for publication

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