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A Study of Applying Machine Vision Inspection on Face Milling Tool Wear

Cheng-Ho Chen[1], Yen-Hsiang Huang[2]
Department of Mechanical Engineering, National Chin-Yi University of Technology, Taiwan
Department of Mechanical Engineering, National Chin-Yi University of Technology, Taiwan

Abstract*— Machine vision technology has many applications in various industries for manufacturing processes monitoring and product quality improvement. A basic machine vision system consists of a camera, a frame grabber, a computer, lighting equipment and image processing software. The goal of this research is to investigate the application of machine vision in tool wear inspection. The images of tool surfaces are examined, and the wear conditions are analyzed by a machine vision system. First, the images are captured by a CCD camera, and then the regions of interest (ROI) are defined. Finally, the image signals are analyzed to determine if the sample passes the quality requirement. Some conclusions are addressed at the end of this paper.

***Index Terms*—Face mill, Machine vision, Tool inspection, Tool wear.**

I. INTRODUCTION

Machining is an important method of mechanical manufacturing. Proper use of cutting tools is critical in machining. Current tool monitoring technologies are mostly indirect, measuring certain signals generated during cutting. For example, a monitoring system for NC machine tool based on power effort and noise is developed in [1]. In [2], collected vibration signals are applied to a neural network for the detection/identification of worn cutting tools. Vibration signals are also used for the monitoring of tool failure in [3]. In [4], the torque data is obtained for the monitoring and supervision of the functional state of the tool and the possible faults in the environment. Spindle power signals are detected for tool condition monitoring in [5]. Reference [6] analyzed tool condition based on force, vibration and acoustic emission signals. In [7], from collected force and vibration signals, a method of pattern recognition based on discrete hidden markov models is applied to tool wear detection. Reference [8] used acoustic emission and cutting force power for tool condition monitoring. In [9], the suitability of a tool wear monitoring system is evaluated based on machine tool internal signals. The condition of the tool wear is identified from acoustic emission in [10]. Measured force and vibration signals are applied to Neuro-Fuzzy algorithms to predict the tool condition as in [11]. Reference [12] measured tool temperature, tool acceleration and spindle motor current for tool wear analysis. Reference [13] monitored tool condition with current signals for a low-power spindle. However, in indirect methods, the signals used might also be affected by factors irrelevant to the tool. For a more direct method, application of machine vision has been considered. Some researchers have done work based on work piece surface features. Reference [14]- [15] analyzed optical sensor data of the tool wear using neural networks. In [16], A vertex extraction algorithm of the tool wear image is developed based on subpixel edge detector and Gaussian filter. A neural network is used to classify the wear level to two classes -low and too high in [17]. Reference [18] inspected tool wear area ion for small lathe based on the machine vision technology. A method for micro-milling tool wear inspection using machine vision is proposed in [19]. In this research, direct monitoring applying machine vision technique will be used to examine the shapes of the tools. Machine vision technology has been successfully applied in many sectors of manufacturing, e.g. process control and quality control. A machine vision system typically consists of a CCD camera, a frame grabber, a computer, lighting equipment and image processing software. The purpose of this paper is to study the development of a tool wear inspection system based on the tool surface images captured by a CCD camera. The images are then processed and analyzed to identify possible worn or fractured areas on the tool.

II. INSPECTION ENVIRONMENT SETUP

A. Designing a Photo mask

When inspected in an open environment, the quality of the image is often interfered by unwanted light sources. A photomask is designed to avoid this problem and provide an easily adjustable inspection environment. Figure 1 shows the structure of the photomask. The designed photomask mechanism incorporates a CMOS camera and direct and sideway light sources. The direct light provides a uniform illumination on the top tool surfaces. However, most tool wear and crack happen around the edges. The low angle sideway lights offer extra illumination around the edges. The positions of the direct and sideway lights can be adjusted by the screws as shown in Figure 2.

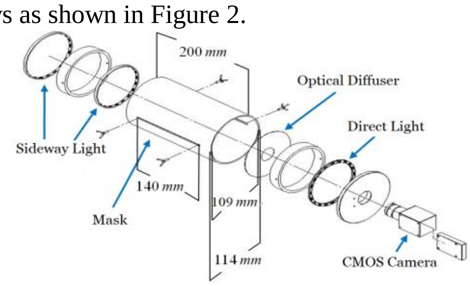

Fig. 1: The structure of the designed photo mask.

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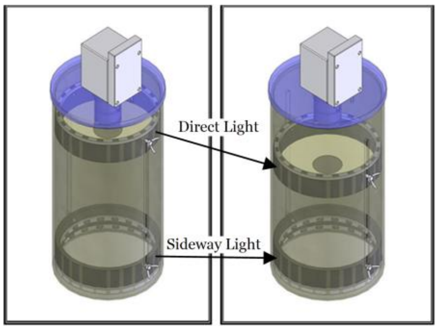


Fig. 2: Adjustment of light positions by the screws.

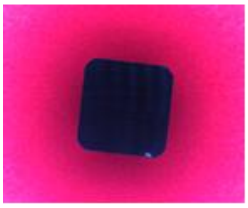
B. *Selecting a Background*

First, a ring white LED light source is put above the tools. Bristol boards of color red, blue, green and yellow are used as backgrounds. The experiment setup is shown in Table 1.

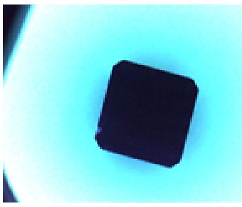
Table 1: Background experiment using Bristol boards

Light Source	White LED Light：28.71-46.30 lux
Light Position	8 cm directly above the tool
Background	Bristol Boards
Color	Red, Blue, Green, Yellow

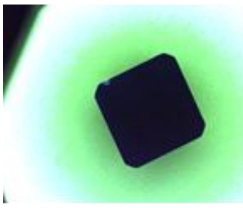
Other colors may also be used. However, it can be seen from Figure 3 that because the tools are of slightly cone shape, shadows are formed around the tool surfaces. These shadows will interfere with the tool surfaces when performing image processing. Therefore, they are not used as backgrounds.



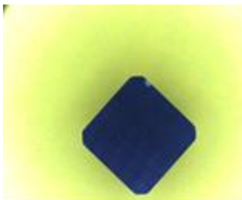
(a) Red Bristol board



(b) Blue Bristol board



(c) Green Bristol board



(d)Yellow Bristol board

Fig. 3: Using Bristol boards as backgrounds.

Next, a red backlit panel is used as the background. The experiment setup is shown in Table 2. The plate is put directly behind the tool. The backlight can eliminate the shadow around the tool and enhance its contour under proper light intensity. Fig. 4 shows the result of the plate when it is (a) too dim, (b) too bright, and (c) optimally set.

Table 2: Background experiment using a backlit panel

Light Source	White LED Light：26.7-41.2 lux, optimal 30.7 lux
Light Position	8 cm directly above the tool
Background	Backlight plate: 0.25-0.39 lux, optimal 0.28 lux
Color	Red

These results demonstrate that the shadows can be effectively eliminated with backlight. However, close examination reveals that the backlight blurred the image on the edge, approximately 4-5 pixels, as shown in Fig. 5.

Finally, a black steel plate is used as the background. The experiment setup is shown in Table 3. The result, Fig. 6, shows that the shadows are eliminated, and edges are not blurred. Therefore, it is chosen as the background.

Table 3: Background experiment using a steel plate

Light Source	White LED Light：33.4-51.61 lux
Light Position	8 cm directly above the tool
Background	Steel plate
Color	Black

(a) Low intensity

(b) High intensity

(c) Optimal intensity

Fig. 4: Results of using a backlit panel.

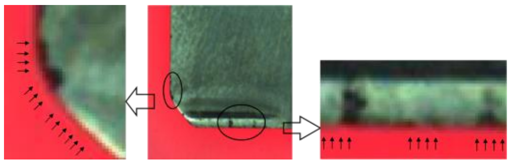


Fig. 5: The edge images using a backlit panel.

Fig. 6: The result of using a black steel plate

C. *Setting Up Light Sources*

After the background is decided, various kinds and colors of light sources are investigated to find the optimal one for tool inspection. Table 4 shows the light sources used in experiment. The results are shown in Fig. 7. Fig. 7(a) shows that infrared light cannot distribute uniformly on the surface. Although Fig. 7(b)-7(c) shows uniform lighting, the wear regions and the rest of the tool have similar colors which may cause difficulties in image analysis. In Fig. 7(f), the wear regions are clearly more distinct. Therefore, a white LED ring light is used for the direct light source.

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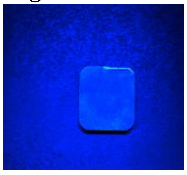
Table 4: Background experiment using a steel plate

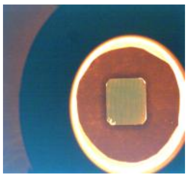
Light Shape	Light Color	Lux	Distance from the tool surface	Angle relative to the tool surface
Bar	Infrared 940nm	N/A	20 cm	45-90°
Bar	Blue LED	10.9-37.1	10 cm	45-90°
Ring	Red LED	43.1-51.6	10 cm	90°
Ring	Blue LED	27.4-43.8	10 cm	90°
Ring	Yellow LED	30.3-45.1	10 cm	90°
Ring	White LED	33.4-51.61	10 cm	90°

In machining, tools not only can develop surface wears, but also may have breaks on the edge. In this study, we find that using only direct light sources cannot capture the complete tool wears and breaks. Therefore, low angle sideway light sources are also implemented. Fig. 8 (a) and (b) show the results without sideway lights and 8 (c) and 8(d) with. It can be observed that the sideway lights significantly improve the wear and break images on the edge. Further experiment shows that the optimal illumination is with a direct light source of 38.61 lux and sideway light source of 420 lux as in Table 5.

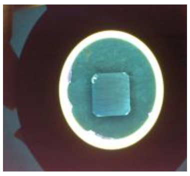
(a) Infrared light



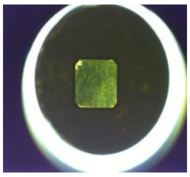
(b) Blue bar light



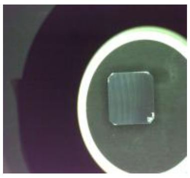
(c) Red ring light



(d) Blue ring light

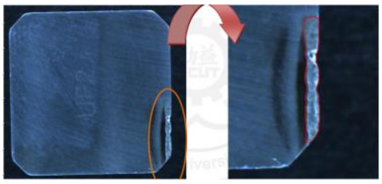


(e) Yellow ring light

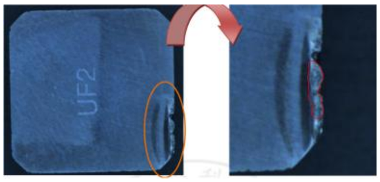


(f) White ring light

Fig. 7: The results of using different light sources.



(a) Images without sideway lights



(b) Images with sideway lights

Fig. 8 Images without and with sideway light sources

Table 5: Light sources setup

Light Shape	Light Color	Lux	Distance from the tool surface	Angle relative to the tool surface
Ring	White LED	38.61	10 cm	90°
Ring	White LED	420	5.5 cm	0°

III. IMAGE PROCESSING

Under the environment setup defined in the previous section, tool images are taken by a CMOS camera, ICDA_UI_5240CP_C_HQ, with an ICL_IDS_25 lens. The images are then analyzed through a series of image processing processes to examine possible tool wear or break. A typical tool image is shown in Fig. 9.

A. Pattern Matching

A reference template, shown in Fig 10, is designed to locate the tool through pattern matching.

B. Wear Feature Extraction

Because wear always happens at the edges of the tool, the edges are divided into squares of 35*35 pixels as shown in Fig. 11. The mean and standard deviation of gray level values are then calculated for each square. The average standard deviation is obtained by summing up all the standard deviations and dividing the sum by the total number of squares. This value can then be used as a reference for possible wear areas. If an area has a standard deviation larger than the reference value, it is then judged as a possible wear area. Fig. 12 illustrates all the possible wear areas in solid red.

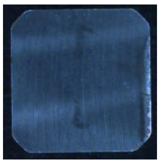


Fig. 9: A typical tool image.

Fig. 10: A reference template.

C. Wear Feature Extraction

Because wear always happens at the edges of the tool, the edges are divided into squares of 35*35 pixels as shown in Fig. 11. The mean and standard deviation of gray level values are then calculated for each square. The average standard deviation is obtained by summing up all the standard deviations and dividing the sum by the total number of squares. This value can then be used as a reference for possible wear areas. If an area has a standard deviation larger than the reference value, it is then judged as a possible wear area. Fig. 12 illustrates all the possible wear areas in solid red.

D. LoG Filtering and Image Binarization

To have a more accurate wear profile, the tool image is then processed by a Laplacian of Gaussian (LoG) filter defined in Eqn. (1) with a standard deviation σ =2. The filtered image is shown in Fig. 13.

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$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1-\frac{x^2+y^2}{2\sigma^2}\right]e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where (x, y) is the x and y coordinates of the pixel relative to the center.

The filtered image is shown in Fig. 13. It is then transformed into a binary image, Fig. 14 by a process called image binarization [20].

E. Morphological Operations

The main wear area in the binary image consists of regions that are not mutually connected as shown in Fig.15 (a), an enlarged image of the lower right portion of Fig. 14. To have an accurate estimate of the wear area, these regions are first connected by closing operation, Fig. 15(b). After closing operation, the wear area still has holes in it. These holes are filled up by hole- filling operation, Fig. 15(c). After hole-filling, the main wear area is filled up but is also connected to other features around the edges. The image is then processed by opening operation to disconnect the main area and these features, Fig. 15(d).

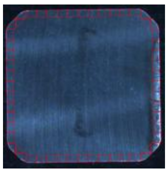


Fig. 11: Tool edge segmentation

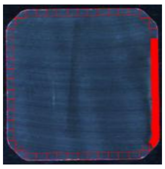


Fig. 12: Wear areas identified by standard deviation.

Fig. 13: LoG filtered image.

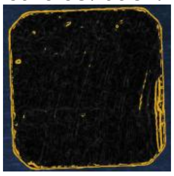
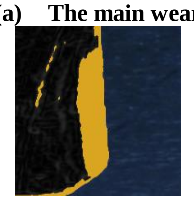


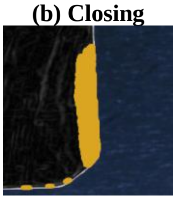
Fig. 14: The binary image.

(a) The main wear

(b) Closing



(c) Hole-filling



(d) Opening

Fig. 15: Morphological operations

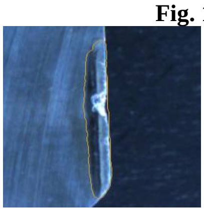


Fig. 16: Filtering

Fig. 17: Thresholding

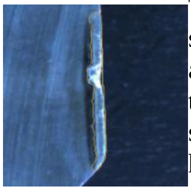


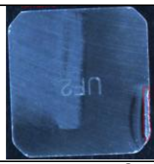
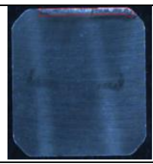
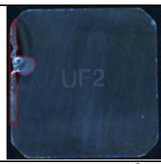
Fig. 18: Subtraction

F. Area Filtering and Subtraction

The small independent areas in Fig. 15(d) are eliminated by area filtering. In Fig. 16, the identified wear area is imposed on the original tool image. However, the darker region is not caused by actual tool wear. This region is picked up by thresholding, Fig. 17. The wear area is then subtracted by this region. The final wear area is shown in Fig. 18.

IV. RESULTS

The size of the wear is calculated by the number of pixels in the area. The results are compared to previously gathered tool data to determine whether the tool should be replaced. The following table illustrates these results.

Tool Image			
Defect Area	4.482 mm^2	9.436 mm^2	13.117 mm^2
Defect Ratio	1.663%	3.511%	4.915%
Tool Change	No	Yes	Yes

V. CONCLUSION AND FUTURE ENHANCEMENT

A. Conclusion

The inspection system established in this research detects the surface wear area of disposable face milling tools based on machine vision technology. Experiments showed that it can provide rapid, stable and consistent inspections results, not to be affected by human fatigue or lack of experience. The results can then be used to monitor the tool condition and improve the process stability. The following conclusion can be made: The inspection system established in this research detects the surface wear area of disposable face milling tools based on machine vision technology. Experiments showed that it can provide rapid, stable and consistent inspections results, not to be affected by human fatigue or lack of experience. The results can then be used to monitor the tool condition and improve the process stability. The following conclusion can be made: The inspection system established in this research detects the surface wear area of disposable face milling tools based on machine vision technology. Experiments showed that it can provide rapid, stable and consistent inspections results, not to be affected by human fatigue or lack of experience. The results can then be used to monitor the tool condition and improve the process stability. The following conclusion can be made: The inspection system established in this research detects the surface wear area of disposable face milling tools based on machine vision technology. Experiments showed that it can provide rapid, stable and consistent inspections results, not to be affected by human fatigue or lack of experience. The results can then be used to monitor the tool condition and improve the process stability. The following conclusion can be made:

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1. The most frequent problem in machine vision inspection is the disturbance of the environment. This study designed a photomask and improved the lighting by a mechanism incorporating light sources at various positions. The design of the photomask and light sources can effectively enhance the illumination and highlight the image features, reduce the image noise and the complexity of image processing.
2. In image processing, a standard tool reference template is established before the inspection, this can shorten the time of the tool detection. By combining Gaussian filter and standard deviation feature extraction algorithm, the wear features can be more accurately measured for an accuracy of up to 1 $(pixel)$=32.5 (μm) 。
3. The developed machine vision system can calculate the tool wear area quickly. The total time of inspecting 34 tool samples is 4.556 seconds, about 0.134 seconds for each sample. Operators can learn the information through the program interface and judging from the results whether it is necessary to change tools. This can reduce tool costs, control the process quality, and maximize the machine tool efficiency.

B. Future Enhancement

There are still a lot of improvement can be made in the developed system. Some probable future enhancements are proposed in the following:

1. A machine vision platform that can be set up on the machine tool, directly retrieve the tool image inline. The inspection time can be further reduced. However, many factors must be considered in the actual machining environment, for example: the machine vibration will cause the camera or the light source to be unstable, the cutting chips produced by machining process may affect the quality of captured image. These problems may be reduced or avoided by proper design of a machine-vision embedded station.
2. The tool inspection results can be used for statistical process control (SPC) so that the machine vision technology is incorporated into the entire production and management system and making it be more in line with the needs of the industry.
3. At present, the inspection technology calculates only the tool wear surface area. In the future, one can try to use the structure light or set up two cameras to produce 3D stereo vision to detect the wear depth.

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AUTHOR BIOGRAPHY

C.-H. Chen completed the doctoral program at the Department of Mechanical Engineering at Ann Arbor, University of Michigan in 1994, then became an associate professor in the Department of Mechanical Engineering at National Chin-Yi University of Technology.

Y.-H. Huang completed the master program at the Department of Mechanical Engineering at National Chin-Yi University of Technology in 2013, under the supervision of associate professor Cheng-Ho Chen.