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Wear Detection of Drill Bit by Image-based Technique

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Abstract. Image processing for computer vision function plays an essential aspect in the manufacturing industries for the tool condition monitoring. This study proposes a dependable direct measurement method to measure the tool wear using image-based analysis. Segmentation and thresholding technique were used as the means to filter and convert the colour image to binary datasets. Then, the edge detection method was applied to characterize the edge of the drill bit. By using cross-correlation method, the edges of original and worn drill bits were correlated to each other. Cross-correlation graphs were able to detect the difference of the worn edge despite small difference between the graphs. Future development will focus on quantifying the worn profile as well as enhancing the sensitivity of the technique.

1. Introduction
Drilling is one of many basic machining operations in the industry. This operation is widely used in manufacturing since the beginning of industrial innovation. According to [1], nearly 40% of all drilling operations are in the manufacturing industries. Despite its simplicity, in terms of maintenance aspects, its failure, due to tool wear and breakage, accounts to about 7-20% of the average machine tool downtime [2]. The tool failure could also contribute to machine failure. On top of the machine repair cost, the increasing cumulative non-productive time further adds to the loss of opportunity and profit by the company [3].

Drill bit wear is considered critical, as the wear and tear can give the negative effects to the drill bit itself. High quality products have a relatively narrow tolerance margin and require optimal condition of the cutting tool, to ensure the products produced are well within the quality control. Wear drill bit can cause the drilling process to become longer than usual as the bit loss its sharpness or certain tolerance on the surface. Such problems can affect surface quality of finished workpiece in manufacturing industry.

In recent years, wear monitoring was controlled by computers and sensor. The sensor and signal processing method used for direct or indirect techniques in the chatter, tool wear or breakage and surface roughness [4]. Indirect method of tool condition monitoring (TCM) typically utilizes single or multiple sensors to capture process information that correlates to the tool condition [5]. Indirect method measurement such as the acoustic emission (AE), cutting force, vibration, power or current use of spindle and surface roughness of the machine generally involves gathering signals that can be harvested continuously [6]. Despite the indirect nature of the measurement, the technique is widely used in the industry due to its ease of installation in existing or new machines without directly impacting the machine functions.

Direct method is a common way to measure the actual wear. The method measures the tool wear directly by means of tool images and tactile sensors. Direct method is employed to monitor tool wear
images for drilling operation. It is based on observations of the actual tool wear and may require removal of the tool [7]. By using direct measurement, it will give an immediate appraisal of the tool wear such as optical measurement.

The optical method is typically applied in the inspection of geometry using a camera to capture the image of the tool tip. In separate study by [9], they utilized a suitable thresholding technology to convert and quantify the amount of flank wear. Introduced a flank wear measurement method of multilayer coated twist drill [10]. The study discovered the edges of the wear profile on the cutting plane. Detection was done by utilizing the smoothed edges using B-spline technique and spatial moment edge detector with sub-pixel accuracy. The Gaussian was applied at low-pass filtering technique to smoothest the curvature curve and finally, to select the accurate threshold valued for extracting the accurate wear profile for precise measurement of maximum flank wear width by applying a statistical process control measurement.

A study [11] proposed a new technique for precise edge detection algorithm utilizing neural network technique for tool wear detection. The study utilized Scanning Electron Microscopic (SEM) images of the flank wear images of a 4-fluted high-speed steel milling cutter. In [12] study, the error calculated using image processing counted 4% in classified the flank wear and breakage of the cutting tool. The image displayed the flank wear featured texture to be sharper and brighter in the machine vision system. Meanwhile, smooth and rough textures were included in the breakage of the tool. Based on this phenomenon, they measured flank wear area and sorted the types of wear.

In 2006, another research in a classified of wear, resulted in the machine vision system showing the flank wear feature. Developed a new technique measurement namely DEFROL (Deviation from Linearity) to classify the sharp and dull drilling tool by their images [13]. However, due to the wearing effect, the emphasis was done on the change point of angle and linearity deviation of the cutting edges.

This proposed study is based on the image processing technique to characterize the wear. This research is aimed at characterizing the bit’s edge profile wear by using cross-correlation technique, applied to the original and worn bits.

2. Methodology
The experiment was conducted using 40 AUT Scantool machine. It started with minimum spindle speed of 120 rpm. In the experiment, High Speed Steel (HSS) drill bit with diameter 3mm was used. The investigation was operated 6mm of the depth of cut. All drilling test were carried out under dry conditions and drilled continuously until wear appeared, which tool approximately made 1000 drills.

Figure 1 shows the schematic diagram of a tool wear measurement. The machine vision system for the tool wear monitoring consists of a camera with 266μm per pixel, light source, a PC for image processing, and MATLAB software. Images of original and used bits were captured at exactly similar location and orientation for further analysis. In the image processing, the image was analysed by several steps as shown in Figure 2.

![Figure 1. Schematic diagram of tool wear measurement](image)
2.1. Image Segmentation

By using image segmentation method, the images were divided into several parts. The function of image segmentation is to identify objects or other relevant information in digital images. Figure 3 shows the segmentation of the image. The texture image described the character of the image regions that are critical for accomplishing robust segmentations.

Figure 3 (a) and (b) shows the original and grayscale image respectively which has a size of 225x535 pixels each. The histogram graph displays distribution of pixel number of grey-scale image (Figure 3(b)) as illustrated in Figure 4. For an 8-bit grayscale image there are 256 different levels between black and white, with 0 being black and 255 represents white colour. Then thresholding was applied to the images that converted grayscale input images to binary images. The binarized image has only 0 (black) and 1 (white). Next, the bit edge, represented by the change of white and black pixel, was characterized and plotted in graphs.

![Figure 3](image1.jpg)

**Figure 3.** (a) Original and (b) Grayscale image

![Figure 4](image2.jpg)

**Figure 4.** Histogram of grayscale image
2.2. Cross-correlation technique
Cross-correlation measures the similarity between x and shifted copies of y as a function of the lag. If x and y have different lengths, the function appends zero at the end of the shorter vector. Hence, it has the same value as the other. Equation 1 represents a formula for the cross-correlation technique. The equation is applied to determine the difference between the edge profile of original and worn bits, where \( f \) is the image, \( \bar{t} \) is the mean of the template, and \( \bar{f}_{u,v} \) is the mean of \( f(x,y) \). The graphs that represents original and worn bits were correlated to each other and comparison between them were made.

\[
\sum_{x,y} [ f(x,y) - \bar{f}_{u,v} ] [ \bar{f}(x-u,y-v) - \bar{t} ] \\
\left\{ \sum_{x,y} [ f(x,y) - \bar{f}_{u,v} ]^2 \right\}^{0.5} \sum_{x,y} [ \bar{f}(x-u,y-v) - \bar{t} ]^2
\]

(1)

3. Result and Discussion

3.1. Pre-processing
To further analyse the image and ensure optimized computational time, only one side of the edge profile is considered by cropping the image. Binarization of the grayscale image through thresholding was performed to the grayscale image and illustrated in Figure 5(a) and 5(b). The edge of the drill bit was clearly defined. The edge of the drill bit was then characterised by determining the change of pixel number from 0 to 1 and vice versa.

The edge of the original and worn bits were plotted and showed in Figure 5(c) and 5(d). It can be noticed that the edge profiles of both worn and new bits are mostly like each other except near the cutting edge. For comparison purposed, the edge profiles were plotted in similar graphs as shown in Figure 6. Despite having similar geometry at other region, near the cutting edge, a small geometric discrepancy was noticed due to some wear or damage to the drill bits, caused by the imposed extensive drilling. Significant wear of approximately 10 pixels in size can be noticed at the sharp edge of the bit. With the small pixel size of 266μm, this method provides high resolution detection and able to quantify slight discrepancy between the profiles.

|          | Unworn image | Worn image |
|----------|--------------|------------|
| Binary   | ![Image](a)  | ![Image](b) |
| Pixels of edge | ![Image](c) | ![Image](d) |

**Figure 5.** (a) Image crop of unworn bit; (b) Image crop of worn bit; (c) The edge of unworn bit; (d) The edge of worn bit
3.2. Cross-correlation

The original and worn profiles were cross correlated to each other and the original profile was also cross correlated with itself (auto-correlation) and comparison between both graphs are made and shown in Figure 7. Figure 7 shows the cross-correlation graphs for original bit and difference between original and worn bits. Small discrepancy can be seen based on the graphs. Despite the plots being almost similar on the right-hand side of the peak, a different shape can be seen on the left-hand side of the peak. The auto correlation of the new bit showed a minimum value at around -250 whereas the correlation between worn and new bits had minimum value at around -240. The negative values at -240 and -250 represent perfect negative correlation of minimum values for unworn and worn plot. The difference of about 10 pixels between both minimums value of auto correlation shows some pattern to the wear size which has about similar value. Despite being able to detect such small wear size, it is hypothesized that the detection can be further improved by applying smaller interrogation window to the image.

![Figure 6. Plot of worn and unworn bit](image_url)

![Figure 7. Cross-correlation of unworn with worn plot](image_url)
4. Conclusion
In this study, an image-based analysis for the tool wear quantification is proposed. Through common image analyses such as filtering and thresholding, the edge of the drill bits was characterized through the change of pixel number of a binary image. The plots, which represent the profile of drill bit edge, were then cross correlated to each other. It was found that the difference of the minimum values between the correlation graphs reflect the physical size. In the experiment performed, the difference of about 10 pixels in the correlation graphs conforms with the wear imposed to the drill bits. With a small pixel size, this technique offers high resolution and sensitivity to the wear detection of cutting bits.

Future study involves the implementation of interrogation window that divides the image into smaller sub-regions. With the implementation of cross-correlation technique to smaller window, it is expected that the cross-correlation graph will show prominent difference between worn and new bit and offer higher resolution and sensitivity to the technique.

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