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Real-time Grinding Wheel Condition Monitoring Using Linear Imaging Sensor

E. Taewan Lee Zhaoyan Fan* Burak Sencer

School of Mechanical, Industrial, Manufacturing Engineering, Oregon State University, Corvallis, Oregon 97331

* Corresponding author. Tel.: +1 541 737 2619. *E-mail address:* Zhaoyan.Fan@oregonstate.edu

Abstract

Grinding is a widely used process in precision finishing of machined part surfaces. Grinding wheels, the key component of the grinding process, consist of a mixture of abrasive grains and bonding materials with or without a metal core. During the grinding process, the grits are either removed or broken on the wheel surface due to multiple mechanisms. Such tool wear on grinding wheel determines the quality of the ground surface as well as the part dimension accuracy and machining efficiency. This work presents a new method to monitor the health status of the grinding wheel using linear Charge-coupled Device (CCD) sensor, which captures one-dimensional grayscale images of the grinding wheel surface. The statistical features were extracted from the sensor data to estimate the present tool wear. Compared to general camera imaging method, the proposed approach is able to achieve high speed sampling with the CCD sensor to scan across the width of wheel in milliseconds, which enables the method a potential solution for monitoring the wheel condition in real-time. The method was tested by capturing surface images of a silicon carbide wheel on a commercial grinding machine. Statistical features such as standard deviation, kurtosis, and entropy were extracted from the grayscale color intensity of the image data and compared to the measured wheel life represented by the counted grinding cycles. The statistical features were fused by an Artificial Neural Network (ANN) model to estimate the life of the grinding wheel. Experimental results show a good match between the estimated and true wheel life with an average error less than 5%.

Keywords: Real-time monitoring; Grinding; Tool wear; Image sensor;

1. Introduction

Grinding is a commonly used machining method to finish part surfaces with high precision and low roughness. Grinding wheel is core component of grinding machine, composed of grits, bonding material, and an optional metal core. During the grinding process, the grits attached to the grinding wheel surface cut through the part surface, taking off certain amount of material and at the same time generating heat due to friction and material deformation. On the wheel surface, some of the grits break or detached under the mechanical vibration and cause the tool wear [1-3]. For a grinding process with consistent operation conditions, by referring to the worn-out diameter of the wheels at a unit time period, a typical tool wear process can be divided into three major stages (1) initial wear, (2) wear in normal use, and (3) end of tool-life, as shown in Figure 1. In the initial wear stages, the tool wear increases quickly within a short period of time, because of geometrical changes on the grinding wheel surface from contacting with the workpiece at the beginning [4-5]. In the second stage where the wheel is under normal use, the tool wear is continuously developed along a linear trend. When the grinding wheel is or approaching the end of its lifetime, the cutting efficiency drops quickly. The exponentially increased friction force results in additional vibration and high temperature in the grinding zone, which consecutively damages the part surface being ground.

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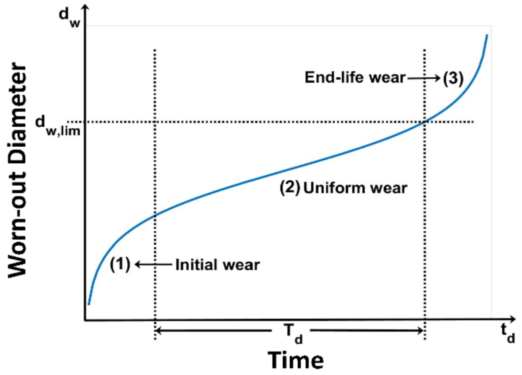


Figure 1. Tool wear during a grind wheel life

During the full lifetime of a grinding wheel, the tool wear is one of the critical factors determining the quality of finished surface in the manufacturing process [6]. For instance, wear of grinding wheel causes dimensional errors and product deformation due to abnormal cutting temperatures. To avoid these problems, in conventional solutions, the grinding wheel are replaced or re-dressed repeatedly. However, replacing and re-dressing operation requires to stop the machine completely, and consequently have a tremendous impact on production time and efficiency [7]. Alternatively, various techniques have been investigated to estimate the remaining lifetime based on the parameters measured from the grinding wheel and other parts of the grinding machine [8-11]. Research in [9] studied the method to determine wheel wear by measuring the phyllotactic pattern generated from grinding process. The in-process parameters measured during the grinding process, i.e. vibration and acoustic emission, of the ground workpiece [10], was used as the input for estimating the wheel condition. An advantage of the method is the possibility of being applied online to measure wheel condition in real-time but with a relative low accuracy. In addition, wear in the grinding process implies damage to the grains constituting the side grinding wheel. For improved detection accuracy, research [11] studied the textural features extracted from the 2D images taken from the wheel surface and correlated them with the wheel operation time. The 2D surface images of the grinding wheel are generally collected offline, after stopping the wheel. The major reason come from the constrained frame speed of the camera. For a general grinding machine, the velocity of grits on the surface can reach up to the level of 1-10 [m/s] depending on the applications [12]. To achieve the resolution of 10 μm for identifying 50 μm scale grits in the image, it would require the camera to operate at 10 [μm] /1 [m/s] = 0.1 μs per image. Such a speed is far beyond the capability of commercial high-speed video cameras which take a frame every 1ms or even longer.

This report presents a new approach to monitor the health status of the grinding wheel by sampling linear one-dimensional images across the wheel, based on the consumption that the 1D images are affected by the wheel surface conditions, i.e. wheel wear and present life time. The advantage of the new method is that the 1D images can be sampled by the Charge Coupled Device (CCD) sensors with a fast speed up to the 0.1 μs per image [13], which enables the method a potential solution for monitoring the wheel condition in real-time. The challenge of the work is to prove the correlation between the 1D images and the wheel conditions, which has yet been reported in the literatures. This paper contributes to experimentally test the relationship, by quantifying the correlations between the statistical features extracted from the 1D images, (i.e. standard deviation, kurtosis, entropy) and the actual wheel life. The tests presented in this paper is based on a simplified version of the design, where a photo camera is adopted to capture 2D images of the wheel surface. The 1D image from linear CCD sensor is simulated by extracting a single line of pixels from the 2D image. The proposed technique was experimentally tested on a commercial grinding machine equipped with silicon carbide grinding wheel. The remainder of this paper will be organized as follows. Section 2 will introduce the theoretical basis for extracting the statistical features from the 1D image data. Section 3 will illustrate the experimental setup for testing the proposed technique and discuss the results.

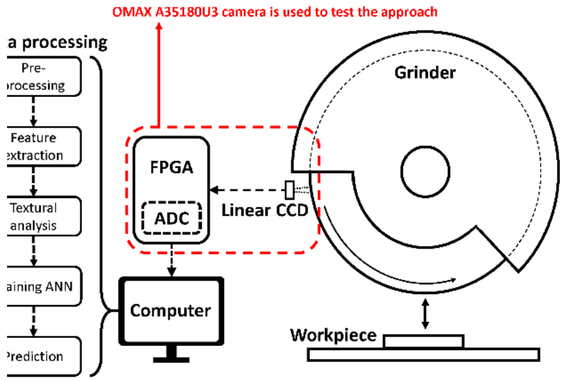


Figure 2. Proposed 1D image sensing system for tool wear monitoring

2. Methodology

The designed system is composed of a linear image sensor that is scanning across the grinding wheel and the associated data process program on a computer platform to extract the statistical features and correlate the features with wheel statue through machine learning (as shown in Figure 2).

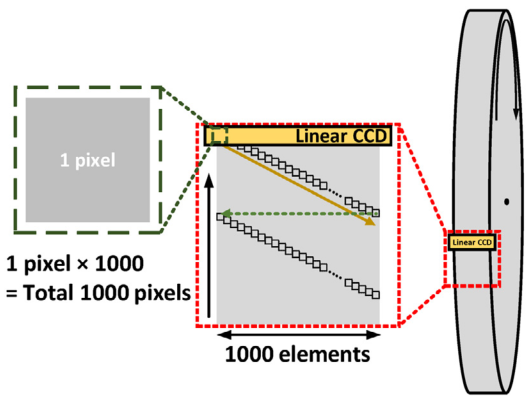


Figure 3. Capturing surface images from the grinding wheel

In order to test the approach, an OMEX A35180U3 camera was adopted to take the role of CCD sensor to capture images across the grinding wheel. The camera generate 2D images with a resolution of 4912 x 3684 pixels. To simulate the output of the CCD sensor set along the width of the wheel, the distributed pixels on a line of the 2D images were extracted after rescaling the raw image to a matrix of 1000 x 1000 pixels, as shown in Figure 3. As the approach assumes the 1D image is taken without stopping the wheel during the grinding process, the extracted line of pixels is inclined along the wheel rotation direction, with a horizontal shift determined by the wheel rotation speed.

As the grits, abrasive material, and residue of the ground product have different reflectance to the visible light, they show different grayscales in the sampled 1D image samples. Generally, the grits made of silicon oxide crystals appear brighter in the image than the bonding material (ceramics) and residue (metal oxide powder). In this study, the standard deviation, kurtosis, and entropy of the pixels, are chosen as the statistic features representing the wear of the grinding wheel. Physically, standard deviation represents the variance of grit distribution in bonding material background. Kurtosis represents a measure of the clustering of pixels at the same/similar grayscale on the wheel surface. In the grinding process, higher kurtosis means that individual grits became flatter after wearing and fractures. As a result, the cluster of the color intensity values is getting closed to the average. The entropy represents the randomness of grayscale distribution, which indicates the geometric patterns of the grits with new cutting edges. The three features can be calculated as:

$$\text{Standard Deviation, } \sigma(X) = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\mu)^2}{n-1}} \quad (1)$$

$$\text{Kurtosis}(X) = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^4}{\left[\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2\right]^2} - 3 \quad (2)$$

$$\text{Entropy}(X) = \sum_{i=1}^{n} P(x_i)\, log_2 \frac{1}{P(x_i)} \quad (3)$$

where X is the input data array; x_i is individual data in the i^{th} micro-state within X; μ is the mean values of X; n is the length of data (n=1024); $P(x_i)$ is the probability that the system is in the i^{th} micro-state within X; and $H(x_i)$ is the frequency of its grayscale intensity in the i^{th} micro-state within X. To correlate the extracted features with the wheel life, Artificial Neural Networks (ANN) is adopted in this research.

The ANN model is trained in two main stages: the feedforward stage to estimate the wheel condition; and backpropagation stage to update the weights and biases based on the error between the estimated values obtained from the feedforward stage and the true wheel condition. Constrained by the number of data sampled from the experiment, data processing adopts one hidden layer with seven neurons. In total 90% of the data collected in the grinding process was randomly selected to train the ANN. The remaining 10% was used for validation.

3. Experimental Validation

Figure 4 shows the prototyped system established on a Tormach's PSG 612 grinder platform. The image camera (OMEX A35180U3) is fixed on a tripod, capturing the bottom section of the grinding wheel exposed from the bottom of the wheel cover. A ring-shaped LED light is used as the consistent light source for the imaging system.

The grinding machine has installed an aluminum wheel with a diameter of 178 mm and a thickness of 6.35 mm rotating at a speed of 3,450 RPM. The workpiece is fed at a rate of 66 mm/s. Additionally, the depth of cut was set to a constant increment at 0.0508 mm per round. The experiment was conducted for a total of 300 passes. For every 10 passes, 25 images were taken at arbitrary locations along the peripheral of the grinding wheel. Figure 5 shows the sampled 2D image by the camera and the extracted 1D image before grinding, after 150 passes, and after 300 passes. From the raw images, as seen in Figure 5, it is difficult to identify the status of the grinding wheel from the raw data before extracting the statistical features.

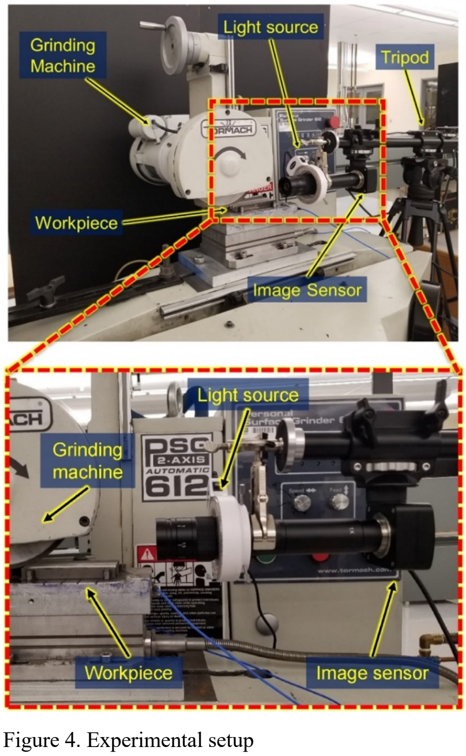
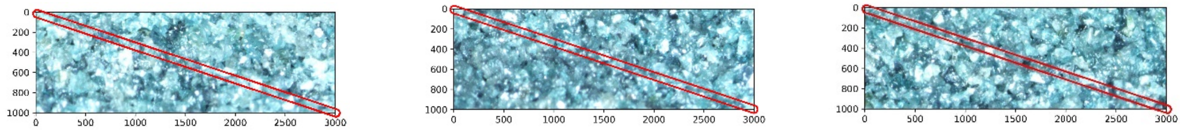
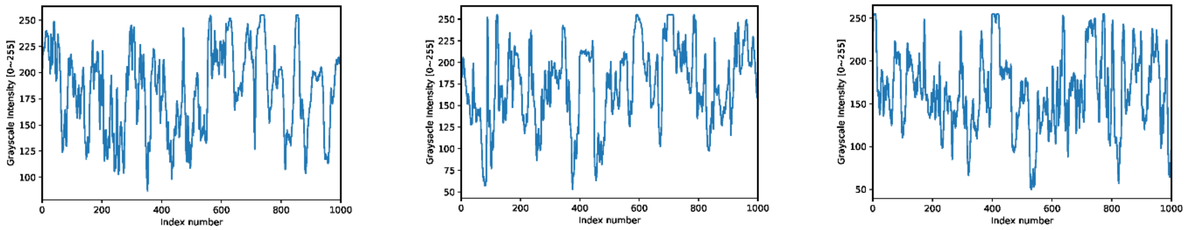


Figure 4. Experimental setup

The statistical features of the raw 1D image data are calculated based on Eq. (1) - (3). The results are shown in Figure 6, where each of the blue data points represents the average values of each feature across all 31 wheel life stages, from the round 0 to round 300. The error bars show the total variation of the calculated feature values. Slight trends can be observed on the averaged standard deviation, kurtosis, and entropy with the proceeding of grinding process. Such a trend enables to correlate the averaged features with the wheel life (number of passes shown in the horizontal axis) using machine learning technique.

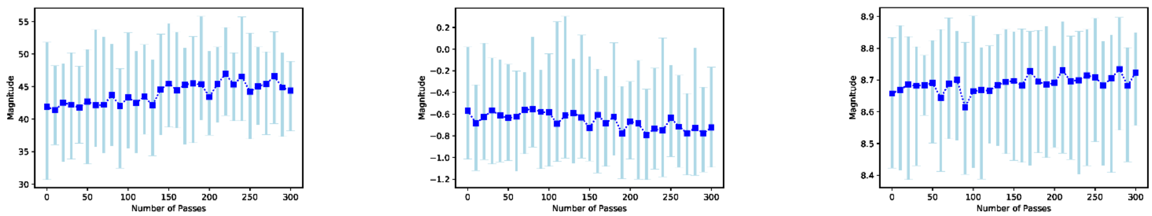


(a) Surface image before grinding (b) Surface image at 150 passes (c) Surface image at 300 passes



(d) Extracted data before grinding (e) Extracted data at 150 passes (f) Extracted data at 300 passes

Figure 5. Pre-processing for the feature extraction at before grinding, 150 passes, 300 passes of grinding process



(a) Standard deviation (b) Kurtosis (c) Entropy

Figure 6. Statistical results for image texture analysis with error-bars

To test the approach, the ANN model is adopted as the algorithm to build the correlation between wheel life and the statistical features. The extracted standard deviation, kurtosis, and entropy values are used as the input to the model. The model output is set to the wheel life represented by the number of passes for each data set. Among all the data sets sampled in the 31 wheel life stages, three different stages are selected for validation while the rest is used for training the ANN model. Table 1 shows the counted number of grinding wheel life versus the results estimated by the trained ANN model, when the validation data sets are sampled when the wheel life at 100 passes, 110 passes, and 180 passes. The estimation errors for each of the estimated wheel life values are calculated as:

$$error = \left|\frac{Y_{estimated} - Y_{true}}{Y_{true}}\right| \times 100\% \qquad (4)$$

where $Y_{estimated}$ and Y_{true} represent the wheel life estimated by the ANN model and the true wheel life, respectively. The estimation error for each wheel life stages are concluded in the last row of Table 1. Figure 7 shows the distribution of the error in the three tested wheel life stages, where the diagonal represents the ideal estimation with 100% accuracy. A mean estimation error of 4.0~5.0% can be observed in the experimental results.

Table 1. Estimation results from the ANN model

Estimated results of the wheel life (number of passes)			
True Wheel Life	**100**	**110**	**180**
Estimated Life	104	113	189
Estimation Error of the wheel life (%)			
Estimation Error	4.0	2.7	5.0

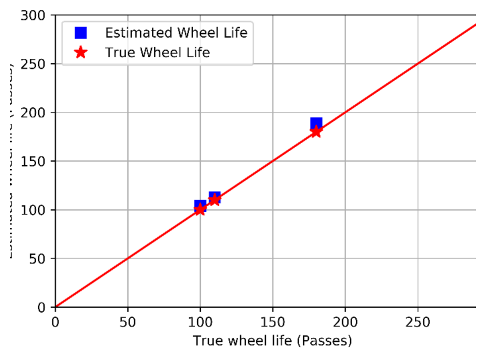


Figure 7. Comparison of the estimated and true wheel life

4. Conclusion

This work has designed a new methodology to measure the lifetime of grinding wheel using linear CCD sensors monitoring the grayscale distribution across the wheel surface. The method extracted statistical features, i.e. standard deviation, kurtosis, and entropy that physically representing the cutting edges/planes of grits one the wheel. Artificial Neural Network was adopted to correlate the extracted features with the true wheel life that is counted in test. The approach was tested on a commercial grinding machine with silicon carbide wheel installed. The experimental results have demonstrated an average estimation error less than 5%, which indicates the potential of applying the method for online grinding process monitoring. The designed methodology and system will help the manufacturing and industry to improve the accuracy of estimating the wheel life and correspondingly assign appropriate maintenance period to maximize the efficiency of the grinding process.

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