Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 72 (2018) 1439–1444

www.elsevier.com/locate/procedia

51st CIRP Conference on Manufacturing Systems

Grinding wheel redress life estimation using force and surface texture analysis

Kalpana Kannan, N. Arunachalam*

Department of Mechanical Engineering, Indian Institute of Madras, Chennai 600 036, India

* Corresponding author. Tel.: +91-442-257-4722; fax: +91-442-257-4652. *E-mail address:* chalam@iitm.ac.in

Abstract

Grinding characterized by low material removal rate and high surface finish is an abrasive machining process. Geometrically undefined grits of grinding wheel influences part surface finish. Cutting edges worn out during grinding are retained by timely dressing. Operators on shop floor decides on the dressing interval based on end of wheel life such as burns, chatter marks and deterioration in the workpiece surface finish. Incorrect dressing of grinding wheel increases unnecessary machining time and wheel wastage. The present work defines the usefulness of grinding force signal and ground surface texture analysis in the estimation of grinding wheel redress time. Grinding experiments were performed in surface grinding machine with white Alumina wheel on D2 tool steel specimen. During the experiments, the force signals were acquired from 9257B Kistler dynamometer, for each grinding pass with 16 KHz sampling frequency. Ground workpiece surface images were captured using multi-sensor Coordinate Measuring Machine (CMM). Experiments were continued till the grinding wheel reaches its end of life. Grinding force signal features prominent to the assessment of grinding wheel deterioration in time, frequency and time-frequency domains were extracted based on prognostic metric evaluation. Hough transform based image texture features were also extracted. The test results depict that a good correlation exists between grinding force signals and ground surface images in measuring the wear deterioration level and thus the ground surface features can be considered as an explicit criterion in the redress life estimation of the grinding wheel.

Keywords: Grinding wheel redress life; grinding force; surface texture analyses; signal processing; features extraction; automated dressing;

1. Introduction

Grinding is a metal removal process, which defines the interaction between the grinding wheel surface and the workpiece material. It is composed of large number of small abrasive grains for removal, inter-granular spaces for coolant flow and storage of removed material and bond material to retain the grains together. It is a multi-point cutting tool as each grain acts as a cutting edge. When the grinding wheel passes through the work piece material, normal and tangential forces are generated. These forces cause the grains to penetrate through the workpiece material. At the arc of contact between the grinding wheel and the work piece material, the grains undergo three different stages of metal removal namely rubbing, cutting and ploughing. Depending on the forces acting on the grains and the depth of penetration, these metal removal stages cause grain wear and fracture. Dressing the wheel removes the worn grits and provides sharp grit protrusion. Excess dressing of the grinding wheel results in increased machining time and under dressing the wheel before reaching its life time increases wheel wastage. To prevent this intelligent decision on dressing interval is necessitated.

Many researches have performed direct and indirect condition monitoring of grinding wheel topography deviation, grinding processes variation and studied its effects on workpiece surface. Susic and Grabec [1] estimated the ground surface properties using acoustic signals emitted by the grinding process. The empirical model based on the correlation function of acoustic emission and surface roughness was developed in the memory of the neural network. It was inferred that the proposed method was desirable to predict the surface characteristics of the stable grinding process except with worn

10.1016/j.procir.2018.03.031

out or newly dressed grinding wheel. Furutani, et. al. [2] proposed a strain gauge type hydrodynamic pressure based in-process measurement of the grinding wheel topography. It was observed that the pressure was decreased with an increasing trend of gap. It was found from FFT analysis that the high frequency components were increasing with the progressing effect of loading and dulling.

Yulun and Haolin [3], presented an application using simulation technique based generation and analysis of the grinding wheel topography. An experimental investigation of the 3D surface topography of SiC grinding wheel (60 grit size), SiC dressing wheel (100 grit size) and diamond grinding wheel (W20) wheels were performed using ZETA 20 imaging and metrology microscope. GMM simulation method was employed to transform the non-Gaussian fields to Gaussian fields and the simulated wheel topographies were generated. The effective 3D topography parameters were calculated and compared with the simulation results. It was observed that for greater values of k (mixture components), the measured and the simulated wheel topographies were found to be close to each other. Liao et al., [4] presented a wavelet based methodology for grinding wheel condition monitoring using Acoustic emission sensor. AE signals of sharp wheel and dull wheel were collected and analysed using discrete wavelet decomposition procedure. It was observed that the presented methodology can achieve 86.7% clustering accuracy for low material removal rate condition, 97% for high material removal rate and 76.7 % for combined grinding conditions.

Su and Tarng [5] proposed a machine vision approach to measure the wear on the grinding wheel. Edge detection image processing method was employed to detect the boundary of the wheel contour. It was observed that the wear measurement of the grinding wheel with repeatable accuracy of ±3 µm was achieved. Yan et al., [6] employed Wyko NT9300 white light interferometer to measure 60 and 120 grit sizes alumina grinding wheel topography. It was observed that the density of grit and the average of principle curvature of grits decreases with increasing sampling intervals. Ye et al., [7] recommended a 3D-motif analysis technique to extract significant grain protrusion features of the grinding wheel. Alicona Infinite Focus an optical measurement system was employed to measure the surface topography of the wheel. It was observed that the wolf pruning at 5% counts correct number of samples whereas for above 5%, the surface appears to be over-merged.

Arunachalam and Ramamoorthy [8], assessed the grinding wheel wear texture using Grey Level Co-occurrence method (GLCM). Parameters such as energy, variance, diagonal moment, ASM, Ga and IDM were observed to discriminate the grinding wheel condition effectively. Arunachalam and Vijayaraghavan [9], found the number of dressing passes required for grinding wheel based on grinding wheel image analysis. It was observed that the image intensity histogram variance and percentage of loaded area were significant in defining the number of dressing passes required for the wheel. Researches on detection of grinding wheel dressing time are limited. Hence, in the present work, an attempt is made to identify the effective parameters of grinding forces and ground surface images signify the dressing time are extracted as a step towards development of intelligent dressing.

2. Experimentation

Table 1 summarizes the experimental conditions under which grinding processes were carried out. Traverse wet grinding was carried out on a CNC Chevaliar surface grinding machine. White alumina grinding wheel (AA46K5V8) and D2 tool steel workpiece were used in the experimentation. Figure 1 shows the grinding experimental setup with 9257B Kistler dynamometer. Begin of grinding; the grinding wheel was dressed using a single point diamond dresser. Roughing (20µm), semi-finishing (10µm) and finishing (5µm) operations resultant to 1mm stock removal were carried out on each workpieces. During grinding, the force signals for each grinding passes were acquired from dynamometer with 16 KHz sampling frequency. The grinding direction along which the force is acquired is shown in Figure 2. The acquired force signal is shown in Figure 3a. The experiments were continued till the occurrence of burn mark on workpiece surface was observed as shown in Figure 2b. After each set of grinding, the workpiece surface images were captured using CMM.

Fig.1. Experimental set-up

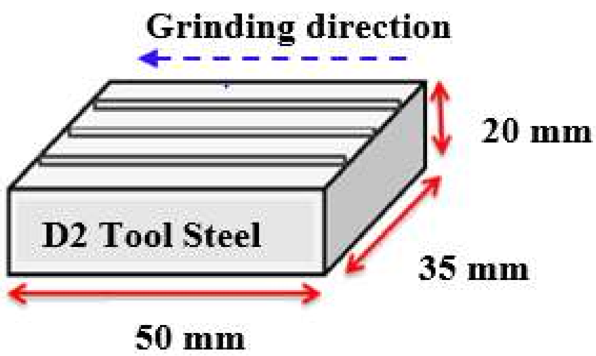


Fig. 2. Grinding direction

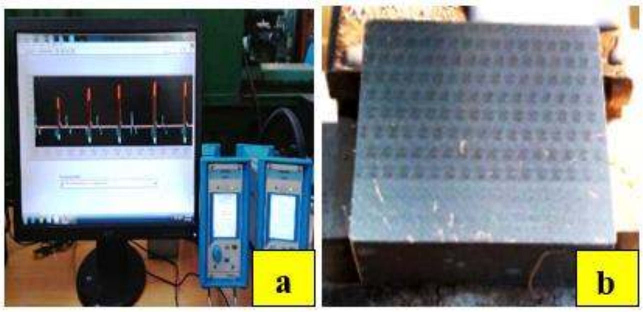


Fig. 3. (a) Grinding force signal acquisition; (b) Workpiece surface burn mark

Table 1. Grinding Experimental conditions

Grinding parameters	Specification	Values
Grinding Type	Traverse grinding	Wet condition
Grinding Wheel	Type	AA46K5V8
Workpiece	Outer/Inner Diameter	180/31.75 mm
	Type	D2 tool steel
	Dimension	50 x35x20 mm
Grinding condition	Workpiece velocity	8 m/min
	Wheel velocity	2500 rpm
	Stock removal	1 mm
	Roughing	20µm, 2 passes
	Semi-finishing	10µm, 4 passes
	Finishing	5µm, 4 passes
Dresser	Spark out	0.1µm
	Type	Single point Diamond
	Feed rate	0.2 mm/rev
	Depth of cut	0.01 mm

3. Results and Discussion

3.1. Force signal analyses

Grinding wheel wears due to rubbing, grain fracture and bond fracture occurrences during the grinding process. These modes of wear are observed to have a direct relation to the forces acting during grinding [10].

3.1.1. Grinding force signal acquisition

In the present work, grinding forces signals of each grinding passes under different depth of cuts (20µm, 10µm, 5µm) are collected for 30s with 16 KHz sampling frequency using dynamometer. Figure 4a-b shows the force signals of fresh and worn out wheels acquired during 20µm depth of cut. At the initial stages of the grinding process, less force is requried for material removal due to the sharp cutting edges of the grinding wheel as shown in Figure 4a. Over a period of grinding, the wheel losses its cutting ability due to wear flat and loading effect. Hence the force required for material removal increases as shown in Figure 4b and thus signifies the wheel worn out condition. To extract more useful information on grinding wheel characteristics variation, the acquired force signal is further analysed in various domains as follows.

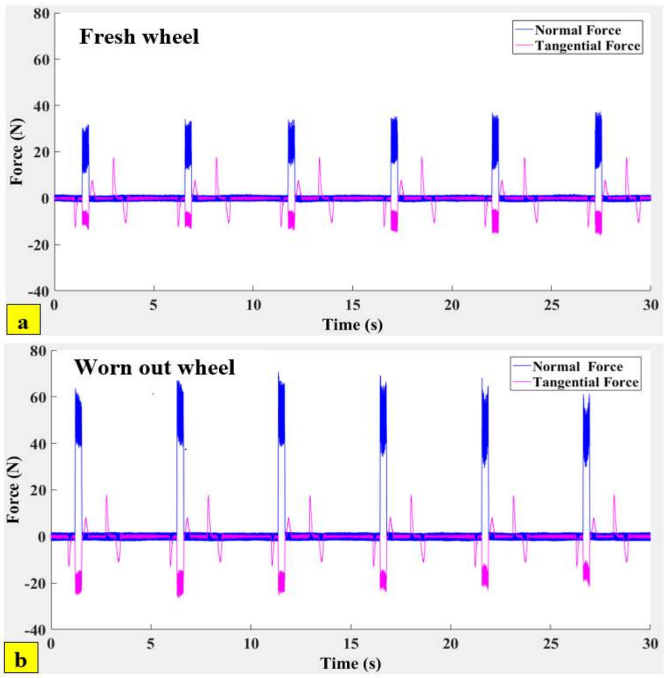
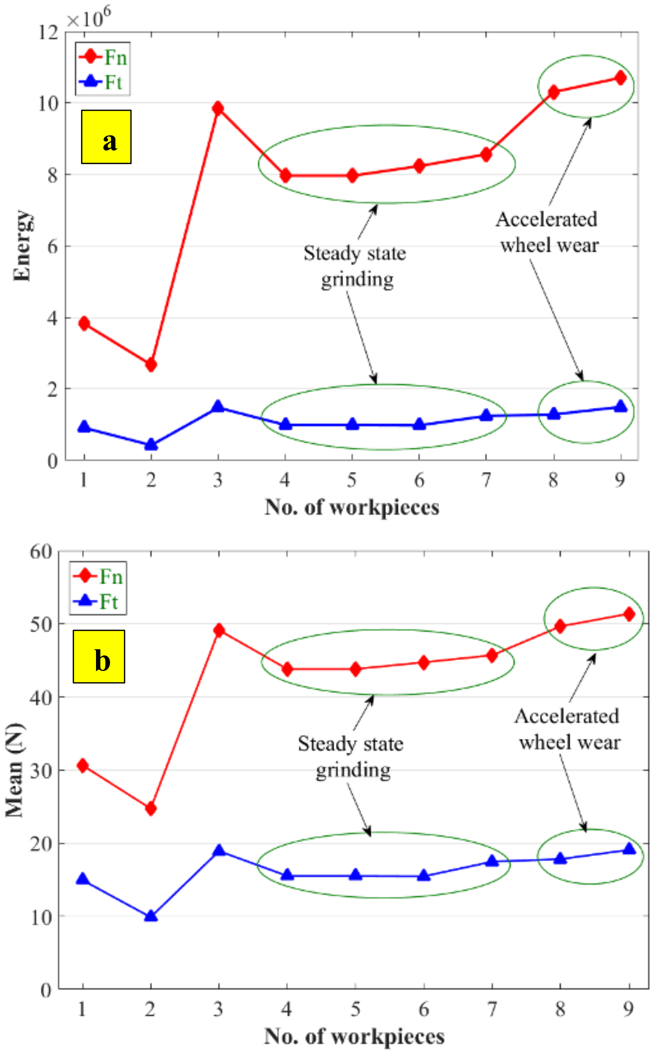


Fig. 4. Grinding Forces: (a) Fresh wheel; (b) Worn-out wheel

3.1.2. Grinding Force features extraction

Force analyses are carried out for each passes obtained during the transverse grinding. However, the results are shown only for the end passes of 20µm depth of cut traverse grinding as similar variation is observed for other depth of cuts. To extract the best reliable features signifying the dressing time, signal analyses on different domains such as (1) time domain, (2) frequency domain, (3) time-frequency domains, (4) complexity measurement and (5) phase-space dissimilarity are performed on the measured grinding force signals. Figure 5a-e shows the best extracted features based on prognostic metrics (monotonicity, trendability and prognosability) evaluation.



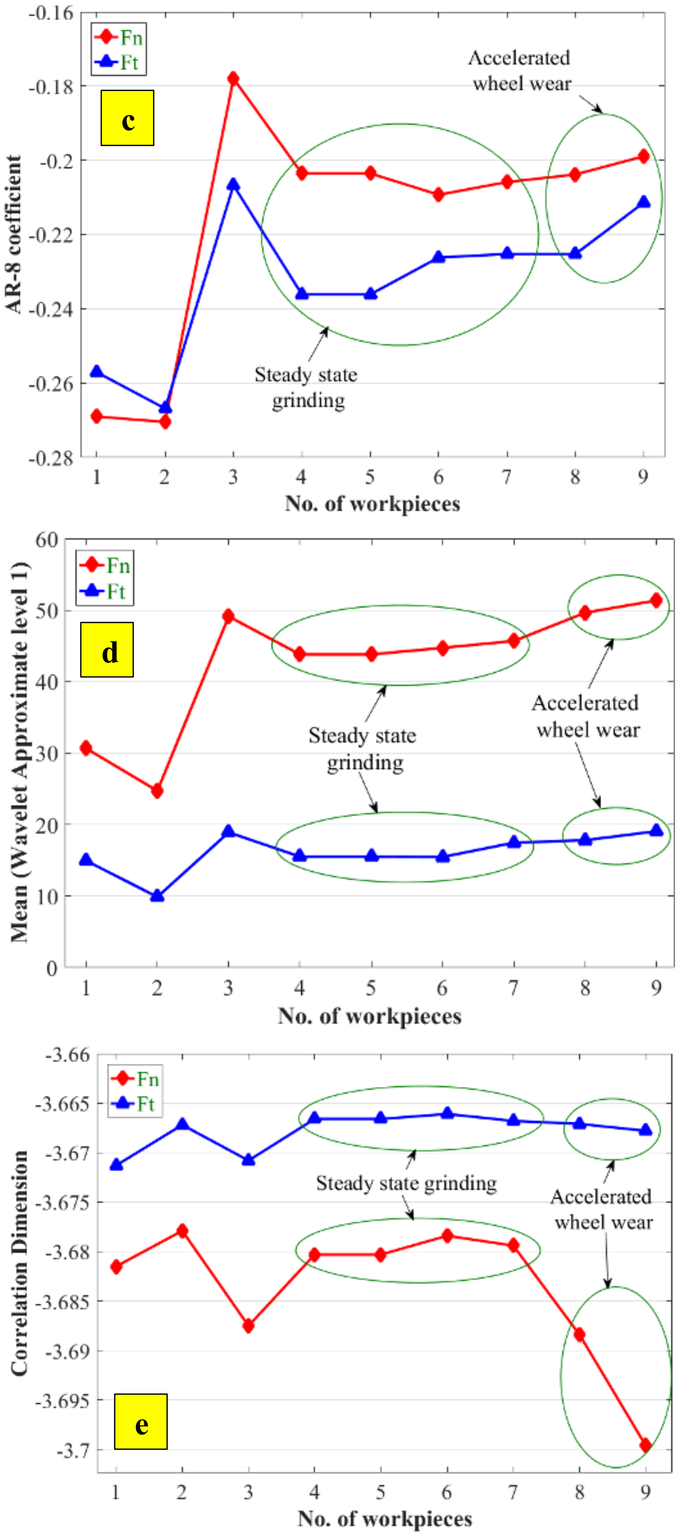


Fig. 5. Effective grinding force features: (a) Energy; (b) Mean; (c) AR-8 coefficient; (d) Mean wavelet level 1 approximate coefficient; (e) Correlation dimension

As the grits losses its sharpness over the grinding passes, the grains require more energy for material removal and thus the force increases. Also the blunt grits result in rubbing action and thus the force increases over the grinding period. Due to this, features such as energy, mean force, auto regressive coefficient (AR8) and mean of wavelet approximate coefficient level 1 values are observed to have increasing trend over the ground workpieces signifying the grinding wheel deterioration. It is also observed that with increasing wear, the force signal exhibits high degree of complexity and reduced self-similarity indicated by correlation dimension variation over the number of ground workpieces.

3.2. Ground surface texture analyses

Grinding wheel topography variation has direct relation to the texture patterns generated on the ground workpiece surfaces. Texture discrimination based on statistical and structural approaches are commonly used to discriminate the machined surfaces produced by fresh and worn out tool. Statistical texture parameters such as first, second and higher order statistics though effective to analyze the machined surfaces, lacks its usefulness due to its sensitivity towards poor image quality and operating condition [11]. Hence in the present work, the surface texture analysis is performed using Hough transform, a structure based texture analysis.

3.2.1. Hough Transform

Hough Transform invented by Duda and Hart [12], maps the spatial space feature points to parameter space (ρ, θ). The line passing through a point (x, y) in x-y space mapped to the parameter space can be expressed as,

$$x\cos\theta + y\sin\theta = \rho \tag{1}$$

Here ρ – perpendicular distance between origin and the line passing through point (x, y), θ - angle between the perpendicular line passing through point (x, y) and the x axis. The points connecting the lines as shown in Figure 6a are accumulated which is represented by the intersections of (ρ, θ) curves at the same point in the parameter space as shown in Figure 6b.

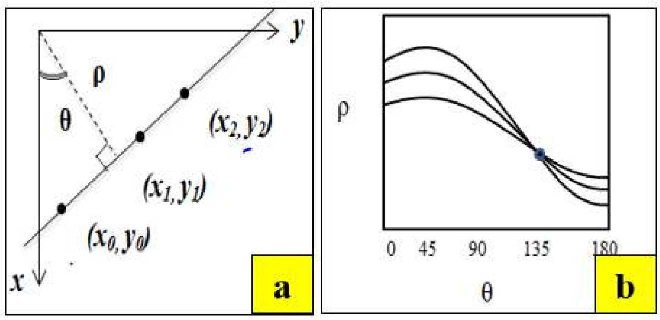


Fig. 6. (a) Spatial space; (b) Parameter space

3.2.2. Detection of line segments

The images of ground workpiece surface at five different locations were captured using CMM. Each of the images is cropped to 256 x 256 pixels as shown in Figure 7a. Canny edge detector is applied to convert the grey level image to binary edge image. Figure 7b shows the canny edged binary image. Followed, the Hough transform is applied to the edge image to detect the line segments in the ground workpiece surface. Figure 7c-d shows the Hough transform in parameter spaces and the detected line segments produced by fresh and worn out

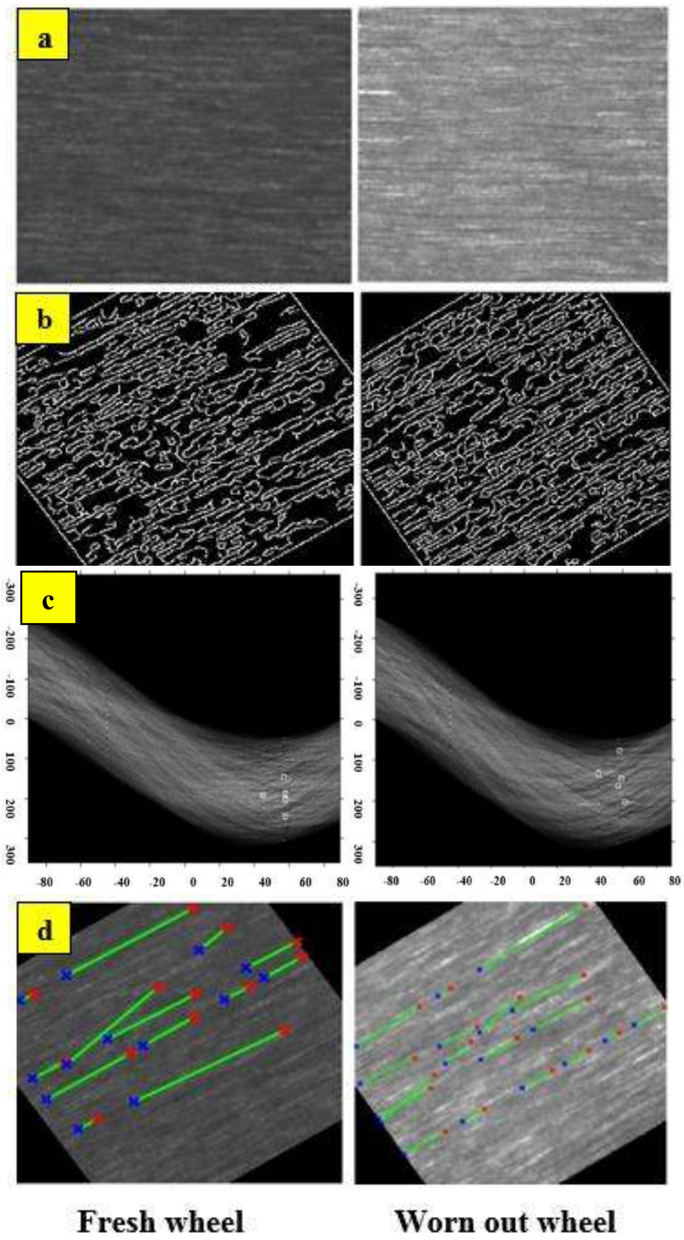


Fig. 7. Fresh and worn out wheel: a) Cropped ground surface image; b) Canny edge image; c) Hough transform (parameter space); d) Detected line segments

grinding wheel. From the Figures 7a-d it is observed that the line segments of ground surface produced by fresh wheel are found to be long due to rather even texture pattern generation. As the grinding wheel reaches its end of life, the grits in the grinding wheel losses its cutting ability and produces irregular texture pattern on workpiece surface signified by the broken lines segments.

3.2.3. Hough Transform features

Figure 8a-b shows the distribution of lines and orientation of the detected line segments of the fresh and worn out wheel ground surfaces. With fresh wheel, the sharp edges of the wheel perform smooth material removal without any friction and thus the ground surface have a regularity with less variation in the orientation of lines as shown in Figure 8a. As the wheel worn, the distribution of lines and orientation of detected line segments spreads and the line length reduces as blunt cutting edges increases irregularity in ground surface texture as shown in Figure 8b. These distributions and variations in line length and orientation allows extraction of essential Hough transform features such as average line length and standard deviation of lines orientation which finds usefulness in the assessment of grinding wheel characteristics.

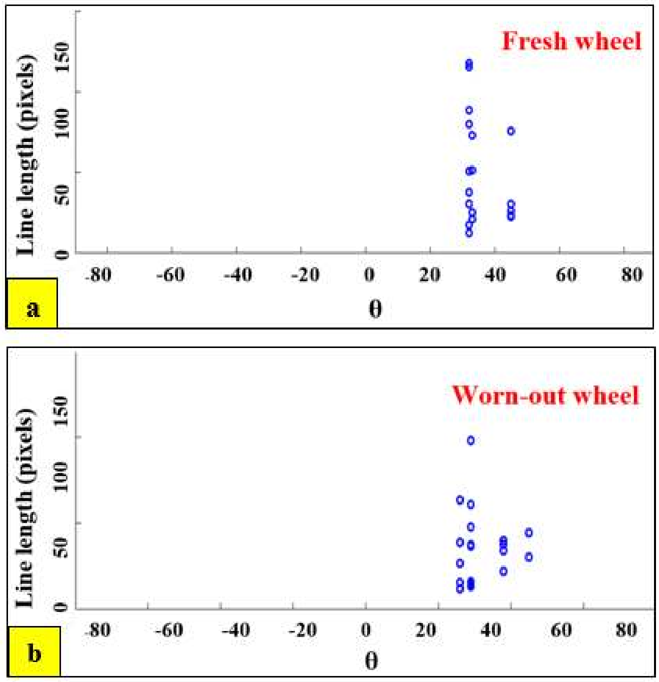


Fig. 8. Detection of line length and orientation: (a) Fresh wheel; (b) Worn-out wheel

Figures 9-10 shows the plots of variation in average line length and standard deviation of lines orientation over the number of ground workpiece. It is observed that the average line length shows a decreasing trend and the standard deviation of lines orientation shows an increasing trend over the ground workpiece. During grinding, as the number of passes increases, the cutting grains losses its cutting ability which results in ground surface texture irregularity. Hence the texture irregularity on the ground surface sources reduced average line length and wider spread of standard deviation of lines orientation over the number of ground workpiece thus directly relating to wheel life deterioration.

Fig. 9. Standard deviation of line orientation variation over number of ground workpiece

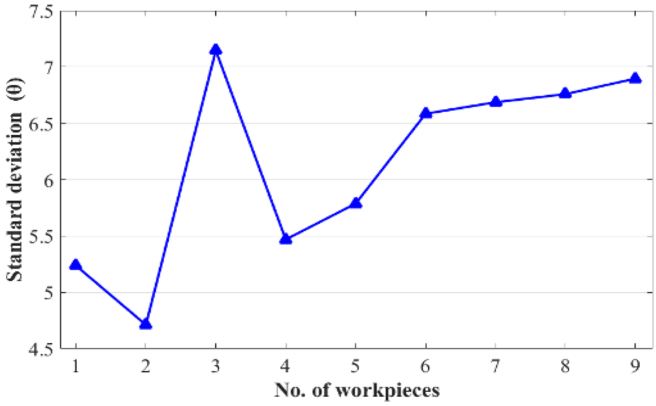


Fig. 10. Standard deviation of line orientation variation over number of ground workpiece

3.3 Identification of grinding wheel redress life

From the extracted force and ground surface features it is observed that grinding wheel critical wear begins after 6th workpiece as a substantial increment in the values of energy, mean, auto regressive coefficient, mean of approximate coefficient, correlation dimension, standard deviation of lines orientation and decrement in average line length are observed. This signifies the need for dressing of grinding wheel after 6th workpiece which is also witnessed by the burn mark occurrence observed during experimentation on the ground surface of 7th workpiece. The correlation between the energy feature of the grinding forces and the standard deviation are studied using regression analysis as shown in Figures 11 a-b.

It is observed that the correlation coefficient between the energy features of the grinding forces (Tangential and Normal) and the ground surface standard deviation of line orientation are obtained as 0.8199 and 0.809 respectively. This clearly signifies, that the line segment length and distribution of the ground surface as a measure of surface texture non-uniformity due to grinding wheel degradation.

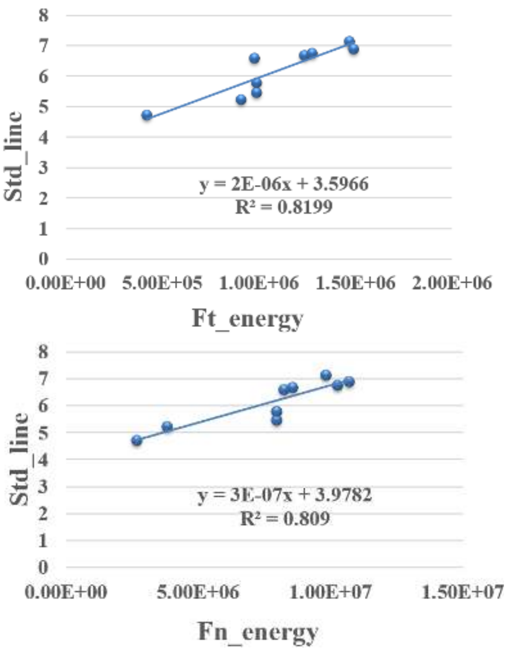


Fig. 11. Correlation between grinding forces and ground surface feature

Conclusion

Based on the results obtained, the following conclusions are inferred:

- Grinding force signal analyses such as time, frequency, time frequency domain, phase-space measurement and complexity measurement have been performed. Based on prognostic metrics, the grinding force signal features such as energy, mean force, auto regressive coefficient, mean of wavelet approximate coefficient, correlation dimension were evaluated as prominent features.
- Structure based texture analysis is used to analyze the ground surfaces. Hough transform based features such as average length of line segments and standard deviation of lines orientation were extracted.
- The extracted features clearly signified that the dressing of grinding wheel must be carried out after 6th workpiece.
- A good correlation is observed between the energy feature of the grinding forces and the standard deviation of line orientations and thus the ground surface images can be considered as an explicit criterion for the redress life estimation of the grinding wheel.

Thus the extracted features of ground surface images forms the basis towards the development of robust intelligent dressing system.

References

[1] Susic E, Grabec I. Characterization of the grinding process by acoustic emission. International Journal of Machine Tool and Manufacture, 2000;40:225-238.
[2] Frutani K, Ohguro N, et al. In-process measurement of topography change of grinding wheel by using hydrodynamic pressure. International Journal of Machine Tool and Manufacture, 2002;42:1447-1453.
[3] Chi Y, Li H. Simulation and analysis of grinding wheel based on Gaussian mixture model. Frontiers of Mechanical Engineering, 2012;7(4):427–432.
[4] Liao T, Ting CF, Qu J. Blau PJ. A wavelet based methodology for grinding wheel condition monitoring. International Journal of Machine Tool and Manufacture, 2007;47:580-592.
[5] Su JC, Tarng YS. Measuring wear of the grinding wheel using machine vision. International Journal of Machine Tool and Manufacture, 2006;31:50–60
[6] Yan L, Rong YM, Jiang F, Zhou ZX. Three-dimension surface characterization of grinding wheel using white light interferometer. International Journal of Advanced Manufacturing Technology, 2011;55:133-141.
[7] Ye R, Jiang X, Blunt L, Cui C, Yu Q. The application of 3D-motif analysis to characterize diamond grinding wheel topography. Measurement, 2016;77:73-79.
[8] Arunachalam N, Ramamoorthy B. Texture analysis for grinding wheel wear assessment using machine vision. Journal of Engineering Manufacture, 2007;221(3):419-430.
[9] Arunachalam N, Vijayaraghavan L. Assessment of grinding wheel conditioning process using machine vision. Proceedings of Prognostic and Health Management (PHM), 2014;221(3):419-430.
[10] Tonshoff HK, Friemuth T, Becker JC. Process Monitoring in Grinding. CIRP Annals, 2002;51:551-571.
[11] Glossop K, Lisboa PJG, Russell PC, et al. An implementation of the Hough transformation for the identification and labelling of fixed period sinusoidal curves, Computer Vision and Image Understanding, 1999;74:96-100

.