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Application of Gray Level Co-occurrence Matrix as a feature extraction technique to monitor wear of cutting tool

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Abstract: *The traditional methods make use of sensors to monitor the wear of a cutting tool. The application of digital image processing in determining tool wear is gaining importance. GLCM is the most widely used higher order statistical technique for feature extraction to monitor tool wear. Contrast and homogeneity has been proved as the two best texture descriptors of GLCM. The accuracy of GLCM largely depends on the orientation of the pixels considered to obtain these descriptors. This paper presents the effect of varying pixel pair spacing (pps) and pixel pair direction (ppd) on contrast and homogeneity. An attempt is made to provide one of the solutions to consider the orientation of the pixels while computing GLCM.*

Key Words: *Contrast, GLCM, Homogeneity, Pixel pair spacing, Tool wear*

I. Introduction

With the advent of new technology in the manufacturing industry, any unproductive time increases the cost of manufacturing a component. Manufacturing industry is now working on edge to earn profit in the competitive market. In such scenario, there is a need to zero down any scope for downtime due to tool failure or breakage. This has forced the industry to try online techniques to determine the exact time of tool replacement. The tool replacement may cause a downtime of around 20% reported **Zhang[1]** which is sufficient to increase the lead time of the product. Around 3% to 12% of the total production cost accounts for the cost of cutting tools and their replacement. It thus becomes necessary to monitor the health of cutting tool in terms of its wear. In regards to this the cutting tool should be replaced exactly when it is worn out (i.e. average flank wear reaches to 300 microns) and should not be underused or overused as both causes unnecessary downtime. Whereas in the latter case the tool itself would get machined that may not be identified in real time**Loizou et al.[2]**, the former is not advisable from economic point of view. Unmanned production system is possible only if a proper tool condition monitoring (TCM) is available. Also, cutting speed can increase 10–50% states **Dutta et al.[3]**but with appropriate TCM technique the remaining useful life (RUL) of cutting tool can be determined online.

The indirect techniques of digital image processing that extract important textural features from work piece images are advantageous than sensor based techniques.

A texture is characterized by arrangement of pixels in an image and feature describes the assets of an object that contains some quantifiable information about the image. To extract features from an image means to convert the redundant information in the pixels to a reduced set of features. Analysis of a huge data and redundant information takes higher computational time, larger memory space and makes it difficult to be used in online situations. Also the accuracy of the implementation of the algorithm depends upon the correctness of information from the extracted feature.

An approach using Gray Level Co-occurrence Matrix (GLCM) was used by **Gadelmawla [4]** to characterize surface roughness from captured images. The obtained images were characterized by using GLCMSurf software by studying the effect of pixel pair spacing. **Gadelmawla [5]** further used texture features from GLCM to predict the surface roughness of turned components. Authors found that only six features were highly correlated with surface roughness. But the study did not cover the selection of pixel pair direction.

Assessment of surface roughness of inclined component was studied by **Priyaand Ramamoorthy [6]** using GLCM technique. Images were taken by keeping the component flat as well as inclined in either direction. They observed that flat surface shown in fig. 1, gives the optimum value for surface roughness when subjected to GLCM technique.**Dutta et al. [7]** studied GLCM technique to investigate the wear of cutting tool by capturing images of machined surface. As the tool wears out the feed mark formed on machined surface becomes short, discontinuous, uneven and distorted. GLCM features like contrast and homogeneity were found to be suitable for TCM.

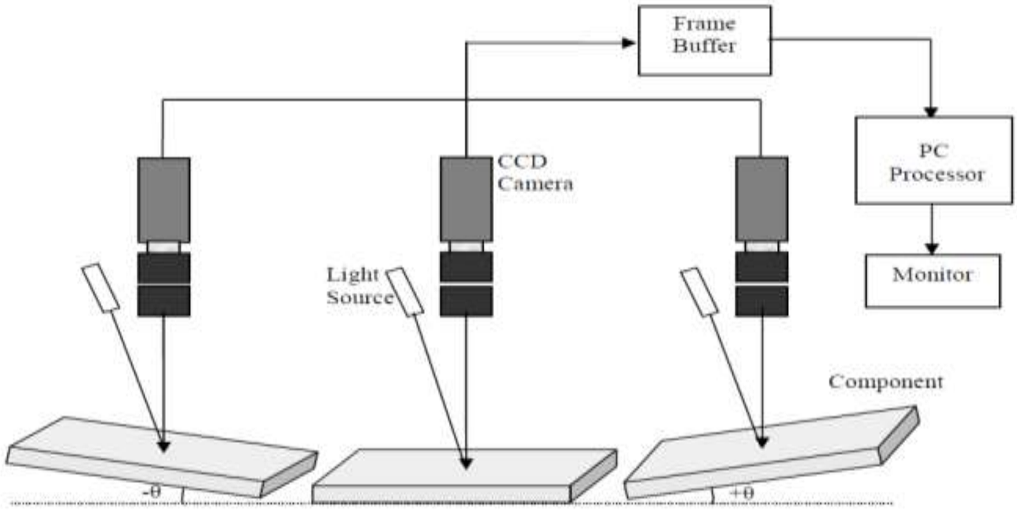


Fig. 1 Images of component captured at various angles

In another study, **Dutta et al. [8]** used power spectral density, as shown in fig. 2 (a) and 2(b) to obtain exact pixel pair spacing values to form a GLCM. However they got a good correlation between extracted features and surface roughness but the values of pixel pair spacing shows a large difference that may miss the texture information. Further the method is limited to be used for contrast and homogeneity features only.

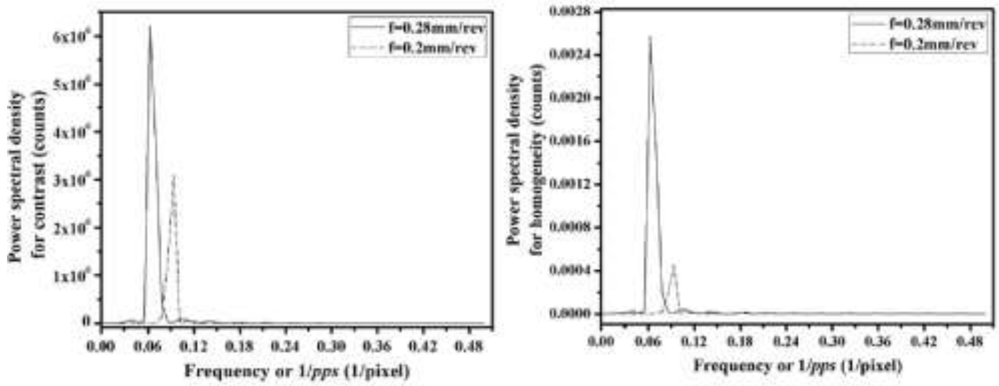


Fig. 2 Power spectral density plot based on (a) contrast and (b) homogeneity

Khalili and Danesh[9] generated the surface images from the vibration between tool and work piece. DWT was performed on this image and texture analysis was done using GLCM. Selection of pixel pair was not focused in the study. **Danesh and Khalili [10]** further used DWT and GLCM to determine wear in turned image of component**.** The texture of such image was analysed by using GLCM. **Saeidi [11]** used GLCM technique to evaluate wear of cemented carbide drill bit along with other two image processing methods namely surface metrics and minimum distance classifier. While GLCM features were computed at 0°, 45°, 90° and 135° authors used a different method to consider pixel pair spacing and found that contrast and entropy features of GLCM can be used to predict tool wear.

Lihong and Qingbin [12] acquired images of turned surface and analysed them using GLCM with the entropy feature as a pps decider. A new method to obtain pixel pair spacing (pps) was presented as shown in fig.3 but the method is limited to be used with entropy feature of GLCM. Here entropy denotes the randomness or un-orderliness in the texture which is more in dull tool as compared to sharp tool.

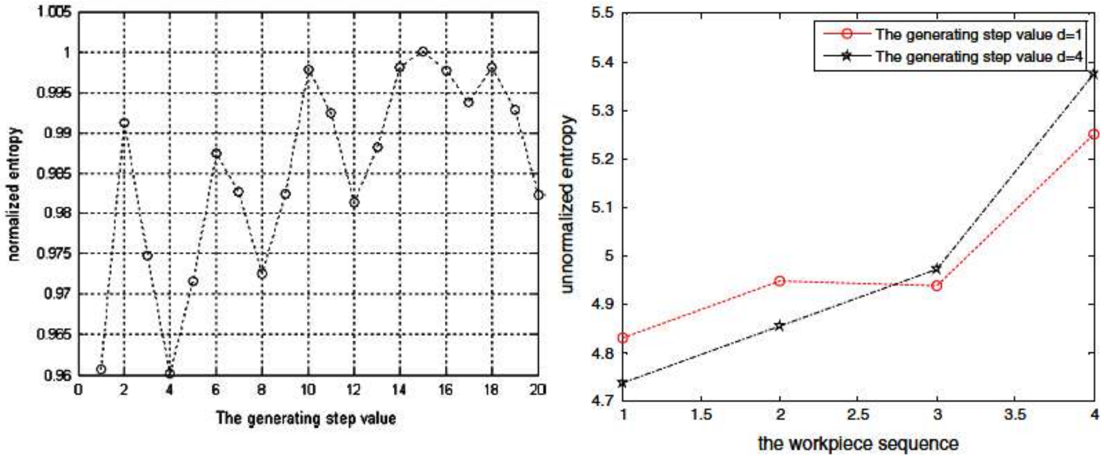


Figure 3 Entropy based pps values (a) relation between entropy and pps (b) Simulation curves

Literature reveals that use of GLCM in tool condition monitoring is of prime importance. Use of many feature extraction techniques like Fractal, Run Length Statistics, Wavelet and Principal Component Analysis are found but Gray Level Co-occurrence Matrix is very popular technique as it has high accuracy rate. Proper spacing and orientation between two pixels need to be focused as it decides the textural features selected. Even though much of the work used GLCM, there is no unique theory for accepting pixel pair spacing in the machining domain. Different authors **[8]**, **[11]**, **[12]** have used different methods to obtain pixel pair spacing. There is a strong need to develop a flawless feature extraction technique that will extract important features, monitor the tool wear and predict the life of cutting tool. The rest of the paper is organized as follows. Section 2 gives brief information about GLCM. Section 3 provides the experimental details and the analysis of results are presented in section 4. Section 5 addresses the conclusion.

II. Gray Level Co-occurrence Matrix (GLCM)

A GLCM is a matrix where the number of rows and columns is equal to the number of distinct gray levels or pixel values in the image of that surface. It describes the frequency of one gray level appearing in a specified spatial linear relationship with another gray level within the area of investigation. Given an image, each with an intensity, the GLCM is a tabulation of how often different combinations of gray levels co-occur in an image or image section. Texture feature calculations use the contents of the GLCM to give a measure of the variation in intensity at the pixel of interest.

Haralick[13] introduced GLCM technique in 1973, in order to extract the second order statistical textural features of an image. It is a matrix formed by the combined occurrence of gray level pixel that gives information about the probability of co-occurrence of different combinations of pixel intensity values in an image. Two parameters "pixel pair spacing" (s) and "pixel pair direction" (d) are needed to construct a matrix. Each element (i, j) of the matrix represents the number of times the pixel with intensity value i pairs with a pixel with intensity value j, which are at a spacing 's' relative to each other. The GLCM of an image is defined by the two parameters stated above and in its general term can be represented as given in equation (1):

$$GLCM\ (i,j)_{s,\theta} = |\ \{[\ (m, n), (s, d)]\ |\ i,\ j\ \}\ |\ \ ....(1)$$

where, (m, n) Ɛ (M × N) and (s, d) is at distance of s from (m, n) and in the direction of dand |.| stands for the cardinality of the set. M × N is the image size and i and j represent the intensity value of pixel at s, d.

The GLCM, being second order texture, considers the intensity of two pixels which are adjacent and offset **[8]**. The adjacency is decided by the spacing between two pixels under consideration, which depends upon the pixel intensities. The offset is decided from any one of the four defined directions of 0°, 45°, 90° and 135°. A GLCM contains information about the similarity or dissimilarity of the gray level values (intensity) of the considered pixels.

The GLCM plot of a component machined by a sharp tool and a dull tool taken in MATLAB software (release 18 a) is shown in fig.4. It is evident from the figure that uniform texture will have GLCM concentrated around the diagonal and less spread, whereas for an unstructured texture it spreads out away from the diagonal.The inference that can be drawn from the figure is that if most of the entries in the GLCM are concentrated along the diagonal, the texture of work piece is smooth (i.e. surface roughness is less) and hence the cutting tool is not worn out.

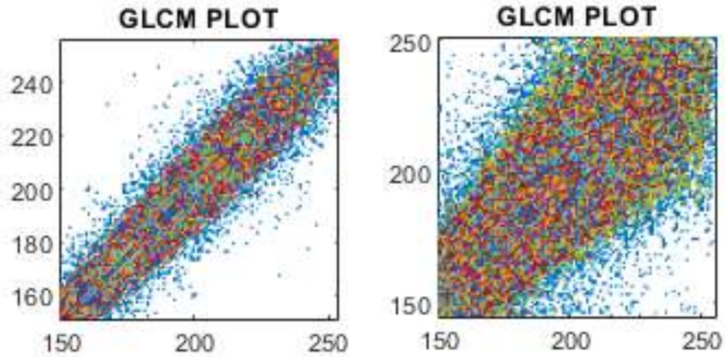


Figure 4: GLCM plot of sharp and dull tool machined component

2.1 Contrast

Contrast is the difference in gray levels of two pixels. Contrast (CON) is a measure of difference in intensity level of a pixel and its neighbour over the image. A zero contrast image means there is no difference between any reference pixel and its neighbor and all the non-zero values in the GLCM are along the GLCM matrix diagonal.

The contrast increases away from the diagonal and is zero if the elements are along the diagonal. Thus for a surface machined by fresh tool the contrast lies along the diagonal with a small value and it increases with the wear of cutting tool.

Contrast feature of GLCM is calculated by the formula

$$\mathrm{CON} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}[(i-j)]^2[P(i,j)]$$

2.2 Inverse Difference Moment

Inverse Difference Moment (IDM) also called as Homogeneity is a measure of closeness of the distribution of elements in the GLCM to its diagonal. Thus homogeneity measures the local uniformity of an image. Homogeneity has high value when local gray level is uniform and more diagonally distributed. Thus a worn out toolimage will have low value of homogeneity and the surface machined by sharp tool will have higher value of homogeneity. Contrast and homogeneity are strongly but inversely correlated in terms of uniform distribution of gray level values.

The Homogeneity feature of GLCM is calculated by the formula

$$\mathrm{IDM} = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{[P(i,j)]}{1+(i-j)^2}$$

Here P(i,j) denotes the probability of occurrence of i and j.

III. Experimentation

The experimental setup encompasses the hardware and software systems and the setup required for image acquisition, and defines the machiningparameters and tool conditions considered in the experiments.

3.1 Machining Setup and Conditions

The experimentation was performed on CNC lathe of MTAB made as shown in fig.5. The program was executed using Fanuc controller in dry cutting conditions. The cutting tool used was right hand coated carbide insert. The entire machining was performed by the same tool to study the condition of the tool for a considerable time. Also the cutting parameters were kept fixed so as to have uniformity in obtaining the results.

Figure 5: CNC Lathe Machine on which experimentation was performed

Table 1 shows the experimental conditions.

Table 1 Experimental Conditions

S.N.	Parameters	Unit	Value
1	Spindle rpm	rpm	2000
2	Cutting speed	m/min	158.8
3	Feed	mm/min	100
4	Depth of cut	mm	0.5

Aluminium was selected as the work piece material as it can be easily machined without the use of coolant. Bars of original diameter 30 mm and a length of 120 mm were given a rough cut of 1 mm to make the surface uniform and aesthetically better. It was decided to machine till a difference in surface roughness is obtained. 10 work pieces were machined to reduce the diameter as per the written program. The machined work pieces are shown in fig.6 in properly arranged fashion.

After machining was over, the work piece were placed on V block as shown in fig. 7 and images were taken by a 13 mega pixel camera. All the images were cropped into 300 x 300 pixels by using Microsoft Office software 2010 to have uniformity in image size and for further processing.

Figure 6: Machined Components

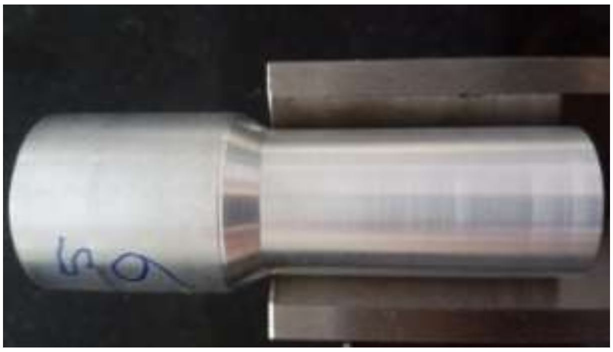


Figure 7: Work piece on V block

3.2 Image Pre-processing

Non uniform illumination and little change in lightening while capturing image can result in inhomogeneity in image and needs a better contrast. Therefore a preprocessing stage is required to distribute the intensity levels uniformly. Contrast Limited Adaptive Histogram Equilisation (CLAHE) was used on the images to control the contrast and provide a noise free image for processing. All image processing was done in MATLAB environment. Fig.8 shows a raw image and preprocessed image using CLAHE technique and the corresponding variation in histogram is shown in fig. 9.

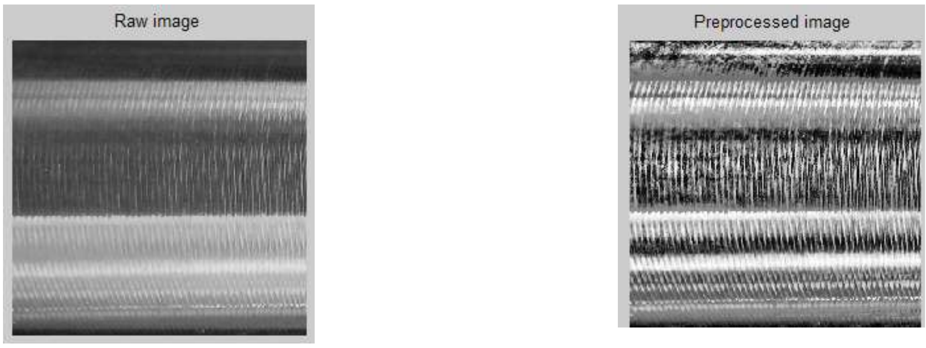


Figure 8Component image before and after applying CLAHE technique

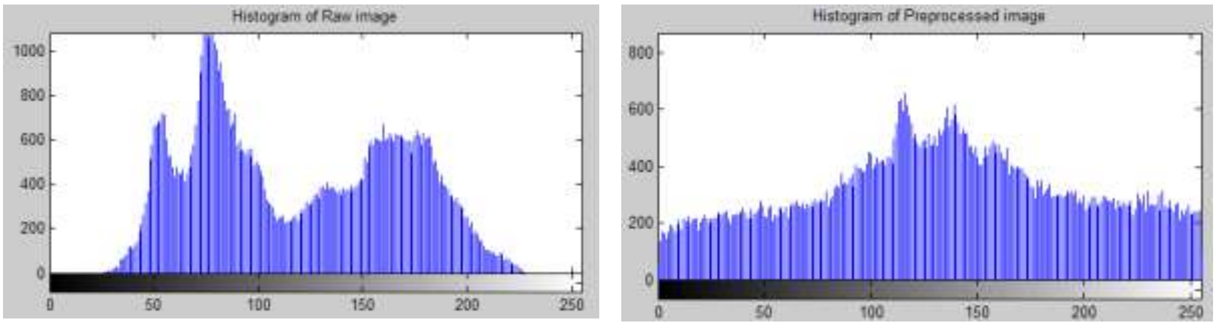
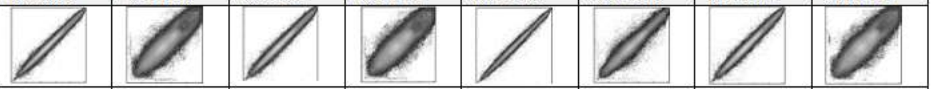
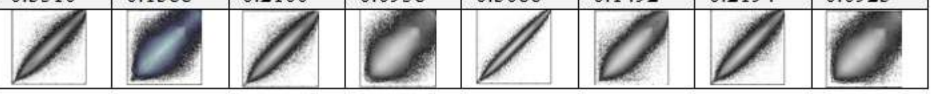


Figure 9 Histogram before and after CLAHE

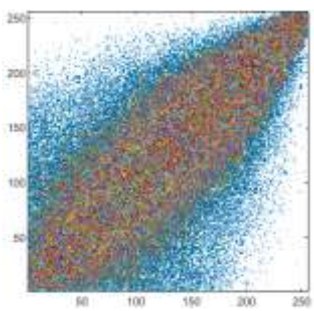
IV. Result and Discussion

Contrast and homogeneity are the two features which are mostly correlated with tool wear **Dutta et al. [14]**, so these features are selected for analysis. Different orientations of pixel pair spacing and pixel pair direction are selected and the two features namely, contrast and homogeneity are determined using a source code in MATLAB.

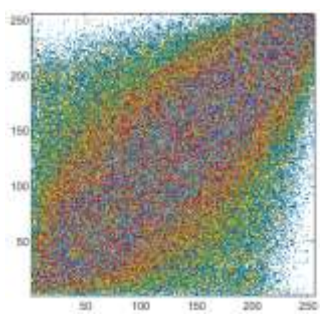
Table 4.2 : Features extracted from GLCM

Ima -ge No.	Features	Orientation of pixel pair spacing and pixel pair direction							
		At 0° angle		At 45° angle		At 90° angle		At 135° angle	
		[0 1]	[0 5]	[-1 1]	[-5 5]	[-1 0]	[-5 0]	[-1 -1]	[-5 -5]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1	CON	23.920	271.54	28.583	288.15	9.4410	48.375	28.572	282.60
	IDM	0.6876	0.2578	0.3621	0.1500	0.8036	0.6548	0.3647	0.1544
	GLCM Plot								
3	CON	49.774	186.02	102.05	661.56	11.943	169.34	103.71	667.01
	IDM	0.5608	0.2459	0.2872	0.1172	0.7258	0.3293	0.2884	0.1172
	GLCM Plot								
5	CON	82.341	404.9	136.57	1250.4	31.496	344.09	136.21	1247.0
	IDM	0.3805	0.1911	0.2691	0.1009	0.5785	0.2160	0.2716	0.1018
	GLCM Plot								
7	CON	99.238	703.33	154.27	1306.2	48.645	465.95	160.15	1298.9
	IDM	0.3748	0.1618	0.2441	0.0999	0.4239	0.1856	0.2430	0.0970
	GLCM Plot								
9	CON	142.74	1089	178.92	1388.1	61.828	556.97	186.17	1379.1
	IDM	0.3510	0.1388	0.2100	0.0958	0.3086	0.1492	0.2194	0.0923
	GLCM Plot								

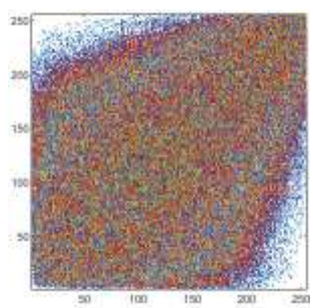
The table 4.2 shows the descriptors for five images of work piece. It also shows the GLCM plot for the respective images. Column (3) and (4) shows the value of CON and IDM corresponding to pps equal to 1 and 5 respectively at ppd of 0° for image no. 1. The value of contrast increases, as the pps increases from 1 to 5. Similarly the value of homogeneity decreases when pps increases from 1 to 5, which can be understoodfrom column (3) and (4) respectively. The GLCM plot for pps of 0 is concentrated along the diagonal elements and its spread goes on increasing as the spacing between the pixels increases. The same can be noticed for other combination of pixel orientation of 45°, 90° and 135° and also for image no. 3, 5, 7 and 9. Another point to be noticed from the above table is that the values of CON and IDM and the GLCM plot for 45° and 135° is almost similar as shown in fig.10. This is because the GLCM is symmetric about its diagonal. But the spread is less as compared to 0° orientation. Further at 90° ppd, the values of contrast and homogeneity and the GLCM plot suggests that the GLCM is more concentrated around the diagonal. This is because the feed marks in turning operation are perpendicular to the work piece axis (i.e. 90°), so the variation in pixel intensity is not significant in this direction. Finally at 0° ppd, the work piece image shows considerable feed marks because of which, the GLCM elements are more off diagonal. This results in more variation in frequency in the work piece image and thus should be considered for ppd. The pps can be more than one in case the feed is high, as it will create coarse feed mark or texture on the work piece surface.



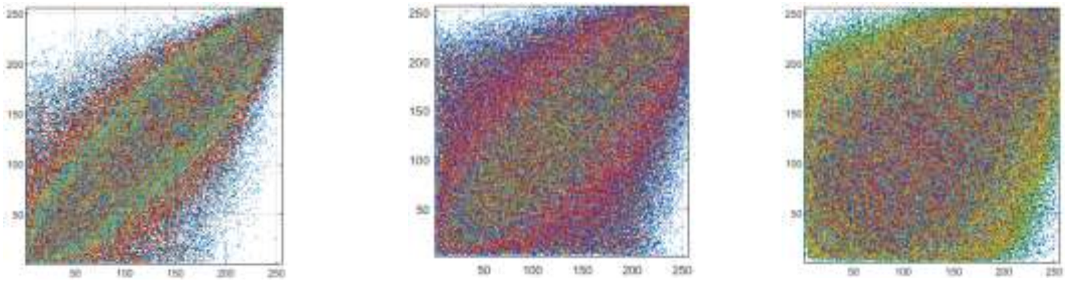
[0,1] CON= 847IDM= 0.17



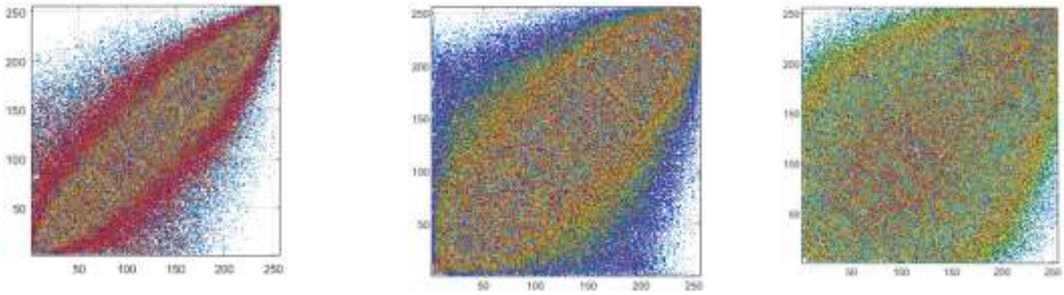
[0,3]CON= 2830IDM= 0.08



[0,5] CON= 4040IDM= 0.06



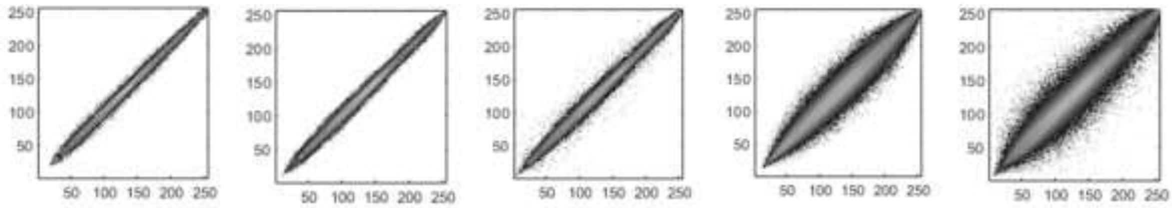
[-1,1]CON= 922IDM= 0.14 [-3,3] CON= 3330IDM = 0.06 [-5,5] CON= 5070IDM = 0.05



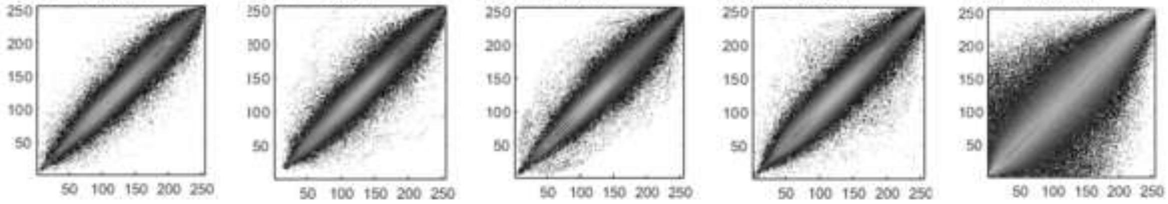
[-1,-1]CON= 948 IDM = 0.13 [-3,-3]CON= 3190IDM = 0.06 [-5,-5] CON= 4750IDM= 0.05

Figure 10 GLCM Plot at different orientation

Fig.11shows the variation in contrast and homogeneity for different images of work piece. The values of contrast are increasing and that of homogeneity are decreasing as shown. Also the GLCM plotreflects the increase in spread and randomness from first to last image. These also projects the fact that as the wear of tool increases, the surface roughness of work piece increases, which results in non- uniformity in the GLCM matrix as well as GLCM plot.



CON = 23.920 IDM = 0.6876 CON = 12.1112 IDM = 0.6351 CON = 49.774 IDM = 0.5608 CON = 69.1909 IDM = 0.4301 CON = 82.341 IDM = 0.3805



CON = 99.5374 IDM = 0.3757 CON = 99.2389 IDM = 0.3748 CON = 105.4967 IDM = 0.3586 CON = 142.7470 IDM = 0.3510 CON = 847.5312 IDM = 0.1719

V. Conclusion

This study is based on use of GLCM technique of image processing that is used to predict tool wear. The GLCM plot gives information about the tool status without stopping the machine or measuring the wear of the tool. The successful implementation of this technique needs a proper image acquisition and a strong illumination system.

As the GLCM matrix is formed by considering the pixel pair spacing, it is vital to select the proper pixel pair orientation. A sharp tool creates feed mark that is periodic in nature. This periodicity depends upon following factors, a) the condition of cutting tool (sharp or dull), b) cutting conditions (speed, feed, depth of cut and coolant), c) machine condition (new or old) and d) tool work piece material combination. As these conditions cannot be same all the time, the periodicity of feed mark varies and hence the pps cannot remain uniform. As there is no unique theory in the literature for determining pixel pair spacing, so to ensure that all information on the component is captured, the pixel pair spacing should be taken as one. Also the angle to be considered for obtaining pps (i.e. pixel pair direction) should be horizontal, as the feed marks in turning are perpendicular to the machined component axis. It becomes more importantto take pps as one when the tool is about to enter the high wear zone. This will results in low contrast, high homogeneity and diagonal GLCM for images obtained by machining with a sharp tool. At the same time it will create a more off diagonal GLCM plot for the rapidly wearing tool to quickly identify that the tool is in a stage to enter the high wear zone and should be replaced.

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