Mansoura Engineering Journal

Volume 34 | Issue 3 Article 7

3-18-2021

# Characterization of the Cutting Conditions in Turning Operation Using the Gray Levels CO-Occurrence Matrix.

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## Recommended Citation

Gadelmawla, Elamir (2021) "Characterization of the Cutting Conditions in Turning Operation Using the Gray Levels CO-Occurrence Matrix.," *Mansoura Engineering Journal*: Vol. 34 : Iss. 3 , Article 7.
Available at: https://doi.org/10.21608/bfemu.2021.157684

# CHARACTERIZATION OF THE CUTTING CONDITIONS IN TURNING OPERATIONS USING THE GRAY LEVELS CO-OCCURRENCE MATRIX

# وصف ظروف القطع في عمليات الخراطة باستخدام مصفوفة حدوث درجات الرمادي

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**الملخص العربي:**

يعتبر مصطلح "سمات النسيج " مصطلحا أساسيا في مجالي تحليل الصور والرؤية بالحاسب لأنه يرتبط بالخصائص النوعية للأسطح. ويعتبر تحليل نسيج الصور هاما في كثيرمن التطبيقات، حيث خضع لأبحاث مكثفة في تطبيقات كثيرة مثل: تحليل الأسطح المعدنية، ووصف المنسوجات، تحليل الصور الخاصة بالموجات فوق الصوتية، وتقييم جودة الطعام. ومن أهم طرق تحليل نسيج الصور ما يعرف باسم "مصفوفة تكرار درجات الرصاصي"، والتي تستخدم بكثرة في الصناعة لأنه يمكن من خلالها تعريف عدد كبير من سمات النسيج للصور بحيث يمكن استخدامها لوصف الأسطح. ويقدم هذا البحث دراسة عملية لوصف وتحليل تأثير عوامل القطع المختلفة في عمليات الخراطة السطحية باستخدام سمات نسيج الصور. وقد تم تشغيل مجموعة من العينات على ماكينات خراطة بظروف قطع مختلفة ثم استخدمت هذه العينات للدراسة. وتم استخدام نظام رؤية بالحاسب لالتقاط مجموعة من الصور لكل عينة وتحليل هذه الصور بواسطة برنامج تم تصميمه خصيصا لحساب كل سمات نسيج الصور المتاحة. وقد تم حساب ومناقشة معامل الارتباط بين معاملات القطع (التغذية والسرعة وعمق القطع)، كل على حدة، وبين سمات النسيج. وقد تبين من الدراسة وجود ارتباط قوي (أكبر من ٩٠%) بين ثمانية من سمات النسيج والسرعة، ووجود ارتباط قوي بين خمس من سمات النسيج والتغذية، في حين لم يوجد ارتباط قوي بين أي من سمات النسيج وعمق القطع.

## Abstract

The term texture features is considered a basic issue in image processing and computer vision because it is related to the qualitative properties of surfaces. Image texture analysis is useful in a variety of applications and has been a subject of intense study in many applications such as metal surface analysis, textiles characterization, ultrasonic images processing, and food qualities evaluation. One of the most common methods for texture analysis is the gray level co-occurrence matrix (GLCM), which has been widely used in industries because it has a large number of texture features that can be used to describe object textures. This paper introduces an application of the image texture features to characterize the effect of changing the cutting conditions in turning operations (feed, speed and depth of cut). A set of turning specimens with different cutting conditions were used for the characterization process. A vision system was employed to capture images for the specimens under investigation, then the images were analyzed using special software, which has been fully developed in-house to calculate all available texture features from the captured images. The correlation coefficients between each texture feature and the three cutting conditions were calculated and discussed. The results showed that eight texture features have good correlations with the feed; five have good correlations with the speed, while no texture features found to be have good correlations with the depth of cut.

## Keywords

Computer vision, Co-occurrence matrix, Cutting conditions, Texture features, Turning.

Accepted September 7, 2009.

## Abbreviations

| | |
|---|---|
| ASM | Angular second moment |
| CON | Contrast |
| COR | Correlation |
| CPR | Cluster prominence |
| CSH | Cluster shade |
| CVAR | Coefficient of variation |
| DAVR | Difference Average |
| DENT | Difference Entropy |
| DIS | Dissimilarity |
| DM | Diagonal moment |
| DVAR | Difference Variance |
| ENT | Entropy |
| GLCM | Gray Level Co-occurrence Matrix |
| GLCMTF | GLCM Texture features |
| IDM | Inverse difference moment |
| MaxP | Maximum probability |
| MCOR1 | Mean Correlation 1 |
| MCOR2 | Mean Correlation 2 |
| MEAN | Mean |
| SAVR | Sum Average |
| SDM | Second Diagonal Moment |
| SENT | Sum Entropy |
| SIM | Similarity |
| SVAR | Sum Variance |
| VAR | Variance |

## 1. Introduction

The term texture features is considered a basic issue in image processing and computer vision. Therefore, it has been an active research topic for more than three decades [1]. Texture is related to qualitative properties of surfaces, but due to its complexity and great variety, there exists neither a unique definition of texture nor an accepted computational representation of it. Image texture analysis is useful in a variety of applications and has been a subject of intense study by many researchers.

The first study of image texture is dated back to the 1950s when the autocorrelation functions method was firstly employed as a technique of image texture analysis [2]. Statistical approaches based on gray tone, and structural approaches based on some complex primitives, were some new technologies developed in the 1970s. As suggested by Haralick [3], statistical technology generalized for structural primitives can result in more methods for analyzing image texture. Investigation about image texture continued and new techniques including fractal model and transform-based texture were continually proposed during the last twenty years.

In industry, statistical texture is the most widely used method for quality grading or classification. Transform-based texture and model-based texture might also be used, but not as often as statistical texture. However, applications of structural texture are very limited in the industry because the structural primitives that used in this method can only describe very regular textures [6].

Among the statistical texture methods, the gray level co-occurrence matrix (GLCM) is the most widely used in industry and its accuracy is usually the best [4]. This is possibly due to the large amount of information that can be extracted using this method. It is possible that there will be at least one feature from the images that can reflect changes of texture patterns among different images. GLCM was first introduced by Haralick et al. [3] and it was among the first to characterize texture as an overall or average spatial relationship between gray tones in an image. The GLCM reveals certain properties about the spatial distribution of the gray levels in the texture image. For example, if most of the entries in the GLCM are concentrated along the diagonals, then the texture is coarse with respect to the displacement vector [5].

Image textures have been introduced into a wide range of applications. In the field of surface roughness, Gadelmawla [7] used the GLCM to characterize and to evaluate surface roughness of machined products. Using fuzzy neural network (FNN) approaches, texture features were utilized to establish relationship between actual surface roughness and texture features of the surface image by many researchers [8-11]. In the medical fields, Tsai and Kojima [12] used the texture features of ultrasonic images to classify the heart disease. In food industry, which is one of the top ten industries using computer vision [13], texture has been used regularly. For example, Chandraratne et al. [14] investigated the usefulness of raw meat surface characteristics in predicting cooked meat tenderness. Other usages cover a variety of food including baked products [15], cereal grains [16], fruits [17], and vegetables [18]. In addition, texture features were used for the inspection of wood [19], paper [20] and leather [21].

The use of machine vision in the determination of tool wear is fairly wide spread in the manufacturing literature, and dates back thirty years [22]. Many researchers used texture descriptors for tool wear monitoring using computer vision [23-25].

Tool wear affects both the dimensional precision and surface quality. On the other hand, the tool wear itself can be affected by machining parameters such as spindle speed, feed, and depth of cut. Therefore, an optimal selection of these parameters is very important in order to obtain high precision parts and to reduce the cost. The aim of this work is to characterize the effect of cutting conditions in turning operations using texture features, then classifying the texture features according to their correlation coefficients with the cutting conditions. This could help, in the future, to predict the values of the cutting conditions for existing products using image texture features.

## 2. Textures of the Gray level Co-occurrence Matrix

Generally, the co-occurrence matrix, $M_c(i,j)$ is calculated using the following equation:

$$M_c(i,j) = P(i,j) / \sum_{i,j}^{n} P(i,j) \tag{1}$$

Where $M_c(i,j)$ is defined as the co-occurrence of gray level occurring, $P(i,j)$ is the frequency of occurrence of gray levels $i$ and $j$; and $n$ refers to the total number of pixel pairs. A normalized matrix is produced by dividing each element of the GLCM by the summation of all elements.

In a previous work [26], all texture features that can be calculated from the GLCM were collected from the literature and discussed. The mathematical equations of these texture features are listed next. If $M_c$ is the normalized GLCM, $i,j$ are the row and column of each element in the GLCM and $n$ is the number of the GLCM elements, then the following mathematical equations are used to calculate the GLCM texture features:

$$\text{ASM} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)^2 \tag{1}$$

$$\text{CON} = \sum_{i=0}^{n-1} n^2 \sum_{j=0}^{n-1} M_c(i,j)\,(i-j)^2 \tag{2}$$

$$\text{COR} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{M_c(i,j)\,((i-\mu_x)(j-\mu_y))}{\sigma_x \sigma_y} \tag{3}$$

where $\mu_y$ is the mean for every column, $\sigma_x$ is the Standard Deviation for every row and $\sigma_y$ is the Standard Deviation for every column.

$$\text{CPR} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)\,((i+j)-(\mu_x+\mu_y))^4 \tag{4}$$

$$\text{CSH} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)\,((i+j)-(\mu_x+\mu_y))^3 \tag{5}$$

$$\text{CVAR} = \sigma / \mu \tag{6}$$

$$\text{DAVR} = \sum_{i=0}^{n-1} \mathrm{i} * M_{cx-y}(i) \tag{7}$$

Where:

$$M_{cx-y}(k) = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j) \text{ and } k = i - j.$$

$$\text{DENT} = -\sum_{i=0}^{n-1} M_{cx-y}(i) \ln (M_{cx-y}(i)) \tag{8}$$

$$\text{DIS} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)\,|i-j| \tag{9}$$

$$\text{DM} = \sum_{j=0}^{n-1} j \sum_{i=0}^{n-1} (0.5 M_c(i,j)|i-j|)^{0.5} \tag{10}$$

$$\text{DVAR} = \sum_{i=0}^{n-1} M_{cx-y}(i)\,(i - DENT)^2 \tag{11}$$

$$\text{ENT} = -\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j) \ln(M_c(i,j)) \tag{12}$$

$$\text{IDM} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{M_c(i,j)}{1+(i-j)^2} \tag{13}$$

$$\text{MaxP} = \max_{i,j}^{m,n} M_c(i,j) \tag{14}$$

$$\text{MCOR1} = \frac{ENT - HXY1}{Max(HX, HY)} \tag{15}$$

Where

$$HXY1 = -\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)\ln(M_{cx}(i)M_{cy}(j)),$$

$$M_{cx}(i) = \sum_{j=0}^{n-1} M_c(i,j),\ M_{cy}(j) = \sum_{i=0}^{n-1} M_c(i,j),$$

$HX$ and $HY$ are the entropies of $P_x(i)$ and $P_y(j)$, respectively.

$$\text{MCOR2} = \sqrt{1 - \exp^{-2(HXY2 - ENT)}} \tag{16}$$

where

$$HXY2 = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_{cx}(i)M_{cy}(j)\ln(M_{cx}(i)M_{cy}(j))$$

$$\text{MEAN}\ (\mu) = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} i\, M_c(i,j) \tag{17}$$

$$\text{SAVR} = \sum_{i=2}^{2n} i\, M_{cx+y}(i) \tag{18}$$

where $M_{cx+y}(i+j) = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)$

$$\text{SDM} = \sum_{j=0}^{n-1} j \sum_{i=0}^{n-1} (0.5 M_c(i,j)|i-j|) \tag{19}$$

$$\text{SENT} = -\sum_{i=2}^{2n} M_{cx+y}(i)\ln(M_{cx+y}(i)) \tag{20}$$

$$\text{SIM} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} \frac{M_c(i,j)}{1+|i-j|} \tag{21}$$

$$\text{SVAR} = \sum_{i=2}^{2n} M_{cx+y}(i)\,(i - SENT)^2 \tag{22}$$

$$\text{VAR} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1} M_c(i,j)\,(i - \mu_x)^2 \tag{23}$$

where $\mu_x = \sum_{i=0}^{n-1} i \sum_{j=0}^{n-1} M_c(i,j)$

## 3. Experimental work

A vision system, shown in Figure 1, has been employed to characterize the effect of changing the cutting conditions in turning operation using the image texture features. The vision system consists of two main parts, hardware and software. The hardware was used to capture images for specimens machined by turning operations and the software was used to analyze the captured images. The software, named GLCMTF (GLCM Texture Features), was fully developed in-house and was previously discussed in [26]. It is capable of calculating all texture features, discussed in section 2, for up to 100 position operators (direction $\theta$ and distance $d$) of the GLCM.

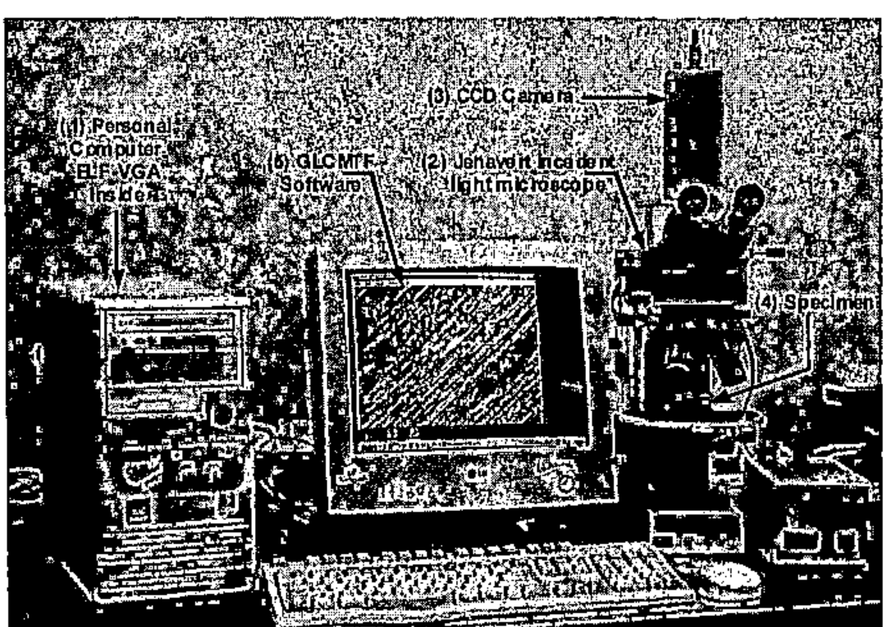



**Fig. 1: Photograph of the employed vision system**

### 3.1 Specimens Preparation

A steel bar "Steel 37 type" with 45 mm diameter was used as a raw material to prepare the specimens of investigation. A total of 54 specimens were machined by turning machine using face operation. The specimens were machined using cutting tools have tips of commercial type Widadur coated hard metal (TNMG160412P25) with nose radius of 1.2 mm. For each cutting condition (feed, speed, and depth of cut), 18 specimens were divided into six groups (3 specimens in each group) and each group was machined using six different values for each cutting condition as shown in table 1. The other cutting conditions were kept constant and chosen as intermediate values. Before performing the turning operations, all specimens were machined using fine surface grinding to remove the effect of the previous machining.

### 3.2 Capturing Images

The vision system was used to capture three images for each specimen at different areas. Therefore, nine images were captured for each cutting condition. All specimens were set under the microscope objective lens so that the machining marks (lays) appeared vertically. To avoid varying illumination conditions, which may affect the values of texture features, the microscope light was adjusted to constant light intensity while capturing all images through all tests. Figure 3 shows sample images for specimens with different feeds and constant speed and depth of cut.

### 3.3 Image Analysis:

To calculate the texture features for each cutting conditions, the following procedures were performed:

**Table 1: Cutting conditions data of the specimens under investigation**

| Cutting condition | Groups (3 specimens in each group) | | | | | | Constant cutting conditions |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | |
| $f$ (mm/rev) | 0.08 | 0.114 | 0.228 | 0.31 | 0.455 | 0.585 | $s$ =560, $d_c$ = 0.30 |
| $s$ (rpm) | 140 | 224 | 355 | 560 | 710 | 900 | $f$=0.16, $d_c$ = 0.30 |
| $d_c$ (mm) | 0.1 | 0.3 | 0.75 | 1.0 | 1.5 | 2.0 | $f$=0.16, $s$ = 560 |

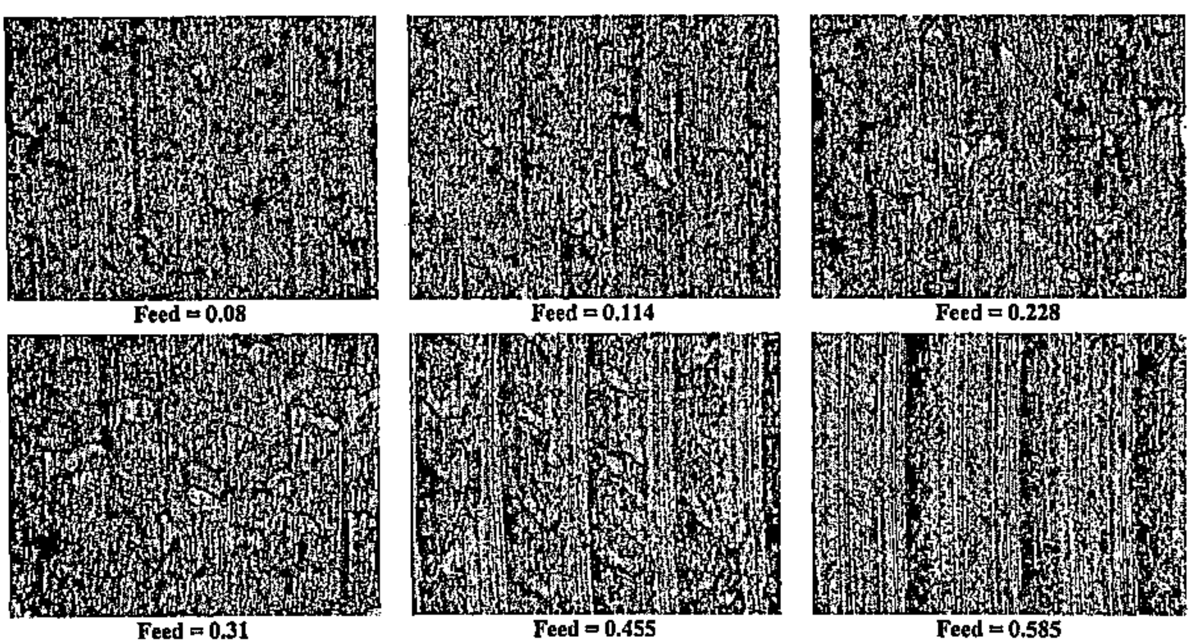



**Fig. 2: Sample images of specimens machined with different feeds (mm/rev), constant speed (560 rpm), and constant depth of cut (0.3 mm)**

1- For each cutting condition, the texture features were calculated for all images by the GLCMTF software using a position operator of (1,0), i.e.. (distance=1 and angle=0).

2- The average of each texture feature was calculated from the nine values obtained from the nine images.

3- The relationship between the value of each texture feature and the values of the three cutting conditions (feed, speed, and depth of cut) were plotted using MS Excel then used for analysis.

4- The correlation coefficients between each texture feature and the corresponding cutting conditions were calculated using the following equation:

$$Correlation(c,f)=\frac{\sum(c-\bar{c})(f-\bar{f})}{\sqrt{\sum\left(c-\bar{c}\right)^2\sum\left(f-\bar{f}\right)^2}} \quad (24)$$

where *c, f* are the data sets of the cutting conditions and texture features, respectively, and $\bar{c}$, $\bar{f}$ are the averages of the cutting conditions and the texture features data sets, respectively.

## 4. Results and Discussions

Figure 3 shows the relationship between each texture feature and the three cutting conditions. As shown in the figure, some texture features have approximately the same trend with the three cutting conditions, despite of the correlation coefficient values. Considering this, all texture features can be categorized into four groups as shown in the figure (A1:A7, B1:B5, C1:C6, D1:D5). This means that the mathematical definitions of the texture features in each group may have the same physical meaning about the change in cutting conditions.

Figures 4, 5, and 6 show the correlation coefficients between the texture features and the feed, speed and depth of cut, respectively. Additionally, Fig. 7 represents a collective chart for all texture features and their correlations with the three cutting conditions.

From figures 4, 5, 6, and 7, the following points could be observed:

1- Eight texture features (COR, CPR, SAVR, DAVR, MEAN, VAR, SENT, SAVR) have good correlation (> 90%) with the change in feed.

2- Only five texture features (MEAN, DENT, DIS, DAVR, ENT) have good correlation with the change in speed.

3- No texture features that have good correlations with the change in depth of cut were found.

5- It can also be seen that there is no texture features that have good correlations with the three cutting conditions at the same time. The MEAN is only the texture feature that has good correlation with both feed and speed.

Taking into consideration both the trend and the correlation coefficient of the texture features, the following points could be concluded:

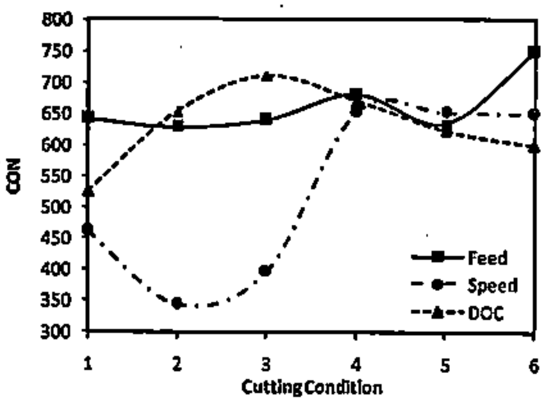
1- The first group (Fig. 3, A1:A7) is mostly sensitive to the change of speed. Therefore, four texture features (DENT, DAVR, DIS, and ENT) are highly correlated with the change in speed.

2. All textures features (COR, DVAR, SAVR, SENT, SVAR) in the second group (Fig. 3, B1:B5) are highly correlated with the change in feed.

3. All textures features (CSH, CVAR, IDM, SIM, MCOR1, MCOR2) in the third group (Fig. 3, C1:B6) are not highly correlated with any of the cutting condition.

4- The forth group (Fig. 3, D1:D5) is mostly sensitive to the change of feed. Therefore, three texture features (CPR, MEAN, and VAR) are highly correlated with the feed. In addition, the MEAN is also highly correlated with the speed.

Finally, the texture features that have good correlation with the cutting conditions might be used, in other work, to predict the cutting conditions of existing specimens.

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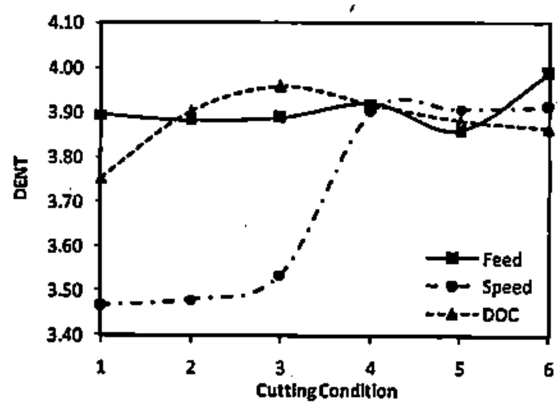
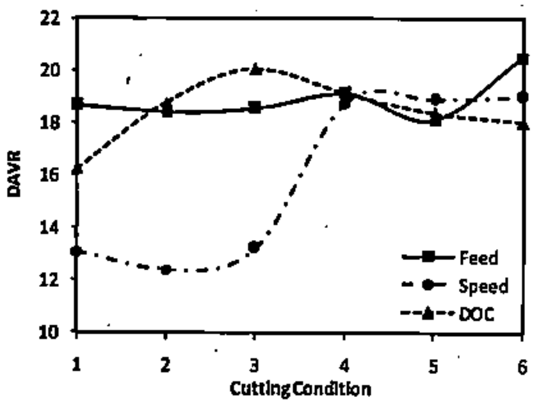



(A-2)

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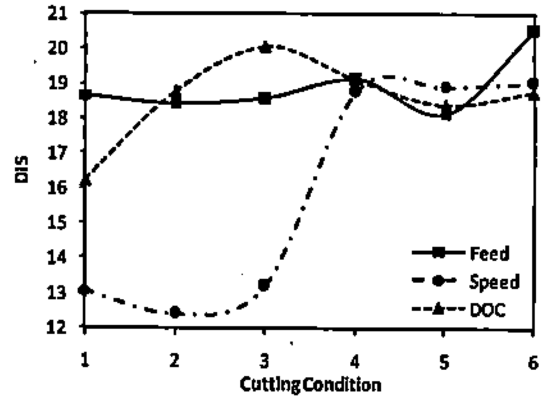


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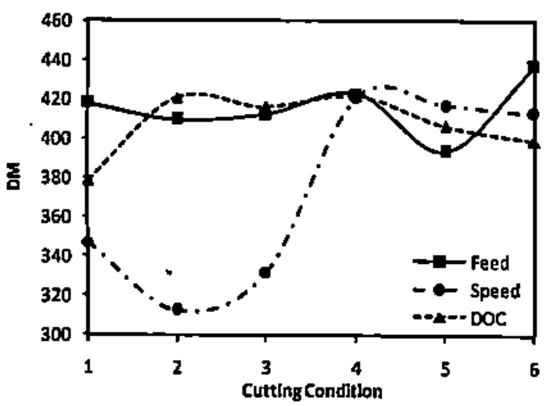


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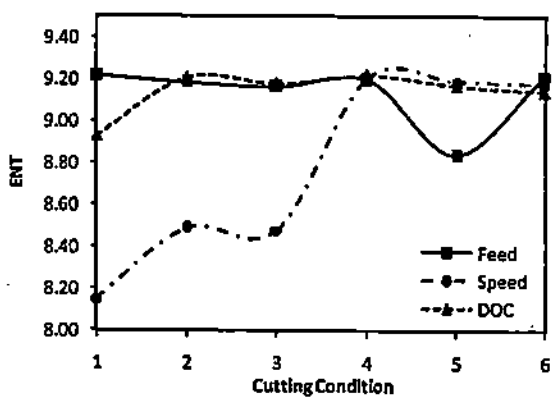


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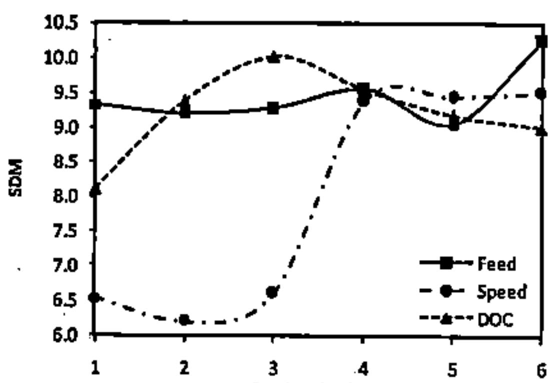
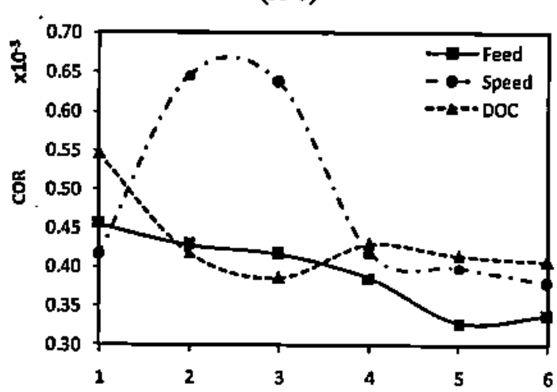
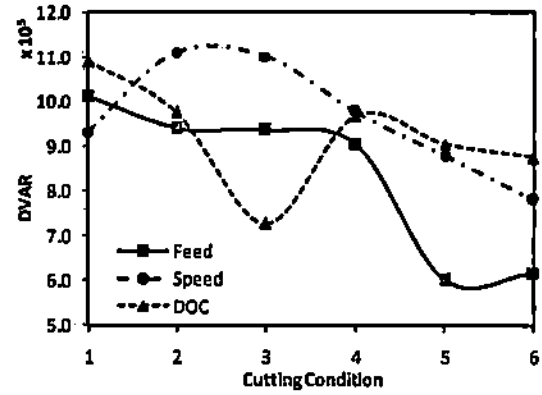



(A-7)




(B-1)

**Fig. 3: Relationship between the GLCM texture features and the cutting conditions**



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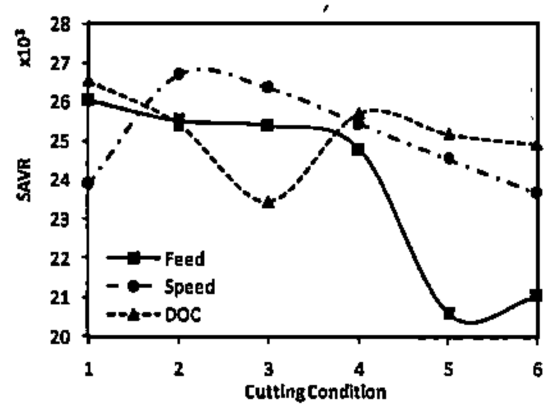

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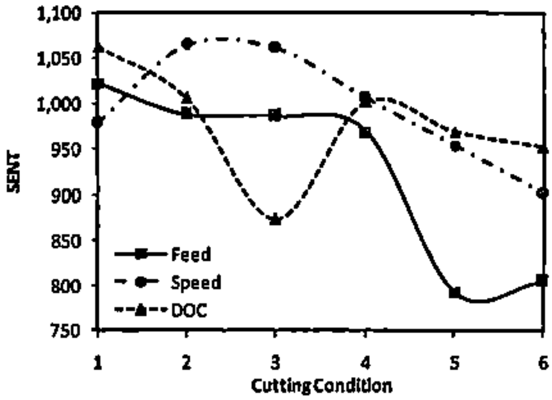

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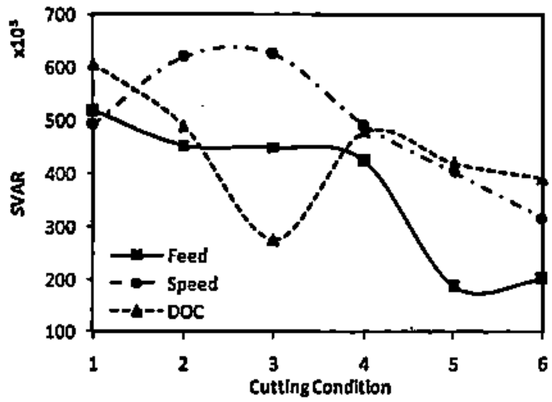

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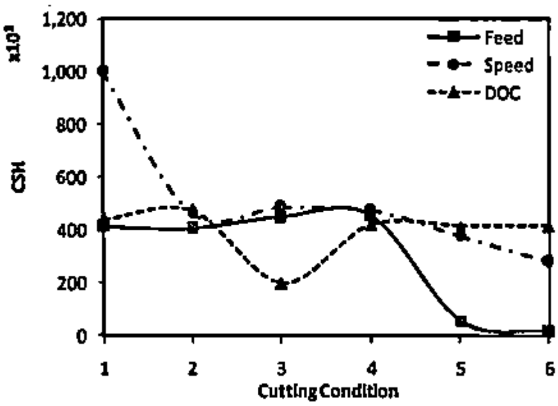

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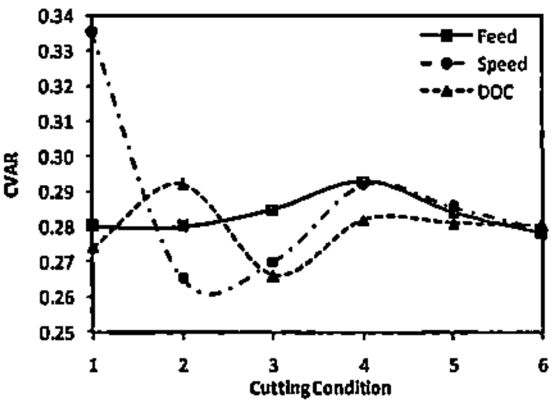
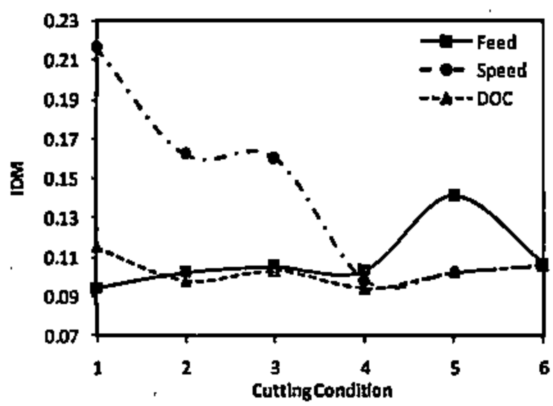


(C-2)



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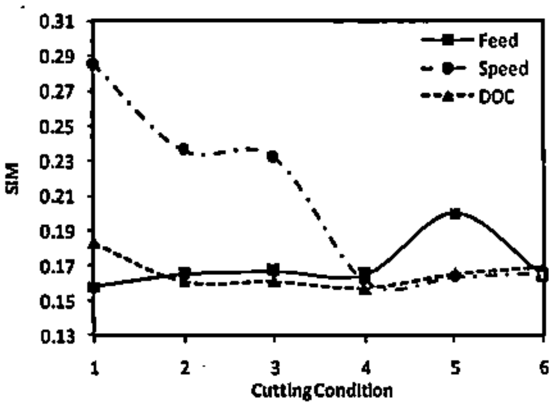
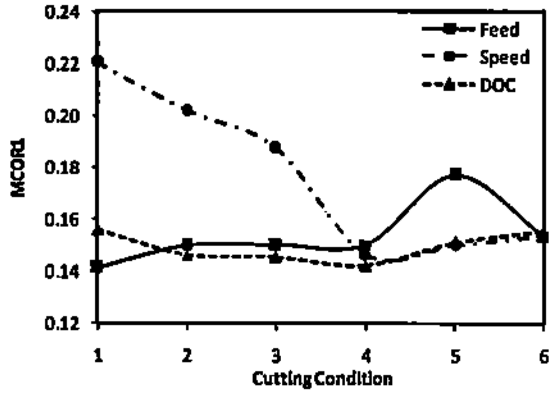
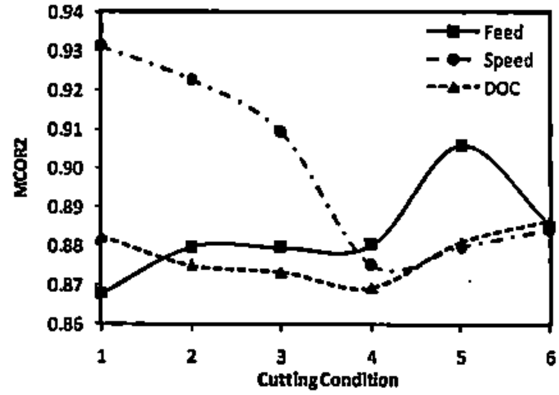


(C-4)

**Fig. 3: Relationship between the GLCM texture features and the cutting conditions … continue**




(C-5)

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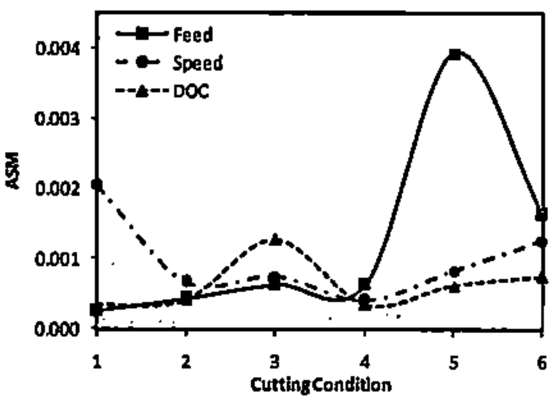
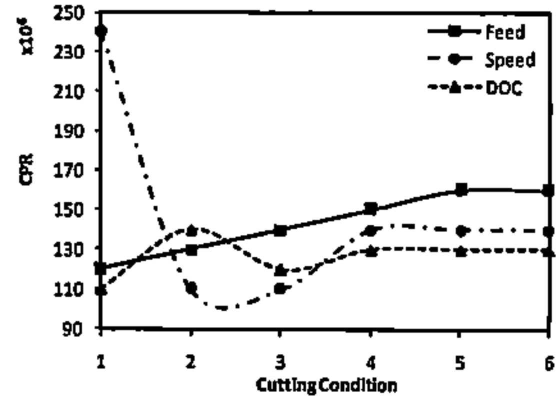
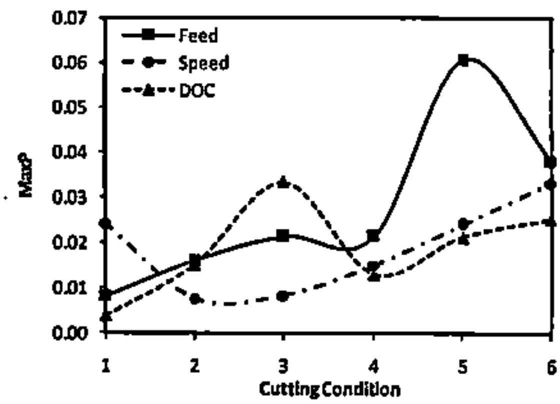


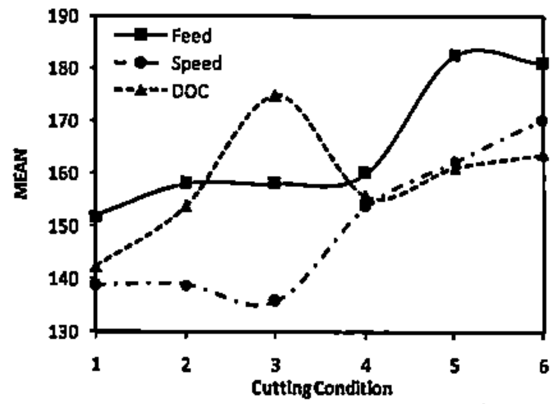

(D-1)



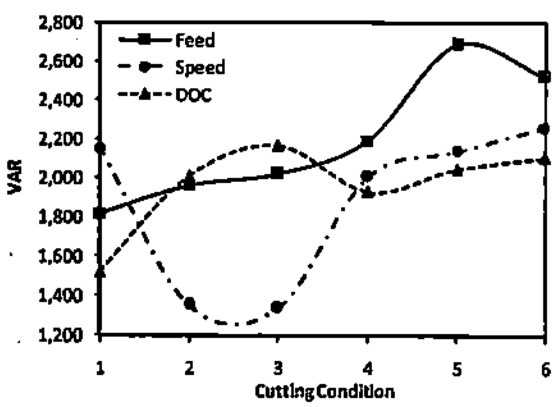

(D-2)




(D-3)




(D-4)




(D-5)

**Fig. 3: Relationship between the GLCM texture features and the cutting conditions ... continue**

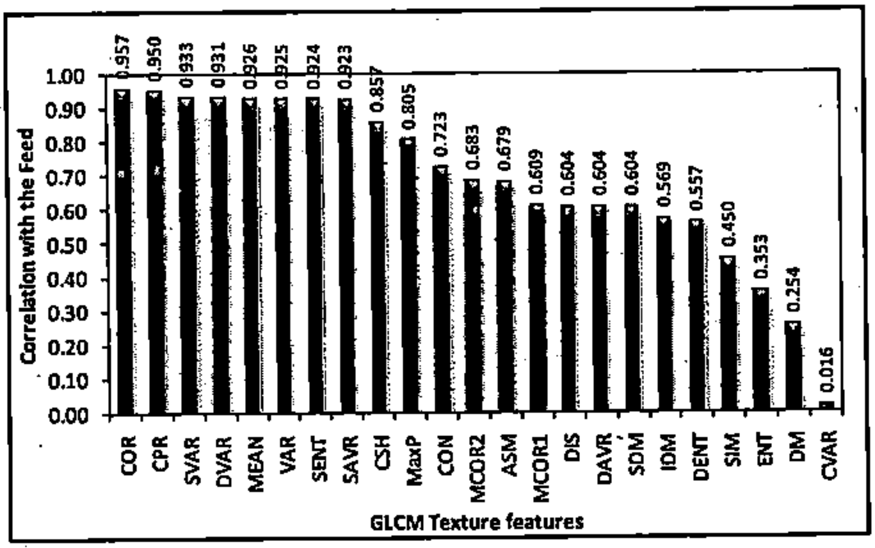



**Fig. 4: GLCM texture features sorted according to their correlation with the Feed**

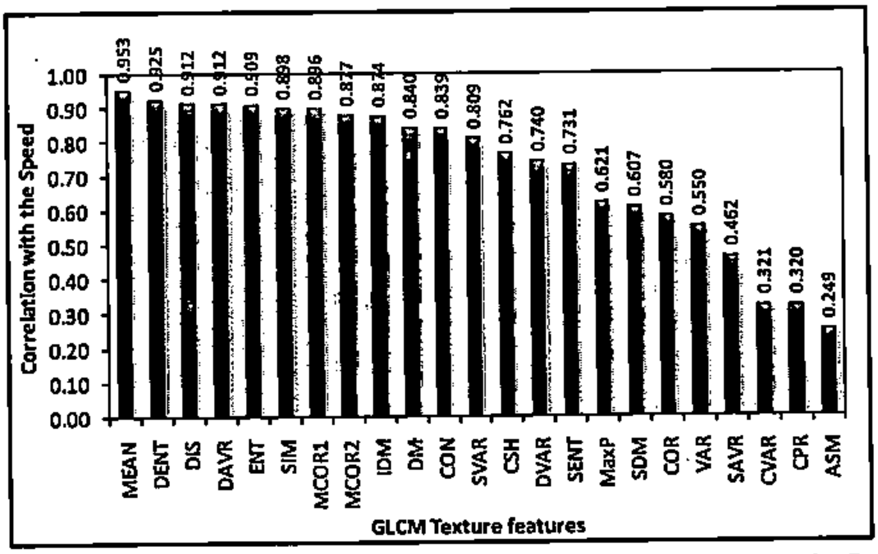



**Fig. 5: GLCM texture features sorted according to their correlation with the Speed**

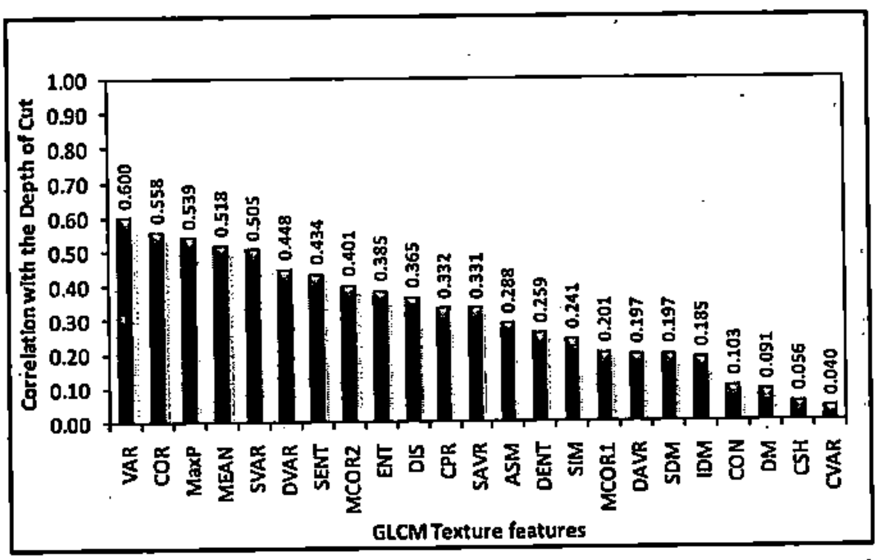



**Fig. 6: GLCM texture features sorted according to their correlation with the Depth of cut**

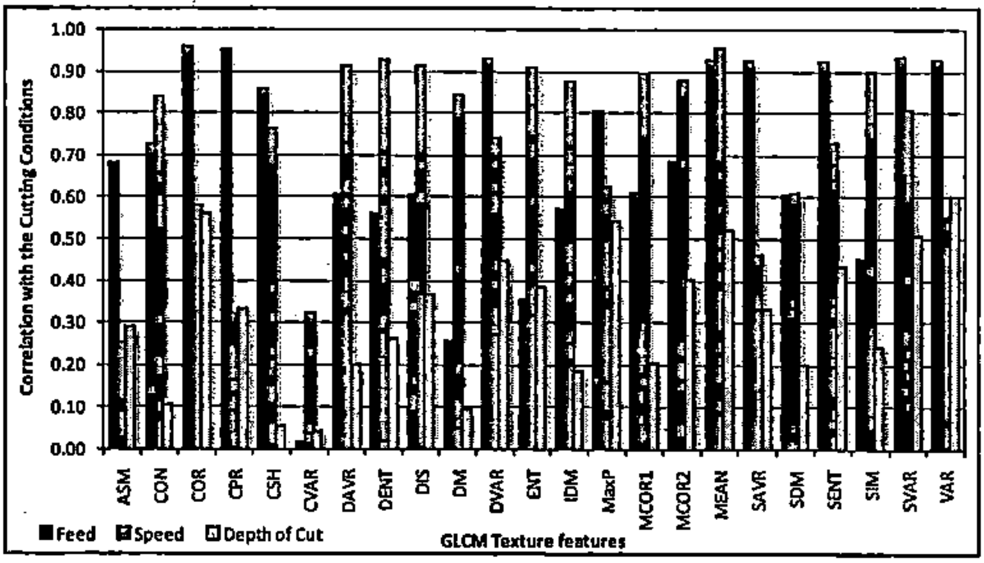



**Fig. 7: Correlation between the GLCM texture features and the cutting conditions (Alphabetic sort)**

## 5. Conclusions

The GLCM texture features have been employed to characterize the effect of changing the cutting conditions (feed, speed and depth of cut) in turningoperations. A set of circular specimens were produced by face turning operation using different cutting conditions and a vision system was employed to capture images for these specimens. A software, specially developed for this purpose, was used to calculate all GLCM texture features for the captured images.

The results showed that eight texture features have good correlations with the change in feed and five have good correlations with the change in speed. No texture features found to be have good correlations with the change in the depth of cut. In addition, there is no texture features found to be have good correlations with the three cutting conditions at the same time. The MEAN is only the texture feature that has a good correlation with both feed and speed. Finally, the highly correlated texture features might be used to predict the cutting conditions of existing specimens.

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