A Computer Vision System for Detecting Tufted Carpet Defects

نظام رؤية بالحاسب الآلي لاكتشاف عيوب الموكيت

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ملخص

يختص هذا البحث بدراسة استخلاص، تحليل، واختيار الخصائص الضرورية للصور اللازمة لإنشاء نظام رؤية بالحاسب الآلي والذي يتمكن من اكتشاف و تصنيف عيوب الموكيت.
يوجد أربعة أنواع مختلفة من الموكيت، وأيضا أربعة أنواع من أشهر عيوب هذا النوع من المنتجات : وبرة مفقودة، وبرة مرتفعة، وبرة منخفضة ، بالإضافة إلي وبرة متجمعة ومتكتلة.
تم عمل تحليل إحصائي للصور الرقمية للموكيت وذلك حتى يتم استنتاج الكميات الإحصائية التالية: الوسط، والانحراف المعياري ، والتماثل والتفلطح وأيضا الانتروبيا، والتي تعرف مجتمعة بالخصائص (المعالم) المتناغمة.
أما بالنسبة للخصائص أو الصفات الجوهرية للصور فيتم استنتاجها باستخدام مصفوفة خاصة بالتحليل الإحصائي، وهي تقوم بتصوير العلاقة بين كثافة نقطتين ضوئيتين بينهما مسافة وزاوية محددتين، ثم تتم الحسابات بواسطة أسلوب التحليل بواسطة فرق اللون الرمادي الجزئي في نفس الوقت مع أسلوب آخر للتحليل الإحصائي بطريقة فرق اللون الرمادي.
يتم عمل عرض تصويري وتقييم مرئي وذلك لاختيار معظم الصفات و الخصائص، ثم يتم التصنيف بواسطة تصميم وتدريب مجموعة من الشبكات العصبية الصناعية،والتي يطلق عليها برسبترون (الإدراك الحسي أو العقلي) ويتم اختبار هذا التصميم بواسطة أسلوب الانتشار الأصلي " back propagation"، وينتهي البحث إلي أن عملية التعرف علي الصور واكتشاف العيوب قد تمت بنجاح.

ABSTRACT

This work presents an approach to extract, analyze and select image attributes necessary for building a vision computer system that is able to detect and classify tufted carpet defects. Four different tufted carpets and four different defects were considered; missing pile, higher pile, lower pile, slobs and knots. Carpet digital images were statistically analyzed to calculate Mean, Variance, Skewness, Kurtosis, and Entropy, known as tonal features. Texture features were extracted from co-occurrence matrices describing the relationships between intensities of two pixels at a certain distance and angle from each other and evaluated using SGLDM and GLDM statistics. Graphical presentation and visual assessment were made to choose the most significant features. For classification, artificial neural networks were built and trained using perceptron and back propagation algorithms. The recognition was successful in detecting common tufted carpet defects.

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1. Introduction

Computer vision is an objective methodology that can be considered as an excellent alternative to replace visual inspection by human workers. The advantages of the computer vision over human vision are especially valid in the processes in which human performance regarding the speed, reliability, objectivity, and accuracy are insufficient, and where other alternatives lead essentially to higher expense. Computer vision is a relatively new technology that combines computers and digital cameras to acquire, analyze, and interpret or classify images in a way that parallels human vision. For this purpose, neural perceptron is a very efficient tool in interpreting the data extracted from digital images [1, 2].

The issue of using image processing for assessment of the quality of textile products has proven itself as a robust technique. It can be used starting from fibers to garments for testing, inspection, and monitoring during and after production [3 to 10]. Recent advances in imaging technology have resulted in high quality image acquisition, and the advances in computer technology allow image processing and pattern recognition to be performed quickly and inexpensively. Development of such systems is expected to continue as long as the imaging technology and digital processing develop.

Many researches have been conducted to the subject of carpet inspection for appearance, structure, defects or wear out. D. Jose, *et al.* [11] studied carpet appearance change, focusing on new textural measurements of pile carpets. Gray level histograms were correlated with change in appearance, differences in tuft spacing, and related carpet properties. Lee *et al.* [12] applied for carpet texture assessment four texture matrix methods; gray level run length matrix (GLRLM), spatial gray level dependence matrix (SGLDM), neighboring gray level dependence matrix (NGLDM), and gray level difference matrix (GLDM). Wood and Hodgson [13, 14, 15] measured carpet texture and appearance using digital image analysis. Full color images were analyzed but found to require more rigorous control of illumination and camera characteristics, than monochrome color. The texture of an image was characterized by its spatial distribution of the gray levels and tonal features. Texture algorithms of the statistical approach were applied to the carpet texture measurements. Fourier power spectrum analysis and auto correlation function were used to extract image features. Results showed that relating subjective grades to objective results is difficult when diverse carpet types are considered.

J. Sobus and B. Pourdeyhimi *et al.* [16] applied image processing technique to binary carpet images for the purpose of measuring aspects of texture periodicity by mechanical wear. The results of carpet samples show changes in amplitude and overall mean of image covariance with wear. They also [17] attempted to isolate the periodic components of textures in wool carpets to study the effect of wear on carpet textures. Images files with 256 gray levels were converted to 32 levels using histogram equalization. Textural features were evaluated by two methods, spatial gray level dependence (SGLDM) and gray level difference (GLDM). Further work by the same authors [18] evaluated carpet appearance loss due to mechanical wear; surface intensity and roughness. Their research described the application of gray scale image analysis to the measurement of microstructure variation and roughness or relief. They attempted to characterize microstructure with tonal features and spatial co-occurrence statistics. Their samples show that simple mechanical wear generally entails a loss of relief and variation, but carpet construction has an important effect on the observed trends. Y.WU et al [19] explored an image enhancement technique for assessing tuft geometry. Original images were converted to binary images for measuring textural features of carpet construction and appearance by calculating the tonal features only. S. Sette *et al.* [20] used image processing and self-organizing Kohonen networks for objectively analyzing carpet wear and set marks. For each digital image they calculated intensity average and standard deviation for red, green and blue color components and used it as an input to the neural network.

W.Van Steenlandt *et al.* [21] used image analysis and neural network for the assessment of carpet wear, especially on cut pile carpets. The color image was made of red, green, and blue components with a matrix for each color. To extract the features they used a combination of mean intensity and deviation and applied Fourier power spectrum. Their parameters and results for neural networks were very limited.

This work aims to build a vision system that is able to detect and classify some of the famous tufted carpet defects. The basic idea is to take images of the carpet and extract from them some statistical mathematical attributes, called features. These features have to be able to distinguish between normal and defected carpet and the type of defect. After selecting proper features, Artificial Neural Networks were used to classify the defects.

2. Experimental work

The experimental part of this work is a series of steps, very well defined in the field of image analysis and classification. These steps are; material, image acquisition, features extraction, and classification.

2.1. Material

The test material for this work was selected to represent wide variety of tufted carpets. Closed loop, cut loop, one-color, and multi-colored. Four different tufted carpet products were considered. Structural carpet parameters are kept the same for all samples; pile height of 5 mm, stitch density of 25 / cm2, and pile yarn of 6/2 Nm made of nylon
Four different types of defects were considered: 1- missing pile, 2- higher pile, 3- lower pile, and 4- slobs and/or knots.
Carpet types are marked; A, B, C, and D. A0, B0, C0, D0 refer to non–defective samples from the types A, B, C, D respectively. Defects are marked; 1, 2, 3, and 4. The studied defects are; missing pile (B1), higher pile (A2), lower pile (A3), slobs and knots.(C4 and D4). See Figure 1.

2.2. Carpet Imaging

Image capture in this context is the process of obtaining the image of the object in the form that can be interpreted by digital systems. Images (Figure 1) are taken for carpets with and without defects. The image capture was made using two systems. First is a CCD camera 1/3 inch with different lenses, linked to a PC through a frame grabber. Second is a video camera with zoom option connected to a personal computer through a video card. Sample images were captured from the real time stream when they were satisfactory.
Image files were manipulated in three different formats: true color, 256 color and 256 gray levels. Each image represented 40mm x 32mm of carpet sample. Image files were first stored as RGB true color. A visual basic program, shown in Figure 2, was written to read the image and have it ready to be manipulated in three different formats; RGB true color, 256 color and 256 gray. First, the image is read as three 600*480 matrices, one for each of the three basic colors; red, green and blue, where each point i,j of the image has three values Ri,j, Gi,j, and Bi,j, one for each color. The matrix "Xij" for the 256 color was constructed using the following equation :

$$X_{ij} = \frac{255(R_{ij} - 256G_{ij} + (256)^2 B_{ij}}{256 + (256)^2 + (256)^3}$$

To get the 256 gray level matrix from the RGB format, the following equation was used:

$$X_{ij} = 0.299R_{ij} + 0.5876G_{ij} + 0.114B_{ij}$$

2.3. Features Extraction

Feature extraction aspect of image analysis aims at identifying inherent characteristics (features) of objects found within an image. These characteristics are used to describe the object or attributes of the object. Features are statistical and mathematical description values extracted from the two dimensional image arrays to be used for classification. The nature of the object which is the carpet and carpet defects dictates using feature extraction techniques that deal with the inputs of the entire image and not work on individual objects in an image. The types used in this study are tonal and texture features extracted from the original images matrices and co-occurrence matrices computed from the originals.

2.3.1. Tonal Features

Tonal features computed from the original image matrix are: Mean, Variance, Skewness, Kurtosis, and Entropy. This set of features is useful for describing the image as a whole. They are extracted for each color matrix (image tensor is 3 matrices, one for each color RGB). Therefore we will have three sets of these values, one set for each color. If $\Phi(i)$, (i = 1,2,.........,n) is the number of points whose intensity is "i" in the image and A is the total number of the points in the image, the estimated probability of intensity in the image is defined by $h(i) = \Phi(i)/A$. Therefore, various tonal features are given by the following relationships [16]:

$$Mean = \sum_{i=1}^{n} ih(i) \qquad Variance = \sum_{i=1}^{n} (i-\mu)^2 h(i)$$

$$Kurtosis = \sum_{i=1}^{n} (i-\mu)^2 h(i)/\sigma^2 \qquad , \qquad Skewness = \sum_{i=1}^{n} (i-\mu)^2 h(i)/\sigma^{3/2}$$

$$Entropy = -\sum_{i=1}^{n} h(i)\log(h(i))$$

2.3.2. Texture Features

Texture features are usually computed on the basis of a texture algorithm. For this purpose, in this study we used the "Gray Level Difference Method" (GLDM) and "Spatial Gray Level Dependence Method" (SGLDM).

2.3.2.1. Spatial Gray Level Dependence Method "SGLDM"

In this algorithm, features are extracted not from the original image matrix but from the so called the co-occurrence matrix. Co-occurrence matrices specify the relative frequency p(i,j) of occurrence of pairs of intensity values (i and j) separated by distance "d" and angle "θ" in the original image matrix. Using Cartesian coordinates, a pair of pixels will be separated by "dx" and "dy". The dimensions of the new matrix is n*n, where n is the number of color intensity levels. In our case it is 256 color intensity levels. Angular second moment, contrast, correlation, and entropy, are computed for each set of "d" and θ for each color matrix in the image. Therefore, various texture features are given by the following relationships [16]:

$$ASM = \sum_{i=1}^{n} \sum_{j=1}^{n} p(i,j)^2 \qquad , \qquad Contrast = \sum_{i=1}^{n}\sum_{j=1}^{n} (i-j)^2 P(i,j)$$

$$Entropy = -\sum_{i=1}^{n}\sum_{j=1}^{n} P(i,j)\log(P(i,j)) \qquad , \qquad Correlation = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} ijP(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y}$$

Where;

$$\mu_y = \sum_{j}^{n} j \sum_{i}^{n} p(i,j) \qquad , \qquad \mu_x = \sum_{i}^{n} i \sum_{j}^{n} p(i,j)$$

$$\sigma_x = \sqrt{\sum_{i=1}^{n} (i-\mu_x)^2 \sum_{j=1}^{n} p(i,j)} \qquad \sigma_y = \sqrt{\sum_{j=1}^{n} (j-\mu_y)^2 \sum_{i=1}^{n} p(i,j)}$$

2.3.2.2. Gray Level Difference Method "GLDM"

In this algorithm, features are extracted also not from the original image matrix but from an n-dimensional vector computed for each color matrix, where n is the number of color intensity levels. In our case n=256 color intensity levels. This vector, for any given displacement between two points in color matrix specifies the probability density function of the absolute difference between the intensities of these two points. The displacement can be taken Cartesian(Δx, Δy) or Polar (d, θ). Contrast, Angular Second Moment, Correlation, and Entropy, are computed for each set of "d" and θ for each color matrix in the image using the following equations [16]:

$$Cotrast = \sum_{i=1}^{n} i^2 P(i) \qquad , \qquad ASM = \sum_{i=1}^{n} P(i)^2$$

$$Entropy = -\sum_{i=1}^{n} P(i)\log(P(i)) \qquad Mean = \frac{1}{n}\sum_{i=1}^{n} iP(i)$$

2.4. Classification

Artificial Neural Networks (ANN) were used for classification and detection of carpet defects since it showed promise for solving difficult problems in areas such as pattern recognition and classification [1, 2].

Neural networks have been developed as generalization of mathematical models of human cognition. The neural network consists of a group of simple elements called neurons which process the input to develop the output. These neurons are connected with each other with links to carry the signals between them. There is a weight for each connection link which acts as a multiplication factor to the transmitted signal. An activation function is applied to each neuron's input to determine the output signal [2].

Using neural networks as a classifier requires two phases – a training phase and a testing phase. In the training phase, the neural network makes the proper adjustment for its weights to produce the desired response. When the actual output response is the same as the desired one, the network has completed the training phase (i.e., it has acquired knowledge). In the testing phase the neural network is asked to classify a new set of images and its success is evaluated. In this work the neural networks were trained by the perceptron and back propagation algorithms to detect and classify the carpet types and defects. The features' vectors were used as the input to the ANN and the outputs were the carpet type and/or defect type.

For classification, five neural networks were built by changing both of the network structure and the number of training samples. The first neural network was built to classify the non defective carpets while the other four neural networks were designed to classify defect types within each carpet type.

3. Results

An intensive analysis was made to identify most robust features. Applying the two algorithms of texture feature extraction (4 features each) on the three image formats at different distances (pixel steps) form 1 to 60 pixels and at angles 0, 45, 90, 135, 180, 225, 270, and 315 degrees resulted in a huge number of possible selection of features. This number would be 2*4*3*60*8= 11520 and it would be very hard to feed to any classification system. To reduce this number we studied the effect of each parameter. A visual basic program was written to extract all features starting from reading the image. Visual assessment of the graphs for normal and defected carpets was the first approach used for features' selection. Furthermore, features were normalized and plotted versus number of images. Final features selection was made during the training of the classifier system.

Selection of angle

Analyzing the effect of angle, it was found that all features at angles 180°, 225 °, 270 °, and 315 ° coincide with angles 0°, 45 °, 90 °, and 135 ° due to symmetry. Figures 2 and 3 show the "*CONTRAST*" and "*ENTROPY*" features versus distance at all the eight angles selected for carpet A1..

The same was observed for all other carpets normal and defected, not all graphs are shown in this paper. As a result of that the angles at which texture features were computed were limited to 0°, 45 °, 90 °, and 135 °.

Selection of Distance

At the beginning a wide range of steps from 1 to 60 pixels (from 0.06mm to 4 mm) at different angles for different normal and defected carpets were selected. Samples of the relationship between the extracted features and distance are shown in Figures 4 to 7. At angle 0°, the "*ANGULAR SECOND MOMENT*" levels out after few steps and the difference between the values of normal and defected carpets almost remains the same. At angle 45°, the shape of the "*ANGULAR SECOND MOMENT*" curves changes in a similar manner to that of angle 0°. The same behavior was also detected for "*ENTROPY*" (Figures 6 and 7) and all other features. The main criterion of feature selection is its ability to differentiate between classes (normal and defected carpets). So, from the previous analysis it is clear that steps of 1, 3, 5 pixels are enough for classification in this study.

Selection of Feature sets

Before determining which features will be fed to the neural networks for classification, an intensive analysis was made on the produced features. For this purpose, features were normalized for easy comparison. Normalized feature values ranges between 1 and -1 using the following equation:

$$F_i normalized = 1 - 2\left[\frac{F_i \max - F_i}{F_i \max - F_i \min}\right]$$

Features were calculated for 30 images from each class then normalized and graphically presented versus the image number. Figure 8 shows normalized values of the tonal feature "*VARIANCE*" for the four carpet types. The distinction between carpet types is clear and emphasizes the importance of this feature in classifying carpet types. Figure 9 shows the normalized texture feature "*CORRELATION*" for carpet type A without defects and with higher and lower pile. This is an example for a feature that can barely classify between defected and non defected carpet without providing much information about the type of defect. Many other graphs not shown in this article were constructed to make the final selection of the features for each classification process.

As a result of this analysis the following can be derived:

-Tonal features satisfactory classified the different types of carpets, when used as inputs to the first ANN. Tonal features were not able to recognize the type of carpet defect.

-Texture feature "*CORRELATION*" of SGDLM statistics at step 1 pixel and angle 90° was found able to classify the type of defect within the type "A" carpet using the second ANN. It was not successful enough with other carpet types.

-The third ANN was dedicated to classify the defects within carpet type "B". Texture features "*ENTROPY*" of GLDM statistics at step 3 pixels and angle 90° was found able to classify the type of defect. It was not successful enough with other carpet types.

-The fourth ANN was dedicated to classify the defects within carpet type "C". Texture features "*CONTRAST*" of SGDLM statistics at step 3 pixels and angle 90° was found able to classify the type of defect. It was not successful enough with other carpet types.

- Tonal feature "*ENTROPY*" of 256 color images was found able to classify the type of defect within the type "D" carpet using the fifth ANN. It was not successful enough with other carpet types.

4. Conclusions

In this paper, tonal features were extracted from image matrices. Co-occurrence statistics (GLDM and SGLDM) were used to identify texture features. Images were manipulated as RGB true image, 256 color, and 256 gray formats. Graphical presentation and visual assessment of features were used to select the most effective features. For classification, artificial neural networks were built and trained using perceptron and back propagation algorithms. Both methods produced the same degree of accuracy. Using above mentioned feature extraction techniques collectively revealed higher percentage of recognition success than using one technique alone. Because of the huge number of extracted features, the recognition success ranged between 97% and 100% for all the carpet defects including missing pile, higher pile, lower pile, slobs and knots. The approach used in this study could be successful if applied in classification of other textiles.

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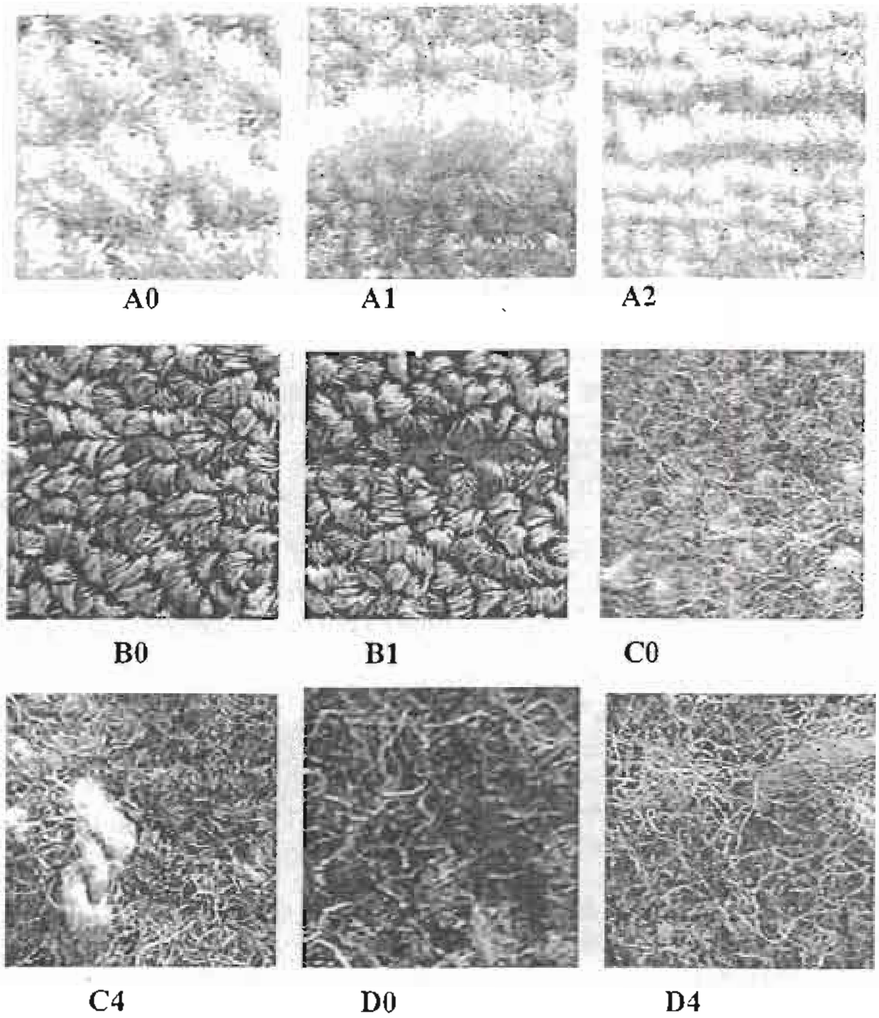

Figure 1: Tufted carpet samples

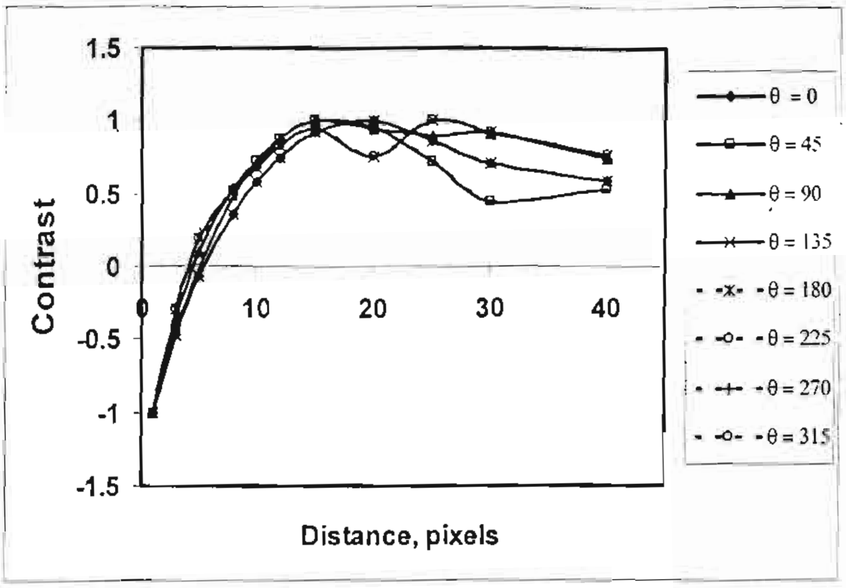

Fig. 2: The effect of angle on the contrast feature extracted for carpet A1

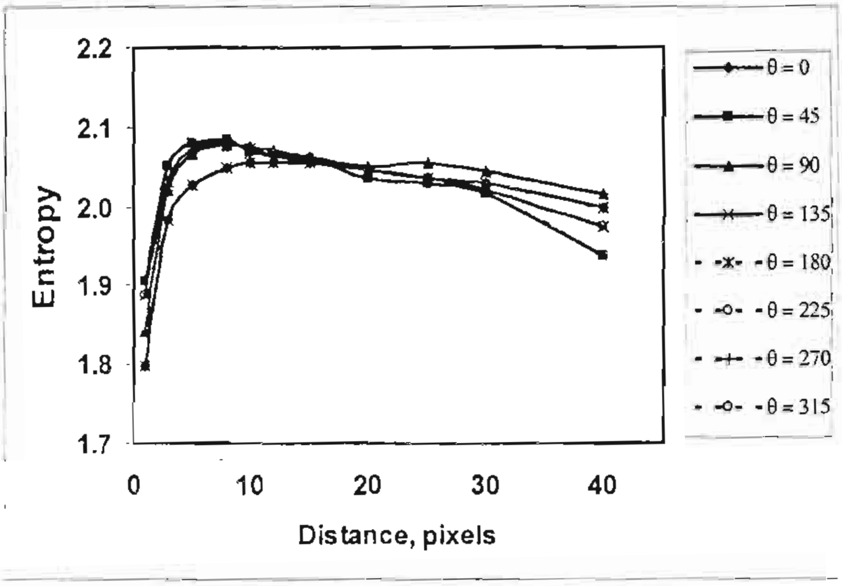

Fig. 3: The effect of angle on the "ENTROPY" feature for carpet C4

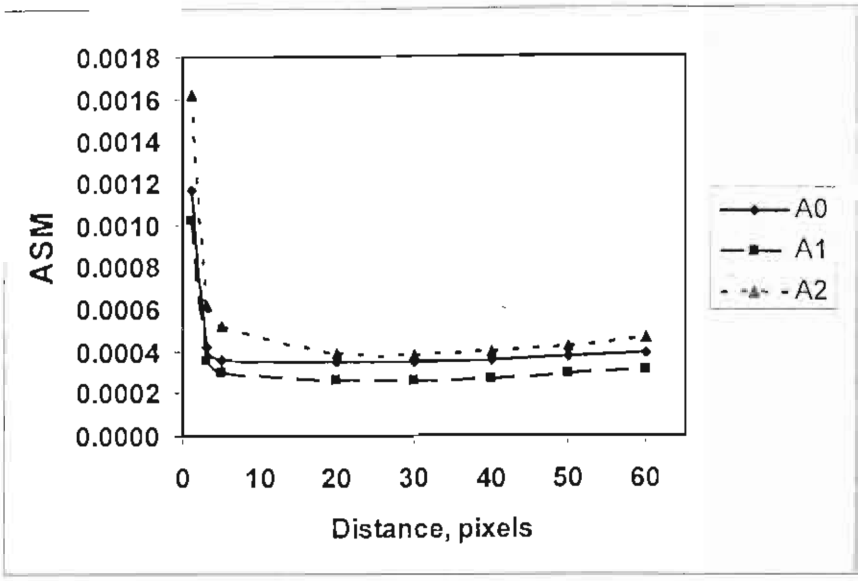

Figure 4: The effect of distance on the ASM feature extracted for carpet A at angle 0°

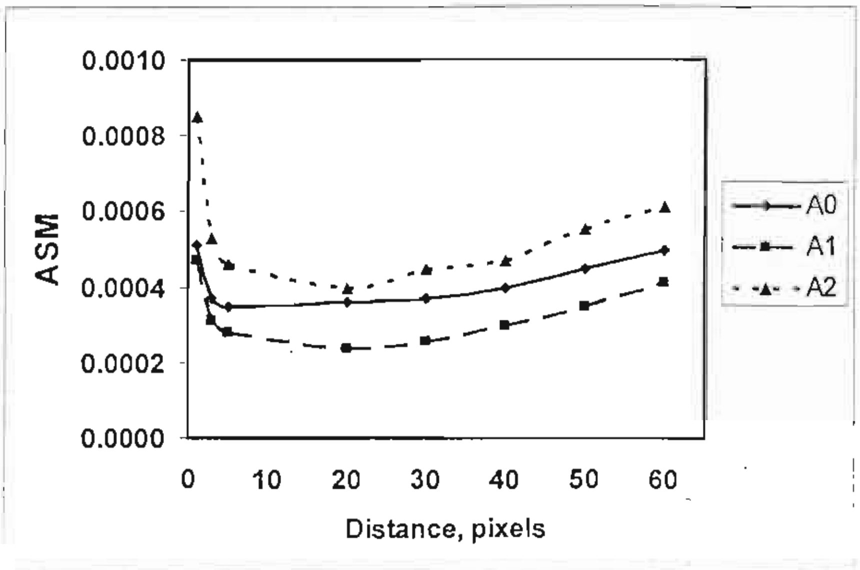

Figure 5: The effect of distance on the ASM feature extracted for carpet A at angle45°

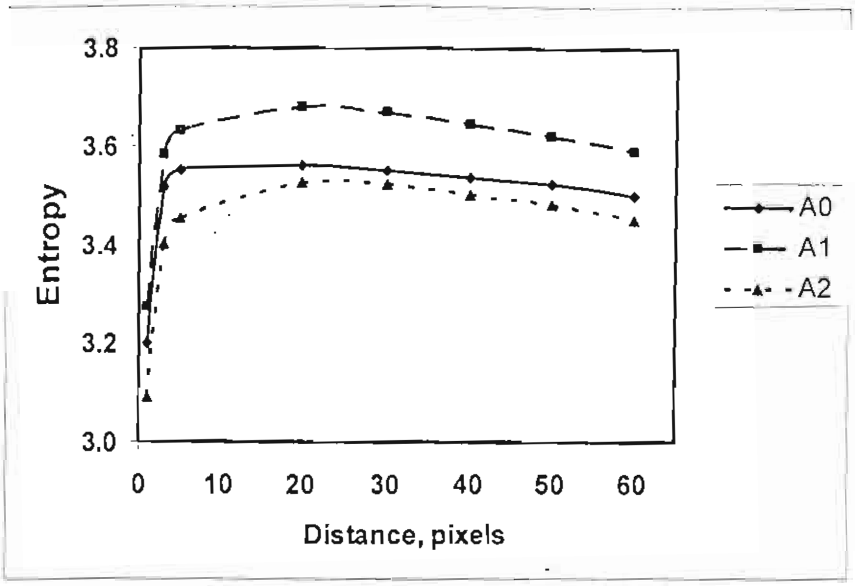

Figure 6: The effect of distance on the Entropy feature extracted for carpet A at angle 0

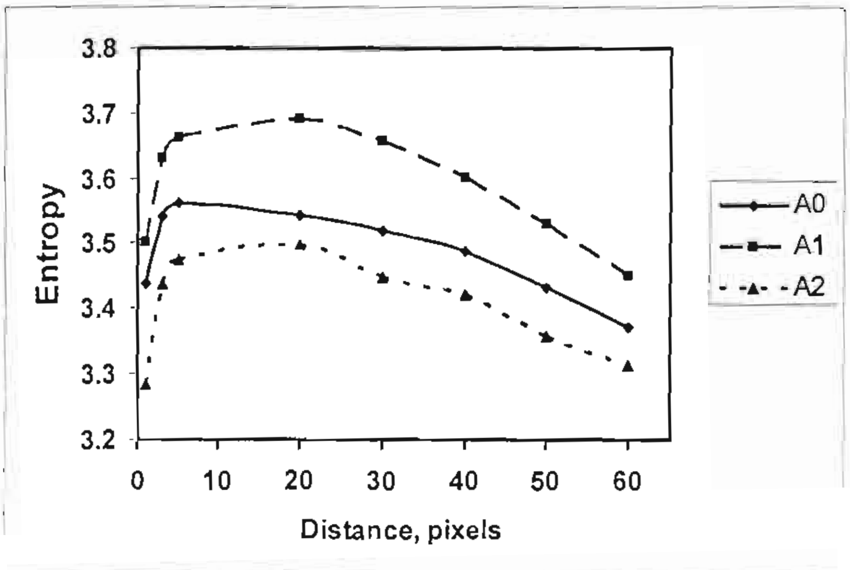

Figure 7: The effect of distance on the "ENTROPY" feature for carpet A at angle 45°

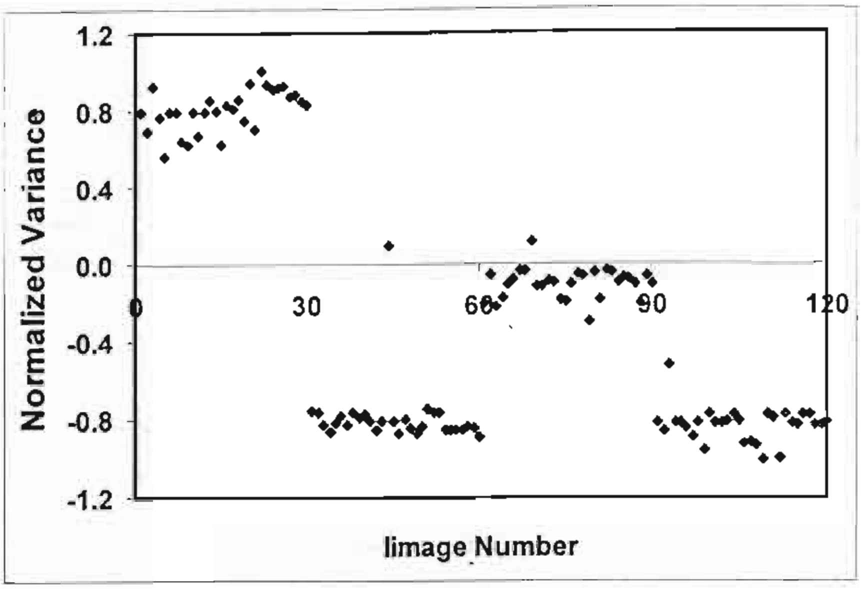

Figure 8. Normalized values of the tonal feature "*VARIANCE*" for the four carpet types, 30consiqutive images for each type A, B, C, D consequently.

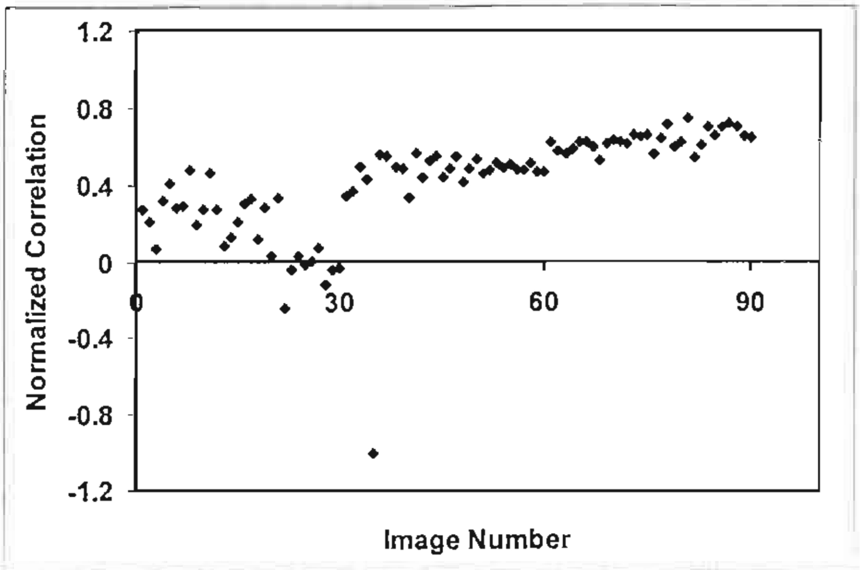

Figure 9. Normalized texture feature "CORRELATION" for carpet type A without defects and with higher and lower pile, 30consiqutive images for each type