GLCM and its application in pattern recognition

Conference Paper · August 2017

DOI: 10.1109/ISCBI.2017.8053537

3 authors:

Shruti Singh

2 PUBLICATIONS **32** CITATIONS

Divya Srivastava
Motilal Nehru National Institute of Technology

10 PUBLICATIONS **52** CITATIONS

Agarwal S.
Motilal Nehru National Institute of Technology

164 PUBLICATIONS **1,033** CITATIONS

GLCM and Its Application in Pattern Recognition

Shruti Singh
Computer Science and Engineering
MNNIT Allahabad
Allahabad, India
e-mail: shruti.singh9192@gmail.com

Divya Srivastava
Computer Science and Engineering
MNNIT Allahabad
Allahabad, India
e-mail: divyalknw@gmail.com

Suneeta Agarwal
Computer Science and Engineering
MNNIT Allahabad
Allahabad, India
e-mail: suneeta@mnnit.ac.in

***Abstract*— Grey Level Co-Occurrence matrix is one of the oldest techniques used for texture analysis. The Grey Level Co-Occurrence matrix has two important parameters i.e. distance and direction. In this paper various combinations of distance and directional angles used for GLCM calculation are analyzed in order to recognize certain patterned images based on their textural features. Patterns considered in this paper are horizontally striped, vertically striped, right diagonally striped, left diagonally striped, checkered and irregular. Our proposed method has achieved a percentage accuracy of 96, 98, 96, 90, 96 and 94 for horizontally striped, vertically striped, right diagonally striped, left diagonally striped, checkered and irregular patterns respectively. Thus an overall percentage accuracy of 95 is achieved for pattern recognition using GLCM.**

Keywords*— *GLCM, texture analysis, pattern recognition, distance and direction parameter

I. Introduction

Apart from color and shape, texture feature is also an important source of information about an image that is visually perceptive. Texture analysis has thus been a major area of computer vision research. Texture analysis has its applications in Content based Image Retrieval [1], Image Classification [2], Medical Image processing [3], etc. Various approaches such as structural, statistical, model based and signal processing based have already been developed over the past. Grey Level Co-Occurrence Matrix (GLCM) method [4] is a second order statistical method applied for texture feature extraction.

GLCM is a matrix that represents the relative frequencies of a pair of grey levels present at certain distance *d* apart and at a particular angle ϴ. Distance *d* ranges from 1 to size of image while ϴ ranges in four directions i.e., 0°, 45°, 90° and 135°. GLCM generated from different pairs of angles and distances gives quite different feature values. Extraction of textural information from images containing highly directional characteristics is majorly dependent on selection of correct angle ϴ. Usually all the four directions are taken and the mean of features calculated from all the four GLCMs is used [5]. But in such process of taking the mean the directional information of textured images is lost and thus classifications do not achieve good accuracy. Since the texture characteristics calculated along the relevant direction is quite different from those calculated along the other three directions.

This paper presents the effect of change of angle ϴ used in creating GLCM for recognizing various patterns. Four features i.e. Contrast, Correlation, Energy and Homogeneity out of thirteen Haralick features [5]-[6] are used from GLCM for this purpose. Selection of appropriate angle is made to ensure that more textural information is obtained.

II. Method

A. Grey Level Co-Occurrence Matrix Calculation

GLCM is calculated for a selected pair of distance and angle. The relative frequencies of pair of each reference pixel and its neighboring pixel at a certain distance and angle are calculated for finding its GLCM matrix. The matrix thus obtained is divided by sum of all the frequencies in order to get normalized matrix [4]. Fig. 1 shows how GLCM is calculated from greycomatrix of 4-by-5 image I for D=1 and ϴ=0°.

Image

1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

GLCM

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Figure 1. GLCM calculation from greycomatrix of 4-by-5 image I [7]

Multiple GLCMs can also be calculated for various offsets. These offsets define pixel relationships of varying direction and distance. The Fig. 2 shows spatial relationships

978-1-5386-1772-4/17/$31.00

of pixels that are defined offsets for various angles i.e., 0°, 45°, 90° and 135° and distance D where D is any fixed integer between 1 to size of image. Other angles i.e., 180°, 225°, 270° and 315° can also be taken but it will give the same result as 0°, 45°, 90° and 135° respectively. That is why only four angles are considered.

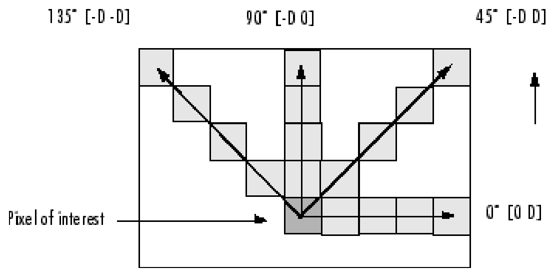

Figure 2. Various offsets for multiple GLCM calculation [7]

B. Feature Extraction

The four textural features extracted from grey level co-occurrence matrix i.e., Contrast, Correlation, Homogeneity and Energy are defined below. Where, Ng stands number of grey levels in the image, P_d^{θ}(i,j) stands (i, j)th entry in GLCM representing probability of presence of pixel pairs at certain d distance and Θ angle.

1) Contrast: The grey level variation in a GLCM matrix is represented by Contrast. It basically tells about the linear dependency of grey levels of two neighboring pixels [5]. Its value ranges from 0 to (size(GLCM,1)-1)2 [7].

$$Contrast(d,\Theta) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} |i-j|^2 P_d^{\Theta}(i,j) \quad (1)$$

The Contrast value is 0 for textures that are constant.

2) Correlation:

Correlation gives us information about how correlated a pixel is to its neighboring pixels. Its value ranges from -1 to 1 [7], where -1 is perfect negatively correlated, 0 is uncorrelated and 1 is perfect positively correlated.

$$Corr(d,\Theta) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \frac{ijP_d^{\Theta}(i,j) - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (2)$$

where μ_x & μ_y represents GLCM mean based on reference pixel and neighbor pixel respectively and σ_x & σ_y represents standard deviation along the two means, given as:

$$\mu_x = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} iP_d^{\theta}(i,j) \quad (3)$$

$$\mu_y = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} jP_d^{\theta}(i,j) \quad (4)$$

$$\sigma_x = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \sqrt[2]{(i-\mu_x)^2 P_d^{\theta}} \quad (5)$$

$$\sigma_y = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \sqrt[2]{(j-\mu_y)^2 P_d^{\theta}} \quad (6)$$

3) Energy:

Energy measures the textural uniformity of an image i.e., pixel pair repetitions. It also helps in determining disorders in texture. Its value ranges from 0 to 1 [7].

$$Energy(d,\Theta) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \left[P_d^{\Theta}(i,j)\right]^2 \quad (7)$$

4) Homogeneity:

Homogeneity measures the uniformity of the non-zero entries in the GLCM [8]. Its value ranges from 0 to 1 [7].

$$Homo(d,\Theta) = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} \frac{1}{1+(i-j)^2} P_d^{\Theta}(i,j) \quad (8)$$

C. Directional Texture Analysis

When GLCMs are calculated for all the directions and their mean are used the computation cost increases. And also the relevant textural information of directionality is lost [9]. GLCM generated from different pairs of angles and distances contain quite different feature values. Fig. 3 shows the sample image types taken from DTD database [10] for this experimentation.

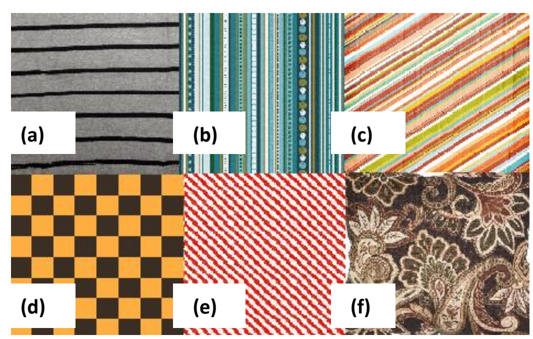

Figure 3. Sample images from ‘DTD’ database [10] with (a) Horizontal Stripes, (b) Vertical Stripes, (c) Right Diagonally Striped, (d) Checkered, (e) Left Diagonally Striped and (f) Irregular Patterns respectively.

For the sample shown in Fig. 4, a series of GLCMs with four directions and 16 distances were calculated. Four aforementioned features were calculated from each matrix. Fig. 5 (a), (b), (c) & (d) shows the contrast, correlation, homogeneity and energy features calculated for various pairs of angles and distances for Vertical Striped image shown in Fig.4.

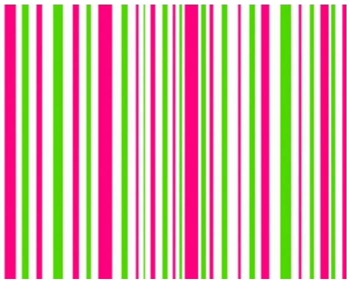

Figure 4. Vertical striped image.

It can be observed from the Fig. 5 (a), (b), (c) & (d) that the values of all the four features i.e., Contrast, Correlation, Energy and Homogeneity are constant for 90° angle at different distances. This angle can be considered as the main directional angle. Also the value of Contrast is minimum at the main directional angle while Correlation, Energy and Homogeneity are maximum. This is expected also since vertical striped image has constant grey values along the 90° angle that is why Contrast is coming out to be minimum while Correlation, Energy and Homogeneity each are coming out to be maximum. For the other three angles the four features calculated are almost the same.

Similar results are obtained for horizontal striped images with main directional angle coming out to be 0. At this main directional angle Contrast is coming out to be minimum while Correlation, Energy and Homogeneity are maximum.

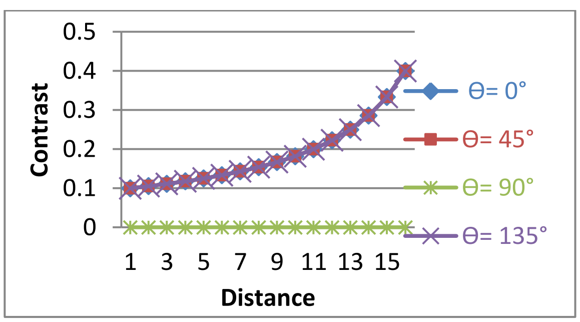

Figure 5 (a). Contrast vs. Distance Plot at different angles for vertical striped image

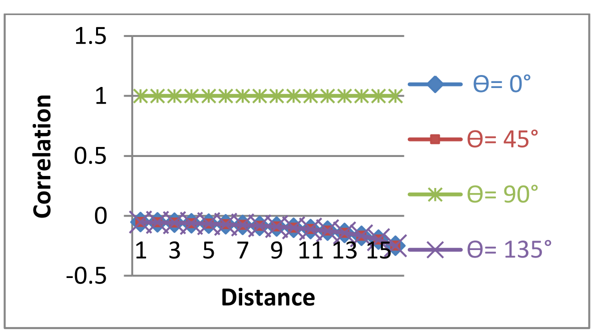

Figure 5 (b). Correlation vs. Distance Plot at different angles for vertical striped image

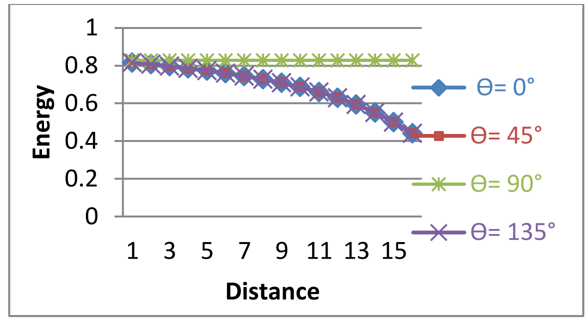

Figure 5 (c). Energy vs. Distance Plot at different angles for vertical striped image

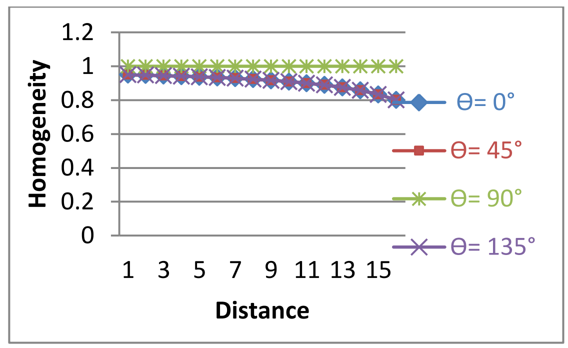

Figure 5 (d). Homogeneity vs. Distance Plot at different angles for vertical striped image

Fig. 6 shows a sample right diagonally striped image used for analyzing the effect of change in angle and distance whose four features Contrast, Correlation, Energy and Homogeneity calculated are shown in Fig. 7 (a), (b), (c) and (d) respectively.

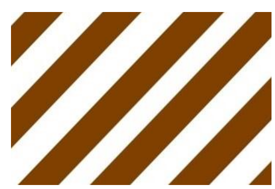

Fig.ure 6. Right diagonally striped image

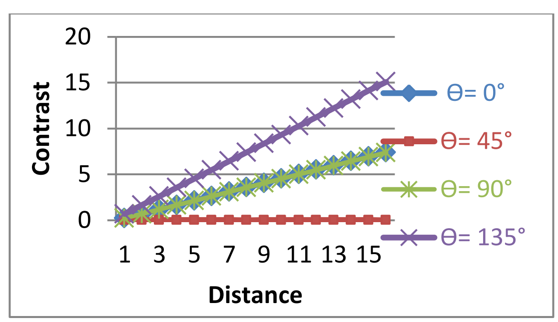

Figure 7 (a). Contrast vs. Distance Plot at different angles for right diagonally striped image

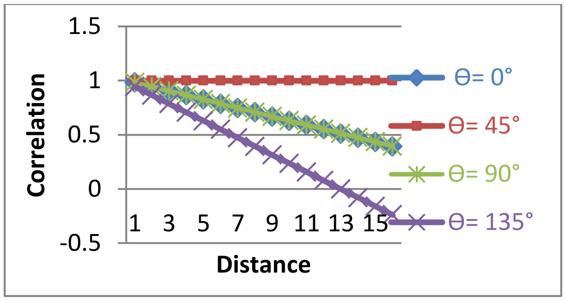

Figure 7 (b). Correlation vs. Distance Plot at different angles for right diagonally striped image

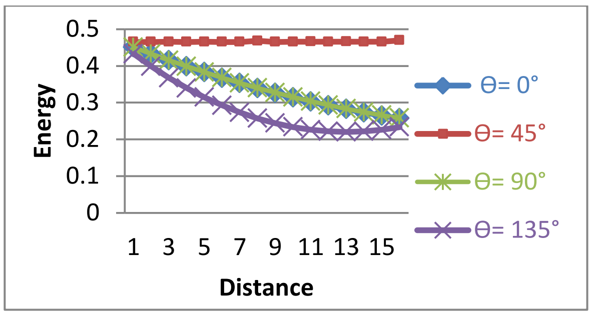

Figure 7 (c). Energy vs. Distance Plot at different angles for right diagonally striped image

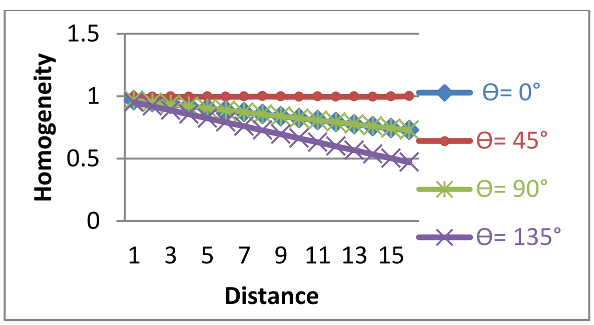

Figure7 (d). Homogeneity vs. Distance Plot at different angles for right diagonally striped images

For the right diagonally striped image it can be observed that all the four features are constant at an angle of 45° as shown in Fig. 7 (a), (b), (c) and (d). Thus 45° angle is the main directional angle. The value of Contrast is again minimum at the main directional angle while Correlation, Energy and Homogeneity are maximum. This is expected also since right diagonally striped image has constant grey values along 45° angle that is why Contrast is minimum along that angle and Correlation, Energy and Homogeneity each are maximum. While if we move along 135° in right diagonally striped image its grey value will be non-uniform that is why it is observed along 135° Contrast is maximum while Correlation, Energy and Homogeneity are minimum.

Similarly for left diagonally striped image the four features are constant at an angle of 135° which is the main directional. Thus when recognizing such pattern, these angles can specifically play an important role in giving us more accurate results.

For these directional image patterns i.e. vertical striped, horizontal striped, left and right diagonally striped images it is observed that Contrast and Correlation features are more noticeable compared to other two features. Contrast is minimum and correlation is maximum along the main directional angle. Thus minimum contrast angle and maximum correlation angle independently plays a significant role in determination of directionality of images and in the process of pattern recognition.

Fig. 8 shows a sample checkered image used for analyzing the effect of change in distance and angle parameter. Its four features Contrast, Correlation, Energy and Homogeneity calculated are shown in Fig. 9 (a), (b), (c) and (d) respectively.

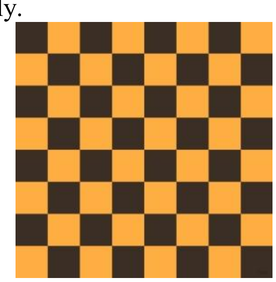

Figure 8. Sample checkered image

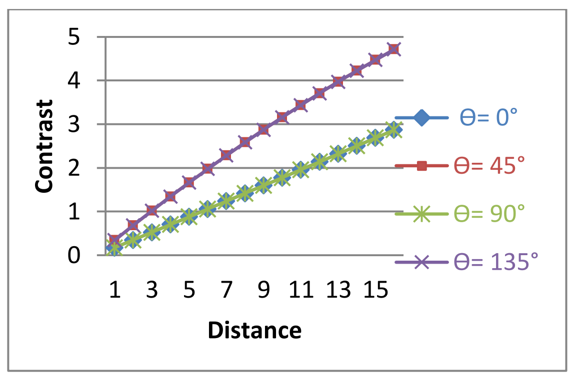

Figure 9 (a). Contrast vs. Distance Plot at different angles for checkered images

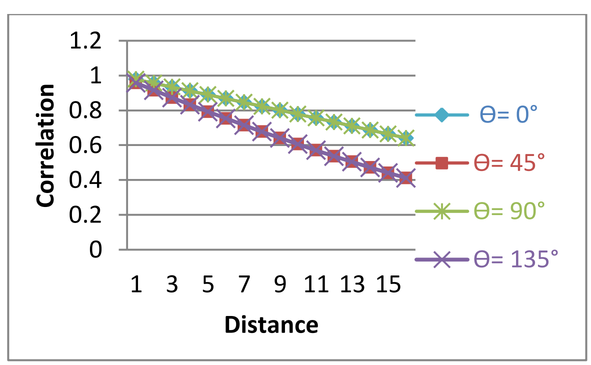

Figure 9 (b). Correlation vs. Distance Plot at different angles for checkered images

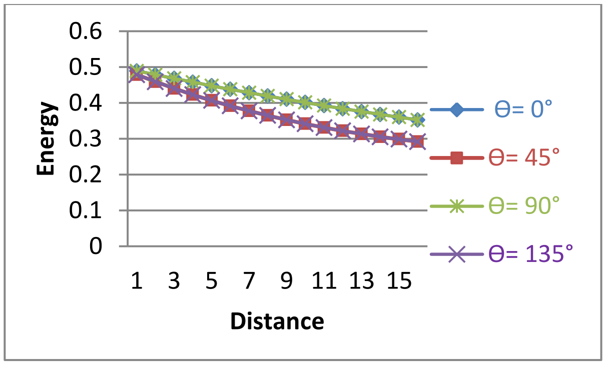

Figure 9 (c). Energy vs. Distance Plot at different angles for checkered images

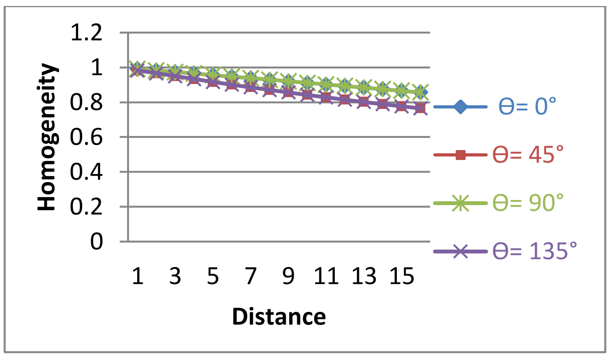

Figure 9 (d). Homogeneity vs. Distance Plot at different angles for checkered images

It can be observed from the Fig. 9 (a), (b), (c) and (d) that all the four features for the pair of angles 0° & 90° and 45° & 135° angle are approximately same at various distances. Since the checkered image is lacking any special directional component as in vertical stripes, horizontal stripes and diagonal stripes that is why the features calculated are not constant at any specific angle with changing distances.

For checkered patterns the variation in values of Contrast and Correlation for various angles are more noticeable as compared to variations in Energy and Homogeneity. So Contrast or Correlation feature obtained from GLCM can be used independently for better checkered pattern recognition based on angle pairs and distance parameter.

III. RESULTS

To analyze GLCMs of various combinations of angles and distance, 300 images from DTD database [10] grouped as 50 images each of Horizontal Stripes, Vertical Stripes, Right Diagonally Striped, Left Diagonally Striped, Checkered and Irregular patterns are used. TABLE I. shows the Confusion Matrix [6] for the pattern recognition system where VS, HS, LDS, RDS, C and I denote Vertical stripes, Horizontal stripes, Left-diagonal stripes, Right-diagonal stripes, Checkered and Irregular patterns respectively.

TABLE I. CONFUSION MATRIX FOR THE SYSTEM

		PREDICTED					
		VS	HS	LDS	RDS	C	I
A	VS	48	0	0	0	0	2
C	HS	0	49	0	0	0	1
T	LDS	0	0	48	0	0	2
U	RDS	4	0	0	45	0	1
A	C	2	0	0	0	48	0
L	I	0	1	0	0	2	47

From the confusion matrix shown in TABLE I, Precision and Recall are calculated as:

Precision: Precision is the proportion of the predicted positive cases that were correct [11].

$$Precision = \frac{TP}{TP + FP} \tag{9}$$

Recall: Also called as True Positive Rate is the proportion of positive cases that were correctly identified [11].

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

Overall accuracy [11] is given as

$$Overall\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

Where, TP is number of true positive predictions, TN is true negative predictions, FP is false positive predictions and FN is false negative predictions. TABLE II shows the precision and recall calculated from the confusion matrix for the system performing pattern recognition.

TABLE II. PRECISION AND RECALL CALCULATED FROM CONFUSION MATRIX.

Patterns		Precision	Recall
Vertical Stripes		0.88	0.96
Horizontal Stripes		0.98	0.98
Diagonal Stripes	Left	1	0.96
	Right	1	0.90
Checkered		0.96	0.96
Irregular		0.88	0.94

Overall accuracy calculated is 95%.

IV. CONCLUSIONS

The effect of change in angle parameter ϴ in GLCM is analyzed along with distance parameter d for recognition of various patterns. It was observed that minimum contrast angle and maximum correlation angle independently are sufficient enough in determining the directionality of any image. This could also be applied on other texture images having highly directional properties thus giving more significant texture information being rotationally invariant. This can have wide applications in fashion e-commerce sites in image retrieval based on particular patterns which can also be used as a tool for filtering the results.

REFERENCES

[1] A. Khatra, "Content based Image Retrieval using Texture image," *IJSER*, vol.1, pp. 39-41, Dec. 2013.

[2] D.S. Guru, Y.H. Sharath and S. Manjunath, "Texture features and KNN in classification of flower images,", *IJCA, Special Issue on RTIPPR* (1), pp. 21-29, Aug. 2010.

[3] W.H. Nailon, "Texture analysis methods for medical image characterization," INTECH Open Access Publisher, 2010.

[4] Mryka Hall-Beyer (2008, August 29). The GLCM texture tutorial [Online]. http://www.fp.ucalgary.ca/mhallbey/tutorial.htm

[5] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification," *IEEE Trans. Syst. Man Cybern*., vol. SMC-3, no. 6, pp. 610-621, Nov. 1973.

[6] R. M. Haralick and L.G. Shapiro, *Computer and Robot Vision. (1st ed.).* Vol. 1, Addison-Wesley Longman Publishing Co., Boston, MA, USA, Addison-Wesley, 1992, p. 459.

[7] Mathworks' Matlab [Online]. http://in.mathworks.com/help/images/ref/graycoprops.html

[8] A. Gebejes and R. Huertas, "Texture characterization based on grey-level co-occurrence matrix," *Proc.Conf. Informatics and Manage. Sci.*, vol. 2, March 2013.

[9] Y. Hu, C. X. Zhao and H. N. Wang, "Directional Analysis of Texture Images Using Gray Level Co-Occurrence Matrix," IEEE Pacific-Asia Workshop on Computational Intell. and Ind. Applicat., Wuhan, 2008, pp. 277-281. Dec. 2008.

[10] M.Cimpoi, S. Maji, I. Kokkinos, S. Mohamed, A. Vedaldi, "Describing Textures in the Wild," *Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR)*, 2014.

[11] [Online].http://www2.cs.uregina.ca/~dbd/cs831/notes/confusion_matrix/confusion_matrix.html