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MATLAB BASED FEATURE EXTRACTION AND CLUSTERING IMAGES USING K-NEAREST NEIGHBOUR ALGORITHM

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***Abstract–* Being the most successful methods for texture discrimination the Spatial Gray Level Dependence Method, Run Difference Method and Local Binary Pattern method we have investigated its effectiveness in extracting features to classify or categorize an image. The Spatial Gray Level Dependence aspect of texture is concerned with the spatial distribution and spatial dependence among the gray levels in a local area. RDM is similar to SGLDM which extracts features that describe the size and prominence of texture elements in the image.LBP features can provide robustness against variation in illumination. The extracted features such as contrast, correlation, homogeneity, energy, sharpness facilitates the subsequent learning leading to a better interpretation of the image. K-nn is a non-parametric method used for classification and regression. We classify the image using K-Nearest Neighbour Algorithm from the LBP image output which helps to represent the details with more significance.**

***Keywords* – SGLDM, GLCM, LBP, RDM, K-nn.**

I. INTRODUCTION

The objects similar in characteristics in an image are considered as Features. Basically, objects are a convenient way of storing information. Every image differ from the other by its features such as contrast, sharpness etc., which can be extracted to analyze and explore the image. The texture is said to be the related pixel information and visual patterns. Spatial Gray Level Difference Method [5] – SGLDM helps to extract the Gray Level Co-occurrence Matrix [3] – GLCM features such as Contrast, Correlation, Energy and Homogeneity. The Run Difference Method – RDM measures the predominance and variation of Gray Level Differences and the sharpness which defines an image. The Local Binary Pattern – LBP method study the texture with its pattern and strength. The features extracted these algorithms serve as an input to K-Nearest Neighbour algorithm [4] which classifies the objects in an image based on its k nearest neighbour.

II. FEATURE EXTRACTION ALGORITHMS

2.1 Spatial Gray Level Difference Method – SGLDM

SGLDM is based on second order conditional probability density function. SGLDM is a statistical method which constructs co-occurrence matrices [5] [15] to reflect the spatial distribution of gray levels in the region of interest [8]. SGLDM is based on the estimation of the second order conditional probability density g(i, j, d, ϴ). This means that an element at location (i, j) of the SGLD Matrix signifies the probability that two different resolution cells which are in a specified orientation ϴ from the horizontal and specified distance d from each other, will have gray level values i and j respectively. The angle is used to evaluate the direction of texture, and the application of several distance values can provide a meaningful description of the size of the periodicity texture. Thus for different ϴ and d values, different SGLD Matrices result. The angle ϴ is usually restricted values of 0, 45, 90, and 135°, and the distance d is limited to values restricted to integral multiples of pixel size.

The SGLDM matrix is formed by computing the number of occurrences of each pixel with gray level i that are away by distance d from any pixel with gray level j in a direction defined by angle θ. The choice of distance and angle combination, as well as the quantization level, is somewhat arbitrary. Fig.1 shows the co-occurrence for one pixel (yellow pixel) with d=3 pixel and θ {0, π/4, 2π/4, 3π/4}.

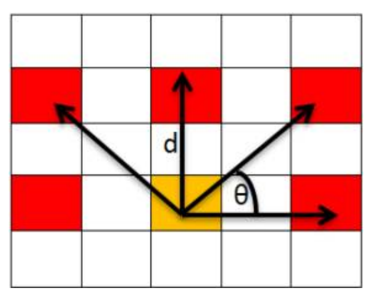

Fig. 1 the Co-occurrence for one pixel (yellow pixel) with d=3 and θ {0, π/4, 2π/4, 3π/4}.

Different parameter of texture reflects different property in the image. Robert M. Haralick, K.Shanmugam, I.Dinstein proposed a large number of features called Haralick's texture features [11] derived from the co-occurrence matrix.

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Contrast: It is a measure of the local variations of gray levels present in an image. Images with large neighbouring gray level differences are associated with high contrast. This parameter can also characterize the dispersion of the matrix values from its main diagonal. Contrast is defined as follows:

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \quad (1)$$

-where p(i, j) corresponds to the elements of co-occurrence matrix, i.e. the probability of moving from a pixel with gray level i to a pixel with gray level j.

Homogeneity: This parameter, called also Inverse Difference Moment, measures the local homogeneity of an image. It assigns larger values to smaller gray level differences within pixel pairs. This parameter has opposite behaviour of the contrast. More the texture has homogeneous regions, more the parameter is high. Homogeneity is defined as:

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (2)$$

Energy: This parameter is a measure of image homogeneity; it reflects pixel-pair repetitions. Homogeneous images have very few dominant gray tone transitions, which result into higher energy. Energy is defined as follows:

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \quad (3)$$

- **Correlation**: Measures the correlation of a pixel to its neighbour.

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \quad (4)$$

III. RUN DIFFERENCE METHOD – RDM

RDM is based on the estimation of the probability density function of the gray differences in an image.RDM is similar to SGLDM which extracts features that describe the size and prominence of texture elements [12] in the image. RDM measures the pdf to p(r, gdif |θ) where gdif is the absolute difference between attenuation values of 2 pixels at a distance r away from each other in the direction of θ.

- **Three characteristic vectors that describe the texture description**

(i) DGD- Distribution of Gray level Differences

DGDgdif = (5)

(ii) DOD – Distribution Of average Difference

DODr = (6)

(iii) DAD – Distribution of Average Distance

DADgdif = (7)

- **Features of RDM**

With the above three characteristic vectors we define the following features of RDM.

- **LDE** – Large Difference Emphasis measures the predominance of large gray level differences.

$$LDE = \sum_{gdif=0}^{G-1} DGD(g_{dif}).\ln(2/g_{dif}). \quad (8)$$

- **Sharpness** – measures contrast and definition of an image.

$$\text{Sharpness} = \sum_{gdif=0}^{G-1} DGD(g_{dif}).(g_{dif})^3 \quad (9)$$

- **Second moment of DGD** (SMG) – measures variation of gray level differences.

$$SMG = \sum_{gdif=0}^{G-1} \left(DGD(g_{dif})\right)^2. \quad (10)$$

- **Second moment of DOD (SMO) – measures the variation of average gray level differences.**

$$SMO = \sum_{r=1}^{L/2} (DOD(r))^2. \quad (11)$$

- **Long Distance Emphasis** (LDEL) – measures the prominences of large differences which are at a long distance from each other present in the matrix.

$$LDEL = \sum_{gdif=0}^{G-1} DAD(g_{dif}).(g_{dif})^2 \quad (12)$$

IV. LOCAL BINARY PATTERN – LBP

This approach was introduced in 1996 by T. Ojala, M. Pietikainen and D. Harwood [13] as a basic binary operator. LBP features can provide robustness against variation in illumination [14]. With LBP it is possible to describe the texture and shape of a digital image. This is done by dividing an image into several small regions from which the features are extracted.

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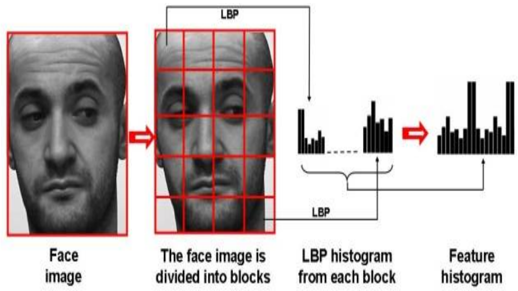

Fig 2 : Phases in LBP process

LBP is simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighbourhood of each pixel and considers the result as a binary number.

5	6	1
4	4	6
7	2	3

Thresholding →

1	1	0
1		1
1	0	0

Binary value=11010011
Decimal=211

Fig 3 : Original LBP Operator

The value of the centre pixel acts as a threshold which is compared with all its neighbouring pixel values, if the neighbours have value greater than or equal to the centre value then it is substituted with 1 else 0. Thus the image is divided into small regions from which the features are extracted which is concatenated and represented in a single feature histogram. Therefore, LBP-method can be applied on images to extract features which can be used to get a measure for the similarity between the images. The main idea is that for every pixel of an image the LBP-code is calculated. The occurrence of each possible pattern in the image is kept up. The histogram of these patterns, also called labels, forms a feature vector, and is thus a representation for the texture of the image. These histograms can then be used to measure the similarity between the images, by calculating the distance between the histograms.

Due to its discriminative power and computational simplicity, LBP texture operator [2] has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity [7], which makes it possible to analyze images in challenging real-time settings.

V. K- NEAREST NEIGHBOUR – Knn

K-nn is a non-parametric method used for classification and regression [1]. K-nn classification algorithm is a supervised algorithm which assigns a test pattern or object to a class based on majority of it K-nearest neighbours in the feature space. The classifier uses training samples with class labels. The algorithm is very simple and relies on three operations:

- **Distance Computation:** First, distance of every training sample from the test sample is computed.
- **Sorting:** Distances are sorted to select k closest training samples from the test pattern.
- **Vote Count:** Finally, the test pattern is assigned to that class which has the largest number of representatives among this k nearest neighbours. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours. If k=1, then the object is simply assigned to the class of that single nearest neighbour.

The issues that affect the performance of the K-nn classifier are the value of k and the choice of distance measure. The value of k is supplied by the user, and if features of the training and test samples are real values then Euclidean distance is commonly employed. Each training sample is represented by a feature vector x_i which corresponds to a point in a multidimensional feature space with a class label c_i. The distance between the unknown object and pattern is represented by a feature vector y and each of the training samples is computed.

Let d_i=dist(y, xi) for i=0, 1, 2,...n-1. Then, these distances are sorted such that d'_0 d'_1 d'_2 .... d'_{n-1} and with each d'_j original class label cj remains attached. Finally, c_js for counted and the unknown object y are assigned to the class whose labels has maximum frequency in $\{c_0, c1,....,c_{k-1}\}$.

VI. EXPERIMENTAL RESULTS

6.1 DATASET

The features were extracted and tested from more than 50 images taken under various illuminations using MATLAB R2014a. The image database was split into 8 and 16 level representations to extract SGLDM features such as Contrast, Homogeneity, Correlation, Energy and RDM features such as Large Difference Emphasis (LDE), Sharpness (SHP), Second

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Moment of DGD (SMG), Second Moment of DoD (SMO), and Long Distance Emphasis (LDEL).

6.2 PRE-PROCESSING

The sample database shown here consists of three images applied with 8 and 16 gray levels and the features were extracted and compared. All the three feature extraction algorithms and K-nn algorithm were coded in MATLAB R2014a. Some of the important MATLAB functions used for the coding are:

- graycomatrix(): creates a Gray-Level Co-occurrence Matrix (GLCM) from an image.

  Syntax: glcm=graycomatrix(I);

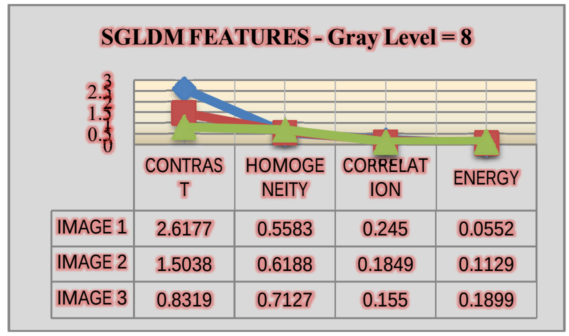
glcms=graycomatrix(I,param1,val1,param2,val2,...)returns one or more gray-level co-occurrence matrices, depending on the values of the optional parameter/value pairs. Parameter names can be abbreviated, and case does not matter. The Parameters used in graycomatrix() are:

- 'GrayLimits'- Two element vector, [low, high], that specifies how the values in I are scaled into gray levels.
- 'NumLevels' – Integer specifying the number of gray-levels to use when scaling the gray scale values in I.
- 'Offset' – px2 array of integers specifying the distance between the pixel of interest and its neighbour.
- 'Symmetric' – Boolean that creates a GLCM where the ordering of values in the pixel pairs is not considered.

Image 1 ***Image 2*** ***Image 3***

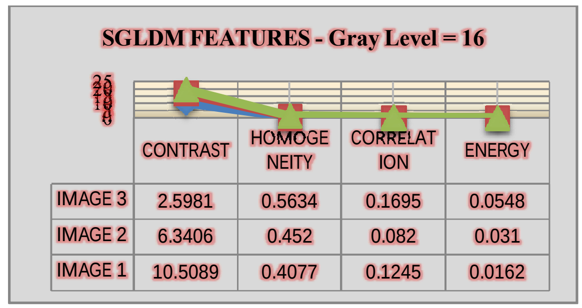
Fig.4 Images used to extract features and classify

C. SGLDM FEATURE EXTRACTION:



	CONTRAST	HOMOGENEITY	CORRELATION	ENERGY
IMAGE 1	2.6177	0.5583	0.245	0.0552
IMAGE 2	1.5038	0.6188	0.1849	0.1129
IMAGE 3	0.8319	0.7127	0.155	0.1899

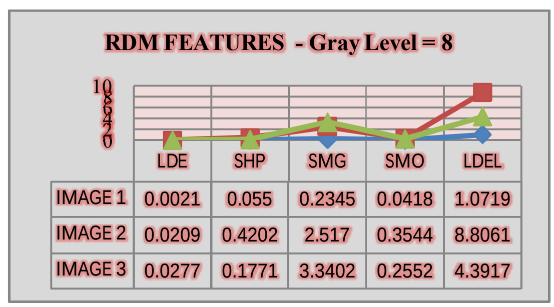
Fig 5 : Graph depicting the SGLDM feature values for Gray Level =8



	CONTRAST	HOMOGENEITY	CORRELATION	ENERGY
IMAGE 3	2.5981	0.5634	0.1695	0.0548
IMAGE 2	6.3406	0.452	0.082	0.031
IMAGE 1	10.5089	0.4077	0.1245	0.0162

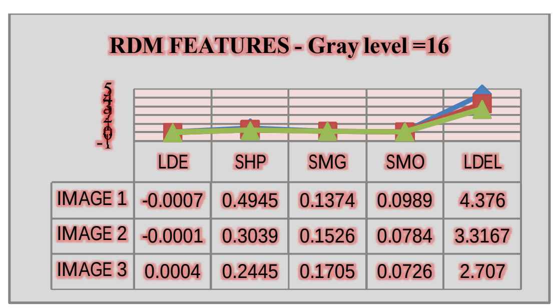
Fig 6 : Graph depicting the SGLDM feature values for Gray Level =16

RDM FEATURE EXTRACTION



	LDE	SHP	SMG	SMO	LDEL
IMAGE 1	0.0021	0.055	0.2345	0.0418	1.0719
IMAGE 2	0.0209	0.4202	2.517	0.3544	8.8061
IMAGE 3	0.0277	0.1771	3.3402	0.2552	4.3917

Fig 7 : Graph depicting the RDM feature values for Gray Level=8



	LDE	SHP	SMG	SMO	LDEL
IMAGE 1	-0.0007	0.4945	0.1374	0.0989	4.376
IMAGE 2	-0.0001	0.3039	0.1526	0.0784	3.3167
IMAGE 3	0.0004	0.2445	0.1705	0.0726	2.707

Fig 8: Graph depicting the RDM feature values for Gray Level =16

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LBP

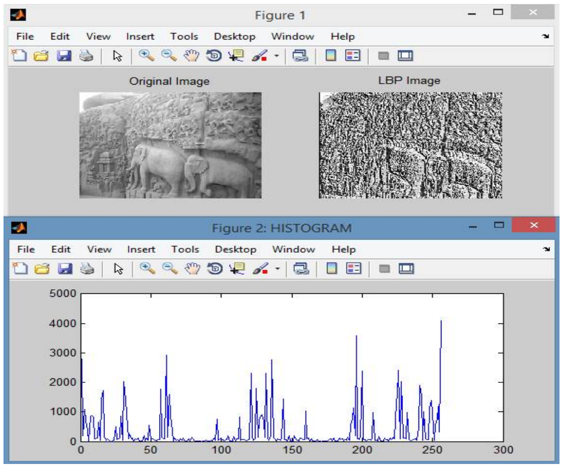

Fig 9 : LBP output of IMAGE1 with the histogram

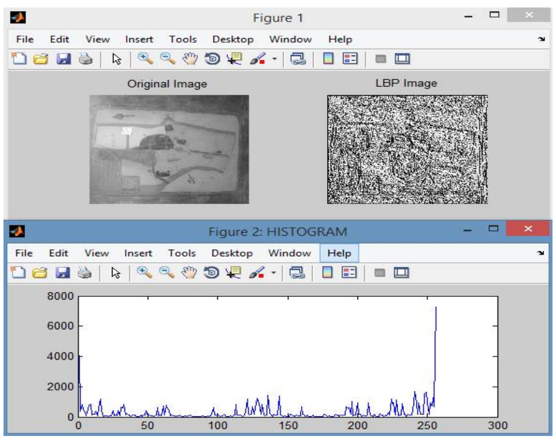

Fig 10 : LBP output of IMAGE2 with the histogram

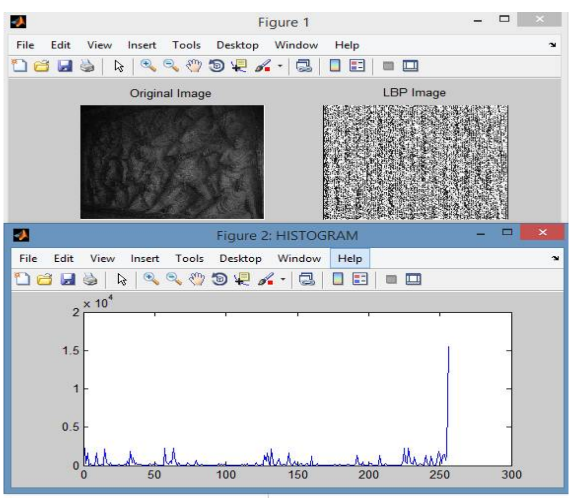

Fig 11: LBP output of IMAGE3 with the histogram

K-nn CLASSIFICATION:

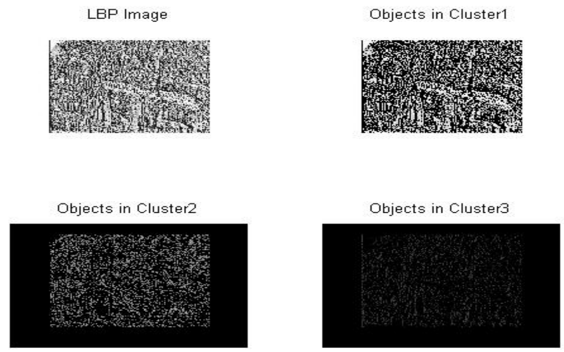

Fig 12 : K-nn classification of IMAGE1

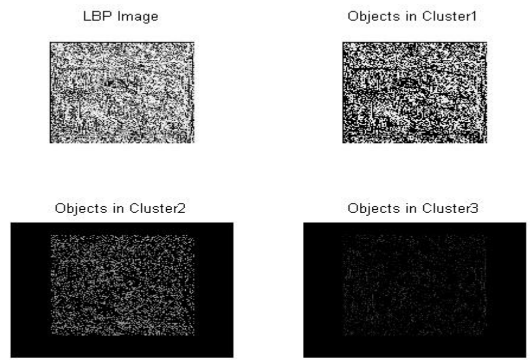

Fig 13 : K-nn classification of IMAGE2

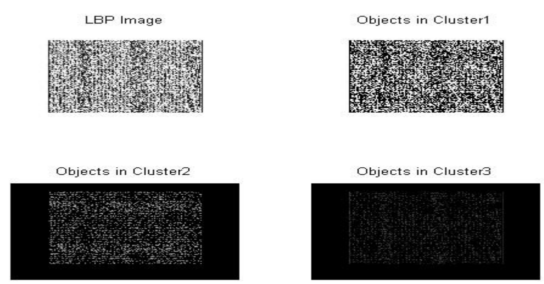

Fig 14 : K-nn classification of IMAGE3

VII. CONCLUSION

In this paper we have worked with images in gray scale level 8 and 16 and have considered three feature extraction algorithms such as SGLDM to extract GLCM features – contrast, homogeneity, energy, correlation and RDM to extract features - LDE, sharpness, DOD, DAD, DGD and LBP is used to transform the image by thresholding and construct histogram for the LBP image constructed. The resultant LBP image which highlights the features of an image accurately is used as the input image for the K-nn classification process, where K-nn partitions the image into 3 clusters that represents the

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details of the image in significance. The accuracy of the K-nn algorithm is degraded by the presence of noise or irrelevant features. The best choice of k depends upon the data generally larger values of k reduce the effect of noise on the classification, but make boundaries between classes less distinct.

VIII. FUTURE WORK

We have intended to study Edited Nearest Neighbour – E-nn since it is said to improve the classification accuracy in comparison with the K-nn method. Unlike K-nn, E-nn makes use of a two way communications for classification- it considers not only who are the nearest neighbours of the test sample, but also consider the test sample as their nearest neighbours. Thus E-nn can learn the global distribution, therefore improving pattern recognition performance and providing a powerful technique for a wide range of data processing applications.

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