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Texture Based Image Retrieval Using GLCM and Image Sub-Block

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***Abstract**— This study proposed an approach to retrieve images based on texture features using GLCM and image sub-blocks. Each image is divided into three rows and three columns with equal sizes. Texture features are extracted based on GLCM (Gray Level Co-occurrence Matrix) using four statistical features that is contrast, homogeneity, energy and correlation. The features are calculated in four directions (0^0, 45^0, 90^0, and 135^0). A total of 16 texture values are calculated per image sub-blocks. In this retrieval system Euclidean distance and City block distance are used to measure similarity of images. This retrieval system performance is measured in terms of its recall and precision. The performance of retrieval system is also measured based on AVRR (Average Rank of Relevant Images) and IAVRR (Ideal Average Rank of Relevant Images) that is proposed by Faloutsos. The retrieval results show that the performance using City Block distance has achieved higher than the performance using Euclidean distance.*

***Keywords**— AVRR, City Block distance, Content Based Image Retrieval (CBIR), Euclidean distance, GLCM, IAVRR, precision, recall.*

I. Introduction

Recently, huge collections of images have grown rapidly. Corresponding to this growth, Content based image retrieval are required to access visual information. As powerful technique, content based image retrieval systems have to provide easily data structures indexing and faster query execution facilities. The CBIR system retrieves relevant images from an image collection based on automatic derives features. The derived features include primitive features such as texture, color, and shape.

Texture is one of important primitives in human vision and texture features have been used to identify content of images. Texture is a property that represents the surface and structure of an Image. In general, Texture can be defined as a regular repetition of elements or patterns on a surface. Image texture are complex visual pattern that consisting of entities or areas with sub-pattern with characteristic brightness, color, shape, size, etc. An image region has a constant texture if a set of its characteristics are constant, slowly changing or approximately periodic [8].

Texture contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification [3]. Texture can be considered as repeated patterns of pixels over a spatial domain. The repetition frequencies results in textures can appear to be random and unstructured. A number of techniques have been used for measuring the texture features such as Gabor filter, fractals, wavelets, co-occurrence matrix etc.

Texture features are extracted based on GLCM (Gray Level Co-occurrence Matrix). The Gray Level Co-occurrence Matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels [4], [6]. GLCM contains information about the position of the pixels that have the same value of gray levels. A GLCM is a 2-dimensional array, P, in which both rows and columns representing a set of possible values of the image [4], [6].

There are several studies proposed content based image retrieval using texture feature. Ramamurthy and Chandran proposed texture based image retrieval using GLCM and K-Means clustering [1]. The retrieval results have high precision value. Sebastian, et al also proposed texture based image retrieval using GLCM [9]. The retrieval results are effective. However both studies have not used local analysis. Using local analysis the query image and database image are divided into several sub-blocks. Each image sub-block query is compared with all of image sub-blocks database therefore the retrieval result could be better than using global analysis.

This paper presents a texture based image retrieval using GLCM and image sub-block. The rest of paper consists of: Section II describes the proposed method. Section III presents the experimental results. Finally, Section IV describes the conclusions.

II. Proposed Method

A. Method

The scheme of method in this experiment is described as follows:

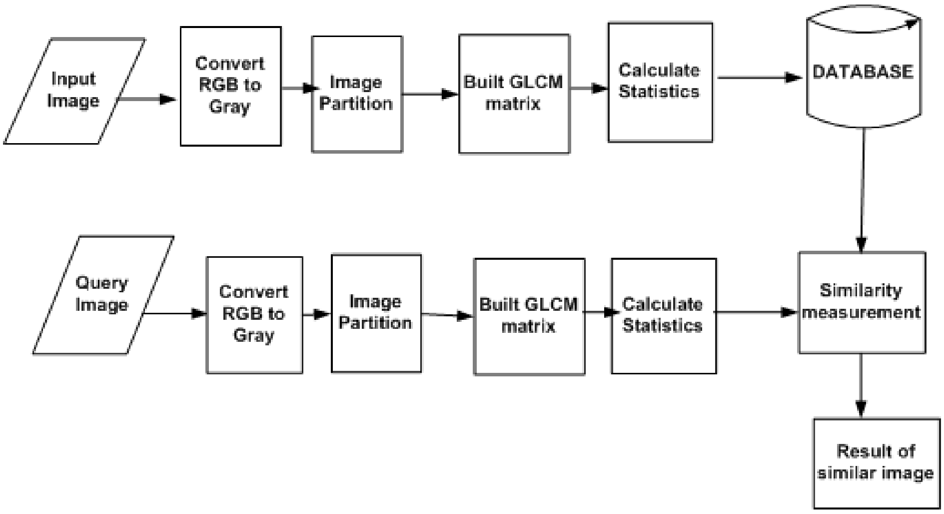

Fig. 1 Scheme of image retrieval

Method scheme of texture image retrieval using GLCM and image sub-block has two stages. The first stage is image feature extracting and the second stage is image retrieval. Fig. 1 represents the first stage that is a feature vector is extracted from each image in the database and the set of all feature vectors is organized as a database index. As can be seen in fig. 1, while an image query is selected, the RGB color space is converted to gray. The next step is the image is divided into three column and three rows in equal size. Texture feature for each sub block is extracted based on GLCM (Gray Level Co-occurrence Matrix). The sub-block image is analyzed by using four statistic features. The Statistic features used are contrast, homogeneity, energy and corelation. These four features are computed in four directions (0^0, 45^0, 90^0, and 135^0). Therefore 16 texture values are computed in each image sub-block.

In stage 2, extraction process is the same with stage 1, however in this stage after calculating statistics using four statistic features and four directions, the similarity measurement is computed. Each image sub-block query is computed with every image sub-block database using Euclidean distance and city Block distance. Therefore, each image sub-block query is compared with all of image sub-blocks database. The retrieved image are then ranked according to the relevance between the query image and images in the database in proportion to a similarity measure computed from the features.

B. Gray Level Co-occurrence Matrix (GLCM)

Texture representation methods can be classified into two categories: structural and statistical. Structural methods describe the texture by identifying the primitive structure and rules of their placement. Statistical methods characterize texture by the statistical distribution of the image intensity [7].

The Gray Level Co-occurrence Matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels [4], [6]. GLCM contains information about the position of the pixels that have the same value of gray levels. A GLCM is a 2-dimensional array, P, in which both rows and columns representing a set of possible values of the image [4], [6]. It is a matrix showing how often a pixel with intensity (gray-level) value i occurs in a specific spatial relationship to a pixel with the value j. It is defined by P(i,j|d,Θ), which expresses the probability of the couple of pixels at Θ direction and d interval. Once the GLCM is created various features can be computed from it [4], [6].

In order to estimate the similarity between different gray level co-occurrence matrices, Haralick had proposed 14 different statistical features extracted from GLCM [2], [3], [6]. To reduce the computational complexity, only some of these features are selected in this paper, specifically: Energy, Contrast, Homogeneity and Correlation.

The four statistics applied to co-occurrence probabilities are discussed before

1) Energy :
$$Energy = \sum_i \sum_j g_{ij}^{\ 2}$$

This statistic measures the uniformity of texture that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value that equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normal range. The GLCM of less homogeneous image will have large number of small entries [4], [6].

2) Contrast :
$$Contrast = \sum_i \sum_j (i-j)^2 g_{ij}$$

This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a set of adjacent pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the main diagonal and low spatial frequency features [4], [6].

3) Homogeneity :
$$Homogenity = \sum_i \sum_j \frac{1}{1+(i-j)^2} g_{ij}$$

This statistic measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are equal. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant [4], [6].

4) *Correlation :*

$$Correlation = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$$

The feature correlation is a measure of linear dependency of gray tones in the image. The rest of the textural features are secondary and derived from those listed above. The statistic features of this study used are taken in four directions : (0^0, 45^0, 90^0, and 135^0). Thus 16 texture feature vectors are calculated for each sub-block.

C. Distance Metrics

Distance metric used in this study are City Block and Euclidean Distances. Both methods are used for measuring similarity of image retrieval. Both methods are defined as:

$$L\,(C_1, C_2) = \left(\sum_{k=1}^{K} \sum_{m=1}^{M} \sum_{n=1}^{N} |(C_1\,(\mathrm{k,m,n}) - C_2\,(\mathrm{k,m,n})|\,\mathrm{q} \right)^{1/q}$$

When q = 1 the distance metric becomes City Block. When q=2 the distance metric becomes the Euclidean distance.

D. Performance Evaluation

Performance evaluation are usually used in imaged retrieval are Precision and Recall. Recall signifies the relevant images in the database that retrieves in response to a query. Precision is the proportion of the retrieved images that are relevant to the query. More precisely, the formula can be shown below.

$$\text{precision} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{retrieved documents}\}|}$$

$$\text{recall} = \frac{|\{\text{relevant documents}\} \cap \{\text{retrieved documents}\}|}{|\{\text{relevant documents}\}|}$$

In order to consider the ranking of each displayed image, Faloutsos et *al* have defined an effectiveness measurement to evaluate the effectiveness of image retrieval system [5]. The average rank (AVRR) of all relevant retrieved images is calculated as well as the ideal average rank of relevant images (IAVRR) for each image query. The system is assumed returns all the *P* relevant images which, in the ideal case (IAVRR), occupies the first *P* positions. This effectiveness measure certainly considered the ranking of relevant images. However, The deviation between the ideal ranking and the actual ranking of a relevant image is not considered. For example, if the following formula returns a perfect effectiveness value (= 1), the system returns images in a totally opposite order of the ideal ranking [5].

Effectiveness= $\frac{\mathbf{AVRR}}{\mathbf{IAVRR}}$, where $IAVRR = \sum_{i=1}^{P} \frac{i}{P}$ and $AVRR = \sum_{i=1}^{P} \frac{ri}{P}$

Where *P* is the total number of relevant images *i* = (1, 2, · · · , *P*) is similarity image ranking by human expert judgment and r_i corresponds to system image ranking.

In this study we used precision, AVRR & IAVRR to evaluate the performance of image retrieval.

III. EXPERIMENTAL RESULT

This study used Texture Library database using 78 images Forest category and 94 images Wood category. The study used Gray color space in JPEG format and conducted in Matlab environment. The method of Image retrieval is ilustrated in the block diagram Fig. 1. In this study the image query and image database that are represented in the RGB color space is converted to Gray. Firstly all images are stored to the database. Secondly in retrieval system, system addresses image queries from the whole database stored.

This study used Precision, Recall and Effectiveness computation based on participant's ranking of similar images for performace evaluation. Firstly, an image query from database was addressed to the system. Similarity measurement used to measure the distance between the image query and the image stored in the database is City Block and Euclidean distances. An image in the database is to be considered as a match to a query if the distance of feature vector image in the databases and the distance between feature vector of the image query is equal to zero. The retrieval result is based on similarity is computed after then the retrieval results are ranked according to the similarity index. Secondly is the retrieval performance results are evaluated using recall, precision and effectiveness using AVRR and IAVRR. The Retrieval Effectiveness is computed based on the averaged ranked of retrieval (AVRR) and the results divided by the Ideal Averaged ranked (IAVRR) which is ranked by participants.

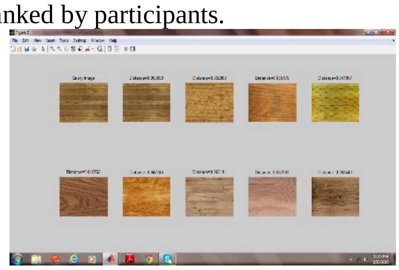

Fig. 2 Image retrieval results of Wood image using City Block Distance

The retrieval results for Wood category is ilustrated in Fig. 2. The distance metrics used is City Block distance. Whereas Fig. 3 the distance metric used is Euclidean distance. When an image is addressed, a searching process will retrieve the closest images in the database. The retrieved image are displayed according to their distance with the image query. The query image is diplayed on top left corner in each set of image retrieval. The distance from the image query is shown on top of every retrieved image. In each set of retrieval, the first image retrieved is the image query itself that is presented in the database. The image that indicating perfect match will be retrieved first.

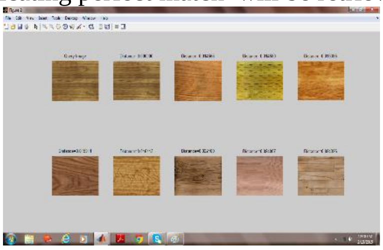

Fig. 3 Image retrieval results of Wood images using Euclidean Distances

Fig. 4 and Fig.5 depicts retrieval results using texture features for Forest category. Fig. 4 presents the retrieval result using City Block distance and Fig. 5 presents the retrieval result using Euclidean distance.

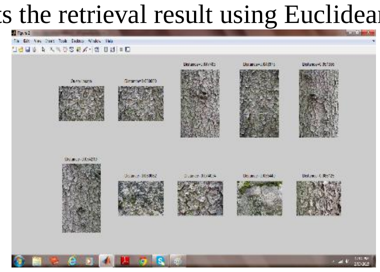

Fig. 4 Image retrieval results of forest images using City Block Distances

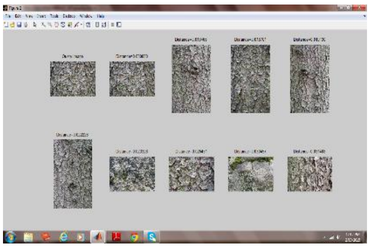

Fig. 5 Image retrieval results of forest images using Euclidean Distances

TABLE I PRECISION AND EFFECTIVENESS

	Effectiveness		**Precision**	
	City Block	**Euclidean**	**City Block**	**Euclidean**
Wood	2.400	2.300	0.808	0.678
Forest	1.381	1.400	0.888	0.883

Table 1 depicts the retrieval results of Wood category and Forest category. The average precision of Wood category using City Block distance is 0.808 and the average precision of Wood category using Euclidean distance is 0.678. The average precision of Forest category using City Block distance is 0.888 and the average precision Forest category using Euclidean Distance is 0.883. Table 1 depicts that the average of precision value of Wood category using City Block distance is higher than the average of precision value of Wood category using Euclidean distance. The average of precision value of Forest category using City Block distance is also higher than the average of precision value of Forest category using Euclidean distance.

The distance metric of effectiveness retrieval used are AVRR and IAVRR. As can be seen in table 1 the effectiveness of Wood category using City Block distance is 2.400 and the effectiveness of Wood category using Euclidean Distance is 2.300. The effectiveness of Forest category using City Block distance is 1.381 and the effectiveness of Forest category using Euclidean Distance is 1.400. Table 1 shows that retrieval result of Forest category using City Block distance is more effective than using Euclidean distance whereas retrieval result of Wood category using City Block distance is less effective than using Euclidean distance.

As the experiment result is shown in table 1, the retrieval result using City Block distance has higher precision than using Euclidean distance. The retrieval result using both Euclidean distance and City Block distance using AVRR and IAVRR that is shown in table 1 has effective as the value retrieval effectiveness is nearest to 1. From the retrieval performance using both precision average and effectiveness using ratio of AVRR and IAVRR is found that Euclidean distance performs slightly lower than City Block distance.

IV. CONCLUSIONS

This paper proposed Texture Based Image Retrieval Using GLCM and image sublock. The database used in this experiment is Texture library images database. The texture features are extracted based on GLCM (Gray Level Co-occurrence Matrix) using four statistic features that is contrast, homogenity, energy and corelation. These four features are computed in four directions (0^0, 45^0, 90^0, and 135^0). A total of 16 texture values are computed per an image sub-block. The image is divided into nine sub-blocks in equal size.

From the experiment of the study the retrieval result of texture features using both Euclidean distance and City Block distance has high precision. The effectiveness of retrieval result using City Block distance is better than the result using Euclidean distance. In order to improve the effectiveness of the study, method proposed should combine with other feature and extent the number of image database to be tested.

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