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Texture Feature based Image Retrieval Algorithms

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***Abstract*— Image Retrieval is the process of retrieving the most closely matched images automatically by extracting the basic features such as edge, shape, color and textures from the query image. The proposed image retrieval system is used texture feature by using grey – level co-occurrence matrix (GLCM) and Color Co – occurrence matrix (CCM). The GLCM and CCM separately combined with a color feature with the use of quantization of HSV color space. The multi-feature extraction is achieved through the Euclidean distance classifier. The proposed system performance is also measured by conducting experiments in different ways.**

***Index Terms*— Feature extraction, Texture, Image retrieval, Euclidian distance**

I. Introduction

Texture is another important property of images. Texture is a powerful regional descriptor, which helps in the retrieval process. Texture, on its own does not have the capability of finding similar images, but it can be used to classify textured images from non-textured ones and then be combined with another visual attribute like color to make the retrieval more effective. Texture has been one of the most important characteristic which has been used to classify and recognize objects and have been used in finding similarities between images in multimedia databases [1]. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, they describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform. Characterize texture by the statistical distribution of the image intensity [2]. There are many researchers worked on CBIR survey [3]-[5], texture feature extraction [9] [16], multi-feature [11]-[12] algorithms for retrieving image.

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A. *Gray level co-occurrence matrix:*

Gray level co-occurrence matrix (GLCM) is well known and widely used methods to extract texture feature [18]. The co-occurrence matrix is defined by joint probability density of two pixels which have different positions. It not only reflects the brightness distribution characteristics, but also shows position distribution characteristics of pixels which have the same brightness or close to it. The co-occurrence matrix is second order statistical characteristics related to image brightness changes. It is the foundation that local pattern and arrangement rules of images are analysis. For a digital image f of size $M \times N$, which is denoted as $I(x, y)$. It's gray level is defined as $P(i, j \mid d, \theta)$. The Gray Level co-occurrence Matrix is defined as

$$p(i,j \mid d,0) = \#\{(x1,y1),(x2,y2) \in M \times N \\ I(x1,y1)=i, I(x2,y2)=j, \mid x1-x2 \mid = 0, \mid y1-y2 \mid = d\}$$
(1)

$$P(i,j \mid d,45) = \#\{(x1,y1),(x2,y2) \in M \times N \\ I(x1,y1)=i, I(x2,y2)=j, (x1-x2=d, y1-y2=-d) \\ or (x1-x2=-d, y1-y2=d)\}$$
(2)

$$P(i,j \mid d,90 = \#\{(x1,y1),(x2,y2) \in M \times N \\ I(x1,y1)=i, I(x2,y2)=i, I(x2,y2)=j, \mid x1-x2 \mid = d, \mid y1-y2 \mid = 0\}$$
(3)

$$p(i,j \mid d,135) = \#\{(x1,y1),(x2,y2) \in M \times N \\ I(x1,y1)=i, I(x2,y2)=j, (x1-x2=d, y1-y2=d) \\ or (x1-x2=-d, y1-y2=-d)\}$$
(4)

Where the $\#\{\}$ is the number of occurrences of the pair of gray level i and j, which are a distance d apart. The angle is denoted as θ between the pair of gray level and the axis. ($\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$ four directions). So this Gray level Co-occurrence is defined as $P(i, j \mid d, \theta)$ according to the distance d and the angle θ.

An Example of Gray Level co-occurrence Matrix, the following Figure 4-1 shows how co-occurrence matrix calculates the first three values in a Gray Level Co-occurrence Matrix. In the output Gray Level co-occurrence Matrix, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively element(1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the Gray Level Co-occurrence Matrix has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Co-occurrence matrix continues processing the input image, scanning the image for other pixel pairs (i, j) and recording the sums in the corresponding elements of the Gray level co-occurrence matrix.

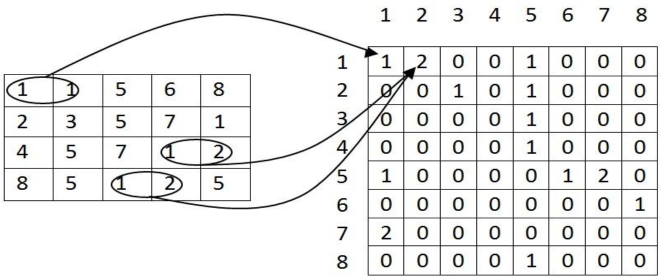

Figure 1: Example of Gray Level Co-occurrence Matrix

Gray Level co-occurrence is composed of the probability value: it is defined by $P(i, j \mid d, \theta)$ which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, $P(i, j \mid d, \theta)$ is showed by $p_{i,j}$.

Distinctly Gray Level Co-occurrence Matrix is a symmetry matrix; its level is determined by the image gray-level. Elements in the matrix are computed by the equation showed as follow:

$$p(i, j \mid d, \theta) = \frac{p(i, j \mid d, \theta)}{\sum_{i=1}^{256} \sum_{j=1}^{256} p(i, j \mid d, \theta)} \tag{5}$$

Gray Level Co-occurrence Matrix expresses the texture feature according the correlation of the couple pixels Gray-Level at different positions. It quantification ally describes the texture feature, In this proposed method, four features is selected, include energy, contrast, entropy, inverse difference.

$$\text{Energy}: \quad E = \sum_{x=1}^{256} \sum_{y=1}^{256} p(x, y)^2 \tag{6}$$

Energy is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$\text{Contrast}: \quad I = \sum_{x=1}^{256} \sum_{y=1}^{256} (x-y)^2 p(x, y) \tag{7}$$

Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. A larger contrast would mean a deeper texture.

$$\text{Entropy}: \quad S = -\sum_{x=1}^{256} \sum_{y=1}^{256} p(x, y) \log p(x, y) \tag{8}$$

Entropy measures image texture randomness, when the space co-occurrence matrixes for all values are equal, it achieved the minimum value; on the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

Inverse difference:

$$H = \sum_{x=1}^{256} \sum_{y=1}^{256} \frac{1}{1+(x-y)^2} p(x, y) \tag{9}$$

Inverse difference measures local changes in image texture number. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly.

II. Methodology

The texture feature is extracted by grey co-occurrence matrix and co-occurrence matrix in which the results of those two methods are used in the Euclidean Distance function to get the exact match of the images.

A. Image Database

The experimental data set contains 1000 images from the Corel database [14]. The Images divided into 10 categories and each category contains 100 images of size 256x384 or 384x256.

B. Image to Feature Vector

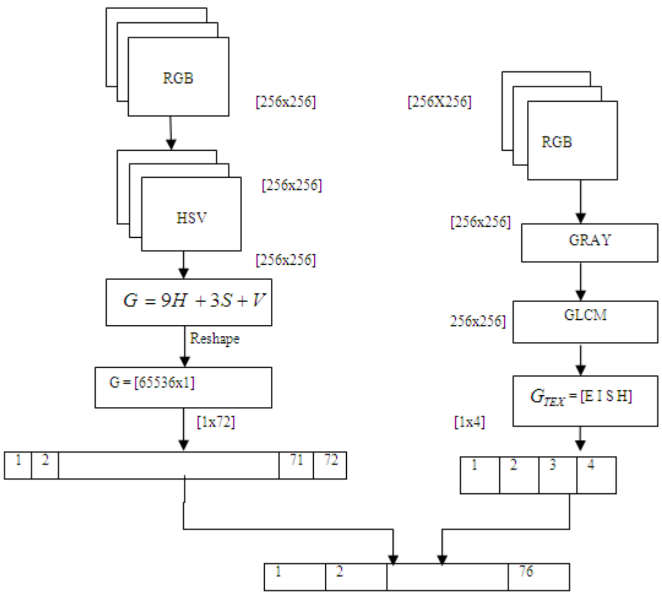

Figure 4: Derivation of the Feature Vector of GLCM

The above figure represents the extraction of texture features using GLCM. In the extraction of the feature vector process, the RGB images are converted to grey scale images. The GLCM method creates a symmetric matrix composed of the probability value based on the distance and the direction amongst the pixels of the image. The level of the images is determined by the image grey level. From the matrix obtained by GLCM the statistical features such as Energy, Contrast, Entropy, inverse difference (6)-(9) are computed to form a 4-dimensional texture feature.

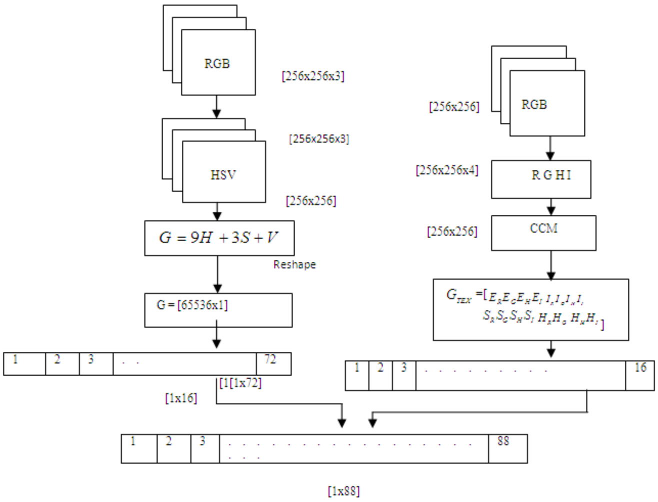

Figure 5: Derivation of the Feature Vector of CCM

The color components R, G in RGB color space I and H in HSV color space are respectively are extracted based on the co-occurrence matrix with a direction of $90°$. The statistic features extracted from the co-occurrence matrix are as follows: Energy, Contrast, Entropy, Inverse difference shown as (6) to (9). In this method, a 16 dimensional texture feature is obtained from the components of R, G, H, I and their respective statistic values such as E, I, S and H.

C. Feature Extraction Algorithm based on GLCM

The following steps shows the process of how the image retrieval using the grey level co-occurrence matrix.

Step 1: Separate the R, G, B planes of the images.
Step 2: Convert the Color channel conversion R, G, B to the grey level scale.
Step 3: Compute GLCM matrices as given by Equation (2)
Step 4: Probability value of GLCM as given by Equation (5)
Step 5: Probability value of GLCM matrix compute the statistical feature Energy, Entropy, Contrast, Inverse Difference as given by Equation (6)-(9).
Step 6: Normalize the Energy, Entropy, Contrast, Inverse difference values.
Step 7: Query image constructed by cumulative HSV color histogram.
Step 8: Construct a combined feature vector for color and texture.
Step 9: Calculate the Euclidean distance between the constructed normalized and texture feature vector of the query image and the database image.
Step 10: Retrieve the first 10 most similar images with minimum distance.

A query image will be converted into the grey scale after which it creates a GLCM matrix with the directions and distance between pixels, composed by the probability value. The statistical features, Energy, Entropy, Contrast and Inverse Difference are computed for each GLCM matrix. The similarity of each of the images is measured from the two types of characteristic features such as the color features and the texture features. The Euclidean similarity is measured to combine. The distance values are then sorted accordingly in ascending order. Display the matches showing the ten best images.

D. Feature Extraction Algorithm based on CCM

Step 1: Separate the R, G, B planes of the images.
Step 2: Convert the Color channel conversion R, G, B to H, S, V scale.
Step 3: Separate the R, G, H, I planes of the image.
Step 4: Repeat steps 5-6 for each plane
Step 5: Compute GLCM matrices as given by Equation (2)
Step 6: Probability value of GLCM as given by Equation (5)
Step 7: Probability value of the GLCM matrix compute the statistical feature Energy, Entropy, Contrast, and Inverse Difference as given by Equation (6)-(9).
Step 8: Query image constructed by cumulative HSV color histogram.
Step 7: Construct a combined feature vector for color and texture.
Step 9: Find the distances between the feature vector of the query image and the feature vectors of the target images using the normalized Euclidean distance.
Step 10: Retrieve the first 10 most similar images with minimum distance.

A query image will be converted into the R, G in RGB color space and H, I in HSV color space and create a CCM matrix with the directions and distance between pixels, composed by the probability value. For each CCM matrix the statistical features such as Energy, Entropy, Contrast and Inverse Difference are computed. The similarity between each of the images is measured from two types of characteristic features such as color features and texture features. The Euclidean similarity measured to combine. The distance values are then sorted accordingly in ascending order. Display the matches showing the ten best images.

E. Distance Calculation

The distance between two images is used to compare and find the similarity between query image and the images in the database. Finding the distance between the feature vectors is similar to that of finding the similarity between the feature vectors. In this method the proposed method used the Euclidean distance between the two feature vectors.

Let $P = (p_1, p_2, ... p_n)$ and $Q = (q_{1,} q_2, ... q_n)$ are two points in an n – dimensional space. Then the distance can be calculated as follows: The Euclidean distance between two vectors P and Q is defined as

$$d(P,Q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + ... + (p_n - q_n)^2} \quad (10)$$

F. Method of Evaluation

The feature vectors of all the images are calculated using HSV, GLCM and CCM. The resultant feature vectors are then stored in the database for further comparison. In the proposed system the retrieved image is compared with the exact image from the same category of the query image Q. The accuracy is calculated by the equation (11). Let $N_{returned}$ is the number of images that are returned to the user after a query has been made. Out of the $N_{returned}$ image, $N_{corrent}$ is the number of images that belongs to the same category as the query image Q. Precision *P* for a query image Q is defined as

$$P_Q = \frac{N_{correct}}{N_{returned}} \times 100 \qquad (11)$$

The greater the value of value *P*, the more accurate is the system.

III. RESULT AND DISCUSSION

A. *Graphical User Interface*

MATLAB was used to develop the frontend GUI for the IR application. Figure 7 shows a screenshot taken from the application.

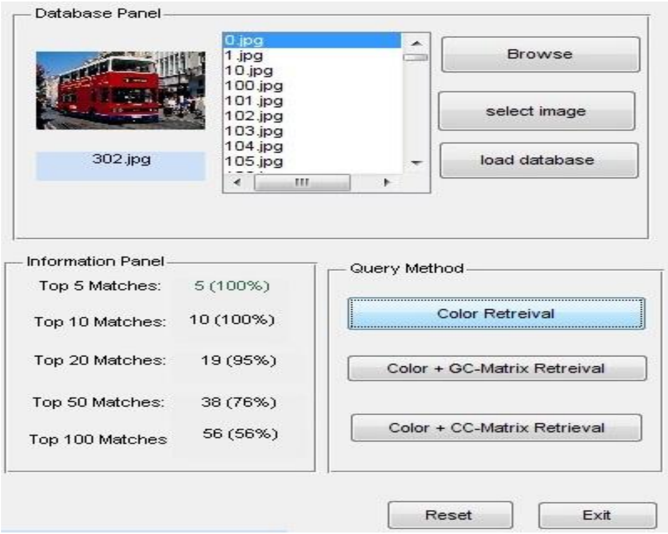

Figure 7: GUI of the CBIR System for user control

The Image Retrieval application provides user with two options to query an image. The user can click on “Browse” and select a folder which lists all the images in the list-box, or click on “Select Image” and click the “load database”. The user can select the Query Method. The system will perform the necessary processing and display ten best matched images. A green box indicates a correct returned image while a red box indicates a wrong image. The user could see the display of result. If the user wants to change the image can click “Reset” or Click “Exit” to exit the application.

B. *Performance Evaluation*

Table 1 shows the overall average precision for top 10 images. An overall precision by GLCM is 82.92 percent and CCM is 82.7 percent.

Table 1: Percentage of image retrieval GLCM vs. CCM

Category	**GLCM**	**CCM**
Africans	85.3	86.33
Beaches	65	63
Monuments	74	76
Buses	93	95.33
Dinosaurs	98	98.33
Elephants	69.33	71.3
Flowers	97	95.33
Horses	94	93.33
Mountains	69.3	65
Food	84.33	84
Average Precision	82.92	82.7

Table 2 Average precision by GLCM for top different number retrieved images

Category	**Gray Level Co-occurrence Matrix**				
	TOP 5	**TOP 10**	**TOP 20**	**TOP 50**	**TOP 100**
African	93.3	85.3	80	65	52.1
Beaches	72	65	55.16	42.12	34.2
Monuments	82.6	74	62.1	44.66	33.06
Buses	92.66	93	81.5	76.33	59.8
Dinosaurs	98	98	95.8	85.06	63.26
Elephants	76.6	69.33	53.16	37.33	27.13
Flowers	98	97	93.1	77.6	53.46
Horses	94.6	94	91.5	80.8	77
Mountain	79.3	69.3	71.6	44.6	35.4
Food	86.66	84.33	74.5	64.33	51.26
Average Precision	96.57	82.92	85.42	61.78	48.6

Table 3 Average precision by CCM for top different number of retrieved images

Category	**Co-occurrence Matrix**				
	TOP 5	**TOP 10**	**TOP 20**	**TOP 50**	**TOP 100**
African	88	86.33	81.16	66.46	52.6
Beaches	72	63	53.83	43.73	36.5
Monuments	82	76	61.6	44.53	34.43
Buses	91.33	95.33	87	75.93	60.53
Dinosaurs	98	98.33	98.16	94.86	75.8
Elephants	84	71.3	56.33	95.6	46.3
Flowers	97.3	95.33	85.5	95.6	46.3
Horses	93.33	93.33	95.5	87.73	76.93
Mountain	72.66	65	56.66	45.2	39.6
Food	91.33	84	82.66	63.55	48.06
Average Precision	86.9	82.7	66.84	65.7	49.87

It can be seen that GLCM given better result value than the CCM for top retrievals.

IV. CONCLUSION

This proposed method provides an approach based on HSV color space and texture characteristics of the image retrieval. The similar two types of characteristic measure color and texture features. Through the quantification of HSV color space, we combine color features and gray-level co-occurrence matrix as well as co-occurrence matrix separately, using normalized Euclidean distance classifier. Through the image retrieval experiment, indicating that the use of color features and texture characteristic of the image retrieval method is superior to a single color image retrieval methods, and color characteristics combining color texture features for the integrated characteristic of color image retrieval has obvious advantages retrieval. In future, we can expect to use color and shape for the retrieval of the images. We have to find the other ways to reduce the computational cost but without reducing the accuracy.

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