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IMAGE RETRIEVAL USING QUADRATIC DISTANCE BASED ON COLOR FEATURE AND PYRAMID STRUCTURE WAVELET TRANSFORM AND GLCM BASED ON TEXTURE FEATURE

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Abstract— **Content Based Image Retrieval (CBIR) is one of the most active in the current research field of multimedia retrieval. It retrieves the images from the large databases based on images feature like color, texture and shape. In this paper, Image retrieval based on multi feature fusion is achieved by color and texture features as well as the similarity measures are investigated. The work of color feature extraction is obtained by using Quadratic Distance and texture features by using Pyramid Structure Wavelet Transforms and Gray level co-occurrence matrix. We are comparing all these methods for best image retrieval.**

Index Terms— **Quadratic Distance Metric, Pyramid Structure Wavelet Transforms, Gray Level Co-occurrence Matrix**.

I. INTRODUCTION

CBIR aim to recover pictures from large image repositories, according to the user's interest. Usually, a CBIR system represents the images in the repository as a multi-dimensional feature vector extracted from a series of low level descriptors, such as color, texture or shape. The subjective similarity between two pictures is usually quantified in terms of a particular measure of distance defined on the corresponding multi-dimensional feature space. In this paper we proposed a method in which both color and texture features of the images are used to improve the retrieval results in terms of its accuracy. In CBIR, images can be retrieve based on visual features such as color, texture and shape. In Traditional methods like image indexing, keyword have proven to be insufficient. In CBIR, every image can be stored in the database and its features extracted and compared to the features of the query image. Like this we can get the similar images based on the query image.

A. Color

Computing distance measures based on color similarity is achieved by computing a color histogram for each image that identifies the proportion of pixels within an image holding specific values. Examining images based on the colors they contain is one of the most widely used techniques because it can be completed without regard to image size or orientation. However, research has also attempted to segment color proportion by region and by spatial relationship among several color regions.

B. Texture

Texture measures look for visual patterns in images and how they are spatially defined. Texture are represented by texels which are then placed into a number of sets, depending on how many textures are detected in the image. These sets not only define the texture, but also where in the image the texture is located. Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness, and directionality may be estimated.

II. COLOR FEATURE CALCULATIONS

A. Quadratic Distance Metric

We use Quadratic Distance Metric for image classification. This method is used to describe the distance between two color histogram:

$$D^2(Q,I) = (H_Q - H_I)^t A (H_Q - H_I)$$

In Quadratic distance method, images can be retrieve using color histogram of images. In The above equation defines three terms. The first term $(H_Q - H_I)$ defines the difference between two color histograms or we can say that it indicates number of pixels differences in each bin. The number of bins in a histogram is defined by number of vector column. Vector transpose $(H_Q - H_I)^t$ is denoted by the third term. Similarity matrix (A) is defined by middle term. Color distance between the two images is represented by D. Based on the D value we can retrieve similar images. When comparing the query image with database image, if the both images distance zero, we can get the similar images to the query image, otherwise less color similarity images will have greater distance from zero.

B. Similarity Measure

Instead of depending upon exact matching, we calculate visual similarities between a query image and images in a large database. Hence the result of retrieval image is not a single image but a list of images ranked by their similarities with the query image. Many similarity measures have been developed for image retrieval based on observed estimates of the distribution of features in recent years. Performance of an image retrieval system is dependent on the type of similarity measures used. By using below similarity matrix equation obtained through a complex algorithm.

$$\mathbf{A = [a_{q,i}]}$$

$$\mathbf{A_{q,I} = 1 - [(v_q - v_i)^2 + (s_q\cos(h_q) - s_i\cos(h_i))^2 + (s_q\sin(h_q) - s_i\sin(h_i))^2]^{1/2}}$$

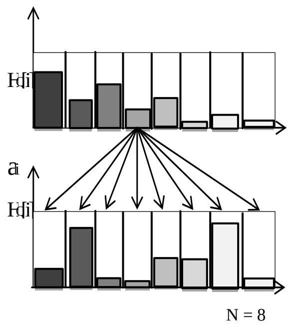

Fig.1 Quadratic Distance Approach

This is continue until we have compared all the color bins of H_Q. By doing we get an N×N matrix, N representing the number of bins. Which indicates whether the color patterns of two histograms are similar is the diagonal entirely consists of ones then the color patterns are identical. The further the numbers in the diagonal are from one, the similar the color patterns are. Thus the problem of comparing totally unrelated bins is solved.

III. Texture Calculation

Texture is that typical property of all surfaces and it describes visual patterns, each having properties of homogeneity. Texture is nothing but information about the structural arrangement of surface, such as; clouds, leaves, bricks, fabric, etc. It also relation between the surface to the surrounding environment. In short, it is a feature that describes the distinctive physical composition of a surface.

Texture properties include (Coarseness, contrast, directionality, regularity, roughness) texture is one of the most important defining features of an image. It is characterized by the spatial distribution of gray levels in a neighborhood. In order to capture the spatial dependence of gray-level values, which describe the images of texture, a two dimensional dependence texture analysis matrix is taken into consideration. The two dimensional matrix have different file formats like: .jpg, .bmp, .tip, etc.

A. Pyramid Structure Wavelet Transform

The pyramid structured wavelet transform is used for texture classification. All images can be decompose at the low level sub-band to get accurate results, so we all this method as Pyramid Structure wavelet. Due to the innate image properties that allows the most information will provide in lower sub-bands, the pyramid structured wavelet transform is more acceptable.

Using the pyramid-structured wavelet transform, the image can be decomposed into four sub images, in low- low, low-high, high-low and high-high sub-bands. We are calculate the energy level of each sub-band. This is first level decomposition. Using the low-low sub-band for further decomposition, in this paper, we reached to fifth level decomposition. The reason for this is the basic assumption that the energy of an image is concentrated in the low-low band and to get accurate values.

1) Energy Level Algorithm:

a) Image can be decompose into four sub-images.

b) Calculate the energy of all decomposed images at the same scale, by using E.

Where ***M*** and ***N*** are the dimensions of the image, and ***X*** is the intensity of the pixel located at row ***i*** and column ***j*** in the image map.

c) Repeat from step 1 for the low-low sub-band image, until index ***ind*** is equal to 5. Increment ***ind***.

Using the above algorithm, the energy levels of the sub-bands were calculated and further decomposition of the low-low sub-band image. This is repeated five times, to reach fifth level decomposition. These energy level values are stored to be used in the Euclidean distance algorithm.

2) Euclidean Distance:

Euclidean Distance Algorithm

a) Decompose query image
b) Get the energies of the first dominant ***n*** channels.
c) For image ***i*** in the database obtain the ***n*** energies.
d) Calculate the Euclidean distance between the two sets of energies, using D.
$D_{i=}\sum_{n=1\wedge n(}x_n-y_{i,n})^2$
e) Increment i. Repeat from step 3.

Using the above algorithm, the query image is searched from the image database. The Euclidean distance is calculated between the query image and images in the database. This process will continue until all the images in the database have been compared with the query image. Upon completion of the Euclidean distance algorithm, we have an array of Euclidean distances, which is then sorted. The ten topmost images are then displayed as a result of the texture search.

IV. Gray Level Co-occurrence Matrix (GLCM)

GLCM creates a matrix based on the directions and distances between pixels, and extracts the statistics from the matrix as texture features. GLCM texture features commonly used are shown in the following:

GLCM is composed of the probability value, it is defined $P(i,j \mid d,\theta)$ which express the probability of the couple pixel 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 GLCM is a symmetry matrix, Elements in the matrix are computed by the below equation:

$P(i,j \mid d,\theta)= P(i,j \mid d,\theta))/(\sum i\sum jP(i,j \mid d,\theta))$

GLCM expresses the texture feature according the correlation of the couple pixels Gray level at different positions. It direction describes the texture features. But here mainly four things are considered they are energy, contrast, entropy and the inverse difference.

1) Energy

$E = \sum x\sum yP(x,y)^2$

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

2) *Contrast*

$I = \sum\sum (x-y)^2 P(x, y)$

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Contrast describe the distribution of pixel power, Which measures the value of the matrix is distributed and images of local changes in the number, reflecting the image clarity and the texture of the shadow depth if the contrast is large then the texture is deeper.

3) Entropy

$$\mathbf{S} = -\sum_x \sum_y P(x,y)\log P(x,y)$$

Entropy measures image texture irregular, when the space co-occurrence matrix 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.

***4)** Inverse difference*

$$H=\sum_x \sum_y (1/(1+(x-y)^2))\, P(x, y)$$

It 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.
Here p(x, y) is the gray level.

V. RESULTS

A. WANG Database

The database we used in our evaluation in WANG database. The WANG database is a subset of the Corel database of 10000 images. This is a major advantage of this database because due to the given classification it is possible to evaluate retrieval results. This database was used extensively to test many CBIR system because this size of the database and the availability of class information allows for performance evaluation. This database was created by the group of professor Wang from the Pennsylvania State University and is available for download.

Database

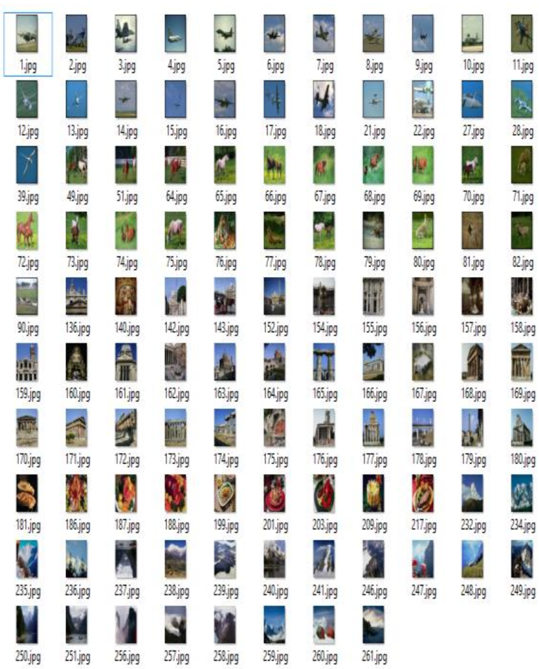

Fig.2 Database Image (More Images)

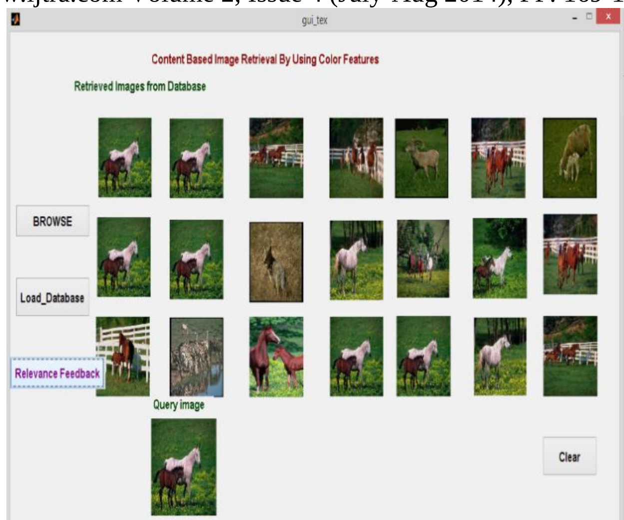

Fig.3 Color Feature Results using Quadratic Distance

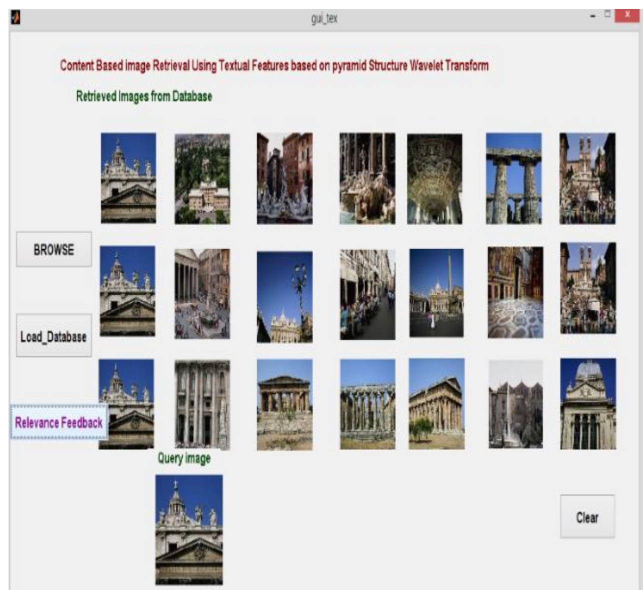

Fig.4 Texture Feature Results using Pyramid Structure Wavelet Transform

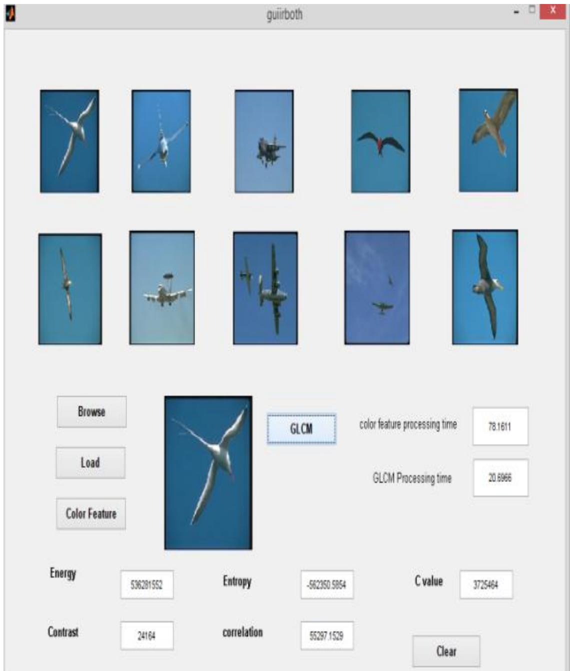

Fig.5 Texture Feature Results using Gray Level Co-occurrence Matrix (GLCM)

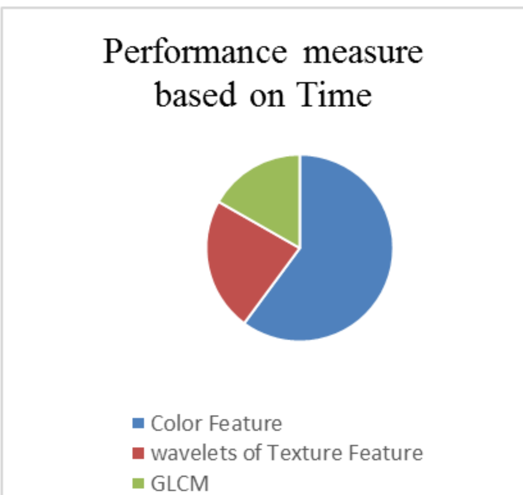

Fig.6 Performance of Color and Texture Features Based on Time

VI. CONCLUSION

In this project we are analyzing an integrated approach of color and texture features of image content descriptor and metadata based system for different gallery image database. This proposed algorithm will provides an effective approach for query based image retrieval system. The timing results for the integrated approach will be less and accurate, this can be improved by integrating other spatial relationship.

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