Content Based Image Retrieval Using GLCM & CCM

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Abstract—The growth of digital image archives is increasing the need for the tools that effectively filter and efficiently search through large amounts of visual data. Towards this goal we propose a technique by which the color content and texture features of images is automatically extracted by using content based image retrieval (CBIR). CBIR has become one of the most active research areas in the past few years. Many visual feature representations have been explored. Image CBIR is emerging as an important research area with application to digital libraries, data mining, education, medical imaging, crime prevention and multimedia databases. The focus is on image processing aspects and in particular using color and texture features. Color feature is extracted by HSV. The color feature is represented by color histogram and texture feature extraction is obtained by using gray-level co-occurrence matrix (GLCM) or color co-occurrence matrix (CCM). Through the quantification of HSV color space, we combine color features and GLCM as well as CCM separately.

Keywords- Digital Image, color, CBIR, GLCM & CCM.

1 .Introduction

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases..

"Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results.

In CBIR, images in database are represented using such low level image features as color, texture and shape, which are extracted from images automatically. Among this level features, color features are the most widely used features for image retrieval because color is the most intuitive feature and can be extracted from images conveniently. However image retrieval using color and features often gives disappointing results, because in many cases, image with similar colors do not have similar content. This is due to the global color features computed often fails to capture color distributions or textures within the image. Several methods have been proposed to incorporate special color information in attempt to avoid color confusion by machine. However, this methods often results in very high dimensions of features which drastically slow down the retrieval speed of the system. In this paper we propose a method combining both color and

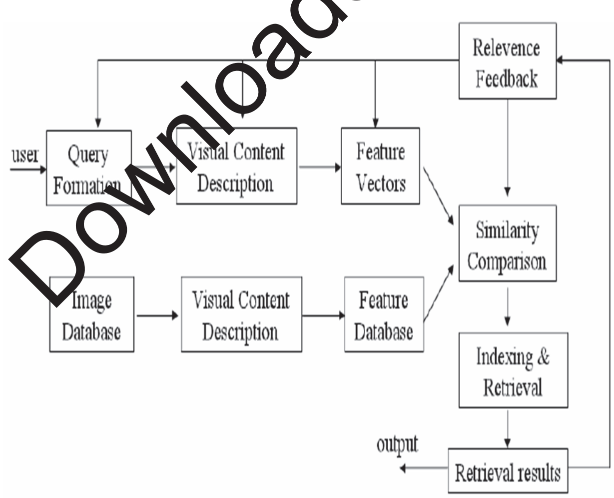

Diagram for content-based image retrieval system texture features to improve retrieval performance. We compute both the color and texture features from the images and images in the database are indexed using both type of features. During retrieval process, given a query image, images in the database are firstly ranked using color features. Then in the second process, a number of top ranked images are selected and re–ranked according to their texture features. Because the texture features are extracted globally from the image, they are not an accurate description of the image in some cases. Therefore, we provide two alternatives to user, one is the retrieval based on color features, and the other is retrieval based on combined features. When the retrieval based on color fails, the user will use the other alternative which is the combined retrieval.

2. Color Feature Extraction

Basically there are three properties or three dimensions of color that being hue, saturation and value HSV means Hue, Saturation and Value. It is important to look at because it describes the color based on three properties. It can create the full spectrum of colors by editing the HSV values. The first dimension is the Hue. Hue is the other name for the color or the complicated variation in the color. The quality of color as determined by its dominant wavelength. This Hue is broadly classified into three categories. They are primary Hue, Secondary Hue and Tertiary Hue.

Saturation is the degree or the purity of color. Then the second dimension is the saturation. Saturation just gives the intensity to the colors. The saturation and intensity drops just by mixing the colors or by adding black to the color. By adding the white to the color in spite of more intense the color becomes lighter. Then finally the third dimension is the Value. The value is the brightness of the color. When the value is zero the color space is totally black with the increase in the color there is also increase in the brightness and shows the various colors. In accordance with the quantization level above, the H, S, V three-dimensional feature vector for different values of with different weights to form one dimensional feature vector and is given by the following equation:

G = Qs*Qv*H+Qv*s+V

Where Qs is the quantized series of S and Qv is the quantized series of V. And now by setting

$$H=\begin{cases}0 & \text{if } h\in[316,20]\\ 1 & \text{if } h\in[21,40]\\ 2 & \text{if } h\in[41,75]\\ 3 & \text{if } h\in[76,155]\\ 4 & \text{if } h\in[156,190]\\ 5 & \text{if } h\in[191,270]\\ 6 & \text{if } h\in[271,295]\\ 7 & \text{if } h\in[296,315]\end{cases}$$

$$S=\begin{cases}0 & \text{if } s\in[0,0.2)\\ 1 & \text{if } s\in[0.2,0.7)\\ 2 & \text{if } s\in[0.7,1)\end{cases}$$

$$V=\begin{cases}0 & \text{if } v\in[0,0.2)\\ 1 & \text{if } v\in[0.2,0.7)\\ 2 & \text{if } v\in[0.7,1)\end{cases}$$

Qs = Qv = 3, Then G = 9H+3S+V

In this way three component vector of the HSV from one dimensional vector, Which quantize the whole color space for the 72 kinds of the main colors. So we can handle 72 bins of one dimensional histogram. This qualification is effective in reducing the images by the effect of the light intensity, but also reducing the computational time and complexity.

3. Proposed Method

We are proposing two algorithms for image retrieval based on the color histogram and wavelet-based color histogram.

3.1 Color Histogram

Step-1. Convert RGB color space image into HSV color space

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Step-2. Color quantization is carried out using color histogram by assigning 8 level each to hue , saturation and value to give a quantized HSV space with 8*8*8=512 histogram bins

Step-3. The normalized histogram is obtained by dividing the total number of pixels.

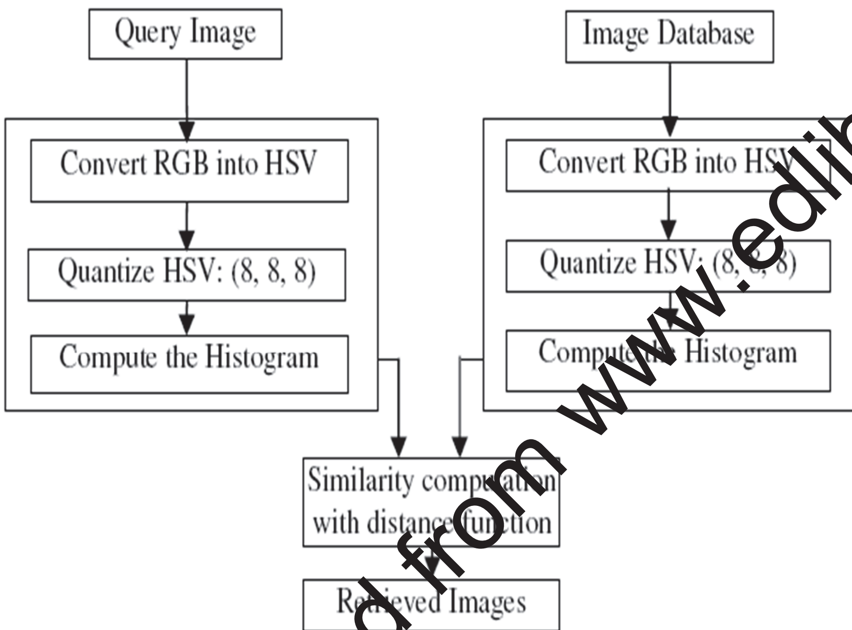
Step-4. Repeat step-1 to step-3 on an image in the database.

Step-5. Calculate the similarity matrix of query image and image present in the database.

Step-6. Repeat the steps from 4 to 5 for all the images in the database.

Step-7. Retrieve the images.

3.2 Wavelet-Based Color Histogram (WBCM)



Block diagram of proposed Color Histogram

Step1. Extract the red, Green and Blue components from an image.

Step2. Decompose each Red, Green and Blue Component using Haar wavelet transformation at 1st level to get approximate coefficient and vertical, horizontal and diagonal detail coefficients.

Step3. Combine approximate coefficient of Red, Green and Blue component.

Step4. Similarly combine the horizontal and vertical coefficients of Red, Green and Blue component.

Step5. Assign the weights to approximate components to horizontal and vertical coefficients.

Step6. Convert the approximate, horizontal and vertical coefficients into HSV plane.

Step7. Color quantization is carried out by color histogram by assigning 8 level to HSV space with 8*8*8=512 histogram bins.

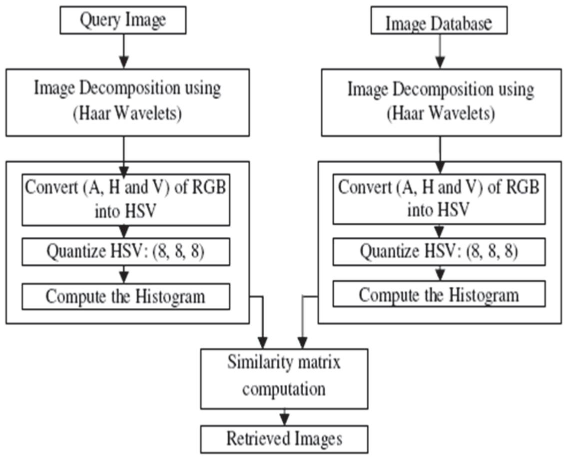
Step8. The normalized histogram is obtained by dividing with total number of pixels.

Step9. Repeat step1 to step8 on an image in the database.

Step10. Calculate the similarity matrix of query image and image present in database.

Step11. Repeat the steps from9 to 10 for all the images in the database.

Step12. Retrieve the images.

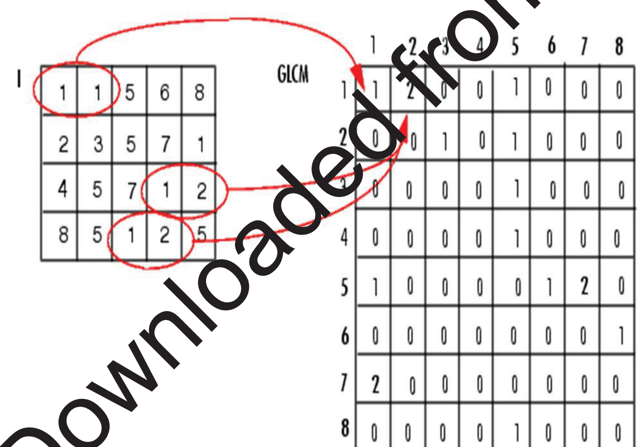


Block diagram of proposed Wavelet-Based Color Histogram (WBCH).

4. Texture Feature Extraction by GLCM

Gray-co-matrix function can be used to create the GLCM (Gray level co-occurance matrix). Graycomatrix function calculates how often the relationship between the pixel value i occurs with respect to the pixel value j. The pixel to its immediate right and by default the spatial relationship is defined as the pixel of interest. Even though the spatial relation between the two pixels is verified. Each element in the GLCM is nothing but the sum of the number of times that the pixel value i occurs with relation to the pixel value j.in the input image. For the full dynamic range of an image the processing required to calculate a GLCM is prohibitive. The input image was scaled by the gray matrix. By default to reduce the intensity values from 256 to 8 in Grayscale image graycomatrix use scaling. Using the num levels and the gray limits parameters of the graycomatrix function the number of gray levels and the scaling of the intensity values in the GLCM can be controlled. The properties about the spatial distribution of the Gray level in the texture image can be revealed by the Gray level co-occurance matrix.

The following figure shows how gray co matrix calculates the first three values in a GLCM. In the output GLCM, 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. GLCM (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 GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. Gray co- occurance continues processing the input image, scanning the image for other pixel pairs (*i, j*) and recording the sums in the corresponding elements of the GLCM.



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

Energy:

$$E = \sum_x \sum_y p(x,y)^2$$

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.

Contrast:

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

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Contrast is the main diagonal near the moment of inertia, 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.

Entropy:

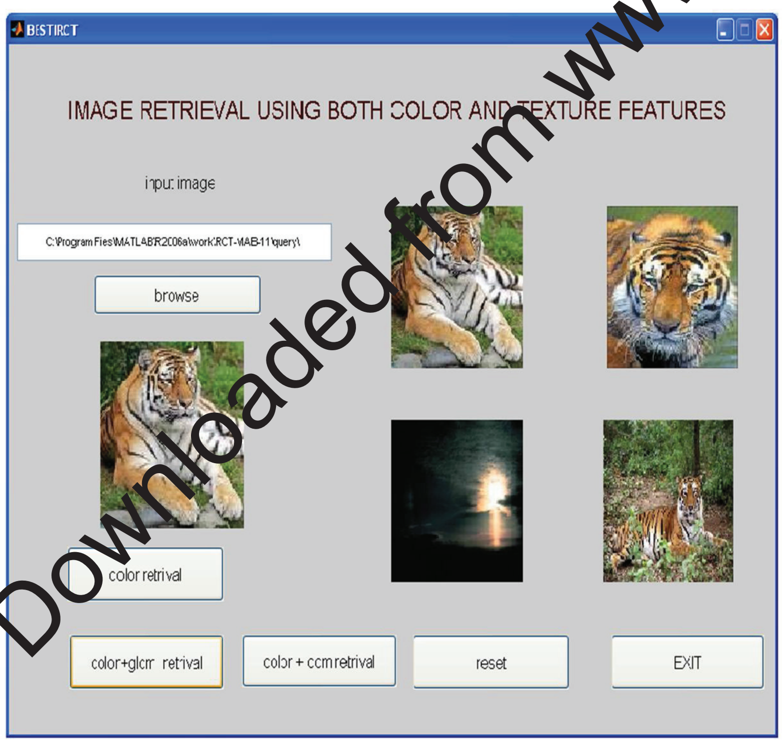
$$S = -\sum_x \sum_y p(x,y) \log p(x,y)$$

Entropy measures image texture randomness, when the space co- occurrence matrix for all values is 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:

$$H = \sum_x \sum_y \frac{1}{1+(x-y)^2} p(x,y)$$

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 value at the co ordinate (x , y).



4.1 Texture Feature Extraction Based on CCM

A co-occurance matrix or co-occurance distribution is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset. Mathematically a co-occurance matrix c is defined over an n*m image I, Parameterized by an offset. The value of the image originally referred to the grayscale value of the specified pixel. The value could be anything, from a binary on/off value to 32-bit color and beyond. Note that 32-bit color will yield a 2^{32}x2^{32} co-occurrence matrix. Really any matrix or pair of matrices can be used to generate a co-occurrence matrix, though their main applicability has been in the measuring of texture in images, so the typical definition, as above, assumes that the matrix is in fact an image. It is also possible to define the matrix across two different images. Such a matrix can then be used for color mapping. The statistic features extracted from the CCM are as follows:-

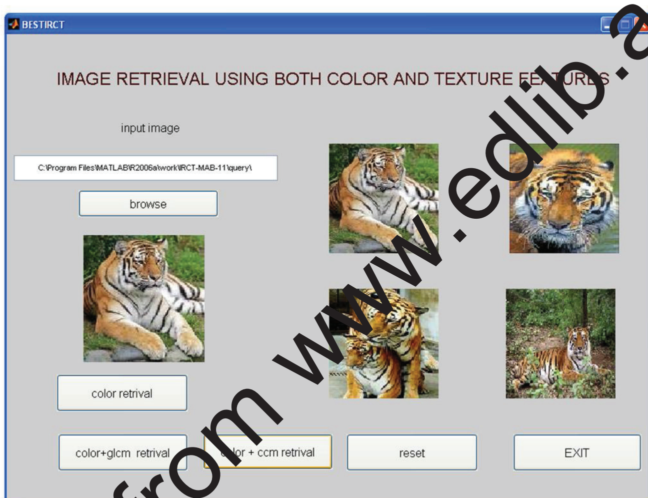
$$\text{Energy} \quad E = \sum_{i=1}^{D} \sum_{j=1}^{D} [m(i,j)]^2$$

$$\text{Contrast} \quad I = \sum_{i}^{D} \sum_{j}^{D} (i-j)^2 \bullet m(i,j)$$

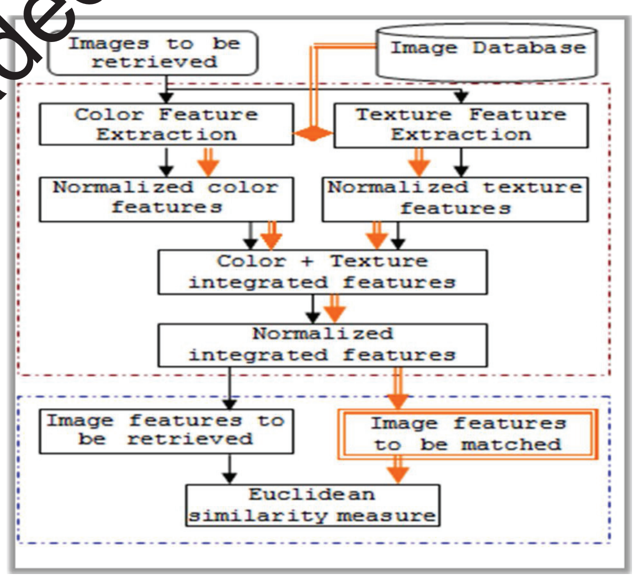
$$\text{Entropy} \quad S = -\sum_{i}^{D} \sum_{j}^{D} m(i,j) \bullet \log[m(i,j)]$$

$$\text{where,} \quad \text{if} \quad m(i,j) = 0, \quad \log[m(i,j)] = 0$$

$$\text{Inverse difference} \quad H = \sum_{i}^{D} \sum_{j}^{D} \frac{m(i,j)}{1+(i-j)^2}$$



5. Algorithm



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6. Applications

1. In the military to find tanks or airstrips.
2. In urban development to determine the extent of housing sprawl.
3. In local government to track highway assets.

7. Conclusion

We presented a novel approach for Content Based Image Retrieval by combining the color and texture features called Wavelet-Based Color Histogram Image Retrieval (WBCHIR). Similarity between the images is ascertained by means of a distance function. The experimental result shows that the proposed method outperforms the other retrieval methods in terms of Average Precision. Moreover, the computational steps are effectively reduced with the use of Wavelet transformation. As a result, there is a substation ally increase in the retrieval speed. The whole indexing time for the 1000 image database takes 5-6 minutes.

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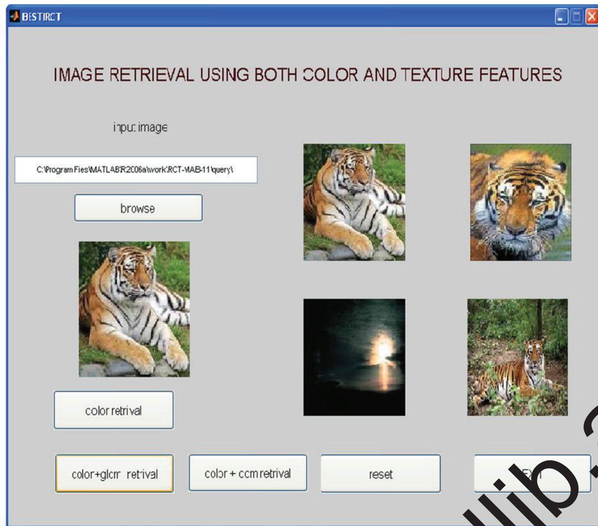
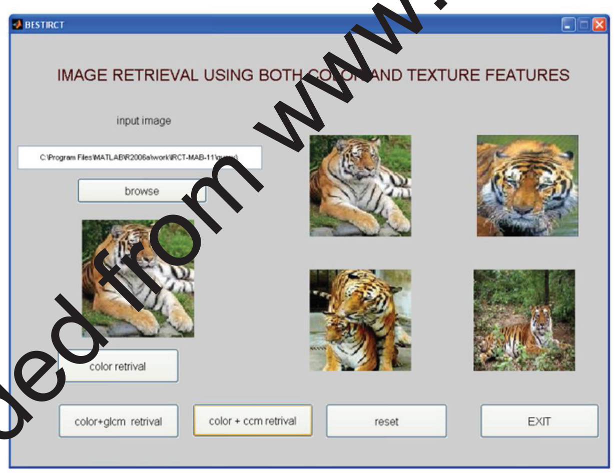
Experiment Results

1. Color + GLCM retrieval



2. Color + CCM retrieval



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