Image Retrieval using Wavelet Transform and Color Histogram

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Abstract— In many application areas such as education, crime prevention, commerce, and biomedicine, the volume of digital data is increasing rapidly. The problem materializes when retrieving the information from the storage media. Content-based image retrieval systems aim to retrieve images from large image databases similar to the query image based on the similarity between image features. This paper proposes a technique to retrieve images based on color feature using histogram and texture feature using wavelet transform. The color from image is extracted by quantifying the HSV color space into 8x8x8 histogram. In this retrieval system, Euclidean distance is used to measure similarity of images. This algorithm is tested by using WANG image database. The performance of retrieval system is measured in terms of its recall and precision.

Key words: CBIR, Color Histogram, Energy Level, Euclidean Distance, HSV, Texture, Wavelet Transform

I. Introduction

Content based image retrieval (CBIR) techniques are becoming increasingly imperative in multimedia information systems. A main building block in an image retrieval system is image indexing (automatically or manually). Indexing means characterization of images based on one or more image properties. CBIR uses [1] an automatic indexing scheme where implicit properties of an image can be included in the query to reduce search time for retrieval from a large database. Features like color, texture, shape, spatial relationship among entities of an image and also their combination are generally being used for the computation of multidimensional feature vector. The features color, texture, shape are known as primal features. The proposed work is based on one such primitive feature and can be used in the lowest level of query [2]. In this paper we propose an image retrieval system based on the combination of color and texture features. The color histograms for color feature and wavelet representation for texture and location information of an image are used. This lessens the processing time for retrieval of an image with more promising representatives. Color is usually represented by color histogram, color correlogram, color coherence vector and color moment, under certain a color space [3-5]. The color histogram feature has been employed by many researchers for image retrieval [6 and 7]. A color histogram is a vector, where each element symbolizes the number of pixels falling in a bin, of an image [8]. The color histogram has been used as one of the feature extraction elements with the advantage like toughness with respect to geometric changes of the objects in the image. The distance formula employed by many researchers, for image retrieval, includes Histogram Euclidean Distance, Histogram Intersection Distance, Histogram Manhattan Distance and Histogram Quadratic Distance.

Texture is also regarded as one of the feature extraction attributes by many researchers [9-12]. Although there is no formal definition for texture, instinctively this descriptor provides computes of the properties such as smoothness, coarseness, and regularity. Mainly the texture features of an image are examined through statistical, structural and spectral methods [13].

II. Fundamentals of Image Retrieval

The main idea behind CBIR systems is to permit users to find images that are visually similar to the query image. To allow different methods for similarity, different image descriptors are required. Image descriptors may comprise different properties of images. Image descriptors mean image features. A feature means anything that is localized, meaningful and detectable. If we talk about image features, we mean objects in that image such as corners, lines, shapes, textures, and motions. Features extracted from an image describe and define the content of that image.

A. Features

A wide assortment of features had been regarded for image retrieval. Color, texture, and shape are some image features that can be utilized to describe an image. Color images need color features that are most appropriate to describe them. Images containing visual patterns, surface properties, and scene require texture features to describe them. In reality, no one particular feature can portray an image completely. Many images have to be described by more than one feature. For example, color and texture features are best features to illustrate natural scenes.

1) Color

Color is the sensation caused by the light as it relates with our eyes and brain. Color features are the fundamental characteristics of the content of images. Human eyes are responsive to colors, and color features facilitate human to distinguish between objects in the images. Colors are used in image processing because they offer powerful descriptors that can be used to recognize and mine objects from a scene. To aid the specification of colors in some standard, color spaces (also called color models or color systems) are recommended. A color space is a specification of a coordinate system and a subspace within the system where each color is characterized by a single point. In most digital image processing, RGB (red, green, blue) color space is used in practice for color monitors and CMY (cyan, magenta, yellow) color space is used for color printing.

To extract the color features from the content of an image, we require to choose a color space and use its properties in the extraction. The intention of the color space is to aid the specification of colors in some standard, accepted way. Several color spaces are used to characterize images for different purposes. The RGB color space is the most extensively used color space. RGB color space coalesces the three colors in different ratio to create other colors. The HSx color space is regularly used in digital image processing that changes the color space of the image from RGB color space to one of the HSx color spaces. HSx color space includes the HSI, HSV, HSB color spaces. They are common to human color perception. HS stands for Hue and Saturation. I, V, and B stand for Intensity, Value, and Brightness, respectively. The different difference between them is their transformation method from the RGB color space. Hue describes the actual wavelength of the color. Saturation is the measure of the purity of the color. Intensity expresses the lightness of the color. HSV color space is the most commonly used when transferring the color space from RGB color space.

2) Texture

Texture is that innate property of all surfaces that illustrates visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. In short, it is a feature that depicts the distinctive physical composition of a surface. Texture properties include: Coarseness, Contrast, Directionality, Line-likeness, Regularity, and Roughness.

III. IMAGE RETRIEVAL BASED ON CONTENTS

The proposed system is CBIR system. In proposed system, some color features are extracted to represent the image and use these features to compare between the images.

A. Color Feature Extraction

The extraction of color features from digital images rest on an understanding of the theory of color and the representation of color in digital images. The color histogram is one of the most commonly used color feature representation in image retrieval. The power to recognize an object using color is much larger than that of a gray scale.

1) Color Space Selection and Color Quantization

The color of an image is represented, through any of the popular color spaces like RGB, XYZ, YIQ, L*a*b*, U*V*W*, YUV and HSV. It has been reported that the HSV color space gives the finest color histogram feature, among the different color spaces. In HSV color space the color is presented in terms of three components: Hue (H), Saturation (S) and Value (V) and the HSV color space is based on cylinder coordinates.

Color quantization is a process that optimizes the use of distinct colors in an image without affecting the visual properties of an image. For a true color image, the distinct number of colors is up to 224 = 16777216 and the direct extraction of color feature from the true color will bring about a large computation. In order to lessen the computation, the color quantization can be used to represent the image, without a major reduction in image quality, thereby reducing the storage space and enhancing the process speed.

2) Color Histogram

A color histogram signifies the distribution of colors in an image, through a set of bins, where each histogram bin corresponds to a color in the quantized color space. A color histogram for a given image is represented by a vector:

$$H = \{H[0], H[1], H[2], H[3] \dots\dots\dots\dots H[i], \dots\dots\dots, H[n]\} \quad (3.1)$$

Where i is the color bin in the color histogram and H[i] represents the number of pixels of color i in the image, and n is the total number of bins used in color histogram. Typically, each pixel in an image will be assigned to a bin of a color histogram. Accordingly in the color histogram of an image, the value of each bin gives the number of pixels that has the same corresponding color. In order to compare images of different sizes, color histograms should be normalized. The normalized color histogram H` is given as:

$$H' = \{H[0], H'[1], H'[2], \dots\dots, H'[i], \dots\dots, H'[n]\} \quad (3.2)$$

H'[i]=H[i]/ p,

Where p is the total number of pixels of an image

B. Texture Feature Extraction

Like color, the texture is a potent low-level feature for image search and retrieval applications. Much work has been done on texture analysis, classification, and segmentation for the last four decade, still there is a lot of prospective for the research. So far, there is no unique definition for texture; however, an encapsulating scientific definition as given in can be stated as, "Texture is an attribute representing the spatial arrangement of the grey levels of the pixels in a region or image". The common known texture descriptors are Wavelet Transform, Gabor-filter, co-occurrence matrices and Tamura features. Wavelet Transform is going to be used here, which putrefies an image into orthogonal components, because of its better localization and computationally inexpensive properties.

1) Haar Discrete Wavelet Transforms

Discrete wavelet transformation (DWT) is exercised to transform an image from spatial domain into frequency domain. The wavelet transform represents a function as a superposition of a family of basis functions called wavelets. Wavelet transforms dig up information from signal at different scales by passing the signal through low pass and high pass filters. Wavelets supply multi-resolution capability and good energy compaction. Wavelets are robust with respect to color intensity shifts and can incarcerate both texture and shape information efficiently. The wavelet transforms can be computed linearly with time and thus allowing for very fast algorithms. DWT decomposes a signal into a set of Basis Functions and Wavelet Functions. The wavelet transform computation of a two-dimensional image is also a multi-resolution approach, which relates recursive filtering and sub-sampling. At each level (scale), the image is decomposed into four frequency sub-bands, LL, LH, HL, and HH where L denotes low frequency and H denotes high frequency as shown in Fig 1 [17].

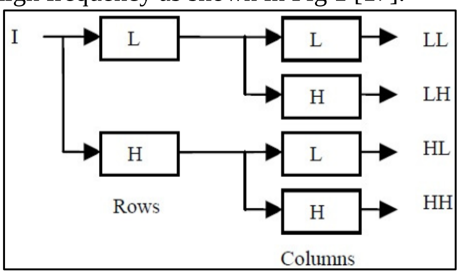

Fig. 1: Discrete Wavelet Sub-band Decomposition

In this work the pyramid-structure wavelet transform is going to be used, in which, the texture image is decomposed into four sub images, as low-low, low-high, high-low and high-high sub-bands. The energy level of each sub-band is calculated. This is first level decomposition. Using the low-low sub-band for further decomposition is done. Decomposition is done up to third level in this project.

The reason for this type of decomposition is the supposition that the energy of an image is concentrated in the low-low band.

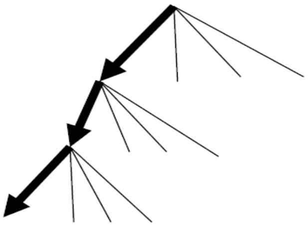

Fig. 2: Pyramid-Structure Wavelet Transform

2) Energy level

Energy Level Algorithm [14]:

– Decompose the image into *four* sub-images
– Calculate the energy of all decomposed images at the same scale, using:

$$E = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} |X(i,j)| \qquad (3.3)$$

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.

– Repeat from step 1 for the low-low sub-band image, until it becomes third level.

By means of the above algorithm, the energy levels of the sub-bands are computed, and more decomposition of the low-low sub-band image is also done. This is repeated three times, to achieve third level decomposition. These energy level values are stored to be used in the Euclidean distance algorithm.

3) Euclidean Distance

The Euclidean distance D between two vectors X and Y is

$$D = \sqrt{(\sqrt{((X-Y)\hat{}2)})} \qquad (3.4)$$

Using the above algorithm, the query image is explored for in the image database. The Euclidean distance is computed between the query image and every image in the database. This process is recurred until all the images in the database have been matched up with the query image. After completing the Euclidean distance algorithm, an array of Euclidean distances is acquired and which is then sorted [17].

C. Feature Similarity Matching

The Similarity matching is the process of approximating a solution, based on the computation of a similarity function between a pair of images, and the result is a set of likely values. Exactness, however, is a precise concept.

1) Histogram Intersection Distance

Swain and Ballard [15] suggested histogram intersection for color image retrieval. Intersection of histograms was formerly defined as:

$$dID = \frac{\sum_{i=1}^{i=n} \min[Q[i], D[i]]}{[|D[i]|]} \qquad (3.5)$$

Smith and Chang [16] extended the idea, by modifying the denominator of the original definition, to include the case when the cardinalities of the two histograms are different and expressed as:

$$dID = \frac{\sum_{i=1}^{i=n} \min[Q[i], D[i]]}{min[|Q[i]|, D[i]]} \qquad (3.6)$$

And $|Q|$ and $|D|$ represents the magnitude of histogram for query image and a representative image in the Database.

IV. PROPOSED METHODOLOGY

A. Proposed System

The block diagrams of the proposed methods are shown in Fig 3.

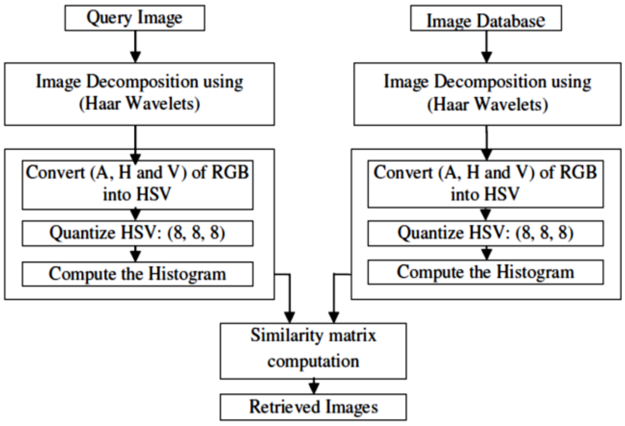

Fig. 3: Block Diagram of Proposed System

– Input: Query Image.
– Output: Retrieved Images.

1) Method:

– Extract the Red, Green, and Blue Components from an image.
– Decompose each Red, Green, Blue Component using Haar Wavelet transformation at 1st level to get approximate coefficient and vertical, horizontal and diagonal detail Coefficients.
– Combine approximate coefficient of Red, Green, and Blue Component.
– Similarly combine the horizontal and vertical coefficients of Red, Green, and Blue Component.
– Assign the weights 0.003 to approximate coefficients, 0.001 to horizontal and 0.001 to Vertical coefficients.
– Translate the approximate, horizontal and vertical coefficients into HSV plane.
– 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 8x8x8=512 histogram bins.
– The normalized histogram is obtained by dividing with the total number of pixels.
– Repeat step1 to step8 on an image in the database.
– Compute the similarity matrix of query image and the image present in the database.
– Repeat the steps from 9 to 10 for all the images in the database.
– Retrieve the images [17].

B. Performance Evaluation

The performance of retrieval of the system can be determined in terms of its recall and precision. Recall measures the capacity of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only the models that are relevant. It has been accounted that the histogram gives the finest performance through recall and precision value They are defined as:

$$Precision = \frac{Number\ of\ Relievant\ images\ retrived}{Total\ Number\ of\ images\ retrieved} = \frac{A}{A+B} \qquad (4.1)$$

$$Recall = \frac{Number\ of\ relevant\ images\ retrieved}{Total\ number\ of\ relevant\ images} = \frac{A}{A+C} \qquad (4.2)$$

Where A represent the number of relevant images that are retrieved, B, the number of irrelevant items and the C, number of relevant items those were not retrieved. The number of relevant items retrieved is the number of the returned images that are similar to the query image in this case. The total number of items retrieved is the number of images that are returned by the search engine.

The average precision for the images that belongs to the qth category (Aq) has been computed by

$$p' = \sum_{k \in A_q} \frac{p(i_k)}{|A_q|} \qquad (4.3)$$

Where q=1, 2……10.

Finally, the average precision is given by:

$$p' = \sum_{q=1}^{10} \frac{p'_q}{10} \qquad (4.4)$$

V. EXPERIMENT RESULT

The proposed method has been implemented using Matlab and tested on a general-purpose WANG database including images of JPEG format. The performance of the proposed image retrieval technique has been estimated by comparing the results with the results of different authors. The precision values, computed by using the equation and also the average precision using equation are shown in Table 1.

Category	WBCH	CH	CTCHIRS[3]
Beach	0.62	0.53	0.54
Building	0.71	0.61	0.53
Flower	0.76	0.66	0.86
People	0.65	0.64	0.69
Mountains	0.49	0.47	0.52
Avg. Precision	0.65	0.58	0.63

Table 1: Precision of the Retrieval by different methods

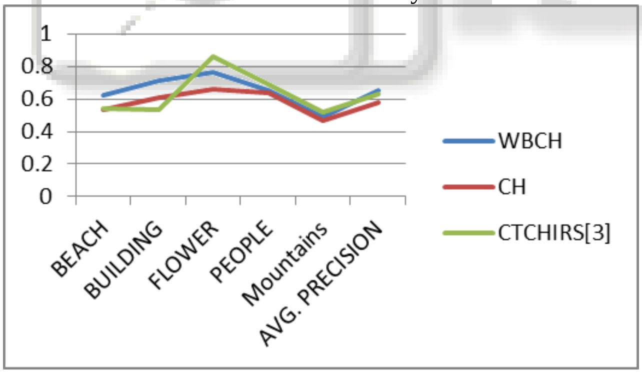

Fig. 4: Graph of precision for Table 1

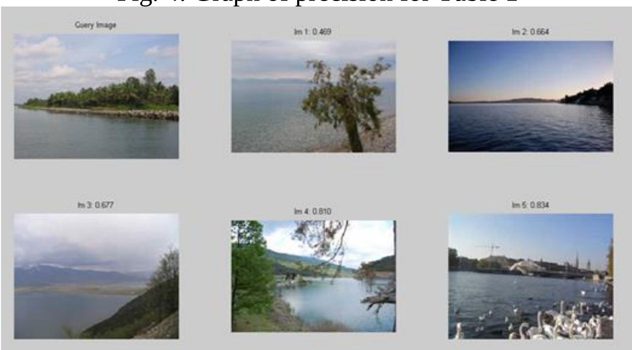

Fig. 5: Retrieve result for Beach Area.

VI. CONCLUSION

In this paper, a novel approach is presented for Content Based Image Retrieval by uniting the color and texture features. Color Histogram are used to extract color feature from images. And to extract texture feature wavelet transform is employed. Similarity between the images is established by means of a distance function. The proposed method surpasses the other retrieval methods in terms of Average Precision. Moreover, the computational steps are successfully lessened with the use of Wavelet transformation. As a result, there is a substantial boost in the retrieval speed.

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