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CONTENT BASED IMAGE RETRIEVAL USING MULTI-SEQUENTIAL SEARCH

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Abstract— **In Content-Based Image Retrieval (CBIR) the indexing of the image and the representation is done using visual contents of an image like color, shape, texture and spatial layout. The on-going development and research in CBIR are mainly focused on the improvement of various methods for examining, cataloging and indexing image databases. Along with this development, several efforts are also being made in evaluating the performance of the image retrieval systems. Depending on the method incorporated to generate the similarity measure for the comparisons of different features and the vectors the accuracy and response of the system would vary. The proposed system is exclusive as it takes into consideration one particular feature at one step and uses the result of the above prior step as the input for the next step instead of fusing all the features at one step and thus providing an edge over the earlier used methods and also showing improvement in the retrieval quality. In the proposed system the accuracy of color histogram-based matching can be increased by using Color Coherence Vector. Instead of taking into consideration the exact shape, the approximation of the boundary is considered in order to enhance the speed of shape-based matching.**

Keywords- Content-Based Image Retrieval, Color, Shape, Texture, multi-sequential

1. INTRODUCTION

Visual information, particular in form of images, is becoming increasingly important and hence effective methods for dealing with these collections are highly sought after. Since most images are un-annotated, there has been a lot of interest in content-based image retrieval (CBIR) which extracts image features directly from the image data and uses these, coupled with a similarity measure, to query image collections. Image features typically describe the color, texture, and shape "content" of the images and in this system, we highlight how CBIR features can be extracted directly from the compressed image domain without the need of fully decompressing the images. The CBIR system uses the color, texture and shape features, that is the retrieving of images is based on images that possess similar content of colors, textures or shapes. The objective is to retrieve significant images from an assorted collection using image queries as search argument using color, texture and shape features. Images make the communication process more interesting, descriptive, detailed, logical, understandable and clear. "Content-based" means that the search examines the details of the image rather than the metadata linked with the images. The traditional approach of annotating images by entering keyword data in a large database is time consuming and we may not get the desired image output.

Color, texture and shape features have been used to retrieve visually similar images from an image database. "Most of the systems have used one or two features whereas few systems have used all the features. [1]" "Querying by color, texture, shape or by one of the combinations of these features has been proposed in several systems [2, 3, 4] using single-level sequential searching." In the single-level sequential search, features are fused to generate one feature vector or different feature vectors. Then the features are used in the same level with or without weightings for searching. It seems that the multi-level sequential search has not yet been considered even though it is simple and shows improved retrieval results. To the best of our knowledge multi-level sequential search is yet to be studied to improve the retrieval results. Thus, we plan to develop a CBIR system which is based on multi-level sequential searching which aims at achieving adequate precision during image retrieval.

II. Methodology

A single-level sequential search fuses all the three feature vectors together for one step extraction. Though commonly used, the combined feature method may not give an accurate result. There is a possibility of one feature dominating the retrieval performance. The feature vectors need to be weakly correlate with each other for an improved result [7].

The proposed system suggests a multi-sequential method to deal with the problem stated above. It considers one feature at a time and makes use of the result of the previous step as an input for the next step. The working of the proposed system is as follows:

1. User submits a query image from their machine to the system.
2. The color feature of the input is extracted first and compared with the color feature database.
3. The first top N_1 images found using the similarity matrix and color feature database are fed to the second stage for the texture computation.
4. In the second stage, texture feature is extracted using texture feature database. The first top N_2 images are selected from the list N_1 as the output of this stage. These results are given to the third stage as the input.
5. Top N_3 are selected using the shape feature database and displayed.

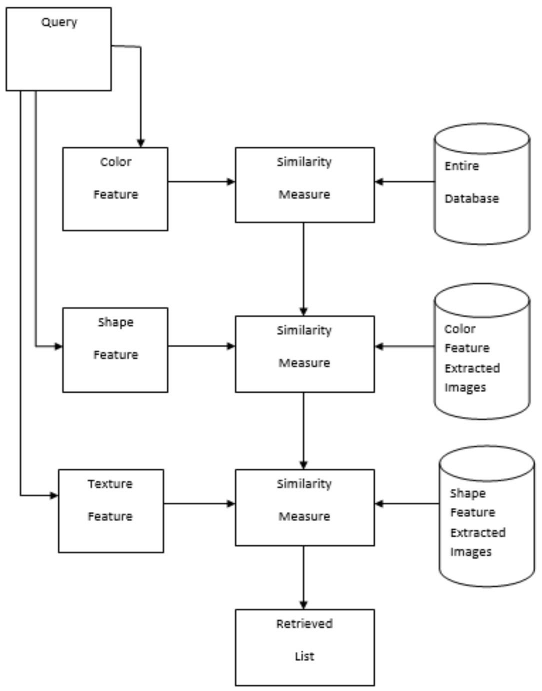

Fig.1: Multi-sequential approach

III. Overview

The application uses the following software resources for making the system functional.

A. COLOR FEATURE EXTRACTION

Feature extraction performs a critical role in CBIR. Color, texture and shape features are used for the proposed system. A single vector is used to represent every feature for an image.

Several techniques for color extraction are mentioned in literature, like color correlogram and color coherence vector.

Color Histogram is a widely used extraction technique. The reason for this is that it is very easy to compute and is insensitive to small variations in the image. Histogram, basically, gives the frequency distribution of the color bins in the image. An image histogram can be defined as the probability mass function of the image intensities. It is given by,

$H_{P,Q,R}$ (p,q,r) - N.Prob(P=p, Q=q, R=r)

where P, Q and R indicate the three-color channels (R, G, B or H, S, V) and N is the number of pixels in the image. A typical computer represents images with up to 224 colors. Therefore, quantization of the color space into the nearest 256*256 pattern is needed. RGB mode is not perceptually uniform, and thus, HSV is preferred. It represents the Hue, Saturation and Value or Intensity with equal significance (three color variants for characterization). This separation results in independent processing of color image that prevents introduction of false colors.

The images added in the collection are initially analyzed to compute individual histograms that indicate the frequency of

different color pixels present in the image. These histograms are then stored in the database. The user submits his search argument in the form of an image to the system. Color histogram of the input image is then calculated and compared with the ones that are present in the system database. Similarity measure with respect to the perception of color content is computed using the three color distance formulas:

1. Euclidean distance

Let 'h1' and 'h2' represent two color histograms. The Euclidean distance between the histograms 'h1' and 'h2' can be computed as:

$$\mathbf{d^2 (h1, h2) = \sum \sum \sum (h1(p,q,r)-h2(p,q,r))^2}$$

This does not consider the cross-correlation between histogram bins.

2. Intersection distance

There is no contribution of colors that are not present in the input image given by the user in the histogram intersection distance. Normalization of sum is done by the histogram with few samples. Cross-correlation between the bins is based on the colors represented by the bins and their perceptual similarity. The formula is as follows:

$$\mathbf{d(h1, h2) = (h1-h2)t\ A(h1-h2)}$$

Where A is the similarity matrix which represents the set of cross-correlation values.

The a (i,j)th element in the similarity matrix A for HSV space[6] is:

$$a_{ij} = 1 - \frac{1}{\sqrt{5}} \left[(v_i - v_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2 + (s_i \cos h_i - s_j \cos h_j)^2 \right]^{1/2}$$

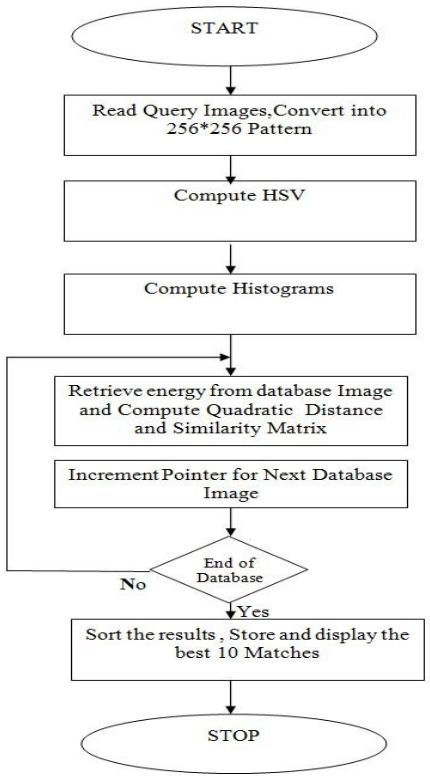

Fig. 2: Histogram algorithm

B. SHAPE FEATURE EXTRACTION

In CBIR, for image retrieval one of the important low level key part is the shape representation. It is important that this shape representation should satisfy certain properties like robustness, similarity measure, consistency, should be invariable. Most of the shape descriptors that are available are non-robust, many of them being application dependent. The shape representations are generally of two types: contour-based and region-based. Contour-based representation is the one that deals with the extraction of the boundary information and details and the extracted information plays a crucial role in judging the shape similarity from a human perspective. There is a limitation to this, in some cases the boundary is not that evident. Region-based on the other hand does not confide to the boundary information but they do not also reflect the local features of the particular shape, they are just associated with exploiting the interior information of the shape. So for common purpose, both these types of representation play an important role and thus being equally necessary. The different shape descriptors that are widely available are Generic Fourier Descriptor, Edge Histogram Descriptor (EHD), Zernike Moments. Edge Histogram is a widely used extraction technique for shape extraction. Shape plays an

The EHD is the commonly used method for shape detection. The Edge Histogram descriptor basically gives the dispersion of the edges in a particular image with the aid of a histogram which is based on local edge distribution. [8,9] It basically shows the relative frequency of occurrence of 5 types of edges in each local area called a sub-image or image block. The image space is partitioned into 16 non-overlapping blocks as shown in figure 3 which defines the image block. The partition of image definitely results into 16 equal-sized blocks inconsiderate of the size of the initial image. Then, a histogram of edge distribution for each image block is generated for defining the characteristics of the image block. The Edges of the image block are identified into 5 types, as shown in Figure 4 [5]. Thus, the histogram for each image block shows the relative distribution of the 5 varieties of edges in the matching sub-image.

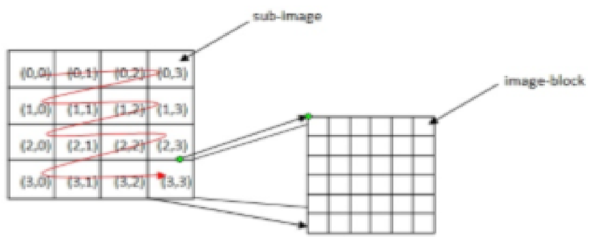

Fig. 3: Sub-image and Image-block in the Edge Histogram Descriptor

Fig. 4: Types of Edges in the Edge Histogram Descriptor

a. Pragmatics of Local Edge Histogram Descriptor [LEHD]

For extracting an edge histogram in the sub-image we can apply digital filters in the spatial domain. To this end, first the image-block is divided into four sub-blocks as shown in Figure 3.

Then, the labels of the four sub-blocks are numbered. The average gray levels for the four image block are represented at (x,y)th sub-block as i1(x,y), i2(x,y) , and i3(x,y) respectively. The filter coefficients for the five types of edges are represented as fcv(m) (vertical edge) , fch(m) (horizontal edge), fcd45(m) (45 degree edge), fcd135(m) (135 degree edge), and fcnd(m) (non-directional edge) respectively, where m = 0,…,3 represents the position of the sub-blocks. The coefficients of the fcv(m) are shown in Figure 5a). Similarly, the filter coefficients for the others are shown in Figure 5 – b), c), d) and e).

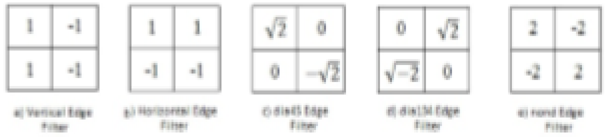

Fig. 5: Filters for Edge Detection

b. Global Edge Histogram Descriptor [GEHD]

We can't achieve high retrieval performance only by applying the LEHD alone. It may not suffice the needs. Rather, it is necessary to know the edge distribution of the entire image. That is, the LEHD must be coupled with GEHD. The latter shows the edge partition for the entire image space. But the bin values for all GEHD are taken directly from the LEHD. As there are 5 edge types, the GEH also has 5 bins. As a result, there are total 80 bins (LEHD) + 5 bins (GEHD) = 85 bins.

Algorithm:

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Step1: Transform the RGB image into gray image.

Step2: Divide the image into four by four (16) blocks. [section I]

Step3: Calculate the LEHD.

Step4: Calculate the percentage of the number of pixels that correspond to an edge histogram.

Step5:Compute the GEHD [section I] on the entire image and then determine the percentage of the number of pixels that correspond to a GEHD bin.

Step6 Save both LEHD and GEHD values in feature vector F.

Step7: Pass the Feature Vector F to next stage.

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C. TEXTURE FEATURE EXTRACTION

Texture represents the picture surface and constitution. Picture textures are complex visual patterns which are composed of regions or entities with sub-patterns with traits of brightness, color, form, measurement...and so on. The well-known texture descriptors are Wavelet Transform, Gabor-filter, and Tamura features.

Gabor wavelet transform was invented by Dennis Gabor. It is widely used in CBIR, face recognition and palm print recognition and security purpose. GWT transform is a popular and powerful tool to decompose all the images of training set at different levels of scaling and dilation [6]. There is different detection of GWT. Mostly edge detection, corner detection, and blob detection are used for extraction of contents from images. The response of primary visual samples of Gabor wavelet filters are plane wave avoids by using Gabor wavelet transform. The GWT is applicable for spatial frequency domain as well as for spatial relevant of the given input image [10]. The different illumination of the database like orientation and frequency selectivity are used to identify the visual features in GWT.

Algorithm:

Step 1: In GWT, the image is represented as set of color components

X ij = {Rij , Gij , Bij} .Where Rij , Gij and Bij are color components of the database.

Step 2: Each set is the combination of S number of classes and I number of training images.

Step 3: The query image is of the dimensions of a x b, where a is the number of rows and b is number of columns.

Step 4: M is the total number of images in the given dataset. **Step 5**: Create a new sub band filter using Gabor filter bank each being u by v matrix based on x scales and

y orientations. Where u and v represent rows and

columns of square matrix. The filter bank can be

expressed as

$$G(p,q) = g_{\sigma}(p,q) * \exp(2\pi j\tau(p\cos\theta + q\sin\theta))$$

Where the Gaussian function can be denoted by

g (p , q) V and described as below

$$g_{\sigma}(p,q) = \left(\frac{1}{\sqrt{2x\sigma_p\sigma_q}}\right) * \exp\left(\frac{-1}{2}\left(\frac{p^2}{\sigma_p^{\;2}} + \frac{q^2}{\sigma_{q^2}}\right)\right)$$

Step 6: Then the input image is applied to each subset of gabor filter bank.

Step 7: After this step*, x* x *y* matrices of GWT are obtained. The feature vectors are extracted from the decomposed image based on down-sampling *D* and up-sampling *C*

Step 8: The feature vector from D and C are obtained for all the images.

Step 9: Finally, the test images are applied to the training images based on as mentioned classifiers

IV. CONCLUSION

The CBIR system mentioned in this paper is simple yet competent approach based on multi-level sequential searching. The system has three different feature extraction stages viz. color, shape and texture feature. This feature order is selected for general purpose datasets and this order can be varied depending on the dataset. The multi-sequential CBIR system is developed to enhance the retrieval quality. The proposed system is evaluated and compared to validate by using two standard datasets. According to the experimental results obtained, the proposed CBIR approach surpasses the other existing systems in terms of advancement in retrieval quality.

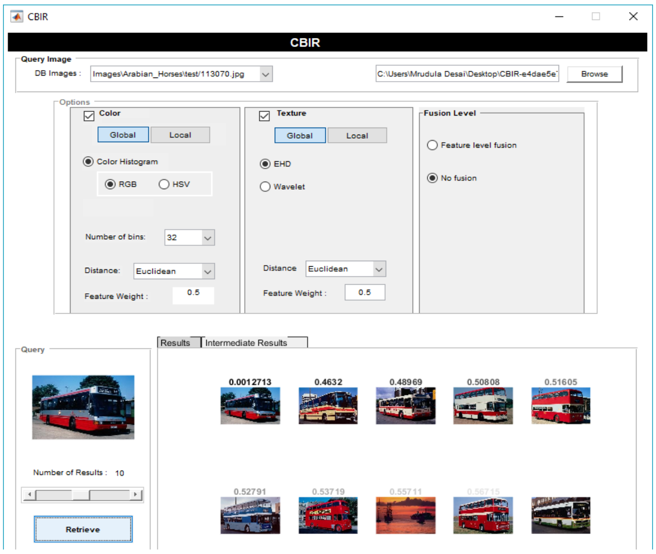

Fig. 6: Snapshot of the system

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