System for Content-Based Image Retrieval using Wavelet Transform and Histogram Features

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Abstract: Content- based image retrieval (CBIR) has been wide researched for the retrieval of contently similar pictures. In several applications like education, biomedicine, crime hindrance the importance of digital information is increasing speedily. During this paper we have a tendency to area unit planned a content-based retrieval model , initial user must offer a question image that is then accustomed retrieve the pictures that area unit similar from information. Image retrieval is being done by mistreatment content of digital image referred to as options i.e. color and texture feature. To extract these options the system uses color histogram for color feature and wavelet transform for texture and site info of a picture. The planned system reduces the interval for retrieval from information containing 651 general color images with more brilliant representatives.

*IndexTerms - **Image Retrieval, Color Histogram, Quantization, Haar Wavelet Transform.***

I. INTRODUCTION

With the event of the web, and therefore the availableness of image capturing devices like digital cameras, image scanners, the dimensions of digital image assortment is increasing speedily. economical image looking, browsing and retrieval tools area unit needed by users from numerous domains, as well as remote sensing, fashion, crime hindrance, publishing, medicine, design, etc. For this purpose, several general purpose image retrieval systems are developed. There area unit two frameworks: text-based and content-based. The text-based approach may be derived back to Nineteen Seventies. In such systems, the pictures area unit manually annotated by text descriptors, that area unit then employed by a direction system (DBMS) to perform image retrieval. However, with the substantial increase of the dimensions of pictures additionally because the size of image information, the task of user-based annotation becomes terribly cumbersome, and, at some extent, subjective is incomplete because the text usually fails to convey the made structure of the pictures. There is conjointly quality in annotation because of the judgment of human perception. To beat these disadvantages in text-based retrieval system, content-based image retrieval (CBIR) was introduced within the early Eighties. In CBIR, pictures area unit indexed by their visual content, like color, texture, shapes. the elemental distinction between content-based and text-based retrieval systems is that the human interaction is a vital a part of the latter system. As a result, content-based image retrieval (CBIR) from un-annotated image databases has been a quick growing analysis space recently. Content primarily based Image Retrieval may be a method framework for with efficiency retrieving image from a group of pictures by similarity. The retrieval depends on extracting the acceptable characteristic qualities describing the specified contents of pictures. Additionally, appropriate querying, matching, categorization and looking techniques area unit needed. This approach retrieves or search digital pictures from giant information mistreatment the contents of pictures themselves or grammar image options while not human intervention. To help image retrieval, techniques from statistics, pattern recognition, signal process and laptop vision area unit unremarkably deployed. Different terms used interchangeably for CBIR area unit question by image content (QBIC) and content-based visual info retrieval (CBVIR).Research on content-based image retrieval has gained tremendous momentum throughout the last decade. A lot of research work has been carried out on Image Retrieval by many researchers, growing in both depth and breadth. The term Content Based Image Retrieval (CBIR) seems to have originated with the work of Kato [1] for the automatic retrieval of the images from a database, based on the color and shape present. Since then, the term has widely been used to describe the process of retrieving desired images from a large collection of database, on the basis of syntactical image features (color, texture and shape). The techniques, tools and algorithms that are used, originate from the fields, such as statistics, pattern recognition, signal processing, data mining and computer vision.Many image retrieval systems have been successfully developed, such as the IBM QBIC System [2], developed at the IBM Almaden Research Center, the VIRAGE System [3], developed by the Virage Incorporation, the Photobook System [4], developed by the MIT Media Lab, the VisualSeek System [5], developed at Columbia University, the WBIIS System [6] developed at Stanford University, and the Blobworld System [7], developed at U.C. Berkeley and Simplicity System [8].

II. LITERATURE SERVEY

Following is a summary of existing work.

Lin et al. [9] planned a color-texture and color-histogram based mostly image retrieval system (CTCHIR). during this 3 image options square measure planned for image retrieval. the primary and second image options square measure supported color and texture options, severally known as color co-occurrence matrix (CCM) and distinction between pixels of scan pattern (DBPSP). The third image feature relies on color distribution, known as color bar graph for k-mean(CHKM). CCM is that the standard pattern co-occurrence matrix that calculates the likelihood of the prevalence of same constituent color between every constituent and its adjacent one in every image, and this likelihood is think about because the attribute of the image, in step with the sequence of motif of scan patterns, DBPSP calculates the distinction between pixels and converts it into the likelihood of prevalence on the whole image. every constituent alter a picture is then replaced by on alter the common color palette that's most almost like color therefore on classify all pixels in image into k-cluster, known as the CHKM feature. Difference in image properties and contents indicates that completely different options square measure contained. Some pictures have stronger color and texture options, whereas others square measure additional sensitive to paint and spatial options. Thus, this study integrates CCM, DBPSP and CHKM to facilitate image retrieval. to boost image detection rate and alter computation of image retrieval, ordered forward choice is adopted for feature choice. Besides, supported image retrieval system (CTCHIRS), a series of research and comparison square measure performed. 3 image databases with completely different properties square measure will not to perform feature choice. best options square measure elite from original options to boost the detection rate. From the experimental results they found that, their planned methodology outperforms the Jhanwar et al. [10] and decorated and Dai [11] ways. Jhanwar et al. [10] bestowed a method for content based mostly image retrieval victimization motif co-occurrence matrix (MCM). MCM comes employing a motif remodeled image. the total image is split into 2x2 constituent grids. Every grid is replaced with the scan motif that minimizes the native gradient whereas traversing a pair of the two} x 2 grid forming a motif remodeled image. MCM is then outlined as a three dimensional matrix whose (i,j,k) entry denotes the likelihood of finding a motif i at a distance k from motif j within the remodeled image. Conceptually the motif co-occurrence matrix is sort of almost like color co-occurrence matrix (CCM). MCM performs far better than CCM since it captures the third order image statistics within the native neighborhood. Decorated and Dai [11] bestowed an economical image retrieval system with high performance of accuracy supported two novel options, the composite sub-band gradient vector and energy distribution pattern string. Each options square measure generated from the sub-images of a ripple decomposition of the initial image. A fuzzy matching mechanism supported energy distribution pattern strings surf as a filter to quickly take away unwanted pictures within the info from the any thought. The pictures passing the filters square measure compared with the question image supported composite sub-band gradient vectors that square measure extraordinarily powerful for discriminating careful textures. Through many experiments by sweat this epitome system with the info of 2400 pictures, they incontestable that each high accuracy and high potency will be achieved at a similar time by this approach. Raghupathi et al. [12] have created a comparative study on image retrieval techniques, victimization completely different feature extraction ways like color bar graph, physicist remodel, color histogram+gabour remodel, Contourlet remodel and color histogram+contourlet remodel. Hiremath and Pujari [13] planned CBIR system supported the colour, texture and form options by partitioning the image into tiles. They gift a completely unique framework for combining all the 3 i.e. color, texture and form info, and achieved higher retrieval potency victimization image and its complement. The image and its complement square measure partitioned off into non-overlapping tiles of equal size. The options drawn from conditional co-occurrence histograms between the image tiles and corresponding complement tiles, in RGB color house, function native descriptors of color and texture. This native info is captured {for 2|for 2} resolutions and two grid layouts that offer completely different details of a similar image. AN integrated matching theme, supported most similar highest priority (MSHP) principle and also the closeness matrix of a bipartite graph fashioned victimization the tiles of question and target image, is provided for matching the pictures. form info is captured in terms of edge pictures computed victimization Gradient Vector Flow fields. Invariant moments square measure then wont to record the form options. the mix of the colour and texture options between image and its complement in conjunction with the form options offer a tricky feature set for image retrieval. Y. Chen and J. Wang [14] planned a symbolic logic approach, UFM (unified feature matching), for region-based image retrieval. During this retrieval system, a picture is described by a collection of metameric regions every of that is characterized by a fuzzy feature (fuzzy set) reflective color, texture, and form properties. As a result, a picture is related to a family of fuzzy options such as regions. Fuzzy options naturally characterize the gradual transition between regions (blurry boundaries) among a picture, and incorporate the segmentation-related uncertainties into the retrieval formula. The alikeness of 2 pictures is then outlined because the overall similarity between 2 families of fuzzy options, and quantified by a similarity live, UFM live, that integrates properties of all the regions within the pictures. Compared with similarity measures supported individual regions and on all regions with crisp-valued feature representations, the UFM live greatly reduces the influence of inaccurate segmentation, and provides a really intuitive quantification. The UFM has been enforced as a neighborhood of our experimental simplicity image retrieval system. The performance of the system is illustrated victimization examples from a picture info of regarding 60,000 general pictures.

J. Li, J. Wang and G Wieder hold [15] present IRM (Integrated Region Matching), a novel similarity measure for region based image similarity comparison. Content-based image retrieval using region segmentation has been an active research area. The under attack image retrieval systems represent an image by a set of regions, roughly corresponding to objects, which are characterized by features reflecting color, texture, shape, and location properties. The IRM measure for evaluating in general similarity between images incorporates properties of all the regions in the images by a region-matching scheme. Compared with retrieval based on individual regions, the overall similarity approach reduces the influence of inaccurate segmentation, helps to clarify the semantics of a particular region, and enables a simple querying interface for region-based image retrieval systems. The application to a database of about 200,000 general-purpose images shows exceptional robustness to image alterations such as intensity variation, sharpness variation, color distortions, shape distortions, cropping, shifting, and rotation. Compared with several existing systems, this system in general achieves more accurate retrieval at higher speed.

III. RESEARCH METHODOLOGY

In this paper, image retrieval is done by content based image retrieval. First user has to provide a query image which is then used to retrieve the images which are like from database. Image retrieval is being done by using content of digital image called features i.e. color and texture feature. To extract these features the system uses color histogram for color feature and wavelet representation for texture and location information of an image. This reduces the processing time for retrieval of an image with more capable representatives. For database images, feature vectors are calculated are stored in file. After extracting the features for query image, the similarity matching is performed by comparing its features with that of all features stored for database images. For feature matching, similarity measures method being used is distance method. For color features, histogram intersection distance is being used.

The Euclidean distance is used to calculate texture feature similarity. On the basis of this similarity matching the images are most similar are retrieved from database. The system presents the sequence of images ranked in decreasing order of their similarity. In order to perform the retrieval process two steps are involved.

3.1 Feature Extraction

The first step is the 'feature extraction' step, which identifies unique signatures, termed as feature vector, for every image based on its pixel values. The feature vector is the characteristics that describe the contents of an image. Visual features such as color and texture are used in this step.

3.2 Similarity matching

The second step is the similarity matching step which matches the features extracted from a query image with the features of the database images and group's images according to their matching.

3.3 Color Feature Extraction

The color feature has widely been used in CBIR systems, because of its easy and fast computation. Color is also an spontaneous feature and plays an important role in image matching. The extraction of color features from digital images depends on an considerate of the theory of color and the representation of color in digital images. The color histogram is one of the mainly commonly used color feature representation in image retrieval. The authority to identify an object using color is much superior than that of a gray scale.

3.3.1 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. The HSV color space gives the best color histogram feature, amongthe different color spaces. In HSV color space the color is accessible 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 discrete colors in an image without disturbing the visual properties of an image. For a true color image, the distinct number of colors is up to 2^{24} = 16777216 and the direct extraction of color feature from the true color will lead to a large computation. In order to reduce the computation, the color quantization can be used to represent the image, without a significant reduction in image quality, thereby reducing the storage space and enhancing the process speed.

3.3.2 Color Histogram

A color histogram represents 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:

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

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. Usually, each pixel in an image will be assigned to a bin of a color histogram. Hence in the color histogram of an image, the value of each bin gives the number of pixels that has the same analogous color. In order to compare images of different sizes, color histograms should be normalized. The normalized color histogram H` is given as:

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

H'[i]=H[i]/ p , Where, p is the total number of pixels of an image.

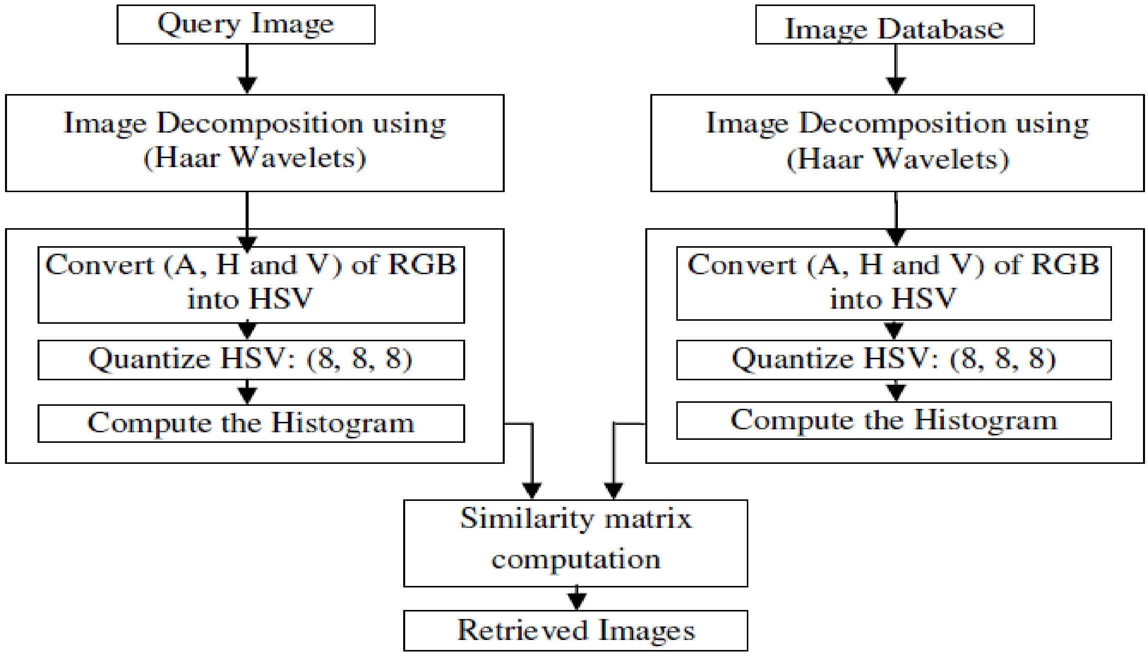

Fig.3.1: Proposed System

3.4 Texture Feature Extraction

Like color, the texture is a powerful low-level feature for image search and retrieval applications. 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 ordinary known texture descriptors are Wavelet Transform, Gabor-filter, co-occurrence matrices and Tamura features. We have used Wavelet Transform, which decomposes an image into orthogonal components, because of its better localization and computationally inexpensive properties.

3.4.1 Haar Discrete Wavelet Transform

Discrete wavelet transformation (DWT) is used to transform an image from spatial domain into frequency domain. The wavelet transform represents a function as a superposition of a family of basic functions called wavelets. Wavelet transforms haul out information from signal at dissimilar scales by passing the signal through low pass and high pass filters. Wavelets provide multi-resolution capability and good energy compaction. Wavelets are vigorous with respect to color intensity shifts and can capture both texture and shape information proficiently. 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 applies 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 Figure.

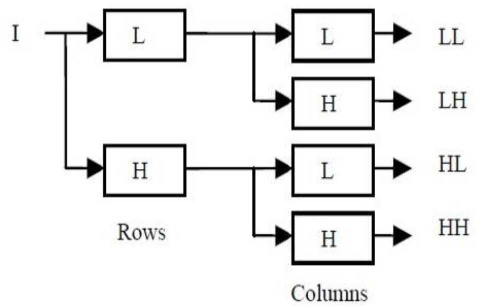

Fig. 3.2: Discrete Wavelet Sub-band Decomposition

Haar wavelets are broadly being used since its invention after by Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. Here, Haar wavelets are used to compute feature signatures, because they are the fastest to compute and also have been found to perform well in practice. Haar wavelets allow us to speed up the wavelet computation phase for thousands of sliding windows of changeable sizes in an image. The Haar wavelet's mother wavelet function can be described as:

$$\Psi(t) = \begin{cases} 1, & 0 \le t \le \frac{1}{2} \\ -1, & \frac{1}{2} \le t < 1 \\ 0, & otherwise \end{cases} \quad (3)$$

and its scaling function φ(t) can be described as:

$$\varphi(t) = \begin{cases} 1, & 0 \le t \le 1 \\ 0, & otherwise \end{cases} \quad (4)$$

In this system, 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.

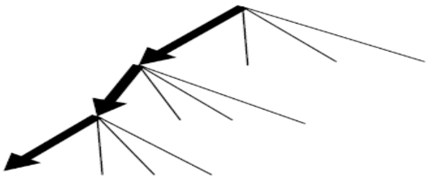

Fig. 3.3: Pyramid-Structure Wavelet Transform

3.5 Feature Similarity Matching

The Similarity matching is the process of resembling 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.

3.5.1 Histogram Intersection Distance

The histogram intersection is used for color image retrieval. Intersection of histograms was originally defined as:

$$dID = \frac{\sum_{i=1}^{i=n} \min[Q[i], D[i]]}{[|D[i]|]} \quad (6)$$

The original definition is modify to consider the case when the cardinalities of the two histograms are different and is expressed as:

$$dID = \frac{\sum_{i=1}^{i=n} \min\,[Q[i], D[i]]}{min\,[|Q[i]|, D[i]]} \quad (7)$$

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

3.5.2 Euclidean distance

The Euclidean distance D between two vectors X and Y is

$$D = \sqrt{(\sqrt{((X-Y)^\wedge 2)})} \quad (8)$$

Using the above algorithm, the query image is searched for in the image database. The Euclidean distance is calculated between the query image and every image in the database. This process is recurring until all the images in the database have been compared with the query image. After carrying out the Euclidean distance algorithm, an array of Euclidean distances is obtained and which is then sorted.

IV. RESULTS AND DISCUSSION

4.1 Experimental Data

The experimental results are presented to show that the propos dataset. About 651 images are used in this experiment. In this step, texture features are obtained by Haar wavelet transform and color features are extracted by color histogram calculation.

Category	Proposed	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
AVG. PRESION	0.69	0.61	0.65

Table 4. 1: Precision of the Retrieval by different methods

Similarity Matching is done by calculating Euclidean distance from energy levels obtained from wavelet transform. Histogram junction distance is calculated between query and database images.

4.2 Performance Evaluation

The performance of the retrieval of the system can be calculated in terms of its recall and precision. Recall measures the capability of system to retrieve all the models that are similar and precision measures the ability of the system to retrieve only the images that are similar.

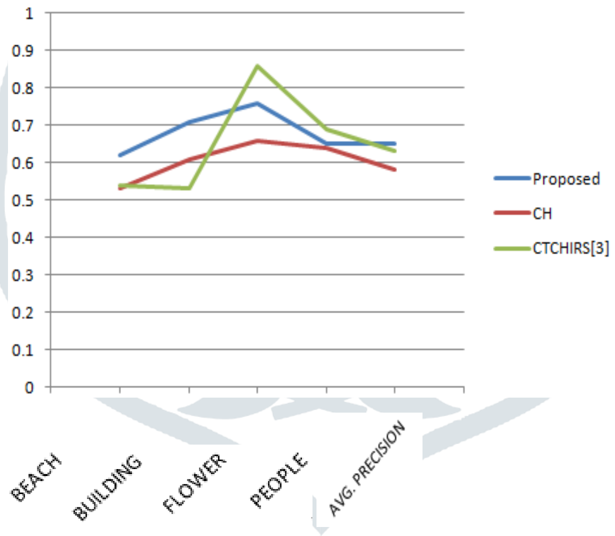

Fig. 4.1 : Graphical Representation of Results

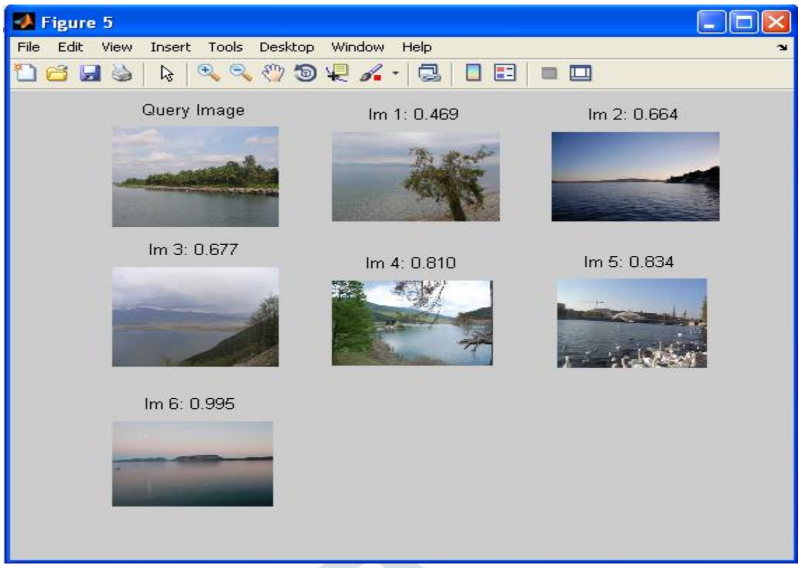

Fig.: Retrieval Result of Beach

V. ALGORITHMIC APPROACH SCOPE

In this system, two algorithms for image retrieval based on the color histogram and Wavelet-based Color Histogram are to be used.

5.1 Color histogram

A color histogram represents the division of colors in an image, through a set of bins, where each histogram bin corresponds to a color in the quantized color space.

5.2 Wavelet-based Color Histogram

It extracts the Red, Green, and Blue Components from an image. Decompose each Red, Green, Blue Component using Haar Wavelet transformation at 1st level to obtain approximate coefficient and vertical, horizontal and diagonal detail Coefficients. Combine approximate coefficient of Red, Green, and Blue Component. Also merge the horizontal and vertical coefficients of Red, Green, and Blue Component.

Fig. Query Image

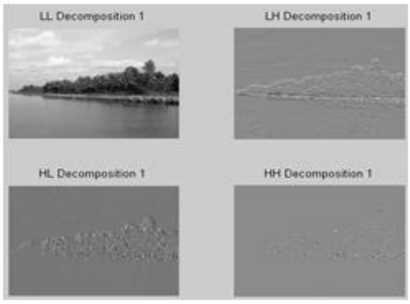

Fig. First-level decomposition.

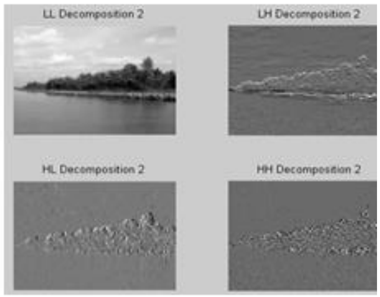

Fig. Second-level decomposition

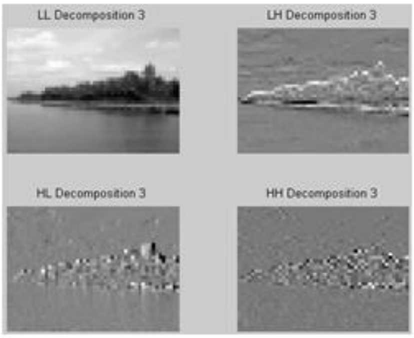

Fig. Third-level decomposition

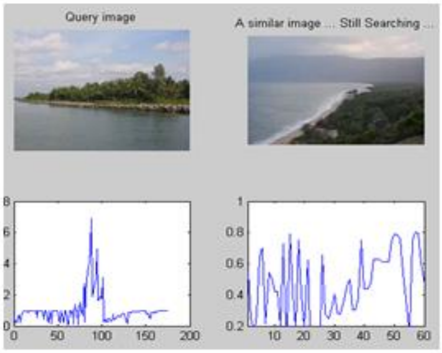

Fig. GUI of similar image searching

Fig.: Three-Level Query Image Decomposition using Haar Wavelet Transform

VI. FUTURE SCOPE

The proposed method uses color and texture feature for retrieving the images from database. In this method we can combine other features such as shape for retrieving the images. By incorporating user-feedback into the system the retrieval result can be improved. Euclidean distance is used in this report because of its simplicity and interpretability, but it would be valuable to evaluate other distance measures and their effect on retrieval performance.

VII. CONCLUSION

In this system, image retrieval system using digital contents i.e. color and texture is described. For color features color histogram is used for extraction. And HSV color space is used for the color histogram representation. For texture feature retrieval pyramid structure wavelet transform is being applied. The computational steps are effectively reduced with the use of Wavelet transformation. As a result, there is a substantial increase in the retrieval speed. Energy level algorithm is proposed to calculate energies at each level of decomposition in transform.

For similarity measure, histogram intersection distance is calculated and compared for query and database images. Euclidean distance is evaluated between query and database images. These similarity measurements are used to sort the images to be display for retrieval result. The resulting images retrieved are result of hybrid approach using both color and texture features.

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