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EFFICIENCY IMPROVEMENT OF CBIR BY USING SVM

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ABSTRACT: Content-Based Image Retrieval (CBIR) uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image. Active research in CBIR is geared towards the development of methodologies for analyzing, interpreting cataloging and indexing image databases. In addition to their development, efforts are also being made to evaluate the performance of image retrieval systems. The quality of response is heavily dependent on the choice of the method used to generate feature vectors and similarity measure for comparison of features. In this paper we proposed an algorithm which incorporates the advantages of various other algorithms to improve the accuracy and performance of retrieval. The accuracy of color histogram based matching can be increased by using Color Coherence Vector (CCV) for successive refinement. The speed of shape based retrieval can be enhanced by considering approximate shape rather than the exact shape. In addition to this a combination of color and shape based retrieval is also included to improve the accuracy of the result.

The primitive features required to compute an image feature vector are color and holistic structure features. If spatial distribution is considered when extracting color features of an image along with the LBP, then the resultant feature vector is considered to give high retrieval accuracy. Thus, we used an approach, based on feature extraction by integrating the CH in the HSV space, the CCV, and the LBP histogram, for CBIR.

In case of huge image data sets, CHs proved to be efficient and robust features for image indexing if the color pattern was unique compared with the remaining data sets. The CH [10, 8, 1] of an image portrays the frequency of each color level present in the image in the pixel domain. An image is quantized into sets of colors called bins to extract a CH. The CH is then computed by counting the frequency or the number of times each quantized color level is present in the image. The CH is robust for translation and rotation, and tolerant to changes in the viewing angle, scale, and occlusion.

The CCV includes the information about the spatial location of colors in an image [3]. The CCV is constructed by first blurring the image and then quantizing the color space such that it only contains n distinct colors. The CH of the image is then computed. Each histogram bin is then classified into two categories: coherent and incoherent. Thus, this forms a histogram-based CCV feature vector consisting counts of coherent and incoherent pixels of all the bins. The CCV corresponds to this classification for each color in the image.

The LBP [8-9] is a simple method, which integrates different orientations by maintaining a small size of the feature vector. The LBP level varies from 0 to 255 and represents a spatial relationship between nine color levels in a pixel block of size 3 × 3.

KEYWORDS: Image Information Classification, Feature Extraction. CCV, LBP, HSV, SVM

I INTRODUCTION

Image Processing is one of the most explored research area that is been defined under the specification of various associated processes. Image processing is having its importance and requirements in many application areas. These application areas include medical image processing, agricultural image processing, etc. The associated fields to the image processing further divided in several sub areas so that the information processing is defined as the framework so that the image information processing will be done. The work is here defined to apply various information stages to process on data values and relative results will be obtained from the work.

The image processing is here defined under the specification of image level analysis applied on the information process also described with associated process stages and each process stage itself defines an application area. This process stages includes the recognition system, feature generation, segmentation, classification etc. In recent years, image processing comes up with better functionality and with its integration to many other sub domains such as video system processing, animated image processing will be done in effective and relative way. This kind of information systems are described under the specification of relative image processing issues such as outlier identification, image noise reduction, image feature enhancement etc. This kind of information process is here described with specification of cost adaptive computation so that the information objects will be processed. The image processing is itself devised as the hybrid mechanism defined under application specification with associated processes. This broad process area is defined along with the specification of various sub stages or the sub processes. Some of these sub processes associated to the system are described under.

- Image Information Classification
- Object Detection
- Feature Extraction
- Image Enhancement

The representation of image is described with data processing form of image processing along with various data processing toolkits. These integrated toolkits includes neural network, genetics, differential equation based processing, Self-Organizing Map etc.

II OBJECTIVE

The proposed work is defined under following objectives there are few goals resultant from this thesis. Main purpose is to learn new information from the topic of an image processing area. In additional, dissertation presented here will cover the following aspects related to our research:

- Implementation of the CBIR system in which we input the query image and match the query image with the large database of images and retrieve the top 20 matches based on the similarity index.
- Reduce the semantic gap by changing the feature extraction process of the CBIR system by combining LBP, CCV and HSV. Using 24 bins for HSV histogram and 8 bins for the LBP histogram.
- SVM implementation for Classification for better retrieval time.
- Variation of Results while changing the feature length of methods used for the feature extraction.

III LITERATURE SURVEY

Zhang et al. [1] extracted low-level features by using a 3-dimensional dominant color vector (H, S. and V) and a 24-dimensional Gabor feature vector. This paper proposed a new approach for digital image retrieval by using intermediate semantic features and multi-step search. This approach suggests a new direction from the existing image retrieval approaches, which works with high- or low-level semantic features. Unlike the existing systems in literature, the proposed system was capable of capturing regional and global features using semantic and low-level features. The results suggested that this system had notable advantages and is more promising compared with the existing techniques. In addition, it has a powerful SQL-based retrieval interface to support semantic and low-level retrieval.
Li et al. [2] represented the image by computing the HSV histogram as a color feature, pyramid wavelet transform (PWT) by using the Haar wavelet as a texture feature (in YCbCr color space), and an edge histogram as a shape feature (in YCbCr color space). This work focused on solving the small sample size problem and improving the capability of a kernel machine compared to traditional SVM-based RFs. Hong et

al. [3] used visual features, such as CM and wavelet moments, for computing feature vectors and Comparing the query image and database images by using Mahalanobis distance.
Gosselin and Cord [4] exploited the color and texture information using the L*a*b* space and Gabor filters respectively. Tests were conducted on the generalist COREL photo database containing 50,000 pictures. This method merged all the semantic information based on binary annotations provided by users during retrieval sessions. Therefore, the kernel matrix framework, which offers acceptable properties of matrices and efficient combinations with kernel-based techniques for image retrieval classifiers, was adopted.

Ruiet al. [5] used the CH and CM and co-occurrence matrix for the COREL test set in an interactive approach Using relevance feedback. Similarity matrix used for CH vectors was CH intersection and that for CM was Euclidean distance (ED). The authors also used the MESL test set for which the visual features used are the CH, CM, Tamura, co-occurrence matrix, Fourier descriptors, and Chamfer shape descriptors. Chamfer matching was used for Chamfer shape representation where as weighted ED was used for the remaining features.

Broilo and Natale [6] presented the feature vector comprising of 32 CH bins, 9 CMs, 16 edge histograms and wavelet texture energy values. The HVS color space was used to extract the CM, and the RB space was used for the CH. Weighted ED was used for similarity matching. The image retrieval problem was formulated as an optimization problem and was solved by using particle swarm optimization.

IV RESEARCH METHODOLOGY

The primitive features required to compute an image feature vector are color and holistic structure features. If spatial distribution is considered when extracting color features of an image along with the LBP, then the resultant feature vector is considered to give high retrieval accuracy. Thus, we used an approach, based on feature extraction by integrating the CH in the HSV space, the CCV, and the LBP histogram, for CBIR.

A. PRIMITIVE FEATURES

In case of huge image data sets, CHs proved to be efficient and robust features for image indexing if the color pattern was unique compared with the remaining data sets. The CH [8, 9, 10] of an image portrays the frequency of each color level present in the image in the pixel domain. An image is quantized into sets of colors called bins to extract a CH. The CH is then computed by counting the frequency or the number of times each quantized color level is present in the image. The CH is robust for translation and rotation, and tolerant to changes in the viewing angle, scale, and occlusion.

The CCV includes the information about the spatial location of colors in an image [8]. The CCV is constructed by first blurring the image and then quantizing the color space such that it only contains n distinct colors. The CH of the image is then computed. Each histogram bin is then classified into two categories: coherent and incoherent. The pixel value is considered coherent when it belongs to a large, uniformly colored region, or it is considered to be incoherent. All the coherent and incoherent pixels of each bin are then counted and stored together in a vector

The LBP [5-7] is a simple method, which integrates different orientations by maintaining a small size of the feature vector. The LBP level varies from 0 to 255 and represents a spatial relationship between nine color levels in a pixel block of size 3 × 3 as shown in Fig. 2. The color level of the centre-most pixel is represented byb . For each block in the image, the center-most pixel level is compared with every neighboring pixel

value. When the color level of the neighboring pixel is greater than or equal to the center-most pixel value, it is coded as 1; otherwise it is coded as 0.
The LBP value of the block is calculated as shown in Equation (1).

$$V_{LBP} = \sum_{k=0}^{7} f(n)(b_x - b) * 2^x \ldots (1)$$

where, the function "f(n)" for the comparison is expressed as shown in Equation (2).

$$f(n) = \begin{cases} 1, & y \geq 0 \\ 0, & x < 0 \end{cases} \quad \ldots\ldots\ldots\ldots\ldots..(2)$$

b0	b1	b2
b7	b	b3
b6	b5	b4

Fig.1. Pixel Block of size 3 × 3.

The LBP levels fall between 0 and 255. The LBP histogram is computed as shown in Equation (3).

$$H_{LBP} = \{h_0, h_1, \ldots\ldots, h_{255}\} \ .(3)$$

Here h_i, $(0 \leq i \leq 255)$ represents the frequency of an LBP level "i" extracted from the complete image pixels.

B PROPOSED ALGORITHM

- Load the database image D_n $D_n = \{D_i | \ i=1,2,\ldots..1000\}$
- Transform an RGB image into the HSV color space.
- Compute the feature vector $Fi = \{ f_h , f_l , f_c \}$ where, f_h is the HSV histogram, f_l is the LBP histogram, and f_c is the CCV of the database image.
- Compute the feature matrix F_D of all database images where $FD = \{F_1, F_2, \ldots\ldots\ldots., F_{1000}\}$.
- Save F_D. Input a query image Q_i
- Compute the feature vector $Fi = \{ f_h , f_l , f_c \}$ where, f_h is the HSV histogram, f_l is the LBP histogram, and f_c is the CCV of the query image.
- Calculate ED or the L2 metric as shown in Equation (4).

$$ED(x,y) = \sqrt{\sum_{p=1}^{i} (x_p - y_p)^2} \quad ..(4)$$

Where, xp and yp are the l-dimensional feature vectors of the database and query images respectively.

- Compute ED for all the database images and retrieve the similar top 20 images having least ED.

We implemented the retrieval system using different feature extraction methods (Table 1) and compared the results to evaluate the performance of our proposed algorithm represented by proposed method 1 (PM-3) and proposed method 2 (PM-4).

Table 1. Details of the Methods Implemented (Numbers in Curly Braces Show Feature Length

Name of the method	Color features	Texture features	Shape features	Structure features
M-1	Color structure descriptors (CSD)	Edge histogram descriptors (EHD)	-	-
M-2	CH{9} and HSV histogram (HSV- H){9}	Tamura{4}	Sobel {1}	-
M-3	CH {24} and (CM){7}	-	-	CCV {48}
M-4	-	Mean, variance, skewness, and kurtosis {20}	Area, eccentricity, Euler number, convex area, perimeter, orientation, and Centroid {40}	-
PM-1	HSV- H{24}	LBP{16}	-	CCV {48}
PM-2	HSV- H{48}	LBP{48}	-	CCV {48}
PM-3	HSV- H{24}	LBP{8}	-	CCV {24}

Furthermore, we integrated the shape feature along with the color and texture features[3]in method 2 (M-2).The features used were Tamura (texture), RGB and HSV histogram (color), and Sobel operator (shape) .“Hue histogram reduction” was used for a quick retrieval from a large database.

In this work, we implemented an algorithm for image retrieval using primitive color structure features [5,2,4].Method3 (M-3), used for image retrieval, was based on color features such as CH, CM ,and color Structure features such as CCV.

Another hybrid approach [10,3] using shape and texture was used in method 4 (M-4) .The shape features Used were the area ,eccentricity, Euler number, convex area, perimeter, orientation, and Centroid. The shape features are useful when an image has prominent objects. The first-order histogram-based features were used as texture features. Mean, variance, skewness, and kurtosis were used to detect the image texture. Similarity between features was measured using the ED.

V EXPERIMENTATION

Experiments were conducted using a standard database [3] of 1000 images. This database is a collection of colored images from 10 different categories such as African people, buildings, beaches, buses, dinosaurs, elephants, roses, horses, snowy mountains, and food plates. The image features were extracted using different primitive feature extraction methods, as shown in Table 1. In addition, similar features were extracted from the query and stored images. The distance between the query image and database images was computed, by calculating the EDorL-2 distance, and arranged in an ascending order array .The top20 similar images were displayed and evaluated. The performance parameter i.e. precision is evaluated using Equation (5).

$$\textbf{Precision}=\frac{R}{T}$$

Where R is the number of relevant image retrieved and T is the total number of image retrieved.

VI.RESULTS AND DISCUSSION

The retrieval results based on MEG-7descriptors are showninTable2.These results indicated that color structure features provide more information than texture features. However, it was not possible to retrieve the entire semantic image through color features alone therefore a combination of multiple features was adapted for the semantic image retrieval. It was observed that M-1 (the combination of color structure descriptor [CSD] and edge histogram descriptor [EHD] for feature extraction) proves to be useful for the retrieval of more semantically significant images.

The retrieval results vary according to the method used and the image type. For example, EHD and the integrated method show prominent results in the presence of a distinct object in the background, such as buses or flowers. CSD method is out performed when an image comprises principal colors. The combined approach was found to be better for images with principal colors and distinct objects. Furthermore, the approach proved to work best when the database contained images, such as dinosaurs, which have similar texture, color, and background. The CSD and integrated method of color and texture work better in “multiple object images, “which contain many objects such as horse, pony, fencing, and green field. However, the three approaches perform poorly when retrieving images from the food category In spite of the fact that the average performance is more than 65%, yet a feature vector length is huge (278). Along these lines computational time needed s high and it is cumbersome for a vast database.

Table2. Retrieval results using MPEG-7 color-texture descriptors (M-1).

Precision (%)			
Image category	Feature extraction by CSD	Feature Extraction by EHD	Feature Extraction by CSD and EHD
Building	53	45	55
Bus	73	96	97
Footplates	51	36	45
Afrikaans’s	56	38	60
Beach	39	32	48
Dinosaurs	87	89	98
Elephants	62	48	63
Flowers	83	92	100

Snowy mountains	46	30	47
Horses	75	70	73
Average Performance	62.5	50.6	68.6

In another approach (M-2) , we integrated texture features (Tamura) with color (CH and HSV-H) and shape (Sobel) features. Here only23 features were used to reduce he computational time .Furthermore ,the "hue histogram reduction "was used for quick retrieval from a large data base [33] . Although three different primitive features were integrated in this method, no remarkable improvements were observed; the results were rather degraded in most case (Table3).

The method M-3 was used for image retrieval by using CH, CM, and CCV .The feature vector length was moderate. The results were similar for most images. However, improvements were observe din there trivial accuracy of images such as food plates and snowy mountains. Although the hybrid approach (M-4) used shape and texture features for feature extraction, it produced very poor results when compared to other feature extraction methods.
Table3.Category-wiseresults:average precision evaluated for the retrieval of five query images from each category.

Precision (%)						
Image category	Methods implemented					
	M-1	M-2	M-3	M-4	PM-1	PM-2
Building	46	47	47	25	63	61
Bus	96	83	87	17	93	95
Food plates	45	44	53	21	70	61
African people	54	49	55	23	68	72
Beach	48	47	46	23	47	51
Dinosaurs	98	99	98	92	100	100
Elephants	66	59	58	41	64	52
Flowers	99	56	80	37	88	89
Snowy Mountains	47	44	54	32	56	57
Horses	75	98	85	21	89	93
Average Performance	67.4	62.6	66.3	33.2	**73.8**	**73.1**

Our approach (PM-1andPM-2), which integrates the global basic color feature (CH) and features exploring the spatial relationship (LBP and CCV), delivered improved results. This approach out performs the existing methods of CBIR because of a significant improvement in the image retrieval of snowy mountains(56%),buildings (63%),African people (68%),food plates(70%),and dinosaurs (100%). Our approach demonstrated comparable retrieval accuracy for other image categories as well. The retrieval results for a query image from the African category are shown in Fig.2 and Fig.3. It is marked that along with good retrieval accuracy, the positive image were obtained at allow errank ,i.e. fast retrieval is a achieved by using our proposed approach.

Fig.2.Retrieval Results for the Images of the 'Africans' using the Proposed Method1 (Rank1to9)

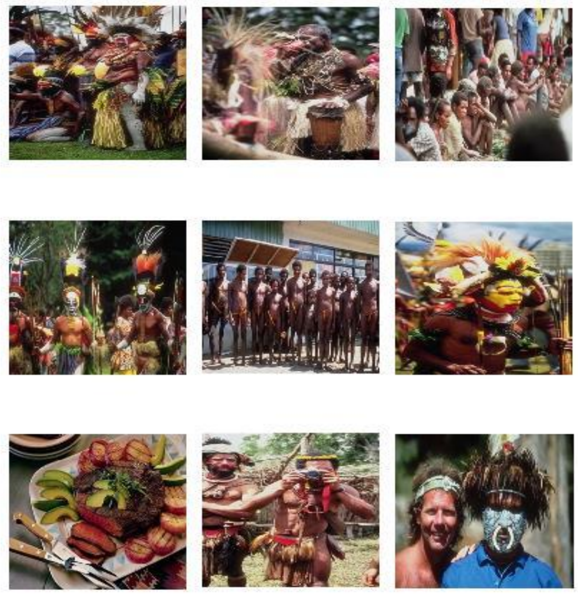
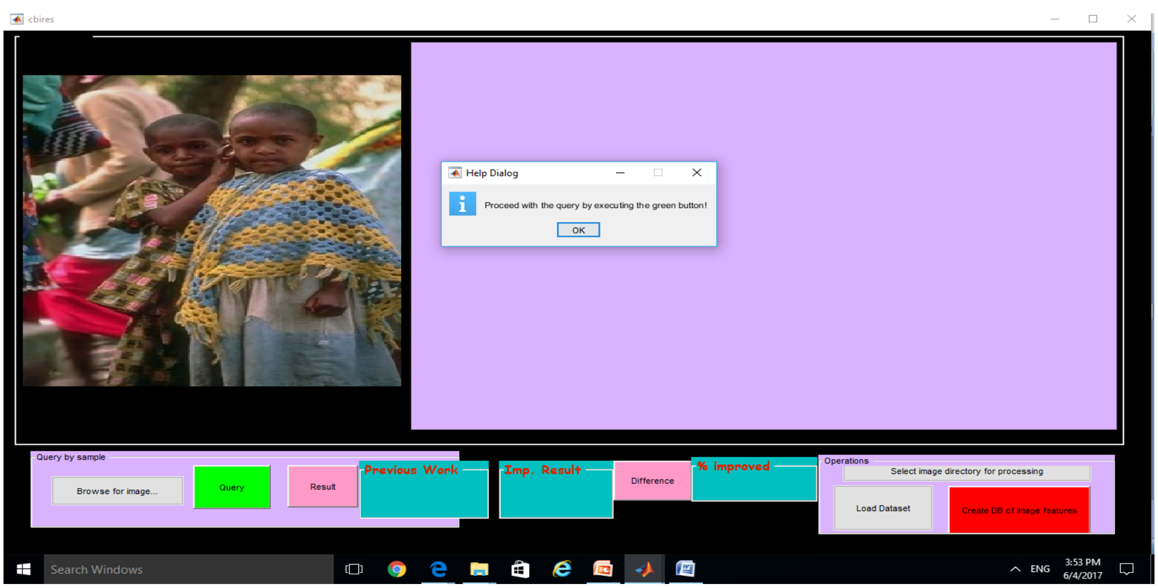


Fig.3.Retrieval Results for the Images of by Africans 'by using the Proposed Method-1(Rank10to18)

INPUT QUERY IMAGE



OUTPUT IMAG

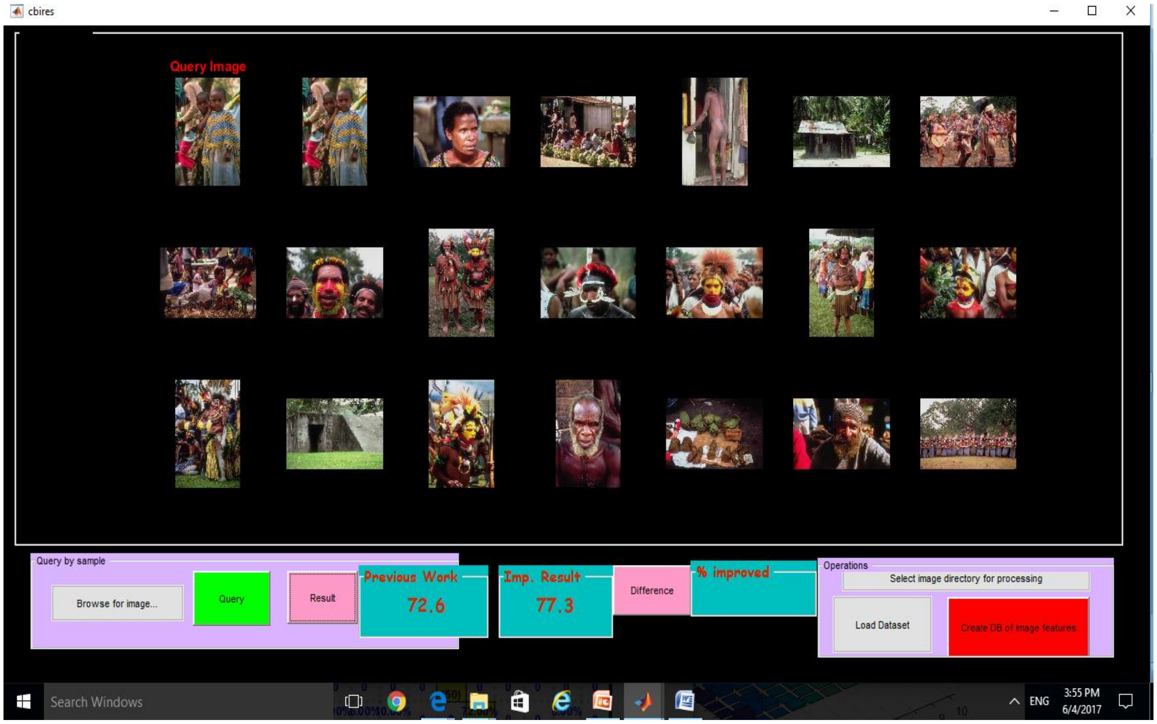


Table 6.2. Category-wise results: average precision evaluated for the retrieval of five query images from each category.

Image category	Precision (%)							
	Methods implemented							
	M-1	M-2	M-3	M-4	PM-1	PM-2	PM-3	PM-4
Building	46	47	47	25	63	61	72	48
Bus	96	83	87	17	93	95	94	83
Food plates	45	44	53	21	70	61	62	52
African people	54	49	55	23	68	72	70	56
Beach	48	47	46	23	47	51	52	46
Dinosaurs	98	99	98	92	100	100	99	95
Elephants	66	59	58	41	64	52	62	57
Flowers	99	56	80	37	88	89	90	81
Snowy mountains	47	44	54	32	56	57	64	52
Horses	75	98	85	21	89	93	92	80
Average Performance	67.4	62.6	66.3	33.2	**73.8**	**73.1**	**72.6**	**77.3**

This work explored the feature extraction system that utilizes structural connections within an image by integrating textured color descriptors and structure descriptors to retrieve semantically significant images. Different feature extraction techniques were studied and implemented to evaluate and compare our proposed method, with the existing methods. After marking the limitations of the combination of other features, we introduced our integrated approach.

The main contribution of this work was the use of global color features and the features exploring the spatial relationship to amalgamate many orientations, textures, and color distributions among the images. Other improvements, such as minimizing the feature vector size and quickening the process, were proposed and discussed. Using a large number of bins was not necessary when extracting the histograms; rather it was observed that a better retrieval accuracy was obtained using 24 bins for HSV histogram and 16 bins for the LBP histogram. Our approach led to a fast and efficient CBIR system that is applicable to a variety of databases. Experiments using Wang's database showed that our method gives progressive results when compared with several other
existing CBIR methods.

The CBIR system used in this paper may be extended to reduce the semantic gap in CBIR. The presented approach can be used for classifying image database to obtain more semantically meaningful retrieval results. The primitive features used in this paper may be mapped to high level semantic concepts by using relevance feedback algorithms.

VII CONCLUSION

This work explored the feature extraction system that utilizes structural connections within an image by integrating textured color descriptors and structure descriptors to retrieve semantically significant images. Different feature extraction techniques were studied and implemented to evaluate and compare our proposed method, with the existing methods. After marking the limitations of the combination of other features, we introduced our integrated approach.
The main contribution of this work was the use of global color features and the features exploring the spatial relationship to amalgamate many orientations, textures, and color distributions among the images. Other improvements, such as minimizing the feature vector size and quickening the process, were proposed and discussed. Using a large number of bins was not necessary when extracting the histograms; rather it was observed that a better retrieval accuracy was obtained using 24 bins for HSV histogram and 8 bins for the LBP histogram. Our approach led to a fast and efficient CBIR system that is applicable to a variety of databases. Experiments using Wang's database showed that our method gives progressive results when compared with several other existing CBIR methods.

VIII FUTURE SCOPE

Even though the aim of the work was completed and overall evaluation of the image processing application is positive. But there are many possibilities for the future development of the application created within this thesis. The CBIR system used in this paper may be extended to reduce the semantic gap in CBIR. The presented approach can be used for classifying image database to obtain more semantically meaningful retrieval results. The primitive features used in this paper may be mapped to high level semantic concepts by using relevance feedback algorithms

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