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Opponent Color and Curvelet Transform Based Image Retrieval System Using Genetic Algorithm

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***Abstract*—**In order to retrieve images efficiently from a large database, a unique method integrating color and texture features using genetic programming has been proposed. Opponent color histogram which gives shadow, shade, and light intensity invariant property is employed in the proposed framework for extracting color features. For texture feature extraction, fast discrete curvelet transform which captures more orientation information at different scales is incorporated to represent curved like edges. The recent scenario in the issues of image retrieval is to reduce the semantic gap between user's preference and low level features. To address this concern, genetic algorithm combined with relevance feedback is embedded to reduce semantic gap and retrieve user's preference images. Extensive and comparative experiments have been conducted to evaluate proposed framework for content based image retrieval on two databases, i.e., COIL-100 and Corel-1000. Experimental results clearly show that the proposed system surpassed other existing systems in terms of precision and recall. The proposed work achieves highest performance with average precision of 88.2% on COIL-100 and 76.3% on Corel, the average recall of 69.9% on COIL and 76.3% on Corel. Thus, the experimental results confirm that the proposed content based image retrieval system architecture attains better solution for image retrieval.

***Keywords*—**Content based image retrieval, Curvelet transform, Genetic algorithm, Opponent color histogram, Relevance feedback.

I. Introduction

CONTENT BASED IMAGE RETRIEVAL (CBIR) describes the automatic retrieval of images from the huge collection of image database based on the features such as color, texture, and shape. Even though numerous products have been developed by various association and individual authors such as QBIC [1], photobook [2], virage [3], and simplicity [4], these systems are still far from user's expectations. Traditional CBIR techniques based on color features are conventional color histogram [5], fuzzy color histogram [6], color corrologram [7], [8], color coherence vector [9], color moment [10]. Color channels are represented in various color spaces to describe the color intensity information like RGB, HSV, Lab, YC_bC_r and CMY model [11]-[15]. The texture features based on four categories such as structural, statistical, model based, and transform methods are presented in [16]-[21]. Though structural methods such as micro texture, morphological operator provide good figurative depiction of an image, it is only suitable for synthesis task rather than texture analysis task [22]. Statistical features like mean, variance, second order statistics which are derived from gray level co-occurrence describe the spatial relationship among gray levels of an image yield higher discrimination rate [23], [24]. Model based method like stochastic model, fractal model, and Markov random field are meant to be the best for analyzing texture images. Stochastic model is suitable for analyzing local image structure. Fractal model is fit for natural textures. Markov random field is able to capture information about local spatial correlation in the image. Some of the works based on model based methods are presented in [25]-[27]. Transform based texture feature extraction method like Fourier transform, wavelet transform, ridgelet transform, and curvelet transform are representing an image in the space whose co-ordinate system has close relationship with texture of an image. Wavelet, and curvelet transforms analyze the images at most suitable scales thereby reducing redundant coefficients. In [28]-[32], many transform based texture analysis methods are presented.

As low level features often fail to represent image semantics and have several limitations when dealing with large image databases [33], it is required to employ the high level features (concepts) to interpret images and measure their similarity. Though low level features are extracted from color, texture, shape of the images, there is no straight connection between high level concepts and the low level features. Semantic gap between low level features and high level concepts are reduced through five categories of methods: (1) embedding object ontology to describe high level concepts, (2) using soft computing tools to link low level feature with high level query concept, (3) incorporating relevance feedback for continual learning, (4) creating semantic template (ST) to maintain semantic image retrieval, (5) deployment of web image retrieval [34]. Tremendous papers have been presented for semantic image retrieval including genetic programming, support vector machine, multimodal retrieval, and relevance feedback in [35]-[45].

This paper is structured as follows: In Section I, introduction of low level features and brief review of the same were given. Related works of semantic based image retrieval system are given in Section II. Section III is emphasized on the proposed method. Experimental and empirical evaluations of the proposed method are described in Section IV. Finally, we conclude the paper in Section V.

II. Related Work

Many researchers made their contribution to semantically retrieving of images by using machine learning tools. Machine

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learning can be classified into two major groups: (i) Supervised learning (ii) Unsupervised learning. Supervised learning such as Bayesian classifier, support vector machine, are often used to learn high level image concepts from low level image features (color, texture) and it requires that network has to be trained with known outcome [46], [47]. Unsupervised learning such as clustering, it is based on how the low level features are organized or clustered to retrieve the similar images. The conventional K – means clustering and its enhancement are used for image clustering [48]. Related works based on machine learning including genetic programming, support vector machine, Bayesian classifier, artificial neural network, association rule learning and association rule learning are presented in [49]-[51]. Relevance feedback can be combined with the retrieval system to pin down the semantic gap hence by increasing considerable performance in the CBIR system [52]. In recent years, several machine learning method have been deployed in image retrieval system, interactive genetic algorithm based image retrieval system, in which HSV color model combined with gray level co-occurrence matrix for texture features and edge histogram descriptor are used to represent low level image features. Reference [36] introduced a fusion of wavelet packets and Gabor filter for image representation then back propagation neural network were used to classify the query image into appropriate semantic class. In [37], dual tree complex wavelet transform is tied with Bayesian framework for texture image retrieval system and experiments were done with ALOT, VisTex and STex texture database. Curvelet based texture image retrieval system is presented in [28], where texture features extracted from curvelet transform are rotation invariant and there has been no learning method used to retrieve images semantically. Several color descriptors, color moments and moment invariants are presented in [53], where opponent histogram, hue histogram, and rg-histogram are compared and tested with the ALOI and PASCAL VOC challenge 2007 dataset. Both query by keyword and query by region of interest are employed in [49], where semantic high level concepts are obtained by decision tree that makes use of semantic template to separate continuous valued region features. Relevance feedback based method [38] has used three kinds of query refinement methods - query point movement, query re-weighting and query expansion by using navigation pattern resulting from user log by which high class of image retrieval are achieved in tiny number of feedback rounds. Multimodal retrieval was performed [39] with the help of genetic programming through some feedback iterations where multimodal presents multiple input streams to address the problem of recognition ambiguity and benchmark was done on two image databases (Washington University and ImageCLEF). An additional method CLUE [43] is presented to reduce the semantic gap which gives top matched target images and NCut clustering is applied to these target images into various semantic classes. This system presents image clusters and changes the module of similarity measure based on user feedbacks.

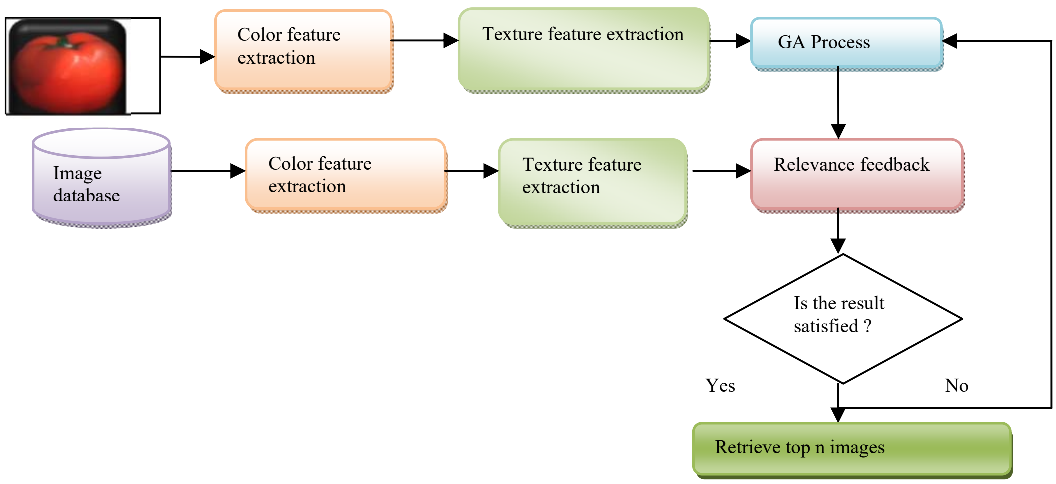

Fig. 1 General structure of proposed framework

III. Proposed Approach

The aforesaid papers ended with expecting better retrieval performance by combining color and texture feature as low level features and by enhancing texture method for extracting line and curved singularities. The intention of this paper is to link low level features with high level concepts by unsupervised learning of genetic programming thus reducing the semantic gap between user's perception and the query. The general structure of the proposed approach is given in Fig. 1.

As contrast to previous papers, the foremost contributions of this paper are as:

(1) Incorporating opponent color histogram so as to reduce the brightness ambiguity problem and to reduce the histogram dimensionality to 2-D.
(2) Enhancing the texture method to multi resolution feature analysis method by curvelet transform thus by representing line and curve like edges well
(3) Embedding machine learning algorithm as genetic programming to learn high level concepts
(4) Applying RF method to retrieve user's preferred images

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A. Color Feature Extraction

$$\begin{pmatrix} r \\ g \\ b \end{pmatrix} = \begin{pmatrix} \frac{R}{R+G+B} \\ \frac{G}{R+G+B} \\ \frac{B}{R+G+B} \end{pmatrix} \quad (1)$$

Because of the normalization, r and g are scale-invariant, and thereby invariant to light intensity changes, shadows, and shading. Since human perception is based on opponent axes, it is indeed to move toward opponent color spaces in image analysis applications. Certain colors cannot be perceived together to occur such as reddish green or yellowish blue while other transformation are possible. In contrary to the trichromacy, there are two kinds of photoreceptors: white-black and yellow-blue. Red-green with R G B Y colors can categorize all visible hues, the simplest opponent color model that derives Kashunen-Loeve transformation of the RGB are O1=(R-G)/2 and O2= (2B-R-G)/4. Figs. 2 and 3 show the calculation of opponent histogram and rg chromaticity histogram. In the proposed approach, color features are extracted by merging rg histogram and opponent histogram. Two dimensions of the normalized RGB color space are taken as rg chromaticity space [54], [55] where intensity information is lost. Bright blue can be represented generally as rgb (0, 0,255) whereas dark blue can be described by rgb (0, 0, 40). In the case of rg chromaticity channel, blue component can be represented by the percentage of red, green and blue rather than by intensity of three colors and the sum of three colors always be 1. Even though rg space contains less information, it has distinctive characteristic in object recognition applications. When an object is viewed by a camera, its perceptible color remains constant as there is no intensity information and it is invariant to changes of surface direction relatively to light sources. In the normalized RGB color model, the chromaticity components r and g describe the color information in the image (b is redundant as r +g +b = 1): calculation. The opponent histogram can be written as:

$$\begin{pmatrix} O1 \\ O2 \end{pmatrix} = \begin{pmatrix} \frac{R-G}{2} \\ \frac{2B-R-G}{4} \end{pmatrix} \quad (2)$$

The intensity information is represented by channel O3 and the color information by O1 and O2. Due to the subtraction in O1 and O2, the offsets will cancel out if they are equal for all channels (e.g., a white light source).

B. Curvelet-Based Texture Feature Extraction

The proposed framework takes advantage of rotation invariant curvelet transform for texture feature representation which extends the functionality of ridgelet transform to different orientations and scales to create the curvelet. Curvelet takes the form of basic elements which exposes very high directional sensitivity and is highly anisotropic. Therefore, curvelet transform represents edges better than wavelets and is well- suited for multi scale edge enhancement [56]. Curvelet requires fewer coefficients for representation, and the edge created from curvelet is smoother than wavelet edge. Wavelet, ridgelet, and curvelet are associated by:

$$\text{Wavelet: } \psi_{scale,point-function} \quad (3)$$

$$\text{Ridgelet: } \psi_{Scale,line-function} \quad (4)$$

$$\text{Curvelet: } \psi_{scale,curve-function} \quad (5)$$

Two implementations of Fast Discrete Curvelet Transforms (FDCT) are proposed: Unequally Spaced Fast Fourier transforms (USFFT), wrapping based Fast Discrete Curvelet Transform. In the proposed approach, wrapping based FDCT is employed which takes a 2D image as input in the structure of cartesian array *f[m,n]* such that $0\leq m<M, 0\leq n<N$, where M and N are the size of array which generates curvelet coefficients *C{j}{l}(k1,k2)* indexed by a scale *j*, an orientation *l* and two spatial location parameters *k1* and *k2* as output. Discrete curvelet coefficients is of the form

$$C(j,l,k1,k2)= \sum_{0\leq n<N}^{0\leq m<M} f[m,n]\,\varphi_{j,l,k1,k2}[m,n] \quad (6)$$

Here, each $\varphi_{j,l,k1,k2}$ is the digital curvelet transform and it should obey parabolic law on the sub bands of frequency domain to extract curved edges in the image. To obtain higher efficiency, curvelet is implemented in frequency domain to gain advantage of fourier transform i.e., 2D fast fourier transform is applied on the image and the curvelet coefficients are extracted by employing inverse fourier transform on the spectral product. Since the frequency of curvelet is non-rectangular wedge, it needs to be wrapped around the rectangle to perform IFFT. Curvelet coefficients are computed by the given formula

$$\text{Curvelet-coefficients}=\text{ifft}(\text{fft}(f(m,n))^* (\text{fft}(\varphi_{j,l,k1,k2})) \quad (7)$$

In our feature extraction step, after acquiring curvelet coefficients, computing the mean and standard deviation value provides the texture features. If there are *l* curvet transform used for transformation then *2l* texture features are extracted to represent each image. If the size of the image is 512 × 512, then the scale can be computed by [*ceil (log2 (min (m, n)) - 3)]* and it is decomposed into 4 scales. Thus, totally 50 sub bands of coefficients are computed due to the fact that curvelet comprises the same coefficients as curvelet at angle $\theta+\pi$, so only half of the sub bands of 2nd and 3rd scale are taken into consideration due to its symmetric behavior.

IV. Genetic Algorithm (GA)

The genetic algorithm is now widely accepted as an effective search paradigm in artificial intelligence, VLSI circuit layout, image processing, optimization of bridge structures, solving of non-linear equations, and many other areas. It is now frequently used as an optimization method,

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based on an analogy to the process of natural selection in biology. The biological basis for the adaptation process is evolution from one generation to the next, based on elimination of weak elements and retention of optimal and near-optimal elements. In a genetic algorithm approach, a solution is called a "chromosome" or string. A GA approach requires a population of chromosomes (strings) representing a combination of features from the solution set, and requires an evaluation or fitness function. This function computes the fitness of each chromosome. The algorithm manipulates a finite set of chromosomes (the population), based on the mechanism of evolution. In each generation, chromosomes are subjected to certain operators, such as selection, crossover, and mutation, which are equivalent to processes which occur in natural reproduction. So GA can be divided to four sequential main operations namely as population, selection, recombination (or crossover) and mutation. The optimization process is performed in cycles called generations. During each generation, a set of new chromosomes are created using crossover, insertion, mutation and other operators. Since the population size is fixed, only the best chromosomes are allowed to survive to the next cycle of reproduction. Genetic algorithm used in the proposed approach is given in Fig. 2

A. Solution Representation

Before applying genetic algorithm to a particular problem, certain decision has to be made to find a suitable gene for solving the problem, i.e., chromosome representation. Chromosome is a collection of genes. In this paper, chromosome has aforementioned two types of image features (i.e., color and texture) in an image, collectively there are 44 genes which constitute chromosomes for all images in the database. So the parent chromosomes can be represented as:

$$Ch= [F_x^c\ F_y^t] \tag{8}$$

where c=[1,2,3,4] are features obtained from color histogram of an image, and t=[1,2,..,40] are the features obtained from texture of an image using Curvelet transform.

B. Initial Population

The GA requires a population of chromosomes to be initialized at the starting of the GA process. Traditionally, the initialization process depends on the application; in our proposed system, feature vectors of the first query image are chosen as the initial candidate image.

C. Fitness Function

The fitness function is applied to evaluate the strength f(x) of each chromosome x in the population which assigns value to an individual gene based on how far the gene is from the solution, the larger the fitness value, the better the solution it contains. Since, the core intention of this system is to retrieve the images that are most satisfied to the user's preferences. Hence, in our approach, the quality of the chromosome x is assessed by

$$f_c = \sum_{i=1}^{p_s}(q_i - d_i)^2 \tag{9}$$

where f_c represents the similarity measure between the features of the images, p_s is the total number of features of an image and q represents the query image, d means the features of image in the database.

```
{Initialization}
For i := 1 to 20 do
      {20 is the number of generations}
      Create chromosome (i);
      i := i + 1;
End for
While (current_gen < 20) do
      Begin
            {Crossover and Mutation}
            No_of_Crossover := (ps * %c)/2
            No_of_Mutation := p * %m
            {ps is the population size}
            For i := 1 to No_of_Crossover do
Pick two chromosomes randomly as the parent;
Generate two offspring chromosomes by performing the
crossover
                  operation;
                  i := i + 1;
            End for
For i = 1 to No_of_Mutation  do

 Pick one chromosome randomly as the parent;
Generate one offspring chromosome by performing the
mutation    operation
                  (breeder genetic alg);
                  i := i + 1;
            End for
            {Fitness evaluation}
For i: = 1 to ps
Calculate the fitness value for chromosome (i) by
 performing fitness  function;
                        fc = Σ_{i=1}^{Ps} (Pi - qi)^2
                  i := i + 1;
            End for
            {Selection operation}
            While (new population < ps)
Choose the chromosome to exist by applying the roulette
 wheel   selection;
            End while
      End begin
End while
```

Fig. 2 Genetic optimization for the proposed approach

D. Genetic Operators

Selection or reproduction operator identifies best individuals from the current population to pass their genes to the next generation for recombination and ensures the survival of the best chromosome in the population. The best individuals have the higher chance of having the best solution. Here, Roulette wheel selection is adopted due to its simplicity, efficient time complexity and it does not require sorting or fitness rescaling. In this selection method, parents are selected according to their fitness. The better the chromosomes are, the more chances to be chosen they have. Chromosome with higher fitness will be selected more times. The generation of successors in a GA is determined by a set of operators that recombine and mutate selected genes of the current population. The two most general operators are crossover and mutation. The crossover operator generates two new offspring from two parent chromosomes, by copying selected genes from each parent. Mutation modifies the one or more gene values in chromosome from the starting state so that the algorithm will arrive at better solution than was previously possible. The GA parameters assumed in this proposed work are presented in Table I.

V. Integration with GA Based Relevance Feedback

In general, an image retrieval system presents a ranked set of images relevant to the user's initial query and from there on iteratively asks for the user to provide feedback on the rank of the images and uses the feedback to make an improved set of images. In our system, relevance feedback is used to modify the rank by computing distance between feature vectors of one that the user gives as initial feedback and all other feature vectors of returned images by selecting closest image relevant to the query image in the returned output. User provides feedback and the process continues until user is satisfied with the retrieved images. Comparison is done by using the fuzzy C means distance function distfcm(q_vector, db_vector).

In our experiments, 500 images were selected randomly and relevance feedback is performed by the system upon receiving the feedback (rank of the expected image in the returned results). Feedback process is performed on top 25 returned images. Totally 5 iterations of RF were performed in our experiments; the performance of the system has been measured as average precision and recall values.

VI. Experimental Results

To show the effectiveness of the proposed approach, we performed extensive experiments on two datasets and these were compared against several existing approaches for CBIR. We have used Corel dataset (DB2) having 1000 images divided into 10 categories namely Africa, Beach, Buildings, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains, and Food. Corel dataset has become de-facto standard in assessing the performance of CBIR systems. COIL-100 database of Columbia University is also used for estimating performance which contains 100 varieties of objects, for each object, 72 different images along with various orientations were created. A user submits an image containing a dinosaur as the query image into the system, and then, the system compares the query features with the features of those images in the database and finds the most similar images to the query image. These images are ranked based on the similarity of the feature values. The 25 query retrievals for dinosaur from Corel dataset and an object in the coil dataset are given in Figs. 3 and 4. To evaluate the effectiveness of the proposed system, we examined how many relevant images to the query image were retrieved. The retrieval effectiveness can be defined in terms of average precision and average recall rates. Precision is the percentage of the number of retrieved similar images to the number of retrieved images, while recall is the ratio of the number of retrieved similar images to the entire number of similar images. They are defined as:

$$P=I_n/N \tag{10}$$

$$R=I_n/K \tag{11}$$

where I_n is the number of similar images retrieved, N is the total number of images retrieved and K is the total number of similar images. In the proposed system, we set N=20 and K=100 for corel datasets. Opponent Color and Curvelet Transform (OCCT) based image retrieval system shows significant improvement in average retrieval precision (93.7%) as compared with other existing methods by [52] (92%), [45] (89%) respectively on coil dataset (DB1). We use the RGB, HSV, YC_bC_r, and Lab color spaces to evaluate the retrieval performance on DB1. Subsequent to the experiment, it was clear that the retrieval precision of the RGB color space is about 2% better than that of the YC_bC_r space (92.8%), Lab (90.2%), HSV (89.1%) color spaces. The performance analysis of the various methods on coil dataset is given in Figs. 5-8. The experiments on corel dataset were also conducted on various color spaces like RGB, YC_bC_r, HSV, and Lab. Based on the retrieval results, the proposed approach achieves better retrieval performance in the YC_bC_r space on Corel dataset. The average retrieval precisions and recalls on corel dataset (DB2) are presented in Figs. 9-12. From the analysis, it is shown that OCCT-RGB system yields better improvement over other methods on DB1 while YC_bC_r offers significant improvement than other spaces on DB2. To evaluate the combined retrieval performance, the harmonic mean of precision and recall, namely balanced F_{score} is used to determine the capacity of the system to retrieve at the same time precise and diverse results and is defined as:

$$F_{score}=\frac{2\times \text{precision}\times \text{recall}}{\text{precision}+\text{recall}} \tag{12}$$

From the F_{score}, it is clear that RGB based OCCT image retrieval system confirms considerable improvement over other methods on Coil dataset while YCbCr color space outperforms other spaces and existing methods on Corel dataset. Finally, OCCT method and relevance feedback scheme are combined together in order to increase the effectiveness of the system.

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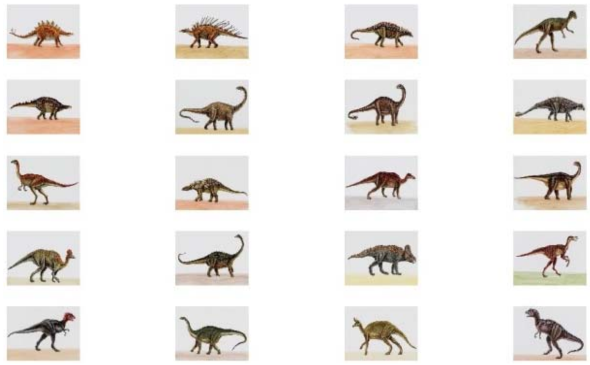

Fig. 3 First retrieval results for the dinosaur in our retrieval system

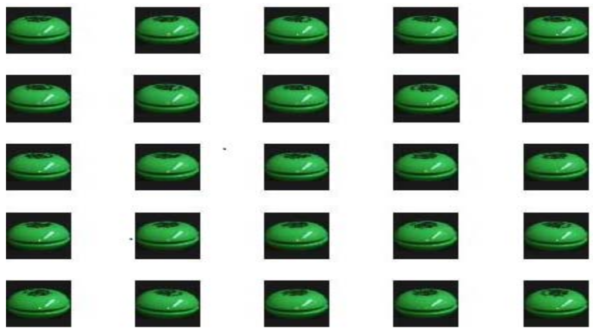

Fig. 4 First retrieval results for the object in Coil dataset by our retrieval system

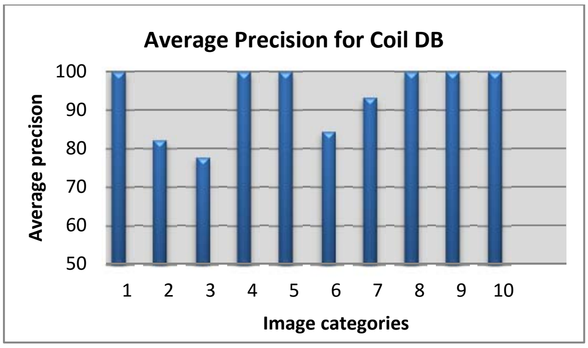

Fig. 5 Average precision for 10 image categories in Coil DB

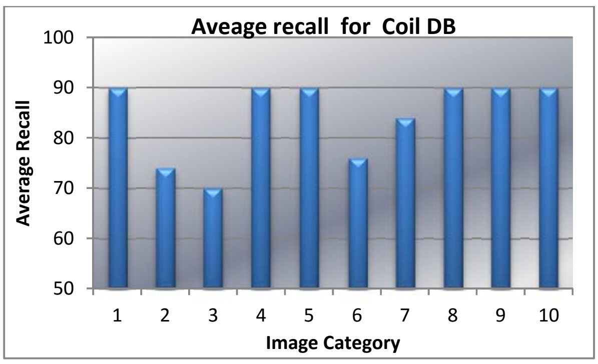

Fig. 6 Average Recall for Coil database

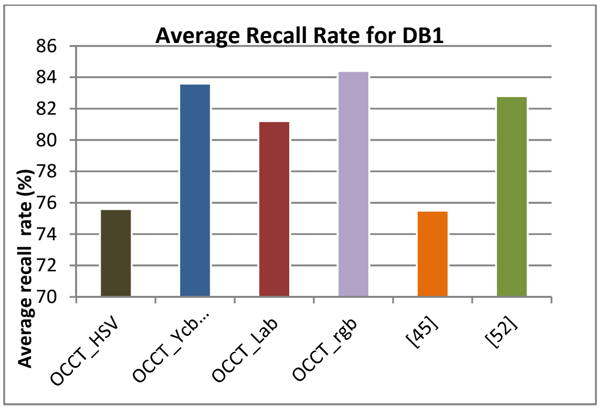

Fig. 7 Average Recall rate for Coil database

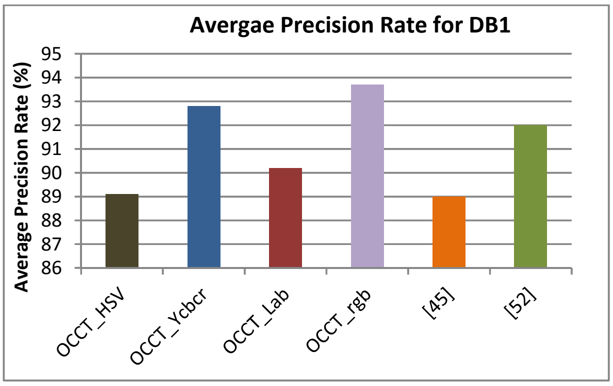

Fig. 8 Average precision rate for Coil database

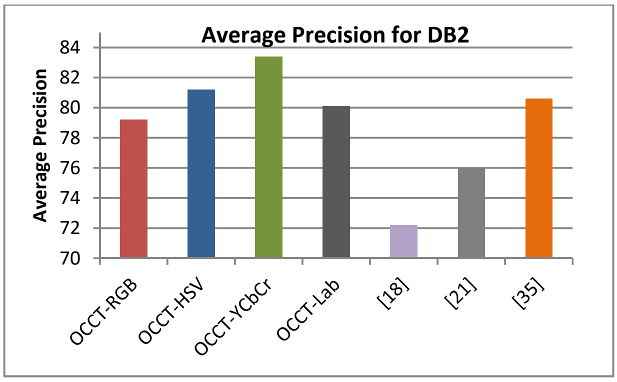

Fig. 9 Average precision for Corel database

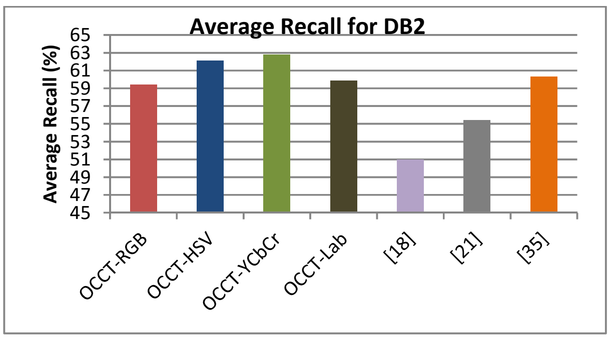

Fig. 10 Average recall for Corel database

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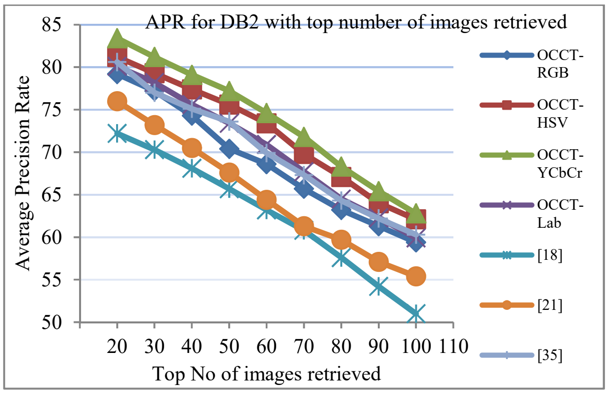

Fig. 11 Average precision rate for Corel database with top number of images retrieved

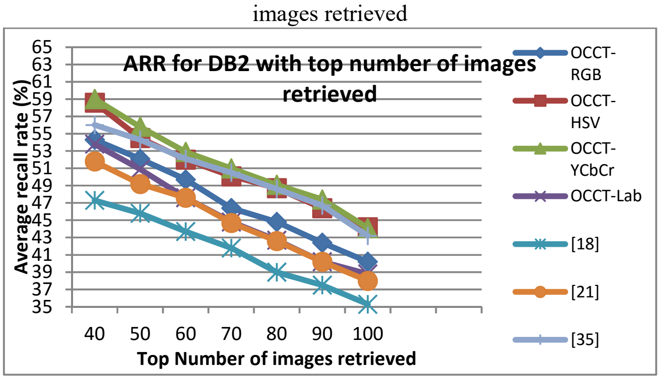

Fig. 12 Average recall rate for Corel database with top number of images retrieved

TABLE I
PARAMETER SETTING IN THE GA PROCESS

Population size	500
Maximum generations	20
Encoder mechanism	Roulette wheel selection
Cross over type	Single point
Cross over Rate	0.9
Mutation Type	Uniform
Mutation Rate	0.1
Mutation Operator	Breeder Genetic Algorithm
Stopping Criteria	100 iterations

VII. CONCLUSION

In this paper, we have introduced a semantic image retrieval system which incorporates genetic algorithm and relevance feedback for associating with low level features. The proposed method has also introduced new phenomena of feature extraction, in which the features are extracted through curvelet transform and are fused with opponent histogram of colour feature extraction method. Extensive experiments on coil and corel dataset are performed. The proposed method is compared with several existing content based image retrieval methods. Results of the comparison have exposed the superiority of the proposed method in terms of precision and recall. Further enhancement is to employ more visual features such as shape, spatial location etc., to provide the CBIR system more robust using other optimization algorithm like ant colony optimization, particle swarm optimization etc.

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