

# An Effective Mechanism to Neutralize the Semantic Gap in Content Based Image Retrieval (CBIR)

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**Abstract:** Nowadays, Content Based Image Retrieval (CBIR) plays a significant role in the image processing field. Images relevant to a given query image are retrieved by the CBIR system utilizing either low level features (such as shape, color etc, ...) or high level features (human perception). Normally, a semantic gap exists between the low level features and the high level features, because the images which are identical in visual content may not be identical in the semantic sense. In this paper, an effective approach is proposed to trim down this semantic gap that exists between the low level features and the high level features. Initially, when a query image is given, images relevant to it are retrieved from the image database based on its low level features. We have performed retrieval utilizing one of the evolutionary algorithms called Evolutionary Programming (EP). Subsequent to this process, query keyword which is a high level feature is extracted from these retrieved images and then based on this query keyword, relevant images are retrieved from the database. Subsequently, the images retrieved based on low level features and high level features are compared and the images which are both visually and semantically identical are identified. Better results obtained by the proposed approach when it is queried using different types of images prove its effectiveness in minimizing the semantic gap.

**Keywords:** CBIR, low level feature, high level feature, semantic gap, color, shape, texture, contourlet, squared euclidean distance, EP.

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## 1. Introduction

Content-Based Image Retrieval (CBIR) methods retrieve images by means of keywords or image contents [24]. In image processing, CBIR is considered as an important domain because of its diverse applications in internet, multimedia, medical image archives, satellite imaging [18], commerce, government [7], and academia and crime prevention [15].

Images are indexed by CBIR using the image features like color, shape and texture with minimal human involvement. CBIR compares the features of the images present in the database with that of the query image for retrieving relevant images [9] from the image data base for a specified query image [4]. CBIR has been developed into a popular field of research. Determining the finest solution for efficient retrieval of multimedia data and utilization of storage space has been attempted by several research domains [10]. Each image is represented in CBIR using image features such as color, texture and shape [26]. Images are retrieved using the relevance that is computed based on the similarity of the features between them and the query image [13, 22].

In content based image retrieval systems, color is one of the vital and widely used visual features. Color histogram is extensively used as a representation

technique. It captures the number of pixels having specific properties and it is statistically described as the combined probabilistic properties of diverse color channels (such as red, green and blue) [1]. Texture is an inherent property of all surfaces and signifies the visual patterns of homogeneity. Important information related to the structural arrangement of the surface, such as clouds, leaves, bricks, fabrics, etc., are present in it. The relationship between the surface and its neighboring environment are also represented by it. In short, the distinctive physical composition of a surface is described by this feature [5]. Texture determination is perfectly appropriate for medical image retrievals [12]. CBIR [20] utilizes some texture features including entropy, energy, contrast and homogeneity [7].

The characteristic surface configuration of an object; an outline or contour can be indicated by the term, shape. By its outline, it enables an object to be distinguished from its surroundings. Boundary based and region based are two general categories of shape representation [5]. The CBIR systems, which employ visual features assumes the existence of a mapping between the low level visual features, and the high level image semantics [20, 27] i.e., they assume that if visual content of the images are identical then their semantic content will also be identical. The term "semantic gap" was later introduced by researchers

[11, 20, 27] because, they did not agree with this assumption. The term semantic gap signifies the disparity between the low level visual features and the high level image semantics. In [11], semantic gap is considered as the loss of information that occurs when an image is represented by its features [27].

Either low level features or high level features are utilized by conventional CBIR systems, for retrieving relevant images. But, because a semantic gap exists between the low level features and high level features of images, the retrieved images are not accurate. So, to minimize this semantic gap, we first extract the low level features such as shape, color and texture from the images and then the relevant images are retrieved from the database with the aid of Squared Euclidean Distance (SED) similarity measure using Evolutionary Programming (EP). After that a query keyword which is a high level feature is obtained from these retrieved relevant images and based on this obtained query keyword another set of relevant images are retrieved from the image database. Subsequently, both sets of retrieved images are analyzed by comparing with each other and the images which are identical both in visual content and semantic meaning are retrieved. The rest of the paper is organized as follows: Section 2 reviews the recent related research works i.e., CBIR methods based on low level and high level features. Section 3 details the step by step processes present in the proposed approach with required illustrations and mathematical formulations. Section 4 discusses about the simulation results and section 5 concludes the paper.

## 2. Recent Related Researches: A Review

A handful of research works available in the literature are briefly reviewed in this section. Rao *et al.* [16], have proposed a CBIR method which is based on automatically-derived image features, for the retrieval semantically-relevant images from an image database. They have obtained better favored image results by using hierarchical clustering at the initial stage to filter most of the images before employing the clustered images to the RBFN network.

Suhasini *et al.* [21] have used Conventional Color Histogram (CCH), Invariant Color Histogram (ICH) and Fuzzy Color Histogram (FCH) in their proposed method for color extraction and comparison. The frequency of occurrence of each color in an image has been indicated by the CCH of an image. Simplicity and ease of computation have been the appealing characteristics of CCH. However CCH has several problems. First, even after radical quantization of the color space the dimensionality of CCH has been high. The second disadvantage has been its inability to handle rotation and translation because it has not taken into account the color similarity across different bins.

Reddy *et al.* [17] have used high level features known as semantic indexing in their proposed approach. From their results, first they have understood that their approach could retrieve images of diverse shape, color and size. Second, they have observed that the images that take up maximum area have been retrieved correctly. The performance of their approach has not been satisfactory for images of small segment size.

Adnan *et al.* [2] have proposed an object based search technique where geometrical shapes and other features like color and texture have been used to identify the object in the image. Also, the search process has been enhanced by object-co-relation augments. Though, they have chosen simple images to decrease the role of segmentation in the overall process in order to focus more on object identification, the same method has been applicable to other images also.

Wang *et al.* [23] have proposed a method for extraction and representation of objects spatial relationships semantics that exists among objects present in images. Extraction of low level features integrated with their proposed line detection techniques have been used to identify all the objects. Minimum Bound Region (MBR) with a reference coordinate has been used to represent the objects. The spatial relation among the objects has been calculated using the reference coordinate. "Front", "Back", "Right", "Left", "Right-Front", "Left-Front", "Right-Back" and "Left-Back" are the 8 spatial relationship concepts that have been identified. Semantic meaning and representation have been obtained by automatically translating the user query that is available in text form.

Abbas *et al.* [1] have proposed CBIR and mainly concentrated on Text Based Image Retrieval (TBIR). Comparison of their results have shown that content based has been visual whereas text based has been semantic. Compared to CBIR, the text based image retrieval has been faster.

Wu *et al.* [25] have proposed a color and texture feature combination based retrieval method. The information of texture has been represented by Dual-Tree Complex Wavelet Transform (DT-CWT) and Rotated Wavelet Filter (RWF) based on the characteristics of the image texture. The color histograms in RGB and HSV color space have been chosen as the color feature. It has been proved by experimental results.

## 3. Proposed Approach

CBIR [3] plays a significant role in many of the fields such as medical imaging, education, surveillance applications and more. In order to retrieve image based on the given query image, either low level or high level features of the database may be used. There is a semantic gap between the low level features and the high level features of the images. The semantic gap

indicates the dissimilarities in the semantic content of images that have identical visual content. In order to solve the aforesaid problems an effective mechanism is needed. In our work, we have three main processes, they are CBIR based on low level features, CBIR based on high level features and analysis on low level and high level featured images.

### 3.1. CBIR Based on Low Level Features

The shape, color and the texture features are the low level features used in this CBIR for retrieval. For this CBIR, feature extraction and similarity measure are the main processes. In the feature extraction process, the low level features shape, color and the texture features are extracted from the query image and also from the database images. After the completion of the feature extraction, the query image features and the database image features are compared by means of the SED. Hence the images which have similar low level features are retrieved. The subsequent sections detail the aforesaid process that is shown in Figure 1.

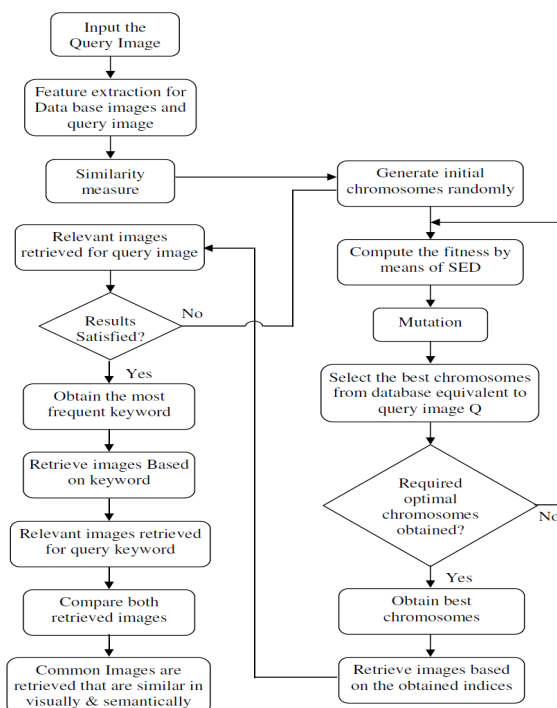


Figure 1. Flow chart for the proposed system.

#### 3.1.1. Feature Extraction

In this feature extraction process, the low level features shape, color and texture are retrieved from the query image and also from the database images. The shape, color and texture feature extraction are detailed in the following sections.

##### 3.1.1.1. Shape Feature Extraction

Shape is an important visual feature and it is one of the primitive features for image content description [6]. Let  $D$  be the image database which contains images of

dimension  $m \times n$ , where each image  $I$  of the database has its own semantic index  $hid$ . For the filterization process, the image  $I$  is converted to gray scale  $I_g$  from RGB color space. Let,  $I_R, I_G, I_B$  be the  $R, G, B$  weights of the image  $I$  then:

$$I_g = 0.2989 * I_R + 0.5870 * I_G + 0.1140 * I_B \quad (1)$$

Equation 1, which is known as the Craig's formula is applied for the conversion of RGB to gray scale image and then the mean filter is applied on the converted gray scale image  $I_g$  for the removal of noises. The mean filter smoothes the image data, thus the noise has been eliminated. Using the grey level values, this filter performs spatial filtering on each individual pixel in an image in a square or rectangular window surrounding each pixel. And then the filtered image is clustered to identify the various regions in the image. This can be discovered by identifying groups of pixels that have similar gray levels, colors or local textures utilizing clustering in the image analysis. Clustering is a method of grouping data objects into different groups, such that similar data objects belongs to the same group and dissimilar data objects belongs to different clusters [19]. For clustering process, numerous techniques exist and among them a vital role is played by the  $k$  means clustering method. For many practical applications, the  $k$ -means method has been shown to be effective in producing good clustering results. In this work, we use  $k$  means clustering to identify the various regions in the image. The denoised image  $I_g$  is then clustered by means of  $k$  means clustering. The steps involved in the  $k$  means clustering process is described below:

*Input: Denoised image  $I_g$  with  $m \times n$  pixel  $K$ -number of clusters*

*Output: Set of  $K$  clusters*

*Step 1: Arbitrarily select  $K$  data items from the input as initial centroids.*

*Step 2: Repeat*

*Assign the remaining data items apart from the selected initial centroids to the cluster  $K$ , which has the closest centroid.*

*Calculate the new centroid for each cluster until convergence occurs.*

After applying the  $k$  means clustering algorithm, the clustered regions of the denoised image  $I_g$  is identified. Then, utilizing canny edge detection algorithm the diverse edges present in the clustered regions of the image  $I_g$  are identified. The steps performed by the canny edge detection algorithm are shown below:

1. *Smoothing:* The  $k$  clustered regions of the image  $I_g$  are blurred in order to remove the noises.
2. *Finding Gradients:* Then the edges of the clustered regions are marked wherever the gradients of the image possesses large magnitudes.
3. *Non-Maximum Suppression:* Only the local maxima of the clustered regions in the denoised image  $I_g$  should be marked as edges.

4. **Double Thresholding:** Potential edges of the clustered regions of the image  $I_g$  are determined by a thresholding process.
5. Finally, the edges of the diverse clustered regions have been determined by suppressing all the edges which are not connected to a very certain edge.

Hence, the edges of the clustered  $k$  regions are tracked and then the edges are smoothed for sharpening, in order to remove the number of the connected components that occur unnecessarily in the clustered regions. Therefore, the diverse shapes which exist in the image  $I_g$  are extracted and the shape feature is retrieved from the image  $I_g$ . Subsequently, the shape feature of the diverse images existing in the database are also extracted and stored as a shape feature vector set  $S_f$ .

### 3.1.1.2. Texture Feature Extraction

LBP operator is considered as one of the most powerful means for texture description among the numerous available texture descriptors. In our work, we have used the rotation invariant LBP-HF (which has been improved from the LBP operator), features based on the uniform LBP histograms. The image  $I$  is rotated with the  $\omega^\circ$  and hence, we obtain the rotated image  $I^{(\omega)}$ .  $\omega^\circ = \frac{360^\circ}{N_n}l$ ;  $0 \leq l \leq N_n - 1$ . Then, the existing

uniform pattern  $U_{z'}(N_r, N_{r'})$  at the point  $(p_1, p_2)$  has been replaced with the uniform pattern  $U_z(N_r, N_{r'})$  at the point  $(p_1', p_2')$  of the rotated image. Subsequently, for the new uniform pattern, LBP histogram  $h(U_{z'}(N_r, N_{r'}))$  is determined. The features determined from the  $h(U_{z'}(N_r, N_{r'}))$  are as follows:

$$H(N_r, N_{r'}) = H(N_r, N_{r'}) \exp\left(-2\pi N_f \cdot \frac{l}{N_n}\right); 0 \leq N_f \leq N_n - 1 \quad (2)$$

Where

$$H(N_r, N_{r'}) = \sum_{N_r=0}^{N_n-1} h_l(U_{z'}(N_r, N_{r'})) \exp(-i 2\pi N_f N_{r'} / N_n) \quad (3)$$

In particular, the fourier magnitude spectrum is also added as features and it can be represented as:

$$|H(N_r, N_{r'})| = \sqrt{H(N_r, N_{r'}) \overline{H(N_r, N_{r'})}} \quad (4)$$

Where,  $\overline{H(N_r, N_{r'})}$  is the complex conjugate of  $H(N_r, N_{r'})$ . Thus, the Rotation invariant LBP-HF features and an effective texture descriptor are determined for all the images and stored as the texture feature set  $T_f$ .

### 3.1.1.3. Color Histogram Feature Extraction

Color histogram is one of the features of the proposed level featured CBIR. This feature is extracted by first resampling the image  $I$ , and then performing color segmentation on the image. For color segmentation,

anisotropic diffusion is employed which is a mechanism used to perform intra-region smoothing in images. By means of anisotropic diffusion, the resampled image  $I$  is segmented according to the color. Then the color histogram  $\{C_h\}$  is computed for the color segmented images by computing the numbers of pixels that carry the magnitude of each color in the images. This color histogram is determined for all the images and it is stored as a color feature set  $C_f$ .

### 3.1.1.4. Contour Let Transform Extraction

The contour let transform is utilized to compute two essential features energy and standard deviation from the database images. At first the input image is re-sampled and then the image is converted into a gray-scale image. After that contour let transform is applied on the converted gray scale image [14] and decomposition is done in the contour let domain by the Laplacian Pyramid (LP) and Directional Filter Bank (DFB), Single level LP decomposition and DFB:

$$\{\sigma_x\}_y = \sqrt{\frac{I}{M \times N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \left( X_x^{(x)}(m, n) - \mu_x^{(y)} \right)^2} \quad (5)$$

$$0 \leq x \leq N_{sb} - 1, 0 \leq y \leq N_I - 1$$

$$\{E_x\}_y = \frac{I}{M \times N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \left| X_x^{(y)}(m, n) \right| \quad (6)$$

The sets of energy  $\{E_x\}_y$  and standard deviation  $\{\sigma_x\}_y$  obtained for each directional sub-band are concatenated into a single feature set for each image  $y$ , termed as  $\{f_{CT}\}_y$ . This feature set is normalized and stored as contour let feature of the image. The normalized feature set is obtained from the original feature set which is termed as  $ct_f$ . Hence, the shape, texture and the color features of the image are determined and the feature set of the image  $\{\hat{F}_I^{(j)}\}$  is formed by combining these features.

### 3.1.2. Image Retrieval Through Evolutionary Programming

When a query image is given as input to the proposed system, all the features from the query image are extracted by it. After this, the feature set of the query image is compared with each feature set present in the feature set library. For the retrieval process, in this work we utilize Evolutionary Programming (EP) which is one of the Evolutionary Algorithms. The feature set of the query image is compared with the feature set of each image present in the database using the SED similarity measure by EP in the retrieval process. Let  $Q$  be the query image and  $\{F_q\}$  be the extracted feature set of the query image. Relevant images are retrieved by comparing the query image  $Q$  with the database images using the feature set computed for each image

in the database  $D$  EP contains 3 basic steps which should repeat until it reaches its threshold or a satisfactory solution is obtained:

1. Choose an initial population of trial solutions at random. The speed of optimization is highly dependent on the number of solutions in a population, but definite answer regarding how many solutions are appropriate is not available.
2. A new population is generated by replicating each solution and each of these offspring solutions are mutated in accordance with a continuous distribution of mutation types that range from minor to extreme. The functional change forced on the parents assesses the severity of the mutation.
3. Then, the fitness of each offspring solution is computed in order to assess the solution. Though traditionally the  $N$  solutions that are to be retained for the population of solutions is determined by performing a stochastic contest, sometimes it is determined deterministically. There is no necessity to keep a constant population size or to restrict the parents to have only one offspring.

### 3.1.2.1. Generation of Random Chromosomes

In our work, initially  $N_p$  numbers of random chromosomes are generated and the chromosomes represent the images and each chromosome has  $N_d$  gene values. Here the gene values indicate the indices of the images in the database and the process utilizes the images that have relevant indices. Each index may represent the image in the database. Then the generated chromosome can be represented as follows:

$$D_l^{(j)} = \{d_0^{(j)}, d_1^{(j)}, d_2^{(j)}, \dots, d_{N_d-1}^{(j)}\} \quad (7)$$

$$0 \leq j \leq N_p - 1, 0 \leq l \leq N_d - 1$$

Here,  $D_l^{(j)}$  indicates the  $l^{\text{th}}$  gene of the  $j^{\text{th}}$  chromosome and here  $d$  represent the index of image. Color, shape, texture and the contourlet features are extracted from the images whose indices are generated as genes. After computing all the afore mentioned set of features from the database  $D$ , the  $s$  features of the image are concatenated as a single feature set and then each featureset is normalized as:

$$\{\hat{F}_l^{(j)}\} = \left[ \frac{|F_l^{(j)}|}{\left[ \sum_{q=0}^{|F_l^{(j)}|-1} (F_l^{(j)}(r))^2 \right]^{1/2}} \right] F_l^{(j)}(r) \quad (8)$$

Where,

$$F_l^{(j)}(r) = F_l^{(j)}(r) \mid F_l^{(j)} \mid - \sum_{q=0}^{|F_l^{(j)}|-1} F_l^{(j)}(r) \quad (9)$$

The normalized feature set  $\{\hat{F}_l^{(j)}\}$  obtained from equation 8 is the final feature set extracted for a

particular database image and it is stored in the feature set database. In a similar manner, the feature set for all the images are determined and a feature set library is created using these feature sets of the images.

### 3.1.2.2. Fitness Function

Here the fitness utilized for this EP is SED which is the distance measure utilized to analyze the similarity between the query image feature set and the database image feature set and the image that has the least deviated distance is considered as the image most similar to the query image. The fitness formulae computed are shown below:

$$F^{(j)} = \frac{\sum_{l=0}^{N_d-1} \delta_l^{(j)}}{|\delta_l^{(j)}|} \quad (10)$$

Where,

$$\delta_l^{(j)} = \left[ \sum_{r=0}^{|\hat{F}_k^{(j)}|-1} \left( \hat{F}_l^{(j)}(r) - \hat{F}_q(r) \right)^2 \right] \quad (11)$$

In Equation 11,  $\hat{F}_q$  is the feature set extracted for the query image,  $\delta_l^{(j)}$  represents the SED between each  $D_l^{(j)}$  of the  $j^{\text{th}}$  chromosome and the query image, i.e., SED of the query image and the indices of database images which are generated in the genes. Subsequently, the  $F^{(j)}$  is sorted in the ascending order and  $N_p/2$  number of mean distances are selected from  $f^{(j)}$ . Then, the corresponding  $D_l^{(j)}$  of the selected  $F^{(j)}$  is obtained and then the selected chromosomes are subjected to the genetic operator, mutation.

### 3.1.2.3. Mutation

The mean of the chromosomes are computed and they are sorted in ascending order and  $t$  numbers of mean values are selected for the mutation process. After that, mutation operation is performed on the chromosomes corresponding to these selected means termed as children chromosomes  $D_{newl}^{(j)}$ . The mutation process replaces  $N_M$  number of genes from every chromosome with the new genes. The  $N_M$  numbers of genes are nothing but genes that have minimum SED value. The replaced genes are the randomly generated genes without any repetition within the chromosome.

### 3.1.2.4. Selection of Optimal Solution

After the process is repeated  $I_{max}$  number of times, chromosomes that have maximum fitness value are selected from the resultant group of chromosomes as the best chromosomes. Here, the best chromosomes are the chromosomes that have maximum fitness. The indices, which are obtained from the genes of the best chromosomes represent the database images that are similar to the given query image and they are retrieved in an effective manner. The retrieved relevant images that have same visual content but different semantics

are stored in a separate vector  $D_l$ . The semantic indices of the retrieved images are analyzed and the most frequent indices are utilized as the semantic query keyword for retrieving the images. The following pseudo code details the extraction:

```

Input:  $N=\{id_1, id_2, id_3, \dots, id_{|N_{DL}|}\}$ 
Output: Query keyword
Steps:
Initialize freq is zero
 $\forall id$  in  $N$  database
  For  $i=0$  to  $|N|-1$ 
    For  $j=0$  to  $|N|-1$ 
      If  $(id_i==id_j)$ 
         $freq_i=freq_i+1$ 
      End if
    Key_freq= $\max(freq_i)$ 
    Key= $id_i$ 
  End for
End for

```

The key obtained from the above pseudo code is utilized as the query keyword for the subsequent process of our proposed work, namely high level based CBIR.

### 3.2. CBIR based on High Level Feature

This CBIR is based on the query keyword which is a high level feature in human understandable form. Relevant images are retrieved by this CBIR utilizing the keyword retrieved from section 4.1. Each image is indexed with its semantic meaning so that they could be identified by the CBIR.

The following pseudo code details this high level feature based CBIR. Let  $N_D$  be the vector of names of images present in a database  $D$  and key be the high level feature based query keyword of the CBIR,

```

Input:  $N_D=\{id_1, id_2, id_3, \dots, id_{|N_D|}\}$ 
      Query keyword
Output: Relevant images
 $\forall id$  in  $N_h$  name vector
  For  $i=0$  to  $|N_h|-1$ 
    If  $(key==id_i)$ 
       $D_h=I_i$ 
    End if
  End for
End for

```

After executing the pseudo code, the image database  $D_h$  contains images that are relevant to the keyword. The retrieved images in the  $D_h$  database are then utilized for the subsequent process of this work.

### 3.3. Analysis on Low and High Level Featured Images

As discussed earlier, there is a semantic gap between the low level feature images and the high level feature images. The drawback of the CBIR based on low level

features is that images which are identical in visual content are not semantically identical and this drawback is avoided in our work. Our work compares the images retrieved based on low level features with those images retrieved based on high level features. The retrieved low level feature CBIR images and the high level feature CBIR images are compared with each other based on their indices. The following pseudo code details the analysis process:

```

For all  $id$  in  $N_l$  &  $N_h$ 
  For  $i=0$  to  $|N_l|-1$ 
    For  $i=0$  to  $|N_h|-1$ 
      If  $(id_i==id_j)$ 
         $I_d=I_i$ 
      End if
    End for
  End for
End for

```

The obtained image database  $I_d$  after the analysis process contains images that are visually as well as semantically identical. Thus, the semantic gap between the low level features and the high level features is minimized in our work.

## 4. Results and Discussion

The proposed mechanism to minimize the semantic gap between the low level features and the high level features present in the images extracted by CBIR was implemented in the working platform of MATLAB (version 7.8). The proposed mechanism was evaluated with different query images. Initially, the relevant images were retrieved based on the low level features like shape, color and texture. Then, the retrieved relevant images were processed and the query keyword was obtained. After this, based on the obtained keyword which is a high level feature, relevant images were retrieved. Finally, the images retrieved using the low level features and high level features were SEDanalyzed by comparing them with each other and only those images that are identical both in visual content and semantic content were obtained as output. The step by step results attained by the proposed CBIR system are given below.



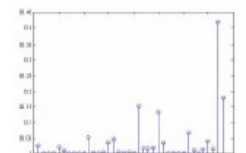
a) Query image.



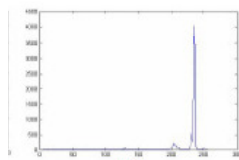
b) Re-sampled image.



c) Shape feature of query image.



d) LBP histogram orientation at 90°.



e) Color histogram of query image.

Figure 2. Query image and the associated re-sampled image, shape feature, LBP histogram orientation at 90° and color histogram.

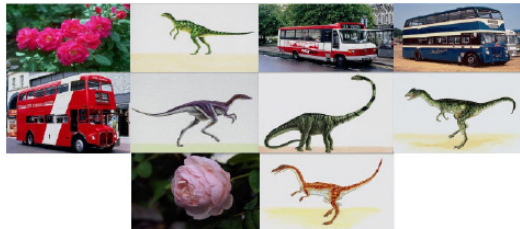


Figure 3. Retrieved images based on low level features (color, shape and texture).



Figure 4. Retrieved images based on high level feature (Query keyword='Dinosaur').



Figure 5. Retrieved images identical in visual and semantic sense.



a) Query image.



b) Retrieved images based on low level features.



c) Retrieved images based on high level feature (Query keyword- 'Elephant').



d) Retrieved images identical in visual content and semantic sense.

Figure 6. Query image and retrieved images based on low level features, high level features and similarity between visual content and semantic sense.

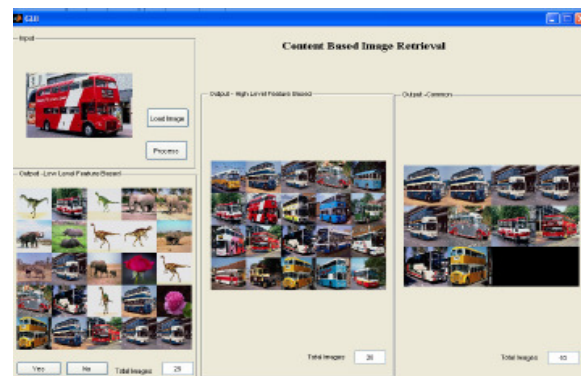


Figure 7. Retrieved result for the input query image 'Bus'.

The original image, re-sampled image, shape feature detected image, LBP histogram for orientation of the image at 90° and the color histogram of the image are shown in Figure 2. The relevant images retrieved by CBIR based on low level features and the extracted query keyword 'Dinosaur' are shown in Figure 3 and Figure 4 respectively. The retrieved images which are identical both in visual content and semantic content are shown in Figure 5. The query images and the actual relevant images retrieved by the proposed system are given in Figure 6. An input query is given and the obtained results are shown in Figure 7.

Tables 1 and 2 details the retrieved results for the previous system [8] and the proposed system. The precision equation 12 and recall equation 13 computed for a given query image in Figure 6-a are tabulated in Tables 3 and 4 and the associated Figures 8 and 9

depicts the precision and recall plot for the proposed system. Table 5 depicts the performance comparison of the proposed system with the existing system. The retrieved images and the precision-recall graph show that the proposed CBIR system claims effectiveness in retrieving images that are most similar in visual content and also in the semantic sense.

$$Precision = \frac{\text{No. of retrieved images relevant to the query image}}{\text{Total number of images retrieved}} \quad (12)$$

$$Recall = \frac{\text{No. of retrieved images relevant to the query image}}{\text{Total number of relevant images in the database}} \quad (13)$$

Table 1. Retrieved image results for the previous system [8].

Input Image	Retrieval Based on Low Level		Retrieval Based on High Level		Retrieved No. of Common Image
	No. of Retrieved	No. of Relevant	No. of Retrieved	No. of Relevant	
1	25	14	50	50	14
2	25	15	50	50	15
3	25	14	50	50	14
4	25	14	50	50	14
5	25	13	50	50	14
6	25	15	50	50	15
7	25	14	50	50	14
8	25	13	50	50	13
9	25	14	50	50	14
0	25	16	50	50	16

Table 2. Retrieved image results for the proposed system.

Input Image	Retrieval Based on Low Level		Retrieval Based on High Level		Retrieved No. of Common Image
	No. of Retrieved	No. of Relevant	No. of Retrieved	No. of Relevant	
Bus 1	25	21	50	50	21
Bus 2	25	20	50	50	21
Bus 4	25	19	50	50	19
Bus 5	25	20	50	50	20
Bus 6	25	21	50	50	20
Bus 18	25	20	50	50	20
Bus 19	25	20	50	50	20
Bus 21	25	22	50	50	22
Bus 23	25	22	50	50	22
Bus 28	25	23	50	50	23

Table 3. Precision for the proposed CBIR system.

S. No	Precision
1	0.9
2	0.87
3	0.76
4	0.68
5	0.67
6	0.61
7	0.52
8	0.48
9	0.4

Table 4. Recall for the proposed CBIR system.

S. No	Recall
1	0.18
2	0.28
3	0.38
4	0.52
5	0.7
6	0.8
7	0.9
8	0.9
9	0.92

Table 5. Performance comparison.

Performance Measure	Low Level Feature		High Level Feature		All Feature	
	[8]	Proposed	[8]	Proposed	[8]	Proposed
Precision	0.54	0.78	0.71	0.84	0.56	0.75
Recall	0.39	0.79	0.33	0.86	0.51	0.78
Quality Level	0.52	0.78	0.52	0.85	0.54	0.76

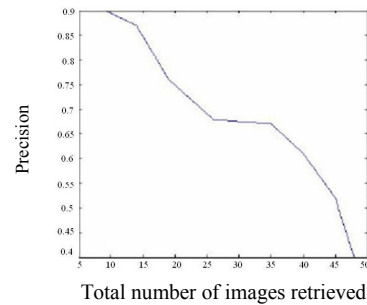


Figure 8. Precision plot for the proposed CBIR system.

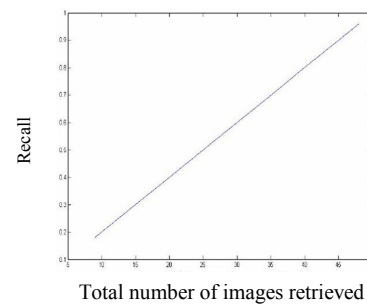


Figure 9. Recall plot for the proposed CBIR system.

### 5. Conclusions

In this paper, an effective approach to minimize the semantic gap between the low level and high level features is proposed. Initially, the low level features color, texture and shape are extracted from the database images and also from the query image. After that, the images which are relevant to the given query image are retrieved from the database based on these low level features with the aid of the EP. By means of these retrieved relevant images, the query keyword which is a high level feature is generated and then by using this query keyword the images which are relevant to the query keyword are extracted. Then by analyzing these images the images which are both visually and semantically identical are retrieved. Finally, the proposed system was proved to be effective by querying it with different types of images.

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