An Interactive Approach for Retrieval of Semantically Significant Images

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ABSTRACT: *Content-based image retrieval is the process of recovering the images that are based on their primitive features such as texture, color, shape etc. The main challenge in this type of retrieval is the gap between low-level primitive features and high-level semantic concepts. This is known as the semantic gap. This paper proposes an interactive approach for optimizing the semantic gap. The primitive features used are HSV histogram, local binary pattern histogram, and color coherence vector histogram. The mapping between primitive features of the image and its semantic concepts is done by involving the user in the feedback loop. Proposed primitive feature extraction method shows improved image retrieval results (Average precision 73.1%) over existing methods. We have proposed an innovative relevance feedback technique in which the concept of prominent features is introduced. On the application of the relevance feedback, only prominent features which are having maximum similarity are utilized. This method reduces the feature length and increases the efficiency. Our own interactive approach for relevance feedback is not only computationally simple and fast but also shows improvement in the retrieval of semantically meaningful relevant images as we go on increasing the iterations.*

Keywords: Semantic Gap, Content-based Image Retrieval, Relevance Feedback, HSV Histogram, Local Binary Pattern, Color Coherence Vector

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1. Introduction

Images play an vital role than the text, even words cannot describe what the information contained in the image. Tremendously, everything is available in digital form in today's digital world. Now a days everyone prefers to store the images digitally than printing, hence digital image database is growing rapidly. And with the above situation comes a need to find an image from the available database as fast as possible. There are number of algorithms available to retrieve similar images. The retrieval algorithm using primitive features contents such as texture, shape, color is known as content-based image retrieval (CBIR). The other algorithm called Text based image retrieval identifies the similar images based on the textual words linked with the images. But it's a lengthy manual labor to assign every image some keywords. In case of CBIR, it is observed that the images retrieved do not pass

the criteria of user's intention and thus there is a semantic gap between the images retrieved and the user's mind. To reduce this gap, we have introduced user's interface in the system in a form of feedback. This approach is known as the interactive approach [1-3].

The analysis in the CBIR system for the image contents for indexing and retrieval via the low-level features, for instance color, shape and texture. These systems pursue to fuse low-level features with high-level features in order to accomplish higher semantic performance that contain perceptual information of human beings [4]. There are two important steps in CBIR – (i) Feature Extraction (ii) The features of database images are matched with the query image [5]. Though, two main characteristics are ignored: (1) the semantic gap amid the high level and low level features, and (2) annotation of human perception of visual content.

Specifically, the important characteristics of the retrieval process of the proposed approaches for CBIR have not explored, i.e. the semantic gap [4]. Here, the author proposed a relevance feedback (RF) based CBIR system, which utilize the primitive features of the high-level query given by the user. In every feedback loop, the feature weights are updated according to the user's feedback. Here, the experimentation is done on a large database and promising results are obtained. An RF model for CBIR is proposed where the user assigns weights to image features which are captured by the model and then the results are obtained for retrieval purposes. The above approach has given a good interpretation of data. In addition to this while formulating the query, the negative examples are integrated and, therefore, the retrieval speed and the accuracy is improved.

A feature adaptation concept is worked based upon relevance feedback [5]. The parameters of the query and feature weights are dynamically regulated along with the image type and image number to congest semantically valid images. When compared to the existing RF techniques, the author suggests that there is a requirement of improvement in the accuracy.

The proposed methodology worked at two levels. Initially, the images are ranked by distances to the query image. In the second level, an interactive approach using relevance feedback is used by involving the user in the feedback loop. After every retrieval cycle, the user labels three relevant images which are used to redefine the query and retrieve similar images. The first level comprising of feature extraction using local binary pattern (LBP), HSV histogram (HSVH) and color coherence vector (CCV) [6]. The retrieval results using this proposed methodology are also compared with another feature extraction method [7]. It was marked that our approach for primitive feature extraction [6] proves to be better than other approaches. The relevance feedback technique proposed by us is simple and computationally fast. In addition to this, the retrieval of semantically meaningful images was improved with the increasing iterations.

The rest of the paper is organized as follows. The literature survey is given in section 2. The methodology is explained in section 3. Experimentation is given in Section 4. The results are discussed in section 5. Section 4 dictates the conclusion of the work proposed.

2. Related Works

Han *et al.* [8] proposed a method that combines primitive features and semantics seamlessly. Classification techniques and an RF are used to reduce the gap between low-level image features and high-level human semantics. Bayesian learning technique is utilized for classification of images whereas color coherence histogram, Gabor filter, edge direction coherence histogram are used for feature extraction. Matching degree between keywords is analyzed for similarity measure. The author B. Patil and B. Kokare [9] used a Riemannian Manifold learning algorithm for reduction of SG in CBIR. The author proposed an RF technique which involved positive and negative (relevant/irrelevant) images stated by the user during the feedback. They have pre-computed the cost adjacency matrix and its Eigenvectors corresponding to the smallest Eigenvalues and then applied the Riemannian Manifolds learning concepts to estimate the boundary between positive and negative images.

A spacious status of late and momentum research on context-based Information Fusion (IF) frameworks was presented by Snidaro *et al.* [10], they following back the bases of the first thinking behind the advancement of the idea of "context". It indicates how its fortune in the appropriated processing world in the long run pervaded in the world of IF, talking about the present systems and methods, and implying conceivable future patterns. On the off chance that procedures can speak to context at diverse levels (structural and physical constraints of the situation, from the earlier known operational tenets in the middle of elements and environment, dynamic connections demonstrated to interpret the framework yield, and so on.). Notwithstanding the overview, a

few novel context exploitation dynamics and engineering perspectives unconventional to the fusion domain are introduced and examined.

Rose *et al.* [11] proposed local texture description framework (LTDF) prior demonstrated the significance of eight sampling focuses that lie circularly at a sure separation separated from a pixel under thought in recognizing diverse face pictures. As of late, a local texture descriptor to be specific local directional number pattern (LDN) is acquainted with encode the directional data of the structure of a face's texture. Consolidating the ideas of LTDF and LDN, this paper proposes another texture descriptor to be specific LTDF-based adjusted local directional number pattern (LTDF_MLDN). LTDF_MLDN depicts a texture pattern with the sampling focuses at disparate range. Viability of the framework is tried for the diverse issues in face recognition utilizing five benchmark databases. Test results uncover the viability of the proposed descriptor over the best in class approaches.

Xu *et al.* [12] presents a novel hybrid relevance feedback (RF) system for shape-based retrieval of spine X-ray images. Another shape similarity measure that considers both entire shape and fractional shape matching is exhibited. The proposed RF architecture incorporates separate retrieval and feedback modes to request client's sentiment for refining retrieval results. A one of a kind short-term memory methodology is actualized to stay away from rehashed demand for client's feedback on the same, officially endorsed, and recovered pertinent images. An automatic weight updating scheme is created to introduce the shape-based retrieval, spine X-ray images, images on which it is best for the client to give feedback. Fusing all these extraordinary features, the proposed RF retrieval system can lessen the crevice between high-level human visual perception and low-level modernized features. Trial results show general retrieval accuracy change of 22.0% and 17.5% after the second feedback cycle for recovering spine X-ray images with comparable osteophytes severity and sort, individually.

3. Proposed Methodology for Retrieval of Semantically Significant Images

The complete flow of the system is as shown in Figure 1. To reduce the gap between low-level primitive features and high-level semantic concepts is the main aim of the CBIR retrieval. This work proposes an interactive approach for optimizing the semantic gap. The primitive features used are HSV histogram, local binary pattern histogram, and color coherence vector histogram. The mapping between primitive features of the image and its semantic concepts is done by involving the user in the feedback loop. We have proposed an innovative relevance feedback technique in which the concept of prominent features is introduced. On the application of the relevance feedback, only prominent features which are having maximum similarity are utilized. This method reduces the feature length and increases the efficiency. Further process in the proposed system is discussed below.

3.1 Preprocessing of Image

Operations at the lowest level of abstraction on images called pre-processing and these step focuses on image feature processing. It has the main purpose to future processing the images that enhances some image features or suppresses unwilling distortions for the improvement of the image. Preprocessing of the image is done so as to get the image in the desired form to perform operations on the image. All the database images are resized to 256x256 pixels for ease of operation. The RGB image is first converted to HSV [13-15] format.

RGB to HSV conversion is done because this recorded RGB color fluctuates significantly with the camera direction, surface orientation, the illumination point, illumination spectrum and the interaction of light with the object. This inconsistency should be allocated with in one way or another. Moreover, the way how a human perceives color is a complex issue where many efforts are taken to retrieve perceptual similarity. The HSV color model is generally used due to its invariant properties. The hue component does not vary with camera view-point and object orientation which occurs due to illumination and therefore mostly used for the retrieval of the object.

3.2 Feature Extraction

Feature extraction is the process of describing the image by considering parameters known as features (color, edge, texture etc) from a given image. A feature is defined as a descriptive parameter that is extracted from an image. The effectiveness of image retrieval depends on the effectiveness of features/attributes used for the representation of the content. An important issue is the choice of suitable features for a given task. Effective image retrieval can be achieved by collaboratively using color, edge density, and histogram bins. The different features such as color, Edge density and histogram pixel n formation are taken which collectively form a 136 dimensional feature vector. Color component consists of average and variance in RGB space and taken a histogram bins. Edges are identified using sobel edge detector and from that obtain edge density. We have used color features [16, 17] like color coherence vector, color histogram, and local binary pattern to identify the similarity between images. Let's see

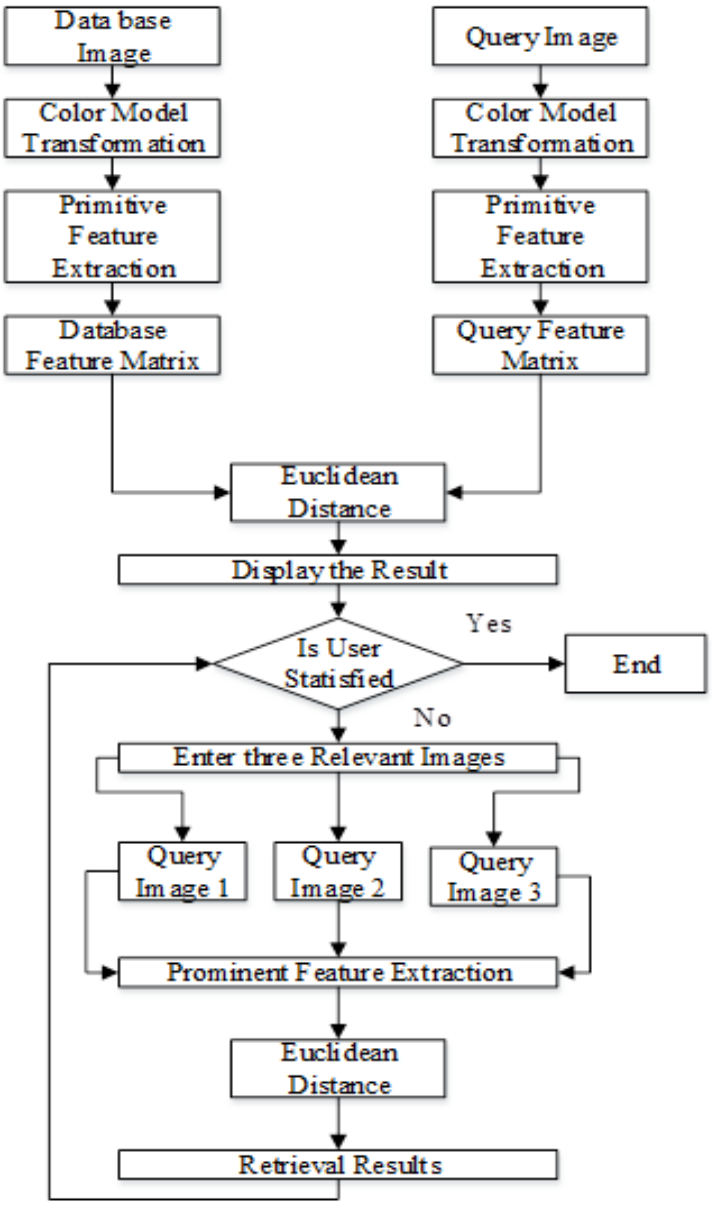

Figure 1. System Flowchart

the brief idea about each used feature.

HSV histogram (HH)

Color histogram [18-21] passes on the information about the quantity of event of each color in an image for a given color space. It is a graph with color on one axis and a comparing number of pixels of each color on another axis. The Color histogram does not vary with rotation, translation about an axis perpendicular to an image and gradually varies with rotation about different axes occlusion and change of distance to the object. Color Histogram is a regularly utilized feature to extract color information of an image and as often as possible utilized as a part of CBIR framework, which contains recurrence of each color. A color histogram is basically a distribution of colors in any digital image. We extract color histogram in RGB and HSV color spaces. Color feature is a standout amongst the most important things to access the image. The color of an image is spoken to from the famous color spaces like RGB, XYZ, YIQ, L*a*b, U*V*W, YUV and HSV. HSV color space gives the best color histogram feature, among the diverse color spaces.

HSV (HSL, HSB) models are much closer to human eye impression of color, yet are perceptually not uniform. The segments of these models are: Hue, Saturation, and Value (gentility or splendor). The hue represents to the chromatic component in this model and it is the meaning of a color by the combination of the primary colors. Immersion alludes to the power of a specific tone in a color. The estimation of a color alludes to the intensity (the softness or the haziness of the color) keeping in mind the end goal to utilize a good color model for a particular application, change between color models is essential. A decent color model for an image retrieval framework ought to protect the apparent contrasts in color.

$$H = \cos^{-1}\left\{\frac{\frac{\left[(R-C)+(R-B)\right]}{2}}{\left((R-C)^2+(R-B)(C+B)\right)^{1/2}}\right\} \tag{1}$$

$$S = 1 - \frac{3(\min(R,G,B))}{(R+C+B)} \tag{2}$$

$$V = \frac{(R+G+B)}{3} \tag{3}$$

A Color histogram of an info image is characterized as a taking after vector $F = \{F(0), F(1), \text{L}, F(i), L, \ldots. F(N)\}$, where i signifies the color bin in the color histogram. N indicates the aggregate number of bins utilized as a part of color histogram and $F(i)$ means the aggregate number of pixel of color I in an image. Commonly, every pixel in an image will be in support to color histogram bin. So that, in the image color histogram, every bin esteem gives the quantity of pixels those have the same comparing color. Color histogram ought to be normalized to think about the images in different sizes. The normalized color histogram F' is characterized as, $F' = \{F'(0), F'(1), \cdots, F'(i), \cdots, F'(N)\}$ Where,

$$F'(i) = {F(i)}/{Total\ number\ of\ pixel\ in\ an\ image}$$

Every pixel for multi-spectral images speaks to a self-assertive number of measurements, the color histogram when all is said in done is N-dimensional, with N being the quantity of measurements taken. We lessen the quantity of bins by quantization for being the computationally proficient.

Color Coherence Vector (CCV)

A [22, 23] gives us the information whether a pixel belongs to a large similarly colored region. We refer the significant regions as the coherent regions in order to characterize the significant images. Color coherence vector classifies each pixel as coherent or incoherent depending on the criteria specified by the user. For a pixel to be coherent, it should be a part of a big connected component. Here we have given an area of 50 as a threshold i.e. area greater than 50 comes under big connected component and areas less than 50 comes under small connected components. In this way, the color coherence vector is being calculated.

In CCV technique pixels of each color are assigned to either coherence or incoherence group. If one pixel belongs to a large similarly-colored region, it is called coherence, otherwise it is incoherence. Since there is additional information stored in the CCV technique, the corresponding results of the image retrieval method have been much better than the histogram method. In CCV method a three dimensional vector is calculated for each image [24]. Subsequently, the resultant vectors are compared in order to find the similar images with the query ones. Euclidean Distance method is investigated to the image comparisons as well as the similarity measurements.

Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is one of the suitable features for texture classification. It assigns a new value to the pixel of an image based on its neighborhood intensity levels. LBP labels the pixels of an image by thresholding the neighborhood of each pixel and we get a binary number as a result. LBP is widely used in many CBIR applications due to its distinguishing power, computational simplicity and robustness to monotonic intensity variations caused due to illumination changes.

3.3 Relevance Feedback (RF)

We know that there is constantly a gap between the high-level human semantic and primitive features because to retrieve the foremost results primitive features are not adequate. We have introduced users interface in the system to reduce the semantic gap in the form of relevance feedback [25 and 26].

The low-level features [27] like HSV histogram (HH), color coherence vector (CCV) and local binary pattern (LBP) are calculated. A matrix is created named F_D, where all feature values are saved as shown in Eqn. (4)

$$F_D = \begin{bmatrix} x_{11} & x_{12} & . & . & . & . & x_{1j} \\ x_{21} & x_{22} & . & . & . & . & x_{2j} \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ x_{i1} & . & . & . & . & . & x_{ij} \end{bmatrix}_{800x88} \tag{4}$$

$$where,\ i = 1\ to\ 800\ and\ \ j = 1\ to\ 88$$

There are 24 values of the color histogram, 16 local binary pattern values, and 48 color coherence vector feature values. So the feature matrix is of dimension 1x88 for the query image. We have created a database of 800 images; the feature matrix of database images is F_q as shown in Eqn. (5).

$$F_q = [y_{11} \quad y_{12} \quad \cdots \quad y_{1j}] \tag{5}$$

As the user enters the query image, we calculate the feature matrix for the query image as shown above as F_q and compare it with the feature matrix of database images and find out the corresponding Euclidean distance D_E as shown in Eqn. (6).

After the 1st iteration, the system will ask the user for user's opinion. If he is not satisfied with the result, the system will ask the user for three most relevant images according to user's intention.

$$D_E = \begin{bmatrix} d_{11} \\ d_{21} \\ . \\ . \\ . \\ . \\ d_{i1} \end{bmatrix}_{800x1} \tag{6}$$

Then these three images are taken as query and again all the features are extracted for these three images. Here we have introduced a concept of prominent features. Prominent Features are the features with a minimum difference. Out of 88 primitive features, 30 prominent features are selected and feature matrix is computed as shown in Eqn. (7).

$$F_{PR} = \begin{bmatrix} p_{11} & p_{12} & . & . & p_{1t} \\ p_{21} & p_{22} & . & . & p_{2t} \\ . & . & . & . & . \\ . & . & . & . & . \\ p_{s1} & p_{s2} & . & . & p_{st} \end{bmatrix}_{800x30} \tag{7}$$

$$where,\ t = 1\ to\ 30\ and\ \ s = 1\ to\ 800$$

In the 2nd iteration, only the prominent features are considered while calculating Euclidean distance and the feature vector length

of the new query is 30. The system asks for three most relevant images from the user, these images are again considered as query image and the process is repeated to retrieve 10 relevant images. While considering the 2nd query image, common images are discarded. The same procedure is applied for the 3rd query provided by the user and the corresponding results are displayed. This process repeats itself until the user is satisfied. This interaction of the user with the system is the relevance feedback. It is observed that the system gives improved results in 2nd or 3rd iteration.

3.4 System Algorithm

```
Step 1: Accept the input query image.
Step 2: Convert the RGB image to HSV format
Step 3: Compute the low-level features of the query image and form the
feature vector matrix
Step 4: Compare the query feature vector with the database feature vector.
Step 5: Calculate the Euclidean Distance.
Step 6: Display the top 20 images with minimum distance.
Step 7: Ask the user if he/she is satisfied with the results,
        if yes go to step 12
Step 8: If no, get the rank of most relevant 3 images from the user.
Step 9: Calculate prominent features for selected images. And find the Euclidean
distance using only these prominent features.
Step 10: Display 10 images per query by discarding the common images.
Step 11: Go to step 7
Step 12: End
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Figure 2. Pseudo code for the proposed algorithm

In our proposed algorithm shown in Figure 2, first accept the query input image, then convert the RGB image in to HSV format. Computing the entire low level features of the query image will form a feature matrix. After extracting the low level features, compare the query feature vector with the database feature vector. Then find out the corresponding Euclidean distance and display the top 20 images with minimum distance. Check whether the user is satisfied with the result, if the user is not fulfilled with the result get the rank of more relevant three images from the user. Next, calculate the prominent features for selected image and find the Euclidean distance for these prominent features. Finally, 10 images get displayed per query by discarding the common images. Then, check the result by the user for satisfaction and if the user not satisfied repeat the process until to satisfy the user.

4. Experimental Results and Discussion

The subset of Corel Database is the database used in this paper [28]. There are 1000 images from 10 different classes in the database. The ten classes are buildings, elephants, Africans, beach, bus, dinosaurs, horses, snowy mountains, roses, and food. Each category of Sample images are shown in Figure 3. The database is divided into 20:80 ratios. 20 images of each category are used for testing and 80 images of each category are trained to create the database.

In the first level of experimentation, the image features were extracted using two primitive feature extraction methods. One method uses a hybrid approach [26] using shape and texture and another method includes an approach which integrates global basic color features and the features exploring the spatial relationships i.e. LBP and CCV. This method integrates many orientations and keeps a comparatively low feature size.

The performance of the proposed algorithm is assessed by using two parameters, recall, and precision. Precision is based on the total number of images retrieved and number of relevant images retrieved. A precision of value 1.0 indicates that every image retrieved by the system was relevant. Let x be the number of relevant images retrieved and y be the total number of images

retrieved. Precision is then given by Eqn. (8).

$$\Pr ecision = \frac{x}{y} \tag{8}$$

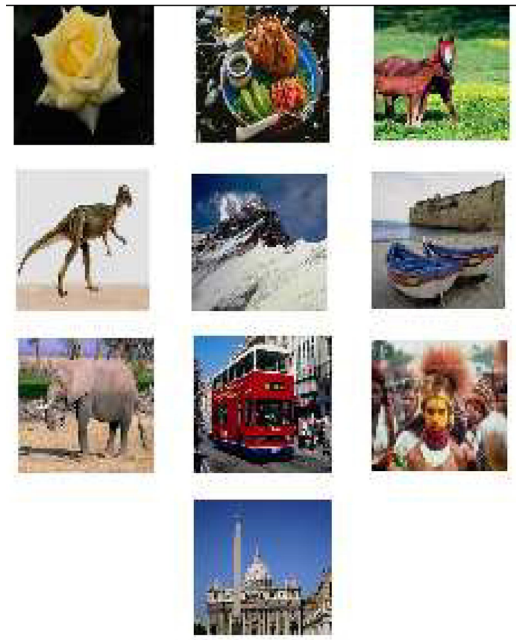

Figure 3. Sample images from COREL database

A recall is based on the number of retrieved relevant images and the total number of images relevant to the database. A perfect 1.0 value for Recall value indicates 100% retrieval of relevant documents or images. Subsequently, it describes how effectively the CBIR system retrieves all the relevant images for a particular query image. Let total number of relevant images be z in the image database.

$$\mathrm{Re}\,call = \frac{x}{z} \tag{9}$$

Table 1 gives the average recall by method 1 and proposed LLIF extraction method for primitive feature extraction i.e. method 2 without relevance feedback (RF). There is a huge difference between the recall by both the methods. The recall by Method 1 lies in the range of 2% to 5.35% maximum. For the class Dinosaurs we are getting the highest recall of 25%. As the images of this class are prominent by shape and there is just one object on the background, both the methods successfully retrieve the correct images. This is not the case with other class images. Still the proposed method which integrates the global basic color features, CH and the features exploring the spatial and structural relationship (LBP and CCV) is highly successful in retrieving large number of number of relevant images. By method 2 we get the recall in the range of minimum 3% up to maximum 25%. In addition to this the average recall is gotten to be more than 13% which is quite higher than that of using method 1. The retrieval results are improved by a significant amount when the RF is applied. Table 2 describes the average precision with RF by method 1 and method 2. The retrieval results show that after the use of RF, the average precision increases iteration wise. As we go on increasing the iterations, the number of relevant images retrieved increases except some exceptional cases. It depends upon the kind of query being feed back to the system. 100% precision is observed in case of Dinosaurs.

By method 1 the average precision goes up to 35.42% in iteration 3. As we go on increasing the iterations, we can achieve better results. Category wise results are shown in Fig. 4 and Fig. 5. Table 2 shows the average precision by proposed method. In first iteration itself this method gives very good results. As we marked that for the classes like Africans, Buses, Horses the precision is very good in first iteration. Here we applied relevance feedback and observed the results for second iteration. The precision improves hardly by some amount in second iteration. We get precision in the range of minimum 30% up to maximum 100% in third iteration. Average precision in this case is found to be 57.03%. We can improve the results by increasing the number of iterations. It is observed that more semantically similar images are gotten as the iteration continues increasing.

Category	Method 1	Proposed method (Method 2)
Africans	2.20	13.44
Beach	4.55	9.94
Buildings	3.65	10.00
Bus	3.15	16.25
Dinosaurs	25.00	25.00
Elephants	3.55	3.25
Roses	3.45	9.31
Horses	3.55	22.38
Snowy mountains	5.35	9.30
Food	3.45	13.00
Average Recall for all test images	5.79	13.19

Table 1. Results (Average Recall) for LLIF extraction for CBIR without relevance feedback

Methods for CBIR	Iterations		
	1st	2nd	3rd
Method 1	26.63	35.63	35.42
Proposed	53.08	54.10	57.03

Table 2. Average Precision with Relevance Feedback

Methods for CBIR	Iterations		
	1st	2nd	3rd
Method 1	5.8	10.2	10.3
Proposed	13.2	16.8	17.6

Table 3. Average Recall with Relevance Feedback

Table 3 gives idea about average recall with RF by both the primitive feature extraction methods. Category wise results are shown in Fig. 6 and Fig. 7. As the iterations increases, the percentage recall increases. By method 1 the average recall lies in the range of 5.8% up to 10.3%. We can improve the recall further by performing more number of iterations.

In case of the retrieval by proposed LLIF extraction method, initially the recall values were found to be good. They improved further with increasing iterations. We get a recall of minimum 10% up to maximum 37%. Average recall is found to be 17.6% in the third iteration. It is observed that proposed method i.e. method 2 is found to be more efficient to give semantically significant results. In addition to this the retrieval results from Table 1 to Table 3 show that the proposed relevance feedback approach is found to be improving significantly irrelevant of any of the LLIF extraction techniques for the retrieval of semantically significant images.

Although the hybrid method (M-1) [26] includes shape and texture features for feature extraction at level 1, it produced insubstantial results as shown in Fig. 4 and Fig. 5. It is observed that the proposed method (M-2) which integrates the global basic color features, CH and the features exploring the spatial and structural relationship (LBP and CCV) [6], delivered improved results as

shown in Fig. 6 and Fig. 7. However, the semantic gap reduces significantly with each feedback loop by using the relevance feedback in both the cases. We have utilized relevance feedback approach as a part of the second level of retrieval for both the strategies. Here, the user's contribution proved to give enhanced retrieval results.

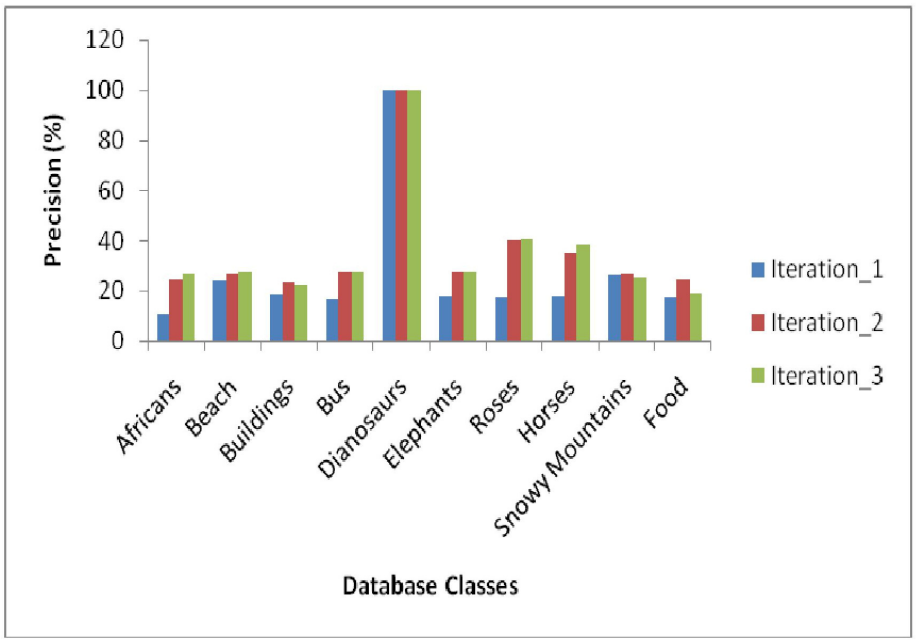

Figure 4. Retrieval Results (% Precision) by proposed RF algorithm. Primitive feature extraction using method M-1)

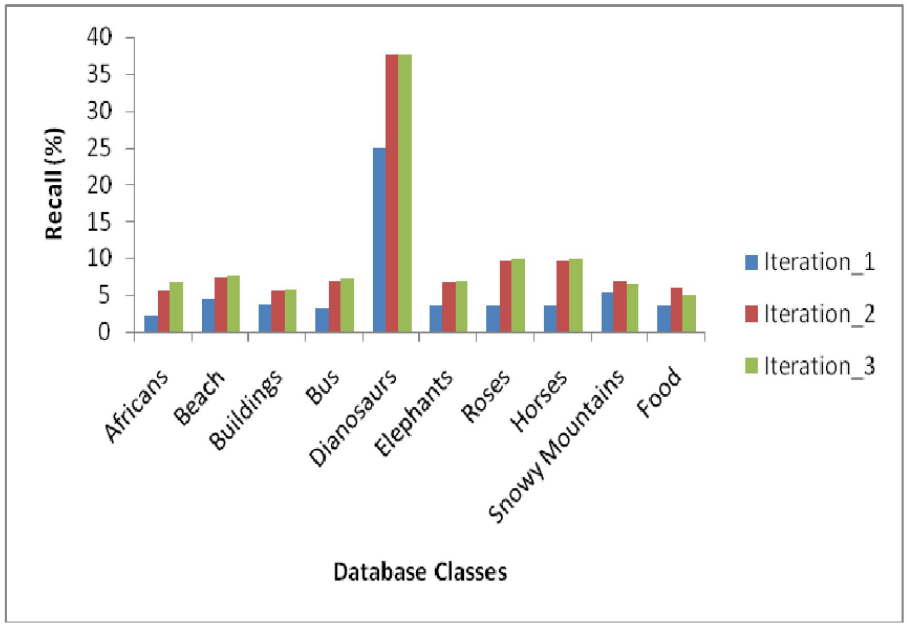

Figure 5. Retrieval Results (% Recall) by proposed RF algorithm. (Primitive feature extraction using method M-1)

With every iteration, the retrieval of semantically significant images increments for every one of the categories. The retrieval results for one of the queries as shown in Fig. 8 are shown in Fig. 9, Fig. 10 and Fig. 11. It is observed that more similar images are obtained as the iteration goes on increasing. It is observed that more semantically similar images are gotten as the iteration

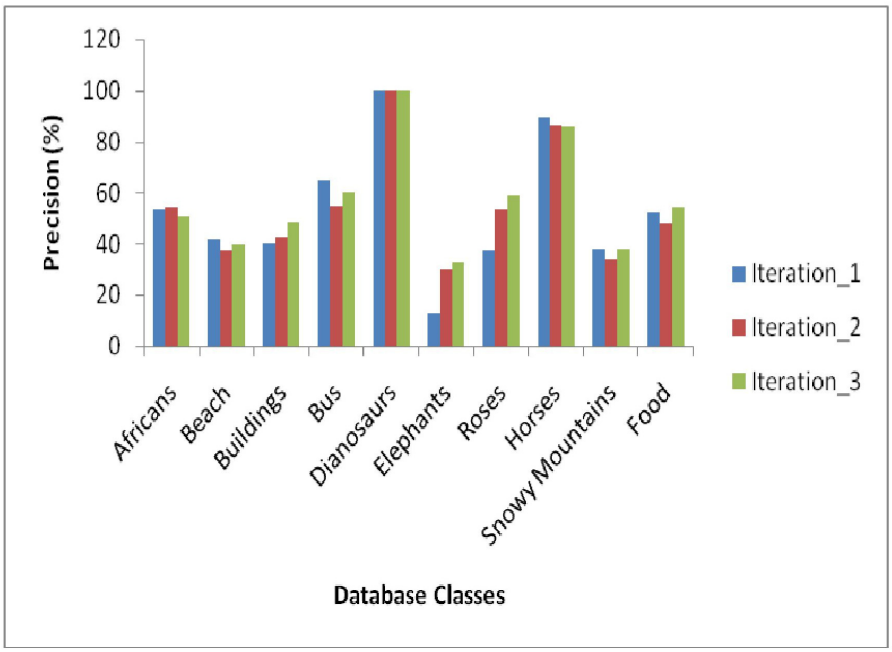

Figure 6. Retrieval Results (% Precision) of proposed RF algorithm. (Primitive feature extraction using our method M-2)

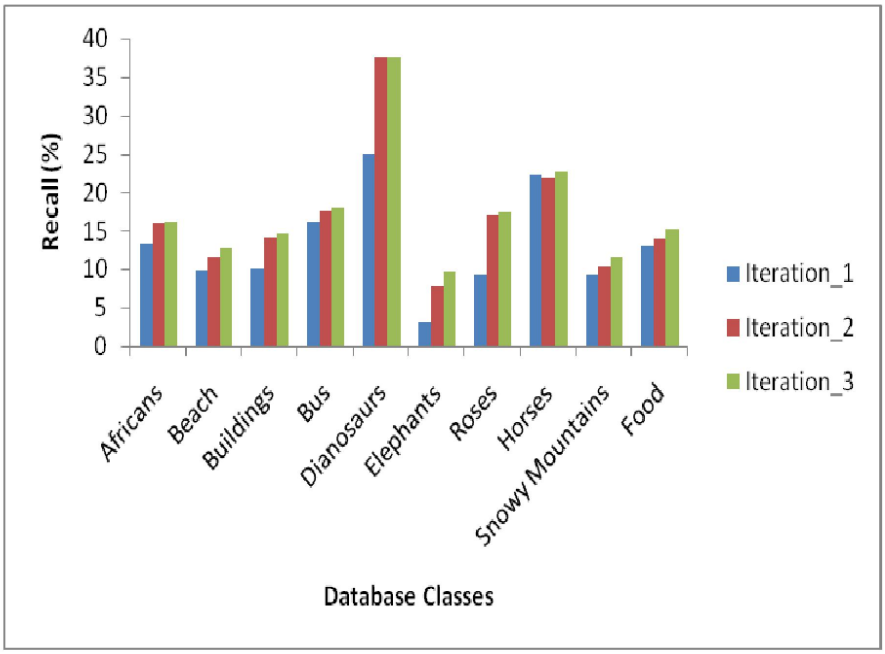

Figure 7. Retrieval Results (% Recall) of proposed RF algorithm.(Primitive feature extraction using our method M-2)

continues increasing.

5. Conclusion

This study explored the CBIR framework utilizing RF that uses prominent features of new query labels to enhance the retrieval performance. Different feature extraction methods and RF strategies were contemplated and after marking the limitations of the

Figure 8. Query Image

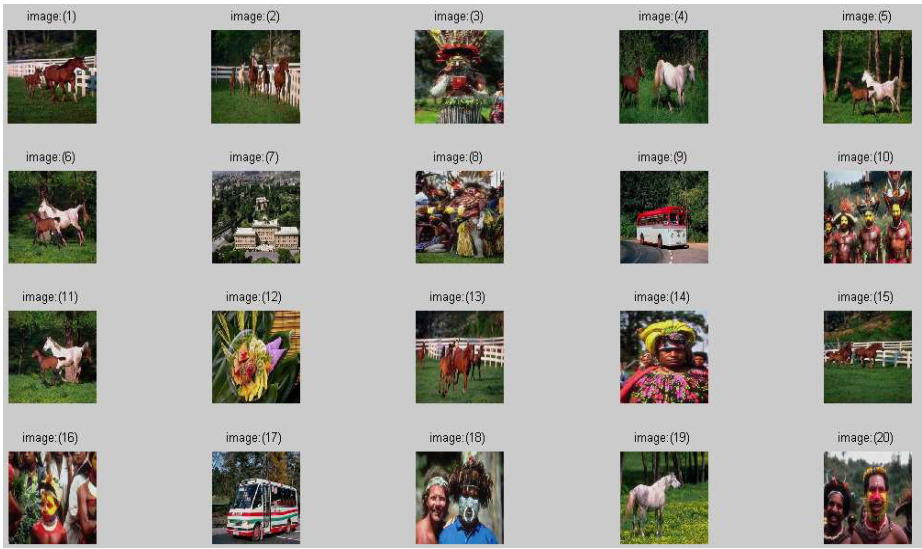

Figure 9. Results of first iteration by proposed approach

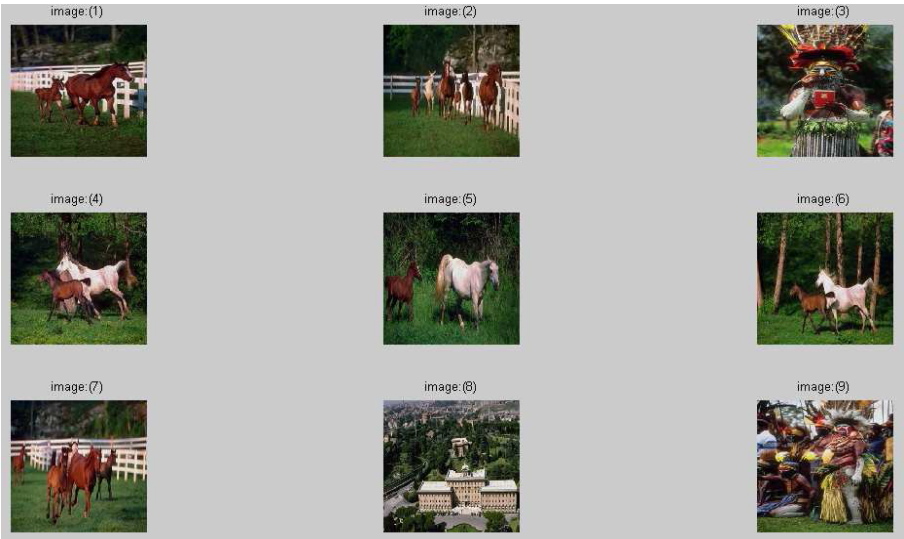

Figure 10. Results of 2nd iteration by proposed RF approach (Rank 1 to 9)

Figure 11. Results of 2nd iteration by proposed RF approach (Rank 10 to 18)

existing routines, our own methodology has been presented. One of the main contributions of this work was the use of global color features and the features exploring the structural connections to amalgamate many orientations, textures and color distributions among the images. Another involvement such as minimizing the feature vector size during re-querying to make the retrieval faster was proposed and the results are discussed. Deciding the weights while applying the RF was not necessary; rather it was observed that a simpler retrieval algorithm for RF was found to be better for optimization of semantic gap in CBIR. Our approach led to a fast, accurate and simpler RF system which can be applicable to large and a variety of databases. In further research, we have to reduce the semantic gap substantially and endeavor could be made to remit it even advance using neural network method.

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