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An Efficient Approach for Image Retrieval using Particle Swarm Optimization

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Abstract— Image retrieval systems are used to search and browse the images from large digital image databases and retrieval of these images. Content-Based Image Retrieval (CBIR) gives an efficient approach to browse and retrieve images from these large databases, but the semantic gap between low-level and high-level features is a big issue. To overcome this issue Particle Swarm Optimization is used with a new combination of low-level features. Moments can be used to characterize the color distribution of an image. A color feature of an image is extracted by calculating color moments which are unique and invariant to rotation and scaling. Rotated Local Binary Pattern is used to extract texture information from the image, it is invariant to rotation and scaling. Edges give the object representation of an image and used as a feature descriptor for image retrieval, Here Edge Histogram Descriptor is used to find out the abruptly changes in the pixel value of the image. Edge Histogram Descriptor (EHD) provides the spatial information about five types of edges of an image. For performance evaluation, we simply used weighted Euclidian distance with optimal weights and calculate Average precision, recall and accuracy. Experiment result shows that the proposed method gives improved precision and recall in comparison to existing method. The efficiency of proposed system is tested for three types of datasets: WANG dataset, LI dataset and Caltech-101 image dataset.

Keywords— CBIR, feature extraction, color Moments, RLBP, EHD, PSO

I. INTRODUCTION

Image retrieval systems are used to search and browse the images from large digital image databases and retrieval of these images. One of the easier way to retrieve images is textual annotation based retrieval. Where images are textually annotated by some text, number, keywords and these text are used to retrieve these images. (In text-based retrieval textual description of images are used to retrieval of images in a very efficient way.) It is very efficient and reliable technique but for the large database, it is very difficult and also takes more time for textual annotation of each and every image in the database. Another way to retrieve images is by giving the query image. A query image is giving to the system and extracting the images from the database that are most similar to the query image. Content-based image retrieval is a very vast area of research, various active researchers are performing their research in this field. CBIR analyses actual content or visual description of the image and used to find images from databases. CBIR used low-level features such as color, texture, shape and spatial information of the image to analyses and retrieve images. Two steps are considered in CBIR. First visual features are extracted from images and on the basis of these features similarity measures are used to calculate the similarity. A big challenge of CBIR system is the semantic gap. The gap between low-level features and human perception is known as semantic gap. Many optimization techniques are used to reduce the gap. In this paper, Particle Swarm Optimization is used as an Optimization technique [1-19].

The content of this paper is organized as follows. In section II literature reviews about previous work in CBIR are discussed. Section III has Image Features and working algorithm of Particle Swarm Optimization. In Section IV, an operation performed to extract from the image using proposed methodology. The experimental result is shown in section V. Section VI illustrate the performance of proposed framework and comparison between existing work. The conclusion is shown in section VII.

II. RELATED BACKGROUND

In [3] was proposed a paper in which k-mean clustering algorithm is used with PSO. K-mean and PSO are used for clustering the images in a number of clusters and with the help of centroid of clusters similarity is calculated and then relevant images were retrieved.

In [5] new approach is proposed to make Local binary pattern rotation invariant. In this, a dominant direction in the neighbor is chosen and then calculate the LBP value.

In [8], S. Sankar Ganesh and K. Ramar proposed an approach for image retrieval with Heuristic particle swarm

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optimization. In this approach, PSO is used to RGB color space and mean and a standard deviation is used to extract the color feature of the image and to calculate the region of the image a region-based method is used to extract the region of the image.

In [9], Mattia Broilo et al. proposed a system for image retrieval with different feature selection methods. In this approach, relevance feedback is combined with an evolutionary stochastic algorithm that is particle swarm optimization to grasp the user semantics about the retrieval result. With the help of stochastic algorithm, it performs better exploration of complex, nonlinear solution space.

In [14] Sawat Somnugpong and Kanokwan Khiewwan proposed an efficient algorithm for CBIR system. This combined approach used color and geometric descriptor to extract the features of the image. In this paper, Color Correlograms to extract the spatial color information of an image and Edge Direction Histogram to extract the geometric information of the edges present in an image is used. This combined approach produced the good results in term of precision and recall over the existing system.

R. Chaudhary et al. [15] proposed an image retrieval approach using color and texture features of an image. Here color moments are taken as a color feature and Local Binary Pattern is taken as a texture feature. In this approach, both color and texture features are merged to form a single feature vector. Euclidean distance is used as a distance measure for calculating distance between a query image and database image. Local Binary Pattern normally used for face recognition but they used it for natural images. This combined approach gives accurate, efficient retrieval system.

III. IMAGE FEATURES AND PSO

A. Color Moments

Color moments are used as a color feature descriptor for image retrieval framework. Distribution of color in an image construed in the form of a probability distribution of color and its moments [13], [16]. Mostly lower order moments of color distribution are used. In this paper, first three moments are used as a distribution of color for feature extraction. The first moment is Mean defined as the average color value in the image. The second moment is standard deviation defined by the inconsistency of the color distribution in the image. The third moment is Skewness can measure the degree of asymmetry in the distribution.

If the value of the i^{th} color channel at the j^{th} image pixel is, then the color moments are as the following:

1) Mean: Mean can be easily understood as the average color value in a whole image.

$$M_i = \frac{1}{N}\sum_{j=1}^{N} P_{ij} \tag{1}$$

2) Standard Deviation: It is calculated as the square root of the inconsistency of the color distribution in the image.

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N} \left(P_{ij} - M_i\right)^2} \tag{2}$$

3) Skewness: Skewness is defined as the degree of asymmetry in the distribution.

$$S_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N} \left(P_{ij} - M_i\right)^3} \tag{3}$$

B. RLBP

T. Ojala et al. proposed local binary pattern (LBP) [11]. LBP is an image indexing technique based on texture analysis of image which is gray scale invariant local pattern measure operator. LBP computes the local feature representation of the image. The LBP representation is calculated by comparing each pixel with the surrounding neighbor pixel. But Local Binary Pattern is not rotationally invariant that means if the image is rotated then its LBP value is changed. To make LBP invariant to rotation weights are shifted according to dominant direction [5]. Dominant direction is defined as a neighbourhood which has the maximum distance from the center. If the image is rotated dominant direction in a neighbourhood is also rotate and weights are started from that neighbour. The neighbourhood that difference is maximum from the center pixel is defined as follows:

$$D = \underset{p \in (0,1,\ldots p-1)}{\arg\max} \left|g_p - g_c\right| \tag{4}$$

The equation used to define the RLBP is given below:

$$RLBP_{R,P} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right) \cdot 2^{\mathrm{mod}(p-D,P)} \tag{5}$$

Where the mod is defined as modules and $2^{\mathrm{mod}(p-D,\,P)}$ is depends on direction D. representation of rotated local binary pattern is shown in figure [5].

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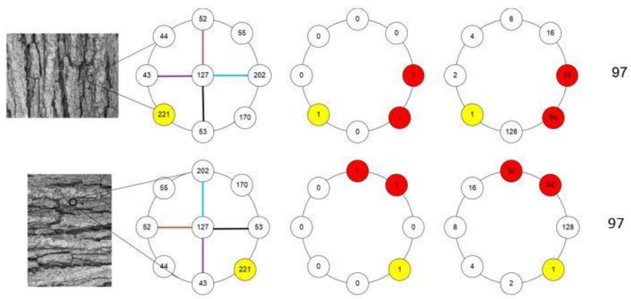

Figure 1. Representation of RLBP

C. *Edge Histogram Descriptor*

Edge is an important feature to extract the information about an image content. The histogram is one of the best way to express the edge feature. Edge is local shape feature and it captures the general shape information in the image. For image retrieval system edges are frequently used as a feature descriptor. The edge histogram descriptor is used to represents the spatial distribution of five types of edges, namely vertical, horizontal, 45^0-diagonal, 135^0-diagonal edges and non-directional edge. These five types of edges calculated the color histogram. More specifically it can be said that these edges absorb from the color distribution of pixels and from an internal feature of edge shape descriptor [12], [17]. The steps are used in EHD to calculate histogram is given below:

1) First, the RGB image converting into the gray image.
2) Now the gray scale image is divided into 4x4 sub-image.
3) Now each sub-image is divided into nonoverlapping small blocks.
4) For each image blocks edge is defined by five types which are- vertical, horizontal, 45^0- diagonal, 135^0-diagonal and nondirectional edges.
5) Calculate the Local as well as the global histogram for all sub-images with relative frequency occurrence of five types of edges in each sub-image.
6) After calculating histogram for each sub image bin values are normalized for a total number of blocks in a sub-image. And then these normalized bins are quantized.

D. *Particle Swarm Optimization*

Particle Swarm Optimization is firstly established in 1995 by Kennedy, Eberhart [1], [2]. It is also known as global best search optimization. It is based on the bird flocking problem that represents the group of particles moves around the best solution for the problem space that is searched by the negotiator.

Kennedy and Eberhart work on 2-dimensional bird flocking to develop particle swarm optimization, where the position of negotiator is x, y and velocity are v_x (for x-axis), v_y (for y-axis). Modification in negotiator's position is based on position and information about velocity [3]. In multidimensional space particle's position is evaluated by the fitness function that provides the solution in form of some quantitative value.

Particle swarm optimization is based on five essential variables. Global best value (gBest), indicates that the current position of the particle is closest to the target. gBest value is the best value among the group of particles. Stopping value indicates when optimization algorithm has been stopped if the target value is not found. The rate of position change is based on velocity; it denotes that how much data will be changed. Personal best value (pBest) denotes the best value obtained by any of the particles in the current population. It indicates the value that has ever come to the target value from starting of the algorithm. Particles denote the candidate solution of the problem and fitness function is used to achieve the best solution that is closer to the target.

Global best value is changed when the pBest value is closer to the target or it is larger to the gBest value. If the pBest value is closer to target value than it becomes the new gBest value.

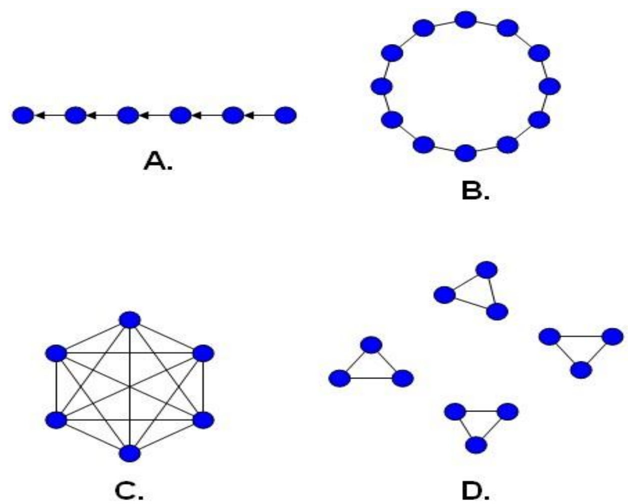

Figure 2. Topological representation of particle swarm optimization[12]

Where A represents the single sighted population topology in which individual only compare themselves to next best neighbor. B represents ring topology where each individual compares only its left and right neighbours. C represents the fully connected topology, where everyone is connected to each and every neighbor. D represents isolated topology, where individuals only compare to neighbor within a specific group.

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The algorithm steps are given as follows:

Step 1- Initialization

Choose some random values from the feature vector of image dataset and assign these value to initial particle position as X[ ][ ].

Step 2- Determines the local best position

Initially, assign the initial particle position as local best position P[ ][ ] = X[ ][ ] and initial velocity of each particle as V[ ][ ] = 0.

Then calculate the difference between X[ ][ ] and P[ ][ ].

Step 3- Determines the global best position

Assign the fitness function and choose the minimum value from the group of particles, assign it as a global best value.

Step 4- Update the position and velocity

Choose two random number according to some criteria and assign new particle position NX[ ][ ] and new velocity NV[ ][ ].
Replace initial position to new position and initial velocity to new velocity as X[ ][ ] = NX[ ][ ] and V[ ][ ] = NV[ ][ ].

Step 5 Termination

Optimization process stops while the process reaches to the highest number of iterations or if global best value remains same till 25 iterations.

In CBIR system, PSO is applied on the feature vector of database images to train these feature vector with optimal weights for getting batter results.

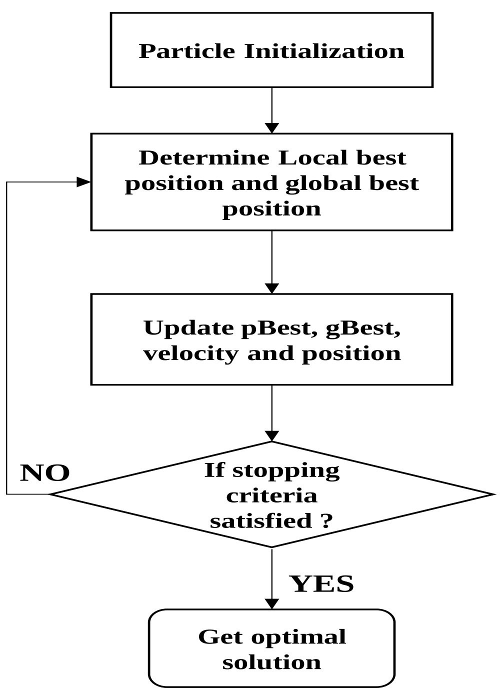

Figure 3. Flowchart of Particle Swarm Optimization

IV. PROPOSED METHODOLOGY

A. Proposed Algorithm

Input: Digital image for query and digital image dataset.
Output: Retrieved n number of digital images that is similar to the query image.
Step 1- Select the RGB color image as a query image.
Step 2- Pre-process the image by resizing all images into 256*384 then convert all the images into RGB color space.
Step 3- Apply Color Moments on RGB image to extract the color information of the image.
Step 4- Apply Edge Histogram Descriptor and Calculate local as well as a global histogram of edges.
Step 5- Apply Rotational Local Binary Pattern on gray scale image for extracting texture information.
Step 6- Combine all feature in a single multidimensional feature vector and store it in the database.
Step 7- Repeat all the step from 1 to 6 for all the images of the dataset and combine all the feature vectors and store in the database.
Step 8- Input an MxN dimensional image as a query image.
Step 9- Apply all the steps from 1 to 6.
Step 10- apply particle swarm optimization to get an optimal solution.
Step 11- Retrieved top n images and calculate precision, recall and accuracy of retrieved images.

B. Proposed Retrieval Scheme

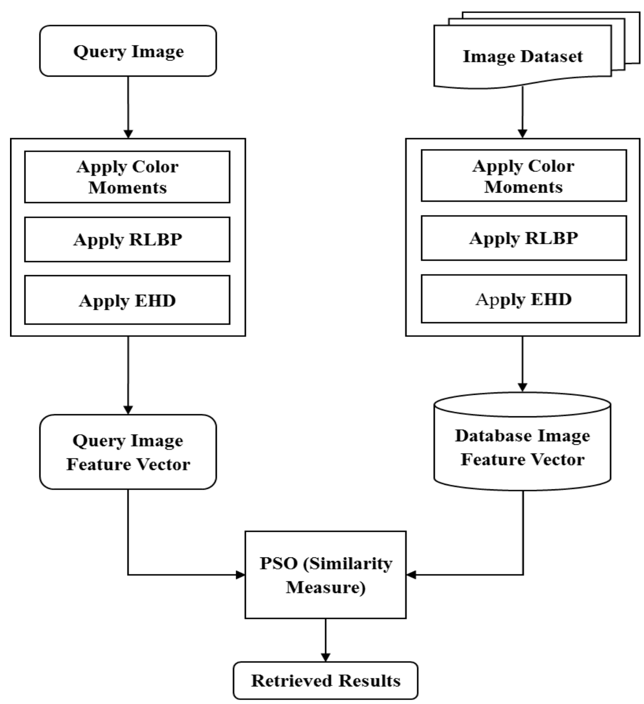

Figure 4. Diagrammatic representation of proposed retrieval system

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V. EXPERIMENTAL RESULTS

Experimental analysis is performed on three different databases such as- WANG database, Caltech 101 object categories and Li database. These image databases have different category of natural images with different image size. Various images in the database have similar class or category is consider as similar images. In WANG image database, it consists of 1000 images of 10 different categories. In each category, it contains 100 images. The WANG image database has image with size 256 x 384. Caltech 101 object categories image database contains 101 categories of images, the total number of images in each category can vary. In li image database, it contains 5 different categories of images, where the size of each category is 256 x 384. A total number of images in each category can vary. A brief description of each database is shown in the table.

Table 1. Summary of Each Database

Database	***Image Size***	***Number of classes***	***Number of images in each class***
WANG database	256x384	10	100
Caltech 101 object database	Image size can vary	101	Total number of images in each class can vary
Li database	256x384	5	Total number of images in each class can vary

The experimental exploration is done with 1000 images of Wang image database containing 10 categories, 500 images of LI database containing 5 categories and 900 images of Catech-101 database containing 9 categories. Wang database containing African, Beach, Monuments, Buses, Dinosaurs, Elephants, Flowers, Horses, Mountains and Food respectively shown in figure [4]. Caltech, which is taken for experimental analysis, are Ketch, Aeroplane, Faces, Piano, Bikes, Leopard, Bonsai and watch respectively shown in figure [5].

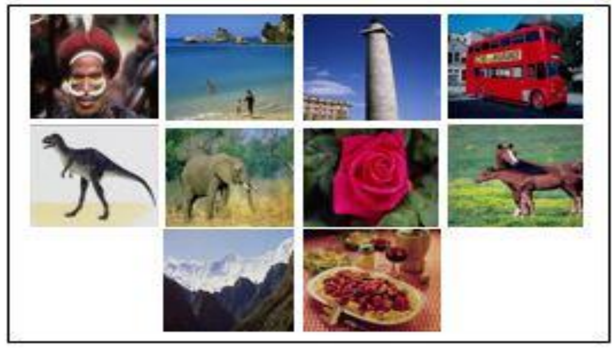


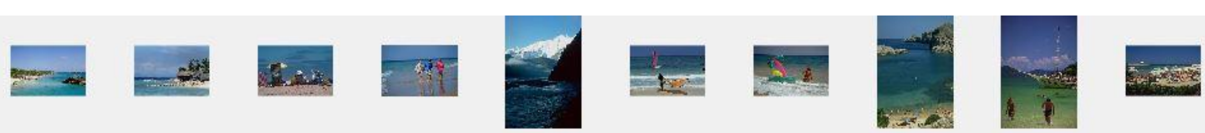
Figure 5. WANG image database

Figure 6. LI image database

Figure 7. Caltech image database

In this proposed method some random images are given as query image and then retrieved some images similar to a query image. Table II contains some similar images retrieved from WANG image database according to a query image. Table III contains some similar images retrieved from li image database according to a query image. Table IV contains some similar images retrieved from Caltech 101 image database according to a query image.

Table 2. User given query images and desired set of retrieved images from WANG Dataset

Query Image	***Retrieval Result from WANG database Similar to the Query image***
	
	

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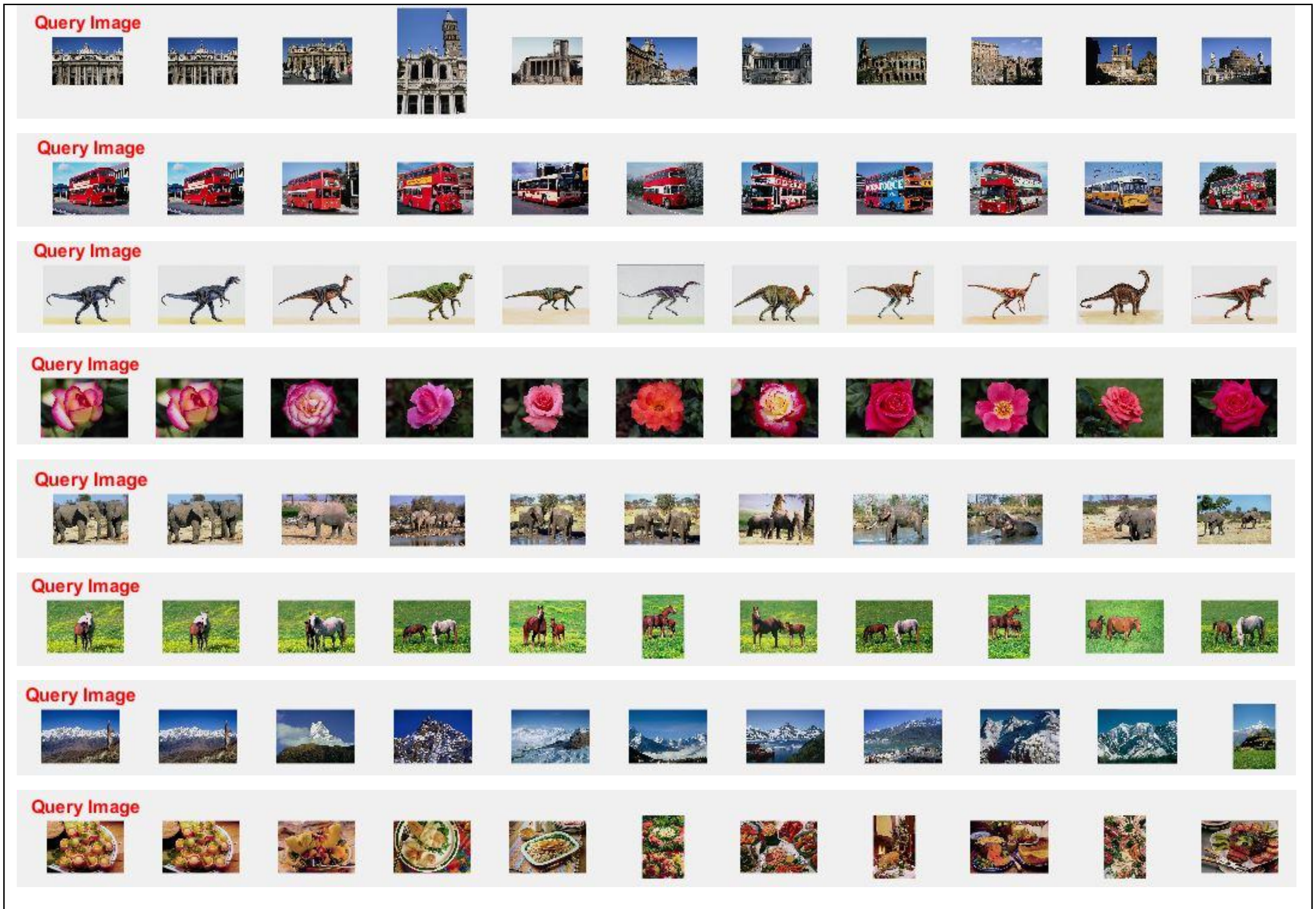

Table 3. User given query images and desired set of retrieved images from LI Dataset

Query Image	***Retrieval Result from WANG database Similar to Query image***

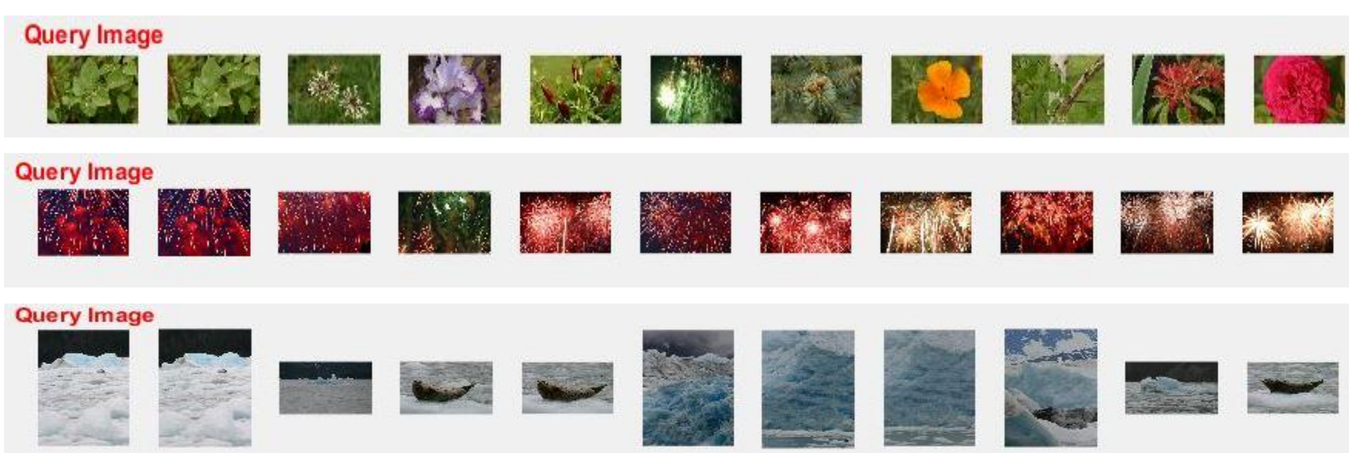

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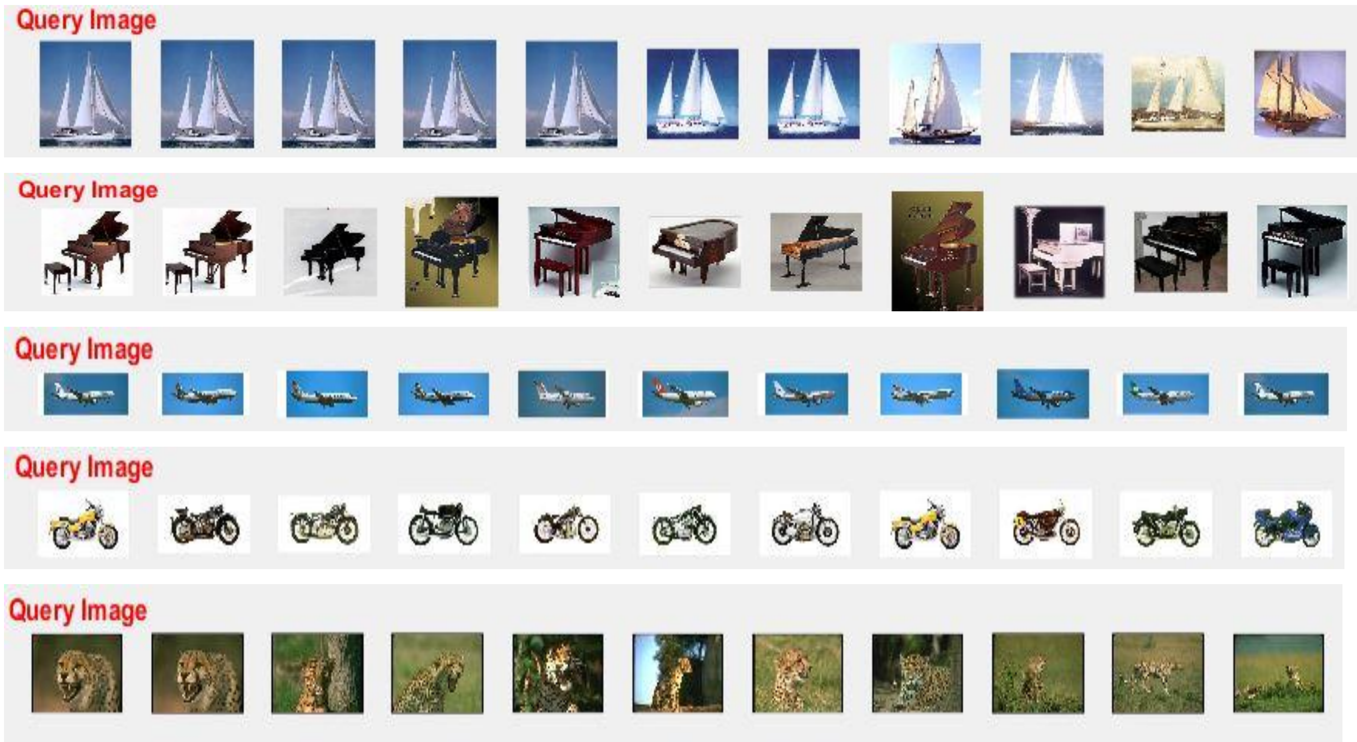
Table 4. User given query images and desired set of retrieved images from Caltech 101 image Dataset

Query Image	***Retrieval Result from WANG database Similar to Query image***
	

VI. PERFORMANCE EVALUATION

The retrieval result is evaluated regarding measures precision, recall and accuracy. Overall accuracy of proposed approach is comparing with existing approaches. Performance evaluation of the proposed system is measured by precision and recall rate. Precision provides information how effective the proposed system is. And recall gives the overall accuracy of the system. Recall also give the robustness of the system.

$$\text{Precision(P)} = \frac{TP}{TP + FP}$$

$$\text{Recall(R)} = \frac{TP}{TP + FN}$$

$$\text{Accuracy(A)} = \frac{TP + TN}{TP + FN + FP + TN}$$

Where,
TP = True Positive
FP = False Positive
TN = True Negative
FN = False Negative

True Positive is the total number of exactly recognized test images. True Negative is the total number of exactly rejected test images. False Positive is the total number of incorrectly identified test images. False Negative is the total number of incorrectly rejected test images.

Table 5. Comparison between Existing Methods and Proposed system

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Methods	Method [6]		Method [9]		Method [10]		Proposed Method	
Category	***Precision***	***Recall***	***Precision***	***Recall***	***Precision***	***Recall***	***Precision***	***Recall***
African People	76.00	43.16	76.78	86	44.80	10.90	76.80	86.66
Beach	58.70	32.87	82.92	68	47.20	11.90	75.00	77.33
Monuments	71.40	35.93	76.08	70	53.40	13.00	88.77	78.40
Buses	96.30	69.37	74.07	80	73.40	11.80	97.62	96.40
Dinosaur	100.0	99.66	75.92	82	99.80	19.90	100	100
Elephant	74.10	35.58	85.41	82	56.80	13.40	86.30	82.40
Flower	94.50	69.56	88.89	80	87.50	17.50	95.22	92.80
Horse	94.10	62.93	75.00	78	70.70	12.10	94.33	90.80
Mountains	45.70	24.00	89.13	82	39.30	16.60	80.16	84.00
Food	73.30	36.47	84.78	78	61.00	12.30	88.40	83.63
Average	**69.41**	**50.95**	**80.89**	**78.60**	**63.39**	**13.90**	**88.26**	**97.08**

The comparison between existing retrieval methods and proposed system in term of precision is shown in Table V. Here it is clear that the proposed system is more efficient and effective result in comparison to existing methods.

Table 6. Accuracy Rate for each category in WANG dataset

Database Name	Experimental Result	
	Category	***Accuracy***
WANG	African People	85.60
	Beach	85.20
	Monuments	87.40
	Buses	87.40
	Dinosaur	84.80
	Elephant	85.40
	Flower	84.20
	Horse	87.20
	Mountains	86.40
	Food	84.20
	Average	**87.78**

Table 7. Accuracy Rate for each category in LI dataset

Database Name	Experimental Result		
	Category	***Precision***	***Recall***
LI	1	76.27	90.00
	2	90.00	90.00
	3	83.03	88.00
	4	95.15	78.00
	5	89.36	84.00
	Average	**86.76**	**86.00**

Table 8. Accuracy Rate for each category in Caltech-101 dataset

Database Name	Experimental Result		
	Category	***Precision***	***Recall***
Caltech-101	Ketch	71.92	72.00
	Airplanes	94.00	84.00
	Faces	98.03	84
	Piano	88.88	96.00
	Bike	97.91	98.00
	Leopards	98.03	80
	Chandelier	69.23	92.00
	Bonsai	86.00	92.00
	Watch	79.59	78.00
	Average	**87.06**	**87.33**

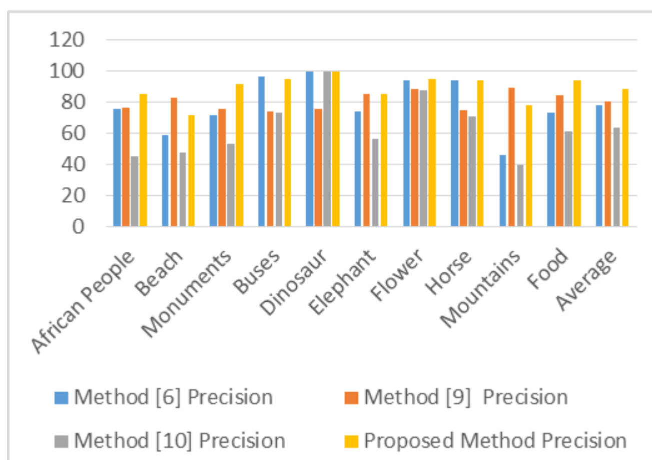

Figure 8. Comparison graph of average Precision between Existing and Proposed system

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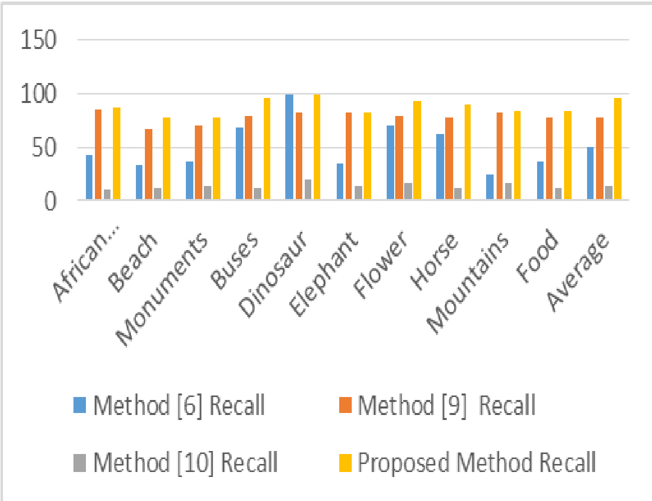

Figure 9. Comparison graph of average Recall between Existing and Proposed system

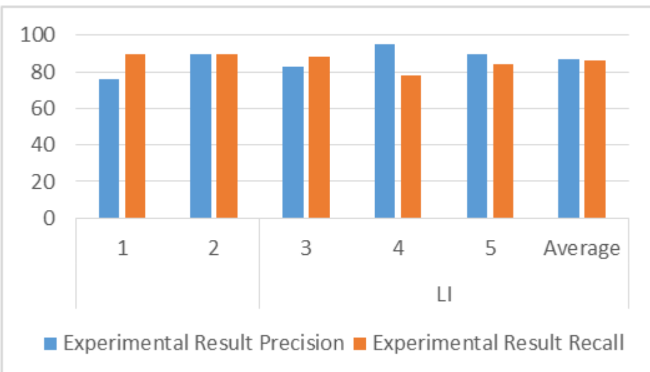

Figure 10. Comparison graph of average Recall between Existing and Proposed system

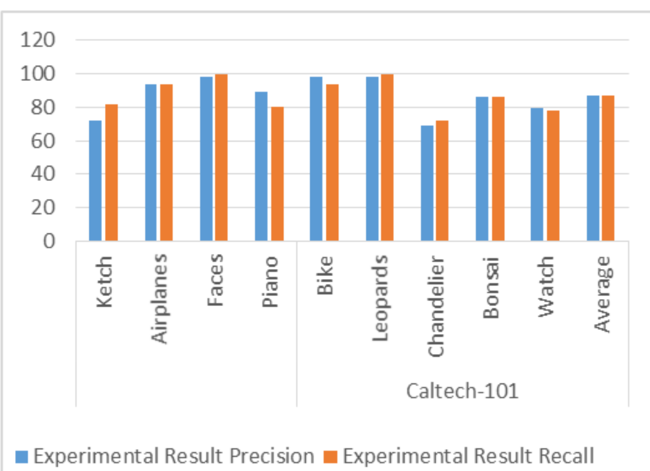

Figure 11. Precision and Recall Graph Caltech 101 dataset

VII. Conclusion

In this Paper, an approach for retrieval of irrelevant images has been discussed. Here, the new combination of low-level features has been used to extract information from images. The mean, slandered deviation and Skewness values of Red, Green and blue are used to extract color information. EHD and RLBP are used to extract edge and texture information of images respectively. PSO is used to optimize these feature vectors with optimal weights and measure the similarity between images. Experiment result gives better result in comparison to other optimization algorithms. The proposed system is performed on three types of databases and all these databases give better result in terms of precision and recall. The proposed framework achieves the average accuracy of 85.62% for WANG database, 84.60% for LI database and 85.20% for the Caltech-101 image database.

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