An Evolutionary Stochastic Approach for Efficient Image Retrieval using Modified Particle Swarm Optimization

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***Abstract*—Image retrieval system as a reliable tool can help people in reaching efficient use of digital image accumulation; also finding efficient methods for the retrieval of images is important. Color and texture descriptors are two basic features in image retrieval. In this paper, an approach is employed which represents a composition of color moments and texture features to extract low-level feature of an image. By assigning equal weights for different types of features, we can't obtain good results, but by applying different weights to each feature, this problem is solved. In this work, the weights are improved using a modified Particle Swarm Optimization (PSO) method for increasing average Precision of system. In fact, a novel method based on an evolutionary approach is presented and the motivation of this work is to enhance Precision of the retrieval system with an improved PSO algorithm. The average Precision of presented method using equally weighted features and optimal weighted features is 49.85% and 54.16%, respectively. 4.31% increase in the average Precision achieved by proposed technique can achieve higher recognition accuracy, and the search result is better after using PSO.**

Keywords—color moments; content based image retrieval; particle swarm optimization (PSO); texture feature

I. Introduction

The development of different images obligates the use of efficient techniques of managing the visual information by its content [1]. An image retrieval system is used the color, shape, and texture features to exact retrieve images from datasets [2]. Content based image retrieval (CBIR) is an open area research for retrieval of information using its contents [3]. From past decade, studies on CBIR have been an active research because in many large image databases, traditional techniques of image retrieval have proven to be insufficient. CBIR system extracts visual information of each image in the dataset and stores in features form and the system extract the related images that are similar to the query image. Color, shape and texture features are used in CBIR systems and practical applications [4].

One of the famous image retrieval systems is QBIC [5]. Shape feature represents the geometrical information [6] and is divided into boundary based shape and region based shape descriptors. The shape of the outer boundary is considered by boundary based shape descriptors. Zernike moments descriptors is a region based shape descriptors that describe the entire region of a shape [7]. Texture information can be used for recognizing an object [8] and structural methods are used [9] to describe it. The fine feature descriptor is applied to reach the truly matched images [10].

Color histogram is a color feature [11] that captures the number of pixels having proper properties [12]. A combined use of color and texture would provide better performance than that of color or texture alone [13] and the feature vector consists of the color and texture features [14]. Most of the image retrieval methods are not stochastic; consequently, searching in different solution space is not possible [15].

By using equal weights for the features we can't have appropriate average Precision, and Recall but applying different weights to each feature is a proper solution. For example, Particle Swarm Optimization (PSO) is an appropriate approach. Applying different weights to each feature and optimizing PSO algorithm is a method to increase the average precision in image retrieval system.

Discrete wavelet transform and particle swarm optimization was proposed by Quraishi et al. for optimizing image retrieval system [16]. The multilevel thresholds image segmentation approach and improved particle swarm optimization was proposed by Hongmei et al. [17]. A multilevel threshold-based image segmentation method and new particle swarm optimization was proposed by Jiang et al. [18]. A color image enhancement method was presented by Gorai et al. [19] in image retrieval system. Also, a histogram equalization approach and PSO algorithm was presented by Masra et al. [20]. Luo et al. introduced a wavelet-histogram image retrieval technique and PSO in CBIR systems [21]. A novel method based on PSO algorithm was proposed by Ye et al. for image retrieval [22]. Also, a new approach based on PSO and wavelet was proposed by Wei et al. that PSO was employed to optimize the weights [23].

Most of the CBIR systems may not perform robustly on image retrieval using the different features. Consequently, the key motivation in this work has been to develop a more robust and accurate image retrieval method which can be effective. In this paper modified PSO is used to effective retrieval in CBIR

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systems. In fact, in this paper, a novel method based on color and texture image retrieval technique and modified PSO is presented to retrieval of images in huge databases to do color textured image retrieval.

It is important to mention that one of the appropriate methods for extraction of the color features is color moments. In this work, color moments including mean, standard deviation, and skewness are used and entropy, standard deviation, local range and contrast is applied to extraction of the texture features

In fact, the key contribution of this paper is given in the following:

- A proposed of an image retrieval system using the color and texture features.
- A proposed of an optimization algorithm for increasing average precision of CBIR system.

The reminder of this work is organized as follows. Section II discusses algorithms conventional PSO and the modified PSO algorithm. Section III explains a novel method for the image retrieval systems. Section IV illustrates the experimental results and finally, Section V provides conclusion and future work.

II. The Particle Swarm Optimization Algorithm

In this section, some information about algorithms conventional PSO and the modified PSO algorithm used in this study is provided.

A. The Standard Particle Swarm Optimization Algorithm

PSO is a heuristic technique and an evolutionary computation model developed by Kennedy and Eberhart in 1995 [24] that is related to genetic algorithms and evolutionary programming. PSO is considered robust in solving problems featuring non-differentiability, non-linearity, and high dimensionality [25] and is used in neural networks [26].

If X be the decision vector in a cost function f (X) then it must be minimize in the optimization problem. In the PSO algorithm, all particles have random coordinates in n-dimensional space. For each particle, pbest and gbest are the best coordinates each particle and the best coordinates among overall particles, respectively that the particles move based on pbest and gbest. X and V are current position vector and velocity vector for each particle, respectively. At the k^{th} time step (iteration), the velocity vector is updated as follows:

$$V_{id}^{k+1} = W \times V_{id}^{k} + c_1 \times rand_1^k (pbest_{id}^k - X_{id}^k) + c_2 \times rand_2^k (gbest^k - X_{id}^k) \quad (1)$$

Also, the position vector of the i^{th} particle is changed as follows:

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \quad (2)$$

$$k = 1,2,..., \max iteration$$

$$id = 1,2,..., p$$

That p is the number of particles. c_1 and c_2 are the relative attraction toward pbest and gbest, respectively and $rand_1$ and $rand_2$ are random numbers uniformly distributed between [0,1]. Also, W is inertia weight parameter. The PSO algorithm can be expressed as Fig. 1.

```
k=1
%initialize random particles
for i=1 to p
   particle(i).X=random value between X_LowerBond and X_UpperBound
   particle(i).V=random value between V_LowerBond and V_UpperBound
   particle(i).cost=cost_function(particle(i).X)
   particle(i).pbest=particle(i).cost
   particle(i).best_position=particle(i).X
end
[global_best_position gbest]=minimum_cost(particle)
%find best position
while(k<=maximum iteration)
   for i=1 to p
      update particle(i).X
      update particle(i).V
      particle(i).cost=cost_function(particle(i).X)
      if (paticle(i).cost<particle(i).pbest)
         particle(i).pbest=particle(i).cost
         particle(i).best_position=particle(i).X
      end
   end
   [global_best_position gbest]=minimum_cost(particle)
   k=k+1
end
return [global_best_position gbest]
```

Fig. 1. Standard PSO algorithm

Each dimension of X and V must be limited between lower bound and upper bound that are determined based on the parameter of the problem. These parameters must be optimized in optimization algorithms.

B. The Improved Particle Swarm Optimization Algorithm

An important problem in PSO method is to determine limits in search space [27]. In standard PSO algorithm, execution time increases with larger search space. Consequently, the domain of each dimension of vector X is limited and the standard PSO routine is called. Improved PSO algorithm is given in Fig. 2 that d is applied to limit search space.

```
k=1 %k is a global counter
do
{
   [global_best_position gbest]=standard_pso(k,X_bond)
   X_lower bound=global_best_position - ((X_UpperBound - X_LowerBound)/d)
   X_Upper bound=global_best_position + ((X_UpperBound - X_LowerBound)/d)
   } while(k<=maximum iteration)
   return [global_best_position gbest]
```

Fig. 2. Improved PSO algorithm

III. The Proposed Image Retrieval System

In this section, proposed image retrieval procedure is provided. In addition, because of color and texture are two of the most widely used features.

A. The Basic Concepts of CBIR Systems

One of the appropriate ways of accessing visual data is image retrieval that use to color, shape, and texture [28]. Feature extraction is one of important steps in CBIR systems. Extraction of features of the images is stored in feature vectors form. The input image is called the query image. The query image feature vector is compared with all feature vectors in the dataset. Consequently, the appropriate images retrieve using distance measurement technique. Fig. 3 illustrates the architecture of CBIR systems. The user interface is consists of a query formulation part and a visualization part, is the front page of most systems dealing with input and output. The matching process does similarity measuring and the necessary comparisons. The indexes of those images which are selected to retrieve are passed into the image pointers process. It obtains image pointers (image id's), and the fetching process physically retrieves the images from the dataset.

B. CBIR Systemsn using the Fusion of Texture Features and Color Moments

In this section, texture features and color moments are investigated.

Entropy, local range, standard deviation and contrast measures are used to extract the texture features.

Texture = (Entropy + Local Range + Standard deviation + Contrast)

Entropy can be used to describe the texture of the input image that can be calculated as:

$$ENT = \sum_{k=1}^{M} P_k \log \frac{1}{P_k} \tag{3}$$

Where, ENT, M, and P are entropy, total number of samples, and probability of occurrences, respectively. Maximum value of chosen pixel-minimum value of chosen pixel is called local range. Standard deviation can be calculated as follows.

$$S = \sqrt{\frac{\sum_{i=1}^{n} (X_i - \overline{X})^2}{n}} \tag{4}$$

$$\overline{X} = \frac{\sum_{i=1}^{n} X_i}{n}$$

That, n is number of pixels in the image. Contrast represents the quality of picture in an image and is calculated by (5)

$$F_{con} = \frac{S^2}{\sqrt[4]{\mu_4}} \tag{5}$$

$$\mu_4 = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} (X(i,j) - \overline{X})^4$$

Where, μ_4 is the 4[th] moment of the mean $\overline{X}$, S^2 is the variance of the gray values in image.

In this work, mean, standard deviation, and skewness to extract color features is used. Mean, standard deviation, and the skewness are effective in representing color distributions of images. Color moments are describe as follows.

Moment 1: Mean

$$\mu_i = \frac{1}{N} \sum_{j=1}^{N} P_{ij} \tag{6}$$

That P_{ij} is the value of the i-th color channel at the j-th image pixel

Moment 2: Standard deviation

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^{N} (P_{ij} - \mu_i)^2}{N}} \tag{7}$$

Moment 3: Skewness

$$S_i = \sqrt[3]{\frac{\sum_{j=1}^{N} (P_{ij} - \mu_i)^3}{N}} \tag{8}$$

In this work, the combination of texture features and color moments is used. Entropy, local range, standard deviation and contrast measures are used to extract the texture features and 13 features are applied.

Features = (Texture Features + Color Features)

C. Stochastic CBIR using Improved Particle Swarm Optimization

Cost function must be minimized in optimization algorithm. A minimization tool is the stochastic PSO method. The solutions space is made of the features f=1,…,F, that are calculated on every dataset image. In the algorithm, the value of F is adjusted to 13. These 13 features are entropy, standard deviation, local range, contrast, mean of red component, standard deviation of red component, skewness of red component, mean of green component, standard deviation of green component, skewness of green component, mean of blue component, standard deviation of blue component, and skewness of blue component, respectively.

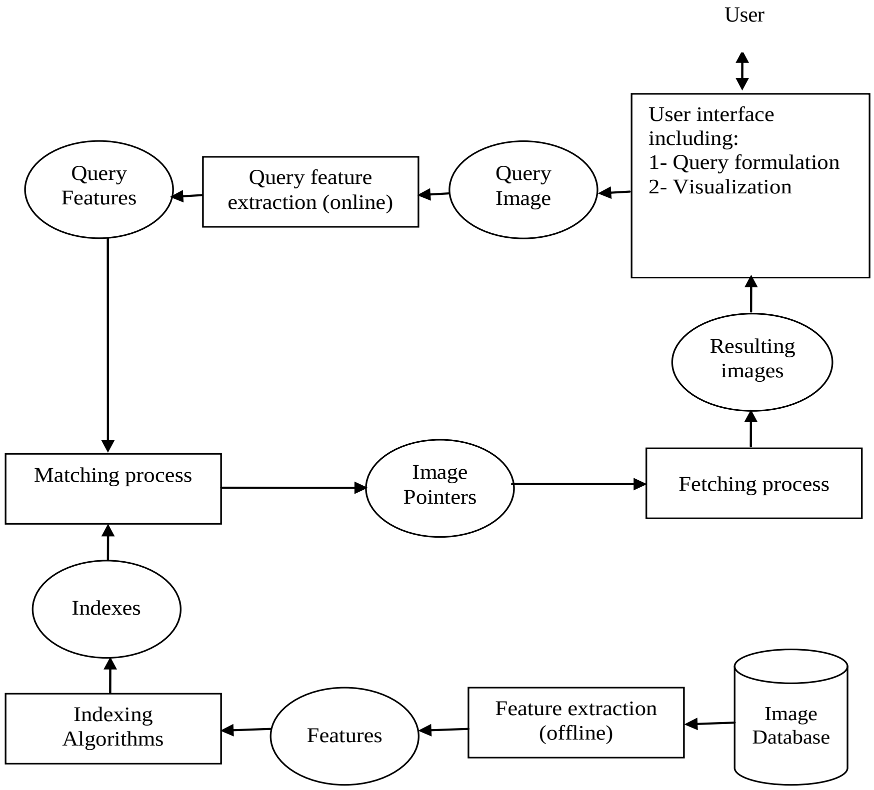


Fig. 3. Architecture of CBIR systems

The images of the database x_j, j=1,…, N_{DB} represent a discrete set of points and the particles can move within the features space. To associate every particle with the nearest image, a weighed city block distance (WCBD) or the Manhattan distance is used which is expressed as follows.

$$WCBD\,(x_q, x_j) = \sum_{f=1}^{F} | x_q^f - x_j^f | \times w^{k,f} \tag{9}$$

By using equal weights for each feature we can't have good average Precision, and Recall. Different weights to each feature are a good solution that is optimized using PSO algorithm. Weighing vector w^k calculate again at each iteration. The proposed algorithm shows in Fig. 4.

In the first iteration (*k=1*), a query image with a feature vector $x_q=[x_q^1,\ldots, x_q^f,\ldots, x_q^F]$ is selected. Then, the distances from all the dataset images x_j; j=1,…,N_{DB} are computed as WCBD(x_q,x_j). The speed vector each particle is set by randomly selecting a value over the features space, and then the stochastic optimization is done. The related and the irrelevant images are updated in each iteration and the new features weights are computed.

After classify the swarm based on the fitness of each particle, the k^{th} iteration is completed. Finally, each particle to the nearest image in the dataset is associated and the best N_{FB} is shown to the user. While a predefined numbers of iterations are reached, the optimization process ends. Then, the relevant solutions are shown.

IV. Experimental Results

The performance of an image retrieval system is computed using the Recall and Precision values. The Recall is defined as the ratio of the number of relevant images retrieved and the number of relevant images in class. The Precision is defined as the ratio between the number of relevant images retrieved and the total number of images retrieved [29]. Precision and Recall is computed as:

$$\mathrm{Re}\,call = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images}} \tag{10}$$

$$\mathrm{Pr}ecision = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \tag{11}$$

Also, the average Precision is computed by:

$$Average\_\mathrm{Pr}ecision = \sum_{k \in A_q} \frac{p(i_k)}{|A_q|} \tag{12}$$

That item belongs to the qth category (A_q). The fusion of color and texture features with optimal weights to a subset of MPEG-7 dataset is used.

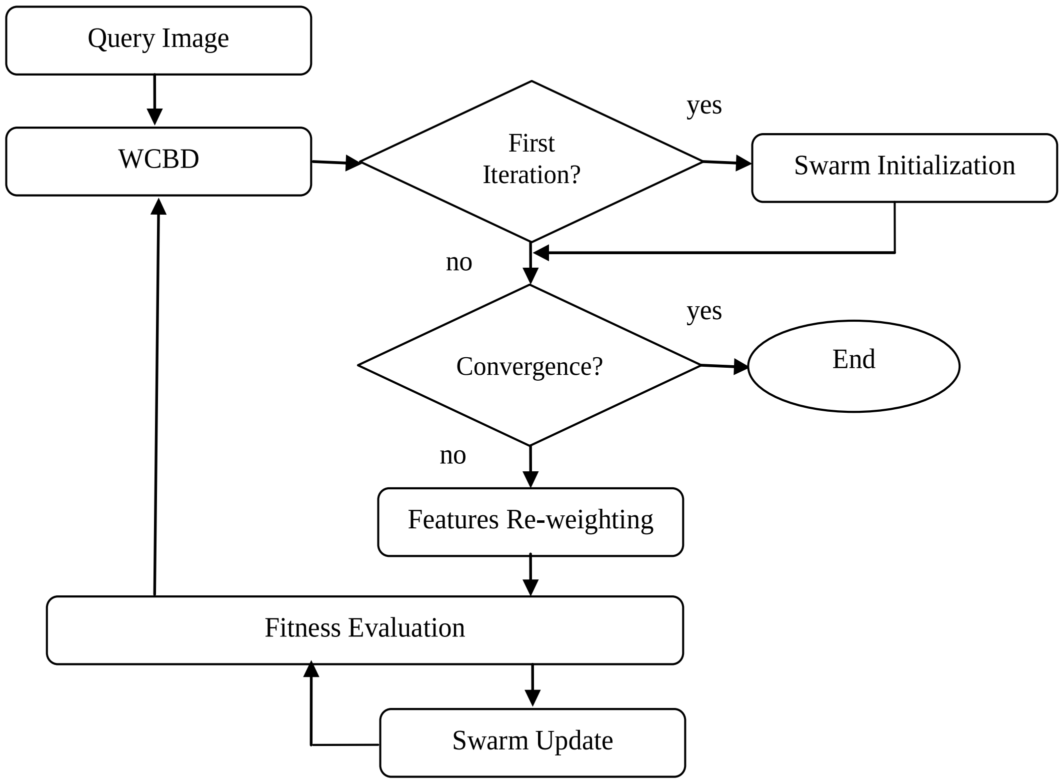


Fig. 4. Flowchart of the proposed method

The images in the dataset are categorized in 23 classes and each class contains 10 pictures in JPEG format that samples of MPEG-7 image dataset are shown in Fig. 5.

Fig. 5. Samples of MPEG-7 image database

Four texture features include entropy, standard deviation, local range, and contrast and nine colour features (mean, standard deviation, and skewness, for R, G, and B components in RGB space).

Precision and Recall are evaluation parameters in our experiments and implementations is done using a PC with Intel Pentium 2.5 GHz and 4 GB RAM. Fig. 6 illustrates the results generated from proposed system using optimal weighted features that show the efficiency of proposed method.

These results show that the performance of the proposed method is better than the other methods.

In experiments, Precision versus Recall curves to evaluate retrieval efficiency is adopted.

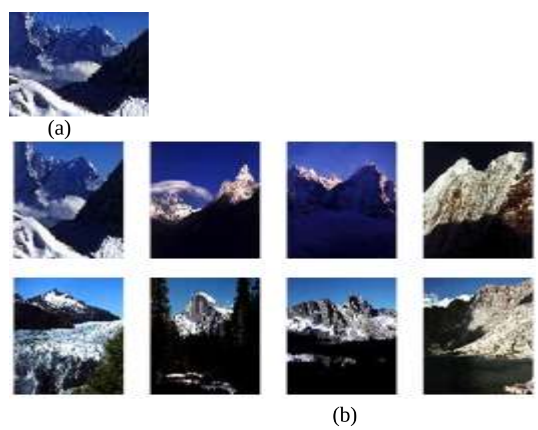


Fig. 6. Content based image retrieval results. (a) input image for retrieval. (b) using the improved PSO

Fig. 7 shows average Precision for when texture features (TF), the color moments (CM), the combination of the texture features and color moment using equally weighted features (TCEW) and optimal weighted features (TCOW), respectively extracted from images.

The average Precision in these four methods is 41.87, 45.64, 49.85, and 54.16 percent, respectively.

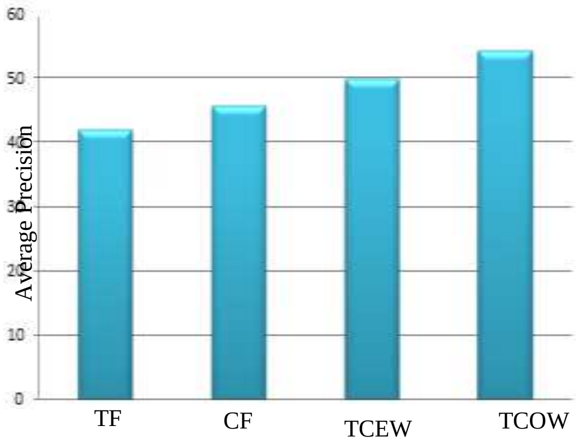
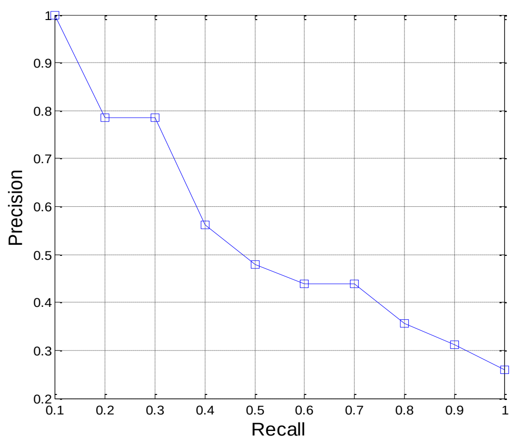


Fig. 7. The Average precision chart for CBIR system using the texture features, the color moments, equally weighted features and system with using improved PSO method.



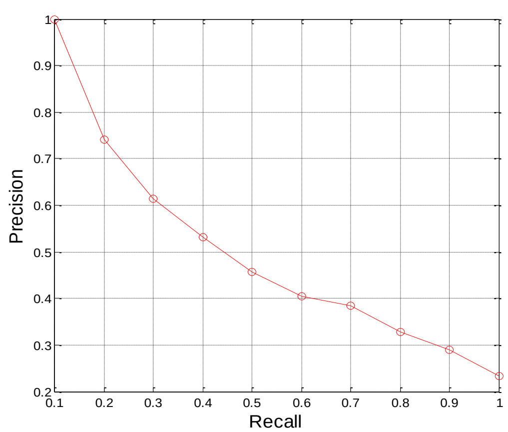


Fig. 8. The Average precision/recall chart for (a) CBIR system using equally weighted (b) CBIR system with using improved PSO method

Fig. 8 (a) and (b) show the Precision-Recall graph for the proposed image retrieval system using equally weighted features and using the improve PSO, respectively that the results of optimal weighted features show better average Precision and Recall.

The average Precision of proposed approach using improved PSO are 54.16%. Also, for the proposed method, the maximum average Precision of 100% at Recall value is 10%, and the Precision value decreases to 25.92% at 100% of Recall. Table I shows the quantitative results obtained by the optimal weighted features to the dataset that a total average of 54.16% retrieved images is achievable using improved PSO algorithm. Fig. 9 illustrates the comparison of average precision the proposed method with the other methods in [8], [9], and [10].

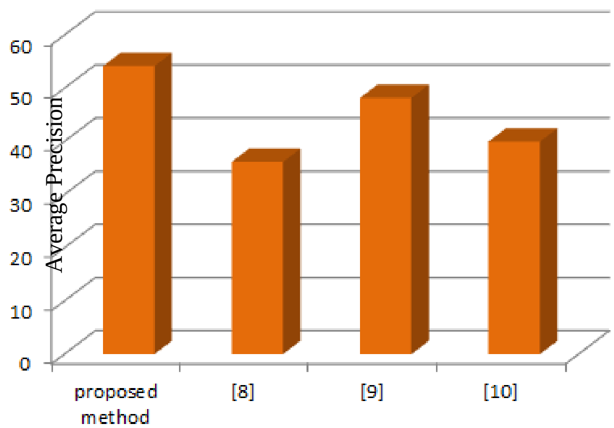


Fig. 9. The Average precision for the proposed method and the other methods

Fig. 10 shows the Precision versus Recall result of 30 query images that the proposed method is better than the fixed weighting.

TABLE I. PRECISION AND RECALL OF THE PROPOSED METHOD

Recall (%)	Precision (%) for the equally weighted features	Precision (%) for the presented method using improved PSO
10	100	100
20	74.05	78.51
30	61.48	78.50
40	53.22	56.15
50	45.76	47.97
60	40.54	43.90
70	38.49	43.89
80	32.78	35.58
90	28.90	31.18
100	23.26	25.92
AR = 55%	**AP = 49.85%**	**AP = 54.16%**

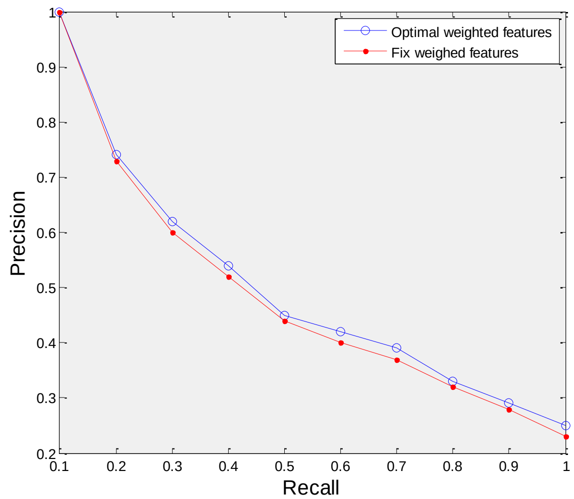


Fig. 10. Average precision vs. recall

In our experiments, size of swarm is 260 particles and sum of c_1 and c_2 variables is smaller 3. Also, the average precision in different iterations is not same. Fig. 11 shows the Precision chart in different iterations.

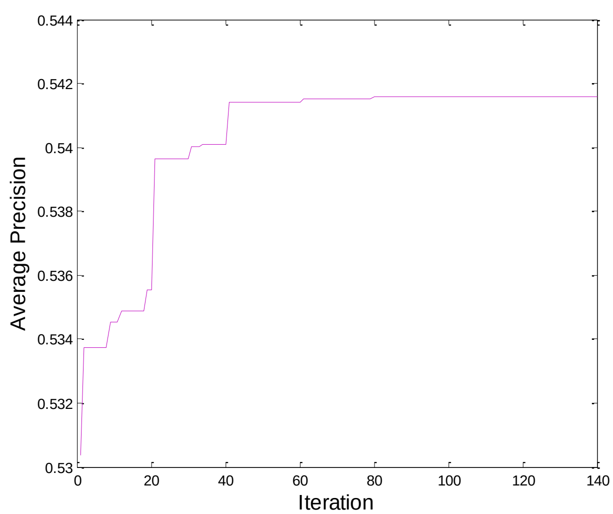


Fig. 11. Precision chart in different iterations

V. Conclusion and Future Work

In this paper, an method PSO to improve the accuracy and ability for image retrieval is presented and the improved PSO algorithm for image retrieval to get higher accuracy is employed. In fact, the use of a stochastic optimization algorithm to achieve a proper CBIR system was investigated. The experimental results showed that the proposed method was effective to the similarity search in images dataset after using PSO. To enhance the retrieval performance, cost function was minimizing. Proposed method was evaluated using Precision, Recall, and average Precision that the average Precision and the average Recall of proposed method are 54.16% and 55.00%, respectively.

In this work, to show the effectivity of proposed PSO algorithm, only color and texture features are selected, selecting more features will achieve better retrieval effect, which is our further work. Furthermore, the approach can be extended for translation and rotation properties, so that the retrieval efficiency can be increased.

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