# Performance Assessment of Content Based Image Retrieval System using Particle Swarm Optimization Algorithm and Differential Evolution

**E. Ranjith, Latha Parthiban**

***Abstract:In this paper, a content-based image retrieval (CBIR) system is presented by employing 12 distance measurements and three types of visual parameters, undergo optimization through particle swarm optimization (PSO) and Differential Evolution (DE) algorithm. Here after, it is called as image retrieval system (IRS) method for the convenience. Initially, IRS derives three types of features of an image: texture, shape and color. Consequently, for every feature type, the similarity among the others and query image in a database D will be estimated, and it uses suitable distance measurements. To optimize the IRS, the closely optimum permutations among the features, similarity metrics and optimum weights for 3 similarities in terms of 3 types of features are determined. In this paper, we made a performance analysis of the application of PSO and DE algorithms to optimize the parameters in the IRS. At the end, simulation outcome shows that the DE method dominates the other traditional methods.***

***Keyword*** **:CBIR; PSO; DE; Similarity metrics.**

## I. INTRODUCTION

With a consequent growth in digital image counts, for a huge number of files, an efficient digital management and the retrieval method is significant. Initially, by keeping a text annotation (keyword sets), an image is determined. In image database, the process of image retrieval is to compare the text annotation of query image with the images. Consequently, with same text annotation, the method shows an individual image. But, it is very impractical to use text annotation [1]. The following are the important issues: (1) While there is rapid growth in database, it is a time taking task to denote the text annotation for large count of images, (2) They may mark various text annotation for similar image due to the various cognition of users and (3) To demonstrate the ambiguity and diversity of image visual content and it is tedious to use text annotations. Due to these issues, the method of Content based image retrieval system (CBIR) is employed during the image retrieval of annotation-based methods. It is raising problem on the previous decade, so researches over CBIR is the upcoming trend [2-4]. Previous CBIR studies use unique feature like shape, texture or color. The main method shows that the multicolored objects histograms given an effective data to index large image databases. A technique named histogram intersection is presented to resolve the identification issue that compares the model with image histogram and histogram enhanced version intersection that attains real-time indexing. It give a method known as histogram back projection to resolve location issue that effectively perform this job in crowded scenes. To undertake broad development and evaluation, [2] has presented a texture and color descriptors. It uses different color descriptors that involve color layout descriptors (CLD), scalable color descriptors (SCD), color structure descriptors (CSD), and dominant color descriptors (DCD).

The texture descriptors enclose a homogeneous texture descriptor (HTD) and edge histogram descriptor (EHD) in [2]. For similarity matching, HTD provides homogeneous texture areas with quantized characterization. It computes a local spatial-frequency of image textures statistics. As same as CLD, the EHD derives the edge spatial distribution. The edge distribution is a fine text feature that is helpful for the retrieval of images while the text feature underlying is not homogeneous. But, an image comprises of different types of visual attributes. Through employing one or two features, it is tedious to attain retrieval result with full satisfaction. At present, many relevant studies were done by employing the visual feature combination and to improve the issue [5]. Hence, it is very significant to derive the efficient visual feature and merge these derived features in CBIR. A technique using 3-level DWT and average rates of L*U*V color spaces as image features is presented [6]. The Earth Mover's Distance (EMD) measurement is used as the similarity degree. In [4], the DCD method is used; pseudo-Zernike moments and steerable filter decomposition are used as image features. Feature set for image retrieval is gained by combining texture, color and shape. To derive texture and color features, [5] uses Gabor filter algorithm and 3D color histogram. To choose the features, it uses GA which reduces dimensionality in feature.

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In this paper, we made an attempt to compare the performance of the PSO and DE approaches on the color image retrieval system. To extract the images, it uses different types of texture, shape and color features.

To gain optimized weights for similarity function, it uses PSO and DE algorithm for selecting the near optimum combination among similarity and visual features. Especially, near optimum similarity function is developed for comparing two images that is done through a linear permutation of three distances of three types of visual parameters. Through PSO and DE methods, the function is optimized that is exposed to find an optimum combination that involves weights and distance methods for three types of visual parameters. The experimental validation takes part and verifies that the PSO shows better performance over the compared ones.

The succeeding portion of the paper is sorted as follows: an overview of PSO and DE is given in Section 2. The IRS is explained in Section 3 and the validation part takes place in Section 4. Finally, the study is ended with concluding remarks in Section 5.

## II. BACKGROUND INFORMATION

### A. PSO Algorithm

In many applications, PSO method is used to solve the issues of optimization [7] [8]. The subsequent direction is decided by birds in PSO algorithm and the movement distance through referring the previous directions of movement and present position while it searches for food. To search out the optimum solutions, a simulation is made for every particle as a biological entity in a much larger solution space approximately [8-9]. The training process for PSO algorithm is demonstrated below:

- Set the primary attributes: range of movement, swarm size, weight, and the iteration count for training. Additionally, the particles are positioned arbitrarily and movement vector is allocated arbitrarily.
- At the present iteration, Gbest and all Pbest locations will be saved in order to an examination procedure using the fitness function of every particle.
- When the iteration count for training is completed or there is a satisfaction in accuracy, then the Pbest and Gbest positions will be obtained, and the algorithm stops operating. Or else, go to next step.
- Estimate the movement vectors of every particle that are demonstrated in Eq. (1).
- Modify the positions of every particle Eq. (2) and jump to step 2.

The movement vector is demonstrated in Eq. (1) and is given as follows:

$$V_i(t+1) = wV_i(t) + c1 \times r1 \times \left(pbest_i - X_i(t)\right) + c_2 \times r_2 \times \left(Gbest - X_i(t)\right) \quad (1)$$

where $V_i = (V_{i1}, V_{i2}, \cdots, V_{im}) \in \Re^m$, $V_i(t+1)$ specifies the particle i movement vector at the $(t+1)$th round, $w$ shows the inertia weight, $c_1$ and $c_2$ indicate the acceleration coefficientthat are arbitrary numbers in [0, 1], $r_1$ and $r_2$are the rates produced arbitrarily in [0, 1]. However, in Eq. (1), the primary term $wV_i(t)$indicates the particle′s inertia, the subsequent one $c1 \times r1 \times \left(pbest_i - X_i(t)\right)$represents the particle′s cognition-only model, and the next one $c_2 \times r_2 \times \left(Gbest - X_i(t)\right)$point out the particle′s social-only model. The particle location i is changed as follows

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (2)$$

where $X_i(t+1)$ represents the particle location $i$ at the $(t+1)$th iteration, $V_i(t+1)$indicates the particle movement vector $i$ at the $(t+1)$ th iteration. Therefore, the fresh particle position $i$ is to insert its present position vector to their movement vector.

### B. Differential Evolution

The DE algorithm is comparatively easy, but works efficiently. It needs three attributes

- NP - size of population,
- F - a attribute to manage the mutation,
- CR - crossover possibility

DE works over a population $\mathcal{X}$of individuals $x_i$, where $i = 1, \dots, NP$ and $x_i = [x_{1i}, x_{2i}, \dots, x_{Di}]^T$ . Initially, we generate at random population $x_i^G$ , where $G = 1$ is the individual count within the population. In the method, the entire individuals are D-dimensional vectors of the real numbers, that the phenotype is same as the genotype. Mutation in this algorithm depends on arbitrary combination of every vector $x_i$through varying two other vectors out of the population $\mathcal{X}$multiplying it through a constant rate. For every vector $x_i^G$, we produce the mutant vector $v_i^G$ and is represented as follows:

$$v_i^{G+1} = x_{r1}^G + F.(x_{r2}^G - x_{r3}^G), \quad (3)$$

with arbitrary indexes $r1, r2, r3 \in \{1,2, \dots, NP\}$ and $r1 \neq r2 \neq r3 \neq i$ and $F \in [0,2]$ is a constant and real factor. Crossover operator is presented to combine arbitrary elements of parent vector $x_i^G$ and the vector elements $v_i^{G+1}$after mutation, whereas the output is expected trial vector

$$u_{ji}^{G+1} = \begin{cases} v_{ji}^{G+1} \; if \; rnd_j < CR \; or \; j = d_i \\ x_{ji}^G \; if \; rnd_j > CR \; and \; j \neq d_i \end{cases}, j = 1, \dots, D, \quad (4)$$

where $CR \in [0,1]$is the crossover constant, $rnd_j$is a uniform random number generator with result $\in [0,1]$and $d_i \in 1,2, \dots, D$is a chosen arbitrary index. The crossover operation denotes to optimization procedure. If $(fu_i^{G+1}) < f(x_i^G)$ then $x_i^{G+1} = u_i^{G+1}$, where $f(.)$is a fitness function. In other hand, $x_i^{G+1} = x_i^G$.

## III. IRS METHOD

The architecture of IRS method is shown in Fig. 1. It primarily derives three types of visual parameters for every image from image database D, which are texture, color and shape in the training phase. For these types of feature extraction, there are huge sum of methods. Furthermore, there are huge sum of distance formulas to measure the similarity for every type of feature. It is a signification issue to choose a near optimum combination between the large count of permutations for every type of visual parameters and its respective distance formulas prior to applying IRS method to extract the image.

To resolve this issue, the IRS method uses PSO/DE method. Over large sum of combination, to find a near optimum solution in the design of IRS method, PSO/DE method is employed.
Additionally, it uses approximately three optimum weights to estimate the similarity by employing the similarity function.

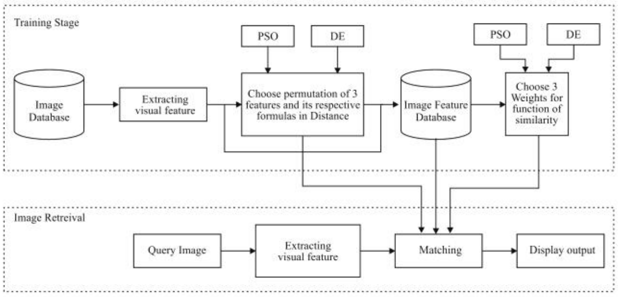


**Fig. 1. Architecture of the IRS**

As demonstrated in Fig. 1, while retrieving the image, 3 visual features of a query image is derived primarily through employing three methods of feature extraction that are decided in the training stage. It is capable of estimating the visual features through employing its respective distance formulas in the training stage. The discrimination procedure applied similarity functions with 3 near optimum weights to estimate the similarity among every image and query image in D. At the end, in order to the above similarity, IRS method results many similar images to the given image. The overall diagram is demonstrated in Fig. 2 for the image retrieval and training phase in IRS method. Especially, Fig. 2 shows the training phase structure. A large sum of combinations, $\Phi_k$, shown above can be demonstrated as:

$$\Phi = \{\Phi_k \; 1 \leq k \; \leq (n_c \times n_d) \times (n_T \times n_d) \times (n_s \times n_d)\} \tag{5}$$

where $n_C, n_T, n_S$, and $n_d$ is the sum of color, texture, shape features and distance formula, correspondingly. Let $\Phi_0$is a near optimum solution chosen from $\Phi$, founded through PSO method and is defined as follows:

$$\Phi_0 = \left\{\left(F_{C_{i_0}}, d_{C_0}\right), \left(F_{T_{j_0}}, d_{T_0}\right), \left(F_{S_{k_0}}, d_{S_0}\right)\right\}, \tag{6}$$

Where $i_0 \in \{1,2,\dots,n_C\}, j_0 \in \{1,2,\dots,n_T\}, k_0 \in \{1,2,\dots,\ n_S\}$, and $C_0, T_0, S_0 \in \{1,2,\dots,n_d\}$ . Here, $\left(F_{C_{i_0}}, d_{C_0}\right)$ demonstrates the $C_{i_0}$ th color features and the $C_0$ th distance formula, $\left(F_{T_{j_0}}, d_{T_0}\right)$ demonstrate the $T_{j_0}$ th texture feature and the $T_0$ th distance formula, and $\left(F_{S_{k_0}}, d_{S_0}\right)$ denotes the $S_{k_0}$ th shape feature and the $S_0$ th distance formula. On the other hand, the IRS technique finds for a set of optimum weights approximately for the similarity function that is a linear permutation of three distances for 3 types of visual features. Let $w^C, w^T, w^S$are the near optimum weights of the similarity function development. It is noted that the 3 visual features $(F_{C_{i_0}}, F_{T_{j_0}}, F_{S_{k_0}})$, their respective distance formulas, $(d_{C_0}, d_{T_0},\ d_{S_0})$, and 3 near optimum weights, $(w^C, w^T, w^S)$, for the similarity function are set subsequent to the training stage. The similarity function is used to determine the differentiation among two images.

At the point of "Visual Feature Extraction", the IRS primarily derives 3 types of visual parameters of images in D: color, shape and texture features. The phase of "Combinations of 3 types of Visual Features and respective Distance Formula" are determined by employing PSO/ DE method, the IRS technique find out the nearly optimum permutations of every type of visual features and respective distance formulas out of $\Phi$; a large count of permutations in Eq. (3). While, "A Linear Permutations of Distances between Features" demonstrate which the PSO algorithm is used to improvise the IRS method through deciding nearly optimum weights employed in the building of similarity function. Here, $\Delta_{l,q}$denotes the similarity among the $l$th image in D and the given image.

In Fig. 2, "Image Retrieval" demonstrates which the visual features $F_q$ of an input image $I_q$ are derived through employing three determined methods of feature extraction. Then, three distances $(d_{l,C_0}, d_{l,T_0}, d_{l,S_0})$for 3 visual features, among the query image and the $l$th image in D, might be estimated through employing its respective distance formulas in the matching procedure. Consequently, the discrimination procedure applied the similarity function with three nearly optimum weights $(w^C, w^T, w^S)$, to estimate the similarity among the query image in addition to every image in D. The methods of feature extraction, the distance formulas, and the weights denoted above are similar as those used in the training stage. Subsequently, many same images are extracted out in order to the query image high similarities.

### A. Feature extraction

In this paper, three visual features types, the shape, the texture, and the color features, correspondingly, are used for retrieving an image. They are enclosed and demonstrated as below.

***1) The color feature extraction***

For evaluation in the IRS method, 15 types of method for the extraction of color feature are used. It is noted that $nC$ is equated to 15. That is, there are 15 color features types that are the color histograms in addition to the color moment in five color spaces.

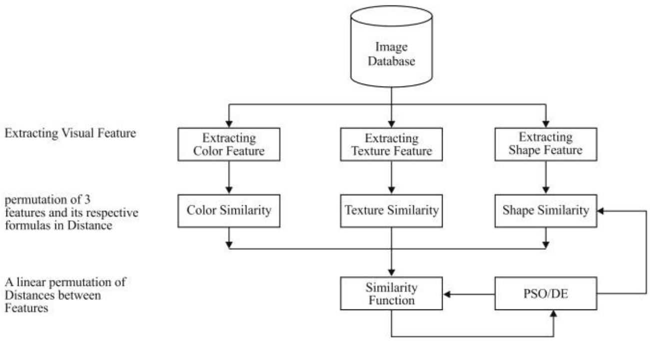


**Fig. 2. Training stage of the IRS**

***2) Texture feature extraction***

For evaluation, 30 types of texture feature extractions are used. Here, $nT$ is fixed to 30. The extraction method comprises of DCT, DWT, DFT, steerable filter, DFT and so on.

***3) Shape feature extraction***

To examine, 7 types of extracting shape features are employed. Here, $nS$ is put to 7.

The method of extracting above for deriving the shape feature are the pseudo-Zernike moments, the chain code, the GVF, the edge histograms in MPEG-7.

**B. Distance measurement**

For retrieval of image, to choose the distance formula for every type of visual features is a significant problem. To choose the distance formula which is suitable [10], there is no common rule. In this paper, twelve general distance formulas are used. They are correlation distance measurement ($X^2$), Chebychev distance measurement, weighted-mean variance (WMV), the $L_1$ norm, the $L_2$ norm, Eqs. (7)–(21) defines the distance formulas as represented below.

$$d_1 = L_1(F_D, F_Q) = \sum_{i=1}^{Q_n} |f_{D_i} - f_{Q_i}| \quad (7)$$

$$d_2 = L_1(F_D, F_Q) = \sqrt{\sum_{i=1}^{Q_n} f_{D_i} - f_{Q_i})^2} \quad (8)$$

$$d_3 = x^2(F_D, F_Q) = \sum_{i=0}^{Q_n} \frac{(f_{D_i} - f_{Q_i})^2}{(f_{D_i} + f_{Q_i})^2} \quad (9)$$

$$d_4 = SE(F_D, F_Q) = \sum_{i=0}^{Q_n} \left(\frac{f_{D_i} - f_{Q_i}}{\sigma(i)}\right)^2 \quad (10)$$

$$d_5 = COS(F_D, F_Q) = \sum_{i=1}^{Q_n} \frac{f_{D_i} f_{Q_i}}{\sqrt{\|F_D\|\|F_Q\|}} \in [-1,1] \quad (11)$$

$$d_6 = Cor(F_D, F_Q) = \sum_{i=1}^{Q_n} \frac{f_{D_i} - \overline{F_D}}{\sqrt{\|F_D - \overline{F_D}\|\|F_Q - \overline{F_Q}\|}}, \quad (12)$$

where

$$\overline{F_D} = \frac{\sum_{i=1}^{Q_n} f_{D_i}}{Q_n} \text{ and } \overline{F_Q} = \frac{\sum_{i=1}^{Q_n} f_{D_i}}{Q_n} \quad (13)$$

$$d_7 = Can(F_D, F_Q) = \sum_{i=1}^{Q_n} \frac{|f_{D_i} - f_{Q_i}|}{|f_{D_i} + f_{Q_i}|}, \quad (14)$$

$$d_8 = Minkowski(F_D, F_Q) = \left(\sum_{i=1}^{Q_n} |f_{D_i} - f_{Q_i}|^M\right)^{\frac{1}{M}}, \; M \notin \{1,2\}, \quad (15)$$

$$d_9 = Fu(F_D, F_Q) = 1 - \frac{\|F_D - F_Q\|}{\|F_D\| + \|F_Q\|}, \quad (16)$$

where,

$$\|F_D - F_Q\| = \sqrt{\left(\sum_{i=1}^{Q_n} (f_{D_i} - f_{Q_i})^2\right)}, \quad (17)$$

$$\|F_D\| = \sqrt{\left(\sum_{i=1}^{Q_n} (f_{D_i} - f_{Q_i})^2\right)}, and\ \|F_Q\| = \sqrt{\left(\sum_{i=1}^{Q_n} (f_{Q_i})^2\right)}, \quad (18)$$

$$d_{10} = WMV(F_D, F_Q) = \frac{|F_D - F_Q|}{|\sigma(\mu)|} + \frac{|\sigma(F_D) - \sigma(F_Q)|}{|\sigma(\sigma)|} \quad (19)$$

$$d_{11} = CB(F_D, F_Q) = \sum_{i=1}^{Q_n} |f_{D_i} - f_{Q_i}|, \quad (20)$$

$$d_{12} = CD(F_D, F_Q) = \max_{1 \le i \le Q_n} \{|f_{D_i} - f_{Q_i}|, \quad (21)$$

where $F_D = (f_{D_1}, f_{D_2}, \dots, f_{D_n})$ demonstrates the image feature vector of in $D, F_Q = (f_{Q_1}, f_{Q_2}, \dots, f_{Q_n})$ demonstrate the query image feature vector, $D_n$ in addition $Q_n$ establish the length of image feature vector in D and length of feature vector for the query image, correspondingly, $Q_n = D_n$. $|.|$ denotes the absolute rate, $\sigma(i)$ is described as the difference of $i$ th dimensional attributes of an image feature vector, $\|\cdot\|$ denotes the $L_2$ rule of an image feature vector, $\overline{F_D}$ and $\overline{F_Q}$ correspondingly set for the average rates of $F_D$ elements and $F_Q$ elements, and $\sigma$ demonstrates as the individual standard deviation.

Using the PSO and DE methods, IRS can be demonstrated. The testing and training sets for Algorithm 1 use a full image equated in D with 25% images and 75% images correspondingly. To choose a set of random optimum weights and near optimum combination for the training set of image in D, PSO method is used.

## IV. PERFORMANCE EVALUATION

### A. Dataset Description

To evaluate this work, two image databases are used. One is a clothing image database. It comprises seven groups and every group has 160 images, which is, there exist a sum of 1120 images and another is the Corel image dataset [11]. It comprises of ten groups and every group comprises of 100 images, there exist a sum of 1000 images.

### B. Measures

For the above specified different methods, recall rate and precision rate are used to perform quality assessment in the experiments. It is described in Eqs. (22) and (23) [6]. The rate of precision is described as a proportion of retrieved images as same as the query image between the entire sum of images that are retrieved. The rate of recall is described as a proportion of images retrieved as same as the query image between the entire sum of images retrieved.

$$precision\ rate = \frac{no.of\ relevant\ images\ extracted}{total\ no.of\ images\ extracted} * 100\%$$

$$= \frac{p}{p+r} * 100\% \quad (22)$$

and

$$recall\ rate = \frac{no.of\ relevant\ images\ extracted}{total\ no.of\ relevant\ images\ in\ database} * 100\%$$

$$= \frac{p}{p+q} * 100\% \quad (23)$$

where p denotes the number of retrieved images that are relevant, q indicates the sum of images which are relevant within the database that are not retrieved, and r denotes the sum of non-relevant images within the database that are retrieved.

### C. Image retrieval results

The performance of the IRS is validated by comparing the results of the proposed and existing methods interms of precision and recall. Figs. 3 and 4 compares the results of different retrieval methods interms of precision and recall respectively.

**Table 1 Precision for DE and PSO**

| | Lu | Han | Wang | DE | PSO |
|---|---|---|---|---|---|
| Clothing image | 30.34% | 26.84% | 25.62% | 69.20% | 77.48% |
| Corel image | 49.76% | 33.74% | 35.74% | 73.88% | 81.52% |

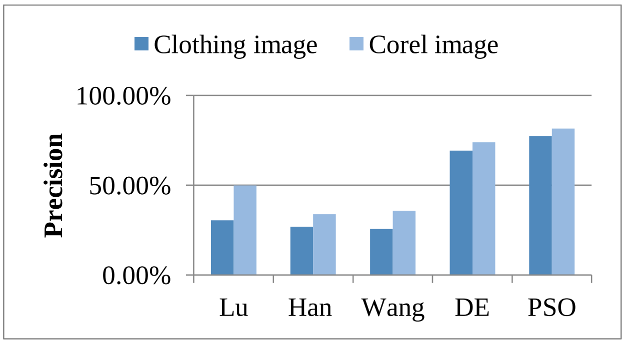


**Fig. 3. Results analysis of different methods interms of precision**

**Table 2 Recall rate for DE and PSO**

| | Lu | Han | Wang | DE | PSO |
|---|---|---|---|---|---|
| Clothing image | 3.79% | 3.35% | 3.20% | 8.65% | 9.69% |
| Corel image | 9.95% | 6.75% | 7.15% | 14.78 % | 16.30 % |

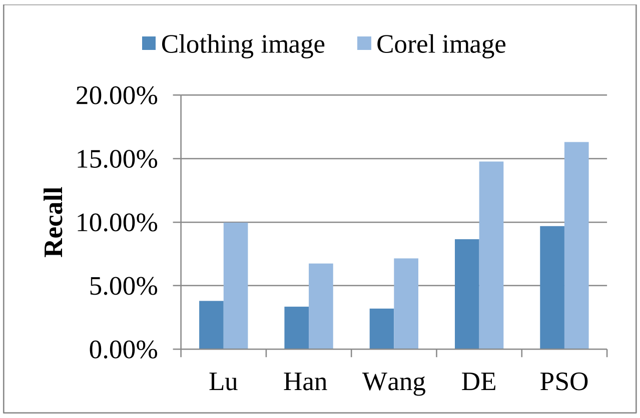


**Fig. 4. Results analysis of different methods interms of precision**

Tables 1 and 2 provide the attained results of different methods interms of precision and recall. From the table 1, it is noted that the PSO algorithm exhibit superior results over the compared methods. For the clothing image dataset, the PSO algorithm achieves the maximum precision level of 77.48% whereas DE achieves only 69.20%. Similarly, for the Corel image dataset, the PSO algorithm showed effective performance with the higher precision level of 81.52% whereas the DE fails to show betterment with a lower precision level of 73.88%.

In line with, from the table 2, it is noted that the PSO algorithm is found to be efficient and show better performance over the other methods including DE interms of recall. On the applied clothing image dataset, the PSO algorithm achieves the maximum recall rate of 9.69% whereas DE achieves only 8.65%. Similarly, for the Corel image dataset, the PSO algorithm showed effective performance with the higher recall rate of 16.30% whereas the DE fails to show betterment with a lower precision level of 14.78%. The PSO proposed algorithm is better than the compared ones during the retrieval process under all the applied dataset. This is due to the fact that the Lu′s and Han′s approaches make use of only particular kinds of features. In addition, an image holds different visual features, for example, color, texture and shape features. So, they failed to attain maximum retrieval results. Even though Wang′s approach employ 3 various types of features, it fails to give importance to the weights of visual features for every category of images are not necessarily equal. From the above tables, it is clear that the PSO algorithm showed superior retrieval results on all the applied images.

## V. CONCLUSION

In this paper, we made a comparative analysis between the performance of the PSO and DE approaches on the color image retrieval system. For extracting the images, different types of texture, shape and color features are employed. To gain optimized weights for similarity function, it uses PSO and DE algorithm for selecting the near optimum combination among similarity and visual features. The validation of the presented methods takes place using the benchmark dataset namely Clothing and Corel image database. The simulation outcome is determined interms of two evaluation parameters namely precision and recall. On the applied dataset, the presented PSO algorithm exhibits superior retrieval performance over the compared interms of precision and recall rate. In future, we will develop a new CBIR method by the use of new machine learning algorithms.

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