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Application of Multi-Objective Artificial Bee Colony Optimization for CBIR System

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Abstract— ***Multi-objective optimization has been a challenging area and focus for research. This paper presents an optimization algorithm based on artificial bee colony (ABC) to deal with multi-objective optimization problems in CBIR. We have introduced a multi-object ABC algorithm which is based on the intelligent scavenging behaviour for content base images. It uses less control parameters, and it can be efficiently used for solving for multi object optimization problems. In the current work, MOABC for discrete variables has been developed and implemented successfully for the multi-objective design optimization of composites. The performance is estimated in comparison with other nature-inspired techniques, which includes Multi-objective Particle Swarm Optimization (MOPSO) and Multi-objective Genetic Algorithm (MOGA). The performance of MOABC is better as par with that of MOPSO, MOGA and ABC for all the loading configurations.***

Keywords— ABC, Content-Based Image Retrieval (CBIR), Pareto Optimal, Gaussian Mixture Model (GMM), Pareto fonts.

I. INTRODUCTION

Content-based image retrieval is a method which expenditures visual contents to search images from bulky scale image databases according to users interests it is also known as query by image content. Since 1900s Content-based image retrieval has been an active and fast advancing research area. [1][5] CBIR comes to picture when many applications with large image database, traditional methods of image indexing have recognized to be unsatisfactory. Finger print scanning system, Automatic face recognition system, Medical image database, Trademark image registration are the application of Content-based image retrieval (CBIR). [6][7] The process of CBIR consists of three stages namely Image acquisition, Feature Extraction and Similarity Matching. In CBIR first query image undergoes the three stages as mentioned above. The query image is then compared with the images in the image database. All the images in the database undergo feature extraction so that the resultant feature vector can be compared with the feature vector of the query image. The closest image in comparison with the query image from the feature database is return [8] [10].

Multi objective optimization is defined as a problem of finding a vector of decision variables which fulfils constraints and enhances a vector function whose element characterizes the objective functions and these functions form a mathematical description of performance criteria which are usually in clash with each other [9] [11][25]. Therefore, the term Multi objective optimization means finding such a solution, which would give the values of all the objective functions acceptable to the decision maker. Economics, Finance, Optimal control, optimal design, and Radio resource management are the some application of Multi objective optimization. To solve Multi objective optimization problem there are some methods are used like a No-preference method, Priori method, Posteriori method, Interactive method.[12][13][25].

The biggest problem for CBIR system is to incorporate useful techniques so as to procedure images of expanded features and types. There are numerous methods for processing of low level cues are distinguished by the characteristics of domain-images.[14] The performance of these methods is tested by various issues like image resolution, intra-image illumination variations, non-homogeneity of intra-region and inter-region textures, multiple and occluded objects etc. [4] [15] The other key trouble, is a gap between inferred understanding semantics by pixel domain processing using low level cues and human perceptions of visual cues of given image[16]. The content-based image retrieval system comprises of multiple inter-dependent tasks performed by various phases and Inter-tuning of all these phases of the content-based retrieval system is unavoidable for over all good results. The diversity in the images and semantic-gap generally enforce parameter tuning & threshold-value specification suiting to the requirements [17].

In 2005 Karaboga proposed the artificial bee colony algorithm (ABC) is an optimization algorithm based on the intelligent foraging behaviour of honey bee swarm [18]. In ABC model, the colony consists of three groups of bees namely employed bees, onlookers and scouts. In this model it is assumed that there is only one artificial employed bee for each food source [19]. Employed bees go to their food source and come back to hive and dance on this area. The employed bee whose food source has been abandoned becomes a scout and starts to search for finding a new food source [2]. Onlookers watch the dances of employed bees and choose food sources depending on dances. Optimal multi-level thresholding, MR brain image classification, cluster analysis, face pose estimation and 2D protein folding etc. these are the applications of ABC [20].

II. PROPOSED METHODOLOGY USING ABC FOR CBIR SYSTEM

The main aim of the propose approach is to design a method to improve the content-based image retrieval performance. We have to propose a multi-objective optimization model for a content base image with the aid of the ABC.

In previous paper [24], we have to use single-objective optimization problem for content-based image retrieval performance but we get:

$$\min f(x);\ x \in s \tag{1}$$

where f is a scalar function

S is the (implicit) set of constraints.

In this paper, we have use multi object optimization technique with mathematical modelling is called "Pareto optimality". Let X be n-dimensional search space, and $F_i(x), i = 1...k$ be k objective functions defined over X. Furthermore, let $G_i(x) \le 1...0$, *i= 1…m,* be m inequality constraints. Then, the multi-objective problem can be defined as finding a vector, $x = (x_{1,}\ x_2, ...x_n)^T \in X$ that satisfies the constraints, and optimizes the vector function,

$$F(x) = (f_1(x), f_2(x), ..., f_n(x)) \tag{2}$$

Where *n>1*and *F* is the set of constraints defined above. The space in which the objective vector belongs is called the objective space, and the image of the feasible set under *f* is called the attained set.

$$C = \{y \in R^n : y = f(x), x \in S\} \tag{3}$$

The scalar concept of "optimality" does not apply directly in the multi-objective setting. Here the notion of Pareto optimality has to be introduced. Essentially, a vector $x^* \in S$ is said to be Pareto optimal for a multi-objective problem if all other vectors $x \ \in S$ have a higher value for at least one of the objective functions f_i, with $i = 1,2,......n$ or have the same value for all the objective functions.

Content Based Image Retrieval with Multi-objective optimization:

The approach supported retrieving images just as if one chosen by the user is named Content based Image Retrieval (CBIR). Each image is represented by Multi-objective optimize dimensional feature extraction. During this approach, Image process algorithms square measure accustomed extract feature extraction that represent image properties like colour, texture, and shape that square measure the visual features. To retrieve the query image from the database images, a similarity measures are notice to check the likeness between a question image and database images. One among the most sanctifications of the CBIR approach is the possibility of an automatic retrieval process, instead of the traditional keyword-based approach, which usually requires very laborious and time-consuming previous annotation of database images. The CBIR technology has been employed in many applications like fingerprint identification, diverseness data systems, digital libraries, crime interference, medicine, historical analysis etc.

Feature Extraction:

In this paper, we present a novel article bee colony (ABC) algorithm to solving multi-objective optimization problems, namely, multi-objective artificial bee colony (MOABC). In our algorithm, we use all three-type feature extraction, color, texture and shape.

Color Feature Extraction:

A content-based image retrieval system is presented that computes colour similarity among images i.e. it supports querying with respect to colour. Colour is one of the most important features of objects in image. The colour histogram of each image is then stored in the database. When the user does the search by specifying the query image, the system registers the proportion of each colour of the query image and goes through all images in the database to find those whose color histograms match those of the query most closely. The colour histogram is widely used as an important color feature indicating the content of the image, due to its robustness to scaling, orientation, perspective, and occlusion of images. Initially, a smoothening operation is performed over each frame of the shot segmented clips. Anisotropic diffusion is utilized in our proposed CBIR approach for the smoothening of the frames, prior to colour histogram. For, a sequence of frames, the anisotropic diffusion is given by

$$\frac{\partial f}{\partial t} = div\left(c(a,b,t)\nabla f\right) \tag{4}$$

where, $div(\nabla f)$ is the divergence operator. $\frac{\partial f}{\partial t}$ is the diffusion co-efficient and denotes the gradient. a,b,c is followed by a normalization function which converts the three dimensional vector into a single dimensional vector. Thus, the color histogram, another important feature for the proposed CBIR scheme is extracted

Texture Feature Extraction:

Texture is a feature that is quite difficult to describe, and subjected to the difference of human perception, and it is hard to extracted by segmentation, because segmentation unable to extract the whole texture but the texture element. Given a texture vector which is indicated as $x = \{x_1, x_2, \ldots, x_n\}$, where n is the dimension of the feature vector. We model the distribution of all samples by the following formula [25]

$$p(x \mid \lambda) = \sum_{i=1}^{M} \omega_i \, p_i(x) \qquad (5)$$

where $p_i(x)$ is a normal PDF, component of the GMM.

μ_i Mean vector

R_i Covariance matrix:

$$p_i(x) = \frac{1}{2\pi \, | R_i |^{1/2}} \exp\left[\frac{-1}{2}(x-\mu_i)^T R_i^{-1}(x-\mu_i)\right] \qquad (6)$$

Were, ω_i is the weight of the component

$p_i(x)$, $0 < \omega_i < 1$ for all components,

$\sum \omega_i = 1$. Mixture model specified in equation (4) is called the Gaussian Mixture Model (GMM).

Shape Feature Extraction:

Shape is also an important low-level feature in image retrieval system; since an object, in most case, can form by a set of shape (e.g. a car is consisted of a few rectangles and a few circles), most similar objects have a high correlation in the set of shapes. Shape-based image retrieval should extract the shapes from images by segmentation, and classify the shape, where each shape should have their own representation and should variant to scaling, rotation, and transition. In shape-based image retrieval the user need to choose an reference image or sketch a desired shape, since the user may not only want the shape that exact matched, so shape based image retrieval should be able to identify similar shapes.

Multi-objective optimization with Pareto optimal solution:

In this paper, introduce a multi-objective optimization technique by using the ABC. The proposed ABC algorithm is performing as neighbourhood search model that fine-tunes the neighbourhood search property from employed and onlooker bees that helps to converge faster than conventional MOPSO and MOGA[25]. This optimization algorithm is giving the benchmark model in eq. (2).

$$D = \left\{ \begin{array}{c} x \in R^n : l_i \le x \le u_i \quad \forall = 1,\ldots.n \\ g_i(x) \ge 0, \ \forall = 1,\ldots.p \\ h_i(x) = 0, \ \forall = 1,\ldots.p \end{array} \right\} \qquad (7)$$

where *m* is number of objectives;

D is feasible search space;

$x = \{x_1\ x_2\ x_3\ x_4\ x_5 \ldots\ldots\ x_n\}^T$ is the set of n dimention decision variable

R is the set of real numbers;

R^n is n-dimensional hyper-plane or space; and

l_i and u_i are lower and upper limits of i^{th} decision variable.

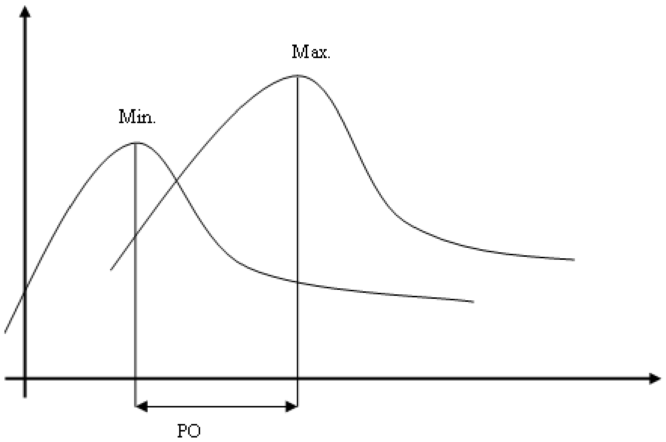

Figure 1: conflicting objectives presented through Pareto fonts in points

The MOOP should simultaneously optimize the all function and produce Pareto optimal solutions. Pareto front is a set of Pareto optimal (non-dominated) solutions, being considered optimal, if no objective can be improved without sacrificing at least one other objective.

III. MULTI OBJECTIVE OPTIMIZATION WITH ABC ALGORITHM

In the ABC algorithm, the colony of artificial bees is classified into three categories: employed bees, onlookers, and scouts. Employed bees are associated with a particular food source that are currently exploiting or "employed". They carry with them information about this particular source and share the information to onlookers. Onlooker bees are those bees that are waiting on the dance area in the hive for the information to share by the employed bees about their food sources and then make decision to choose a food source. A bee carrying out random search is called a scout. In the ABC algorithm, the first half of the colony consists of the employed artificial bees, and the second half includes the onlookers. For every food source, there is only one employed bee. Onlookers are placed on the food sources by using a probability-based selection process. As the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases.

The set of all the multi objectives vectors, is called the multi-optimization problem with image can be seen in Fig.1

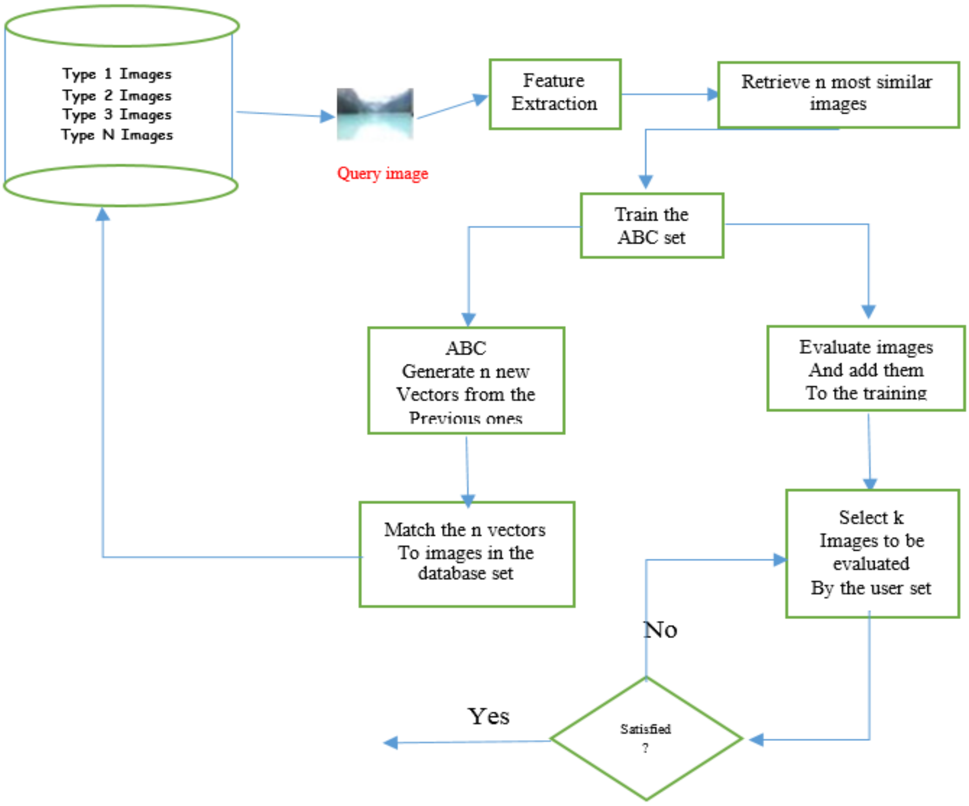

Figure 2: Proposed Diagram of Multi- objective optimization technique with ABC

In our propose algorithm, we use multi-objective optimization concept with ABC and archive strategy to make the algorithm converge to the MOPSO and MOGA[25]. The best advantage of MOABC is that it could use less control parameters to get the most competitive performance. In order to demonstrate the performance of the MOABC algorithm, we compared the performance of the MOABC with those of MOGA, MOPSO optimization algorithms on several two-objective test problems and three-objective functions [24][25].

In the initialization phase, the ABC algorithm generates randomly distributed initial food source positions $F(x)$ of solutions, $F(x)$ where denotes the size of employed bees or onlooker bees. Each solution $F(x)=(f_1(x), f_2(x), \ldots\ldots\ldots, f_n(x))$ is a n-dimensional vector. Here, n is the number of optimization parameters. Then evaluate each nectar amount. In the ABC algorithm, nectar amount is the value of benchmark function.

Employed Bees' Phase:

In the employed bees' phase, each employed bee finds a new food source V_i in the neighbourhood of its current source x_i. The new food source is calculated using the following expression:

$$V_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{8}$$

where $k \in (1,2,3....m)$ and $j \in (1,2,3....n)$ are randomly chosen indexes and $k \neq i. \Phi_{ij}$ k is a random number between [-1, 1]. It controls the production of a neighbour food source position around x_{ij}. Then employed bee compares the new one against the current solution and memorizes the better one by means of a greedy selection mechanism.

Onlooker Bees' Phase:

In the onlooker bees' phase, each onlooker chooses a food source with a probability, which is related to the nectar amount (fitness) of a food source shared by employed bees. Probability is calculated using the following expression:

$$fit_i = \frac{1}{1+f_i} \tag{9}$$

Here f_i is fitness function and fit_i is the fitness after a transformation.

Scout Bee Phase:

In the scout bee phase, if a food source cannot be improved through a predetermined cycles, called "limit", it is removed from the population, and the employed bee of that food source becomes scout. The scout bee finds a new random food source position using

$$p_i = \frac{fit_i}{\sum_{i=1}^{M} fit_i} \tag{10}$$

Here M is the number of food source and f_i is fitness function of the i^{th} food source. Finally, chose a candidate solution based on the section probability by "roulette wheel section", method. The best ones then get quite the same selection probability as the others and the algorithm stops progressing.

Table 1: Pseudo code of MOABC algorithm

Pseudo code of MOABC algorithm:

1. **Step 1:** Generates randomly distributed initial food source in cycle = 1
2. **Step 2:** Initialize the food source positions (solutions)
3. **Step 3:** Evaluate the nectar amount (fitness function) of food sources
4. repeat
5. **Step 4:** Employed Bees' Phase
6. For each employed bee
7. Produce new food source positions
8. Calculate the value
9. If new position better than previous position
10. Then memorizes the new position and forgets the old one.
11. End For.
12. **Step 5:** Calculate the values for the solution.
13. **Step 6:** Go to 2nd Phase (Onlooker Bees)
14. For each onlooker bee
15. Chooses a food source depending on
16. Produce new food source positions
17. Calculate the value
18. If new position better than previous position
19. Then memorizes the new position and forgets the old one.
20. End For
21. **Step 7:** Go to 2nd Phase (Scout Bee Phase)
22. If there is an employed bee becomes scout
23. Then replace it with a new random source positions
24. **Step 8:** Memorize the best solution achieved so far
25. **Step 9:** Cycle = cycle + 1.
26. **Step 10:** until cycle = Maximum Cycle Number
27. Evaluate each particle in the size of home
28. **Step 11:** Perform the Pareto dominance check for all the particles:
29. if the Calculated value is best *xi* is dominated by the new solution, then *xi* is replaced by the new solution.

After Step 11. The proposed algorithm performance of the approach is based on the precision; recall and F-measure cross over points. After evaluating Euclidean distance of the query image, the precision and recall values are generated using the following equations (11), (12) and (13) in [24].

Experimental Result:

In the following, we will first describe the benchmark functions used to compare the performance of MOABC with MOPSO and MOGA. Then we will investigate the performance of the MOABC. For this algorithm, we constrained optimization problem is a considered. The problem involves as large no of decision variables. The propose technique is tested on the five different objective image database of 500 variable images includes five categories as some different types of butterflies and flowers with 200 images for each datasets. The result of all five MOABC test are compared with other algorithm like MOPSO and MOGA. As suggested as [24] [25], we have used an ABC size of home 10 and an archive home size is 100. The precision, recall and F-measure are calculated for the sample query images for each category using Eq. (11), (12) and (13). These measures are the important parameters to judge the performance of the algorithms. Precision is the fraction of the relevant images, which has been retrieved, checks the completeness of the algorithm. Recall is the fraction of the relevant images, which has been retrieved, checks the accuracy of the algorithm. After that, we compare with the proposed result with single object optimization technique of MOPSO and MOGA.

$$precision = \frac{No.of\ relevant\ images\ retreived}{Total\ no.of\ images\ retrivd} \tag{11}$$

$$recall = \frac{No.of\ relevant\ images\ retreived}{Total\ no.of\ relevant\ images\ in\ database} \tag{12}$$

$$F - measure = 2\frac{precision * recall}{precision + recall} \tag{13}$$

We use a convergence measure for exclusive computing the extent of convergence to the Pareto optimal and compare the solution with other algorithms. Since, the test problem is consider the retrieved, checks the accuracy of images. We have to calculate the uniform distribution (on the f_1- f_2- f_3------f_{m-1}) solution on the Pareto-optimal. For each point in the (M-1) diminution plane f_m is calculated form the Pareto optimal value.

MOABC Application and Performance Evaluation:

In this test, we have taken 10 variable (n=10) T_1 problem have find out Pareto optimal solution. We use home size of N=100 and the parameter of solution is $p_s=1$ *and* $n_s=15$ $P_m = 1/n$ and $n_m = 20$. In this paper, we have consider five test for the performance of the proposed algorithms are discussed in table 1. This problem has the difficulty that a part of the unconstrained Pareto optimal solution is not feasible. Thus, the resulting constrained Pareto optimal solution is a concatenation of the first constraint boundary and some part of unconstrained Pareto optimal region. Here the constrained Pareto optimal set is a subset of the unconstrained Pareto-optimal set, which gives difficulty in finding the true Pareto optimal region for the algorithm.

Wang data set

Moreover, the Performance measures of the Proposed MOABC and other existing MOPSO, MOGA, ABC algorithms for CBIR in terms of Mean precision values, Mean recall values and Mean F-measure values for the Wang data set were given in the following table.

	MOABC	**MOPSO**	**MOGA**	**ABC**
Mean precision values	0.533	0.457	0.500	0.504
Mean recall values	0.465	0.313	0.2327	0.212
Mean F-measure values	0.535	0.456	0.465	0.412

Table 25: illustrates the Performance measures of the Proposed MOABC and other existing algorithms for CBIR in terms of Mean precision values, Mean recall values and Mean F-measure values for the Wang data set.

Discussion:

In table 25. the performance of the Proposed MOABC technique is compared with the other existing methods such as MOPSO, MOGA, and ABC in terms of Mean precision values, Mean recall values and Mean F-measure values. By seeing the table the values of the proposed MOABC, technique is considerably higher than the existing techniques. Hence when compared to the MOPSO, MOGA, ABC methods, our MOABC technique has given higher performance rate.

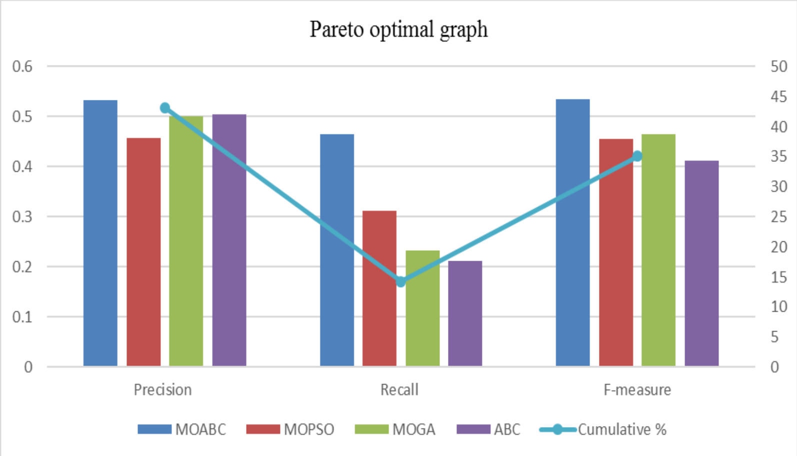

Figure 3: Pareto optimal graph of Proposed MOABC

IV. CONCLUSIONS

The Proposed algorithm is implemented in MATLAB and then well tested using the Wang data set. The parameter position is optimized for multiple objects. The outcome of the proposed algorithm is compared with MOABC, MOGA, MOPSO and ABC. It is observed that the fitness value for precision, recall and F-measure is better than the above stated algorithms. On the basis above results, it is clearly observed that the performance of MOABC is better than individual MOGA, MOPSO and ABC.

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