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Optimization Technique for Improving Iris Recognition System

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Abstract:
Over the years it has been known that the iris patterns have a wonderful and rich structure and are full of complex textures in contrast to other physiological characteristics. Iris is the inner organ of the human body that is directly band easily visible with the nacked eye. Because of its special physiology architecture, the iris becomes very sensitive to the status of all other organs.IRIS recognition is a particular type of biometric system that can be used to reliably identify a person by analyzing the patterns found in the IRIS. Many techniques have been developed for iris recognition. As an open and demanding problem, accurate modeling of polarization curve in proton exchange membrane fuel cell has become the main issue of various researches. In recent years, because of their great potentials, metaheuristic optimization algorithms have represented good performances in identification of the unknown parameters of the proton exchange membrane fuel cell model, but there is the possibility to obtain more accurate results with more capable algorithms. In the literature, many heuristic optimization algorithms have been developed on the basis of natural phenomena. However, there are still some possibilities to devise new ones. In this paper, evolution of bird species has been regarded, and the intelligent behavior of birds during mating season has become an inspiration to devise a new heuristic optimization algorithm, named bird mating optimizer.
we have implemented the BMO(Bird mating optimization) to improve the accuracy of an iris recognition system. This was a research project as it was never implemented and integrated with iris system. PSO (Particle swarm optimization)was also implemented & integrated with iris recognition system and it gave 96% of accuracy. BMO as per the research provides more accuracy than Ant colony optimization/Particle swarm optimization or any Genetic algorithm.

1. Introduction

The pressures on today's system administrators to have secure systems are ever increasing. One area where security can be improved is in authentication. Iris recognition, a biometric, provides one of the most secure methods of authentication and identification thanks to the unique characteristics of the iris. Once the image of the iris has been captured using a standard camera, the authentication process, involving comparing the current subject's iris with the stored version, is one of the most accurate with very low false acceptance and rejection rates. Unlike other biometrics such as the palm, retina, gait, face and fingerprints, the characteristic of the iris is stable in a person's lifetime. Iris patterns are chaotically distributed and well suited for recognizing persons throughout their lifetime with a single conscription. It provides more accuracy in that. IRIS recognition has the advantages of uniqueness,stableness,anti-spoof,non invasiveness and efficiency so it is widely applied in e-passport,banking,forensics,internet access and control.

2. Iris Recognition

Iris recognition is an automated method of biometric identification that uses mathematical pattern-recognition techniques on video images of one or both of the irises of an individual's eyes [5].The complex random patterns of IRIS recognition are unique, stable, and can be seen from some distance.
Iris recognition is a method of identifying people based on unique patterns within the ring-shaped region surrounding the pupil of the eye. The iris usually has a brown, blue, gray, or greenish color, with complex patterns that are visible upon close inspection. Because it makes use of a biological characteristic, iris recognition is considered a form of biometric verification.
Retina scanning is a different biometric technology for which iris recognition is often confused with has been supplanted by iris recognition. Iris recognition uses video camera technology to acquire images of the detail-rich,intricate structures of the iris which are visible externally.For convenience purposes such as passport-free automated border-crossings, and some national ID programs the iris recognition systems are used or have been enrolled by several hundred millions of persons in several countries.Fig 1.shows the structure of human eye [5]. A key advantage of iris recognition is the stability of the iris as an internal and protected.

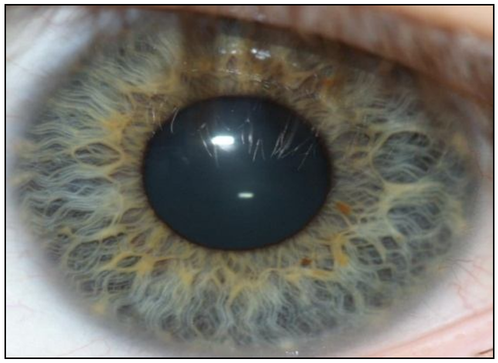

Figure 1: Human eye

3. System Features

To achieve automated IRIS recognition there are three main tasks:First we must locate the IRIS in a given image.Secondaly,it is necessary to encode the IRIS information into a format which is amendable to calculation and computation eg. a binary string.Finally the data must be storable ,to load and compare these encodings.

Our proposed approach targets the three main stages in iris recognition system

1. Image pre processing
2. Feature Extraction
3. Optimization

3.1. Image Preprocessing

3.1.1. Image Acquisition

The user has to select the input image for the system whose recognition has to be done. The image can be captured and then passed on to the system. The input image is verified for validation [12].

3.1.2. Localization

This is the method in which we detect the inner and outer boundary of the iris with the estimate that the shape of the iris is circle. To generate templates for accurate matching, iris localization method can be used. To remove eyelid eyelashes occlusions and spectacular reflections which corrupt the iris pattern, and locate the circular iris recognition, this technique is required.

First you read the image from database the image and it could be indexed. In localization the first step is detection of eye which gives the approximate edges and centre of the pupil. The algorithm for localization proceeds in the following manner:

First of all pixel brightness value is summed. After summation those values are divided by the total number of pixels to obtain average brightness value of pixels. By using trial and error method the average brightness value is multiplied by a factor 0.46. The so obtained matrix is then converted into a binary image. The sum of the values in the binary matrix across the rows and columns is obtained in different vectors. In another two vectors the difference of each value with adjacent value is stored. In localization highest and lowest value are obtained which denotes the maximum change in intensity respectively. After this the maximum and minimum value across the vertical projection of pupil is subtracted to give diameter. Then carry out similar operation for vertical projections. Highest value will be radius and by adding that radius to the columns we can obtain centers are where minimum and maximum values are obtained. Centre of pupil is derived from the radius and the circular outer pupil boundary i.e. inner iris boundary is marked using centre and radius values. Edge of image obtained using canny edge detection. Iris boundary on left and right is obtained assuming the iris radius to be 1.5 times the pupil radius in a By using binary matrix change in intensity is observed around the assumed region and iris boundary is detected on the right and left border. Radius and centre of iris is obtained from iris edges. Mark the centre and radius of the iris circle. The iris region is thus localized.

3.1.3. Segmentation and Normalization

The detected iris image by localization is ring shaped but it does not have the same size or width. However, for further processing we need all the templates to be of same size. Hence, we used unwrap iris with segmentation and normalization. Unwrapping the iris means it turns the iris ring into a strip of standard dimension, which can be used for feature extraction. This process begins with determining the number of points of the iris. That will be used to display the iris, how many parts will divide the angle and radius. The angle is increased by using following factor $di = 2/\pi n$, where ‘n’ is the number of division which is used to obtain every new division of the iris. After this we should decide on further having 64 radial segments. Every part of the iris is bordered by 4 points: we can say pa, pb, pc and pd and the mean of their values gives the pixel value in the image segment. The result of this procedure for all shapes and sizes of the iris ring is a tape of the same size. Further increase the contrast of the tape before proceeding with extracting features.

3.2. Feature Extraction

Generally an image consists of pupil, eye lashes, sclera, eyelid, iris and skin. These parts differ from each other based on their characteristics and grey level too. Here, the features are extracted in two parts namely,

- Pupil Feature Extraction
- Iris Feature Extraction

The features used as input to the neural network consist of several of the segmentation measurements commonly used in iris research and fielded systems. The feature set was composed of both binary (edge detected) and real valued measurements. The common feature sets used are Image gray scale value, mean, standard deviation, skewness, kurtosis, horizontal gradient and vertical gradient measurements composed the core of the real valued feature

4. Optimization

4.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a population-based optimization algorithm that was developed by Kennedy and Eberhart in1995 [6]. It was shaped by investigation the behavior of birds and fishes in swarm to find the near optimal solutions. In this algorithm,each bird is called a particle represented as a vector that is a candidate solution. A population of the particles in an n-dimensional search space is initialized with the random vector position Xi =(xi1, xi2, xi3, :::, xin) in the range of the data set patterns and the velocity Vi =(vi1, vi2, vi3, :::, vin) in the range of [-a, a] where a is:

a=max(data)-min(data) (1)

A fitness function is defined to determine whether a particle is close to the optimal solution or not.Each particle maintains two best experienced vectors.One of them is pbesti that is the best position of a particle Xi experienced so far and the other one is gbest that is the best vector for the entire swarm [6].The particle vectors are iteratively modified using Eqs. (2) and (3) based on the pbesti and the gbest values. Updated population evolves new particles that are closer to the optimal solution. Eq (2) and (3) are as follows

$$V_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i^t - x_i^t) + c_2 r_2 (gbest_i^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

where ω is called the inertia weight which controls the speed of next iteration c_1 and $c_2$are used to guide the search between local and social areas in the range of [0,2]. r_1 and r_2 are uniformly distributed random numbers generated in the range of [0,1] and t is the iteration counter. From the mathematical inference of PSO,larger inertia weight performs more efficient global search and smaller one means more effective local search,so Shiand Eberhart[7] used Eq. (4) that decreases inertia weight with increasing the number of iterations linearly:

$$\omega = \omega_{max} - t\frac{(\omega max - \omega min)}{T} \qquad (4)$$

where ωmin, ωmax , T and t call as the maximum inertia weight,the minimum inertia weight,the total and the current number of iterations for the algorithm, respectively. The purpose of this algorithm is to calculate the RBF unit centers with increased precision in comparison with the CPSO clustering method. The essential difference between two algorithms lies in scale of views. The PSO clustering algorithm looks at the data set as patterns whereas the new approach considers features of the patterns in data set. In the PSO algorithm, final answer is the best particle, whereas the best solution is combination of the best clusters of particles in the proposed approach. In this algorithm, particles are considered the same as the PSO algorithm. The Euclidean distance between each feature of the input pattern and the corresponding cluster centroids is calculated using:

d($M_{jl,} P_{rl}$)=√(s_{jl}-t_{rl}) for 1 ≤ j ≤ k,1 ≤ r ≤ n,1 ≤ l ≤f

5. Bird Mating Optimization

Birds are the most speciose class of tetrapod vertebrates having around 10,000 living species . Mating process in bird's society has very similarities with an optimization process in which each bird breeds or attempts to breed a brood with high quality genes (a perfect state), because a bird with better genes has more chance to live. In the same way, an optimization process searches to discover a global solution (a perfect state) in which the quality of each solution is determined by a criterion named objective (fitness) function. In engineering optimization, decision variables are given values in the search space and a solution vector is made. If a good solution is acquired, that experience is memorized and the possibility of making a better solution increases at the next time. During mating season birds employ a variety of intelligent behaviors such as singing, tail drumming or dancing to attract potential mates[1] . Some courtship rituals are quite elaborate and serve to form a bond between the potential mates. The quality of each bird is specified by its features such as beak, tail, wing, and so on. The related gene of each feature determines the quality of that feature, together making the overall quality of the bird. A gene is a hereditary unit that can be passed on through breeding to next generations. Imagine a bird which has good genes among species. This bird can fly adeptly and get more food. Hence, it is healthier than the other birds, lives longer and breeds more. The bird passes these genes for better ones onto its broods by selecting a superior mate. They also live longer and have more broods and the gene continues to be inherited generation after generation.

The ultimate success of a bird to raise a brood with superior features depends on the strategy it uses. Different ways result in broods with diverse features. Study among bird's society reveals that they employ different strategies to conduct mating process. In general, there are five strategies: monogamy, polygyny, polyandry, parthenogenesis and promiscuity [1-3].
According to its species, each bird makes use of one of these ways to breed. Most birds are monogamous [2] meaning that a male bird only mates with a female one. In the monogamous behavior, parental duties are shared between the pair so that the male bird defends of the territory while the main task of the female is to produce eggs and supply them[3].In polygynous species, a male tends to mate with several females while in polyandrous a female tends to mate with several males. Polygyny is much more common than polyandry in the bird's society.Parthenogenesis denotes a mating system in which a female is able to raise brood without the help of males. Promiscuity is another mating strategy employed by a few bird species, meaning mating systems with no stable relationships in which mating between two birds is a one-time event. This type of mating indicates a rather chaotic social structure in which the male will almost certainly never see his brood or the nest, and most likely will not see the female for another brief visit[3].The BMO proposed in this paper, is a population-based optimization algorithm which employs mating process of birds as a framework. Under this framework, concepts and strategies are metaphorically adopted for designing optimum searching techniques. In BMO, each bird is a feasible solution for the problem and is specified by a vector with predefined number of genes, equal to the problem dimension. During generations, the birds employ probabilistic ways to improve the quality of their broods by selecting better-quality mate(s).
Consider a monogamous bird $\overrightarrow{x_i}$, that wants to mate with his own interesting female $\overrightarrow{x_{i+}}$ The resultant brood is given as follows.

$\overrightarrow{x_b} = \vec{x} + w \times \vec{r}.\times (\overrightarrow{x^t} - \vec{x})$

C=a random number between 1 & n

if $r_1 > mcf$

$x_b(c) = l(c) - r_2 \times (l(c)) - u(c));$

end eq(1)

where $\overrightarrow{x_b}$ is the resultant brood, w is a time-varying weight to adjust the importance of the interesting female, r is a 1×d vector whose each element, distributed randomly in [0, 1], influences on the corresponding element of $(\overrightarrow{x^t} - \vec{x})$,n denotes the problem dimension, mcf is the mutation control factor varying between 0 and 1, ri's are random numbers between 0 and 1, and u and l are the upper and lower bounds of the elements, respectively. Using the first part of Eq. (1), the male bird attempts to pass on good genes to his brood by combining his genes with the genes of his own interesting female.
The male bird then employs the second part to make mutation in one of the brood's genes with the probability of 1- mcf.
Polygyny denotes a mating system in which a male bird tends to mate with two or more females. Possible benefits of extra-pair copulation include getting better genes for the brood. In nature, a polygynous bird mates with several females resulting in a number of broods, but in BMO this behavior is metaphorically adopted in which by mating a polygynous bird with multiple females only one brood is raised which its genes are a combination of the females genes. After the attraction of the females, each male selects his interesting ones with a probabilistic approach, and mates with them.
The resultant brood is produced by the following equation

$\overrightarrow{x_b} = \vec{x} + w \times \sum_{j=1}^{n_i} \vec{r_j} .\times (\overrightarrow{x_j^i} - \vec{x})$

C=a random number between 1 & n

if $r_1 > mcf$

$x_b(c) = l(c) - r_2 \times (l(c)) - u(c));$

end eq(2)

where ni is the number of interesting birds and x_j^idenotes the jth interesting bird. Promiscuity implies mating systems with no stable relationships in which mating between two birds is a one-time event. This type of mating indicates a rather chaotic social structure in which the male will almost certainly never see his brood or the nest, and most likely will not see the female for another brief visit. In promiscuity which is used by a few bird species, a male bird tends to mate with one female. In BMO, promiscuous birds are produced using a chaotic sequence through the generations. However, the way by which a promiscuous bird breeds is same as that of monogamous birds. Parthenogenesis denotes a mating system in which a female is able to raise brood without the help of males[10].In this system, each female tries to pass on better genes to her brood by making a small change in her genes probabilistically. Each parthenogenetic bird produces a brood by the following process.

for i=1:n

if $r_1 > mcf_p$

$x_b(i) = x(i) + \mu \times (r_2 - r_3) \times x(i);$

else

$x_b(i) = x(i);$

end

end eq(3)

where mcfp is the parthenogenetic mutation control factor and l denotes the step size. Polyandry denotes a mating system in which a female bird tends to mate with two or more males. After the attraction of the potential males, each polyandrous bird selects his interesting ones by a probabilistic approach, and mates with them. The resultant brood is produced as same as Eq. (2).

5.1. The steps of BMO algorithm are as follows

- Step 1: Initialization: a society of birds is randomly initialized in the search space. Each bird is a feasible solution of the problem and is specified by a vector, ~x, with the length of n.
- Step 2: Fitness function value: the quality of each bird is computed by putting its elements into the fitness function.
- Step 3: Ranking: the birds are ranked based on their quality.
- Step 4: classification: birds with the most promising genes are selected as females and the others are chosen as males. The females are equally divided into two groups so that the better ones make parthenogenetic birds and the others make polyandrous ones. The males are categorized into three groups. The males included in the first group that have better genes than the others are selected as monogamous. The males of the second group are chosen as polygynous.

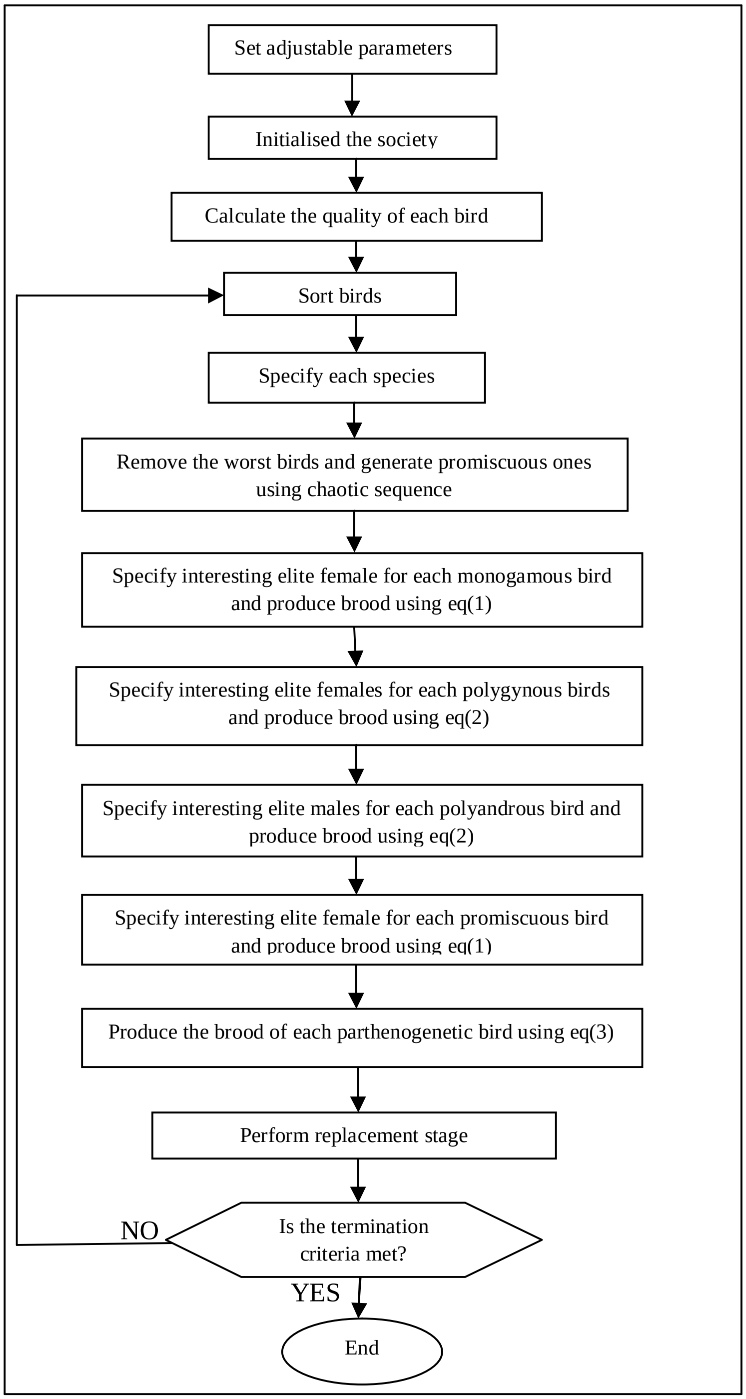

Figure 2: Flowchart of BMO algorithm [3]

- Step 5: Generating promiscuous birds: the males of the third group are removed from the society and new ones are generated using a chaotic sequence. The new birds are considered as promiscuous.
- Step 6: Breeding: each bird breeds a brood using its own pattern.
- Step 7: Replacement: each bird makes a decision to add its brood to the society. The bird evaluates the brood's quality. If the brood is in the search space and includes better quality, the bird will abandon the society and the brood will join to it, otherwise, the brood will be abandoned and the bird will stay in the society.
- Step 8: Steps 3–7 are repeated until a predefined number of generations, gmax, is met.
- Step 9: The bird with the best quality is selected from the society as the final solution. Figs. 1 and 2 depict flowchart and pseudocode of BMO algorithm.

5.2. BMO Parameter Setting

In order to apply BMO algorithm to a problem its adjustable parameters have to be tuned. The performance of each optimization algorithm is affected by its parameters. The optimal tuning of the BMO parameters will be studied in future researches. Nevertheless, some guidelines obtained experimentally are given in the following to tune the BMO parameters[4].

- It seems that the most important parameter which needs to be adjusted is the optimal proportion of each species from the society. We propose the percentage of monogamous, polygynous, promiscuous, polyandrous, and parthenogenetic birds is respectively set at 50, 30, 10, 5 and 5 of the society.
- Two or three interesting mates for polygynous and polyandrous birds will be sufficient.
- It is better that 10 monogamous birds which have better qualities than the other males are selected as interesting candidates for participating in the rituals of polyandrous birds.
- Mutation control factors (mcf and mcfp) are between 0 and 1. mcf can be set at 0.9 or 0.95. Small values of this parameter may result in bad impact on the performance of the algorithm. It is better to select mcfp as an increasing linear function which changes from a small value near-by zero (for example 0.1) to a large one near-by 1 (for example 0.9). This behaviour permits to parthenogenetic birds to change their genes at the beginning of the algorithm with high probability. This probability decreases during the generations and helps the parthenogenetic birds to converge to the solution.
- l which determines the mutation size of each gene of parthenogenetic birds is from order of 10_2 to 10_3.
- In order to provide good balance between local and global search, w decreases linearly from a value near-by 2 to a small one near-by 0

5.3. Experimental setting

The parameter setting used here for evaluating the performance of BMO in optimizing the benchmark functions is as follow.The society size is set at 200 and the birds are initialized uniformly at random in the search space. The number of monogamous, polygynous, promiscuous, polyandrous, and parthenogenetic birds is set at 100, 60, 20, 10 and 10, respectively.The number of interesting elite mates for polygynous and polyandrous birds is set to 3. Polygynous birds select their interesting males from 10 monogamous birds with the most promising genes. mcf and l are set to 0.9 and 0.001. w and mcfp change from 2.5 to 0.25 and 0.1 to 0.9, respectively.The proposed algorithm is coded in MATLAB environment and 50 independent runs are executed for each benchmark function.For f1-f7 the performance of the BMO algorithm is compared with particle swarm optimization[11].In order to investigate the convergence rate of the BMO algorithm some benchmark functions are selected at random and the average results of BMO over 50 runs are plotted. The promising convergence rate of BMO algorithm[8] can be observed from fig(2).

5.4. Comparison of BMO with PSO

Function	Index	BMO	PSO
f1	Mean	1.2932e-246	3.6927e-37
	Standard	0	2.4598e-36
	Rank	1	2
f2	Mean	1.3939e-131	2.9168e-24
	Standard	8.1401e-131	1.1362e-23
	Rank	1	2
f3	Mean	6.4322e-16	1.1979e-3
	Standard	4.4102e-15	2.1109e-3
	Rank	1	2
f4	Mean	1.9308e-8	0.4123
	Standard	1.2335e-7	0.2500
	Rank	1	3

f5	Mean	7.5401	37.3582
	Standard	16.9421	32.1436
	Rank	1	2
f6	Mean	0	0.146
	Standard	0	0.4182
	Rank	1	3
f7	Mean	5.4117e-4	9.9024e-3
	Standard	2.6162e-4	3.5380e-2
	Rank	1	2

Table 1

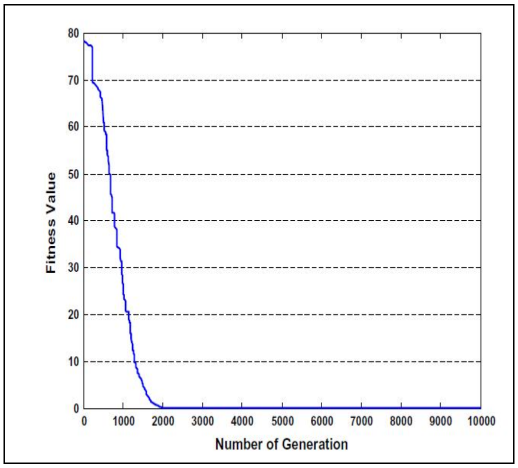

Figure 3: Average results over 50 runs obtained by BMO on Schwefel function(f4)[8]

6. Conclusion

The method aims at improving the iris recognition and optimization system expected to have higher accuracy and optimized result. The system to be developed uses the combination of algorithm to meet its requirements. The BMO algorithm follows metaheuristic approach for optimization and then proceeds to follow different algorithm for normalization, feature extraction, template matching. The main goal is to develop a BMO-based learning algorithm to train ANNs. BMO is a recently devised population based optimization algorithm which imitates the mating behaviour of bird species for breeding superior broods and provides different strategies to effectively seek the search space.

So we tried implementing BMO and did the job of integrating it with the iris recognition system but when integrated with IRIS system we came to know that PSO with iris system provides more accuracy.

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