HYBRID OPTIMIZATION METHOD TO IMPROVE IRIS RECOGNITION SYSTEM

Prof. N.F. Shaikh¹, Sneha Sawarkar², Neha Ranade³, Surashree Bhat⁴, Priyanka Patil⁵ Computer Department Modern Education Society's College of Engineering Pune, India

Abstract: Iris Recognition, an emerging and reliable technology for security purpose has become popular for its ease of use and accuracy. So to make the system efficient, optimization algorithm is implemented on it. Hybrid optimization method to improve iris recognition system has two optimization algorithms-1) BMO (Bird Mating **Optimization**) and 2) **PSO** (Particle Swarm Optimization).BMO is population based search method which tries to imitate mating ways of bird species for designing optimum searching techniques. A bird which has good genes among the species 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 on to 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. PSO is a population-based optimization algorithm which is used for investigation the behavior of birds and fishes in swarm to find the near optimal solutions. This hybrid technique can be applied for weight training of neural networks for clarification of human iris and increase the efficiency of iris recognition.

Keywords: Iris Recognition, BMO, PSO

I. INTRODUCTION

The pressures on today's system administrators to have secure systems are ever increasing. Here 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. 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 Iris recognition method is suited for recognizing persons throughout their lifetime with a single conscription. It provides more accuracy in that.

A. Human Iris

The iris of the human eye which is a thin circular diaphragm lies between the cornea and the lens. Figure 1 shows the structure of the human eye. The eye has a perforation at the center made by the pupil. The iris controls the overall amount of light entering through the pupil by adjusting the sphincter and the dilator muscles. It calculates the average radius of the human iris is 12mm. The iris is layered with the epithelial tissues at the bottom which have dense pigmentation cells. The next layer above it is the stromal layer which determines the color of the iris. They have the blood vessels and pigmentation cells. The outermost layer which is visible has two zones. Also due to the epigenetic nature of the iris pattern the two eyes of the same individual contain has completely different and independent iris pattern. Same is the case of identical twins which possess uncorrelated iris patterns.



Fig.1. Structure of the human iris

B. Iris Recognition

Iris Recognition systems have been studied and proposed earlier but it was not until the beginning of the 20th century that the Cambridge researcher, John Daugman. They have implemented a working model of the pure iris recognition system. Pioneering and extensive work has been done on iris recognition by Daugman using Gabor wavelet. They implemented this system and tested, there remains scope for improvement. Recently, Wildes, Boles and Boas hash have contributed new methods. Sometimes they faced some critical problems and also significant work needs to be done before mass-scale deployment on national and international levels is thought for. This paper contributes a realizable solution to some of the problems since here we use a novel method of algorithm score fusion which would give a mean and more appropriate value.

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

- Image pre processing
- Feature Extraction
- Optimization

II. IMAGE PREPROCESSING

A. 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 evelid evelashes 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 center 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 center 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 center of iris is obtained from iris edges. Mark the center and radius of the iris circle. The iris region is thus localized

B. 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.

III. 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

IV. NEURAL NETWORK

Artificial neural networks (ANNs) are computational modelling tools that are defined as structures comprised of densely interconnected adaptive simple processing elements. They are able to perform massive parallel computations for data processing and knowledge representation. ANN training Process is an optimization task with the aim of finding a set of weights to minimize an error measure. Owing to this fact that search space is high dimensional and multimodal which is usually polluted by noises and missing data, the problem of ANN training needs powerful optimization techniques. Most often, some conventional gradient descent algorithms, such as back propagation (BP) [2], are considered for solving the problem. Neural networks consist of a large class of different architectures. In many cases, the issue is approximating a static nonlinear, mapping $f(\mathbf{x})$ with a neural network () $NN f \mathbf{x}$, where $\mathbf{x} \in \mathbf{R}K$. The most useful neural networks in function approximation are Multilayer Layer Perceptron (MLP) and Radial Basis Function (RBF) networks.



Fig. 2. Schematic diagram of BMO-based ANN.

The ANN tuned by our BMO algorithm is a three-layer feed forward network. The nodes of the input layer are passive, meaning that they do not modify the features, they only receive them. The inputs are connected to all the hidden units, which in turn all connected to all the outputs. All neurons are connected to a bias unit, with constant output of 1.

V. OPTIMIZATION

A. Particle Swarm Optimization (PSO)

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-

space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. 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 $x_i = (x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})$ in the range of the data set patterns in the range of [-a, a] where a is: $a = \max$ (data)-min(data).A fitness function is defined to determine whether a particle is close to the optimal solution. 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 CPSO 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 CPSO algorithm. The Euclidean distance between each feature of the input pattern and the corresponding cluster centroids is calculated using: $d(M_{il}P_{rl}) = \sqrt{(s_{ii}-t_{ri})}$ for $1 \le j \le k, 1 \le r \le n, 1 \le l \le f$

B. Bird Mating Optimization

BMO is a population-based search method which tries to imitate the mating ways of bird species for designing optimum searching techniques. In order to study the usefulness of the proposed algorithm, BMO is applied to weight training of ANNs for solving three real-world classification problems, namely, Iris flower, Wisconsin breast cancer, and Pima Indian diabetes. The performance of BMO is compared with those of the other classifiers. Simulation results indicate the superior capability of BMO to tackle the problem of ANN weight training. BMO is also applied to model fuel cell system which has been addressed as an open and demanding problem in electrical engineering. The promising results verify the potential of BMO algorithm. This algorithm has been applied to an engineering optimization problem and superior results have been obtained in comparison with the other algorithms. Simple concept and good efficiency are the major advantages of BMO algorithm. The adequate efficiency of BMO originates from using distinct moving patterns to explore the search space. Using distinct moving patterns increases the flexibility of the algorithm to provide good balance between exploration and exploitation. The main goal of this paper is to deal with the application of BMO algorithm for finding ANN weights. Mating process in birds society has many similarities with an optimization process in which each bird breeds or attempts to breed a brood with high quality genes, because a bird with better genes has more chance to live. Similarly, an

optimization process searches to discover the global solution 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 made, that experience is memorized and the possibility of making a better one 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. 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, etc. 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 the next generations. Imagine a bird which has good genes among the 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 on to 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 used strategy. Different ways result in broods with diverse features. Study of bird's society reveals that they employ different strategies to perform mating process. In general, there are four strategies: monogamy, polygyny, polyandry, and promiscuity. According to its species each bird makes use of one of these ways to breed. Most birds are monogamous, meaning that a male bird only mates with a female one. In polygynous species a male tends to mate with several females while in polyandrous a female tends to mate with several males. In the birds society, polygyny is much more common than polyandry. 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. In order to study the usefulness of BMO algorithm three real world classification problems, namely, Iris flower, Wisconsin breast cancer, and Pima Indian diabetes, have been considered here. In these cases, the BMO performance will be compared with the results from some sophisticated classification methods. These classifiers are the best result found by an ANN trained by a subset of features selected by a binary encoded GA (GANet-best), the best result of eight least squares SVM classifiers (SVM-best), decision tree ensembles of CCSS and EDTs and hybrid evolutionary decision tree (OC1-best). Decision trees (DTs) are popular classifiers, and there are many algorithms induce a tree classifier from a data set . The results are also compared with an evolutionary ANN ensemble evolved by cooperative coevolution (COOP), a constructive algorithm for training cooperative ANN ensembles (CNNE), and an algorithm which evolves ANN structure and connection weights

(MGNN). The population of BMO algorithm is called society and each society member, representing a feasible solution of the problem, is called bird. The society includes male and female birds. The females are those birds that have the most promising genes. The females of the society are categorized into two groups, namely, parthenogenesis and polyandrous while the males are classified into three groups, namely, monogamous, polygynous as well as promiscuous. Totally, BMO uses five bird species so that each species has its own updating pattern. The way by which each species produces a candidate solution will be explained below in detail. Monogamy is a mating system in which a male bird tends to mate with one female. Most birds are monogamous. During the mating season, males employ the related intelligent behaviors and attract the females towards themselves. Each male evaluates the quality of the female birds, uses a probabilistic approach to select one of them as his own interesting female, and mates with her. Female birds with more promising genes have a more chance of being selected. Consider a monogamous bird \vec{X} , that wants to mate with his own interesting female \vec{X} . The resultant brood is given as follows.

 $\vec{x}_b = \vec{x} + w \times \vec{r} \cdot \times (\vec{x}^l - \vec{x})$

c = a random number between 1 and n if $r_1 > mcf$

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

end

where ~xb 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 ð~xi ~xP, 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 1 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

$$ec{x}_b = ec{x} + w imes \sum_{j=1}^{n_i} ec{r}_j \cdot imes (ec{x}_j^i - ec{x})$$

c = a random number between 1 and nif $r_1 > mcf$ $x_b(c) = l(c) - r_2 \times (l(c) - u(c));$ end 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.

Where ni is the number of interesting birds and ~xi j denotes 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. In this system, each female tries to pass on better genes to her brood by making a small change in her genes probabilistically. Each parthenogenesis 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

Where mcfp is the parthenogenesis mutation control factor and 1 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).

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, $\sim x$, 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 parthenogenesis 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.



Fig. 3. BMO Algorithm steps

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, are 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 pseudo code of BMO algorithm.

C. 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.

- 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 parthenogenesis 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 those 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 parthenogenesis birds to change their genes at the beginning of the algorithm with high probability. This probability decreases during the generations and helps the parthenogenesis birds to converge to the solution
- 1 which determines the mutation size of each gene of parthenogenesis 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.

D. Comparison of BMO with PSO, GA

Function	Index	BMO	GA	PSO
f1	Mean Standard Rank	1.2932e- 246 0 1	3.1711 1.6621 4	3.6927e- 37 2.4598e- 36 2
f2	Mean Standard Rank	1.3939e- 131 8.1401e- 131 1	0.5771 0.1306 4	2.9168e- 24 1.1362e- 23 2

f3	Mean Standard Rank	6.4322e- 16 4.4102e- 15 1	9749.9145 2594.9593 4	1.1979e- 3 2.1109e- 3 2
f4	Mean Standard Rank	1.9308e- 8 1.2335e- 7 1	7.9610 1.50634 4	0.4123 0.2500 3
f5	Mean Standard Rank	7.5401 16.9421 1	338.5616 361.497 4	37.3582 32.1436 2
f6	Mean Standard Rank	0 0 1	3.6970 1.9517 4	0.146 0.4182 3
f7	Mean Standard Rank	5.4117e- 4 2.6162e- 4 1	0.1045 3.6217e-2 4	9.9024e- 3 3.5380e- 2 2



Fig. 4. Average results over 50 runs obtained by BMO on Schwefel function (f2).

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