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Hybridization Framework of Biogeography-Based Optimization and Gravitational Search Algorithm for Efficient Face Recognition

Submitted in partial fulfilment of the requirements of
BITS G540 Research Practice

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APRIL 2016

Acknowledgements

Foremost, we would like to acknowledge Dr. Lavika Goel, Assistant Professor, Computer Science and Information Systems, BITS Pilani, for encouraging us to take this topic and for her continuous support and guidance throughout this research work. Her encouragement and guidance has contributed immensely to this work and the evolution of our ideas. Her comments and suggestions were indispensable for this work.

I acknowledge with thanks Dr. Rahul Banerjee for granting our request for accessing the laboratory facilities without which it would not have been possible to conduct this research.

Certificate from the Supervisor

This is to certify that the report, "**Hybridization Framework of Biogeography-Based Optimization and Gravitational Search Algorithm for Efficient Face Recognition**" submitted by **Lavanya B** with ID No. 2015H103080P and **Pallavi Panchal** with ID No. 2015H112186P in partial fulfilment of the requirements of BITS G540 Research Practice embodies the work done by them under my supervision.

Signature of the Supervisor

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List of Abbreviations

ACO	-	Ant Colony Optimization
BBO	-	Biogeography Based Optimization
GSA	-	Gravitational Search Algorithm
BBO-GSA	-	Biogeography Based Optimization- Gravitational Search Algorithm
MNN	-	Modular Neural Network
PCA	-	Principal Component Analysis
PSO	-	Particle Swarm Optimization
GA	-	Genetic Algorithm
HSI	-	Habitat Suitability Index
SIV	-	Suitability Index Variables
ORL	-	Olivetti Research Laboratory
ICA	-	Independent Component Analysis
AVBN	-	Approximate Voronoi Boundary Network
KPCA	-	Kernel Principal Component Analysis
LFW	-	Labelled Faces in the Wild
NN	-	Neural Networks
NNRW	-	Neural Networks with Random Weight
SVM	-	Support Vector Machine
BPSO	-	Binary Particle Swarm Optimization
ROC	-	Receiver Operating Characteristic
RLEGSA	-	Randomized Local Extrema Based Gravitational Search Algorithm

DCT	-	Discrete Cosine Technique
BAW-GSA	-	Binary Adaptive Weight Gravitational Search Algorithm
BGSA	-	Binary Gravitational Search Algorithm
LBP	-	Local Binary Pattern
MCT	-	Modified Census Transform
LGP	-	Linear Genetic Programming
LDA	-	Linear discriminant analysis
EBGM	-	Elastic Branch Graph Modelling
DWT	-	Discrete Wavelet Transform

ABSTRACT

Face recognition has been one of the most challenging problems in improving the security of biometric systems [1] [2] and evolutionary algorithms are used widely for optimization purposes in a variety of applications as they do not make any assumptions about the problem that they are optimizing. This work aims to apply a novel hybridized evolutionary algorithm [3] to the application of face recognition. Biogeography-Based Optimization (BBO) [4] has some element of randomness to it that apart from improving the feasibility of a solution could reduce it as well [4] [5]. In order to overcome this drawback, this work proposes a hybridization of BBO with Gravitational Search Algorithm (GSA) [6] another nature inspired algorithm by incorporating certain knowledge into BBO instead of the randomness. The proposed BBO-GSA algorithm overcomes the problem of infeasible solution generation and late convergence of the BBO algorithm by eliminating the randomness associated with it. The migration procedure of BBO that migrates SIVs between solutions is done between solutions only if the migration would lead to the betterment of a solution. BBO-GSA algorithm is applied to Face Recognition with the LFW (Labelled Faces in the Wild) [7] and ORL [8] datasets in order to test its efficiency. Experimental results show that the proposed BBO-GSA algorithm outperforms or is in par with some of the nature inspired techniques that have been applied to face recognition so far by achieving a recognition rate of 80% with the LFW dataset and 99.75% with the ORL dataset.

Contents

List of Figures

List of Tables

List Of Algorithms

Chapter 1: Problem Statement

A major step to accurate and efficient face recognition is feature selection where the most distinguishing features of a face that would help us identify that face exactly, is extracted. Principle Component Analysis (PCA) is used for dimensionality reduction and the solution obtained is further optimized by a new hybridized approach to enhance feature selection. Biogeography Based Optimization (BBO) is a population based algorithm that through its two techniques of migration and mutation optimizes the solution of a problem. The set of eigen face vectors (habitats) generated by PCA are considered to be the feasible solutions to the problem. The elements of the eigen face vector (Suitability Index Variables) are migrated and mutated. BBO chooses a random eigen face vector element from a eigen face vector with low fitness (Habitat Suitability Index) and replaces it with another random eigen face vector element from a eigen face vector with high fitness. This could make a eigen face vector a less feasible solution than it was as well, apart from making it better. If we migrate and replace eigen face vector elements that are only better than the eigen face vector elements selected for migration instead of random ones, then the solution would become more feasible and BBO will converge faster. This selection of better eigen face vector elements will be done with Gravitational Search Algorithm (GSA) another nature inspired algorithm which is based on the law of gravity. The hybridized evolutionary algorithm is bound to strengthen the feature selection process thereby improving the accuracy of the face recognition system.

Chapter 2: Introduction

The history of Automatic Face Recognition [2] dates back to the 1960s. From then on it has emerged as one of the most extensively studied research topics in computer vision due to its vast application in security systems for surveillance and authentication as it is more robust and secure as compared to other biometric techniques. Several mechanisms have been applied to recognize human faces automatically the most prevalent of which is the Principal Component Analysis (PCA) using eigenfaces [9]. PCA is used for dimensionality reduction and feature selection purposes in this work. Another category of algorithms that are widely being applied to Face Recognition includes the nature inspired algorithmic techniques. These algorithms optimize a function by repetitively improving candidate solutions with respect to a given measure of quality or fitness function. Ant Colony Optimization (ACO) [10], Biogeography-Based Optimization (BBO), Genetic Algorithm (GA), Gravitational Search Algorithm (GSA), Neural Networks (NN), Particle Swarm Optimization (PSO) are some among the many nature inspired algorithmic techniques that have been applied to face recognition so far.

Biogeography-Based Optimization and Gravitational Search Algorithm are relatively new optimization techniques. Biogeography-Based Optimization performs two major operations, they are, migration and mutation. The steps of these two operations include some randomness that apart from making a solution better might lead to it becoming poorer than what it was before as well. This leads to the generation of several infeasible solutions and also delays the convergence of the algorithm. If the replacement of SIVs is done in such a manner that poor SIVs are replaced with good SIVs only, BBO will converge to the optimal solution faster. It might also result in faster generation of better solutions. This work aims to overcome this drawback of BBO by borrowing certain characteristics of the GSA thus leading to a hybridized BBO-GSA algorithm. The hybridized BBO-GSA algorithm is applied to the problem of face recognition by optimizing the eigenfaces generated by PCA and then a Support Vector Machine (SVM) Classifier is used to classify the faces into different classes.

Chapter 3: Literature Survey

The problem of face recognition has been dealt with by several nature inspired algorithms by employing varying techniques and mechanisms.

Face recognition has been tackled using various techniques as in [11] new model of a Modular Neural Network (MNN) optimized with hierarchical genetic algorithm is proposed for human recognition. In this case the proposed method is tested with the problem of human recognition based on the face information. [12] Uses neural networks with random weights (NNRWs) to implement such learning scheme in the study of face recognition. Improvement in BBO has been presented in [13] in which distinctive features from other successful heuristic algorithms are incorporated in BBO and a new immigration prevention approach is added to BBO.Face Recognition has been done in [14] using a combination of Biogeography Based Optimization, Principal Component Analysis [15] and Gabor filters. In [16] a new approach to face recognition is proposed in which multiple face eigen subspaces are created, with each one corresponding to one known subject privately, rather than all individuals sharing one universal subspace as in the traditional eigenface method. Compared with the traditional single subspace face representation, the proposed method captures the extra personal difference to the most possible extent, which is crucial to distinguish between individuals, and on the other hand, it throws away the most intrapersonal difference and noise in the input improving the performance. A comparison of PCA, KPCA and ICA to SVM has been proposed in [15]. The experiment shows that SVM by feature extraction using PCA, KPCA or ICA can perform better than that without feature extraction. Furthermore, among the three methods, there is the best performance in KPCA feature extraction, followed by ICA feature extraction. An automatic facial feature extraction algorithm is presented [17]. In the face region estimation stage, a second chance region growing method is adopted to estimate the face region of a target image. In the feature extraction stage, genetic search algorithms are applied to extract the facial feature points within the face region. It is shown by simulation results that the proposed algorithm can automatically and exactly extract facial features with limited computational complexity. Features are extracted using Principal Component Analysis(PCA) after applying Gabor filters and then BBO is applied to get the most desirable features based on a well-defined fitness function, a hybrid of Biogeography Based Optimization and Particle Swarm Optimization [18] where position updating strategy of PSO is applied to increase diversity of population in BBO and then obtained biogeography particle swarm optimization algorithm(BPSO) is used to optimize paths in path network obtained by approximate Voronoi boundary network (AVBN) modelling, a local extrema based Gravitational Search Algorithm has been proposed in [19] where two variants of GSA are proposed namely the 2-D version of GSA, in order to cater for the 2-D image data, and the other one is a 2-D randomized local extrema based GSA (RLEGSA), which employs a stochastic local neighbourhood based search instead of a global search, as in basic GSA, a Binary Particle Swarm Optimization (BPSO) for feature selection with SVM has been done in [20], feature selection based on a novel Ant Colony Optimization (ACO) based technique has been applied in [21] in this proposed algorithm classifier performance and the length of the selected feature vector are adopted as heuristic information for ACO therefore the optimal feature subset is selected in terms of shortest feature length and the best performance of classifier. A more brief description of some literatures is given below.

Matthew T. and Alex P. describe how Principle Component Analysis (PCA) a dimensionality reduction technique can be used to greatly simplify as well as enhance the problem of face recognition. PCA represents each face in the form of eigen faces whose dimension is very much less than the dimensions of the original face image. PCA extracts the most distinguishing features of a face and works only on them.

Biogeography Based Optimization is an evolutionary algorithm proposed by Dan Simon in the year 2008 that is based on Island Biogeography. Natural Biogeography and its mathematics are used as the basis to solve this optimization problem. Biogeography describes the migration, speciation and extinction of species. Geographical areas called habitats form the feasible solutions to the problem. Habitats that are well suited for residence are said to have a high Habitat Suitability Index (HSI) which makes them better solutions to the problem. The characteristics of the habitat such as temperature, water areas, etc. are called Suitability Index Variables (SIVs). Habitats with a high HSI are good solutions to the problem, they have a wide variety of species therefore there immigration rates are less as they are already saturated with species whereas their emigration rates will be high. Therefore random SIVs of good solutions (high HSI) are migrated to solutions with lower HSIs solutions randomly. This migration concept is used to improve the quality of the poor solutions into better solutions which forms the exploration step of the algorithm. Due to certain natural phenomena a habitat's HSI can change suddenly (natural disaster, outbreak of disease, etc.). This is modelled in BBO as mutation where random SIVs of a habitat are modified. This step increases the diversity among the population or in other words forms the exploration step of the algorithm. It is not necessary to mutate the SIVs of certain good solutions as it might worsen them. Therefore a predefined number of elite solutions are left untouched in BBO.

Gravitational Search Algorithm is a nature inspired algorithm that is based upon the law of gravity which was proposed in 2009 by Reshedi et al [6]. The law of gravity states "Every particle in the universe attracts every other particle using force which is directly proportional to the product of their masses and inversely proportional to the square of the distance between them". This algorithm calculates the mass of the particle using its fitness value, the forces exerted by the particles on each other are calculated with the mass of the particles and the distance between them and the acceleration of a particle is calculated with the force and mass of a particle and based on this the position and the velocity of the particle are updated. Every particle is attracted to a particle with a greater mass and as the distance between the particles increase the attraction decreases. Every particle gets attracted to a particle that is closer and has greater mass and moves towards it. A particle with a higher mass is considered to be a better solution to the problem and all other particles get attracted to it. In the beginning all particles are present, as iterations pass only particles with higher masses are kept and the remaining particles are discarded. The algorithm tries to explore initially and then tries to exploits to find the best solution to the problem. Finally a single heavy mass remains which forms the optimal solution to the problem.

Matthew T. and Alex P. [9] Describe how Principle Component Analysis (PCA) a dimensionality reduction technique can be used to greatly simplify as well as enhance the problem of face recognition. PCA represents each face in the form of eigen faces whose dimension is very much less than the dimensions of the original face image. PCA extracts the most distinguishing features of a face and works only on them.

A hybrid of Biogeography Based Optimization and Particle Swarm Optimization has been proposed by Barun M. et al [22]. This hybridization technique improves the exploration and exploitation technique of swarm. It takes advantage of the exploration capabilities of PSO and exploitation capabilities of BBO. This hybridization is done in order to merge the best of both the algorithms thereby forming a more efficient optimization approach.

Another hybridization of the above mentioned algorithms has also been done by Hongwei et al [18]. This paper proposes that if no habitat is selected for immigration then the habitat that is selected for emigration is not changed and this decreases the exploration capabilities of BBO. In order to overcome this disadvantage, PSO has been used to update positions of habitat thereby improving the exploration capabilities of BBO.

Biogeography Based Optimization has been applied to face recognition by Navdeep et al [23] for feature selection where the mappings of the optimization technique to a face recognition problem is explained clearly. The BBO algorithm is applied to the coefficients that were extracted from the Discrete Cosine Transform (DCT) technique. This work shows that features selected by BBO are the most optimal ones needed for face recognition.

Biogeography Based Optimization has also been applied to face recognition by Daya et al [24] along with Principle Component Analysis (PCA) and Gabor filters for optimal feature selection. This work shows that after the feature extraction done by PCA and Gabor filters the application of BBO enhances the feature selection process further thereby simplifying the problem and improving the accuracy of the classifier.

A survey on the Biogeography Based Optimization (BBO) by Ammu P K et al. [5] shows the different optimizations that has been done on the BBO technique. Some drawbacks include poor exploitation, no method to select the best solutions and the large number of infeasible solutions that are generated in BBO. This paper discusses the disadvantages of BBO and the solutions to overcome these drawbacks that have been proposed so far.

A survey on Face Recognition by Wei-Lun C. [25] gives an insight into the various techniques that have been implemented so far for face recognition applications and their advantages and disadvantages.

A hybrid algorithm involving PSO/ACO and modified BBO for land cover feature extraction by Goel [26] can be efficiently used in feature extraction as BBO is efficient in classifying desirable features more efficiently than the others and improves solutions at each iteration. In the hybridized algorithm of PSO/ACO and BBO, an image is divided in n clusters and BBO is applied on the cluster which can be classified most efficiently (Species are migrated from universal habitats to feature habitats based on HSI) and PSO/ACO algorithm is applied on other clusters using the extracted rules. Final image is obtained from the combination of outputs of two algorithms.

Chapter 4: Existing Methodologies

Hybridization of BBO and GSA is done to form a novel hybridized nature inspired technique and is applied to the eigenfaces [16] [27] generated from PCA.

4.1. Principal Component Analysis

PCA [1] does feature selection [28] by extracting the common features that are present between face images and outputs eigenfaces [16] [27]. The working of PCA is described below.

Algorithm 1: PCA

1. Each image in the image dataset of M images is represented in the form of a vector I. If the image size is n x n pixels then the dimension of the vector I is n^2 x 1.
2. From all images in the dataset an average face vector X is extracted which represents the common features present in all the faces in the dataset.
3. Each image in the image dataset of M images is represented in the form of a vector I. If the image size is n x n pixels then the dimension of the vector I is n^2 x 1.
4. From all images in the dataset an average face vector X is extracted which represents the common features present in all the faces in the dataset.
5. Then the normalized face vector N is calculated for each person by the formula,
   $$N_i = I_i - X \tag{1}$$
   where i = {1,2,…..M} is the face vector of each person and N is the normalized face vector containing the unique features in each person.
6. To find the eigenfaces we have to calculate the co-variance matrix C, where
   $$C = AA^T \tag{2}$$
   where A = [N_1 N_2 N_3 ..... N_m] a matrix of normalized vectors from (1). The dimension of matrix A is n^2 x M. Therefore the dimension of C becomes n^2 x n^2.
7. To reduce the dimension of C we make (2) as,
   $$C = A^TA \tag{3}$$
   and now the dimension of C becomes M x M which is very small in comparison to its previous dimensions.
8. Finally calculate the eigenvectors and eigenvalues of the covariance matrix C in (3). Each eigenvector has the same dimensionality as the original images, and thus can itself be seen as an

image. The eigenvectors of this covariance matrix are therefore called eigenfaces. They are the directions in which the images differ from the mean image.

After the 8 steps of PCA described above only those top k eigen vectors that are noiseless are selected. The k eigenfaces must be mapped back to M images i.e. each face image is represented with some proportion of each eigenface which gives us the vector of each face image. For example if we generate k eigenfaces for a training set of M face images, each face image can be made up of "proportions" of all these k "features" or eigenfaces,

$$Fi = [w1, w2, w3 \dots wk] \tag{4}$$

where Fi is the ith face vector in the dataset of M images. Each image will now have a vector associated with it.

4.2 Biogeography-Based Optimization

Biogeography [29] is the study of geographical distribution of biological organisms. BBO is based on the mathematical models of biogeography. In BBO, habitats are residential areas that represent candidate problem solutions. The variables that characterize habitability are called Suitability Index Variables (SIVs). Good habitats (well suited for residence) have high Habitat Suitability Index (HSI) and poor habitats have low HSI. BBO [13] optimizes a solution based on two operations, migration and mutation. Habitats with high HSI have high emigration rate and low immigration rate and habitats having low HSI have low emigration rate and high immigration rate. Here original solutions are modified in each iteration as by way of migration of good solutions to poor solution to raise the quality of poor solutions as well as to make good solutions better by randomly selecting solutions for migration. Solutions that are too good are called elite solutions and are left out of the BBO process.

In BBO, each solution has its own emigration rate μ and immigration rate λ. They can be calculated as follows:

$$\text{Emigration rate } (\mu) = \frac{\text{E k}}{\text{N}} \tag{5}$$

$$\text{Immigration rate } (\lambda) = \text{I } (1 - \frac{k}{n}) \tag{6}$$

where E is the maximum emigration rate, I is the maximum immigration rate, k is the solution number in order of goodness; and N is the number of solutions. In the below algorithm for migration and mutation, rndreal (0, 1) is a uniformly distributed random real number in (0, 1), $S_i(j)$ is the j^{th} SIV of the solution S_i, m_i is the mutation rate that is calculated as:

$$m_i = m_{max} \left(\frac{1 - Pi}{Pmax}\right) \tag{7}$$

where m_{max} is an user-selected parameter, and P_{max} = argmax(Pi) where i = 1… N.

The probability P_i is computed with the formula,

$$P_i = \frac{v}{\sum_{i=1}^{n+1} vi} \tag{8}$$

where $v = [v_1, v_2, \ldots\ldots, v_{n+1}]^T$.

$$Vi\ is \begin{cases} \dfrac{n!}{(n-1-i)!\,(i-1)!}\ for \quad (i = 1,2, \ldots .i') \\ v_{n+2-1}\ \ for\ \ (i = i' + 1, \ldots .., n+1) \end{cases} \tag{9}$$

$$i' = \text{ceil}\left(\frac{n+1}{2}\right) \tag{10}$$

The probability of immigration and emigration of a solution is calculated using the following formulas,

Probability of immigration,

$$(P_{mod}) = \lambda i/\sum_{i=1}^{N} \lambda i \tag{11}$$

Probability of emigration,

$$(P_{mig}) = \mu i \,/ \sum_{i=1}^{N} \mu i \tag{12}$$

The algorithms for BBO migration, BBO mutation and BBO have been described below.

Algorithm 2: BBO migration

4

Step 1 : for i = 1 to N do

Step 2 : Select Si with probability Pmod

Step 3 : if rndreal (0, 1) < Pmod then

Step 4 : for j = 1 to N do

Step 5 : Select Sj with probability Pmig

Step 6 : if rndreal (0, 1) < Pmig then

Step 7 : Randomly select an SIV σ from Sj

Step 8 : Replace a random SIV in Si with σ

Step 9 : end if

Step 10: end for

Step 11: end if

Step 12: end for

Algorithm 3: BBO mutation

Step 1: for i = 1 to N do

Step 2: Compute the probability Pi

Step 3: Select SIV Si(j) with probability α Pi

Step 4: if rndreal (0,1) < m_i then

Step 5: Replace Si(j) with a randomly generated SIV

Step 6: end if

Step 7: end for

Algorithm 4: BBO procedure

1. Initialization of BBO parameters including N, maximum migration rates *E* and *I*, maximum mutation rate m_{max}, and an elitism value.
2. Initialization of habitats, each habitat representing a possible solution to the given problem.
3. For each habitat map the HSI to the number of species *P*, the immigration rate λ and the emigration rate μ.
4. Probabilistically use immigration and emigration to modify each non-elite habitat.
5. Re-compute each HSI.

6. Go to step 3 for the next iteration. This loop can be terminated after a predefined number of generations or after an acceptable problem solution has been found.

4.3. Gravitational Search Algorithm

This work makes use of only a small part of GSA and hence that alone is explained in this section. GSA is based upon the law of gravity. Here agents are considered as objects and their performance is measured by their masses. The objects attract towards each other by the force of gravity and this causes a global movement of all objects towards the objects with heavier masses. Every particle is attracted to a particle with a greater mass and as the distance between the particles increases the attraction decreases. Every particle gets attracted to a particle that is closer and has greater mass and moves towards it. A particle with a higher mass is considered to be a better solution to the problem and all other particles get attracted to it. The fitness of each object is its mass which is calculated using the formula below,

$$\text{mass}_i = \frac{fit_i - worst}{best - worst} \tag{13}$$

$$M_i = \frac{mass_i}{\sum_{j=1}^{N} mass_j} \tag{14}$$

where fit_i represents the fitness value of the agent i, worst and best are defined as follows,

$$\text{best} = \max fit_j \text{ where } j = 1, 2, \ldots, N \tag{15}$$

$$\text{worst} = \min fit_j \text{ where } j = 1, 2, \ldots, N \tag{16}$$

Thus the existing works related in to this work have been explained. The proposed work has been built upon these works only.

Chapter 5: Proposed Methodology for Face Recognition Using the BBO-GSA Algorithm.

This section describes the BBO-GSA algorithm proposed and how it can be applied to the problem of face recognition.

5.1 Hybrid BBO-GSA Algorithm

Migration in BBO replaces random SIVs of a solution with random SIVs of another solution. This might lead to a solution becoming a poorer solution than what it was before as well. This leads to the generation of several infeasible solutions and also delays the convergence of the algorithm. If the replacement of SIVs is done in such a way that poor SIVs are replaced with good SIVs only, BBO will converge to the optimal solution and generate better solutions faster. This drawback of BBO can be overcome by borrowing certain characteristics of GSA.

The proposed BBO-GSA algorithm replaces SIVs of a solution only with SIVs that are better. Therefore each SIV is also associated with a fitness value that is taken from the mass fitness function of the GSA algorithm. The replacement of SIVs is done only if the mass of the SIV selected for replacement is lesser than the mass of the SIV with which it will be replaced. Two changes are made to the BBO algorithm. They are, after step 3 of the BBO algorithm illustrated above calculate the fitness of every individual SIV of every habitat using the mass equations of GSA described in (10), (11), (12), (13) and changes are made to the migration procedure of the BBO-GSA algorithm as explained below,

Algorithm 5: Migration procedure of BBO-GSA

Step 1: for i = 1 to N do

Step 2: Select S_i with probability P_{mod}

Step 3: if rndreal (0, 1) < P_{mod} then

Step 4: for j = 1 to N do

Step 5: Select S_j with probability P_{mig}

Step 6: if rndreal (0, 1) < P_{mig} then

Step 7: Randomly select an SIV σ from S_i

Step 8: Randomly select an SIV τ from S_j

Step 9: If mass(τ) > mass(σ) then

Step 10: Replace σ with τ otherwise go to step 8

Step 11: end if

Step 12: end if

Step 13: end for

Step 14: end if

Step 15: end for

5.2 Proposed Methodology for Face Recognition using BBO-GSA.

To the dataset of images the PCA technique explained is applied. Eigenfaces that result from PCA are the habitats and migration and mutation is done between them in order to increase their quality. Eigen vector elements form the SIVs that will be migrated between habitats. According to the modified migration procedure of BBO explained above the eigenface vector elements(SIVs) should also be assigned a fitness value such that the migration of eigenface vector elements between eigenfaces leads only to the betterment of the quality of the eigenface but does not reduce it. This assignment of fitness value to each eigen face vector element is done with the GSA algorithm and is explained below.

Eigenfaces represent the distinguishing features of the faces in the face dataset. Each eigenface contributes to a dimension of the face when mapped back to the face images i.e the face images are mapped back to a space whose number of dimensions equals the number of eigenfaces. This contribution that each eigenface makes in representing a face image is indicated by a weight value. The weight is calculated by a matrix multiplication of the eigen vector with the normalized face vector as shown below,

$$\omega_k = \mu_k^T(\Gamma - \psi) \qquad (17)$$

where μ_k is a eigenface and $k = 1,2,.., K$. K is the total number of eigenfaces and Γ is a face image and ψ is the average face of the face dataset.

After mapping back the face images to a reduced space a vector in the form of F shown below is formed for each image,

$$F = [\omega_1, \omega_2, \ldots\ldots, \omega_k] \tag{18}$$

Eqn. 2 is the representation of a face image F in terms of a weight vector where each weight indicates the contribution of each eigenface in representing the face image. Therefore F is a face vector of length K.

Each eigenface can be represented with a vector μ as,

$$\mu = [\sigma_1, \sigma_2, \sigma_3, \ldots \sigma_m] \tag{19}$$

The weight value ω which is the contribution of an eigen face to a face image is high if the eigenface vector elements (σ_i) have higher values. If the weight becomes high then the amount of contribution that an eigenface makes in the representation a face increases. Therefore only those eigen vector elements (σ_i) that have high values are used to replace eigen vector elements (σ_j) with low values thereby increasing the amount of contribution (ω) that an eigenface makes to every face in the dataset. Therefore the fitness of each eigen vector element is the element itself. This property ensures that the migration between the eigenfaces leads only to the betterment of an eigenface.

The fitness of each eigenface ($\mu_{ifitness}$) is calculated as the sum of the contribution that it makes to every face image divided by the total number of face images. This fitness function ensures that those eigenfaces whose contribution to all the face images in the face dataset is high or in other words makes the maximum total contribution in representing the images in the face dataset has a higher fitness value and those eigenfaces whose contribution to the faces in the face dataset is low has a lower fitness value.

$$\mu_{1fitness} = \omega_{11} + \omega_{12} + \omega_{13} + \ldots\ldots + \omega_{1M} / M \tag{20}$$

where M is the number of images in the face dataset, ω_{ij} is the contribution of eigenface i to face image j where $i = 1, 2, 3\ldots K$ and $j = 1, 2, 3, \ldots M$. Eqn. 4 shows the fitness calculation of eigenface 1. Steps of face recognition using the BBO-GSA algorithm are given below,

Algorithm 6: BBO - GSA for Face Recognition

1. To the training set of images apply PCA.
2. PCA generates a set of eigenfaces, say k lesser than the size of the original training set, which are also face images but represent just the major features of a training set.
3. Each face image is represented as some proportion (weight) of each eigenface forming a weight vector,

$$F_i = [w_1, w_2, w_3 \ldots w_k] \tag{21}$$

where F_i is the i^{th} face vector.

4. On the eigenfaces generated by PCA apply the BBO-GSA technique.
5. The fitness (HSI) of each eigenface vector (habitat) is calculated as the sum of weights in the i^{th} dimension of all the face vectors divided by the total number of face images.

$$Ei_{fitness} = w1_1 + w1_2 + w1_3 + \ldots\ldots\ldots + w1_k \,/\, N \tag{22}$$

6. The highly fit habitats (elite) are left out of the following steps as they are already good solutions.
7. A eigenface vector with high fitness is selected for emigration and a eigenface vector with low fitness is selected for immigration.
8. From the eigenface vectors selected for emigration, select an eigen vector element with high fitness to be replaced with a low fitness eigen vector element.
9. This replacement is done through the Gravitational Search Algorithm (GSA).
10. Fitness of the eigen vector elements is the element itself. High eigenface vector elements have high fitness and low eigenface vector elements have low fitness.
11. From their fitness values mass of each eigen vector element is calculated.
12. This mass is used to calculate the force exerted by every eigen vector element on every other eigen vector element.
13. A eigen vector $element_i$ is selected for immigration to be replaced by another eigen vector $element_j$ if eigen vector $element_j$ > eigen vector $element_i$ i.e. eigen vector $element_j$ corresponds to a greater mass and exerts greater force on the selected eigen vector $element_i$.
14. Perform mutation by selecting eigenface vectors with high mutation rates but replace with randomly generated eigen vector elements.
15. Now use the modified eigenfaces to represent the face images as face vectors as in step 3.
16. Repeat steps 6 to 15 until a desirable solution is reached.

A non-linear, multi-class Support Vector Machine (SVM) is used for the purpose of classification.

The flow of the BBO-GSA algorithm for face recognition is given in fig. 1. The procedure for migration and mutation are repeated a desirable number of times.

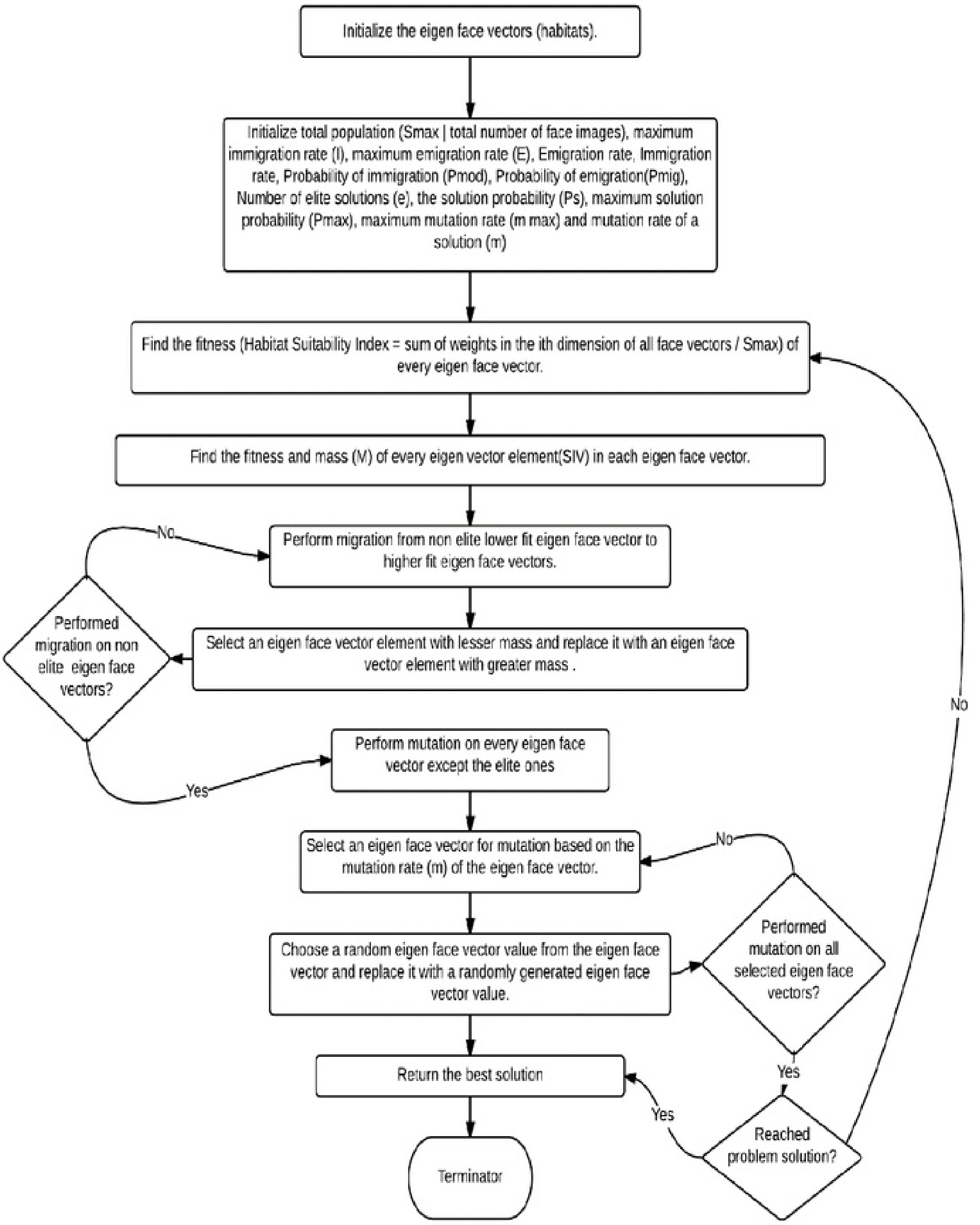

Figure 1 Flowchart showing the BBO-GSA algorithm for Face Recognition.

Chapter 6: Experimental Results and Comparison with existing works

The results obtained and the comparison with existing works are described below.

6.1 Experimental Results

The BBO-GSA algorithm has been applied to solve the problem of face recognition with LFW and ORL datasets. Experimental results show that the BBO-GSA technique either outperforms or is in par with the existing nature inspired techniques applied to face recognition.

6.1.1 Datasets Used

The proposed work has been tested on two datasets, Labelled Faces in the Wild (LFW) people and ORL database of faces, details given in Table 1.

The first dataset to be used is Labelled Faces in the Wild (LFW) people. The dataset contains 13,233 target face images. The dataset contains images of 5749 different individuals. Of these, 1680 people have two or more images in the dataset. The remaining 4069 people have just a single image in the dataset. The images are available as 250 by 250 pixel JPEG images. Most images are in color, although a few are grayscale only.

Second dataset to be used is ORL dataset of faces. ORL dataset acquired at the Olivetti Research Laboratory in Cambridge, U.K. The dataset consists of 400 distinct images that correspond to 40 distinct subjects. Therefore, each subject has 10 facial images each image has got different illumination, pose and facial expression. The size of each image is 92 x 112 pixels and has 8-bit grey levels. For some subjects, the images were taken at different times, varying the lighting, facial expressions. All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement. Four images per person were used in the training set and the remaining six images were used for testing.

Table 1 Dataset Details

Dataset	No. of images	No. of Classes	No. of images used	No. of classes
LFW	13,233	5749	1827	21
ORL	400	40	400	40

6.1.2 Results

The results of the BBO-GSA technique are analysed by applying it to face recognition.

The eigenfaces generated by applying PCA to the LFW and ORL datasets is shown in fig. 2c and fig. 2d respectively.

For the implementation many parameters such as number of eigenfaces, the size of test and train size and the BBO iterations were set. The parameter settings for the implementation are explained in Table 2.

The implementation details of PCA are given below,

Principle Component Analysis

To the training set of images Principle Component Analysis (PCA) is applied. PCA generated 150 eigen faces representing just the major features of the training set of 1824 images. The eigen faces generated were mapped back to the face images.

Method name: RandomizedPCA()

Input: number of eigen faces required, training image data

Output: eigen face vectors

Map face image to the set of eigen faces.

Each face image in the dataset is represented with the generated eigen faces.

Method name: transform()

Input: face image.

Output: face vector represented from eigen faces.

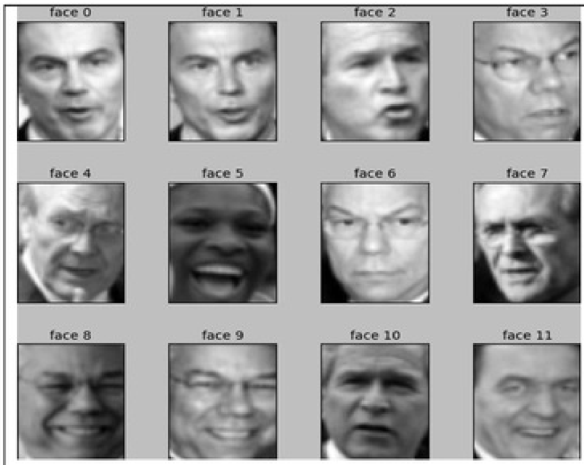

Figure 2a. Representative set of LFW dataset

Figure 2b Representative set of ORL dataset

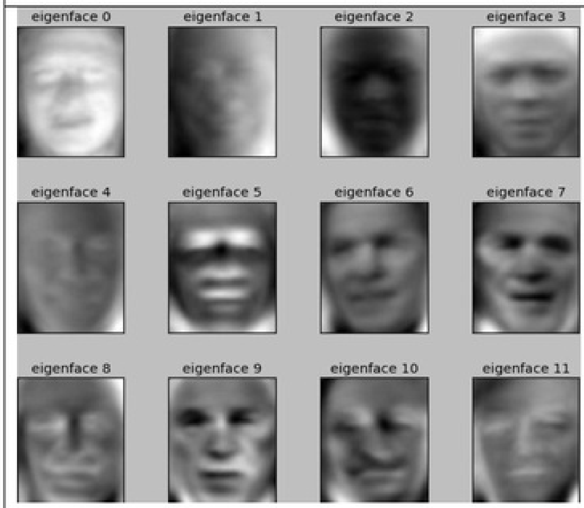

Figure 2c. Eigenfaces extracted from the LFW dataset.

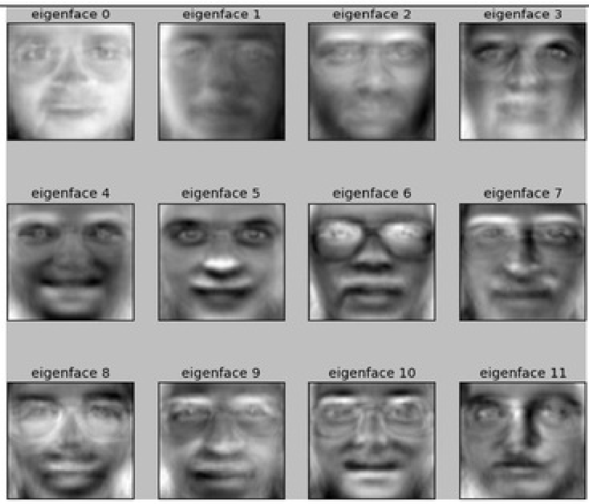

Figure 2d. Eigenfaces extracted from the ORL dataset

Table 2 Parameter Settings

Dataset	No. of eigen faces	BBO iterations	Test set size (%)	Train set size (%)
ORL	150	5	10	90
LFW	150	5	10	90

The performance of the proposed BBO-GSA technique is analyzed by plotting the Receiver Operating Characteristic (ROC) Curve as shown in fig.3 and fig.4 with false positive rate on the X-axis and the true positive rate on the Y-axis.

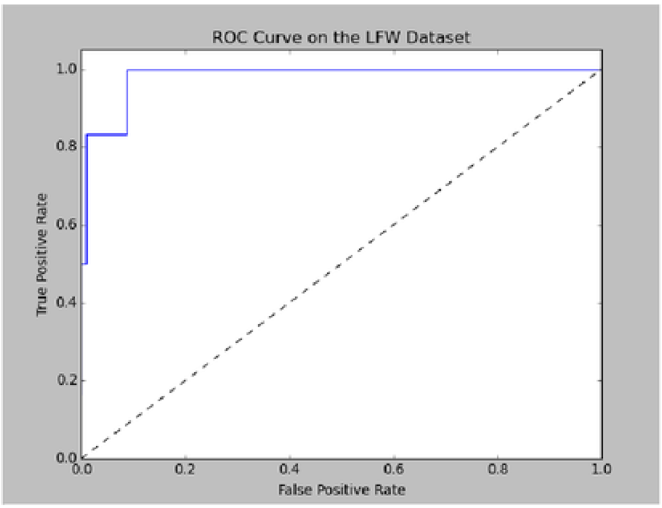

Figure 3. ROC Curve of LFW Dataset

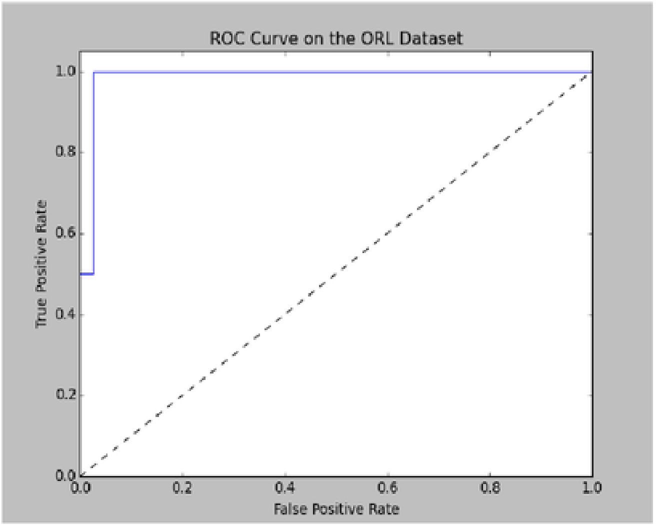

Figure 4. ROC Curve for ORL Dataset.

In addition the precision, recall and accuracy of the algorithm was also measured.

Table 3 Results: Precision, Recall and Accuracy

Dataset	Precision (%)	Recall (%)	Accuracy (%)
ORL	99.75	99	99.75
LFW	80	81	80

From the above results it can be concluded that the proposed algorithm does fairly well for the face recognition application.

The prediction results of the algorithm for the two datasets for a sample set of images is given in fig.5a. and fig.5b.

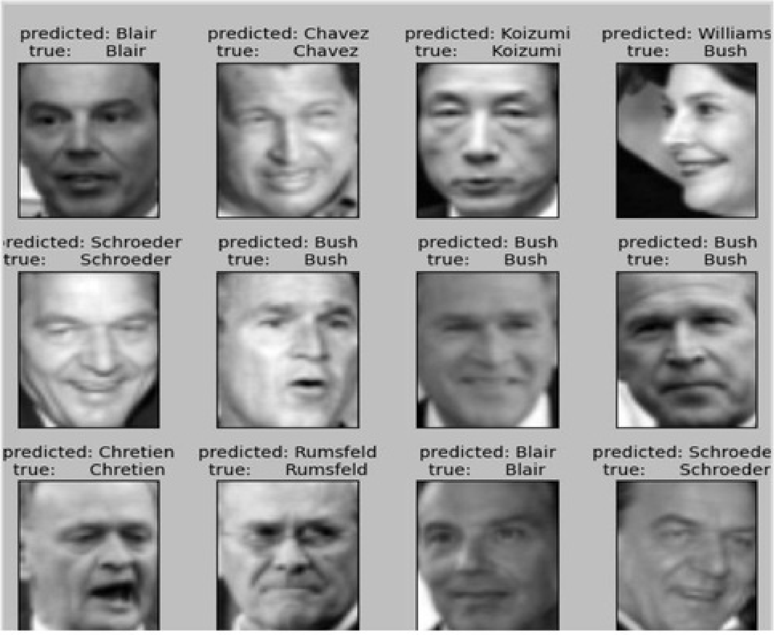

Figure 5a. Prediction results with the LFW dataset

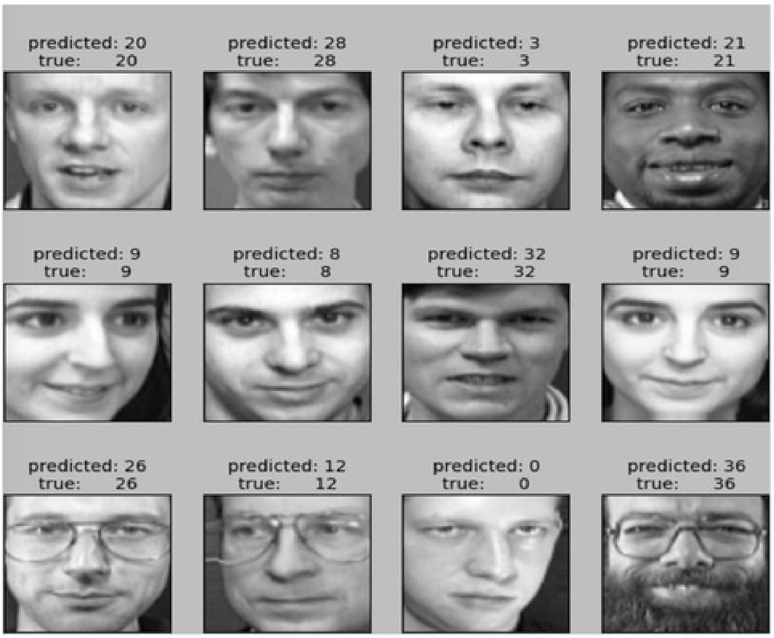

Figure 5b. Prediction results with the ORL dataset

6.2 Comparison with existing works

Recently many Bio-inspired techniques [30] have been proven to be efficient in problem of face recognition. The accuracy of the BBO-GSA technique for the application of face recognition is compared with five different nature inspired techniques combining other techniques.

The nature inspired technique that have been used includes Binary Particle Swarm Optimization [20], Gravitational Search Algorithm [6], here two variants of GSA are proposed namely the 2-D version of GSA, in order to cater for the 2-D image data, and a 2-D randomized local extrema based GSA (RLEGSA), which employs a stochastic local neighbourhood based search instead of global search, as in basic GSA, In [31] Genetic Algorithm is associated with PCA to maintain the property of PCA while enhancing the classification performance. It reconsiders the available training data and tries to find the best underlying distribution for classification. Ant Colony Optimization is used in [21] and a novel algorithm is proposed where classifier performance and the length of the selected feature vector are adopted as heuristic information for ACO. So, the optimal feature subset is selected in terms of shortest feature length and the best performance of classifier and Gravitational Search Algorithm [12], Here binary version of traditional GSA (named BGSA) is further enhanced to propose a novel binary variation of GSA with dynamic adaptive inertia weight (named BAW-GSA). Six new algorithms for face recognition are proposed hybridizing BGSA or BAW-GSA with each of LBP, MCT and LGP algorithms. Comparison of three face recognition algorithms (PCA, LDA, and EBGM) have been presented in [32] in which accuracy rate of EBGM is highest among the three. A novel method of implementation of a stochastic optimization technique is described in [33]. The method proposed divides the original images into patches in space, and seeks a non-linear functional mapping using second-order Volterra kernels using Artificial Bee Colony Optimization Technique. Face Recognition has been implemented in [34]. A Gabor filters based face recognition algorithm named POMA-Gabor is presented in [35] , which combines comprehensive learning particle swarm optimizer (CLPSO) global search and self-adaptive intelligent single particle optimizer (AdpISPO) local search to select Gabor filter parameters. An Adaptive technique using Firefly Algorithm [36] where features are extracted using Discrete Cosine Transform (DCT) and Haar wavelets based Discrete Wavelet Transform (DWT) and Bat algorithm [37] is presented for feature selection for face recognition .Here features are extracted using Discrete Cosine Transform (DCT) and Haar wavelets based Discrete Wavelet Transform (DWT).Face recognition using one of the recent optimization algorithm Cuckoo Search Algorithm has been presented in [38].Its optimization results are better than PSO and ACO. It is based on the principle- new and potentially better solutions (cuckoos) replace a not-so-good solution in the nests, which represents discarding the feature subsets which are least significant (worst feature subset) and these features are dumped from further calculation thus improving features available for face recognition.

Table 4 Comparison of the BBO-GSA technique with existing methods

Technique	Accuracy (%)	Dataset Used
BPSO [20]	95 – 97	ORL
GSA [19]	75 – 77	ORL
GA [31]	97.5	ORL
ACO [21]	99	ORL
GSA [39]	51.5	LFW

Chapter 7: Conclusion and Future Work

This work has proposed a novel hybridized BBO-GSA algorithm that is applied to face recognition. The BBO-GSA algorithm is applied to the eigenfaces extracted from PCA in order to refine the eigenfaces and thereby improve the accuracy of the classifier. The BBO-GSA algorithm overcomes the disadvantage of infeasible solution generation and late convergence of BBO. The performance of the BBO-GSA algorithm is tested on the face recognition application with the LFW and ORL datasets. The experimental results obtained shows that the proposed hybridized algorithm is efficient and optimizes the results of the face recognition system and thus enhances the performance of the system. In future, the BBO-GSA technique can be applied on other problems and its performance on other problems can be tested. It can also be further improved by overcoming the other disadvantages of BBO such as poor exploitation.

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