Journal of Artificial Intelligence Research & Advances
ISSN: 2395-6720 (Online)
Volume 6, Issue 2
www.stmjournals.com

Pattern Recognition Using Hybrid Meta-Heuristic

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Abstract
In this study, two optimization algorithms i.e., Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) are combined to produce a hybrid population-based algorithm PSOGSA. The approach of HPSOGSA is used for the assessment of PSO using the social thinking capability and the manipulation of GSA using the local search proficiency. To increase the performance of HPSOGSA, some benchmark functions are used. Two standard databases, ORL and YALE are used to assess the classification performance of the proposed method. Classification accuracy is compared for diverse number of training samples per class. Further lead of proposed method is confirmed by analyzing percentage improvement in classification accuracy. With limited accessibility of training sample, percentage enhancement is very successful for face recognition applications.

Keywords: *Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Particle Swarm Optimization and Gravitational Search Algorithm (PSOGSA), Hybrid Particle Swarm Optimization and Gravitational Search Algorithm (HPSOGSA).*

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INTRODUCTION

Face Recognition (FR) is a technology which is capable of matching a person's face from the data set by comparing different facial features of an individual. All actions in our day to day life, whether taking use of paper or pencil or talking face to face, are handled electronically. Extraordinary interest for quick and precise client distinguishing proof and confirmation is result of development in involvement of electronics in FR. A face picture can be caught from a distance and can be investigated, without interacting with the client. For instance, if someone steals your ATM cards or in most of the cases, you lost it, an unapproved client can often come up with the correct pin codes and misuse your card. To solve this problem, FR technology comes into place since an individual has a unique face except in case of twins.

Face recognition finds its application in different sectors such as security where electronics are unlocked by face detection, and especially in organizations for handling sensitive data, criminal identification where criminal's face is identified by the matching with the data set, healthcare where medical experts diagnose the patient's illness by noticing patient's features, advertising, payments etc.

PCA (Principal Component analysis) is the conventional and renowned method for face recognition. PCA was first introduced by Sirvovich and Kirby in 1987 [1, 2]. In 1991, eigen face method that was derived from PCA was presented by Turk and Pentland; face images were projected onto a feature space that traverses the noteworthy differences among known face images [3]. From that point forward, a considerable amount of FR strategies that depend on PCA have been proposed, and PCA has been a standout amongst the most essential methodologies in FR [4–10].

PCA strategy has been broadly used to reduce picture dimension, yet it was initially produced for one dimensional information [3, 7, 8]. With respect to this, it is vital for us to change the picture data matrices into the corresponding one-dimensional vectors, while applying PCA to pictures. Unquestionably, the downside of this procedure is computationally costly. Yang *et al*. proposed a discernible calculation 2DPCA in order to improve the current situation [7]. As an augmentation of the PCA, instead of projecting a corresponding vector, features from image matrix are taken out directly by 2DPCA. It can save the running time and evaluate the covariance matrix more accurately to some degree. KPCA (kernel principal component analysis), KFDA (Kernel Fisher Discriminant Analysis) and many more feature extraction methods are used which are related to PCA [11]. The majorities of these calculations are nonlinear changes and beat PCA.

The feature extraction, classifier selection and classification are the three stages of standard FR method. However, the sparse representation method supports a perceptible way to direct the face recognition problem [12]. It does not contain the feature extraction and classifier selection stages. The test sample is represented as a sparse linear combination of the training samples. The meaning of the term 'sparse linear combination of the training samples' is that if the test sample is expressed as a linear combination of all the training samples, the majority of the components of the combination are zero. It seems that the sparse representation method attempts to seek the potential effects of different training samples on 'constructing' the test sample and intends to classify the test sample into the class whose training samples have the extreme effect. In other words, this method assumes that the test sample can be approximated by the sum of the effects of the training samples from different classes and the class that has the maximum effect is the most similar to the test sample.

Many methods have been opted to increase the accuracy with low complexity. Optimization method can be used for doing the task. Many optimization algorithms have been developed such as John Holland presented GA (Genetic Algorithm) in 1970 [13], Marco Dorigo suggested ACO (Ant Colony Optimization) [14] in 1992, Eberhart and Kennedy in 1995 developed PSO (Particle Swarm Optimization) [15], Deferential Evolution (DE) [16] developed by Storn and Price in 1997, BBA (Binary Bat Algorithm) [17] created by Xin-She Yang in 2010, Cuckoo Search Algorithm (CSA) [18] offered by Yang and Deb in 2009 and Gravitational Search algorithm (GSA)[19].

HPSOGSA is a new hybrid model that combines the ability of both PSO and GSA algorithms and it takes the advantage of both the algorithms to produce best values. Hybrid algorithms are aimed at reducing the probability of trapping in local optimum. To match the performance of HPSOGSA algorithm with both standard PSO and GSA, 23 benchmark functions are used. To put into practice, the HPSOGSA algorithm, standard ORL and YALE databases are used.

METHODOLOGY

There are numerous heuristic evolutionary optimization algorithms which have been as of late developed. These algorithms are Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Deferential Evolution (DE), Ant Colony (AC), and Gravitational Search algorithm (GSA). All of them work on the similar primary of finding the best result among every conceivable input. For finding the global optimum, a heuristic algorithm ought to have two noteworthy characteristics i.e. exploration and exploitation. Exploration is the ability of investigating the entire pieces of problem space whereas exploitation is the capacity of an algorithm which merges the best solution near a decent solution. Ultimately, all heuristic optimization algorithms search for global optimum and create a balance between the two characteristics efficiently. According to Eiben and Schippers, in evolutionary computation, strengthening one ability, weakens the other and vice versa [20]. Therefore, the current heuristic optimization algorithms can take care of limited arrangements of problems. Hence, no algorithm is capable to solve all optimization problems [21]. As a result, overall exploration and exploitation ability can be balanced by merging the optimization algorithms. Among all the evolutionary algorithms, PSO is widely used in hybrid methods as it possesses features such as capability to discover global optimum, speed of convergence and simplicity.

Some works have synthesized PSO with other algorithms such as hybrid PSOGA [22, 23], PSODE [24], and PSOACO [25]. A new unaccustomed heuristic optimization method has been proposed named GSA [26]. A new model termed HPSOGSA has been implemented which combines PSO and GSA algorithms to form a hybrid model whose performance is compared to both standard PSO and standard GSA using 23 benchmark functions.

Particle Swarm Optimization

Population-based numerical method called PSO was developed based on the observation of conduct of different living particles in a group. These living particles can be fishes or birds in a group. In the calculation, every particle is viewed as a conceivable answer for the issue. Every particle is characterized by its position and speed vector. The position vector is the required result, and the speed of the particle is dictated by the speed vector and encourages it to reach to the ideal result. At every iteration, each particle can be calculated by its fitness value. For next iteration, the estimations of speeds and the position of every particle are refreshed by utilizing the Eqs. (1) and (2):

$$v_i^{t+1} = wv_i^t + c_1 \times rand\ (pbest_i - x_i^t) + c_2 \times rand\ (gbest_i - x_i^t) \quad (1)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

Gravitational Search Algorithm

Likewise, a new heuristic optimization algorithm called Gravitational search algorithm (GSA) has been proposed. It is motivated by the Newton's hypothesis which states that when the two objects are kept at some distance apart then the force of attraction between them is straightforwardly relative to the product of their masses and contrarily corresponding to the square of the separation between them. In the algorithm, potential solution of the problem is the position of an agent (object) and its performance is evaluated using the inertial mass. Each agent is attracted by the other agent by a force which is used to drive a global movement towards the heavier masses. This corresponds to the optimal global solution. The mathematical formulation of the algorithm is given below.

Consider a GSA framework with k specialists where the situation of ith operator is signified by:

$$\text{Xi}=x_i^1, \ldots, x_i^d \ldots, x_i^n, \ (\text{i}=1, 2 \ldots, \text{k})$$

Where, x_i^d is the situation of the ith specialist in dth measurement, and n is the measurement for the issue. The mass of every specialist is processed subsequent to ascertaining the wellness capacity of the present population. The gravitational force is computed from agent j upon i at the iteration, t and the total force of dimension d over agent i is calculated with by Eq. (3):

$$F_{ij}^d(t)=\text{G(t)}\frac{M_{pi}(t)\times M_{aj}(t)}{R_{ij}(t)+e}(x_j^d(t) - x_i^d(t)) \quad (3)$$

The gravitational constant is given by Eq. (4):

$$\text{G(t)}=G_0 \times \exp(-\propto \times \frac{iter}{maxiter}) \quad (4)$$

The random number, *rand_j*, is uniformly distributed in the interval [0, 1]. In a problem space of dimension d, the total force acting upon agent i is calculated by using Eq. (5):

$$F_i^d(t) = \sum_{j=1, j\neq 1}^{N} rand_j F_{ij}^d(t) \quad (5)$$

According to the law of motion, the acceleration of an agent is proportional to the resultant force and inverse of its mass. Therefore, the acceleration of all agents is calculated using Eq. (6):

$$ac_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \quad (6)$$

The velocity and position of all agents are calculated using the Eqs. (7) and (8):

$$vel_i^d(t+1)=rand_i \times vel_i^d(t) + ac_i^d(t) \quad (7)$$

$$x_i^d(t+1) = x_i^d(t) + vel_i^d(t+1) \quad (8)$$

At each iteration, the velocity and position of each agent are updated using the above equations and when the maximum iterations are elapsed, the algorithm stops.

Hybrid PSO-GSA

The hybridization of PSO and GSA is a metaheuristic streamlining strategy. It tends to be connected for various complex hunt issues. HPSOGSA refreshes the particle positions (answer for the issue) while following the effect of gravitational forces and increasing speed. The calculation is coevolutionary as the two calculations are not utilized in a steady progression. The technique of HPSO-GSA is to utilize the investigation of PSO utilizing the social reasoning (gbest) capacity and the exploitation of GSA utilizing the nearby inquiry ability. The HPSO-GSA starts with the irregular introduction of all the operators, thinking about them as conceivable arrangements. From that point, the calculation computes the gravitational constants, masses, all out drive on every operator and increasing speeds utilizing Eqs. (3)–(6). The best arrangements are refreshed on every emphasis.

$$V_i^{t+1}=\text{w}\times V_i^t+c_1\times rand\times a_i^t+c_2\times\text{rand}\times[gbest^t - X_i^t] \quad (9)$$

$$X_i^{t+1}=X_i^t + V_i^{t+1} \quad (10)$$

The HPSO-GSA is executed as clarified in the flowchart appeared in Figure 1. Speed and position in HPSO-GSA is refreshed utilizing Eqs. (9) and (10). From the hunt space, the operators with higher masses pull in different specialists and are considered as great arrangements. gbest stores the global arrangement position, which is seen by each operator to move towards it, and by altering c1, c2 the worldwide and neighborhood seek capacity of HPSO-GSA is adjusted. The decency of arrangement that characterizes the attributes of operators is framed by GSA.

GSA characterizes the mass, force and increasing speed of the agent though speeds and position of every operator is characterized by PSO which are refreshed in every emphasis. Consequently, with the assistance of these highlights, the calculation can be used to find better arrangements. With this capacity, the calculation investigates for the global ideal arrangement. The best methodology of HPSO-GSA lies in the parallel handling of both the calculations.

RESULT AND CONCLUSION

Simulations are performed using MATLAB. Experiments are executed using two face databases i.e., ORL [27] and YALE [28]. Each image in the database is converted into image feature database and divided into two independent sets of training and testing image features. Training set includes T out of N image features per subject and testing set includes remaining (N-T) image features per subject. Therefore, total number of available training sets is $\frac{N!}{T!(N-T)!}$ for a database. Experiments are conducted for all possible sets of training and testing data.

Experiment-1 for ORL Database

ORL face database has 400 pictures i.e., pictures of 40 subjects with 10 pictures for every subject. Pictures are taken with shifting articulations, enlightenment and other fine subtleties. Foundations of pictures are kept up as dim and position of subjects is kept up to be upstanding frontal. Few pictures with side development are likewise included. Size of pictures is 92×112 pixels and shading variety is between 256 dimensions of Grey. Table 1 demonstrates the percentage mean classification accuracy for distinctive number of preparing tests per subject of ORL database. Mean classification accuracy plot for various number of preparing tests per subject of ORL database appears in Figure 2. It is apparent from Figure 1 that classification accuracy increments with increment in number of preparing tests per subject. Here computational unpredictability ascends due to the increment in preparing tests per subject; in this manner, settles are required between classification accuracy and computational intricacy while choosing the number of preparing tests per subject.

The next subsection presents result on YALE database.

Experiment-2 for YALE Database

Yale database constitutes 165 different images which include 15 subjects with 11 images for every subject. Images are taken in different expressions, with and without glasses and with different patterns of illuminance etc. Original greyscale image size is 220×175 pixels. Experiments are performed on YALE database for all types of training sets and different number of training samples per subject. The percentage mean classification accuracy for different training samples per subject of YALE database is given in Table 2. Mean classification accuracy plot for different number of training samples per subject of YALE database is shown in the Figure 3.

The percentage improvement in classification accuracy for both the databases is shown in the Figure 4. Here it can be clearly seen that percentage improvement is very large for lesser number of training samples per subject. Therefore, as the number of training samples per class increases, improvement in classification accuracy decreases.

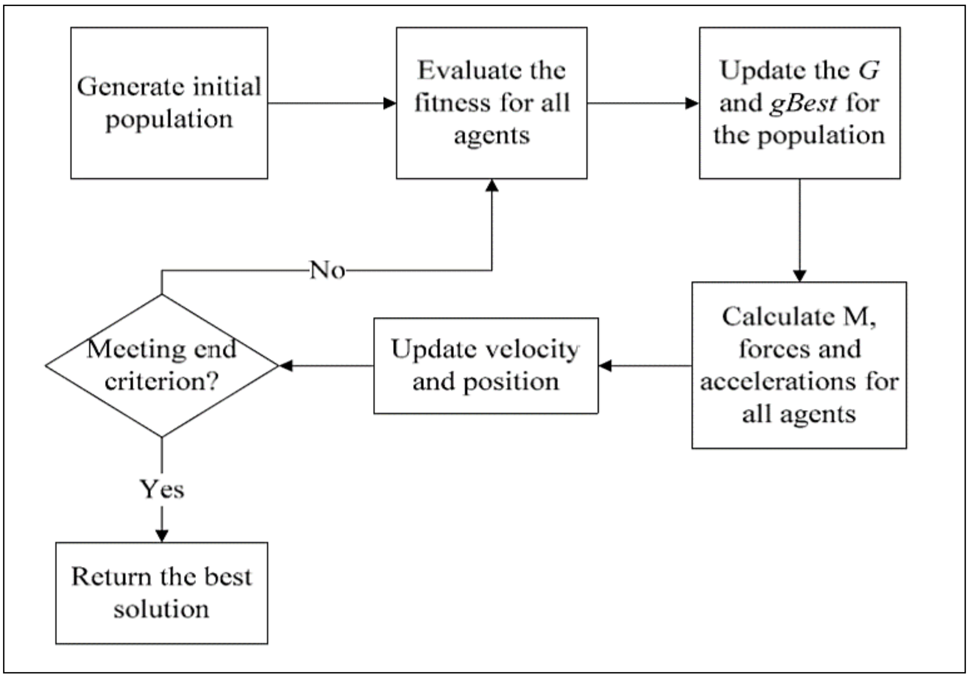

Fig. 1. *Flow Chart of HPSO-GSA Algorithms.*

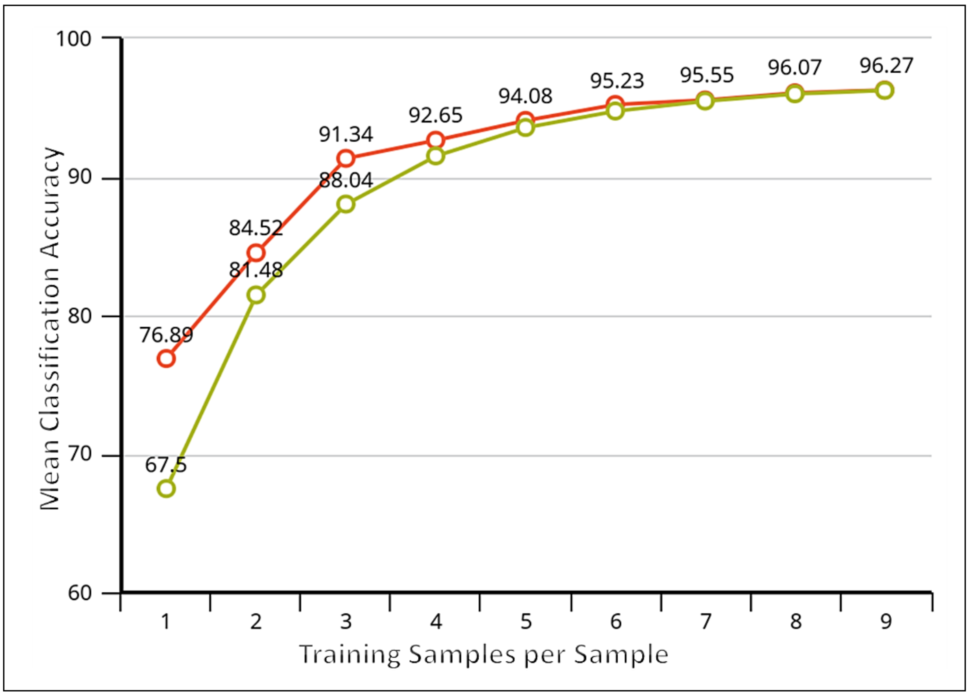

Fig. 2. *Mean Classification Accuracy (%) Plot for ORL Database.*

***Table 1:** Mean Classification Accuracy (%) of PSO-GSA Method and PSO Based on ORL Face Database.*

Training Samples per Subject	Number of Sets	Classification Accuracy using PSO-GSA	Classification Accuracy using PSO	Improvement in Classification Accuracy over PSO
1	10	76.89	67.50	13.91%
2	45	84.52	81.48	3.73%
3	120	91.34	88.04	3.74%
4	210	92.65	91.52	1.23%
5	252	94.08	93.57	0.54%
6	210	95.23	94.76	0.49%
7	120	95.55	95.48	0.07%
8	45	96.07	96.00	0.07%
9	10	96.27	96.25	0.02%

***Table 2.** Mean Classification Accuracy (%) of PSO-GSA Method and PSO Based on YALE Face Database.*

Training Samples per Subject	Number of Sets	PSO-GSA	PSO	Improvement in Classification Accuracy over PSO
1	11	71.48	66.13	8.09%
2	55	81.25	78.03	4.1%
3	165	85.11	83.22	2.27%
4	330	86.00	85.86	0.16%
5	462	90.25	87.50	3.14%
6	462	90.00	88.86	1.28%
7	330	91.55	90.11	1.59%
8	165	92.78	91.30	1.62%
9	55	92.87	92.55	0.34%
10	11	94.12	93.94	0.19%

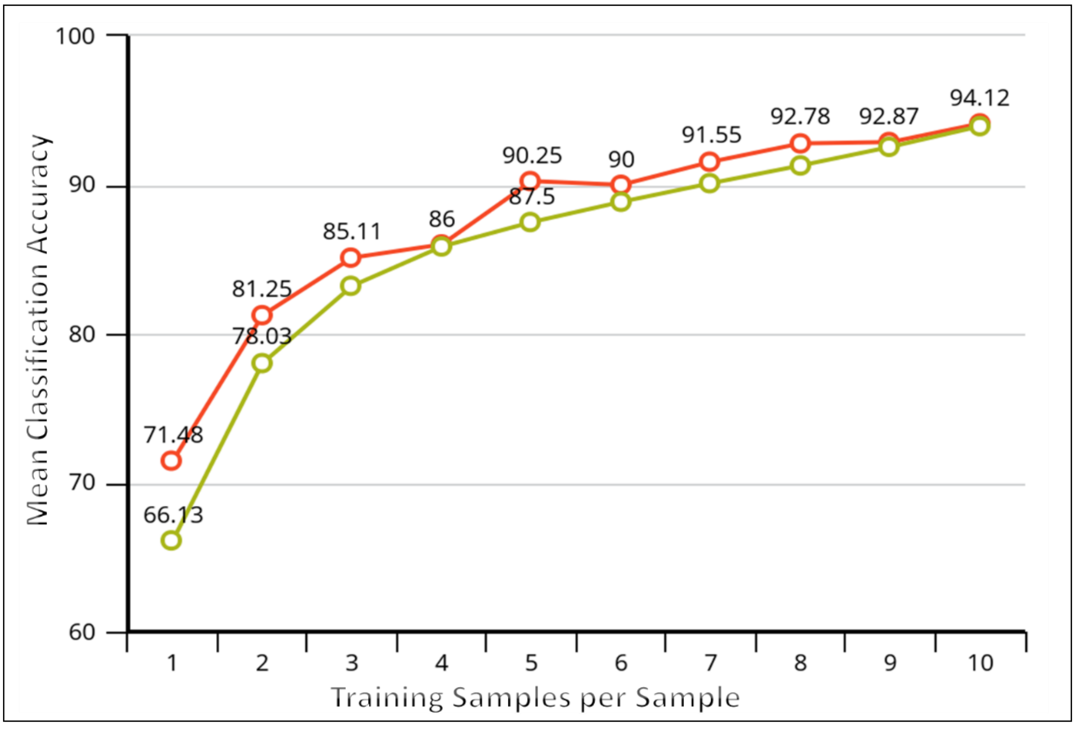

***Fig. 3.** Mean Classification Accuracy (%) Plot for YALE Database.*

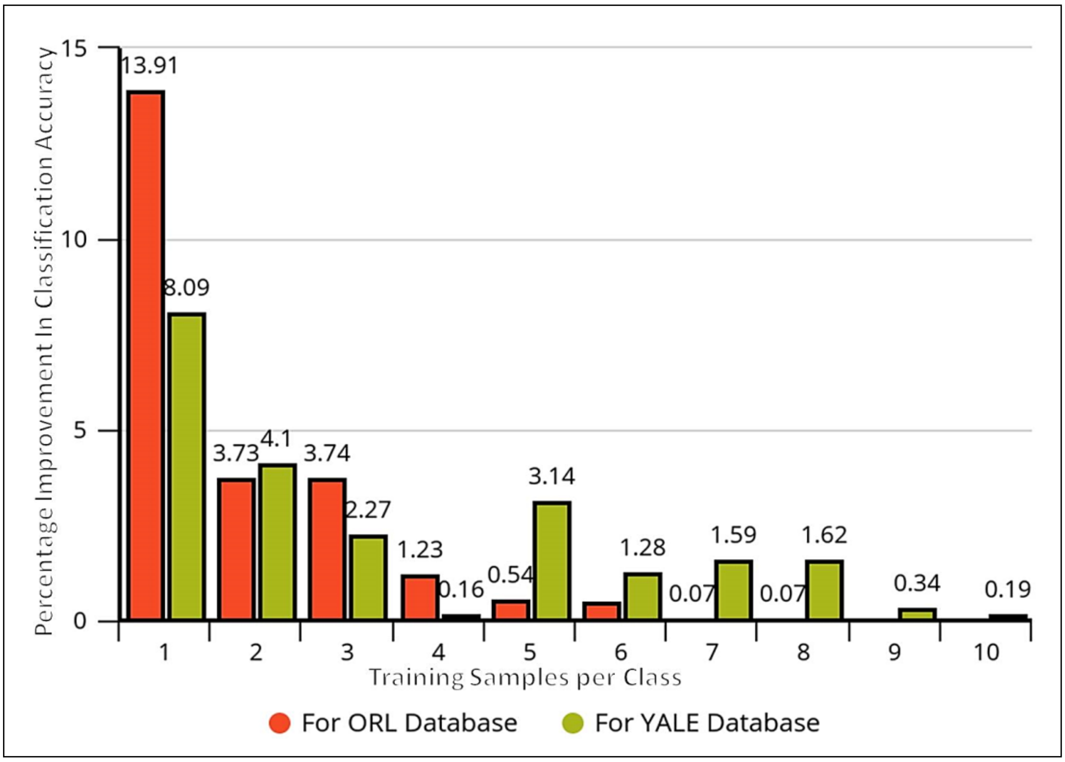

Fig. 4. *Percentage Improvement in Classification Accuracy.*

CONCLUSION

The project presents the effective face recognition using hybrid meta-heuristic algorithm. PSOGSA algorithm gives significantly extreme result by effectively using the benefits of linear widely spaced approximations with multi-modal combined feature extraction. A vector is developed by fusing local texture feature and a global color feature. Two databases ORL and YALE are used to calculate the classification performance of the method. Classification accuracy is compared for various training samples per class. Further, superiority of proposed method is proven by analyzing percentage improvement in classification accuracy. With restricted availability of training sample, percentage improvement is efficacious for face recognition applications. Further, this work can be applied in various applications of image retrieval. Face recognition problems with varying poses and expressions can be dealt more efficiently with this technique in the coming future.

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Cite this Article
Purvaa Saxena, Gargi Mishra, Apoorva Aggarwal, Ayush Priyadarshi, Nitin Kumar, Rahul. Pattern Recognition Using Hybrid Meta-Heuristic. *Journal of Artificial Intelligence Research & Advances*. 2019; 6(2): 100–108p.