PERFORMANCE EVALUATION OF ENHANCED MAYFLY ALGORITHM ON UNIMODAL AND BIMODAL FUNCTION

OLADIMEJI Adegbola Isaac[1], ABOLARINWA Michael Olugbenga[2]
[1]Department of Computer Science, Aminu Saleh College of Education, Azare Nigeria
[2]Department of Cyber Security, Osun State University, Osogbo Nigeria

[1]oladimejiadeisaac@gmail.com, gbenga1abolarinwa@gmail.com

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Abstract: - *The mayfly optimization algorithm was proposed with a better hybridization of the particle swarm optimization and the differential evolution algorithms. In its original form, it cannot be used for high dimensional space problems such as feature selection, due to some of its identified limitations. This study improved the conventional mayfly algorithm, carried out experiments on the performance of the enhanced mayfly algorithm on both single and bimodal functions. The experimental results obtained revealed that the bimodal function under the enhanced mayfly algorithm technique gave 97.36% in terms of recognition accuracy, 1.79% false acceptance rate, 2.92% false rejection rate compared with single modality. Given this, an automated bi-modal recognition system would produce a more reliable accurate, and secure bi-modal recognition system on any repository system as a result of its high accuracy.*

1. INTRODUCTION

Optimization is the process of finding the best solution for a function (its minimum value or maximum value). The Mayfly optimization method can be considered a modification of particle swarm optimization and combines the main advantages of particle swarm optimization, genetic algorithm, and the Firefly algorithm. It provides a powerful hybrid algorithm framework, based on mayfly behavior, for researchers trying to improve swarm optimization algorithm performance using techniques such as crossover [1] and local search [2], as particle swarm optimization, has been shown to require some modifications to ensure optimal scores when run in high-dimensional space [3].

During testing of the baseline Mayfly algorithm, stability issues were identified related to the disruption of existing solutions due to speed. The early convergence behavior of the algorithm was also noted due to the lack of balance between exploitation and exploration [3,4]. To address these shortcomings, improved modifications of the algorithm have been developed. In this paper, the performance evaluation of the improved Mayfly algorithm on single-modal and bi-modal functions is presented.

2. RELATED WORK

Xing et al, 2022 [5], introduces a modified Mayfly Algorithm (modMA), which employs an exponent decreasing inertia weight (EDIW) strategy, adaptive Cauchy mutation, and an enhanced crossover operator to effectively search the UAV configuration space and discover the path with the lowest overall cost. Finally, the proposed modMA is evaluated on 26 benchmark functions as well as the UAV route planning problem, and the results demonstrate that it outperforms the other compared algorithms.

Zhao and Gao, 2020 [6], proposed the modified mayfly algorithm which improved with Chebyshev map, simulation experiments were carried out and results showed that the improved algorithm would indeed increase the capability.

Gao et al., 2020 [7], proposed the improved mayfly optimization algorithm with opposition based learning rules. Literal researches proved that not only the best candidates or the best historical trajectories would perform well in guiding the individuals in swarms to find the best solution, the worst and the worst historical trajectories would also work well in doing so. Such situations could be directly treated as pairs of oppositions, and satisfied the ancient Chinese Yin-Yang philosophy, where the opposition based learning (OBL) rule was directly derived from. In this paper, the improved mayfly optimization (MO) algorithm with OBL rules were proposed, simulation experiments were carried out and results showed that the improved MO algorithm with OBL rules would perform better than usual.

Gao et al., 2020 [8]. The mayfly optimization (MO) algorithm was proposed with a better hybridization of the particle swarm optimization (PSO) and the differential evolution (DE) algorithms. The velocity would be relevant to the Cartesian distance among the relevant individuals. In this paper, a reasonable revision for the velocity updating equations was proposed based on the idea of moving towards each other as capable as they can. Simulation results proved that the improved MO algorithm would perform better than the original one.

Juan and Zheng-Ming, 2020 [9], introduced bare bones mayfly optimization algorithm. Although individuals in the mayfly optimization (MO) swarms would have a chance to dance around the current positions, most of them would still perform exploration according to their best historical trajectories and the global best candidates, which was quite similar to the behavior performed by individuals in the particle swarm optimization (PSO) algorithm. Therefore, there would also exist the stochastic Gauss distribution among the exploration, exploitation for individuals in MO swarms. The paper, the bare bones MO algorithm was proposed and simulation experiments were carried out. Results verified that the bare bones MO algorithm would perform better than before.

Zhang et al., 2022 [10], noted that conventional mayfly algorithm has too many parameters, which makes it difficult to set and adjust a set of appropriate parameters for different problems. In order to avoid adjusting parameters, a bioinspired bare bones mayfly algorithm (BBMA) is proposed. The BBMA adopts Gaussian distribution and Levy flight, which improves the convergence speed and accuracy of the algorithm and makes better exploration and exploitation of the search region. This study provides a mathematical model for solving a variant of the MST problem, in which all points and solutions are on a sphere. By comparing and analysing the results of BBMA and other swarm intelligence algorithms in sixteen scales, the experimental results illustrate that the proposed algorithm is superior to other algorithms for the MST problems on a sphere

4. METHODOLOGY

In the existing algorithm, velocities must be reduced to better control the balance between exploration and exploitation abilities of the Mayflies. The gravity coefficient (g) as described in equation $x^{t+1}{}_{i} = x_{t}{}^{i} + v^{t+1}$ assists the achievement of a sufficient balance between exploration and exploitation. The gravity coefficient was fixed in the range of [0, 1] and gradually reduced over the iterations, allowing the existing algorithm to exploit specific areas in the search space. This has made it difficult for existing algorithm to be used to solve high dimensional problem spaces such as feature selection. This study introduced a new gravity coefficient g to exploit large specific areas and will make it possible for the enhanced algorithm to be used for high dimensional problem spaces. The new gravity coefficient g widens the search space in the range of [-1, 1].

In this paper, a roulette selection process is introduced to model the attraction process as a deterministic process, that is, the probability of attracting the best females and the best male from the following population is proportional to its physical strength, the better the physical strength, the more the chances of attracting the best females and the best male from the next population are directly proportional to his fitness best males to attract the best females, instead of the random selection process used in existing algorithm. The attraction between the best female and the best male can be expressed by spinning a roulette wheel whose number of pockets is equal to the number of best females and males in the current population, with sizes depending on their probability. This was created to solve the fitness function limitations common with most optimization algorithms.

Algorithm1: Enhanced Mayfly Algorithm

Step 1: Initialize the male mayfly population $\boldsymbol{x_{ij}^0}$ (i=1,2, …, N) and velocities $\boldsymbol{v_{ij}^0}$,

Initialize the female mayfly population $\boldsymbol{y_{ij}^0}$ (i=1,2, …, M), $\boldsymbol{Max_{iter}}$ =max. no of iteration

Step 2: Set iteration t = 1

Step 3: Evaluate the objective function values of male and female mayflies as $\boldsymbol{f(x) = f(x_i^t)}$.

Step 4: Find the personal best for each male and female as $\boldsymbol{P_{best,iD}^t = x_i^t}$ and global best as $\boldsymbol{G_{best,iD} = min\{P_{best,iD}^t\}}$

Step 5: Calculate gravity coefficient:

The gravity coefficient g can be a fixed number in the range of [-1, 1], or it can be gradually reduced over the iterations, allowing the algorithm to exploit some worst and best specific areas as demonstrated in the equation

$$\boldsymbol{g = g_{std} - \frac{(g_{std} - g_{\text{mean}}) * (iter_{max} - iter + 1)}{iter_{max}} - iter}$$

Step 6: Update velocities and solution of males and females

Using roulette wheel selection $(\boldsymbol{p_i})$

$$\boldsymbol{p_i = rand \leq \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)}}$$

$$\boldsymbol{V_{std} = p_i * (x_{std} - x_{mean}) \text{ where } rand \,\epsilon\, (0, 1)}$$

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Step 7: Evaluate Solutions

$$\boldsymbol{f(x) = f(x_i^{t+1})}$$

Step 8: Mate the mayflies and Evaluate the offspring

$$\boldsymbol{offsprint1 = L * male + (1 - L) * female}$$

$$\boldsymbol{offsprint2 = L * male + (1 - L) * male}$$

Step 10: Update $\boldsymbol{Gbest}$ of the population

Step 11: If t $< \boldsymbol{Max_{iter}}$ then t $\boldsymbol{= t + 1}$ and GOTO step 1 else GOTO step l2

Step 12: Output optimum feature selected solution as $\boldsymbol{Gbest_{bD}}$.

$$\boldsymbol{Gbest_{bD} = x_b}$$

5. IMPLEMENTATION OF THE SINGLE AND BI MODAL FUNCTION

An interactive Graphic User Interface (GUI) application was developed with acquired Oladimeji Adegbola Isaac (OAI) database of face and iris dataset. The GUI was designed using toolboxes such as image processing and computer vision and optimization in MATLAB 2018a. The MATLAB software package was used for the implementation on a computer system with a considerably specification.

6. PERFORMANCE EVALUATION

A digital camera was used to acquire the face and iris biometric data from users. Face and iris images of 190 subjects with 3 different samples was captured with a size of 640 by 480 pixels. The two biometric traits were downsized into 128 by 128 pixels without any alteration in the images. All images taken have equal uniform illumination conditions and light colour background. The database was populated with 570 images per modality. 60% was used to train the system and 40% was used for authentication. The choice of dataset division was based on random sampling cross-validation method.

The performance was assessed using metrics like False Acceptance Rate (FAR), False Rejection Rate (FRR), and Recognition Accuracy (RA). A digital camera was used to capture the user's face and iris. After applying an appropriate preprocessing technique, such as grayscale conversion, picture enhancement, image cropping, and image segmentation for each modality using Principal Component Analysis, biometric characteristics was recovered from each individual's face and iris. The extracted features was combined using the feature concatenation method at the level of feature extraction. To pick features, formulated Enhanced Mayfly Algorithm (EMA) was used to choose the best characteristics. Support Vector Machine (SVM) was utilized as the classification method.

7, RESULT AND DISCUSSION

The results obtained in Table 1 - Table 2 showed the performance of the techniques employed in this work both on single-modal and bi–modal functions.

The results showed that there is significant variation in the performance metrics with an increase in threshold value and the best result is obtained at the threshold value of 0.76 across all metrics (false rejection rate, false acceptance rate, and accuracy) for Face, Iris (single modal) and fused face – Iris bi – modal) respectively.

Therefore, the performance of the developed technique is more dependent on the threshold value.

Table 1: Result of (face, iris) unimodal using Enhance Mayfly Algorithm (EMA) at 0.76 threshold value

Modalities	Algorithm	FAR(%)	FRR(%)	ACC(%)
Face	EMA	5.36	6.43	93.86
Iris	EMA	5.26	7.02	93.42

Table 2: Result of (fused face and Iris) bi – modal function using Enhance Mayfly Algorithm (EMA) at 0.76 threshold value

Modalities	Algorithm	FAR(%)	FRR(%)	ACC(%)
Face + Iris	EMA	1.79	2.92	97.36

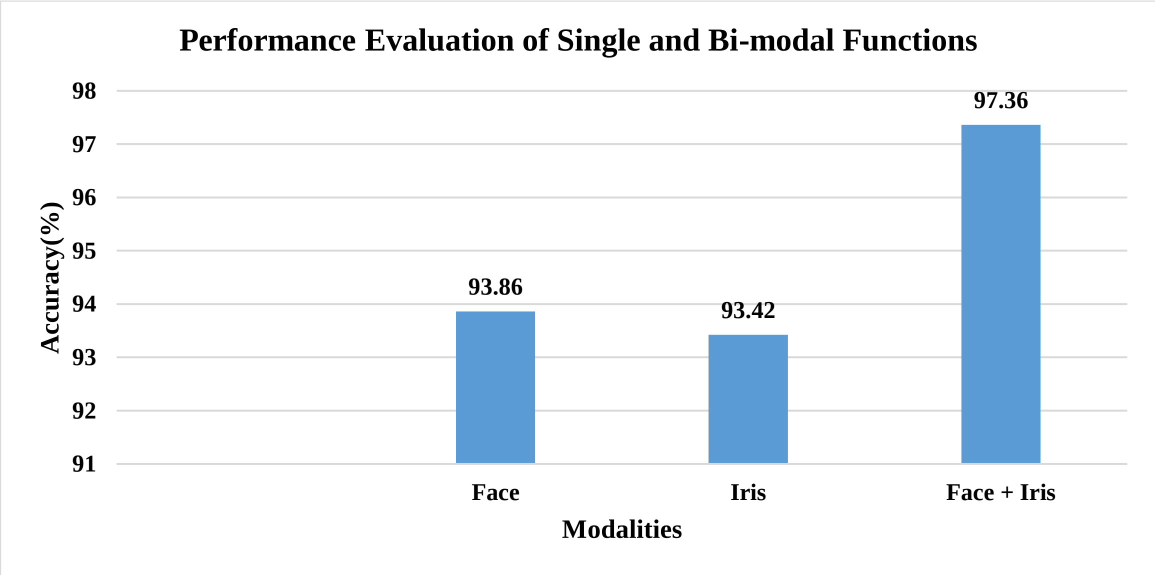

Figure 1. Performance Evaluation of Single and Bi-modal Functions

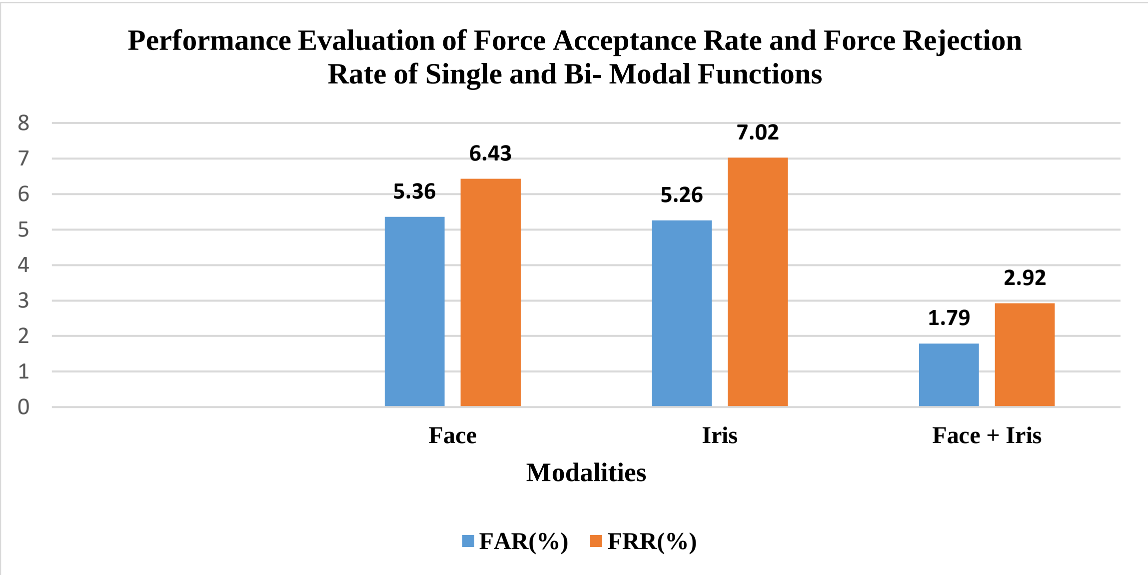

Figure 2. Performance Evaluation of Force Acceptance Rate and Force Rejection Rate of Single and Bi- Modal Functions

The study discovered that (the fused face–iris) bi-modal function has better performance in accuracy, false acceptance rate, and false rejection rate than (face, iris) Single modal function as enumerated in Tables 1 and 2, also in Figure 1 and 2, single modal gave recognition accuracy of 93.42% with iris modality, and 93.86% accuracy with face modality. And 97.36% with bi-modal (face-iris), at a threshold of 0.76 respectively. Likewise, comparing the Force Acceptance Rate and Force Rejection Rate (FRR) between single and bi–modal functions, it was discovered that the bi-modal function has a lower Force Acceptance Rate (FAR) and Force Rejection Rate (FRR) compared to single-modal function. This can be inferred that the enhanced algorithm will perform better on Multimodal functions.

8. CONCLUSION

This paper evaluated the performance of enhanced mayfly algorithm on the essential features of unimodal (iris and Face) and bimodal (fused face and iris) biometrics systems. Three hundred and forty-two (342) irises were trained and two hundred and twenty-eight (228) irises were used to test the developed technique at thresholds 0.76.

The experimental results obtained revealed that the fused face and iris under the enhanced mayfly algorithm technique gave 97.36% in terms of recognition accuracy, 1.79% false acceptance rate and 2.92% false rejection rate compared with face and iris modality. Given this, an automated bi-modal recognition system based on fused iris and face (that is, both face and iris), would produce a more reliable accurate, and secure bi-modal recognition system on any repository system as a result of its high accuracy.

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