University of Ibadan
Journal of Science and Logics in ICT Research

The Enhanced Mayfly Optimization Algorithm with Roulette Wheel Selection

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Abstract
In the year 2020, the Mayfly optimization method was proposed. It is a modification of particle swarm optimization and it combines major advantages of particle swarm optimization, genetic algorithm, and firefly algorithm. Mayfly flight and mating activity were the inspiration for this piece. Simulated in many tests using various benchmark functions, all of which were found to be capable of optimization, although some drawbacks, like a sluggish or premature convergent rate, and a probable imbalance between exploration and exploitation, have yet to be handled, necessitating modification for improved performance. The Mayfly Algorithm hasn't been used much for feature selection problems, to the author's knowledge. In this study, the Mayfly algorithm was enhanced with the Roulette Wheel Selection method been the most common and straightforward method of fitness-proportionate selection, free of bias, because each individual is given a fair chance of selection, preserving diversity. On the constructed database, the evaluation is based on the force acceptance rate, force rejection rate, recognition accuracy, and recognition time. The created database is mainly for purpose of this study. Five hundred and seventy images (570) of face and iris were acquired via digital camera, three hundred and forty-two (342) face and iris images were used for training which equals 60% of the total dataset and two hundred and twenty-eight (228) face and iris images which are equivalent to 40% of the total dataset were used for testing. Both unimodal and multimodal recognition systems were used in the stimulation trials. The optimal result was achieved on a fused recognition system at a threshold of 0.76. The findings reveal a 1.79% force acceptance rate, 2.92% force rejection rate, 97.36% recognition accuracy, and 181.52 sec recognition time for enhanced Mayfly algorithm (EMA) as against 3.51% force acceptance rate, 5.26% force rejection rate, 95.18% recognition accuracy, and 215.75 sec recognition time for original Mayfly algorithm (MA). Obtained results showed that the enhanced algorithm would indeed increase the capability of the original Mayfly algorithm.

Keywords: *Enhanced Mayfly algorithm; Recognition system; Recognition accuracy; Recognition time.*

1. Introduction

Around the world, there is a rapid increase in security risks and challenges. The security domain uses various authentication methods to keep information protected which has resulted in researchers developing several techniques for both identification and verification in trying to proffer solutions to these challenges. Research as it that the human face is a key to security. Face recognition technology has received laudable acceptance by both law enforcement and other agencies [1]. But no single trait can be suitable for all applications and hence using a fused biometric system will compensate for the limitations of a unimodal biometric system [2]. By limiting the limits of unimodal systems, fused or multimodal biometric systems strive to increase recognition accuracy [3].

Fusing two or three biometrics considers no rule for their selection, so by fusing iris and face we can have a multimodal biometric framework. Most time, the selection of biometrics is through experiment and error because there are no guidelines for this, which does not disregard the capability of many proposed frameworks [4]. [3], detailed that several studies have shown the viability and force of multimodal biometric frameworks dependent on combination before coordinating (include level combination) and combination after coordinating (match score-

Oladimeji, A. I., Asaju-Gbolagade A. W. and Gbolagade K. A. (2022). The Enhanced Mayfly Optimization Algorithm with Roulette Wheel Selection, *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 8 No. 1, pp. 29 – 38

level combination). The particle swarm optimization (PSO) algorithm is extensively used to select the features from modality sources in several multimodal systems [5, 6]. In this study, the Mayfly optimization algorithm that was just proposed in the year 2020 combines major advantages of particle swarm optimization (PSO), genetic algorithm (GA), and firefly algorithm FA [7] will be enhanced with roulette wheel selection procedure, the enhanced algorithm will be used to select the features from face and iris modality sources for experimental stimulation.

The rest of this paper will be structured as follows: Section 2 would briefly describe the Roulettes wheel selection and Mayfly algorithm, the proposed enhanced version of the Mayfly algorithm will be compared in Section 3, and Result simulation experiments carried on unimodal and multimodal bench functions would be discussed in Section 4. In Section 5, conclusions would be drawn.

2. Literature Review

2.1 Roulette Wheel Selection

In roulette wheel selection, the fundamental piece of the choice interaction is to stochastically choose from one age to make the premise of the future [8]. It is the most common and straightforward method of fitness-proportionate selection [14]. Each person in the population is given a portion of an imaginary roulette wheel proportional to their fitness. The fittest candidate has the largest wheel section, while the weakest has the smallest. It is free of bias since each individual is given an equal opportunity for selection, sustaining diversity [14].

Roulette wheel selection is a hereditary administrator utilized in genetic algorithms for choosing possibly valuable answers for recombination. The ideal is that the fittest people have a more noteworthy possibility of endurance than more fragile ones. This implies fitter people will generally have a superior likelihood of endurance and will go ahead to shape the mating pool for the future and more vulnerable people are not without a possibility [8]. In nature, such people might have the hereditary coding that might demonstrate valuable to people in the future.

In Implementing roulette wheel selection, the following steps are used –

- S is equal to the sum of finesses.
- Make a number between 0 and S at random.
- Continue adding finesses to the partial total P, starting at the top of the population, until P<S
- The chosen individual is the one for whom P exceeds S.

The fitness level is used to assign a selection probability to each chromosome. If is f_i the fitness of individual I in the population, then its chance of getting chosen is

$$p_i = \frac{f_i}{\sum_{j=i}^{N} f j_i}$$

Where N is the population size [9].

2.2 Mayfly Algorithm

The Mayfly optimization algorithm can be considered as a modification of particle swarm optimization (PSO) and it combines major advantages of particle swarm optimization (PSO), genetic algorithm (GA), and firefly (FA) [10] to simulate the social behavior, especially the mating process displayed by the mayflies in nature [11]. It has a sophisticated hybrid algorithm structure that is based on Mayfly behavior. The mating process and flight behavior of mayflies are translated as a mathematical model to be used in solving the optimization problem [11].

In the Mayfly algorithm, males gather in swarms which implies that the position of each male Mayfly is adjusted according to both its own experience and that of its neighbors.

Basic steps of the Mayfly algorithm:-

Objective function f(x), x=($x1,\ldots,xd$)T
Initialize the male Mayfly population (i = ,2,…,N) and velocities vmi
Initialize the female Mayfly population (i = ,2,…,M) and velocities vfi
Evaluate solutions
Find global best $gbest$

Do While stopping criteria are not met
Update velocities and solutions of males and females
Evaluate solutions
Rank the mayflies
Mate the mayflies
Evaluate offspring
Separate offspring to male and female randomly
Replace worst solutions with the best new ones
Update $pbest$ and $gbest$
End while
Post process results and visualization.

Despite its notable capability, some shortcomings such as a slow or premature convergent rate, and a probable imbalance between exploration and exploitation, have yet to be handled, necessitating modification for improved performance [10].

2.3 Related Literature

Zhao and Gao, [18] present the bare-bones Mayfly optimization algorithm. The study introduced the Monte Carlo method, and further simulation experiments on non-symmetric benchmark functions, which proved to be difficult to optimize for some optimizers were carried out. The study finds out the difference between the bare-bones Mayfly optimization and the traditional Mayfly optimization algorithm which would rely on another opportunity for individuals to update their positions. Individuals would have another chance to change their locations with stochastic rules in the bare-bones Mayfly optimization method. The study concluded that if the individuals had multiple choices to update their positions, their capabilities of optimizing might be increased. Simulation experiments and results verified that the bare bones Mayfly algorithm would perform better than the conventional Mayfly algorithm.

Bhattacharyya et al., [13] presented a new feature selection algorithm called Mayfly-Harmony Search (MA-HS) based on two meta-heuristics namely Mayfly Algorithm and Harmony Search. The suggested approach was tested against twelve different state-of-the-art meta-heuristic FS algorithms on 18 UCI datasets. Three high-dimensional microarray datasets were also used in the experiments. The research continues by demonstrating the algorithm's robustness by applying it to high-dimensional microarray datasets.

Zhao and Gao, [12] present the multi-start Mayfly optimization algorithm, The Mayfly optimization algorithm was updated to include multi-start approaches, and the male mayflies were reinitialized in the same way as before. The multi-start Mayfly method performed better than the original Mayfly algorithm, according to simulation data.

Shaheen et al., [15] introduced an exact demonstration of the PEM energy component improved turbulent Mayfly optimization algorithm. This exploration principally focuses on an exact displaying of the proton trade layer energy unit (PEMFC) that gives a great match between the reenactment results and those deliberate.

Zhao and Gao [16] introduced the Chebyshev map to the enhanced Mayfly optimization algorithm, which could be a decent decision to supplant the irregular numbers in uniform appropriation associated with the first Mayfly optimization algorithm. Simulation experiments were carried out and results showed that the improved algorithm would indeed increase the capability.

Gao et al. [17] present an enhanced Mayfly optimization (MO) method with OBL rules. Simulation experiments were conducted, and the results showed that the improved Mayfly optimization algorithm with OBL rules performed better than usual.

3. Methodology

Algorithm 1. 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 a male and female mayflies as

$$f(x) = f(x_i^t) .$$

where $\boldsymbol{f}: \boldsymbol{R^n} \rightarrow \boldsymbol{R}$ is the objective function that evaluates the quality of a solution

$$f(x) = \sum_{k=2}^{m} \left[\sum_{i=1}^{n} \left(x_{i,k-1} - x_{i,k} \right)^2 \right]$$

Where $\boldsymbol{x_i^t}$ represents the features at *i=1,2, …, n* and *k=2,3, …, m*

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

Step 5: Calculate gravity coefficient:
The gravity coefficient g can be a fixed number in the range of [0, 1], or it can be gradually reduced over the iterations, allowing the algorithm to exploit some specific areas, by being updated through the following equation:

$$g = g_{max} - \frac{g_{max} - g_{min}}{iter_{max}} - iter$$

where $\boldsymbol{g_{max}}$ and $\boldsymbol{g_{min}}$ are the maximum and minimum values that the gravity coefficient can take, $\boldsymbol{iter}$ is the current iteration of the algorithm and $\boldsymbol{iter_{max}}$ is the maximum number of iterations.

Step 6: Update velocities and solution of males and females
$V_{max} = rand * (x_{max} - x_{min})$ *where* $rand \epsilon (0,1)$

where $\boldsymbol{x_{max}}$ and $\boldsymbol{x_{min}}$ are the search space limits for the fitness function,

$$\boldsymbol{v_{ij}}^{t+1} = \begin{cases} \boldsymbol{v_{max}}, & \boldsymbol{if\ v_{ij}}^{t+1} > \boldsymbol{v_{max}} \\ -\boldsymbol{v_{max}}, & \boldsymbol{if\ v_{ij}}^{t+1} < -\boldsymbol{v_{max}} \end{cases}$$

$$\boldsymbol{v_{ij}}^{t+1} = \boldsymbol{g} * \boldsymbol{v_{ij}}^{t} + \boldsymbol{\alpha_1}\, \boldsymbol{e}^{-\beta r_p^2}\left[\boldsymbol{pbest_{ij}} - \boldsymbol{x_{ij}}^{t}\right] + \boldsymbol{\alpha_2}\, \boldsymbol{e}^{-\beta r_g^2}\left[\boldsymbol{gbest_j} - \boldsymbol{x_{ij}}^{t}\right]$$

Where $\boldsymbol{\beta}$ is a fixed visibility coefficient that is used to limit a Mayfly's visibility to others, $\boldsymbol{r_p}$ is the Cartesian distance between $\boldsymbol{x_i}$ and $\boldsymbol{pbest_{ij}}$ and $\boldsymbol{r_g}$ is the Cartesian distance between $\boldsymbol{x_i}$ and $\boldsymbol{gbest}$. The distances are calculated as:

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n}(x_{ij} - X_{ij})^2}$$

Where $\boldsymbol{x_{ij}}$ is the *j^th^* element of Mayfly *i* and $\boldsymbol{X_{ij}}$ corresponds to $\boldsymbol{pbest_{ij}}$ or $\boldsymbol{gbest}$..

$$x_i^{t+1} = x_i^{t} + v_{ij}^{t+1}$$

With $\boldsymbol{x_i}^{\boldsymbol{0}} \sim \boldsymbol{U}(\boldsymbol{x_{min}}, \boldsymbol{x_{max}})$ male Mayfly

$$y_i^{t+1} = y_i^{t} + v_{ij}^{t+1}$$

With $\boldsymbol{y_i}^{\boldsymbol{0}} \sim \boldsymbol{U}(\boldsymbol{y_{min}}, \boldsymbol{y_{max}})$ female Mayfly

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2\, e^{-\beta r_{mf}^2 (x_{ij}{}^{t} - y_{ij}{}^{t})} & \text{if } f(y_i) > f(x_i) \\ v_{ij}^{t} + fl * r & \text{if } f(y_i) \le f(x_i) \end{cases}$$

Where $\boldsymbol{v_{ij}^t}$ is the velocity of female Mayfly $\boldsymbol{i}$ in dimension $j = 1, \ldots, n$ at time step t, $\boldsymbol{y_{ij}}^{\boldsymbol{t}}$ the position of female Mayfly $\boldsymbol{i}$ in dimension $\boldsymbol{j}$ at time step $\boldsymbol{t}$, $\boldsymbol{\alpha_2}$ is a positive attraction constant and $\boldsymbol{\beta}$ is a fixed visibility coefficient, while $\boldsymbol{r_{mf}}$ is the Cartesian distance between male and female mayflies, calculated using equation $\{V_1, V_2, \ldots, V_p\}$.

Finally, $\boldsymbol{fl}$ is a random walk coefficient, used when a female is not attracted by a male, so it flies randomly and r is a random value in the range of [-1, 1].

Step 7: Evaluate Solutions

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

where $\boldsymbol{f}: \boldsymbol{R^n} \to \boldsymbol{R}$ is the objective function that evaluates the quality of a solution

Step 8: Mate the mayflies and evaluate offspring

$$offsprint1 = L * male + (1 - L) * female$$

$$offsprint2 = L * male + (1 - L) * male$$

where $\boldsymbol{male}$ is the male parent, $\boldsymbol{female}$ is the female parent and L is a random value within a specific range. The starting velocities of the offspring are set to zero.

Step 9: Update $\boldsymbol{Pbest}$ of the population

$$pbest_i \begin{cases} x_i^{t+1}, & \text{if } f(x_i^{t+1}) > f(pbest_i) \\ \text{is kept the same}, & \text{otherwise} \end{cases}$$

Step 10: Update $\boldsymbol{Gbest}$ of the population
At time step t, the global best position gbest is defined as

$$\boldsymbol{gbest} \in \{\boldsymbol{pbest_1}, \boldsymbol{pbest_2}, \ldots, \boldsymbol{pbest_N} \mid \boldsymbol{f}(\boldsymbol{cbest})\} = \mathbf{min}\{\{\boldsymbol{f}(\boldsymbol{pbest_1}), \boldsymbol{f}(\boldsymbol{pbest_2}), \ldots, \boldsymbol{f}(\boldsymbol{pbest_N})|\}$$

Where N is the total number of male mayflies in the swarm,

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 $\boldsymbol{Gbest_{bD}}$.

$$Gbest_{bD} = x_b \quad [10]$$

Algorithm 2. Enhanced Mayfly Algorithm with Roulette Wheel Selection

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 a male and female Mayfly as $\boldsymbol{f}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{x_i^t})$. where $\boldsymbol{f}: \boldsymbol{R^n} \to \boldsymbol{R}$ is the objective function that evaluates the quality of a solution

$$f(x) = \sum_{k=2}^{m}\left[\sum_{i=1}^{n}\left(x_{i,k-1} - x_{i,k}\right)^2\right]$$

Where $\boldsymbol{x_i^t}$ represents the features at *i=1,2, …, n* and *k=2,3, …, m*

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

$G_{best,iD} = \min\{P^t_{best,iD}\}$

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

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

where $\boldsymbol{g_{std}}$ and $\boldsymbol{g_{mean}}$ are the standard deviation and mean values that the gravity coefficient can take, $\boldsymbol{iter}$ is the current iteration of the algorithm and $\boldsymbol{iter_{max}}$ is the maximum number of iterations.

Step 6: Update velocities and solution of males and females
Using roulette wheel selection ($\boldsymbol{p_i}$)

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

$V_{std} = p_i * (x_{std} - x_{mean})$ where rand ϵ (0,1)

where $\boldsymbol{x_{std}}$ and $\boldsymbol{x_{mean}}$ are the search space limits for the fitness function,

$$v_{ij}{}^{t+1} = \begin{cases} v_{std}, & \text{if } v_{ij}{}^{t+1} > v_{std} \\ -v_{std}, & \text{if } v_{ij}{}^{t+1} < -v_{std} \end{cases}$$

$$\boldsymbol{v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2\, e^{-\beta r_{mf}^2 (x_{ij}{}^t - y_{ij}{}^t)} & if\ f(y_i) > f(x_i) \\ v_{ij}^{t} + fl * p_i & if\ f(y_i) \le f(x_i) \end{cases}}$$

Where $\boldsymbol{\beta}$ is a fixed visibility coefficient that is used to limit a Mayfly's visibility to others, $\boldsymbol{r_p}$ is the Cartesian distance between $\boldsymbol{x_i}$ and $\boldsymbol{pbest_{ij}}$and $\boldsymbol{r_g}$ is the Cartesian distance between $\boldsymbol{x_i}$ and $\boldsymbol{gbest}$. The distances are calculated as:

$$\|x_i - X_i\| = \sqrt{\sum_{j=1}^{n} (x_{ij} - X_{ij})^2}$$

Where $\boldsymbol{x_{ij}}$ is the *j^th^* element of Mayfly *i* and $\boldsymbol{X_{ij}}$ corresponds to $\boldsymbol{pbest_{ij}}$ or $\boldsymbol{gbest}$..

$$x_i{}^{t+1} = x_i{}^t + v_{ij}{}^{t+1}$$

With $\boldsymbol{x_i{}^0 \sim U(x_{mean}, x_{std})}$ male Mayfly

$$y_i{}^{t+1} = y_i{}^t + v_{ij}{}^{t+1}$$

With $\boldsymbol{y_i{}^0 \sim U(y_{mean}, y_{std})}$ female Mayfly

Using roulette wheel selection $\boldsymbol{p_i}$

$$p_i = r \le \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)}$$

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^t + \alpha_2\, e^{-\beta r_{mf}^2 (x_{ij}{}^t - y_{ij}{}^t)} & \text{if } f(y_i) > f(x_i) \\ v_{ij}^t + fl * p_i & \text{if } f(y_i) \le f(x_i) \end{cases}$$

Where $\boldsymbol{v_{ij}^t}$ is the velocity of female Mayfly $\boldsymbol{i}$ in dimension $j = 1, \ldots, n$ at time step t, $\boldsymbol{y_{ij}{}^t}$ the position of female Mayfly $\boldsymbol{i}$ in dimension $\boldsymbol{j}$ at time step $\boldsymbol{t}$, $\boldsymbol{\alpha_2}$ is a positive attraction constant and $\boldsymbol{\beta}$ is a fixed visibility coefficient, while $\boldsymbol{r_{mf}}$ is the Cartesian distance between male and female mayflies, calculated using equation $V = \{V_1, V_2, \ldots, V_p\}$. Finally, $\boldsymbol{fl}$ is a random walk coefficient, used when a female is not attracted by a male, so it flies deterministically by roulette wheel selection and r is a random value in the range of [-1, 1].

Step 7: Evaluate Solutions

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

where $\boldsymbol{f: R^n \to R}$ is the objective function that evaluates the quality of a solution

Step 8: Mate the mayflies and Evaluate offspring
$offsprint1 = L * male + (1 - L) * female$

$offsprint2 = L * male + (1 - L) * male$

where male represents the male parent, female represents the female parent, and $\boldsymbol{L}$ is a random value within a given range. The offspring's initial velocities are set to zero.

Step 9: Update $\boldsymbol{Pbest}$ of the population

$$pbest_i = \begin{cases} x_i^{t+1}, & \text{if } f(x_i^{t+1}) > f(pbest_i) \\ \text{is kept the same}, & \text{otherwise} \end{cases}$$

Step 10: Update $\boldsymbol{Gbest}$ of the population
At time step t, the global best position gbest is defined as

$$gbest \in \{pbest_1, pbest_2, \ldots, pbest_N \mid f(cbest)\} = \min\{\{f(pbest_1), f(pbest_2), \ldots, f(pbest_N)\}\}$$

Where N is the total number of male mayflies in the swarm,

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 $\boldsymbol{Gbest_{bD}}$.

$$Gbest_{bD} = x_b$$

Algorithm 1 described the existing Mayfly Algorithm (MA) and Algorithm 2 demonstrated the Enhanced Mayfly Algorithm (EMA). In a conventional Mayfly algorithm, male mayflies gathering in swarms, implies that the position of each male Mayfly is adjusted according to both its own experience and that of its neighbors. The velocity of a male Mayfly was calculated as

$$v_{ij}{}^{t+1} = g * v_{ij}{}^{t} + \alpha_1 e^{-\beta r_p^2}\left[pbest_{ij} - x_{ij}{}^{t}\right] + \alpha_2 e^{-\beta r_g^2}\left[gbest_j - x_{ij}{}^{t}\right]$$

(1)

Where β is a fixed visibility coefficient used to limit the visibility of a Mayfly to others, r_p is the Cartesian distance between x_i and $pbest_{ij}$and r_g is the Cartesian distance between x_i and $gbest$. It is important for the functioning of the algorithm that the best mayflies in the swarm continue to perform their characteristic up-and-down nuptial dance. Hence, the best mayflies must keep changing their velocities, which in such a case was calculated as

$$v_{ij}^{t+1} = v_{ij}^{t} + fl * r \tag{2}$$

where $\boldsymbol{fl}$ is the random walk coefficient and $\boldsymbol{r}$ is a random value in the range [-1, 1]. This up and down movement introduces a stochastic element to the algorithm.

But female mayflies do not gather in swarms, unlike male mayflies. They instead fly toward mal to breed. Whereas, the attraction process used was randomized. Consequently, their velocities are calculated as

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2 e^{-\beta r_{mf}^2 (x_{ij}{}^{t} - y_{ij}{}^{t})} & if\ f(y_i) > f(x_i) \\ v_{ij}^{t} + fl * r & if\ f(y_i) \le f(x_i) \end{cases} \tag{3}$$

Where v_{ij}^{t} is the velocity of female Mayfly i in dimension j = 1, …, n at time step t, $y_{ij}{}^{t}$ the position of female Mayfly i in dimension j at time step t , α_2 is a positive attraction constant and β is a fixed visibility coefficient, while r_{mf} is the Cartesian distance between male and female mayflies. Finally, *fl* is a random walk coefficient, which is utilized when a female is not attracted to a male and hence flies randomly, and r is a random number between [-1 and 1].

In this proposed, the roulette wheel selection procedure is introduced to model the attraction process as a deterministic process. That is, the probability of attracting the best female and best male of the next population is proportional to its fitness, the better the fitness is, the higher chance for the best male to attract the best female. The attraction between the best female and best male can be depicted as spinning a roulette that has as many pockets as there are the best female and best male in the current population, with sizes depending on their probability. The probability of attracting the best female to the best male is equal to p_i

$$\mathrm{p_i} = \mathrm{rand} \le \frac{\mathrm{f(x_i)}}{\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{f(x_i)}} \tag{4}$$

Where $f(x_i^t)$ is the fitness of x_i, es$rand \in (0,1)$ and N is the size of the current population
The new velocity and characteristic up-and-down nuptial dance are described in Equation (5).

$$v_{ij}^{t+1} = \begin{cases} v_{ij}^{t} + \alpha_2 e^{-\beta r_{mf}^2 (x_{ij}{}^{t} - y_{ij}{}^{t})} & if\ f(y_i) > f(x_i) \\ v_{ij}^{t} + fl * p_i & if\ f(y_i) \le f(x_i) \end{cases} \tag{5}$$

Where v_{ij}^{t} is the female Mayfly i's velocity in dimension j = 1, …, n at time step t, $y_{ij}{}^{t}$ the position of female Mayfly i in dimension j at time step t , α_2 is a positive attraction constant and β is a fixed visibility coefficient, while r_{mf} is the Cartesian distance between male and female mayflies, calculated using equation
$\mathrm{V} = \{V_1, V_2, \ldots, V_p\}$.

Finally, fl is a random walk coefficient, used when a female is not attracted by a male, so it flies deterministically by roulette wheel selection and p_i is a deterministic value.

4. Results and Discussion

To test the enhanced algorithm's capability, the performance of enhanced Mayfly algorithm (EMA) and conventional Mayfly algorithm (MA) classifier were done using recognition accuracy, False Acceptance Rate (FAR) and False Rejection Rate (FRR), Equal Error Rate (EER) and computation time. 190 subjects of the face and iris images with 3 different samples were captured using a digital camera with a size of 640 by 480 pixels.

The database was populated with 570 images per modality. 60% were used to train the system and 40% were used for authentication. The choice of dataset division was based on the random sampling cross-validation method. The performance of each technique was affected by a threshold value of 0.2, 0.35, 0.5, and 0.76, with the threshold value of 0.76 providing the best results for all techniques involving single and fused features for both the Mayfly algorithm (MA) and the enhance Mayfly algorithm (EMA).

Table 1. (a & b) illustrated a combined result of the Enhanced Mayfly Algorithm (EMA) and Mayfly Algorithm (MA) at the threshold value of 0.76concerningo all matrices at different modalities. All results are obtained in Table 1. (a & b) presume that the enhanced Mayfly algorithm (EMA) model has the lowest recognition time compared with the corresponding Mayfly algorithm (MA) model irrespective of the threshold value at different modalities.

Similarly, the recognition accuracy of the Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) model were compared at a 0.76 threshold value, the study discovered that the enhanced Mayfly algorithm (EMA) model has better performance in accuracy and timing than the original Mayfly algorithm (MA) model as enumerated in Table 1.1(a & b). EMA and MA gave recognition accuracy of 97.36% and 95.18% with fused (face-iris), 93.42% and 92.11% accuracy with iris modality, and 93.86% and 91.67% accuracy with Face modality at a threshold of 0.76 respectively.

Enhanced Mayfly Algorithm (EMA) and Mayfly Algorithm (MA) generated recognition times of 181.52s and 213.75s with fused (face-iris), 105.98s and 142.00s recognition time with iris modality, and 83.20s and 103.07s recognition time with Face modality at a threshold of 0.76 respectively.

Also, the Enhanced Mayfly algorithm (EMA) and Mayfly algorithm MA produced false acceptance rates of 1.79% and 3.51% with fused (face-iris), 5.26% and 7.02% FAR with iris modality, and 5.36% and 7.02% FAR with Face modality at a threshold of 0.76 respectively. EMA and MA got a false rejection rate of 2.92% and 5.26% with fused (face-iris), 7.02% and 8.19% FRR with iris modality, and 6.43% and 8.77% FRR with face modality at a threshold of 0.76 respectively.

Figures 1, 2, 3, and 4 demonstrate a comparison of the Mayfly algorithm and the enhanced Mayfly algorithm for identification accuracy, recognition time, force acceptance rate, and force rejection rate at a 0.76 threshold value, respectively.

When the Mayfly algorithm and the enhanced Mayfly algorithm, both multimodal and unimodal, are compared, it is clear that the enhanced algorithm outperforms the existing approach.

Table 1.a: Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.76 threshold value (multimodal Recognition system)

Modalities	Algorithm	FAR(%)	FRR(%)	ACC(%)	Time(sec)
Face + Iris	EMA	1.79	2.92	97.36	181.52
	MA	3.51	5.26	95.18	213.75

Table 1.b: Comparison of Mayfly algorithm (MA) and enhanced Mayfly algorithm (EMA) at 0.76 threshold value (unimodal Recognition system)

Modalities	Algorithm	FAR(%)	FRR(%)	ACC(%)	Time(sec)
Face	EMA	5.36	6.43	93.86	83.20
	MA	7.02	8.77	91.67	103.07
Iris	EMA	5.26	7.02	93.42	105.98
	MA	7.02	8.19	92.11	142.00

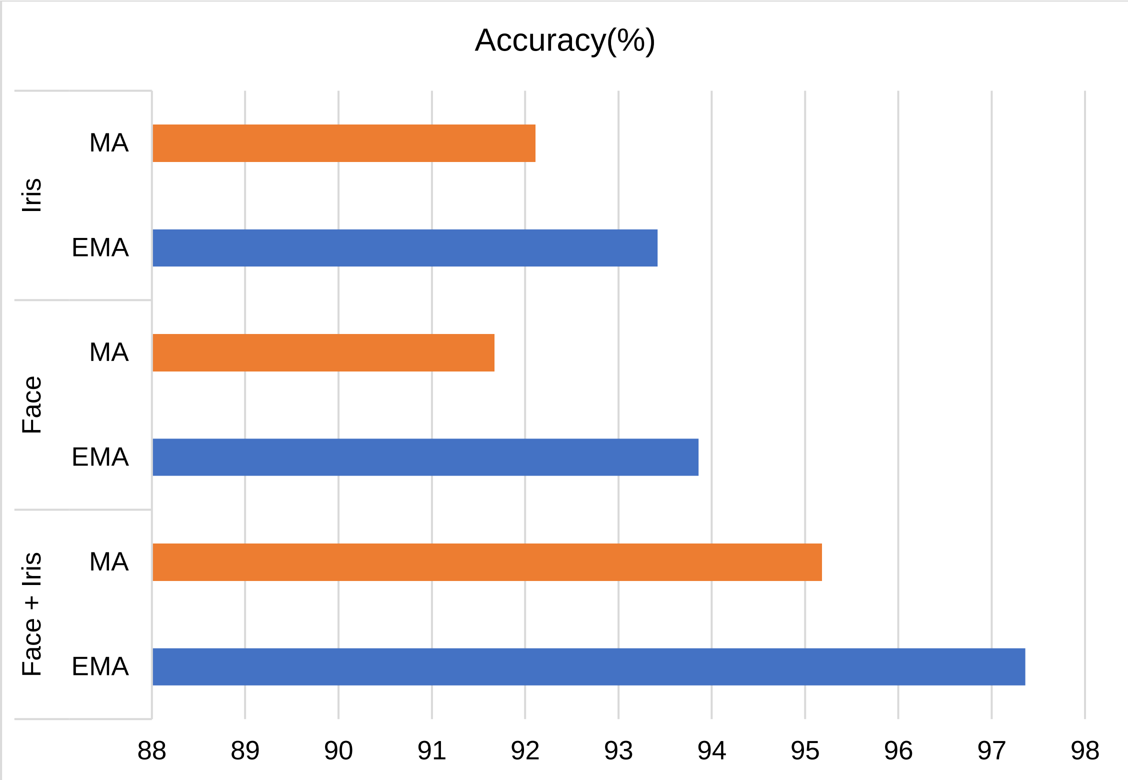

Figure 1. Comparison of MA and EMA at 0.76 threshold value (Recognition Accuracy)

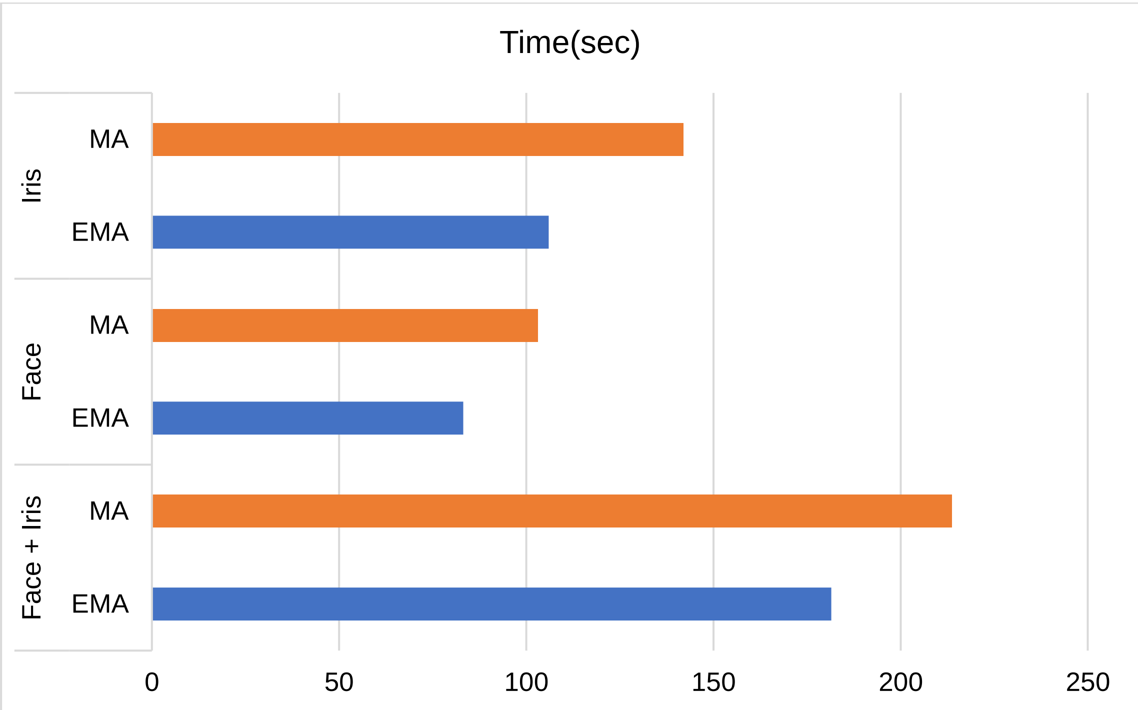

Figure. 2. Comparison of MA and EMA at 0.76 threshold value (Recognition Time)

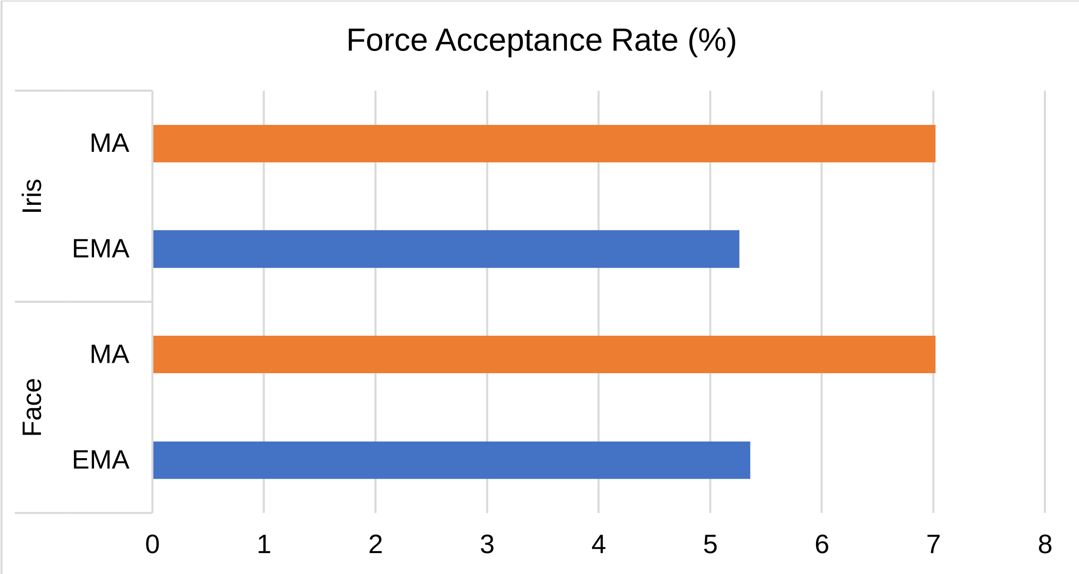

Figure 3. Comparison of MA and EMA at 0.76 threshold value (Force Acceptance Rate)

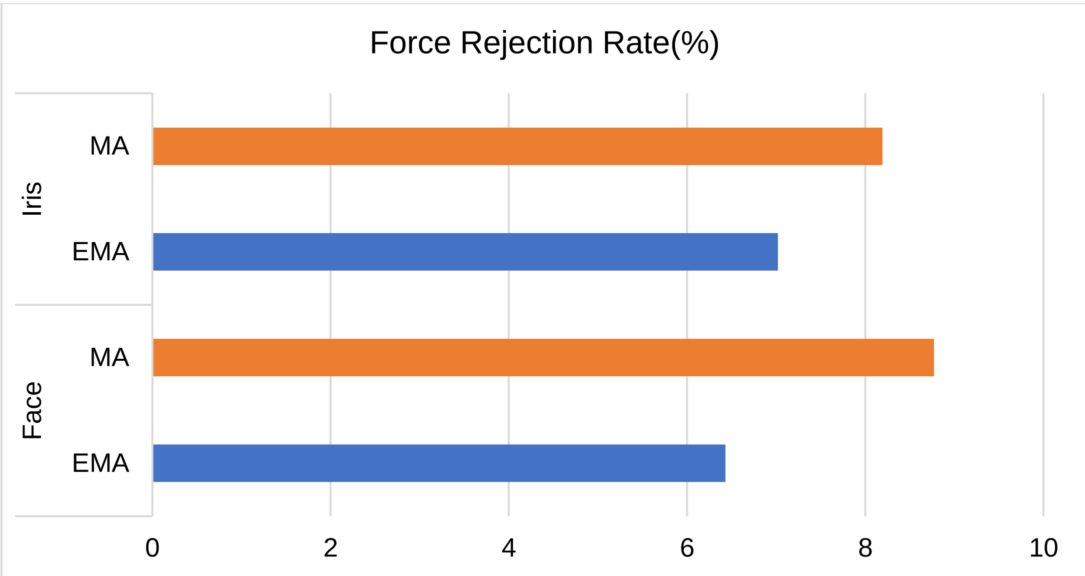

Figure 4. Comparison of MA and EMA at 0.76 threshold value (Force Rejection Rate)

5. Conclusion

This study introduced roulette wheel selection to replace the random numbers involved in the conventional Mayfly optimization algorithm (MA). Simulation testing shows that the enhanced method with roulette wheel selection outperforms the basic Mayfly algorithm. Our proposed algorithm, the enhanced Mayfly algorithm with roulette wheel selection indicates better performance both in the Force Acceptance Rate, Force Rejection Rate, Recognition Accuracy and Recognition Time.

As a result, the enhanced Mayfly algorithm (EMA) with roulette wheel selection produces superior outcomes. Other methods or replacements of other variables might be considered in the future.

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