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Optimizing Fused Face-Iris Biometric Recognition Accuracy and Timing Using Improved Mayfly Algorithm

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ABSTRACT

A multimodal biometrics system is presented in order to improve the recognition performance, system complexity, security, and applicability of current biometrics applications. In this study, an improved Mayfly optimization algorithm was used as a feature selection method to improve recognition accuracy and timing for a fused face-iris biometric recognition system. The improved Mayfly algorithm is an enhancement to the original Mayfly optimization algorithm. The Mayfly algorithm is an optimization method based on the behavior of mayflies that provides a powerful hybrid algorithm structure. It combines the best features of particle swarm optimization, genetic algorithms, and the firefly algorithm. Simulation experiments demonstrated that it is capable of optimizing both benchmark functions, but with significant limitations. Due to the random selection procedure used, which allows the existing algorithm to exploit specific areas in the search space, notable shortcomings included slow convergent rate, premature convergent, and potential imbalance between exploration and exploitation. As a result, the Mayfly algorithm has found it difficult to solve high-dimensional problem spaces such as feature selection. The Mayfly algorithm is enhanced in this study with the roulette wheel selection method, which replaces the random selection method used in the existing Mayfly algorithm. Both the existing Mayfly algorithm and the newly developed improved Mayfly algorithm were used as feature selection on a fused face-iris recognition system in order to improve recognition accuracy and time complexity. The results of simulation experiments revealed that the Improved Mayfly algorithm increased the recognition accuracy and time complexity of the fused face and iris biometrics recognition system.

1. Introduction

Biometrics is the science and technology of measuring and analyzing biological data from the human body, extracting a feature set from the acquired data, and comparing this set to a database template set [1, 2]. A biometric authentication system is a pattern-recognition system that uses a feature vector involved in a certain measurable physical or behavioral attribute that an individual develops to identify them [3]. Depending on the application context, a biometrics recognition system may be used to identify or verify an individual [4]. Dahea and Fadewar [5] stated that a biometric system measures at least one physical or behavioral characteristic, such as a unique fingerprint, palm print, face, iris, retina, ear, voice, signature, stride, and hand-vein data of an individual to determine or confirm his identity. A multimodal biometric system integrates two or more retrieved features from a person to determine authentication [6].

Because of the many sources, the multimodal biometric system has several advantages over the unimodal biometric system, for authentication, unimodal relies on proof from a single source of information. Unimodal biometric systems are missing out on operational advantages in terms of performance and accuracy [5]. Because unimodal biometric systems do not provide high accuracy identification due to non-universality, the use of multimodal biometric systems may result in a more accurate and secure biometric identification system.

The fundamental purpose of multi-biometrics is to lower one or more of the following: false accept rate (FAR), false reject rate (FRR), failure to enroll rate (FTE), and susceptibility to artifacts or mimics [2]. Multimodal biometric system fusion strategies describe how information acquired from several biometric modalities is combined. Enrollment and authentication are the two phases of a biometric-based authentication system [7]. A user's biometric data is detected by a sensor and stored in a database during the enrolment step; during the authentication step, some methods are used to identify or verify the claimed user identity; and adaptation, which is optional, is required to maintain and improve system performance as data changes over time [8]. Sensors, Feature Extraction, Matching, and Decision are the four main modules in a simple biometric system [9]. Biometric modalities are frequently one-of-a-kind, measurable, and automatically validated, as well as permanent [10, 11]. Using an improved Mayfly optimization algorithm, the proposed method deploys a multimodal biometric recognition system that combines face and iris images, which is an enhancement of the conventional mayfly optimization algorithm. The improved Mayfly algorithm will be used to select the features from fused face and iris modality.

1.2 Related work

Jamdar and Boke [12], proposed face identification and recognition using the face reorganization method, the study employed the multimodal biometric by fusion level of matching score level by integrating face iris in the single modal to a multimodal biometric system for security purposes. In order to increase accuracy in comparison to the privies system, this system integrates the features of the face and the eye into a single modal to the multimodal combination. The experimental setup starts with the storage of photographs in a database, then testing findings for each image characteristic that combines the face and iris to find the best accuracy and human identification in a busy environment. Sasidhar et al., [2] investigated the accuracy and performance of multimodal biometric authentication systems based on cutting-edge Commercial-Off-The-Shelf (COTS) products. The research looked at the relatively large face and fingerprint data sets using a variety of normalization and fusion techniques. According to the findings of this study, multimodal biometric systems outperform unimodal biometric systems. Another benefit of fusion at this level is that existing and proprietary biometric systems do not need to be modified, allowing a common middleware layer to handle multimodal applications with a small amount of common information. Xinman et al., [4], devised a novel method for identifying previously registered users or granting authorization on Android devices using multimodal biometrics with face and voice traits. Face and voice feature vectors are extracted independently using the haar - wavelet transforms and then fused at the feature level. The experimental results show that the system can achieve satisfactory performance with an identification accuracy of 93.6 percent and can be used in the financial sector, where information security is paramount. In order to improve performance, Lemmouchi et al., [7] combined several biometric methods used for face and iris simultaneous recognition of an individual. For feature extraction, four methods were used: discrete wavelet transform, singular value decomposition, discrete cosine transform, and principal component analysis. Then, different distance measurements are used to match: city block, Euclidean, Seuclidien, Cosine, Chebychev, and Correlation. The most commonly used normalization methods, such as min-max, are presented, as well as a new method based on geometric mean. At the score level, data fusion is performed using two methods: simple sum and weighted sum. The obtained comparison results show that the PCA (face) and PCA (iris) fusion scenarios, in conjunction with the simple sum rule and the proposed new normalization method (geometric mean), provided the best recognition rate.

Lemmouchi et al., [13] used a combination of biometric modalities (a person's face and iris) to improve recognition performance. For each modality, two approaches were used to extract features: Fast Fourier Transform (FFT) and singular value decomposition (SVD). Then, Euclidean distance measurement was used to classify. The fusion was done at the score level using four different methods: simple sum, weighted sum, min, and max. For learning and testing the proposed system, 40 people's faces from the Olivetti Research Laboratory face database (ORL) and the China Institute of Automation iris database (CASIA) were extracted. The results of the tests showed that the FFT (face) and FFT (iris) fusion scenarios associated with the min rule and the new method (Prctile) produce the highest recognition rate of 98.33 percent. Different feature selection methods have been presented by researchers for iris- and face-based identification systems, but so far, the requisite recognition accuracy, time, false acceptance, and false rejection rates have not been attained [14]. The bulk of the relevant works assessed in the examination of related works suggests integrating currently in use legacy technologies to enhance he fused face-iris recognition system rather than creating an optimization system from start. In this study, a face-iris identification system that can recognize fused faces and iris features more quickly and accurately is proposed. It uses an upgraded mayfly.

1.3 The Improved Mayfly Algorithm

While fused biometrics systems have shown to be able to address some issues with unimodal systems, they are not without their own set of difficulties, including a complicated design process, a low level of user acceptance, and a performance trade-off. By adopting an upgraded mayfly algorithm, a version of the current Mayfly algorithm that was recently published, this study attempts to address some of these implementation difficulties. The Mayfly algorithm combines the benefits of particle swarm optimization, genetic algorithm, and firefly algorithm. It was tested for optimization in various experiments using a variety of benchmark functions, but some of its limitations, such as slow convergence or premature convergence rate and potential imbalance between exploration and exploitation, still need to be addressed [14]. This study enhances the existing mayfly algorithm by expanding the search space which limited the ability of the conventional mayfly algorithm to be used to solve high-dimensional problem spaces such as feature selection and modify the selection procedure to model the attraction process as a deterministic process, that will be used for the feature selection procedure on fused face –iris recognition system. Algorithm 1 depicted the Improved Mayfly algorithm used for feature selection.

Algorithm 1: Improved 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: Determine the objective function values of male and female mayflies using $\boldsymbol{f(x)} = \boldsymbol{f(x_i^t)}$. where $\boldsymbol{f}: \boldsymbol{R^n} \to \boldsymbol{R}$ is the objective function that evaluates a solution's quality.

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

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

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

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

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

Step 6: Male and female update velocities and solutions

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

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

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

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

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

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

Where $\boldsymbol{\beta}$ is a fixed visibility coefficient used to limit the visibility of a mayfly 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:

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

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

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

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

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

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

Using roulette wheel selection $\boldsymbol{p_i}$

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

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

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

Step 7: Evaluate Solutions

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

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

Step 8: Mate the mayflies and Evaluate offspring

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

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

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

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

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

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

The global best position $\boldsymbol{gbest}$ at time step t, is defined as

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

Where N is the swarm's total number of male mayflies,

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 $\boldsymbol{Gbest_{bD}}$.

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

2. Methodology

2.1 Database Setup

A digital camera was used to collect face and iris biometric data from users in order to create the database. Face and iris images of 190 subjects were captured at a resolution of 640 by 480 pixels in three different samples. The images of the two biometric traits were downsized to 128 by 128 pixels without being altered. All of the photographs have the same level of uniform illumination and light color background. Each modality's database was populated with 570 images. 60% of the funds were used to train the system, while 40% was used to authenticate users. The random sampling cross-validation method was used to divide the dataset.

2.2 System Design

On a Core i3 laptop computer with 2.00GHz of RAM, MATLAB R2018a was used to implement both the Improved Mayfly algorithms and the Mayfly algorithm. The experiment used a total of 570 images captured with a digital camera to collect face and iris biometric data from users from the chosen experimental organization, with 60% of the images used in training the database and 40% used in testing the created database. The images are broken down in Table 1. The system is made up of several modules, including image acquisition, image pre-processing, iris segmentation, feature extraction, feature concatenation, feature selection, classification, and evaluation. The two optimization algorithms used in feature selection in multimodal recognition are the Improved Mayfly algorithms and the Mayfly algorithm, and a support vector machine (SVM) was used as a classification technique. Figure 1 depicts the study's scheme, while Figure 2 depicts the architecture of the developed system respectively.

Table 1. Breakdown of images

Breakdown	Number
Number of objects (persons)	190
Number of samples per object	3
Number of total samples	570
Number of the training set	342
Number of testing samples	228

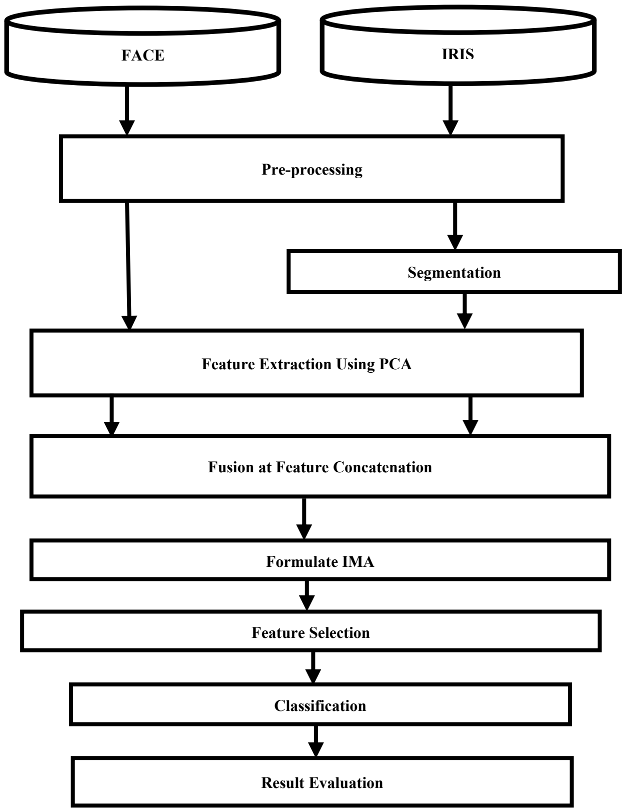

Figure 1: The Scheme of the fused face-iris biometric recognition Syst

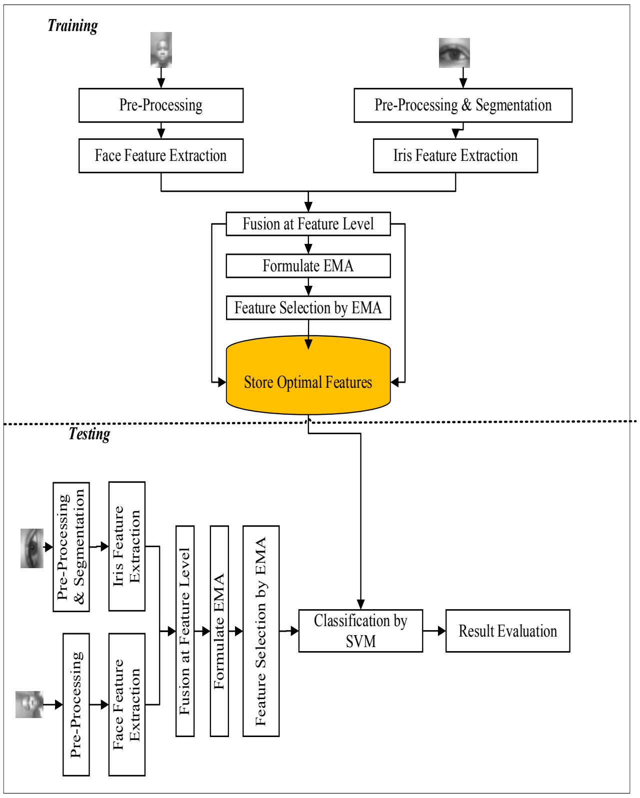

Figure 2: Architecture of the developed fused face-iris biometric recognition system

2.3 Image Acquisition

The users' face and iris biometric data were collected using a digital camera. Face and iris images of 190 subjects were captured with three different samples at a resolution of 640 by 480 pixels. The images were not altered when the two biometric traits were downsized to 128 by 128 pixels. All images should have the same uniform lighting conditions and light colour background.

2.4 Design Approach

After applying appropriate preprocessing techniques such as grayscale conversion, image enhancement, image cropping, and image segmentation for each modality using Principal Component Analysis, biometric features were extracted from individual faces and iris. Using the feature concatenation method, the extracted features were fused at the feature extraction level. As a feature selection algorithm, the improved Mayfly algorithm was derived from the basic Mayfly algorithm. Using formulated improved Mayfly algorithm, the best features were chosen. Support Vector Machine was used as the classification technique. Performance was measured using metrics such as Force Rejection Rate. Force Acceptance Rate, Recognition Accuracy, and Computation Time.

2.5 Support Vector Machine

Support Vector Machine (SVM) was used to classify the features selected by the Improved Mayfly algorithm technique. This method was used to compare the similarity of the test vector to the reference vectors in the gallery. Figure 3 depicts a flowchart of training and testing. A supervised machine learning approach called a support vector machine is employed for data classification and determining the associations between variables (regression analysis). Because there is an initial training step when you input the algorithm data that has previously been classified, it is a "supervised" algorithm (labeled). Future data sets fed to the algorithm can be classified with little to no human interaction once this initial training phase is over. The benefit of utilizing a support vector machine is that many learning algorithms can only perform linear classification, which divides the input points along a straight line.

3. Results and Discussion

3.1 Experimental Result

This section presented the results of the evaluation of fused features of face and iris by application of the Mayfly algorithm and Improved Mayfly algorithm as a feature selection technique for face -iris recognition system of five hundred and seventy face images. The two feature selection methods were thoroughly investigated. Three hundred forty-two (342) face and iris images were used for training, accounting for 60% of the total dataset, and two hundred twenty-eight (228) face and iris images were used for testing, accounting for 40% of the total dataset. The images were saved in JPEG (.jpg) format so that they could be analyzed further in the Matrix Laboratory 2018(a) version. The classifier for the fused feature selection was the Support Vector Machine. Threshold values of 0.2, 0.35, 0.5, and 0.76 influenced the performance of each technique. The optimum performance was achieved for all techniques with respect to fused features for the Mayfly algorithm and Improved Mayfly algorithm techniques at the threshold value of 0.76, as shown in Tables 2 and 3.

Based on identification accuracy and recognition time, Tables 2 and 3 compare the performance of the Mayfly algorithm and the improved Mayfly algorithm on the fused face and iris. It was determined at threshold values of 0.02, 0.35, 0.50, and 0.76, respectively, how accurate the fused face and iris were. The threshold value of 0.76 produced the best result. Finally, the aforementioned results were determined using the optimum threshold value, which was chosen due to its superior performance when compared to other threshold values. According to the above results, fused face and iris with the improved Mayfly algorithm provided greater accuracy and low recognition time.

3.2 Performance comparison of Improved Mayfly algorithm and Mayfly algorithm.

Table 2 revealed that the Mayfly algorithm achieved an accuracy of 95.18% for a 0.75 threshold value, while in table 3, the Improved Mayfly algorithm achieved an accuracy of 97.36% for a 0.75 threshold value. The results disclose that the Improved Mayfly algorithm outperformed the Mayfly algorithm in terms of recognition accuracy. Figures 4 and 5 show both the accuracy and time of the fused face – iris recognition system of the Improved Mayfly algorithm and Mayfly algorithm in the column cluster chart graph.

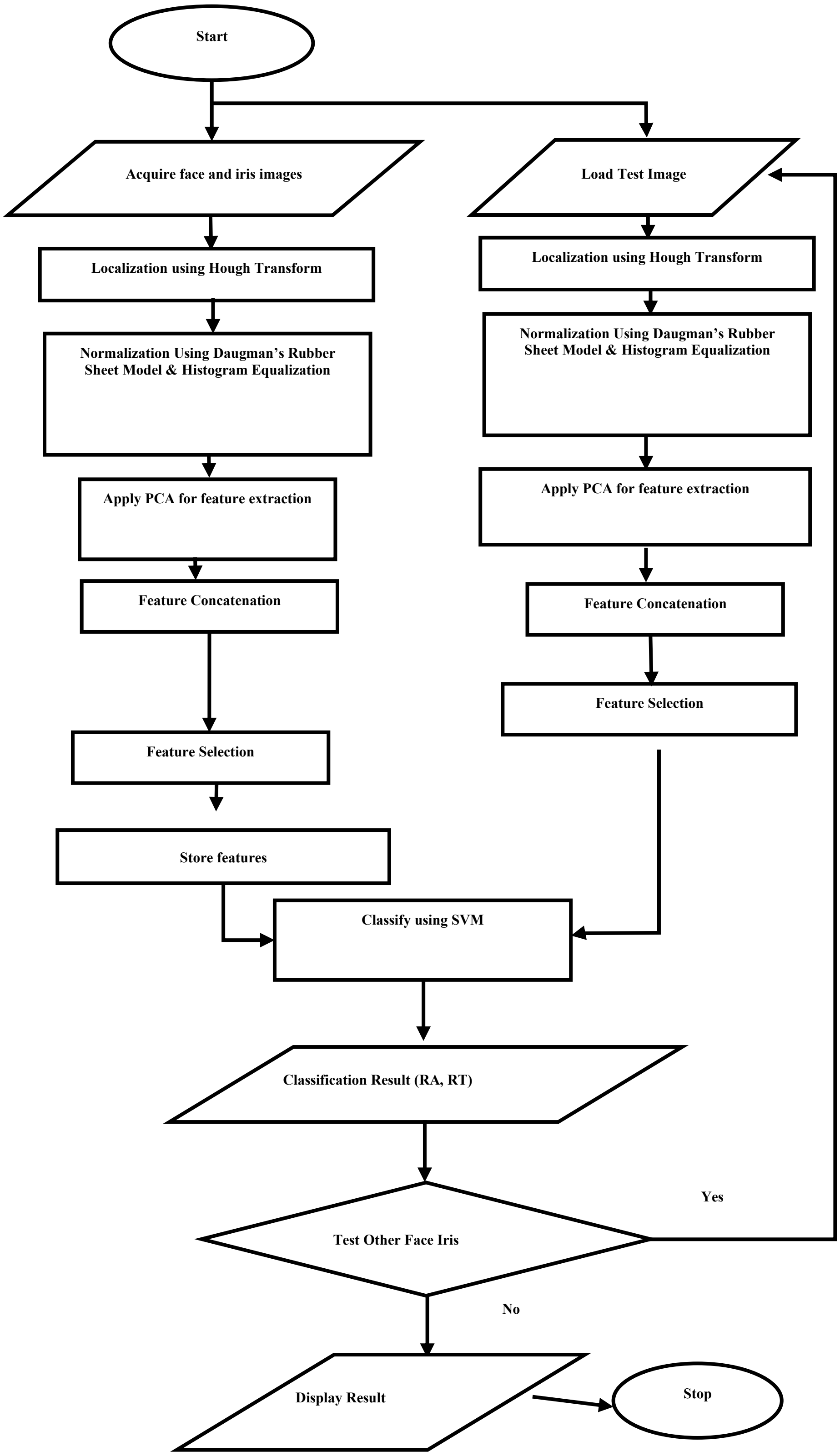

Figure 3: Flowchart for fused face – iris biometric recognition System

Threshold	Accuracy (%)	Time(sec)
0.20	94.74	184.07
0.35	95.61	181.61
0.50	96.49	183.26
0.76	97.36	181.52

Table 2: Fused Iris and face results with Improved Mayfly algorithm

Table 3: Fused Iris and face results with Mayfly algorithm

Threshold	Accuracy (%)	Time(sec)
0.20	92.98	211.77
0.35	93.42	221.55
0.50	94.3	229.52
0.76	95.18	213.75

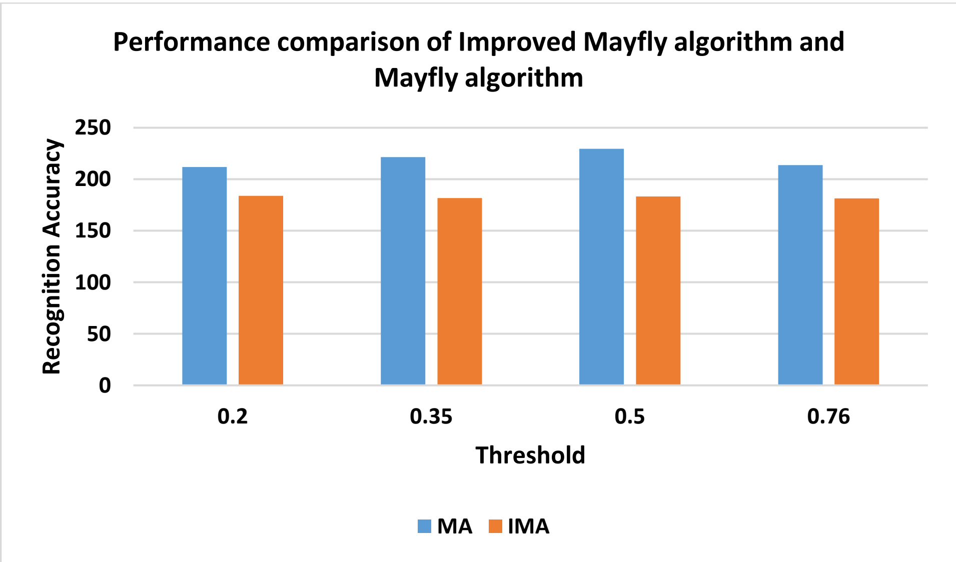

Figure 4: Performance comparison of Improved Mayfly algorithm and Mayfly algorithm (Recognition Accuracy)

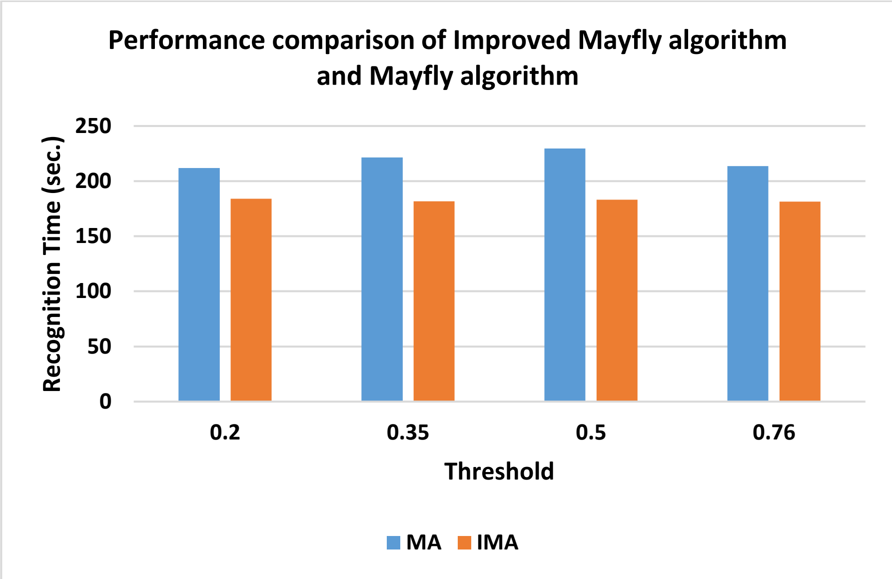

Figure 5: Performance comparison of Improved Mayfly algorithm and Mayfly algorithm (Recognition Time)

4. Conclusion

In comparison to the conventional Mayfly algorithm, which provides a recognition accuracy of 95.18 percent and a recognition time of 213.75 seconds, the experimental results showed that the fused face and iris recognition system using the improved Mayfly algorithm technique provided 97.36 percent recognition accuracy and 181.52 seconds of recognition time. In other words, the improved Mayfly algorithm technique produced has secured the best possible accuracy and time complexity of the fused face and iris biometrics recognition system.

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