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Comparative Analysis of Firefly and Modified Firefly Algorithms in Multimodal Biometric Authentication Systems

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Abstract: This research focuses on addressing the challenges of high-dimensional feature spaces and selecting significant features in multimodal biometric systems. Feature-level fusion poses persistent issues that require extensive investigation due to its potential for enhancing biometric recognition accuracy. This study proposes the integration of meta-heuristic optimization techniques into the feature selection phase of a multimodal biometric system, prior to the classification phase, to identify the most relevant features from two distinct biological traits. To determine the authorization status of an individual, the fused feature vectors are inputted into a Support Vector Machine (SVM) classifier. The study leverages the physiological biometrics of the face and iris to validate the findings of previous research, highlighting the exceptional accuracy of iris recognition and the natural acceptability of face recognition for identity verification purposes.

Keywords: Support Vector Machine, Firefly Algorithm, Feature Extraction, Multimodal biometric

I. INTRODUCTION

A biometric system recognizes people based on feature vectors obtained from their biological characteristics and, has emerged as the most promising recognition approach in recent years [1]. Due to advancements in imaging and computations, identification of criminals, which reduces identity theft or forgeries, and enhanced security in electronic transactions, biometric technology application fields have attracted a lot of interest in recent years [2]. Healthcare, education, time and attendance, e-commerce, forensic, banking and finance are just a few of the application sectors for biometrics [3]. A unimodal biometric system uses only one property to perform a recognition operation, such as a fingerprint, nose, gait, voice, face, iris, or ear [4]. However, [5] observed that existing biometric systems have to deal with a variety of problems with the use of a single trait, such as a fingerprint image with a scar or poor illumination of the subject in face recognition. In real-world scenarios, the majority of biometric technologies are unimodal [6]. The limits of unimodal biometric systems have prompted researchers to focus their efforts on multimodal biometric systems, as the biometric source may become unreliable owing to a variety of factors such as sensor or software failure, noisy data, non-universality, and so on [7]. Also, [8] examined that most problems caused by unimodal biometric systems can be overcome by applying multimodal biometric approaches. Combining two or more biometric systems is a promising solution to provide more security according to [9] and, avoiding the falsification of several biometric traits at the same time [10].

A multimodal biometric system recognizes people using data from many biometric sources [11] and created by combining two or more biometric features to create a recognition system. In multimodal biometric systems, information fusion is a crucial step [12]. At different levels, fusion of different modalities can take place[13]. A multimodal biometric must consider a fusion of features to be unique, in which at several phases of a recognition system, biometric features can be fused [14] either at fusion-before-matching, that involves integrating biometric data before matching templates i.e. sensor level and feature level; or fusion-after-matching, which involves integrating data after the matcher/classification step i.e. score level, match level, rank level and decision level [15]. However, duplication of feature sets from different modalities, incompatibility of the numerous biometric modalities, higher complexity of extracted feature vectors, features redundancy and irrelevant features in high dimensional data that occur as a result of a concatenation-based fusion, and the presence of noisy data all pose significant challenges thus making fusion at the feature level a hard task in practice [9] and difficult to accomplish [16]. Hence, an optimization technique is required as an optimized feature selection method [17] to select the optimal subset of features from the extracted feature vectors at feature level fusion to reduce feature dimensionality space, minimize redundancy and irrelevant features thereby enhancing the classification's performance.

In order to address the issues raised above, particularly high redundancy and irrelevant features, various meta-heuristic optimization techniques, such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Simulated Annealing (SA), Particle Swarm Optimization (PSO) and Firefly Algorithm (FFA) have been used in the literature as feature selection techniques to choose the best subset of the original features. However, it still has significant limitations. Though, FA has been widely used for dimensionality reduction technique due to its effectiveness, simplicity, and eases of implementation but still suffers from premature convergence, an imbalance between exploitation and exploration, and a significant risk of becoming stuck in a local optimum, especially when applied to high-dimensional optimization problems like fusion [18]. Therefore, in order to further improve the performance of multimodal biometric authentication system, this research introduced a meta-heuristic optimization approach using a modified firefly algorithm for feature level fusion as an efficient feature selection algorithm to select optimal features, reduce redundant features in the feature space and speed up convergence rate for better classification and employed Support Vector Machine (SVM) as the classifier.

II. LITERATURE REVIEW

Feature level fusion was adopted in [19] to fuse the feature vectors of the iris and ear extracted by Principal Component Analysis technique, which also reduced the dimension of the feature vectors. Fingerprint and iris were fused at the feature level using a hierarchical data fusion model that combined intra- and inter-modal information in [9]. The recommended data fusion approach allows a better exploitation of the gathered characteristics with an appropriate combination of intra- and inter-modal fusion rules. Despite the practical challenges of putting feature-level fusion into practice, it shows promise for enhancing the precision of human identification.

A multimodal biometric identification method was provided in a study [7] to validate a person's identity based on his face and iris traits. The study used a novel fusion method that combined the canonical correlation process with the proposed serial concatenation to perform feature-level fusion. For the recognition process, a deep belief network was utilized. When the findings were compared to other existing systems, it was discovered that the fusion time was lowered by 34.5 percent. The proposed system also achieved a decreased equal error rate (EER) and 99 percent recognition accuracy. In another study, [20] proposed a multimodal biometrics technique based on the profile face and ear that not only fixes the problems with ear biometrics but also improves the overall rate of recognition. Fusion was performed using PCA at the feature level. In order to produce more discriminative and non-linear features for the KNN classifier's identification of individuals, the combined feature set is finally exploited using the kernel discriminative common vector (KDCV) method. Experimental results on two benchmark databases demonstrated superior performance of the proposed method over individual modalities and other state-of-the-art technologies.

A feature-level fusion and binarization framework for designing a multimodal template protection strategy that creates a single safe template from each user's various biometrics using deep hashing was developed by [22]. While adopting the proposed secure multimodal system, the matching efficiency and template security both increased. A safe face features based authentication system was built in [21] using a multimodal and multi-algorithmic biometric system incorporating ear, iris and face modalities at feature level fusion. PCA was employed for feature extraction, SVM for classification and multiple methods that included features from the human iris, ear, and face were used for person verification. There was a considerable improvement in verification performance and recognition accuracy when compared to unimodal and privies systems.

A multimodal biometric system architecture based on canonical correlation analysis (CCA) and a Support Vector Machines (SVMs) classifier for feature level fusion was introduced in [23] study. The merged features of Iris and Fingerprint modalities are trained and classified using an SVM. The proposed system's performance was measured in terms of SVM classifier average accuracy and reaction time which demonstrated that feature level fusion using CCA and an SVM classifier improves classification accuracy while requiring less training and testing time. Another study [24] built a reliable multimodal identification system using feature-level fusion. For 40 people from the ORL and CASIA-V1 databases, the system's recognition accuracy was improved by combining face and iris features. Using low-resolution iris images from the MMU-1 database, a further evaluation of recognition precision was carried out. The face-iris features were extracted using four comparative procedures. Principle Component Analysis (PCA) and Fourier Descriptors (FDs) approaches obtained 97.5 percent accuracy, while Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) texture analysis techniques reached 100% accuracy.

The performance of multimodal biometric identification was improved by merging fingerprint and iris at the feature level fusion (25). Multimodal biometrics' security phase was made possible by the method of fused picture encryption using the AES algorithm and matching to validate the encryption.

The main goal of [26] novel strategy is to protect fingerprint and signature data against theft and infiltration by fusing at the feature level, which eliminates the possibility of faked data. [27] fused biometric information at the feature level from a person's face, iris, and signature modalities. A wavelet-based feature extraction method that is incredibly effective, reliable, and straightforward was presented for all the three biometric traits. The proposed multi-biometrics system improved the unimodal system with notable results in terms of FAR and FRR, obtaining a maximum accuracy of 98.77 percent for the chimera database.
In another study, [12] introduced Discriminant Correlation Analysis (DCA) as a feature level fusion technique that incorporates class associations in feature set correlation analysis with the goal of finding transformations that maximize pair-wise correlations across the two feature sets while also separating the classes within each set. The study's computing complexity was extremely low, and it can be used in real-time applications. Finger print, palm and finger knuckle prints were fused at the feature level for personal authentication in [28] study. The distinctive properties of these Modalities are extracted using the Grey Level Co Occurrence Matrix (GLCM) feature extraction technique. Using an improved Artificial Neural Network (ANN) with the particle swarm optimization (PSO) algorithm to recognize a person resulted in high levels of security, specificity, and sensitivity during classification.
Another study, [29] examined numerous security flaws, various forms of data transfer and errors such as FAR, FRR, and FTE that occur during data collection, as well as a comparison of multimodal biometric systems against unimodal biometric systems. This method compares an individual's identity using many biometric identifiers and proposed method of enhancing the multimodal system by merging more than one or two biometric samples. Three biometric modalities; finger vein, face and fingerprint were fused at feature level in an effective matching technique that was put forth in [30]. It is based on the secondary calculation of the Fisher vector. Experimental findings show that the suggested technique achieves a superior identification rate and offers higher security than unimodal biometric-based systems, providing a useful strategy for enhancing the security of the Internet of Mobile Things (IoMT) platform.

III.METHODOLOGY

A. Image Acquisition

Face and iris images acquisition refers to the capture of both face and iris images simultaneously using an iris camera. A CMITECH IRIS Camera device was used to accomplish this. The subjects involved some interested Ladoke Akintola University of Technology, Ogbomoso (LAUTECH) students' and staff within the campus. The study took into consideration 840 subjects with three different expressions each for the two biometric traits. The total datasets captured was 7560; 70 percent of the dataset were used for training and 30 percent for testing.

B. Image Preprocessing

Face and iris images were preprocessed to extract only the parts of the image that contain useful information. Preprocessing techniques were performed differently on face images and iris images in their datasets. The preprocessing phase of facial images involved were image cropping, image resizing and image enhancement using Histogram Equalization. The preprocessing phases of iris images involved were iris localization/segmentation and iris normalization.

C. Feature Extraction

Through the process of feature extraction, enormous amounts of redundant data are minimized and reduced computational complexity of the system is made possible. Using Principal Component Analysis, the feature values from the preprocessed data are extracted for this study's feature extraction. A fixed length FaceCode and IrisCode were constructed by extracting the features from the preprocessed images of face and iris using the Principal Component Analysis (PCA) to achieve good performance of the system. The PCA approach was used to extract the face and iris's distinguishing traits and created a set of Eigenfaces and Eigeniris. The steps taken during this period are outlined below.

1) *Creation of a set of Eigenfaces and Eigeniris:* Eigenfaces and Eigeniris was achieved following the steps below:

a) A training set of both face and iris images were created, which were taken under the same lighting circumstances.
b) Average/mean image vector of all learned images were considered and calculated.
c) Each 1D image was subtracted from the mean image vector.
d) The unique image vectors were obtained by subtracting the mean image vector from each 1D picture vector. The normalized image vectors are the resultant vectors.

e) The eigenvectors and eigenvalues of this covariance matrix were calculated when the covariance matrix was calculated. Each eigenvector has the same dimensionality (number of components) as the original images, allowing it to be regarded as an image; consequently, the eigenvectors are referred to as Eigenfaces and Eigeniris.

f) Then, the eigenvalues were sorted in descending order, and the eigenvectors were arranged in the same manner. Only the Eigenfaces and Eigeniris with the highest eigenvalues were picked. These Eigenfaces and Eigeniris were later used to build the feature vectors for both training and testing images, representing both existing and new faces and irises.

2) *Calculation of Feature Vectors:* For each image in the Training set, the weight/feature vector was calculated.
3) *Input a Test Image:* An image is taken from the set of testing images.
4) *Calculation of Feature Vector for Test Images:* The feature vector for the test images was calculated.

D. Feature Selection Using Modified Firefly Algorithm

To enhance performance and reduce extracted feature dimensions for better classification in this study, the best features were selected using a feature selection technique, firefly algorithm (FFA).

1) Modified Firefly Algorithm (MFFA)

In the existing Firefly, the procedure starts from an initial population of randomly generated individuals. The quality of each individual is calculated using equation 1 and the best solution among them is selected. In FFA, the form of attractiveness function of a firefly is depicted by the following:

$$\beta(r) = \beta_0 \exp\left(-\gamma r^2\right) \tag{1}$$

where,
r = The distance between any two fireflies
β_0 = The initial attractiveness at r = 0
γ = An absorption coefficient which controls the decrease of the light intensity

The distance that exist in-between any two fireflies i and j, at a particular position xi and xj, can be defined respectively as a Cartesian or Euclidean distance as shown below:

$$r_{ij} = ||x_i - x_i|| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{2}$$

where,
d is the dimensionality of the given problem.

The pattern of movement of a particular firefly *i* that is attracted by another firefly *j* which is brighter can be represented by the following equation:

$$x_i = x_i + \beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right) + \alpha * \left(rand - \tfrac{1}{2}\right) \tag{3}$$

$$x_i = x_i + \alpha * \left(rand - \tfrac{1}{2}\right) \tag{4}$$

In equation 3, the term x_i which is the first term is the present position of a firefly;

The term $\beta_0 \exp\left(-\gamma r_{ij}^2\right) * \left(x_j - x_i\right)$ which is the second term is meant for movement of firefly towards the most attractive of the fireflies by the intensity of light and;

The third term $\alpha * \left(rand - \frac{1}{2}\right)$ is meant to cater for the random movement of a firefly (random part), when it lacks the brighter ones. The α coefficient is a parameter for randomization, its value depends on the problem that is to be solved, while 'rand' is consistently distributed in the space (0, 1) as it is a random number generator. In equation 4, the movement of the best candidate is done randomly.

The modified Firefly Algorithm was formulated using Equation 5 to model the pattern of movement of firefly as a deterministic process instead of a random process in the existing firefly. The pattern of movement of a particular firefly *i* that is attracted by another firefly *j* that is brighter was modified by roulette wheel selection ($\boldsymbol{p_i}$) as expressed in Equation 2.

$$\boldsymbol{p_i = rand} \leq \frac{f(x_i^t)}{\sum_{i=1}^{N} f(x_i^t)} \tag{5}$$

Where, $f(x_i^t)$ is the objective function value of the firefly. Given the modified pattern of movement of firefly as in Equation 4

$$x_i = x_i + \beta_0 \exp(-\gamma r_{ij}^2) * (x_j - x_i) + \alpha * (p_i - \tfrac{1}{2}) \quad (6)$$

$$x_i = x_i + \alpha * (p_i - \tfrac{1}{2}) \quad (7)$$

In equation 3.7, the term x_i which is the first term is the present position of a firefly, the term $\beta_0 \exp(-\gamma r_{ij}^2) * (x_j - x_i)$ which is the second term is meant for movement of firefly towards the most attractive of the firefly by the intensity of light and the third term is meant to cater for the random movement of a firefly (random part), when it lacks the brighter ones. The α coefficient there is a parameter for randomization, its value depends on the problem that is to be solved, while 'p_i' is consistently distributed using roulette wheel selection. In equation 3.8, the movement of the best candidate is done randomly.

The challenges of imbalance between exploration and exploitation experienced in the existing firefly algorithm were resolved in this study by modifying the attractiveness of the firefly with the application of chaotic theory using a sinusoidal chaotic map function. This describes the chaotic absorption coefficient (CA) which controls the decrease of the light intensity, but not limiting these fireflies to search space boundaries but count on the nature of the chaotic system that generates random and unpredictable outputs from preceding conditions. The new attractiveness of the firefly was expressed in Equation 8, Equation 9 and Equation 10.

$$CA_{old} = \frac{mod(abs(\beta(r), \beta_0)}{\beta_0} \quad (8)$$

$$CA_{new} = \alpha * {CA_{old}}^2 \sin(\pi CA_{old}) \quad (9)$$

$$c\beta(r) = CA_{new} \times sign(\beta_0 \exp(-\gamma r^2)) \quad (10)$$

Where,

β_0 is the initial attractiveness at r = 0,

r is the distance between any two fireflies,

γ is an absorption coefficient which controls the decrease of the light intensity,

$\beta(r)$ is the existing light intensity update;

CA_{new} is the chaotic sinusoidal mapping, where $\alpha = 2.3$ as chaotic map parameter.

CA_{old} is calculated to transform the $\beta(r)$.

$c\beta(r)$ is the modified updated light intensity of the firefly. The modified firefly algorithm (MFFA) is thus established in this section.

E. *Performance Evaluation*

Performance metrics were employed to conduct an efficient evaluation of the multimodal biometric recognition system. To evaluate the performance of the modified firefly algorithm (MFFA) for feature level fusion of multimodal biometric recognition system; recognition accuracy, sensitivity, specificity, precision and error rate that have been applied by different researchers were employed in this study

IV. RESULTS AND DISCUSSION

An Intel Core i7 CPU and 12G RAM were used for the tests' computing needs. Utilizing MATLAB R2016a and the following settings, both techniques were implemented.

1) Population size: 30
2) Number of iterations: 500
3) Light absorption coefficient: 0.01
4) Attraction coefficient: 0.9
5) Randomization parameter: 0.01
6) Scaling factor: 0.5

Table 1: Evaluation Results of Benchmark Functions for Unimodal F_1 to F_7 (Maximum number of iterations = 500, Dimension of Search Space =30)

Unimodal						
F	FA			MFFA		
	Mean	Stand. Deviation	Best	Mean	Stand. Deviation	Best
F1	0.080355	0.939884	8.68E-07	0.012978	0.141001	7.24E-08
F2	0.078993	0.478213	0.00149	0.008869	0.053499	0.000174
F3	7.699777	69.0462	0.005377	1.144783	11.24114	0.000315
F4	0.061685	0.587811	6.64E-07	0.0078	0.080578	1.42E-07
F5	2.196197	14.46019	0.010444	1.104837	12.43687	0.001541
F6	0.105	1.281478	0	0.008647	0.089844	0
F7	0.035832	0.299547	0.000274	0.011059	0.117756	1.83E-05

Table 2: Evaluation Results of Benchmark Functions for Multimodal (F_1 to F_{13}) (Maximum number of iterations = 500, Dimension of Search Space =30)

Multimodal						
F	FA			MFFA		
	Mean	Stand. Deviation	Best	Mean	Stand. Deviation	Best
F8	0.03137	0.213999	0.00051	0.003622	0.020407	4.67E-05
F9	3.925985	4.873716	2.98507	0.304278	0.391903	0.199837
F10	0.139945	0.792781	0.001769	0.013951	0.084061	0.000176
F11	0.014496	0.029829	0.009857	0.003008	0.003195	0.002218
F12	0.081249	1.055911	2.54E-09	0.022429	0.289347	4.86E-10
F13	-2114.63	0.115573	-2114.64	-237.983	16.16861	-267.266

Table 3: Evaluation Results of Benchmark Functions for Fixed-dimensional Multimodal (F_{11} to F_{23}) (Maximum number of iterations = 500, Dimension of Search Space =30)

Fixed-dimensional Multimodal						
F	FA			MFFA		
	Mean	Stand. Deviation	Best	Mean	Stand. Deviation	Best
F14	1.87558	4.314667	0.994977	0.444883	0.423697	0.299241
F15	0.04762	0.021429	0.044342	0.002769	0.001875	0.002227
F16	-18.6985	7.234474	-19.9996	-2.17412	0.358281	-2.53453
F17	-0.86178	0.024747	-0.8655	-0.09989	0.007935	-0.1128
F18	0.859794	4.150791	0.00017	0.419784	0.379623	0.300254
F19	0.125778	0.693727	0.001952	0.011652	0.069361	0.000164
F20	-13.3083	2.161499	-14.1571	-1.5005	0.263311	-1.87538
F21	-9.82347	1.478596	-9.99999	-1.09717	0.137321	1.26717
F22	-18.4061	0.150104	-18.4188	-2.07629	0.142465	-2.33148
F23	-1.64286	3.026111	-1.9245	-0.20302	0.162474	-0.24375

The effectiveness of the proposed MFFA and the existing FFA was assessed in this work using a meta-heuristic benchmark test function. Unimodal, multimodal and fixed dimensional multimodal functions make up the three categories of benchmark test functions. The goals are to compare the accuracy, convergence rate, and efficiency of the two algorithms (FFA and MFFA) on those functions, and to ascertain which approach (FA or MFFA) performs better overall. According to the benchmark test findings shown on tables 1, 2 and 3, the MFFA is typically more effective than FA. The MFFA was successful in achieving lower function values for the majority of the benchmark functions, which suggests improved optimization performance.

The graphical results also show that MFFA performed better in 16 benchmark functions out of the 23 common benchmark test functions employed, indicating that the modified firefly algorithm developed might be appropriate for solving real-life problems.

Table 4: Evaluation performance of Multimodal for FFA and MFFA using Face, Left Iris and Right Iris (Multimodal)

MULTIMODAL (FACE, LEFT IRIS AND RIGHT IRIS)								
METRICS	FFA (FA_LIRIS_RIRIS)				MFFA (FA_LIRIS_RIRIS)			
TP	553	552	551	550	559	558	557	556
FN	14	15	16	17	8	9	10	11
FP	21	19	17	14	16	13	10	8
TN	168	170	172	175	173	176	179	181
FPR (%)	11.11	10.05	8.99	7.41	8.46	6.88	5.29	4.23
SEN (%)	97.53	97.36	97.18	97.00	98.59	98.41	98.24	98.06
SPEC (%)	88.89	89.95	91.01	92.59	91.53	93.12	94.71	95.77
PREC (%)	96.34	96.67	97.01	97.52	97.22	97.72	98.24	98.58
ACC (%)	95.37	95.50	95.64	95.90	96.83	97.09	97.35	97.49
TIME (%)	145.26	141.38	142.04	144.47	130.78	131.92	130.36	130.53
THRES (%)	0.2	0.34	0.5	0.75	0.2	0.34	0.5	0.75

The results as shown in Table 4 for the threshold values of 0.2, 0.34, 0.5 and 0.75 indicated that the FFA technique had a sensitivity of 97.53%, 97.36%, 97.18% and 97.00%; precision of 96.34%, 96.67%, 97.01% and 97.52%, accuracy of 95.37%, 95.50%, 95.64% and 95.90% at 145.26secs, 141.38secs, 142.04secs and 144.47 seconds for the multimodal biometric (Face, Left Iris and Right Iris). The MFFA technique at the same threshold values of 0.2, 0.34, 0.5 and 0.75 achieved a sensitivity of 98.59%, 98.41%, 98.24% and 98.06%; precision of 97.22%, 97.72%, 98.24% and 98.58%, accuracy of 96.83%, 97.09%, 97.35% and 97.49% at 130.78secs, 131.92secs, 130.36secs and 130.53 seconds. In terms of sensitivity, precision, recognition accuracy and time for multimodal biometric, the results showed that the MFFA technique outperformed the FFA technique. In terms of computational speed, the multimodal biometric system (face, left iris and right iris) gave better and more distinguishable results than the unimodal, bimodal, and bi-instance biometric systems utilizing the same threshold values. The MFFA method is hence more precise and computationally faster.

The graphs below depict the effectiveness and efficiency False Positive Rate (FPR) and Computational Time as employed in this study for the standard FFA and the developed MFFA based on the threshold values 0.2, 0.34, 0.5 and 0.75.

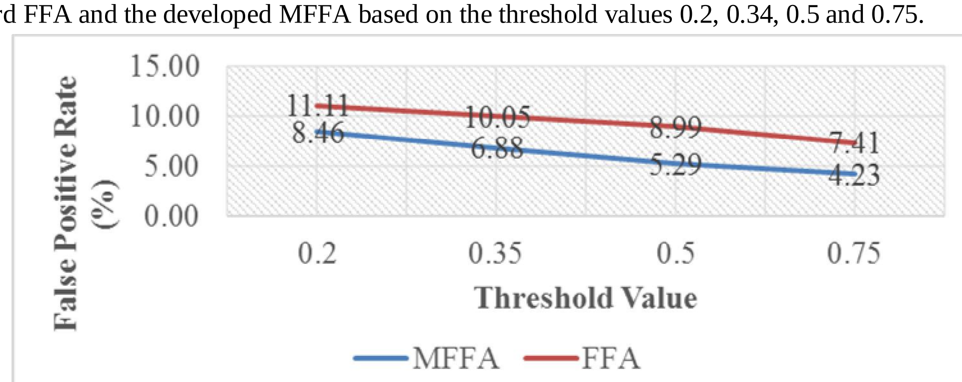

Figure 4.13: Graph showing the Performance of MFFA and FFA based on False Positive Rate

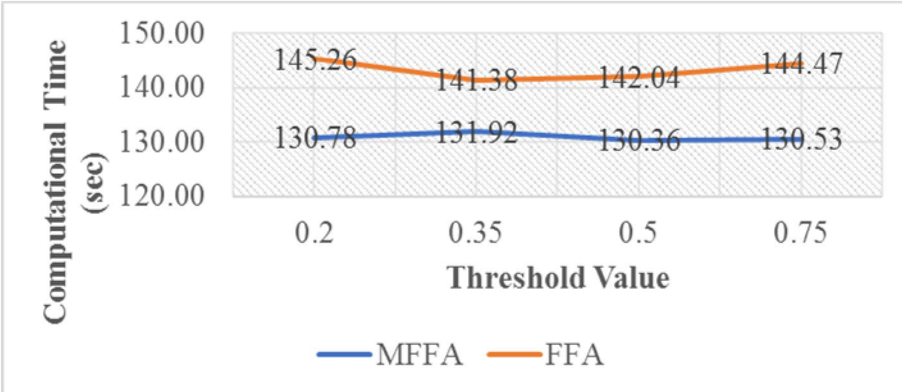

Figure 4.18: Graph showing the Performance of MFFA and FFA based on Computational Time

V. CONCLUSSION

To enhance a multimodal biometric authentication system, a novel approach was devised for feature selection using a modified firefly algorithm (MFFA) based on meta-heuristic principles. The objective was to minimize the dimensionality of feature vectors and identify the most crucial and well-balanced features from facial images and locally acquired iris samples of individuals with African ancestry. By incorporating a chaotic sinusoidal map function and the roulette wheel approach into the existing FFA through the newly developed MFFA technique, the system aimed to improve classification performance and avoid getting trapped in local optima. The MFFA effectively identified relevant characteristics while reducing the high-dimensional feature vector space, making it a valuable feature selection method for biometric identification systems. Our experiments demonstrated the efficacy of this technique in integrating multimodal feature sets. Furthermore, the MFFA technique exhibited high computational efficiency and suitability for real-time applications.

REFERENCES

[1] S. Shrivastava, “Biometric : Types and its Applications,” Int. J. Sci. Res., pp. 10–11, 2015.
[2] E. O. Eludire, A. A., & Adio, “Biometrics Technologies for Secured Identification and Personal Verification,” Biostat. Biometrics Open Access J., vol. 6, no. 2, pp. 42–45, 2018, doi: 10.19080/bboaj.2018.06.555683.
[3] A. Kavitha and A. Vanaja, “ANALYSIS OF AUTHENTICATION SYSTEM IN DIFFERENT,” Int. J. Latest Trends Eng. Technol., pp. 13–17, 2017.
[4] S. M. Prakash, P. Betty, and K. Sivanarulselvan, “Fusion of Multimodal Biometrics using Feature and Score Level Fusion,” Iinternational J. Appl. Inf. Commun. Engineeering, vol. 2, no. 4, pp. 52–56, 2016.
[5] F. Yahya, H. Nasir, and K. Kadir, “Multimodal Biometric Algorithm : A Survey,” Biotechnology, vol. 15, no. 5, pp. 119–124, 2016, doi: 10.3923/biotech.2016.119.124.
[6] H. Jaafar and D. A. Ramli, “A Review of Multibiometric System with Fusion Strategies and Weighting Factor,” Int. J. Comput. Sci. Eng., vol. 2, no. 04, pp. 158–165, 2013.
[7] R. O. Mahmoud, M. M. Selim, and O. A. Muhi, “Fusion time reduction of a feature level based multimodal biometric authentication system,” Int. J. Sociotechnology Knowl. Dev., vol. 12, no. 1, pp. 67–83, 2020, doi: 10.4018/IJSKD.2020010104.
[8] D. Lathika, B . A., &Devaraj, “Artificial Neural Network Based Multimodal Biometrics Recognition System,” in International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014, pp. 973–978.
[9] E. S. Nil and A. Chilambuchelvan, “Multimodal biometric authentication algorithm at score level fusion using hybrid optimization,” Wirel. Commun. Technol., vol. 2, no. 1, pp. 1–12, 2018, doi: 10.18063/wct.v2i1.415.
[10] S. Soviany, V. Sandulescu, S. Puşcoci, C. Soviany, and M. Jurian, “An optimized biometric system with intraand inter-modal feature-level fusion,” Proc. 9th Int. Conf. Electron. Comput. Artif. Intell. ECAI 2017, vol. 2017-Janua, pp. 1–8, 2017, doi: 10.1109/ECAI.2017.08166466.
[11] A. Saha, “An Expert Multi-Modal Person Authentication System Based on Feature Level Fusion of Iris and Retina Recognition,” 2019 Int. Conf. Electr. Comput. Commun. Eng., pp. 1–5, 2019.
[12] M. Haghighat, M. Abdel-Mottaleb, and W. Alhalabi, “Discriminant Correlation Analysis: Real-Time Feature Level Fusion for Multimodal Biometric Recognition,” IEEE Trans. Inf. Forensics Secur., vol. 11, no. 9, pp. 1984–1996, 2016, doi: 10.1109/TIFS.2016.2569061.
[13] C. Kant, “Analysis of Different Fusion and Normalization Techniques,” Int. J. Adv. Res. Comput. Commun. Eng. ISO, vol. 3297, pp. 363–368, 2007, doi: 10.17148/IJARCCE.2018.7369.
[14] P. Sai Shreyashi, R. Kalra, M. Gayathri, and C. Malathy, “A Study on Multimodal Approach of Face and Iris Modalities in a Biometric System,” Lect. Notes Networks Syst., vol. 176 LNNS, no. May, pp. 581–594, 2021, doi: 10.1007/978-981-33-4355-9_43.
[15] S. N. Garg, R. Vig, and S. Gupta, “A Survey on Different Levels of Fusion in Multimodal Biometrics,” vol. 10, no. November, pp. 1–11, 2017, doi: 10.17485/ijst/2017/v10i44/120575.
[16] U. Gawande, M. Zaveri, and A. Kapur, “A Novel Algorithm for Feature Level Fusion Using SVM Classifier for Multibiometrics-Based Person Identification,” Appl. Comput. Intell. Soft Comput., vol. 2013, pp. 1–11, 2013, doi: 10.1155/2013/515918.
[17] M. Eskandari and O. Sharifi, “Optimum scheme selection for face-iris biometric,” IET Biometrics, vol. 6, no. 5, pp. 334–341, 2017, doi: 10.1049/iet-bmt.2016.0060.

[18] I. Ahmia and M. Aïder, "A novel metaheuristic optimization algorithm: The monarchy metaheuristic," Turkish J. Electr. Eng. Comput. Sci., vol. 27, no. 1, pp. 362–376, 2019, doi: 10.3906/elk-1804-56.

[19] S. Sandhya and R. Fernandes, "Lip Print: An Emerging Biometrics Technology - A Review," in 2017 IEEE International Conference on Computational Intelligence and Computing Research, ICCIC 2017, 2018, pp. 1–6, doi: 10.1109/ICCIC.2017.8524457.

[20] R. Mythily and W. A. Banu, "Feature selection for optimization algorithms: Literature survey," Journal of Engineering and Applied Sciences, vol. 12, no. Specialissue1. pp. 5735–5739, 2017, doi: 10.3923/jeasci.2017.5735.5739.

[21] S. D. Jamdar and Y. Golhar, "Implementation of unimodal to multimodal biometrie feature level fusion of combining face iris and ear in multi-modal biometric system," Proc. - Int. Conf. Trends Electron. Informatics, ICEI 2017, vol. 2018-Janua, pp. 625–629, 2018, doi: 10.1109/ICOEI.2017.8300778.

[22] V. Talreja, M. C. Valenti, and N. M. Nasrabadi, "Deep Hashing for Secure Multimodal Biometrics," IEEE Trans. Inf. Forensics Secur., vol. 16, pp. 1306–1321, 2021, doi: 10.1109/TIFS.2020.3033189.

[23] C. Kamlaskar and A. Abhyankar, "Multimodal System Framework for Feature Level Fusion based on CCA with SVM Classifier," Proc. 2020 IEEE-HYDCON Int. Conf. Eng. 4th Ind. Revolution, HYDCON 2020, 2020, doi: 10.1109/HYDCON48903.2020.9242785.

[24] A. B. Channegowda and H. N. Prakash, "Image fusion by discrete wavelet transform for multimodal biometric recognition," IAES Int. J. Artif. Intell., vol. 11, no. 1, p. 229, 2022, doi: 10.11591/ijai.v11.i1.pp229-237.

[25] Z. T. M. Al-Ta'l and O. Y. Abdulhameed, "Features extraction of fingerprints using firefly algorithm," SIN 2013 - Proc. 6th Int. Conf. Secur. Inf. Networks, no. November, pp. 392–395, 2013, doi: 10.1145/2523514.2527014.

[26] M. Leghari, S. Memon, and A. A. Chandio, "Feature-Level Fusion of Fingerprint and Online Signature for Multimodal Biometrics," pp. 2–5, 2018.

[27] P. Cao, "Comparative Study of Several Improved Firefly," no. 6117411, pp. 910–914, 2016.

[28] L. N. Evangelin and A. L. Fred, "Feature level fusion approach for personal authentication in multimodal biometrics," ICONSTEM 2017 - Proc. 3rd IEEE Int. Conf. Sci. Technol. Eng. Manag., vol. 2018-Janua, pp. 148–151, 2017, doi: 10.1109/ICONSTEM.2017.8261272.

[29] G. Kaur and S. Singh, "Comparative Analysis of Multimodal Biometric System," vol. 27, no. 63019, pp. 129–137, 2017.

[30] Y. Xin, L. Kong, Z. Liu, C. Wang, and H. Zhu, "Multimodal Feature-level Fusion for Biometrics Identification System on IoMT Platform," vol. 3536, no. c, 2018, doi: 10.1109/ACCESS.2018.2815540.