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A Feasible Adaptive Fuzzy Genetic Technique for Face, Fingerprint, and Palmprint Based Multimodal Biometrics Systems

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Abstract

A biometric system relies solely on one or a few biometric characteristics to verify a person's identity. Multimodal biometric authentication is a hot emerging area of research. The memory requirements, response times, and adoption/operating costs of conventional multimodal biometric identification methods are all higher than those of single-modal approaches. In this article, we conducted an examination of a framework for multimodal biometric identification systems, which demonstrates a practical implementation of soft computing strategies adaptable to face, finger, and palmprint biometrics. We applied a modified Gabor filter for feature extraction to increase processing speed and reduces the timing. Validation of the proposed system was achieved by the development of a fusion system using principal component analysis as a single matcher classifier. An adaptive fuzzy genetic algorithm was applied for weight optimization which generates verification at a high-rate performance using the fuzzy logic function. Employing fusion in identification mode, the technology was critically examined. The results indicated that the multimodal biometric system outperforms in terms of TPR, FPR, TNR, FNR, Precision, Recall, F-score, and Accuracy, resulting in reduced processing time and memory footprint, and speedier implementation.

Keywords: *adaptive fuzzy genetic algorithm; face recognition; finger recognition; palm recognition; tiny memory; unimodal biometrics; multimodal biometrics*

1. Introduction

Mono biometric systems are plagued by several issues, including noise, restricted universality, intra-class differences, and the possibility of spoofing attacks. In contrast, multimodal biometric solutions, on the other hand, are gradually becoming more popular because of the greater precision, dependability, and enhanced security (Deshpande et al., 2015).

Unimodal biometrics suffer from a number of drawbacks, including noise introduced at the sensor level when recording the trait, non-possession of the trait by some enrolled samples in the system, and susceptibility to counterfeit attacks. These drawbacks collectively reduce the system's ability to accurately recognize individuals (Wang et al., 2022). Multimodal biometrics overcome the shortcomings of unimodal biometrics by significantly improving the system's recognition accuracy and enhancing its resistance to deception (Prabhakar, & Jain, 2002). Multimodal biometrics integrates biometric inputs from various sources, primarily through feature/match score/decision fusion techniques (Roli et al., 2002).

Multimodal authentication systems are a relatively new development in the field of data protection. Multimodal biometrics can identify a person using multiple biometric traits. Multimodal biometrics offer more independent biometric factors, making them more trustworthy than unimodal biometrics. These multibiometric methods are designed to be extremely useful when determining or verifying an individual's identity (Melin et al., 2005). Due to substantial research conducted by the scientific community and advancements in technology, the use of multimodal biometrics in real-world applications has become necessary.

A biometrics system is generally developed based on our physiological or behavioral characteristics. Every person possesses certain characteristics that they maintain; the face is one of them. By observing the face, we can identify these characteristics. There are several types of physiological characteristics, such as fingerprints, iris, and footprint. Similarly, voice, signature, speaking style, typing rhythm, and gait are behavioral characteristics.

The numerous physiological or behavioral factors used in the system determine the reliability of its findings, the legitimacy of an individual's personal authentication, and the system's unique functionality. The fusion of more physical and behavioral characteristics that are used on matching ranks is gaining acceptance and is a highly promising method for boosting accuracy through the use of genetic sets of rules, adaptive fuzzy systems, and other advanced soft computing approaches. This work provides simulated results that may be used to merge matching scores into a multimodal biometric system, which will undoubtedly influence the system's speed and capacity to store. Our work has also been focused on improving the system's performance and reducing memory usage, resulting in enhanced performance and accuracy while requiring less memory. A comparative study is shown in Table 1.

1.1 Related work

Several researchers in this area have published their findings on the following aspects, among many more, that influence the precision of multimodal biometrics at varying levels:

1.1.1 Review of the existing system and applied techniques

In this section, Melin et al. (2005) described a creative method for combining fingerprint, voice, and facial recognition data. The proposed method involves employing a fuzzy system to implement the decision unit of the people identification hierarchical form.

Kovač, & Marák (2022) focused on improving adaptive Gabor filter finger vein patterns. After extracting a region of interest, adaptive contrast enhancement is applied. Second, a vein direction estimation is made using an orientation map. After that, a Gabor filter is convolutionally applied to the finger vein pattern to match its orientation and frequency. An interactive GUI tool selected preprocessing algorithm settings by experimenting with constraint values to observe their effects. In the matching stage, they used OpenCV library functions to compute feature distances using SIFT and SURF features extracted during the extraction phase. They concluded the research with a performance evaluation using FAR/FRR pointers and genuine/impostor distribution graphs. They used Vera, SCUT-FVD, and SDUMLA-HMT databases. Gabor filters achieved the highest SURF feature accuracy score of 99.94% on the SDUMLA-HMT database. SIFT features with the Gabor filter enabled achieved 98.32% accuracy on the Vera database. Adaptive Gabor filters also enhanced recognition rates.

Chang et al. (2005) utilized this criterion to analyze a 2D+3D detection and recognition in order to determine how much of the "multimodal increase" results from merging data from several sensing mechanisms instead of merely numerous images. Matching scores in the various face domains are consolidated, and principal component analysis approaches for multimodal authentication. For the first time, this work provides experimental evidence to support a study of increases in multimodal performance.

Leghari et al. (2021) designed and developed a CNN-based approach to fusing fingerprint and online signature features. In this project, they fuse fingerprint and digital signature features using two different methods. Whereas the late fusion method merges fingerprints and online signatures after fully connected layers, the former method does it earlier. They amassed a new multimodal dataset of 1400 fingerprints and 1400 online autographs from 280 individuals to train and evaluate the proposed model. It supplemented the training data to increase the efficiency of the proposed model training. The accuracy rate for the early feature fusion technique was 99.10%, while the late feature fusion scheme only reached 98.35%.

Table 1 Comparative study of different classifiers used of different modalities by the researchers.

Authors	Work on Modalities	Used Classifiers	Outcomes
Mehdi Cherrat et al. (2020).	Fingerprint, finger-vein and face	Softmax Technique is applied on Face & fingerprint and random forest is used for Finger vein.	The accuracy rate is 99.49%. Computational time (ms)- 69
Olazabal et al. (2019).	Face and voice	K-nearest neighbours (KNN) algorithm.	Computation time For enrolment - 1.34 seconds and for authentication - 0.91 seconds
Vidya, & Chandra (2019).	Face, fingerprint, and iris	Multiclass SVM	Calculate the value of precision, recall, specificity, and accuracy. it was 87.6%.
Mwaura et al. (2017).	Face and fingerprint	K-nearest neighbour algorithm (k-NN) and SIFT scale-invariant feature transform (SIFT) algorithm has been used for feature extraction and image description.	Accuracy was 92.5%, FRR and FAR was 7.5%, 3.75%.
Lee, & Bong (2016).	Face and Palm	*PCA and Neural Network*	The accuracy recognition rate of 89%
Zhu, & Zhang (2010)	Finger geometry, knuckle print and palmprint	Coarse-level similar hand pattern classification	Time consumption for – feature extraction was 151 (ms) and matching was 1.5 (ms)

Barde, & Singh (2022) worked on their own Face and Fingerprint Region database. They extracted facial features using Principal Component Analysis (PCA) and fingerprint nuances using Local Binary Pattern (LBP). To aid with categorization, they developed a dynamic trait-matching system. They used this technique to represent high-dimensional, dense attributes in a more condensed form. When encoding features for the Multi-SVM classifier, they employed fusion. For adaptive face and finger matching, selecting a small fraction of training samples can boost accuracy by 92% and 94%, respectively, because such examples typically better reflect the features of a particular testing sample. The proposed novel approach SVM performed well in many facial recognition circumstances, and the finger exhibits 98% accuracy.

Using a scoring system, Deshpande et al. (2015) approach integrates fingerprints, palmprint s, and facial recognition. At enrollment, three biometric characteristics are taken. At the authentication level, photos are checked against a database of templates to see how closely they match. It is suggested that AOV be used for fingerprint matching. PCA is employed to analyze facial portraits. PCA is a way to calculate a score for comparing palmprints. As part of the fusion procedure, scores are normalized. Biometric features can be prioritized according to their significance. They discovered superior performance when compared to unimodal, with an accuracy of more than 98 percent.

Hammouche et al. (2022) proposed a robust facial recognition system using a combination of the Gabor filter bank and a deep learning technique called Sparse Auto-encoder (SAE). The suggested system's primary goal is to enhance the characteristics recovered by the Gabor filter bank through the application of the SAE technique. The principal component analysis and linear discriminant analysis (PCA + LDA) method are then used to reduce the number of features to the most essential ones. Last but not least, the cosine Mahalanobis distance is used to complete the matching process. Tested in seven public databases (Georgia Tech, CASIA, Extended Yale, JAFFEE, AT&T, Yale, and Essex) demonstrates that the suggested system outperforms other methods offered for this problem and showed ability by combining Gabor and SAE.

Szymkowski, & Saeed (2017) demonstrated that these two traits face, and fingerprint were taken into account concurrently in a multimodal system. User identification accuracy was calculated separately for each of the two attributes, as well as when they were combined. The user identification accuracy was 81% across the two attributes used in the study. The accuracy rate of the suggested fingerprint technique was 62.5%. Combining fingerprints with facial recognition was found to be more effective than fingerprint recognition alone.

Asha et al. (2022) presented a highly efficient face recognition structure by incorporating genetic procedures for an improved search approach. Both face feature extraction and face pattern matching are required for the proposed model to function. They employed Haralick features and PCA-extracted features from face databases in face databases for face recognition. They used the highly prominent artificial firefly swarm optimization algorithm to improve the searching and matching of facial traits. The results of the simulation study run on the faces stored in the database, demonstrated the model's efficacy. The PCA approach has reached an 80.6% recognition rate, while the AFSA has acquired an 88.9% accuracy in the precise recognition percentage.

In order to extract features from photos of the face and ears, Barde et al. (2014) employed a principal component analysis-based neural network classifier, and they used hamming distance to determine iris templates. These features were pooled together and utilized as identifiers. The outcomes were enhanced when many modalities were used together. Characteristics were checked against an internal picture database using Eigenfaces, Eigen ears, and an iris pattern for identification. The use of multiple biometric modalities resulted in higher recognition rates, false acceptance rates, and false positive rates.

In his study, Barde (2017) examined four characteristics: the face, ears, eyes, and feet. The study was tested using a custom-built dataset of one hundred individuals. Principle component analysis was applied to the face, eigen images for the ear, hamming distance-based method to the iris, and modified sequential Haar transform to the foot features during the classification process. Individual weights are separately calculated for each biometric attribute. The matching score was determined using the fusion scheme for every feasible combination of attributes. The utilization of multiple biometric features considerably improved the recognition performance of the multimodal biometric system.

Using both face and palmprint data, Singh, & Barde (2022) demonstrated a new way of identification. For extracting the features, they utilized a Gaussian filter, and for identifying corners, they turned to the Harris approach. Matching scores and decision-level fusion were used to calculate their results. The PCA classifier's matching score for the face was obtained on palm modalities. At the decision level, they obtained the result using the sum rule fusion and fuzzy fusion, which justify and demonstrate the correctness (Das, & Granados, 2022). They discovered that a PCA score between 210 to 426 denotes the actual individual, while a score of more than 430 indicates and imposter after testing the face and palm images. The value of FAR, FRR, and EER are lowered by 19% after fusion.

1.1.2 Problem formulation

Many researchers continue to work on biometrics and multimodalities to upgrade the system. Some of the previously mentioned literature articles described models based on physiological and behavioural characteristics such as the face, finger, Iris, ear, signature, voice, keynotes, etc. These models calculate results at different fusion levels, such as sensor, feature, matching, and decision level. Most of the researchers have done their work on matching scores by applying the different classifiers and analysing the results. However, we observed that the intended system requires more memory, has a worse reaction rate, and has higher costs for both deployment and operation. To address this issue, we designed an innovative AFGA multimodal biometrics system for using three modalities face, finger, and palmprint. The conventional multimodal biometrics system is explained in section 3. In section 4, we will discuss the proposed system architecture, and in section 5, we will review all potential outcomes.

2. Objective

The main motive of this research work will be described below,

1) To design an innovative Multimodal Biometric identification System.

2) To overcome the issue of feature extraction by a modified Gabor filter that increases the processing speed and reduces the timing of performance.

3) In order to accomplish high validation through the use of the fusion system built around one primary component matcher principal component analysis for multimodalities.

4) To generate a high rate of weight optimization by applying an adaptive fuzzy genetic algorithm.

5) To achieve high accuracy of the proposed biometric system.

3. Conventional Multimodal Biometric system

Over the past decade, many researchers have worked on the conventional multimodal biometric system and have developed multimodal biometrics systems at various stages, including the sensor level, feature level, matching level, and decision level by using different approaches. Although the performed techniques provide good results and enhanced the biometrics capabilities. Within a system, each characteristic is equipped with its own set of methods for feature extraction, including matching approaches. These approaches are responsible for calculating the similarity measure by eliminating the disparities in the data using normalization procedures (Atrey et al., 2010). Figure 1 shows some complex fusion methods used at the decision level to calculate the fusion score that determines whether the person is genuine or not. However, this system has a few flaws that have led to an increase in the amount of time, processing, and memory requirements.

4. Proposed Multimodal Biometric System based on AFGA

The development of the proposed architecture serves several major purposes, with one of the most important being to demonstrate that it is possible to establish an implementation of appropriate multimodal biometric identification without the need for two entirely separate unimodal systems. By implementing our framework, we eliminated numerous matching strategies and normalization procedures, thereby reducing the complexity of the conventional multimodal biometrics system. We processed the work in the order illustrated in Figure 2 according to this approach. They compare the initial input picture, which they pre-process and segment, with the database stored in the template using a matching classifier PCA during the features extraction stage. The matcher is employed to compare the input picture with the dataset and produce the match score output, and the first process has completed the production the match performance as an output.

We used the Adaptive Fuzzy Genetic Algorithm (AFGA) to make the decision of matching to enhance the performance of the system. Next, fusion is used to determine whether a person's modalities are compatible. The goal of multimodal biometrics is to reduce biometric parametric errors (Malarvizhi et al., 2020).

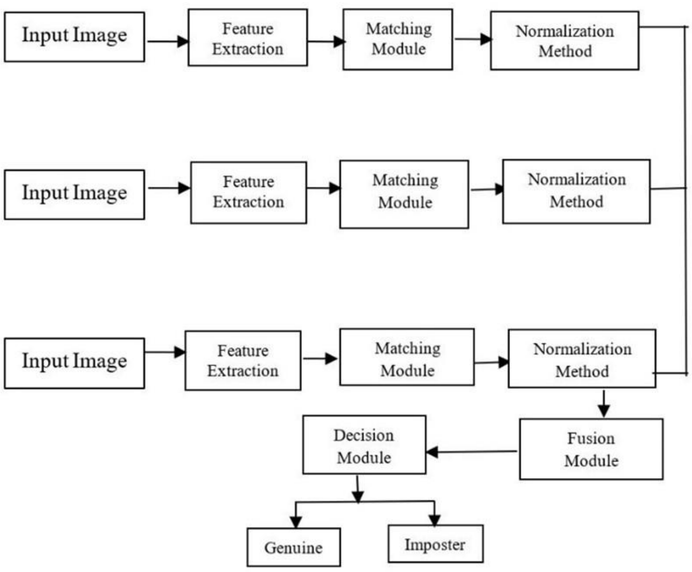

Figure 1 Conventional Multimodal Biometrics System

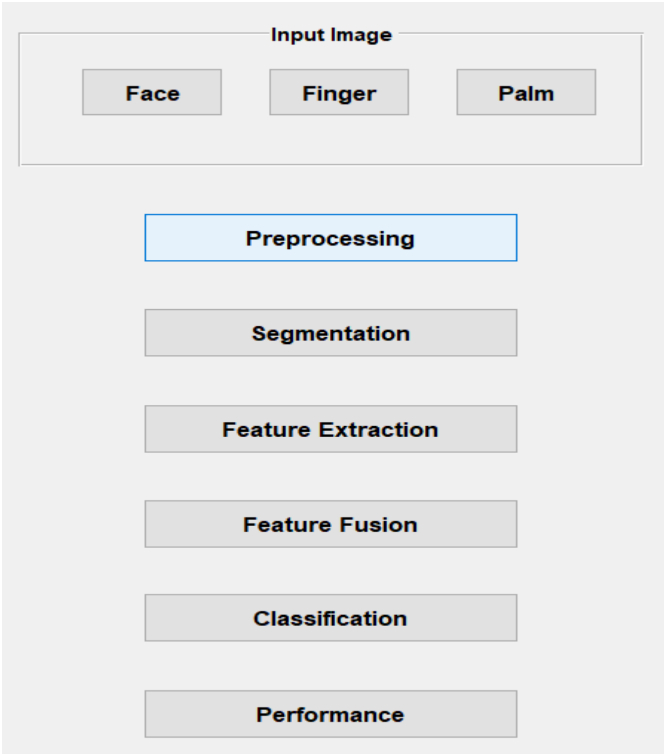

Figure 2 Steps of the proposed multimodal biometrics system

4.1 Enrolment and Pre-processing

For authentication, the system utilized high-quality cameras and other devices to take pictures of a person's face, fingerprints, and palmprint. This system created the standard dataset, which comprises 4 unique photographs of each modality for 100 persons. Although we prepare 400 images for the training dataset, this system only used 100 images for testing. Pre-processing and segmentation remove the noise in the stored data, resulting in an overall improvement in the data's quality.

4.2 Feature extraction from Modified Gabor Filter (MGF)

The modified Gabor filter was invented by Dennis Gabor. It is used for texture analysis and edge detection. In 1995, Daugman has defined 2D filter which is also called The Gabor Filter. Multimodal biometric images, such as shape, size, edge, and texture, are used as input features. Image analysis applications such as texture classification, edge recognition, feature extraction, and others, utilize a type of filter known as a band-pass filter, also referred to as a Gabor filter. When applied to a picture, the Gabor filter modifies the highest response near the edges, resulting in a distinct change in texture (Lu et al., 2015). The Modified Gabor filter increase the processing time. For authentication purpose¸ we employ a modified Gabor Filter in the Face, fingerprint, and Palmprint matching & recognition system.

When trying to extract characteristics from a picture, it is helpful to use a series of Gabor filters with various wavelengths and orientations (Prasad et al., 2022). In the discrete domain, two-dimensional Gabor filters are given by:

$$Gc=Be^{\frac{-(i^2+j^2)}{2\sigma^2}}\cos(2\pi f(i\cos\theta+j\sin\theta)) \quad (1)$$

$$Gs=Ce^{\frac{-(i^2+j^2)}{2\sigma^2}}\sin(2\pi f(i\cos\theta+j\sin\theta)) \quad (2)$$

where B and C are normalizing factors to be determined.

4.3 Principal Component Analysis for matching score (PCA)

Principal Component Analysis (PCA) is a statistical process used to transform a series of observations of potentially correlated variables into a set of values. This is achieved through an orthogonal transformation, which helps reduce the dimensionality of the data. If a matching value always consistently assigns high ratings to legitimate matches while providing extremely low ratings to fraudulent and false results, it demonstrates the accuracy of the matching value (Sinha, & Barde, 2022). Therefore, it is considered a reliable matcher. Since it's a strong matcher, there are no restrictions on how the matcher is chosen. Principal Component Analysis (PCA)then compares the retrieved features of the face, finger, and palm to those in the template database, yielding a matching value between 0 and 1. Steps involved in PCA are as follows:

Step 1: Standardize the Training dataset and we need to calculate the Mean and standard deviation by equation.

$$x_{new}=\frac{x-\mu}{\sigma} \quad (3)$$

Step 2: Calculate the covariance matrix for the features in the dataset.

$$Cov(x,y)=\frac{\Sigma(x_i-x')*(y_i-y')}{N} \quad (4)$$

Step 3: Calculate the eigenvalues and eigenvectors for the covariance matrix. Let A be a square matrix, v is eigenvector and λ is eigenvalue then the equation.

$$(A-\lambda)\, v = 0 \quad (5)$$

Step 4: Sort eigenvalues and their corresponding eigenvectors.

Step 5: Pick k eigenvalues and form a matrix of eigenvectors.

Step 6: Transform the original matrix.

4.4 Weights optimization using the Adaptive Fuzzy Genetic Algorithm (AFGA)

We used the Adaptive Fuzzy Genetic Algorithm (AFGA) to enhance the performance of the face, finger, and palmprint biometric system and test the multimodal system with the dataset (Rajasekar et al., 2022). The features are captured from the three modalities. The matching rate is calculated from equation 6. Where i indicate the weight of the face, finger, and palmprint.

$$M_s=W_i\, Ms_i \quad (6)$$

The weighted sum rule is applied for the fusion that improved the performance of matching rates and the formula of weight optimization as in equation 7.

$$Min_z=F(W),\ W=(W_{fr}, W_{fpr}, W_{ppr}) \quad (7)$$

Where the objective feature is z, the weights vector is w, and W_{fr}, W_{fpr}, W_{ppr} are the weight of the face, finger, and palmprint biometrics respectively giving better results of EER.

5. Experimental Results on Proposed Multimodal Biometrics System

5.1 Dataset Records

The results of our proposed model are superior to those of the standard system, and the framework itself provides a promising way forward. Using a high-quality camera, the proposed solution could distinguish between fake and real images in a dataset of faces, fingerprints, and palmprint developed by the researchers themselves. We displayed images of a face, fingerprint, and palmprint in Figure 3.

5.2 Pre-processing and segmentation results

This process involves utilizing the MATLAB tool to crop and resize each of the sample images of the face, finger, and palm. Figure 4 shows the downsized versions of the face, finger, and palmprint photos. This was done to improve image sharpness. The segmentation of visual representations of hands and fingers into regions representing various elements. Figure 5 illustrates the different methods for categorizing the pixels of an image.

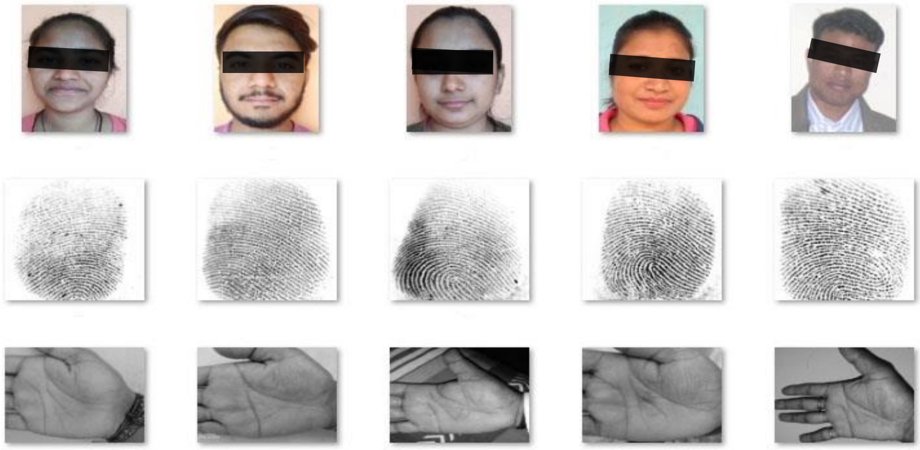

Figure 3 Image samples of palm, fingers, and faces

Figure 4 Resized images of the face, finger, and palm

Figure 5 Segmented image of a face, finger, and palm

5.3 The Modified Gabor Filter produces Feature Extraction

The existing Gabor filter algorithm has slowed down the processing time, so we will try to modify the existing one and trying to create a proposed Gabor filter to overcome the problem, increase processing speed, obtain better-extracted features for identifying the correct person, and minimize the error and false positive rate (Prasad et al., 2022). We will use the Modified Gabor filter on the face to reduce visual contrast, filter out noise, and enable fingerprint recognition, and palmprint recognition. This will allow us to analyse and extract the features by enhancing the ridges and smoothing out the valleys. Figure 6 displays the outcome of face, finger, and palmprint feature extraction and Figure 7 indicate the results using column metrics.

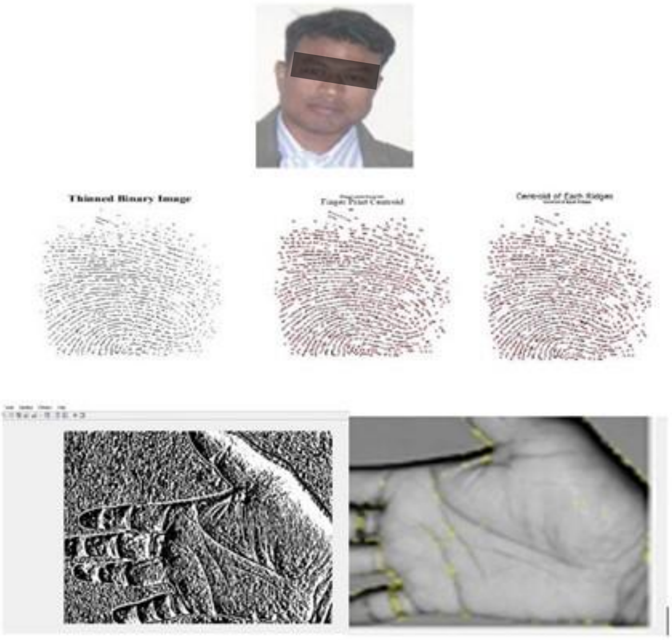

Figure 6 Result of Modified Gabor filter method

Facial Features

	1	2	3	4
1	0	48.8565	2.3870e+03	1.0000

Finger Print Features

	1	2	3	4
1	57	62	62	63

Palm Print Features

	1
1	6.8050

Figure 7 Column metrics of features of a facial, finger, and palmprint

5.4 Matching score of Face, Finger, and Palm from PCA Classification

There are no limitations on the type of fusion algorithm or method that can be used. A straightforward approach to fusion that utilizes accumulators is used here. Since all three matching modalities use the same matcher, the end-result finding rates are identical, making it simple to compile this information. This straightforward accumulator utilizes the powerful features of the matcher, enabling it to generate results on par with those produced by the traditional approach. Despite both methods producing false positives and the highest possible score when applied to unique patterns, the percentage of truly matching cases remains very high. Table 2 shows the comparison results of individual and combined modalities in the proposed system. In this research, face, fingerprint, and palmprint image recognition are compared with each other.

Table 2 Comparison between single and all possible combinations of three modalities

	Genuine	Imposter	FPR	FNR	EER %	Processing Time (In Second)
Face	60	10	15	15	14.82 %	0.12
Finger	65	9	13	13	12.87 %	0.19
Palm	63	9	14	14	13.91 %	0.23
Face + Finger	75	8	13	15	12.21%	0.29
Finger + Palm	69	10	12	14	11.62%	0.21
Face + Palm	72	9	16	13	13.25%	0.17
Face + Finger + Palm	78	6	12	14	10.02%	0.09

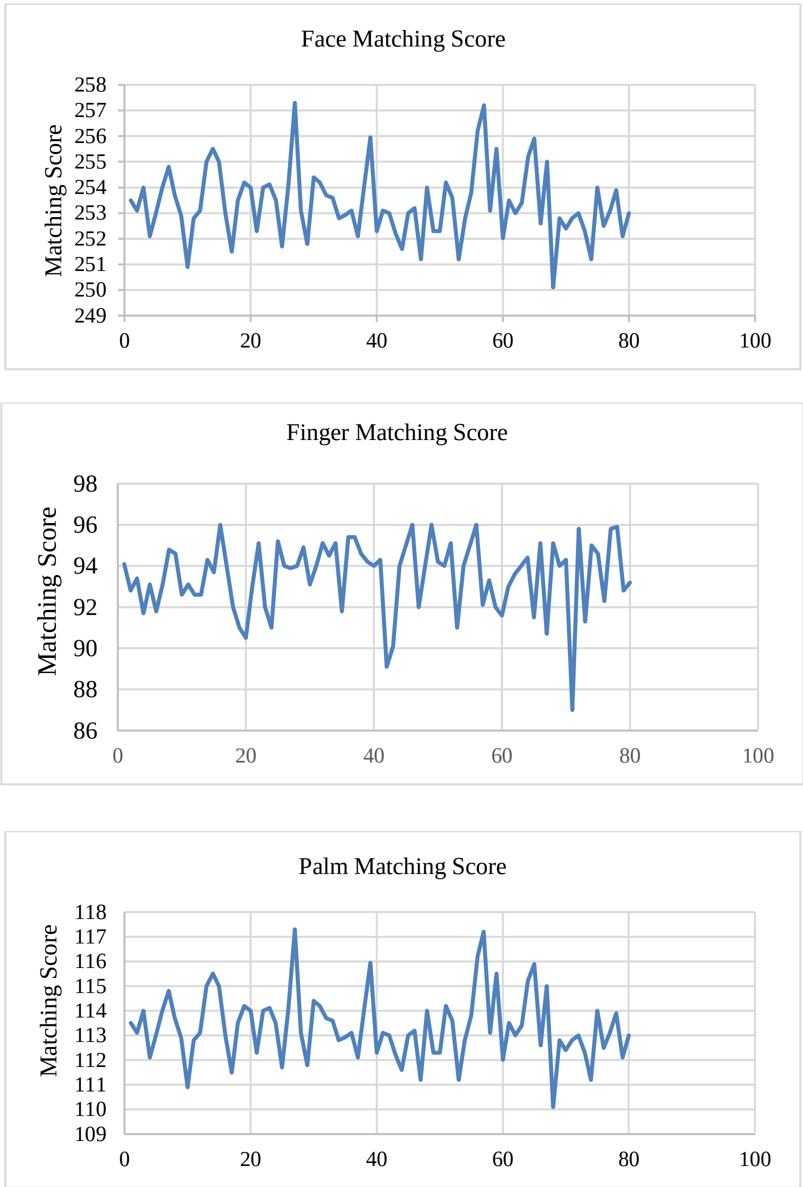

Figure 8 Face, finger, and palmprint matching scores

Through this comparison, we were able to demonstrate that the outcomes produced by the developed framework are superior to those produced by the individual components comprising a unimodal system. The findings demonstrate a significant improvement in the proposed system's effectiveness, alongside a substantial reduction in the equal error rate and the system's response time. When the scores of three distinct matching modalities are combined collectively, the outcome is a more precise match score than if those scores were combined separately. It first collected features individually from the photos of the user's face, fingers, and palm, and then combined those characteristics using an additional operation known as the sum rule. Matching values are shown in Figure 8 for the face, fingerprint, and palm modalities.

Table 3 Performance Measure on Face image recognition

Evaluation by Precision, Recall, Fscore, Accuracy
Precision=True Positive/True Positive + False Positive
Precision = 0.514100833333333 / 0.514100833333333 + 0.428100000000000
Precision = 0.5141100000000000
Recall = True Positive / True Positive + False Negative
Recall = 0.514100833333333 / 0.514100833333333 + 0.0193675000000000
Recall = 1.182905000000000
Fscore = Precision-recall / Precision + Recall
Fscore = 0.5141100000000000–1.182905000000000/ 0.5141100000000000+ 1.182905000000000
Fscore = 1.1453003066530094
Accuracy = (True Positive + True Negative) / (True Positive + True Negative + False Positive + False Negative)
Accuracy = (0.514100833333333 + 0.0381154166666667) /
(0.514100833333333 + 0.0381154166666667+ 0.428100000000000+ 0.0193675000000000)
Accuracy = 0.811225000000000
Memory Space (Byte)= 12736

Table 4 Performance Measure on Fingerprint recognition

Evaluation by Precision, Recall, Fscore, Accuracy
Precision=True Positive/True Positive + False Positive
Precision = 0. 386905800333333 / 0. 386905800333333 + 0. 568800000000000
Precision = 0.4048377652760222
Recall = True Positive / True Positive + False Negative
Recall = 0. 386905800333333 / 0. 386905800333333 + 0.019275000000000
Recall = 1.0192750000000
Fscore = Precision-recall / Precision + Recall
Fscore = 0.4048377652760222–1.0192750000000/ 0.4048377652760222+ 1.0192750000000
Fscore = 1.431452655874465
Accuracy = (True Positive + True Negative) / (True Positive + True Negative + False Positive + False Negative)
Accuracy = (0.386905800333333+0.020101100000016) /
(0.386905800333333+ 0.020101100000016+ 0.568800000000000+ 0.019275000000000)
Accuracy = 0.941312000000000
Memory Space (Byte)= 18892

Table 5 Performance Measure on Palmprint recognition

Evaluation by Precision, Recall, Fscore, Accuracy
Precision=True Positive/True Positive + False Positive
Precision = 0. 467802600120012 / 0. 467802600120012 + 0. 321706200210012
Precision = 0.9869200000000000
Recall = True Positive / True Positive + False Negative
Recall = 0. 467802600120012 / 0. 386905800333333 + 0.016952000000000
Recall = 0.948301000000000
Fscore = Precision-recall / Precision + Recall
Fscore = 1.0251000000000–1.163675000000000 / 1.025100000000000 + 1.163675000000000
Fscore = 1.1453003066530094
Accuracy = (True Positive + True Negative) / (True Positive + True Negative + False Positive + False Negative)
Accuracy = (0. 467802600120012 + 0.02010110000001667) /
(0. 467802600120012 + 0.02810130000001827+ 0. 321706200210012+ 0.016952000000000)
Accuracy = 0.91285000000000
Memory Space (Byte)= 11264

Table 6 Performance Measure on Face, fingerprint and palmprint

Biometrics	TPR	TNR	FPR	FNR	Precision	Recall	F score	Accuracy %	Memory Space (Bytes)
Face	0.5141	0.0381	0.4281	0.0.193	0.5141	1.1829	1.1453	81.12	12736
Finger print	0.3869	0.0201	0.5688	0.0192	0.9869	0.9483	0.8379	94.13	98892
Palmprint	0.4678	0.0281	0.3217	0.0169	0.3976	1.1365	1.0449	91.28	11264

5.5 Performance evolution on Face, Fingerprint, and palmprint recognition

When comparing single biometric verification versus multimodal identity verification, we have found that the latter provides a higher level of protection. In order to determine the total performance of each biometric, the highest potential values that are precisely matched from each individual must be found. The MATLAB simulation makes it simple to obtain the performance measures. Measures for the performance evaluation in terms of True positive rate (TPR), True negative rate (TNR), False positive rate (FPR), False negative rate (FNR), Precision, Recall, F-score, and accuracy. At last, we see the memory space used by the modal. Table 3 to 5 show face image, fingerprint, and palmprint recognition performance.

In this system, each modality face, finger, and palmprint is compared to other modalities and the performance is calculated in the terms of True Positive Rate (TPR), False Positive Rate (FPR), True Negative Rate (TNR), and False Negative Rate (FNR). Performances comparison is performed in terms of precision, recall, F-score, and accuracy for three biometrics such as the face, fingerprint, and palmprint shown in Table 6.

The MATLAB software is used for generating the results of simulation for face, finger and palmprint shown in Figure 3 to 9. To optimize weight for these three modalities, an adaptive fuzzy genetic algorithm is applied. The simulation results show that the strategy is more effective at ensuring safety, and the required range for optimization is minimal. When compared to the conventional method, the proposed optimization strategy produces a greater estimation of them. As shown in Table 3 to 6, when evaluating the accuracy of each biometric, the accuracy of fingerprint biometrics seems to be extra superior at 94.13%.

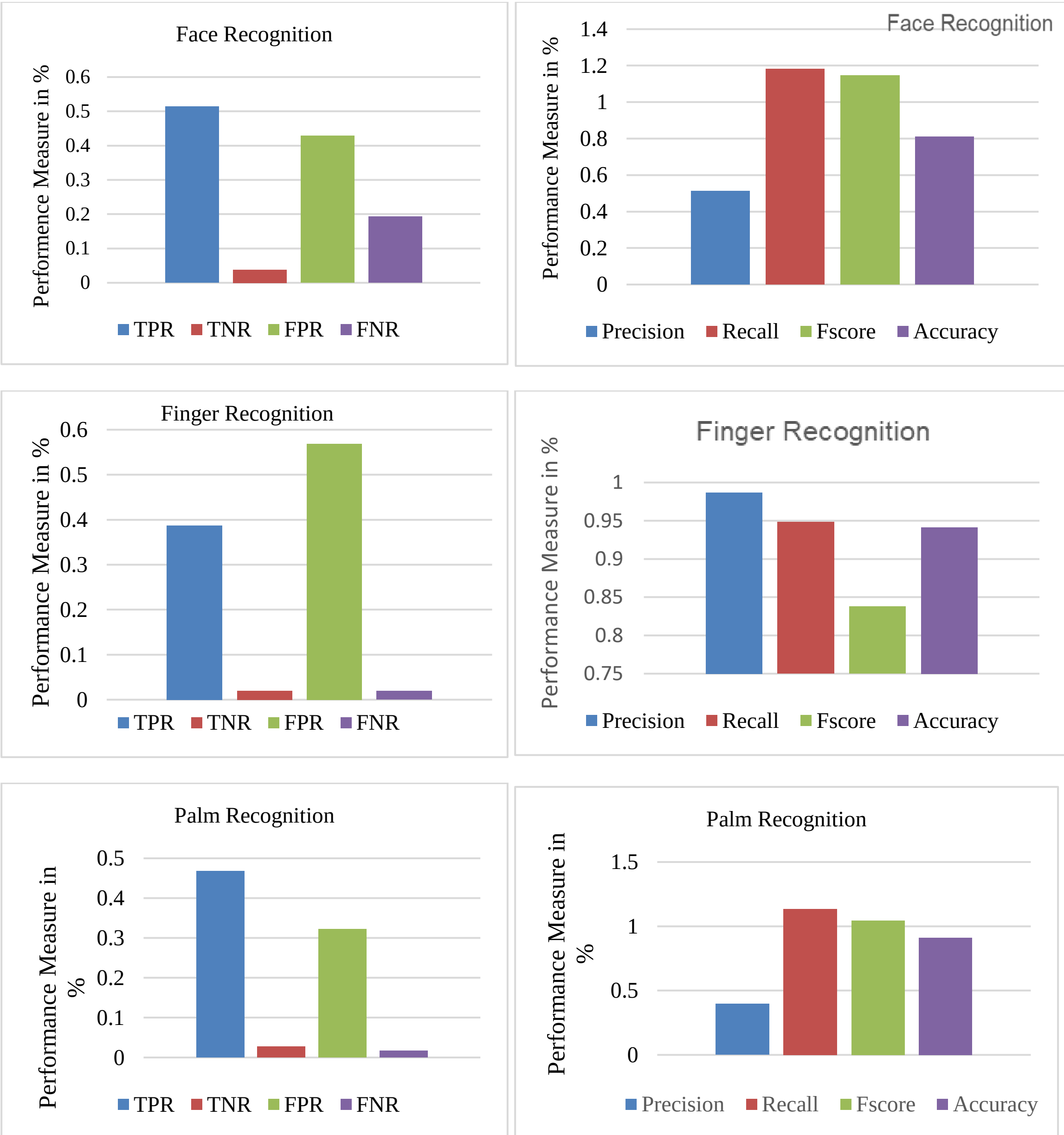

Figure 9 Performance measure on Face, Finger, and Palmprint Modalities

6. Conclusion

Identification, authentication, and non-repudiation are a few security components that biometrics has long helped with. Systems that depend on user passwords, pin identification, and token-based arrangements require those kinds of support. Biometrics, in particular, is used to identify individuals based on specific characteristics to verify the validity of an entry pattern when compared to a template.

The field of biometric authentication is rapidly expanding, propelled by technology and other dangers. However, based on the results of the simulation, it is possible to draw the conclusion that the multimodal fusion of facial images, fingerprint images, and palmprint biometrics can improve authentication performance. The use of matching ratings for face, fingerprint, and palmprint biometrics, which were evaluated across a wide range of scenarios in this study, highlights the true potential of this integration. Due to the improved performance and inherent liveness of biometrics, this strategy must be advantageous for enhancing protection. However, as part of our planned future study, we need to assess the security improvement in a practical application situation.

The proposed architecture can be implemented with minimal effort and expense and requires insignificant memory. The plug-and-play nature of the system is owed in large part to the framework's adaptability and openness, which allow for the quick tuning of several classifiers and matches.

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