Multimodal Biometrics for Robust Fusion Systems using Logic Gates

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Abstract

Many professionals indicate that unimodal biometric recognition systems have many shortcomings associated with performance accuracy rates. In order to make the system design more robust, we propose a multimodal biometric which includes fingerprint and face recognition using logical AND operators at decision-level fusion. In this paper, we also discuss some concerns about the security issues regarding the identification and verification processes for the multimodal recognition system against invaders and threatening attackers. While the unimodal fingerprint and face biometric gives recognition rate of 94% and 90.8% respectively, the multi-modal approach was giving a recognition rate of 98% at the decision level fusion, showing an improvement in the accuracy. Also, both the FAR and FRR have been considerably reduced, showing that the multi-modal system implemented is more robust.

Introduction

Biometrics refers to the use of the physiological or behavioral characteristics of a person to authenticate his or her identity [1]. The increasing demand for enhanced security systems has led to an unprecedented interest in biometric-based person authentication systems. Biometric systems based on a single source of information are called unimodal systems. Although some unimodal systems [2] have made a considerable improvement in reliability and accuracy, they often suffer from problems in the enrollment processes due to non-universal biometric traits, biometric spoofing and insufficient accuracy caused by noisy data [3]. Many of the limitations of unimodal systems can be addressed by deploying multimodal biometric systems, which essentially integrate information from different biometric modalities [4]. The term 'multimodal' is used to describe the combination of two or more different biometric sources of a person (i.e. face, iris, fingerprint) sensed by different sensors. Two different properties (i.e. infrared, reflected light of the same biometric source, 3D shape and reflected light of the same source sensed by the same sensor) of the same biometric can also be combined. In orthogonal multimodal biometrics, different biometrics (i.e. face, iris, fingerprint) are involved with little or no interaction between the individual biometrics whereas independent multimodal biometrics processes the individual biometrics independently [5]. For multimodal biometric recognition systems, information is fused from different biometric traits. The process of fusion can be done at different levels after getting raw data; broadly divided into feature-level, score/match-level, and decision-level fusion. Theoretically, the methodology of a generic biometric system has a sensor module to capture the trait, a feature extraction module to process the data to extract a feature set that yields a compact representation of the trait, a classifier module to compare the extracted feature set with the reference database to generate matching scores, and a decision module to determine an identity or validate a claimed identity. In a multimodal biometric system, information reconciliation can occur at the data or feature levels, at the match score level generated by multiple classifiers pertaining to different modalities, and at the decision level. Figure 1 illustrates that a sample score level fusion in a multi-modal biometric system multimodal biometric system, information reconciliation can occur at the data or feature levels, at the match score level generated by multiple classifiers pertaining to different modalities, and at the decision level. Figure 1 illustrates that a sample score level fusion in a multi-modal biometric system.

Since the feature set contains more information about the input biometric data than the matching score or the output decision of a matcher, fusion at the feature level is expected to provide better recognition results. However, fusion at this level is difficult to achieve in practice because the feature sets of the various modalities may not be compatible and most of the commercial biometric systems do not provide access to the feature sets which they use. Fusion at the decision level is considered to be rigid due to the availability of limited information. Thus, fusion at the match score level is usually preferred as it is relatively easy to access and combines the scores presented by the different modalities [6]. The aim of this paper is to propose a new approach in order to increase the accuracy of multimodal biometric systems and reduce the insufficient accuracy of biometric traits, which are created by noisy data, using fusion levels algorithms between face and fingerprint recognition systems. The paper is organized as follows. Section II discusses various related papers on this topic. Section III explains fingerprint recognition using the minutiae match algorithm. Section IV conducts face recognition using the eigenface approach algorithm. Section V describes the fusion part of the system, which is implemented by fusion at score level. Section VI presents some simulation results, and conclusions are presented in Section VII.
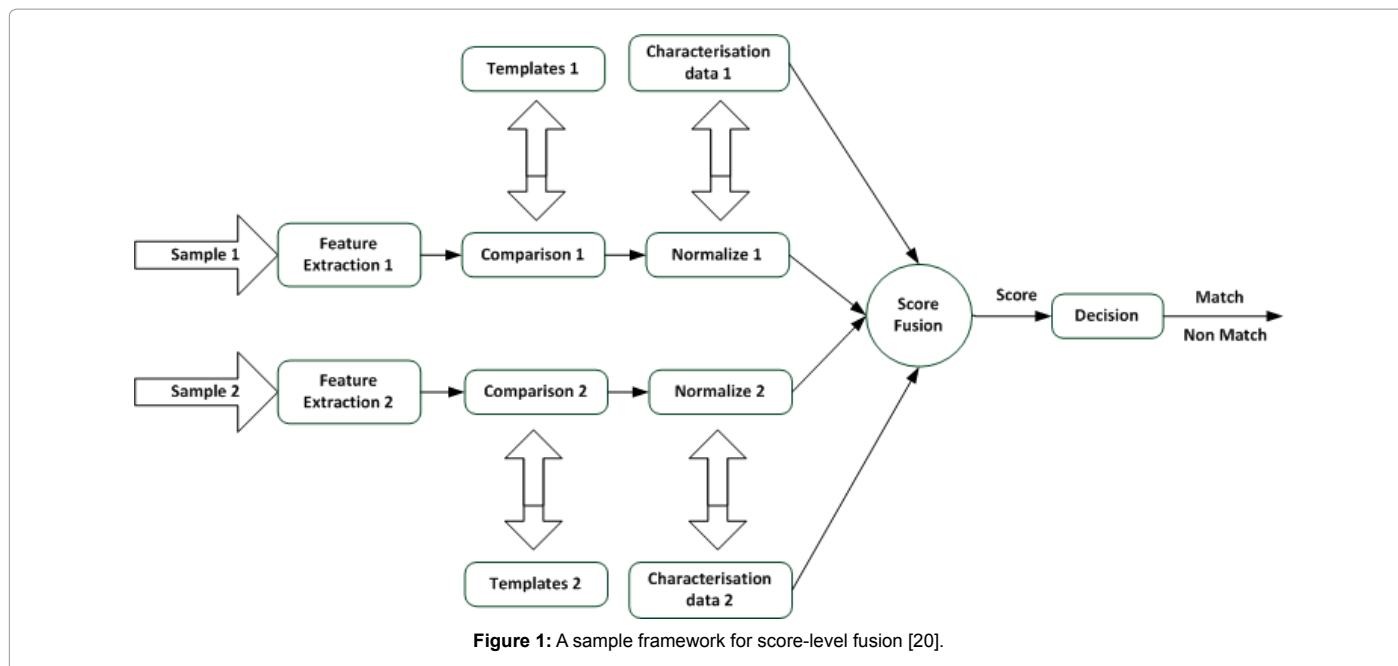
Related Works

Many papers have reported on the use of biometric features to augment the accuracy of unimodal biometric systems with different fusion algorithms. Ross [7] proposed the combination of face and fingerprint to construct an identification system. That system combines the scores of different classifiers operating on the fingerprint and face feature sets to generate a single matching score which is used for identification. Furthermore, multimodal biometric systems integrate

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Figure 1: A sample framework for score-level fusion [20].

information presented by single or multiple biometric indicators. The information can be consolidated at various levels. Derawi Biometrics [8] proposed normalization and fusion methods at score-level fusion. As already mentioned, there are several types of fusion (decision-level, score-level or feature-level). The fusion at feature level is more effective in multimodal biometrics system; however, the fusion at score level is preferable due to practical reasons. Score normalization usually requires that several factors are known before the normalization can be done. In the simplest case, the range of the scores generated by the algorithm needs to be known. For instance, if algorithm X generates scores between 0 and 100, a typical normalization step would be to divide the original score by 100. More complex normalization schemes would require a priori knowledge about the raw score distributions. What is relevant to know is that score normalization is related very closely to score-level fusion since it affects how scores will be combined and interpreted in terms of biometric performance. Hong and Jain [9] proposed a multi-biometric system in which two different biometric systems are cascaded. In their approach, face recognition is used to retrieve the top n matching identities, and fingerprint recognition is used to verify these identities and make a final identification decision. A multimodal system designed to operate in parallel mode generally has a higher accuracy because it utilizes more evidence about the user for recognition. Alternatively, in recent years, sparse representation (SR) based models have become popular for biometric recognition, mostly in unimodal biometric systems. Shekhar, Patel, Nasrabadi and Chellappa [10] proposed a joint sparsity-based framework for multimodal biometric recognition. The methodology of their approach is to integrate information from different modalities of the test subject by constraining them to share their sparse representations. Thus, it simultaneously takes into account correlations as well as coupling information among biometric modalities

As can be seen from the literature, fusion algorithms on the different levels can be quite a sensible means of improving the accuracy of the multimodal biometric systems. For our approach, we chose fingerprint and face modalities for evaluating fusion algorithms. The proposed approach was implemented using the optimum 'decision-level (majority voting fusion)' method for verifying the person's identity. The concept of this decision-level fusion includes Score Combination, using a basic AND logical operator and Dynamic Score Selection. The decision-level fusion presents the combination of matching scores that are coming from the decision levels provided by the unimodal biometrics in the system. At the end of this approach, the multimodal biometric system will become more scalable and robust than other methods to make a final decision (accept or reject) on the score selection.

Fingerprint Recognition System Architecture

A fingerprint raw image is formed of a sequence of ridges and valleys (the ridges appear as dark lines and the valleys are the light areas between the ridges shown in Figure 2), which are also referred to as furrows. There are two common types of minutiae point, bifurcation (the point is separated to two branches on the ridge) and termination (immediate ending of a ridge) points. These points were used for fingerprint feature extraction and also in the minutiae matching stage. Likewise, there are two approaches for fingerprint recognition, the minutiae-based algorithm and the image-based algorithm. Our approach is a minutiae-based algorithm in fingerprint recognition and it represents the fingerprint by its local features or points, such as terminations and bifurcations.

The proposed approach for our fingerprint recognition system comprises a basic fingerprint sensor, a feature extractor part and a minutiae matcher. Optical or capacitive sensors are commonly used for the fingerprint acquisition stage. To deploy a feature extractor, we used a two-stage approach in this work, the pre-processing and the minutiae extraction stages. The pre-processing stage started with the Image Enhancement process using Histogram Equalization and Fourier Transform methods [11]. Then the enhanced image was binarized using the adaptive threshold [12]. Finally, the segmentation process was carried out utilizing ridge direction [13] and region of interest extraction methods by morphological operations [14] in the pre-processing stage. The minutiae extraction part consisted of the thinning process, which was carried out using three thinning
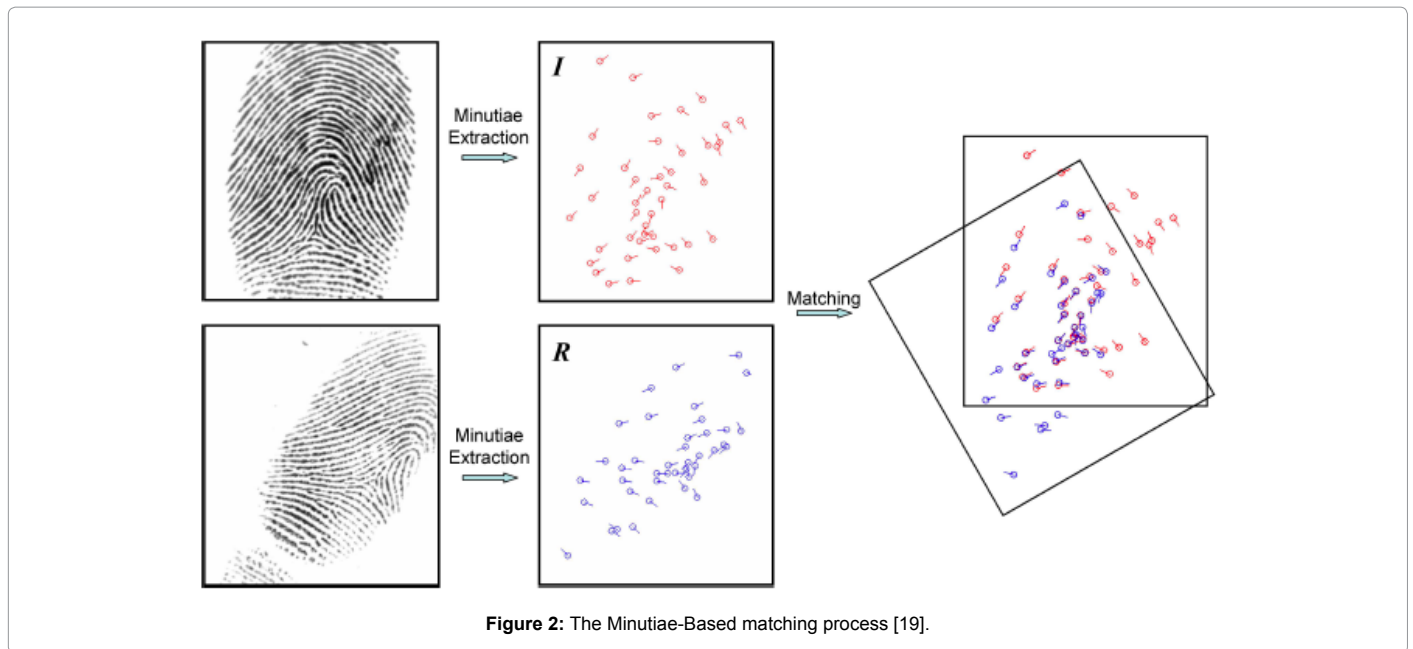
Figure 2: The Minutiae-Based matching process [19].

algorithms [12,15], and also the expanded thinning operations were tested with good thinning quality in the minutiae extraction stage. Then the minutiae marking task was implemented to get over ridge point marking using Wu's implementation [14] and an additional check operation was carried out for this final stage in the feature extraction algorithm. The minutiae matcher then selects any two minutiae images as reference minutiae pair images, and then the algorithm matches their related ridge points. If the ridge points correspond to true scores, then the two images are done as an alignment process and aligned to each other. Finally, the matching process was deployed and applied to all the remaining minutiae images

The minutiae-matching algorithm comprises comparing one set of minutiae data with another set. In most cases, this process compares an input data set with a previously stored data set with a known identity, referred to as a template. The template is created during the enrolment process, when a user presents a finger for the system to collect the data from. This information is then stored as the defining characteristics for that particular user. This algorithm also tries to align the minutiae of the input image and stored templates and finally finds the number of matched minutiae. After the alignment, two minutiae extractions are considered to be matched if the distance and direction difference between them are smaller than a given tolerance. An alignment-based match algorithm was taken from the [16]. Figure 2 illustrates how the minutiae matching process works in the fingerprint recognition system in practice.

Face Recognition System Architecture

This system can operate in either or both of two modes: face verification (authentication) and face identification (recognition). Face verification comprises a one-to-one match which compares a query face image against a template model face image whose identity is being gone through. On the other hand, face identification involves a one-to-many match algorithm which compares a query face image against all template model images in the database to determine the identity of the query face.

In order to identify and verify the face recognition, there are various approaches [17] to operating the system: a) the holistic approach: the face region is taken into a group as input data into the face detection system (i.e. eigenfaces, fisherfaces), (b) the feature-based approach: local features on the face region such as nose, mouth, eyes are segmented and then used as input data for structural classifier; and c) the hybrid approach: the human vision system perceives both local features and the whole face region. In this work, the holistic approach was selected and implemented to analyse and identify it through the system. The principal component analysis technique (PCA) and its component the eigenfaces method, which is described by Turk and Pentland [18], were used in this approach. In Figure 3, the outline of the proposed face recognition system is given. As can be seen, there are six main functions in the typical recognition system. In acquisition part, the face image is taken using a high-resolution camera and then this raw image is constructed and normalized in the pre-processing step to start the extracting process in the next stage. The Image Normalization process was carried out to change the acquired image size to a default image size, and for our system, it was enhanced 128*128, on which the face recognition operates.

After the pre-processing stage, we used a different method from the typical feature extractor module, so the training sets should be created within this method. Our implementation was based on an efficient system to recognize faces from the images with some real-time variations. The conducted approach is essentially close to implement and verifies the algorithm Eigenfaces for recognition [18], which resolves the recognition problem for raw images of faces, using the principal component analysis (PCA). After designing Eigenfaces implementation and calculating the eigenvectors and eigenvalues from the raw images, the classifying process was carried out and determining the face step was implemented at the end of the application to verify a person's face as 'accepted' or 'rejected'. In Section VI, some results are shown of the normalized training faces using eigenfaces.

Fusion Stage Implementation from Unimodal System Through Multimodal System

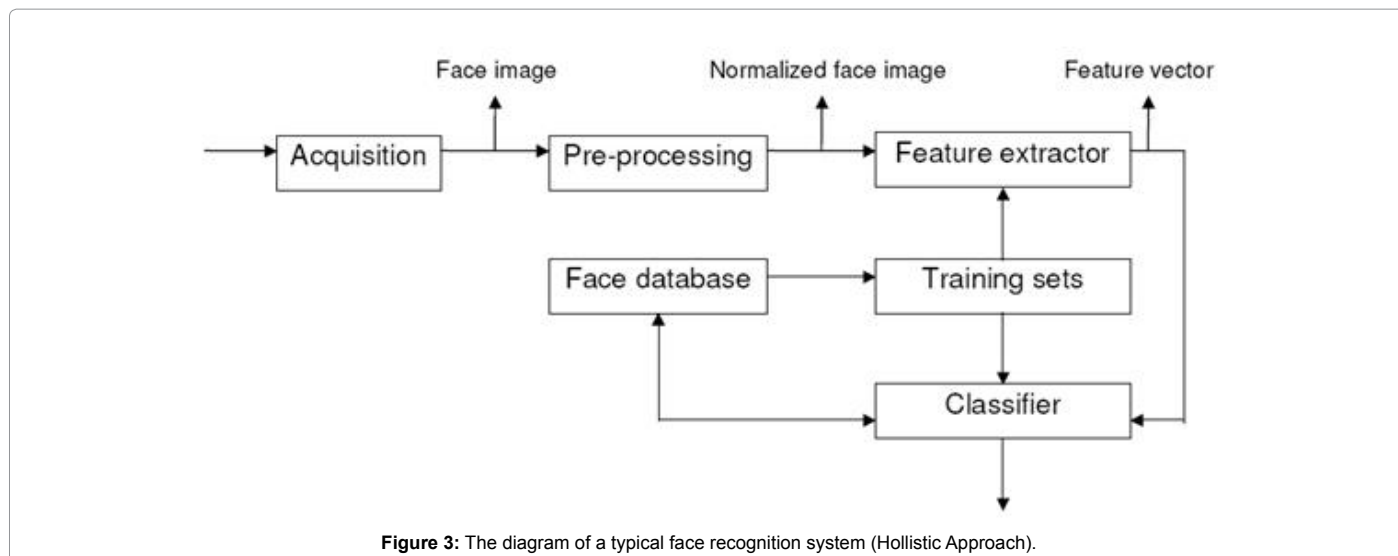The fusion of different unimodal systems can be performed in

Figure 3: The diagram of a typical face recognition system (Hollistic Approach).
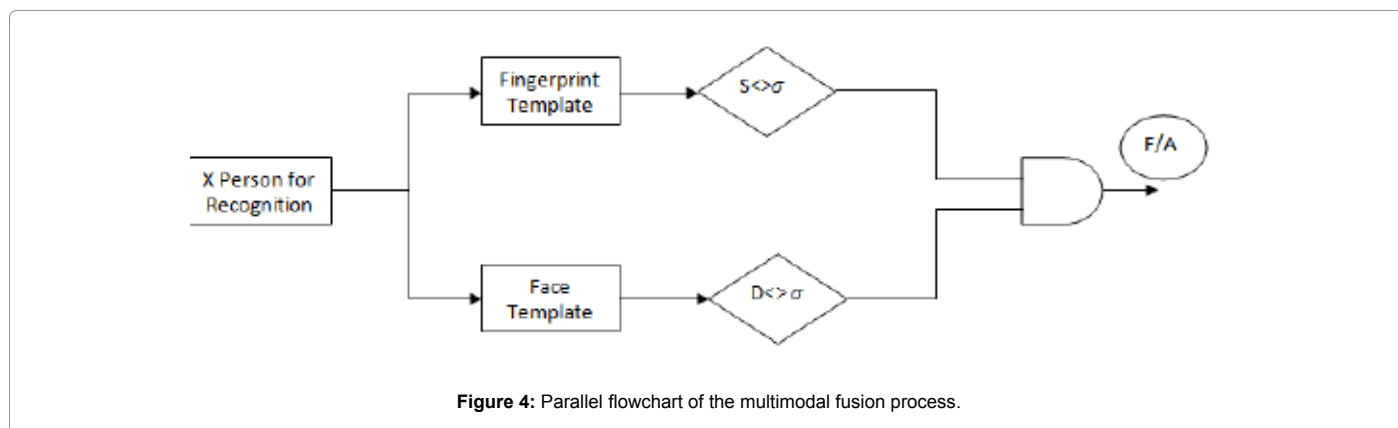

Figure 4: Parallel flowchart of the multimodal fusion process.

two different ways: fusion at decision level or at score level. In the first case, different decisions (acceptance or rejection) are issued from each system independently and then combined together according to simple rules such as AND/OR operators or majority vote.

Our proposed fusion methodology presents a system which can represent a multimodal system using a basic logical AND gate. This multimodal fusion concept is also formed as a decision-level fusion algorithm because of compounding a final score (accept/reject) at the decision stage on both unimodal systems.

Figure 4 shows the acquired raw fingerprint and face images from a selected person using a fingerprint sensor and a high resolution web camera respectively. After this, each expert comprises feature extraction points associated with their progression and can also be calculated in relation to either the similarity score for the fingerprint expert or Euclidean distance for face recognition

Subsequently, the final decision is made for both unimodal recognition systems as comparing threshold values with their similarity scores and distances [19,20]. If the similarity score of the minutiae extraction is greater than the threshold value of acceptability, then a HIGH (1) input comes from the fingerprint part through the logical AND operator. In the same way, if the Euclidean distance between the eigenvectors is bigger than the reasonable threshold value of that expert, then another HIGH (1) input value comes from the facial part through

the AND gate. Otherwise, the LOW (0) result enters the AND operator as an imposter information. Finally, the logical AND operator makes the final decision as accepted or rejected according to the input values which are coming from both unimodal systems. In conclusion, two HIGH (1) input values must come from both individual recognition experts in order to confirm an acceptance to the user as a multimodal recognition system. Therefore, the system might be referred to as a multimodal biometric recognition system using fusion at decision level by AND rule and its operation for fingerprint and facial techniques.

Test and Results

In this section, we present a number of initial simulation results to analyse the performance of a multimodal system. Firstly, we captured 100 raw fingerprint images for fingerprint recognition system using a ZK4000 optical fingerprint sensor. Afterwards, those images will be added to previously taken database called FVC2004 DB1 to test experiments. The proposed approach extracts ten users randomly from the fingerprint database (FVC2004 DB1) which includes 1440 fingerprint raw images. The FAR and FRR results of these ten fingerprint raw images are calculated at the end of fingerprint recognition. Afterwards, the same method was implemented in the face recognition for the same persons. We implemented on a MATLAB simulation to obtain respective performance results. Figure 5 shows that first; the raw image is converted to the enhanced image to give a clear binarization
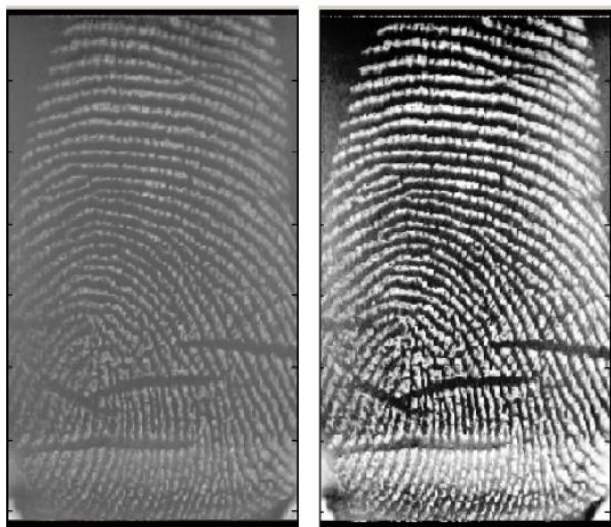
Figure 5: Original fingerprint raw image (left), and the image seen after the enhancement process (right).
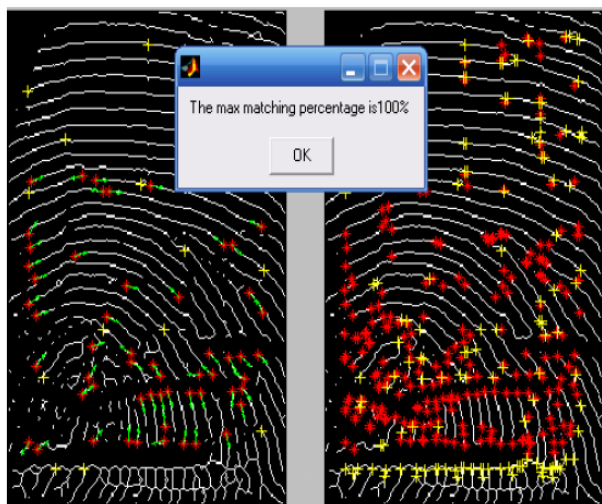

Figure 6: The minutiae extracted image is shown after spur removal on the left, the matching result is also shown on the screen.

stage on the next step. The enhancement process is carried out using histogram equalization which is explained deeply in previous chapter; in addition, the enhancement process could be supplied by the Fourier formulate transform technique in this process. However, the histogram equalization is more useful and easier to implement that function.

After the image enhancement process, the raw image binarization process is implemented using the adaptive threshold algorithm. Subsequently, the area of interest is covered for implementation of the thinning and minutiae extraction processes using morphological techniques. In order to get a clearer image, we developed the idea of removing spurs and discarding spikes from the thinned image. In our test, we only carried out this technique once, but we could acquire more accurate results by testing the spur removal process three or more times. Figure 6 shows that many of the fingerprint image pairs resulted in correct matches. The simple minutiae matching algorithm was used

in the matching stage. This algorithm supplies the distance of the x-axis, y-origin and $\varphi\varphi$ angle between two matching images. Using the minutiae-based approach, this work provided us with similar positive results between 98% and 100%.

After getting results from the fingerprint recognition part, secondly, the face recognition results were obtained using the face database which is called CASIA-Interval. That was used in the testing procedure of the basic eigenface recognition code within our database which was supplied from the 30 megapixels web camera. This was composed of data from ten different individuals with ten different pictures of each individual under different facial expressions and lighting from the face database (CASIA-Interval) that includes totally 960 face raw images. The pictures are coming from the same persons who are used for the fingerprint recognition testing procedure. After calculating eigenvectors related with difference values of the mean image and input image in the formulation, the weight values of the eigenfaces and Euclidean distances between the eigenvectors of each image were found so as to determine whether this face is known (accepted) or unknown (rejected). Figure 7 shows that the training sets of the used ten raw face images and their eigenfaces images after calculation of eigenvectors between the specific facial points.

The percentage values FAR and FRR for 10 persons are given in the Table 1 for the existing unimodal and multi-modal techniques. The value of FRR is more in the case of unimodal compared to multi-modal technique. The value of FAR is 0% in the case of multi-modal (AND rule is operated) compared to unimodal technique (Table 1).

After getting the test results from both fingerprint and face recognition parts, then we can pass through our proposed multimodal biometric system using fusion algorithms that are explained theoretically before. Our multimodal biometric technique allows combining two unimodal biometric systems by using a logical AND operator. As a result, the binary result will come from individual biometrics and the output result will be a logical '1' to accept to the user and '0' to reject to reject to the user. Figure 8 shows the outcomes of individual biometrics and also includes the fusion results together with them as the results of FAR and FRR. Hence, the fusion technique using the AND operation offers a specific solution to multimodal biometrics recognition as giving logical results such as '1' or '0' at the end of the process. As can be seen in Figure 8, when the unimodal recognition points were higher than the threshold value, which means FRR gives a minimal value, then the fusion score creates a logical '1' and thus the
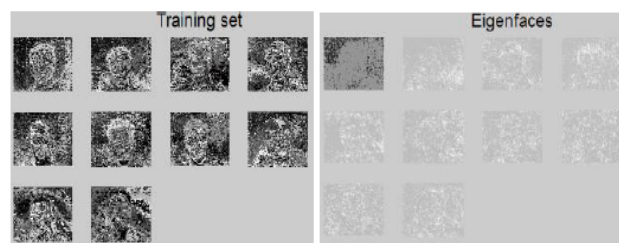

Figure 7: The pictures of training sets and eigenfaces of the tested users before calculating FAR and FRR results.

Biometric System	(FAR) %	(FRR) %
Unimodal Fingerprint	22.36	5.86
Unimodal Face	28.82	9.75
Multi-modal	0	2.2

Table 1: FAR and FRR of proposed AND rule operated system for 10 persons.
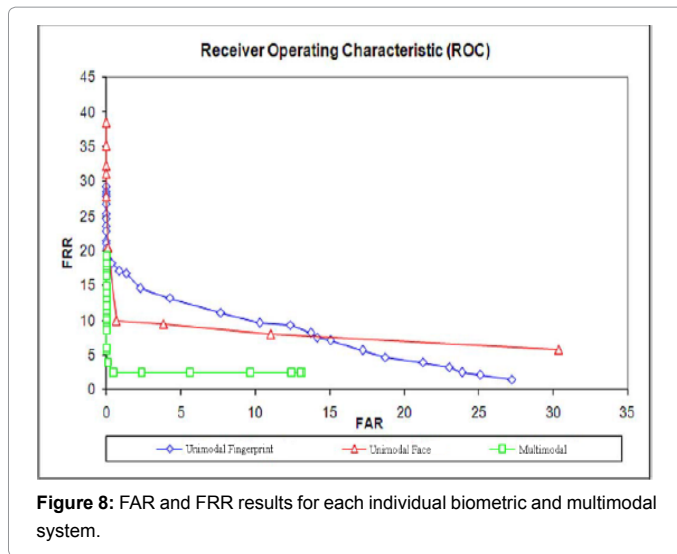
Figure 8: FAR and FRR results for each individual biometric and multimodal system.

system comprises an acceptance value, otherwise it will give a rejection decision. For instance, if the face recognition rate reaches around 90% (FRR=9.75) and the fingerprint recognition rate reaches around 94% (FRR=5.86), the system moves to an acceptance parameter because there is a positive feedback from both recognition systems. Finally, the fusion graph indicates an acceptance result by giving a logical '1'. Thus, the system presents like an impulse signal by generating a value which is between logical '0' to '1' and so on.

Conclusion

Multimodal biometric systems, which combine two unimodal recognition systems into one single method, can be used to overcome the limitations of individual biometrics. This paper has presented an analysis and a test of the multimodal person authentication approach based on static images taken from frontal facial views for a face expert and raw fingerprint images from the optical fingerprint sensor. Thus two reliable independent identification and verification experts were developed as a multi-biometric system. One was based on face recognition only and achieved a recognition rate of around 90%; the other expert was taken from the optical sensor and achieved slightly better results of around 94%. These figures refer to many testing sessions between 20 and 30 matches on the database and by using individual threshold selections in this study. In addition, different fusion techniques have been explained in this work and our proposed fusion technique, which is a decision-level fusion technique using the AND logical operator, has been described and developed. Fusion at decision level by the AND rule is not a popular method of fusion, but we have demonstrated that it can be done in an optimal manner by optimizing the thresholds of the component classifiers of individual systems in a way that can make it very beneficial. Using threshold optimized decision fusion, matching score normalization is not needed and also the component classifiers of individual systems are automatically balanced through the optimization process in the training session, thus reducing the risk of performance losses, which can occur when materials such as these give significantly different performances. To sum up, using decision-level fusion with logical operators delivers a specific acceptance rate and authentication allowance by getting close to a 100% result at the end of the system. This approach might provide a better solution to improving systems and applications such as civilian,

government and security systems by researching the use of multimodal biometric systems.

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