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Performance Analysis of Multimodal Biometric Based Authentication System

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Abstract- **In many real-world applications, unimodal biometric systems often face significant limitations due to sensitivity to noise, intraclass variability, data quality, nonuniversality, and other factors. Multibiometric systems seek to alleviate some of these problems by providing multiple pieces of evidence of the same identity. This paper presents an effective fusion scheme that combines information presented by multiple domain experts based on the rank-level fusion integration method. The developed multimodal biometric system possesses a number of unique qualities, starting from utilizing principal component analysis and Fisher's linear Discriminant methods for individual matchers (face,iris, and fingerprint) identity authentication and utilizing the novel rank-level fusion method in order to consolidate the results obtained from different biometric matchers.The results indicate that fusion of individual modalities can improve the overall performance of the biometric system, even in the presence of low quality data.**

Keywords **—Biometric identification system; Neuro fuzzy; Fisher's linear Discriminant methods (FLD); Multibiometric system; Principal component analysis (PCA); Rank-level fusion.**

1. INTRODUCTION

SOFTWARE and computer systems are recognized as a subset of simulated intelligent behaviours of human beings described by programmed instructive information. Biometric information system is one of the finest examples of computer system that tries to imitate the decisions that humans make in their everyday life, specifically concerning people identification and matching tasks.

A biometric identification (matching) system is an automatic pattern recognition system that recognizes a person by determining the authenticity of a specific physiological and/or behavioural characteristic (biometric) possessed by that person. Multibiometric is a relatively new approach to biometric knowledge representation that strives to overcome the problems by consolidating the evidence presented by multiple biometric traits/sources. Multibiometric systems can significantly improve the recognition performance in addition to improving population coverage, deterring spoof attacks, increasing the degrees of freedom, and reducing the failure-to-enrol rate.

Although the storage requirements, processing time, and computational demands of a multibiometric system can be higher than that for a unimodal biometric system, the aforementioned advantages present a compelling case for deploying multibiometric systems in real-world large-scale authentication systems The key to successful multibiometric system is in an effective fusion scheme, which is necessary to combine the information presented by multiple domain experts. The goal of fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts [1].

In this paper, we provide the first application of fusion at the rank level for consolidating the rank information produced by three separate unimodal biometric systems and discuss its efficiency. The developed multimodal biometric system possesses a number of unique qualities, such as utilization of principal component analysis (PCA) and Fisher's linear discriminant (FLD) methods for individual matchers (face, iris, and fingerprint) in combination with the novel rank-level fusion mechanism. The ranks of individual matchers are combined using the highest rank method. In the rest of this section, we will focus on the performance issues and parameters of a biometric system.

Fig 1. Three traits used in our system

In the rest of this section, we will focus on the performance issues and parameters of a biometric system. In Section 3 will discuss various design methods to consolidate the results of individual matchers in the rank level. Section 4 will illustrate the PCA and FLD methods for the enrollment and recognition of biometric traits. Section 5 will summarize the results of the experiments in terms of recognition rates, error rates, and response times. Section 6 discusses the conclusion.

1.1 *Performances of a Biometric System*

The main goal of this paper is to improve the recognition performance of a biometric system by incorporating multiple biometric traits. Usually, the performance of a biometric system is expressed by some parameters. There are a total of four possible outcomes: A genuine individual is accepted, a genuine individual is rejected, an impostor is rejected, and an impostor is accepted. Outcomes 1 and 3 are correct, whereas outcomes 2 and 4 are incorrect. The confidence associated with different decisions may be characterized by the genuine distribution and the impostor distribution, which are used to establish the following two error rates.

1.1.1 *False acceptance rate (FAR)*: This is defined as the probability of an impostor being accepted as a genuine individual. It is measured as the fraction of impostor score exceeding the predefined threshold.

1.1.2 *False rejection rate (FRR)*: This is defined as the probability of a genuine individual being rejected as an impostor. A small FRR usually leads to a larger FAR, while a smaller FAR usually implies a larger FRR. Generally, the system performance requirement is specified in terms of FAR. A FAR of zero means that no impostor is accepted as a genuine individual. Sometimes, another term, genuine accept rate (GAR), is used to measure the accuracy of a biometric system. It is measured as the fraction of genuine score exceeding the predefined threshold. GAR = 1- FRR.

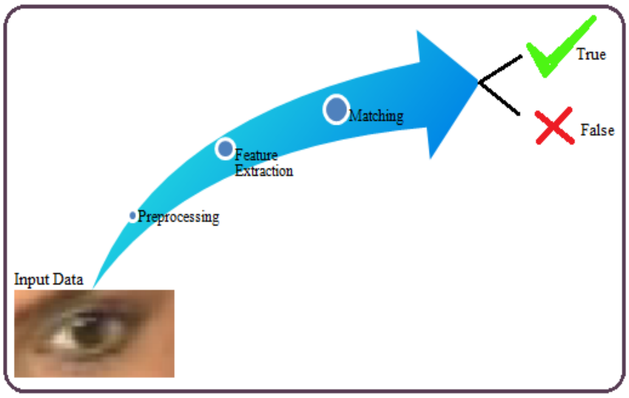

Fig 1(a) Block diagram of the unimodal biometric system

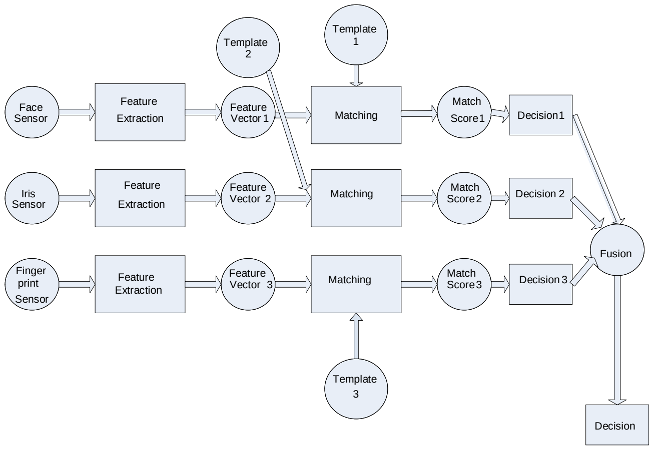

Fig.1 (b).Block diagram of the Multimodal biometric system

In this context, we develop a multibiometric system which makes personal identification by integrating faces, iris, and fingerprint of individuals. We develop three unimodal biometric systems for face, iris, and fingerprint using PCA and FLD methods. These systems produce ranking of individuals which will then be consolidated by the rank-level fusion approach to achieve the consensus rank of individuals. The use of PCA and FLD methods for unimodal biometric systems results in rank determination of individuals very precisely. Thus, utilizing rank-level fusion to consolidate the results produced by these unimodal expert results in a much higher recognition rate. The simple block diagrams of a unimodal system and the proposed multibiometric system are shown in Fig. 1(a) and (b), respectively. The proposed system integrates three different biometric matchers of face, iris, and fingerprint and incorporates a rank-level fusion module to improve the recognition performance.

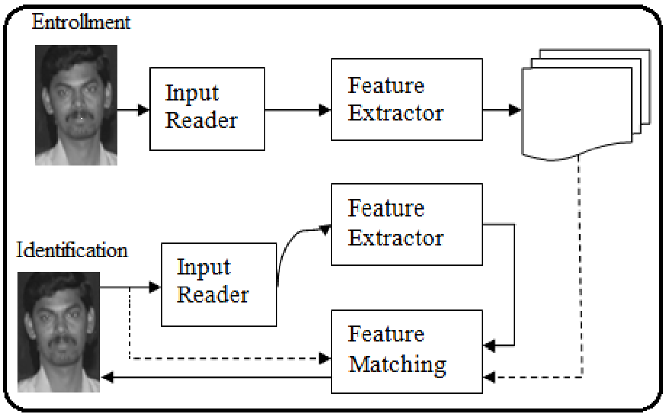

Fig.1(c) Generic biometric system architecture.

2. Review of Related Works

In 1996, N. K. Ratha and A. K. Jain [15] developed a real time matching system for large fingerprint database system.Fingerprint is one of the most widely used biometric techniques in the world. It is a rapidly evolving technology that has been widely used in forensics, such as criminal identification and prison security, and has the potential to be widely adopted in a very broad range of civilian applications. Using fingerprint to make a personal identification.

In 1997, P. N. Belhumeur et al. [16] developed a new commercial approach for fisherfaces recognition using class specific linear projection. Biometric information system is one of the finest examples of computer system that tries to imitate the decisions that humans make in their everyday life, specifically concerning people identification and matching tasks. A biometric identification system is an automatic pattern recognition system that recognizes a person by determining the authenticity of a specific physiological and or behavioral characteristic possessed by that person. In recent years , biometric authentication has seen considerable improvements in reliability and accuracy, with some biometrics offering reasonably good overall performance .However, even the most advanced biometric systems are still facing numerous problems, some inherent to the type of data and some to the methodology itself.

For improve the recognition performance of a biometric system, in the year of 1998 L.Hong and A. K. Jain [13] developed a new approach by incorporating multiple biometric traits. Usually performance of a system is expressed by some parameters. A decision made by a biometric system is either a "genuine individual" type of decision or an "imposter" type of decision. The performance of a biometric system can be expressed in FAR (False Acceptance Rate), FRR (False Rejection Rate), GAR (Genuine Accept Rate), and EER (Equal Error rate).A FAR of zero means that no imposter is accepted as genuine individual. GAR is used to measure the accuracy of a biometric system.

In 2003, T. Wang et al. [18] developed an automatic personal identification system based solely on fingerprints or faces are often not able to meet the system performance requirements. Face recognition is fast but not extremely reliable, while fingerprint verification is reliable but inefficient in database retrieval. We have developed a prototype biometric system which integrates faces and fingerprints. The system overcomes the limitations of face recognition systems as well as fingerprint verification systems.

In 2003, A.Kumar et al. [17] proposed a multimodal approach for a PCA based hand palm print verification system with fusion methods at the score level by using weighted sum rules and neural networks. The identity established by the system is more reliable than the identity established by the hand recognition system. In addition, the proposed decision fusion scheme enables performance improvement by integrating multiple cues with different confidence measures. Experimental results demonstrate that our system performs very well.

In 2006 A. Ross and K. Nandakumar [4] developed the biometric system is basically divided into two modes .i.e. Unimodal biometric system and multimodal biometric system. In Unimodal biometric system the individual trait is used for recognition or identification. Unimodal biometric systems generally suffer from imprecision and difficulties in person recognition due to noisy input data, limited degrees of freedom, intraclass variability, non-universality, spoof attacks and other factors that affect the performance, security and convenience of using such system .

In 2007, Bhatnagar et al. [12] developed Fusion at the rank level which provides the information produced by three separate Unimodal biometric systems. The ranks of individual matchers are combined using the highest rank method, the Borda count method, and the logistic regression method. Rank level fusion is relevant in identification systems where each classifier associates a rank with every input template. Thus fusion entails consolidating the multiple ranks associated with an identity and determining a new rank that would aid in establishing the final decision.

3. MULTIMODAL BIOMETRIC SYSTEM DEVELOPMENT

This section deals with the development procedures of the proposed multimodal biometric system through the rank-level fusion method. Eigenimage and fisherface techniques are used in this system for enrolment and recognition of biometric traits. A more detailed representation of the system is shown in Fig. 1(b).

PCA is a statistical method which involves analysis of *n*-dimensional data. PCA observes correspondence between different dimensions and determines principal dimensions, along which the variation of the data is high.The basis dimensions or vectors computed by PCA are in the direction of the largest variance of the training vectors. These basis vectors are computed by solution of an "Eigen" problem, and as such, the basis vectors are eigenvectors. These eigenvectors are defined in the image space. They can be viewed as images. Hence, they are usually referred to as eigenimage.

The first eigenimage is the average image, while the rest of the eigenimage represent variations from this average image. Each eigenimage can be viewed as a feature. When a particular image is projected onto the image space, its vector (made up of its weight values with respect to each eigenimage) into the image space describes the importance of each of those features in the image. The eigenimage approach has a compact representation—an image of a face, iris or fingerprint can be concisely represented by a feature vector with a few elements.

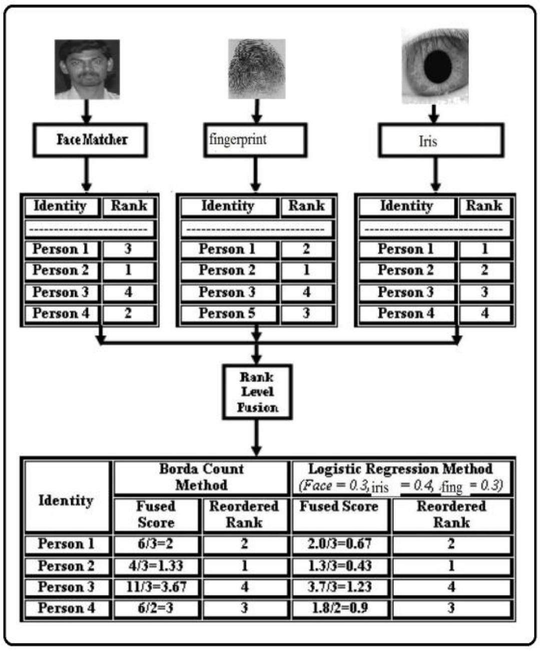

Fig.2. Example of rank-level fusion

The eigenimage technique has some limitations too. This method is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. When substantial changes in illumination and expression are present in the face image, much of the variation in the data is due to these changes. For the aforementioned reasons, we also use the fisher face approach introduced by Belhumeur *et al.* [11] in order to achieve higher recognition rate.. The fisherface method uses both PCA and LDA to produce a subspace projection matrix, similar to that used in the eigenface method. As the iris and fingerprint databases used for our system have very limited illumination change, so we use the FLD method only for face. The following two sections describe eigenimage and fisherface techniques as unimodal experts.

3.1. Recognition Using PCA

Eigenimage feature extraction is based on the wavelet transform and is used to obtain the most important features from the face, iris, and fingerprint subimages in our system. These features are obtained by projecting the original subimages into the corresponding subspaces. We create three image subspaces one for the face subimages, one for the fingerprint subimages, and one for the iris subimages. The system is first initialized with a set of training images. Eigenvectors and eigenvalues are computed on the covariance matrix of these images according to the standard procedure described in [7], for face, iris, and fingerprint, respectively. From the eigenvectors (eigenimages) that are created, we only choose a subset which has the highest eigenvalues. The higher the eigenvalues, the more characteristic features of an image the particular eigenvector describes. Eigenimage with low eigenvalues can be omitted, as they explain only a small part of the characteristic features of the images.

Finally, the known images are projected onto the image space, and their weights are stored. This process is repeated as necessary. After defining the eigenspace, we project any test image into the eigenspace. An acceptance (the two images match) or rejection (the two images do not match) is determined by applying a threshold. Any comparison producing a distance below the threshold is a match [5].

The steps for the recognition process can be summarized as follows.

1) Project the test image into the eigenspace, and measure the distance between the unknown image's position in the eigenspace and all the known image's positions in the eigenspace.

2) Select the image closest to the unknown image in the eigenspace as the match. We define the image with the lowest distance as rank-1 image, the image with the second lowest distance as rank-2 image, and so on. This same technique is applied for ranking of face, iris, and fingerprint.

Fig. 2 shows an example of rank-level fusion. The less in value of the rank, which gives more accurate result.

ALGORITHM

1. Consider a training set of face images T1,T2….TL where L is the total number of training images. Let 'M 'be the dimension of the training images. The mean of these face images is given by,

$$\mu = {}^{1}/_{L} \sum_{i=1}^{L} Ti$$

2. Let's consider the difference image from the mean value is given by the vector as,

$$Xi = \mathrm{Ti} - \mu, \mathrm{i} = 1, \ldots \mathrm{L}.$$

3. Covariance matrix which is given by

$$C = \frac{1}{L} \sum_{i=1}^{L} XiXi' = AA'$$

Where, $A = [X_1 X_2 \ldots\ldots X_L]$

4. Vectors 'u_n' and scalars 'λ_n' are the eigenvectors and eigenvalues, respectively, of the covariance matrix C and the eigen values are given by

$$\lambda n = \frac{1}{L} \sum_{i=1}^{L} (u_n^t Xi)^2$$

3.2. Recognition Using Fisherface (FLD)

Eigenspace representation is very sensitive to image conditions such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change. Due to certain illumination changes in the face images of the database used in this work, a fisherface based face recognition method [8] is developed to compare with the eigenface technique. The fisher face method uses both PCA and LDA to produce a subspace projection matrix, similar to that used in the eigenface method. However, the fisherface method is able to take advantage of within-class information, minimizing variation within each class, yet still maximizing class separation [10].

We define the training set shown, where Γ*i* is a facial image and the training set is partitioned into *c* classes, such that all the images in each class *Xi* are of the same person and that no single person is present in more than one class. Then, we compute two scatter matrices, representing the within-class (*SW*), between-class (*SB*), and total (*ST)* distributions of the training set through the image space

$$\text{Training set} = \left\{ \underbrace{\Gamma_1\Gamma_2\Gamma_3\Gamma_4\Gamma_5}_{X_1} \underbrace{\Gamma_6\Gamma_7\Gamma_8\Gamma_9\Gamma_{10}}_{X_2} \underbrace{\Gamma_{11}\Gamma_{12}\Gamma_{13}\Gamma_{14}\Gamma_{15}}_{X_3} \underbrace{\Gamma_{16}\Gamma_{17}}_{X_4} \ldots\ldots \underbrace{\Gamma_M}_{X_c} \right\}$$

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$$S_W = \sum_{i=1}^{C} \sum_{\Gamma_k \epsilon X_i} (\Gamma_k - \Psi_i)(\Gamma_k - \Psi_i)^T$$

$$S_B = \sum_{i=1}^{C} |X_i| (\Psi_i - \Psi)(\Psi_i - \Psi)^T$$

$$S_T = \sum_{n=1}^{M} (\Gamma_n - \Psi)(\Gamma_n - \Psi)^T$$

Where $\Psi = (1/M)$

Like the eigenface system, the components of the projection Matrix can be viewed as images.

4. EXPERIMENT AND RESULTS

4.1 Experimental Data

In multibiometric system, it is quite often that the database used is the true database which contains records. In this work, we have used a true database which contains three unimodal databases for face, iris, and finger print respectively.

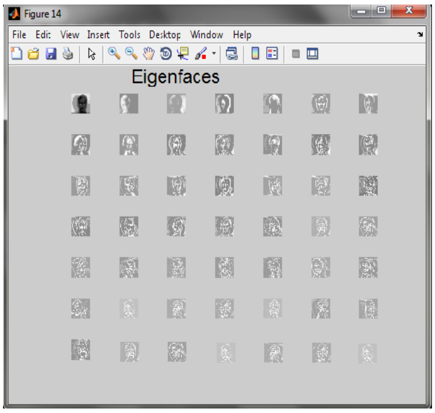

Fig. 3 Databases of Face

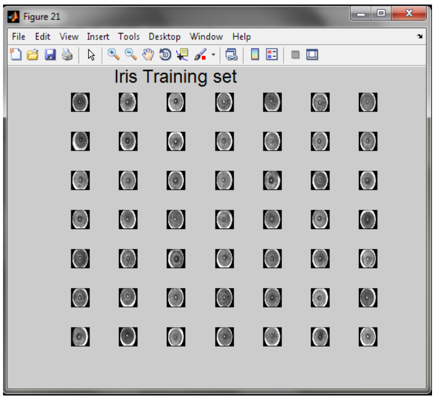

Fig. 4 Databases of iris

Here we have used different sensor for capturing images in face, iris, and finger print like camera, scanner etc.

The face training set is given in the following Fig.5.

We can use virtual database for training dataset.For face, we can use Olivetti Research Lab database, which contains 49 images, 7 for every 7 different persons. For iris recognition there are several public databases (e.g., UBIRIS data base, Casia database, Upol database, Nist ice database) are available for testing.

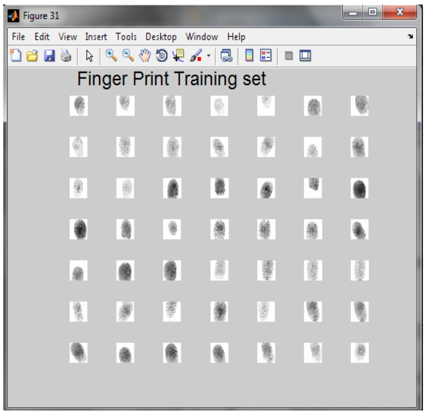

Fig. 5(a) Databases of fingerprint

Among that Nist ice database is the largest public database and was proposed by NIST for the Iris Challenge Evaluation in 2005. It is consist of nearby 3000 infrared images from 244 different users.In this project work, taken the real time data from various place, time and situations.

4.2 Results

We compare various eigenimage techniques and the fisherface technique in terms of FAR and GAR.

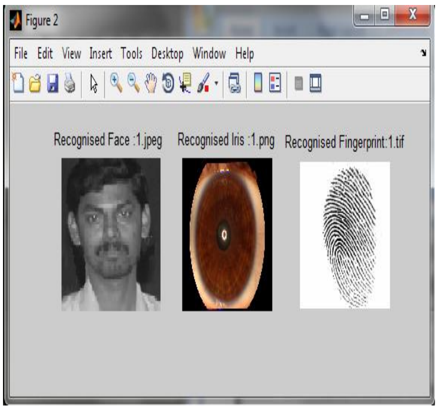

Fig.5 (b) Recognized output

From the results shown in the graph of Fig.6, it is clear that fisherface works more efficiently than eigenface [Fig. 6(a)]. Therefore, in this system, we obtained better recognition performance by the fisherface method.

Fig. 6(b) shows the performance rate of three different kinds of rank-level fusion approaches in terms of GAR

(Genuine Acceptance Rate) and FAR (False Acceptance Rate). From this, it is clear that the equal error rate (EER) would be reasonably high without incorporating any fusion method. Significant performance gain can be achieved with the combination of rank information of different unimodal experts.
These two parameters are usually expressed in a single curve called the receiver operating characteristic (ROC). Fig. 6(b) depicts the obtained ROC curve for the proposed system.

4.3 Accuracy

An ideal biometric system should always provide the correct identity decision when a biometric sample is presented. However, a biometric system seldom encounters an Rank (m) Rank−m Identification Rate (%) the Cumulative match characteristic (CMC) curve for the Face-G matcher in the NIST BSSR1 database which plots the rank-*m* identification rate for various values of *m*. In this example, the rank-1 identification rate is ¼ 78% which means that for ¼ 78% of the queries, the true identity of the query user is selected as the best matching identity. Sample of a user's biometric trait that is exactly the same as the template. This result in limit shows the system accuracy. The main factors affecting the accuracy of a biometric system are noisy biometric data,

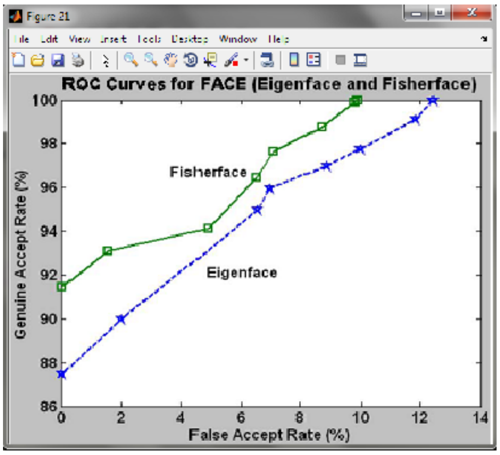

Fig. 6(a) Output Response Comparison

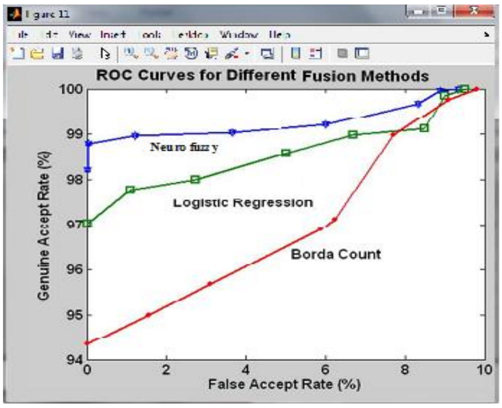

Fig. 6(b) ROC curve for different Rank Fusion Method

(a) A noisy fingerprint image due to smearing, residual deposits, etc.
(b) A blurred iris image due to loss of focus.
(c) A improper face image due to hazy.

We can analyze the security of the fuzzy vault framework by measuring the average min-entropy of the biometric template given in the system.

5. CONCLUSION

Different methodologies were studied for biometric authentication scenarios. Four unimodal biometric have been considered for this work. Each trait specifically focused on understanding the complex mechanisms employed to find a good combination of multiple biometric traits and various fusion methods to get the optimal identification results. We present a comparison between the results obtained before and after using Neuro fuzzy fusion. The above said extensive experimentation, some of the suggestions for the choice of the most appropriate technique (PCA or FLD) was drawn. For instance, on the studies' databases, the Neuro fuzzy fusion method demonstrated better recognition performance compared to others as well as the eigenimage technique.

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