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A Multimodal Biometrics Authentication System

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Abstract: ***An automatic authentication system based solely on fingerprints or faces is 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. This work proposes a system, which integrates face and fingerprint modalities. The system overcomes the limitations of face recognition systems as well as fingerprint verification systems. The proposed system operates in the verification mode with an admissible response time. The proposed face modality incorporates the Gabor Wavelet features and the Local Binary Patterns Variance (LBPVar) features. Those two facial descriptors are complimentary in the sense that LBPvar captures small appearance details, while the Gabor features encodes facial shape over a broader range of scale. Both feature sets are high dimensional, so it is beneficial to use the Principal Component Analysis (PCA) to reduce the dimensionality prior to normalization and integration. The Kernel Discriminative Common Vector (KDCV) method is then applied to the combined feature vector to extract the discriminant nonlinear features for recognition. As for the fingerprint module, an algorithm based on extracting finger Minutia is adopted to build a feature vector for each sample fingerprint. The two modalities are fused at the score level using a simple rule. The proposed system performance is evaluated over CMU Multi-PIE face and CASIA-FingerprintV5 public databases. The performance of the proposed model in the verification mode surpasses the performance of a number of multimodal biometrics state-of-the-art systems with a maximum verification accuracy of 99.2%.***

Keywords: LBPVar, Gabor Wavelet, PCA, KDCV

1. Introduction

Biometric solutions based on a single (one-modal) biometric in many cases are incapable of meeting the intended overall performance prerequisites, and also have to cope with a wide variety of challenges, including intra-class variations, noisy data, constrained level of freedom, spoof attacks as well as undesirable error rates [1]. A few of these disadvantages can be handled by implementing multimodal biometric platforms, which typically incorporate the information offered by several sources. NIT recently reported [2] to the US Congress that approximately 2% of the population does not have legible fingerprints and, therefore, cannot be enrolled in fingerprint biometric systems. The report recommends a system employing dual biometrics in a layered approach for large-scale applications such as border crossing. The use of multiple biometric indicators for identifying individuals, known as multimodal biometrics, has been shown to increase accuracy and population coverage, while decreasing vulnerability to spoofing. The key to multimodal biometrics is the fusion of various biometric modality data at the feature extraction, the matching score, or the decision levels [3].

Multimodal biometric systems indicate employing some sort of fusion of several biometric modalities within a verification system. Performing identification depending on several biometrics offers a growing innovation. Probably the most persuasive motive towards incorporating several modalities would be to enhance recognition percentage, which could be performed once biometric features associated with distinct biometrics are statistically independent. Furthermore, there are other reasons for combining several biometric modalities. One is the fact that several biometric modalities are more suitable for diverse applications. Another reason is solely consumer's preference [4].

In this work, we are concerned with developing a multimodal biometric structure that incorporates face and fingerprint towards personal identification. The selection of these two particular biometrics is dependent upon the concept that has already been utilized repeatedly in the law enforcement community. Such biometric modalities complement one another through their strengths. Whilst fingerprint offers a remarkably significant verification precision, it is troublesome for an inexperienced human to match fingerprints. Human beings have the capability to identify individuals through their faces. The proposed system aims at identifying terrorists and criminals at identity checkpoints in public facilities, particularly international airports. The interest in face recognition is moving toward uncontrolled or moderately controlled environments, such that either the probe or gallery images or both is assumed to be acquired under uncontrolled conditions. Also of interest are the more robust similarity measures or, in general, techniques to determine whether two facial images correctly match, i. e., whether they belong to the same person [5]. An important real-life application of interest is automated surveillance, where the objective is to recognize and track people on watch-list. In this open world application, the system is tasked to recognize a small set of people, while rejecting everyone else as being one of the wanted persons [6]. Thus, this paper proposes a novel approach to fuse face and fingerprint biometrics at the score level. Experimental results on publicly available databases are reported, confirming the validity of the proposed approach in comparison to fusion at the feature and decision levels. The rest of the paper is organized as follows. Section 2 summarises a number of the state-of-the-art multimodal biometrics systems involved in the experimental part. The proposed module for fusing the face and finger modalities is discussed in section 3. The experimental results are discussed in section 4. Finally, the conclusion is presented in section 5.

2. Related Work

Generally, unimodal biometric recognition systems present different drawbacks due its dependency on a unique biometric feature. For example, feature distinctiveness, feature acquisition, processing errors, and features that are temporally unavailable can affect a system's accuracy. A multimodal biometric system should overcome the aforementioned limits by integrating two or more biometric traits. Many researchers have demonstrated that the fusion process as effective, because fused scores provided better discrimination than individual scores. Such results were achieved using various fusion techniques.

Conti et al. [1] proposed a multimodal biometric system using two different fingerprint acquisitions. The matching module integrated fuzzy-logic methods for matching-score fusion. Experimental trials using both decision-level fusion and matching-score-level fusion were performed. Experimental results showed an improvement of 6.7% using the matching-score-level fusion rather than a monomodal authentication system.

Chen et al. [2] applied a wavelet probabilistic neural network classifier for face and iris combination. The features of the face and iris were extracted using ID energy signal and ID wavelet transform. Two matching scores from a Laplacian face-based verifier and phase information-based iris verifier were combined to form a feature vector and the SVM-based fusion rule was then applied.

Besbes et al. [3] proposed a multimodal biometric system using fingerprint and iris features. They used a hybrid approach based on: 1) fingerprint minutiae extraction and 2) iris template encoding through a mathematical representation of the extracted iris region. This approach was based on two recognition modalities and every part provided its own decision. The final decision was taken by considering the unimodal decision through an "AND" operator. No experimental result was reported on the recognition performance.

Zhang et al. approached the problem of fusing face and iris biometrics under near-infrared lighting using a single sensor [4]. Frontal face images were acquired using a 10 megapixel CCD camera. Eye detection and face alignment were performed using Local Bit Pattern histogram matching as described in Li et al. [5]. The eigenface algorithm and Daugman's algorithm were used to perform face and iris recognition, respectively, and the score-level fusion was accomplished via the sum and product rules after min-max normalization.

In contrast to the approaches found in the literature detailed earlier, the proposed approach introduces an innovative idea to unify and normalize the final biometric descriptor using two different strong modalities—the fingerprint and the face. As opposed to our previous [6], this paper shows the improvements introduced by adopting the fusion process at the score level, the related comparisons against the unimodal elements, as well as the classical matching-score fusion-based multimodal system. In addition, the system proposed in this paper has been tested on the official fingerprint CMU Multi-PIE face and CASIA-FingerprintV5 databases.

3. The proposed model

The proposed multimodal biometrics system combined face and fingerprint modalities. The two modalities were fused at the score-level using a simple summing rule. Figure 1. depicts a description of the proposed multimodal system.

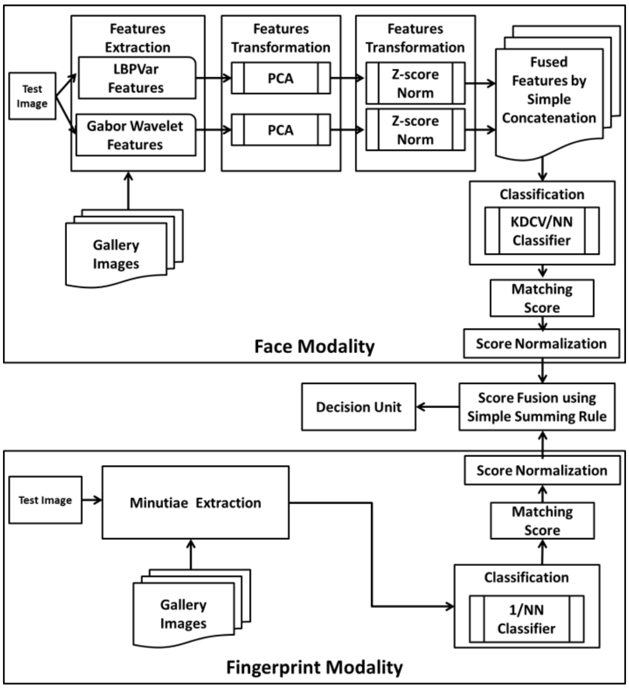

Figure 2. The proposed multimodal biometrics system. Face modality: A face test image is passed to the proposed system. After extracting both LBPVar and Gabor Wavelet feature sets, they are transformed into a PCA presentation, normalized using the z-score rule, and fused by a simple concatination. The final feature set is tested against all gallery images feature sets and classified using 1-nearest neighbor classifier, and then the matching scores are produced. Fingerprint Modality: a fingerprint test image is passed to the proposed system. Following feature extraction from both tests and gallery images, the test feature set is tested against all gallery images feature sets and classified using 1-nearest neighbor classifier, and then the matching scores are produced. The matching scores from face and fingerprint modalities are fused using a simple summing rule and the final score is passed to the decision unit.

As Figure 3. shows, in the face modality adopted in the proposed model, a face test image was first passed to the feature extraction unit where two facial feature sets namely: LBPVar and the Gabor wavelet were extracted from both the test and gallery images. The two feature sets were then projected separately to a PCA subspace for dimensionality reduction. Following that, a simple concatenation was used to fuse the two feature sets. Finally, the fused features set was transformed into a Kernel Discriminative Common Vectors (KDCV) [7] presentation to extract as much information as possible from the fused feature set (for more information about the facial feature fusion model, refer to our previous work [8]). The final feature set was tested against all feature sets in the image gallery and classified using 1-nearest neighbor classifier. The matching scores were then produced. In the fingerprint modality, the feature vectors were extracted using a method based on the work presented in [9]. The main steps for extracting the fingerprint features are discussed in detail in subsequent sections. Following feature extraction from both tests and images in the gallery, the test feature set was tested against all gallery images feature sets and classified using 1-nearest neighbor classifier. The matching scores were then produced. The matching scores from face and fingerprint modalities were normalized and then fused using a simple summing rule. The final score was then passed to the decision unit.

Score Normalization

Normalization is very important [10], especially in the score level combination techniques. The output lists by a single subsystem may contain numerical values resulting from measuring different features, and using different procedures and different scales, in which a direct combination would give incorrect results because the scores need to be comparable. A review on the most popular normalization techniques can be found in [11], together with a discussion about their merits and limits. Among the others, the cited work compared min-max, z-score, a scheme using median and median absolute deviation (MAD), and a double sigmoid function. The limitation of the min-max technique is that it assumes that the minimum and maximum generated by a matching module are known. Moreover, it is influenced by outliers [12]. The z-score does not always guarantee a common interval for values from different subsystems. Compared to z-score, the quite robust median/MAD is more effective when the values have Gaussian distribution.

LBP Variance (LBPV) Texture Descriptor

LBP variance (LBPV) was first introduced by Zhenhua Guo et al. [71] to characterize the local contrast information into one-dimensional LBP histogram. It is a simplified, yet effective when combined with LBPs, as well as a method for contrast distribution. LBPp, r /VARp, r is robust because it exploits the complementary information of local contrast and spatial pattern. LBPV/VAR descriptor exploits the supporting information for the local spatial pattern, as well as local contrast. The VAR possesses a continuous value that needs to be quantized. Quantization can be carried out by first computing the feature distributions of all training images to acquire an overall distribution. Following that, few threshold values are calculated to partition the overall distribution into N bins using an equal number of entries [60] to guarantee the maximum quantization resolution. The threshold values are employed to quantize the VAR of the test images. There are three specific limitations to this quantization technique as pointed out by [29]. The LBPV offers a way to handle difficulties associated with descriptor. Typically, the information associated with the variance VAR will not be involved in the calculation of the histogram of the LBP. The histogram operation allocates identical weight to every LBP pattern independent of the LBPV for the local region.

The LBPV is presented by equations 1 and 2 as follows:

$$LBPV(K) = \sum_{i=1}^{n}\sum_{j=1}^{m} W(LBP(i,j),k), k \in [0,k] \qquad (1)$$

$$W(LBPV(i,j)k) = \begin{cases} VAR(i,j), & LBP(i,j) = k \\ 0, & Otherwise \end{cases} \qquad (2)$$

LBPV can be described as a simplified descriptor whose feature size is small such that it can be employed in several applications. Additionally, it is training free and does not require quantization.

Gabor Features Set

The second set of facial features incorporates the texture feature extracted from the face image using Gabor wavelet. Gabor wavelets were introduced to image analysis due to their biological relevance and computational properties [13]. Gabor wavelets are frequently employed as filters to extract the orientation and frequency of a photo, leading to a Gabor-filtered photo. The discriminant facial features could then end up being obtained from Gabor-filtered photos as the particular foundation pertaining to facial recognition. The Gabor filter represents a band-pass linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Thus, a dimensional Gabor filter constitutes a complex sinusoidal plane of a particular frequency and orientation modulated by a Gaussian envelope [14]. It achieves an optimal resolution in both spatial and frequency domains. The optimum values for the Gabor filter bank parameters have been determined empirically as follows: wave length=8, orientations degree= 30, 90, 150, phase offsets degree=0, 90, aspect ratio=0.5, and bandwidth=1. The number of orientations and number of scales for a Gabor filter bank determine the number of desired features according to the expression (orientation x scale). In the proposed model, we considered 8 orientations and 5 scales as parameters for the Gabor filter (the popular Gabor parameters, 5 scales x 8 orientations, have been assumed as the best choice in many studies [15], [16]), which yielded a feature vector of 40 relevant features for each image. Figure [2] shows a sample face image collected from the CMU Multi-PIE face database and the set of Gabor wavelet features extracted from the RIO (area of interest), where Figure [2] (a) illustrates the real part of the Gabor filters, Figure [2] (b) illustrates the imaginary part of the Gabor filters, and Figure [] (d) illustrates the Gabor wavelet kernels produced from the input image.

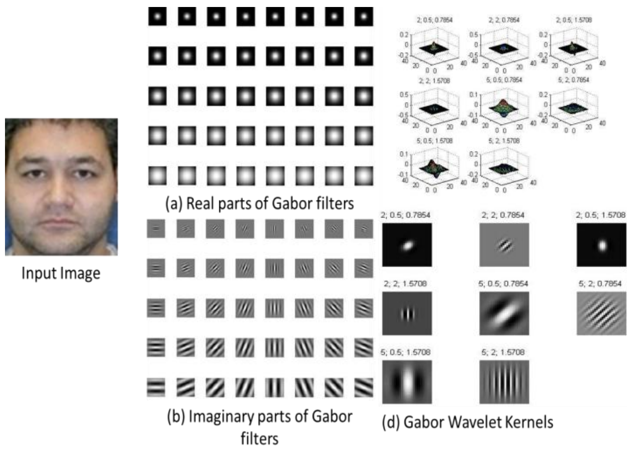

Figure 4. Face Gabor Wavelet features set for 5 scales and 8 orientations.

Fingerprint features set

Recently, majority fingerprint authentication platforms employ minutiae points (ridge bifurcation as well as ridge ending) as the distinctive attributes. The minutiae-based matching technique is commonly used for fingerprint identification, which usually first acquire the local minutiae (ridge bifurcations and ridge endings) out of the thinned ridge chart or the greyscale image [8], and then match their particular relative positioning within the query fingerprint together with the stored template. Figure [3] demonstrates the particular steps associated with minutiae extraction. The typical main procedures in minutiae matching technique for fingerprint identification following photograph acquisition are photo improvement, minutiae extraction, and minutiae matching. The main steps involved in the fingerprint feature extraction model adopted in the proposed model are discussed in details in the following sections.

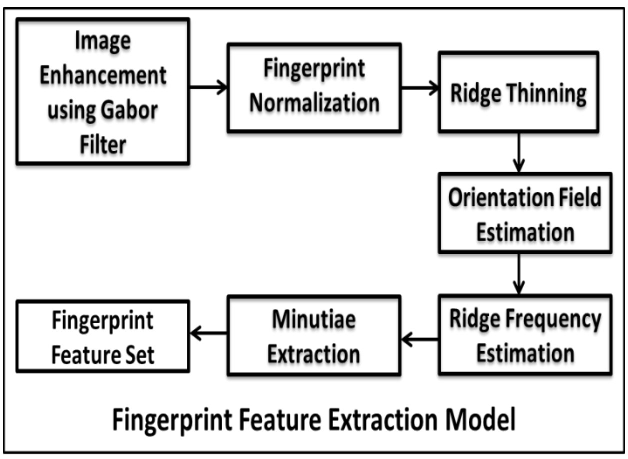

Figure 5. Fingerprint Feature Extraction Model.

Fingerprint image enhancement using the Gabor Filter:

Fingerprint enhancement methods based on the Gabor filter have been widely used to facilitate various fingerprint applications such as fingerprint matching [17] [18] and fingerprint classification [Jain, A. K., Prabhakar, S., and Hong, L. "A multichannel approach to fingerprint classification". IEEE Transactions on Pattern Analysis and Machine Intelligence 21, 4 (1999), 348-359.]. Gabor filters are band-pass filters that have both frequency-selective and orientation-selective properties [Daugman, J. G. Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters. Journal of the Optical Society of America (A) 2, 7 (July 1985), 1160-1169.], which means that they can be effectively tuned to specific frequency and orientation values. One useful characteristic of fingerprints is that they are known to have well-defined local ridge orientation and ridge frequency. Therefore, the enhancement algorithm takes advantage of these regular spatial structure by applying Gabor filters tuned to match the local ridge orientation and frequency. The Gabor filter was applied to each pixel location in the image based on the local orientation and ridge frequency around each pixel. In effect, the filter enhanced the ridges oriented in the direction of the local orientation, and decreased anything oriented differently. Hence, the filter increased the contrast between the foreground and background ridges, whilst reducing noise.

Fingerprint Normalization:

Due to imperfections in the fingerprint image capturing process such as non-uniform ink intensity or non-uniform contact with the fingerprint capture device, a fingerprint image might exhibit distorted levels of variation in the grey-level values along the ridges and valleys. Thus, normalization is used to reduce the effect of these variations, which facilitated subsequent image enhancement steps. Normalization was used to standardize the intensity value in an image by adjusting the range of the grey-level value so that it lies within a desired range of values. Let $\mathrm{I_m(i,j)}$ represent the grey-level value at $\mathrm{pixel(i,j)}$, and $\mathrm{Norm(i,j)}$ represent the normalized grey-level value at $\mathrm{pixel(i,j)}$. The normalized image is defined as:

$$\mathrm{Norm(i,j)} = \begin{cases} \mathrm{A_{0}} + \dfrac{\sqrt{\mathrm{S_0\ (I_m(i,j) - A)^2}}}{\mathrm{S}} & \text{if} \quad \mathrm{I_m(i,j)} > A, \\ \mathrm{A_{0}} - \dfrac{\sqrt{\mathrm{S_0\ (I_m(i,j) - A)^2}}}{\mathrm{S}} & \text{if} \quad \text{otherwise}, \end{cases} \tag{3}$$

where A and S are the estimated mean and variance of $I_m(i,j)$, respectively, and A_0 and S_0 are the desired mean and variance, respectively. Normalization was used to standardize the intensity value in an image by adjusting the range of the grey-level value so that it lies within a desired range.

Ridge Thinning:

The application of the thinning algorithm on a fingerprint image preserved the connectivity of the ridge structures, while forming a skeletonized version of the binary image. This skeleton image was then used for subsequent extraction of minutiae. Each sub-iteration began by examining the neighborhood of each pixel in the binary image, and based on a particular set of pixel-deletion criteria, it checked whether the pixel can be deleted or not. These sub-iterations continued until no more pixel could be deleted.

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Orientation Field Estimation:

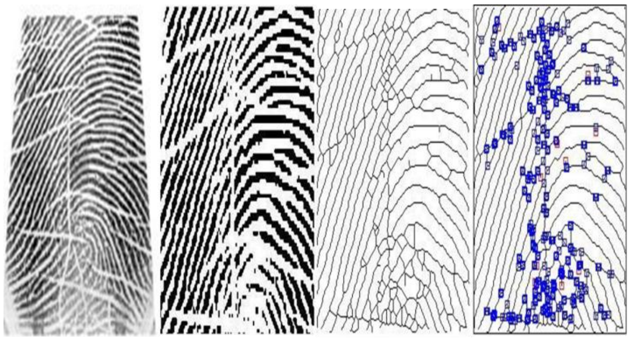
The Gabor filtering stage of the enhancement process relied heavily on filtering along the local ridge orientation in order to enhance the ridge structure and reduce noise. Hence, it was important to obtain an accurate estimation of the orientation field. The method proposed by Thai et al. [Thai, Raymond. "Fingerprint image enhancement and minutiae extraction. " The University of Western Australia (2003).] and Hong et al. [Hong, L., Wan, Y., and Jain, A. K. Fingerprint image enhancement: Algorithm and performance evaluation. IEEE Transactions on Pattern Analysis and Machine Intelligence 20, 8 (1998), 777-789.] for estimating orientation fields was adopted in the fingerprint modality. The default set of parameters specified by Hong et al. were used throughout the experiments, namely an averaging block size of 16×16, and a Gaussian filter size of 5×5.

Ridge Frequency Estimation:

The frequency image defined the local frequency of the ridges contained in the fingerprint. Firstly, the image was divided into square blocks and an oriented window was calculated for each block [Hong, L., Wan, Y., and Jain, A. K. Fingerprint image enhancement: Algorithm and performance evaluation. IEEE Transactions on Pattern Analysis and Machine Intelligence 20, 8 (1998), 777-789.]. For each block, an x-signature signal was constructed using the ridges and valleys in the oriented window. The x-signature was the projection of all grey level values in the oriented window along a direction orthogonal to the ridge orientation. Consequently, the projection formed a sinusoidal-shape wave in which the center of a ridge maps itself is the local minimum in the projected wave. The distance between consecutive peaks in the x-signature could then be used to estimate the frequency of the ridges.

Minutiae Extraction

The most commonly employed method of minutiae extraction is the Crossing Number (CN) concept [Amengual, J. C., Juan, A., Prez, J. C., Prat, F., Sez, S., and Vilar, J. M. Real-time minutiae extraction in fingerprint images. In Proc. of the 6th Int. Conf. on Image Processing and its Applications (July 1997), pp.871-875.]. This method involves the use of a skeleton image where the ridge flow pattern is eight-connected. The minutiae were extracted by scanning the local neighborhood of each ridge pixel in the image using a 3×3 window. The CN value, defined as half the sum of the differences between pairs of adjacent pixels in the eight-neighborhood, was then computed. Using the CN properties, the ridge pixel was then classified as a ridge ending, bifurcation or non-minutiae point. For example, a ridge pixel with CN of one corresponded to a ridge ending, and CN of three corresponded to a bifurcation. Figure [] shows the output of each of the sub-processes involved in the task of minutiae extraction.



(a) Input Image
(b) Enhanced and Normalized Image
(c) Image After Ridge Thinning
(d) Extracted Minutiae

Figure 6. Main Steps for Extracting Minutiae from a Fingerprint Image Collected from CASIA Fingerprint Image Database Version 5.0

The processed photograph was utilized for extracting minutiae points which include the points of ridge endings and bifurcations. The position of minutiae points together with the orientation were extracted and stored in order to create a fingerprint feature set. Typically, minutiae-based matching involved acquiring alignment between the template and the input minutiae set, resulting in the highest number of minutiae pairings.

Fusion of face and fingerprint modalities

Given a number of biometric systems, the matching scores for a pre-specified number of users can be generated without the knowledge of the underlying feature extraction and matching algorithms of each system. Therefore, combining the information obtained from individual modalities using score level fusion seems both feasible and practical [S. C. Dass, K. Nandakumar, and A. K. Jain, A Principled Approach to Score Level Fusion in Multimodal Biometric Systems, Proceedings of AVBPA, Rye Brook, July 2005, pp.1049-1058.]. In the proposed model, the scores generated from individual biometric modality (face and fingerprint) were combined at the matching score level using a simple summing rule. The matching scores generated from individual modality matching modules, which were distance measurements (NN Euclidean distance) were then passed to the fusion module. Let $Sface_i, Sfinger_i$ be the scores of the i-th face and i-th fingerprint respectively, the fused matching score MS_{final} was calculated as follows:

$$MS_{final} = Sface_i + Sfinger_i \qquad (3)$$

The fused matching score was then passed to the decision module where a person was declared as genuine or imposter.

The Multi-PIE face database:

The CMU Multi-PIE face database [Gross, Ralph, Iain Matthews, Jeffrey Cohn, Takeo Kanade, and Simon Baker. "Multi-pie. " Image and Vision Computing 28, no.5 (2010): 807-813.] contains more than 750, 000 images of 337 people recorded in up to four sessions over the span of five months. Subjects were imaged under 15 view points and 19 illumination conditions, while displaying a range of facial expressions. In addition, high resolution frontal images were acquiredas well. Figure [] depicts sample images from the CMU Multi-PIE database.

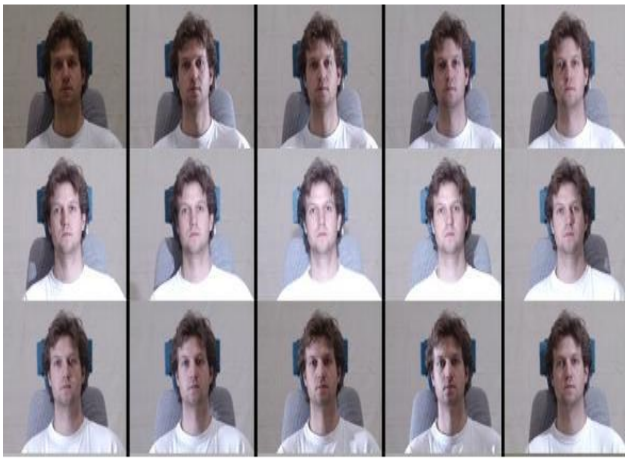


Fig.4. Sample images from the CMU PIE face database

CASIA-FingerprintV5

CASIA Fingerprint Image Database Version 5.0 (or CASIA-FingerprintV5) [6] contains 20, 000 fingerprint images from 500 subjects. The fingerprint images were captured using URU4000 fingerprint sensor in one session. The volunteers of CASIA-FingerprintV5 included graduate students, workers, waiters, etc. Each volunteer contributed 40 fingerprint images of his/her eight fingers (left and right thumb/second/third/fourth finger),i.e. five images per finger.

The volunteers were asked to rotate their fingers with various levels of pressure to generate significant intra-class variations. All fingerprint images were 8 bit gray-level BMP files and the image resolution was 328x356. Some sample images from CASIA-FingerprintV5 are illustrated in Figure [].

Figure 7. Sample images from CASIA-FingerprintV5

4. Experiments and Results

We performed several verification experiments following the rule adopted by [Snelick, Robert, Umut Uludag, Alan Mink, Mike Indovina, and Anil Jain. "Large-scale evaluation of multimodal biometric authentication using state-of-the-art systems. " Pattern Analysis and Machine Intelligence, IEEE Transactions on27, no.3 (2005): 450-455.] to test a face-fingerprint multimodal system. The fingerprint image database used was CASIA-FingerprintV5 [CASIA-FingerprintV5, http://biometrics. idealtest. org/".]. We used two fingerprint images for each of the 500 individuals, and two frontal face images of 500 individuals from the CMU Multi-PIE face database. Assuming that the face and fingerprint biometrics were statistically independent for each individual, which is a widely accepted and reasonable practice in multimodal biometrics research, we associated an individual from the face database with an individual from the fingerprint database to create a virtual subject. Continuing in this fashion consistently, we arrived at our database consisting of 500 subjects, each having two faces and two fingerprint images. One face and one fingerprint image for each subject was labeled as a gallery; the remaining face and fingerprint images were labeled as test. To determine the normalization and fusion parameters, we used the entire database. The need for virtual subjects arose since there was no real multimodal database (where multiple biometrics attributes from the same individual are measured) of comparable size available in the public domain. All test set images were matched against all target set images, yielding 500 genuine scores (where images were from the same subject) and 249, 500 (500X499) imposter scores. The normalization and fusion operations were carried out using the generated similarity matrices to obtain the final fused matching scores. The performance of individual matches and different normalization and fusion methods were presented in terms of verification accuracy (VA), equal error rate (EER), and half total error (HTER).

The results of evaluating the proposed system performance in verification mode using different fusion techniques are illustrated in Table 1. The verification results are presented in terms of verification accuracy, EER, and HTER. The verification rate was measured as false acceptance rate (FAR=1%). Statistical 95% confidence intervals (CI) for the verification rate (VR), the HTER, and the EER and for each algorithm were obtained empirically by bootstrapping the outputs of each algorithm [Seo, H. J., Milanfar. : , P. : Face verification using the lark representation. IEEE Transactions on Information Forensics and Security 6 (2011) 1275{1286] [Micheals, R. J., Boult. : , T. E. : E_cient evaluation of classification and recognition systems. Computer Vision and Pattern Recognition (1)]. The criterion employed for establishing the statistical differences in the performance, while comparing two algorithms, was that if the observed quantity for either algorithm fall within the 95% confidence interval of the other, then the performance of the two algorithms were regarded as not statistically significantly different. Otherwise, they were regarded as significantly different. The confidence intervals upper and lower limits were introduced in two separate columns for each evaluation metric in all the tables of results.

Table 1. The Verification Results of the Proposed System using Different Fusion Levels

Fusion Technique	**VR (%) at FAR =1%**	**CI**		**EER (%)**	**CI**		**HTER (%)**	**CI**	
		lower	Upper		lower	Upper		lower	Upper
Features Level Fusion	85.71	82.29	88.52	7.86	6.86	8.76	7.33	6.33	8.23
Decision Level Fusion	93.67	90.94	95.86	7.37	6.47	8.47	6.91	6.01	8.00
Score Level Fusion	99.20	98.05	100.0	2.61	1.31	3.61	1.66	1.06	2.56

The results illustrated in Table 1 show clearly that fusing different modalities at the score level yielded superior performance to those of the features and decision fusion levels with the maximum verification accuracy of more than 99%. Such results are in line with the conclusions derived in [He, Mingxing, Shi-Jinn Horng, Pingzhi Fan, Ray-Shine Run, Rong-Jian Chen, Jui-Lin Lai, Muhammad Khurram Khan, and Kevin Octavius Sentosa. "Performance evaluation of score level fusion in multimodal biometric systems. "Pattern Recognition 43, no.5 (2010): 1789-1800.] [Dass, Sarat C., Karthik Nandakumar, and Anil K. Jain. "A principled approach to score level fusion in multimodal biometric systems. " In Audio-and Video-Based Biometric Person Authentication, pp.1049-1058. Springer Berlin Heidelberg, 2005.], which acknowledged the feasibility and practicality of the concept of score level fusion. Fusing the biometrics modalities at the decision level yielded a relatively good performance with over 93% accuracy, followed by the feature level fusion, which achieved a verification accuracy of more than 85%.

In Table 2, the results of evaluating the proposed system using different matching scores normalization methods are illustrated in terms of VR, EER, and HTER. The median and median absolute deviation (MAD) method stood out as the best normalization method with a maximum verification accuracy of more than 99% and minimum error rates. This was followed by double sigmoid, Z-score, and min-max normalization methods.

Table 2. The Verification Results using Different Score Normalization Techniques

Score Normalization Technique	**VR (%) at FAR =1%**	**CI**		**EER (%)**	**CI**		**HTER (%)**	**CI**	
		lower	Upper		lower	Upper		lower	Upper
Min-Max	97.50	96.29	98.55	3.54	1.84	5.84	3.08	1.38	5.38
Z-score	98.13	95.94	99.77	2.91	1.70	4.00	2.45	0.90	3.20
Double Sigmoid	98.75	97.60	99.58	2.29	1.09	3.39	1.83	1.26	2.36
Median and Median Absolute Deviation (MAD)	99.20	98.05	100.0	2.61	1.31	3.61	1.66	1.06	2.56

The conclusion derived from the results presented in Table 2 is that the optimal score normalization method to be adopted in the proposed system was the median and median absolute deviation method.

The results of comparing the performance of the proposed multimodal biometric system with the performance of several feature sets and fused feature sets are illustrated in Table 3. First, the verification results related to the independent feature sets including face edge map, Gabor wavelet, and minutia are presented to show the effect of fusing the different feature sets with their independent verification performance later. Following that, the results of evaluating the independent performance of the face modality are illustrated. Finally, the results of evaluating the effect of fusing the fingerprint modality with each of the two face feature sets separately are illustrated.

Table 3. The Verification Results of Different Feature Sets

Feature Set	VR (%) at FAR =1%	CI		EER (%)	CI		HTER (%)	CI	
		lower	Upper		lower	Upper		lower	Upper
Face Edge Map	60.00	52.89	66.55	16.41	13.61	20.71	13.75	10.85	18.15
Gabor Wavelet	77.27	70.17	83.83	9.65	7.25	13.25	8.74	7.57	10.81
Fingerprint Minutia	83.33	80.33	86.19	8.57	6.71	12.17	8.01	7.00	8.90
Face Edge Map + Gabor Wavelet	89.96	87.46	92.46	7.22	6.22	8.12	6.66	5.73	7.16
Fingerprint Minutia + Face Edge Map	86.67	83.25	89.48	7.15	6.15	8.05	6.37	5.07	7.97
Fingerprint Minutia + Gabor Wavelet	93.50	91.53	95.46	6.51	4.92	7.22	5.56	5.06	7.16
Multimodal Biometric System	99.20	98.05	100.0	2.61	1.31	3.61	1.66	1.06	2.56

Again, the proposed multimodal biometric system stood out as the best among all feature sets presented in Table 3. Here, we should indicate that the fusion scores in conjunction with the median and median absolute deviation normalization method was adopted for this part of the experiments. As for the performance of the independent feature sets, the verification results show clearly that the performance of the fingerprint minutia surpassed the performance of both the face edge map and Gabor wavelet feature sets. The fingerprint minutia feature sets achieved a verification accuracy of 83.33% followed by the Gabor wavelet with a verification accuracy of 77.27% and face edge map with a verification accuracy of 60%. The results could not be compared directly due to the differences in the database, number of subjects, and the underlying feature extraction method. Usually, larger number of subjects and database variation in terms of orientation, lighting, and illumination would lead to smaller verification performance. Finally, combining the fingerprint minutia with the Gabor wavelet face feature set in the score level enhanced the performance of the two feature sets and increased the verification accuracy to more than 93%. Moreover, such combination outperformed the combination of the fingerprint minutia with the face edge map feature set, which achieved a verification accuracy of 86.67%.

The following conclusions can be derived from the results presented in Tables 1, 2, and 3:

- Fusing the proposed biometrics modalities improved the verification performance of the independent modalities.
- Fusing the proposed biometric modalities at the score level was the best option and led to maximum verification performance.
- Normalization of matching scores prior to combination improved the verification performance of a multimodal biometric system using face and fingerprint traits for user authentication.
- The experimental results suggest that there was no single normalization technique that performed the best for all systems and all modalities. Therefore, different normalization techniques should be considered and evaluated in order to select the best-performing technique.
- The optimal score normalization method adopted in the proposed system was the median and median absolute deviation method.

In the final part of the experiment, the performance of the proposed system (operating in the verification mode) was compared with the performance of a number of the state-of-the-art multimodal biometric systems including those proposed by Robert et al. [10], Lin et al. [11], Chin et al. [12], and Benaliouche et al. [13]. All the systems involved were implemented and tested on the same platform (i. e. MATLAB R2013a) and the same system with the following specifications: AMD APU 2.10 GHz, 4.00 GB RAM, and x64-based processor.

As mentioned before, the database used for evaluating the face biometric was the Multi-PIE face database [Gross, Ralph, Iain Matthews, Jeffrey Cohn, Takeo Kanade, and Simon Baker. "Multi-pie. " Image and Vision Computing 28, no.5 (2010): 807-813.] and the database used for evaluating the fingerprint database was CASIA-FingerprintV5 [CASIA-FingerprintV5, http://biometrics. idealtest. org/”.]. Since the systems introduced in [12] and [13] both involved iris modality, a publicly available iris database was used for validation in this series of experiments, namely: CASIA-IrisV4 [CASIA Iris Image Database, http://biometrics. idealtest. org/]. CASIA-IrisV4 contains a total of 54, 601 iris images from more than 1, 800 genuine subjects and 1, 000 virtual subjects. All iris images were 8 bit gray-level JPEG files, collected under near infrared illumination or synthesized. The same pattern used earlier for evaluating the verification performance of the face-fingerprint biometrics multimodal systems was used here for evaluating the verification performance of the face-iris and fingerprint-iris biometrics multimodal systems presented in [12] and [13].

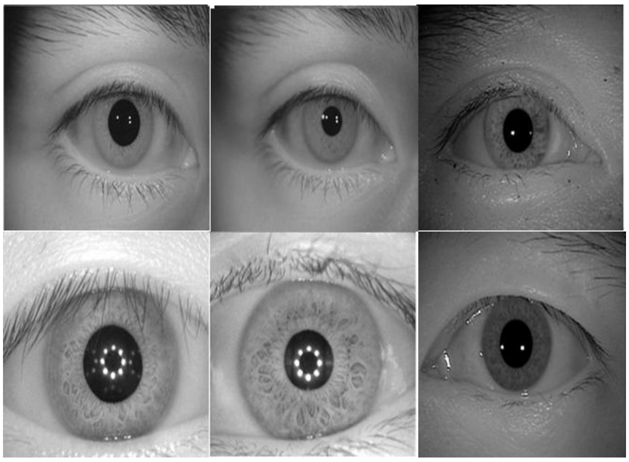


Figure 8. Sample images collected from CASIA-IrisV4 Database

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The verification results of the proposed system and a number of the state-of-the-art multimodal biometric systems are illustrated in Table 4.

Table 4. Verification Results of the Proposed System and State-of-the-Art Multimodal Biometric Systems

Reference	**Multimodalities**	**Fusion Technique**	**VR (%) at FAR=1%**	**CI**		**EER (%)**	**CI**		**HTER (%)**	**CI**	
				lower	Upper		lower	Upper		lower	Upper
Zhang et al.	Face + Iris	Score Simple Summing Rule	94.20	91.75	96.75	5.66	4.56	6.56	5.05	4.15	6.15
Conti et al.	Face + Fingerprint	Score Level Fusion	93.40	91.43	95.36	5.85	4.85	6.77	5.46	5.06	7.16
Chen et al.	Face + Iris	Score Level Fusion	95.00	91.70	97.71	4.17	2.47	6.78	3.86	2.16	6.16
Besbes et al.	Fingerprint + Iris	Decision Level Fusion	90.89	88.39	93.39	6.78	5.48	8.39	6.32	5.02	7.92
The proposed model	Face+ Fingerprint	Score Level Fusion	99.20	98.05	100.0	2.61	1.31	3.61	1.66	1.06	2.56

The proposed system performed evidently better than the state-of-the-art multimodal biometric systems in terms of verification accuracy, HTER, and EER, followed by the systems proposed by Chin et al. [12], Robert et al. [10], Lin et al. [11], and finally Benaliouche et al. [13]. Moreover, the confidence intervals related to the different systems clearly show that there was a significant difference between the performance of the proposed system and the performance of the state-of-the-art multimodal biometric systems in terms of VR, HTER, and EER. Figure [] illustrates the ROC curve for the performance of the proposed system against a number of the state-of-the-art multimodal biometrics systems. The probability of verification (VR) was calculated and plotted against different FARs (1%, 0.1%, and 0.01%). Varying the reference threshold moved the operating point along the ROC curve.

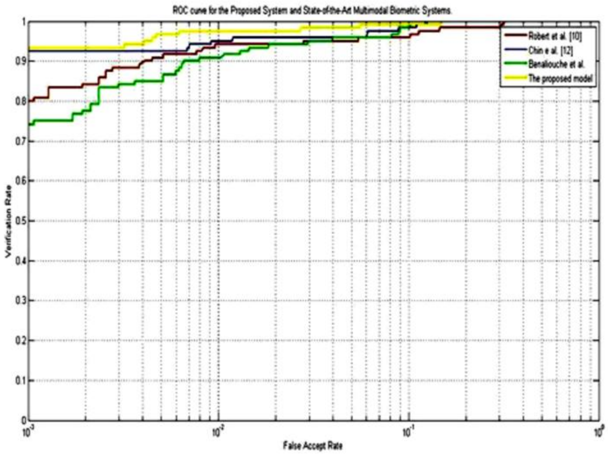

Figure 9. The ROC curve for the performance of the proposed system and a number of the state-of-the-art multimodal biometrics systems. The verification rate is plotted at different values of false acceptance rate (1%, 0.1 %, 0.01 %, 0.001%).

5. Conclusions and Future Work

This work presented a multimodal biometric system based on the integration of a fingerprint and face traits at the matching score level. These two traits are the most widely accepted biometrics in most applications including law enforcement and automated surveillance systems.

From the system point of view, redundancy can always be exploited to improve accuracy and robustness, which is achieved in many living systems as well. Human beings, for example, use several perception cues to recognize other living creatures, including visual, acoustic and tactile perceptions. Based on these considerations, this work outlined the possibility of augmenting verification accuracy by integrating multiple biometric traits. In this work, a novel approach was presented where both fingerprint and face images were processed with effective feature extraction algorithms to obtain comparable features from the raw data.

The results of evaluating the proposed multimodal face and fingerprint system demonstrated the effect of combining multiple biometrics modalities on the verification accuracy. The performance of the system was evaluated in the verification mode using several fusion levels and score normalization techniques. The maximum verification accuracy was obtained by the proposed system when the face and the fingerprint modalities were fused at the score level using a simple summing rule and the matching scores were normalized using the Median and Median Absolute Deviation (MAD) rules. The system was able to achieve a maximum verification accuracy of 99.2%, which was above the highest accuracy reported in the literature review.
Future work includes enhancing the overall processing time and testing the system using larger benchmarking face and fingerprint datasets. Moreover, the system performance in terms of computational complexity will be evaluated and compared with the state-of-the-art multimodal biometrics systems.

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