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A Personal Identification Framework based on Facial Image and Fingerprint Fusion Biometric

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ABSTRACT
Biometric based person identity verification is gaining more and more attention. Several studies have shown that multimodal biometric identification systems improve the recognition accuracy and reliability compared with recognition using a single biometric. The present paper introduces a new personal identification framework that is based on the fusion of face and fingerprint biometrics. The proposed framework overcomes the limitations of face recognition systems as well as fingerprint verification systems. The gray-level co-occurrence matrix and the minutiae extraction are used to represent the features of face and fingerprint image respectively. This framework uses the correlation coefficient as a similarity measure to retrieve the closest face and the corresponding fingerprint images with a query image. Experimental results performed on a given database of face and fingerprint images show that the proposed framework improved greatly the security and recognition rate.

General Terms
Multimodal biometric, Personal identification, Fingerprint verification, Face recognition.

Keywords
Personal identification, Facial image, Fingerprint, Gray-level co-occurrence matrix, Minutiae feature extraction, Correlation coefficient.

1. INTRODUCTION
Biometric identification has the potential of becoming an increasingly powerful tool for public safety. Many techniques have looked at the fusion of multiple biometric modalities. Multi-modal biometric fusion, where the recognition is performed on multiple biometric samples acquired from different biometric sources of a subject (e.g., face and fingerprint), has received increasing interest and is demonstrated to be more accurate and reliable compared with recognition performed on a single biometric modality [1- 2]. Fingerprint verification has been widely accepted as a key biometric identification technique in many applications such as physical access control, information system security, law enforcement and health care etc. [3]. A fingerprint recognition system involves several phases. The acquisition phase, where the fingerprint is scanned using a fingerprint sensor. The feature extraction phase, which involves calculation of the directional field, enhancement and segmentation of the fingerprint, and extraction of the appropriate feature. Finally, the matching phase, where the features of the tested fingerprint are compared with a template that is found in the fingerprint database [4]. The effectiveness of a feature extraction depends greatly on the quality of the images. Consequently, fingerprint image enhancement has become a necessary and common step after image acquisition and before feature extraction in most fingerprint identification systems [5]. Therefore, preprocessing is an essential step to reduce the noises and increase the contrast between ridges and valleys. Many methods have been proposed to enhance the quality of fingerprint images. In practice, there are three methods to enhance the fingerprint images: Gabor filter [6-7], anisotropic filter [8-9] and topographic analysis [10]. Generally, methods for extracting fingerprint features can be classified into two primary categories. The first category is the ridges pattern based feature extraction and the second category is the minutiae based features extraction. Several methods have been developed to extract useful information from fingerprint ridges. Some of these methods examine the frequency and orientation of the ridges, while others develop mathematical models to represent the structure of the ridges [11]. Most fingerprint recognition systems utilize minutiae points as features. The location and angle information of ridge endings and bifurcations extracted from gray-scale or thinned binary fingerprint images are determined [12-14]. A minutiae-based approach is generally accepted by a majority of developers since it outperforms other approaches in terms of reliability and matching accuracies [3]. The accuracy of the system is determined by computing the False Acceptance Rate (FAR) and False Rejection Rate (FRR) of the system. If a registered user of a system is wrongly recognized as an imposter, the corresponding error rate is called the False Rejection Rate (FRR). An imposter could be also mistakenly recognized as genuine person, the corresponding error rate is called the False Acceptance Rate (FAR) [15]. Face recognition has been attracting the attention of the researchers as one of the most important techniques for human identification. Face recognition technique extracts low-level features which are inbuilt in the images to present the contents of images. The low level features are classified into three main classes: color [16], texture [17] and shape [18] features. Texture is an important visual property that characterizes a wide range of natural and artificial images which makes it a useful feature for retrieving images. A variety of techniques have been used for measuring texture such as gray level co-occurrence matrix (GLCM) [19], markov random fields (MRF) [20], two dimensional autoregressive (2D-AR) [21], gabor filters (GF) [22], fractals [23], texture spectrum (TS) [24], wavelet transform [25], complexity curve [26], run length matrices [27], and cross diagonal texture matrix [28]. However, the most common way to extract texture features for face recognition is the use of gray level co-occurrence matrices. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix [29].

The present paper introduces a new framework based on multi-modal biometric fusion (face and fingerprint) for improving the performance of the personal verification. Each face image and the corresponding fingerprint are represented by a GLCM and the moments respectively. During the testing process, the features of the query face image and the corresponding fingerprint query image are extracted and matched against the features stored in the database. The correlation coefficients are used for similarity measure. The rest of this paper is structured as follows. Section 2 briefly summarizes the related works. Section 3 introduces the feature extraction from the personal face image. Section 4 presents the feature extraction from fingerprint image. The matching strategy is described in section 5. Section 6 reports the experiments and analyzes the results. Finally, section 7 concludes the paper.

2. RELATED WORKS

There are many multi-biometric system approaches through various biometric modalities. For example, an identification model based on face and fingerprint is introduced, where fingerprint matching is applied after pruning the database through face matching [30]. While Frischholz and Dieckmann [31] present a model based on the face, lip movement and voice. The features are dynamic and collected from video image. Then, through using ranking approach, the decision is made by collecting the percentage of recognition of each biometrics. In addition, Ross and Jain [32] introduced a model that integrates face, fingerprint, and hand geometry biometrics with sum rule, decision tree, and linear discriminant-based methods. Multimodal approach that combines a face verification system based on a global appearance representation scheme, a minutiae-based fingerprint verification system, and an online signature verification system based on HMM modeling of temporal functions with fusion methods was presented by [33]. Kumar et al. [34] introduced a multimodal approach for palmprint and hand geometry, with fusion methods at the feature level through collecting by concatenation, and the matching score level by using max rule. Toh et al. [35] presented a model that utilizes hand geometry, fingerprint, and voice biometric with weighted sum rule-based match-score-level fusion. They dealt with the multimodal biometric decision fusion problem as a two-stage problem that includes learning and decision. While, face and palmprint were combined by Feng et al. [36] through concatenated the features extracted by using PCA and ICA with the nearest neighbour classifier (nnc) and SVM as the classifier. Snelick et al. [37] proposed a multimodal approach for face and fingerprint, with fusion methods at the score level through employing three fingerprint recognition commercial systems and one face recognition commercial system. Kumar et al. [38] developed multimodal personal verification system utilizing hand images through combining hand geometry and palm image using directional convolution masks to extract the palm futures from normalized palm image, whereas, finger length and width were extracted for hand geometry palm. Also, Zhou et al. [39] proposed multimodal authentication system using face and fingerprint, and multi route detection was employed through SVM fusion, while the face image with zero turning is used as face template and other face images are used for self learning. Rattani et al. [40] used face and fingerprint, where the scale invariant feature transform features (SIFT) is applied for face feature extraction and minutiae matching technique for fingerprint. Shahin et al.[41] employed the hand veins, hand geometry and fingerprint to obtain high security through calculating the ridges. In addition, the direction is calculated in frequency domain. Tayal et al. [42] developed multimodal iris and speech authentication system using decision theory by combining iris and speech biometrics through energy compaction and time frequency resolution. Multimodal finger veins recognition using score level fusing for finger geometry and finger veins was developed by Kang and Park [43]. Besides, Monwar and Gavrilova [44] presented a multimodal biometrics system that uses face, ear and signature. The features of the biometrics are extracted respectively by using eigenface, eigenear and eigensignature. Darwish et al. [45] proposed a multimodal biometric system depending on the face and fingerprint fusion biometrics. The face recognition was done by uniform local binary patterns (ULBP), while fingerprint recognition was performed by minutiae extraction. Gargouri Ben Ayed et al. [46] presented a multimodal biometric recognition system that integrates two modalities which are face and fingerprint. For face trait, features are built based on Gabor Wavelet Networks (GWNs), while Local Binary Patterns (LBP) is used for fingerprint trait. Finally, Jinfeng Yang et al. [47] proposed a new fingerprint-vein based biometric method to make a finger more universal in biometrics. The unimodal features of fingerprint and finger-vein were used to extract a unified Gabor filter framework that is significant for canonical correlation analysis (CCA) and its extension in order to obtain the most correlated features between fingerprints and finger-vein.

3. FACIAL IMAGE FEATURES

Many researchers have used the gray-level co-occurrence matrix as an effective method for extracting the texture features in the face recognition. Gelzinis et al. [48] presented a new approach to exploiting information available in the co-occurrence matrices computed for different distance parameter values. In [49], an extension is introduced, where a new matrix called motif co-occurrence matrix was proposed. Walker et al. [50] have proposed to form co-occurrence matrix-based features by weighted summation of co-occurrence matrix elements from localized areas of high discrimination. The GLCM contains the second-order statistical information of spatial relationship of the image pixels. In deed, the co-occurrence matrix is computed based on two parameters which are; the relative distance between image pixels (d) and their relative orientation (φ). Normally, φ is quantized in four directions (horizontal: 0, diagonal: 45, vertical: 90 and anti-diagonal: 135) [51]. These orientations refer to the 4-adjacency pixels. In practice, for each d, the resulting values for the four directions are averaged out. In the present paper, texture features are the entropy, energy, contrast, and homogeneity. They are extracted from the co-occurrence matrix of gray levels of an image. The gray level co-occurrence matrix C(i,j) is defined by a first specifying of a displacement vector dx,y = (δx, δy), where δx, δy are the displacements in the x and y directions respectively. All pairs of pixels separated by displacement dx,y and having gray levels i and j are computed . The matrix C (i, j) is normalized by dividing each element in the matrix by the total number of pixel pairs. Using this co-occurrence matrix, the texture features matrices are computed as follows [51]. The feature that measures the randomness of gray-level distribution is the entropy which is defined as:

$$\text{Entropy} = \sum_i \sum_j C(i,j) \log (C(i,j)) \qquad (1)$$

The highest value of the entropy is obtained when all entries in C(i, j) are equal; such a matrix corresponds to an image in which there are no preferred gray-level pairs for the specified distance vector d. The energy, contrast, and homogeneity features are also defined using the gray-level co-occurrence matrix as given below:

$$\text{Energy} = \sum_{i}\sum_{j} C^2(i, j) \quad (2)$$

$$\text{Contrast} = \sum_{i}\sum_{j} (i-j)^2\, C(i, j) \quad (3)$$

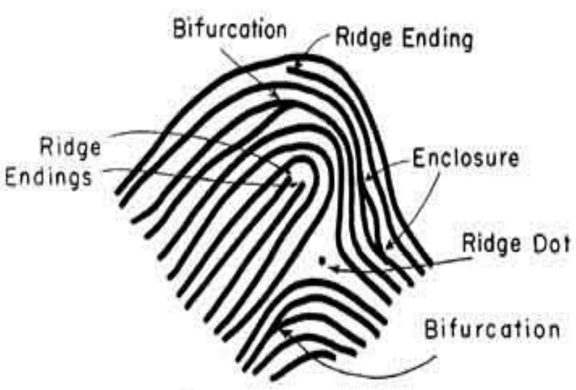
$$\text{Homogeneity} = \sum_{i}\sum_{j} \frac{C(i, j)}{1+|i-j|} \quad (4)$$

4. FINGERPRINT FEATURES

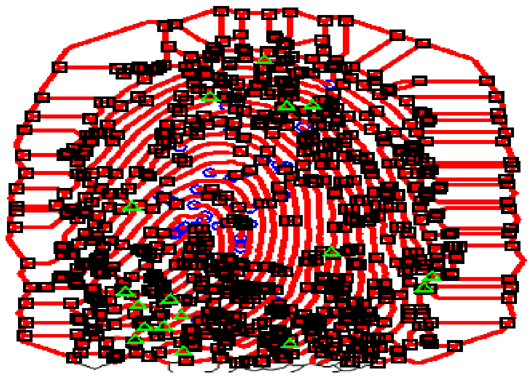
Fingerprint recognition consists of two main phases; image preprocessing phase and feature extraction phase. Generally, image preprocessing phase consists of image enhancement, binarization, filtering, and thinning process [52-53]. Fingerprint feature extraction phase is classified into two categories namely; local and global features [54]. The local features are the tiny and unique characteristics of fingerprint ridges that are used for identification. They are found in the local area only and are invariant with respect to global transformation [55]. The global features are characterized by the attributes that capture the global spatial relationships of a fingerprint [56]. Many algorithms have been proposed in the literature utilize the local features (called minutiae) to improve the overall performance of an automatic fingerprint identification system [57-59]. A minutiae-based approach is generally accepted by a majority of developers since it outperforms other approaches in terms of reliability and matching accuracies. A Crossing Number (CN) method for feature detection and extraction from the thinned image had been implemented in [60-62]. In the CN method, the features extraction is performed through the scanning of the 3 x 3 neighborhood of each ridge pixel in the thinned image. The CN value is then calculated from half the sum of the differences between pairs of adjacent pixels in the eight-neighborhood as shown in the following equation.

$$CN = 0.5\sum_{i=1}^{8}|p_i - p_{i+1}| \quad , \qquad p_9 = p_1 \quad (5)$$

The minutiae points are classified into five major categories according to the value of the CN. A CN of zero corresponds to an isolated point, a CN of one corresponds to a ridge ending point, a CN of two corresponds to a continuing ridge point, a CN of three corresponds to a bifurcation point, and a CN of four corresponds to a crossing point as shown in figure 1.



(a)



(b)

Fig 1 (a-b) : Fingerprint minutia

The present paper introduces a statistical algorithm for extracting the fingerprint features from the five categories of the minutiae points. The proposed algorithm separates each minutiae category from fingerprint minutiae matrix, which was calculated by crossing number method, while preserving their original spatial the X and Y coordinates, as shown in figure 2.

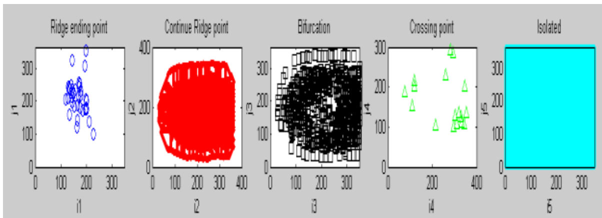


Fig 2: Minutia category separation

The K-means clustering technique is used in the proposed algorithm to group fingerprint minutiae based on its category into K number of group. The grouping is performed by minimizing the sum of squares of distances between minutiae and the corresponding cluster centroid. Figure 3 shows the k-means clusters for fingerprint minutia.

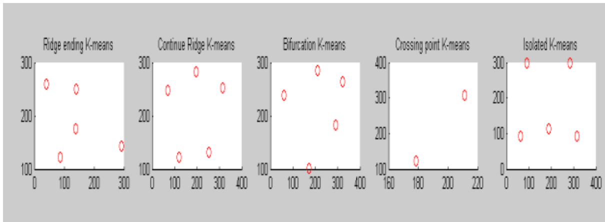


Fig 3: Centroid of k- cluster for minutia type

For each category we can draw a polygon whose vertices are the center's of the clusters as shown in figure 4. The centroid (C_x, C_y) of each polygon can be calculated as follows:

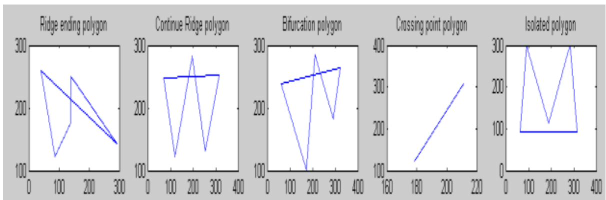


Fig 4: Polygon's of fingerprint minutia category

$$C_x = \frac{1}{6A}\sum_{i=0}^{n-1}(x_i + x_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \quad (6)$$

$$C_y = \frac{1}{6A}\sum_{i=0}^{n-1}(y_i + y_{i+1})(x_i y_{i+1} - x_{i+1} y_i) \qquad (7)$$

Where A is the polygon signed area and can be formulated as:

$$A = \frac{1}{2}\sum(x_i y_{i+1} - x_{i+1} y_i) \qquad (8)$$

Each minutia category has its centroid location which was determined by (C_x, C_y). Consequently, we can get the average of the five centroids (C_{xT}, C_{yT}). Figure 5 shows the five centroids and the average centroid for fingerprint minutia.

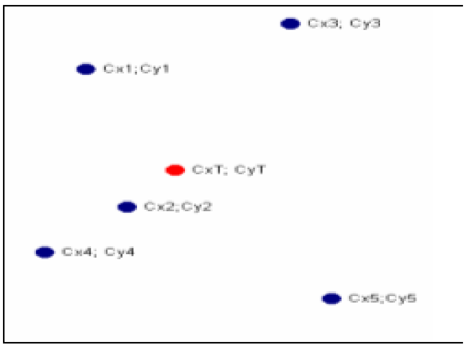


Fig 5: Average centroid for minutia type

Using the average centroid as an origin and calculating the polar coordinates (R, θ) of the five centers as shown in figure 6.

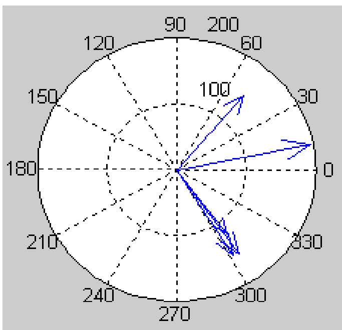


Fig 6: The polar coordinates as feature vector

Finally, we can represent the features vector of the fingerprint as follows:

$$V_m = [(R_n, \theta_n)]_m \qquad (9)$$

Where:

n : Is the number of fingerprint features (n = 0,………,4)
m : Is the number of fingerprint images

5. MATCHING STRATEGY

The matching strategy consists of three modules namely; face module, fingerprint module and fusion module. To identify the user, the face template storage and the fingerprint template storage are constructed by registering the number of face images and the corresponding fingerprint images for each user in the proposed framework. Let V ={V_{11}, …….. V_{ij}, ……….V_{nm}} denotes the face template storage, where V_{ij} represents the gray-level co-occurrence matrix of face image for particular user i^{th} and the corresponding specific face image j^{th} where, i = 1, ….…..n and j = 1, …………m. Let U ={U_{11}, …….. U_{ik}, ……….U_{np}} denotes the fingerprint template storage, where U_{ik} represents the minutia of fingerprint image for particular user i^{th} and the corresponding specific fingerprint image j^{th} where, i = 1, ….…..n and k = 1, …………p. The similarity measure is used to perform the matching between a query face and each face image of the face template storage, and between a query fingerprint and each fingerprint image of the fingerprint template storage. The present paper used the correlation coefficient as a similarity measure and it can be expressed by [63]:

$$Correl(V^k, V^q) = \frac{\sum(v_i^k - \overline{v^k})(v_i^q - \overline{v^q})}{\sqrt{\sum(v_i^k - \overline{v^k})^2 \sum(v_i^q - \overline{v^q})^2}} \qquad (10)$$

Where:

v_i^k : The ith feature value in the kth pattern

v_i^q : The ith feature value in the query pattern

$\overline{v^k}$: The mean value of the kth pattern

$\overline{v^q}$: The mean value of the query pattern

Therefore, face module retrieves the face image which has the highest score with the query face from the face template storage and the fingerprint module retrieves the fingerprint image which has the highest score with the query fingerprint image from the fingerprint template storage. The fusion module integrates the results of the face module and fingerprint module to support the final decision. If face image and fingerprint image belong to the same particular user i^{th} then the identity authentication is related to i^{th} user. Figure 7 shows the face and fingerprint fusion at decision level.

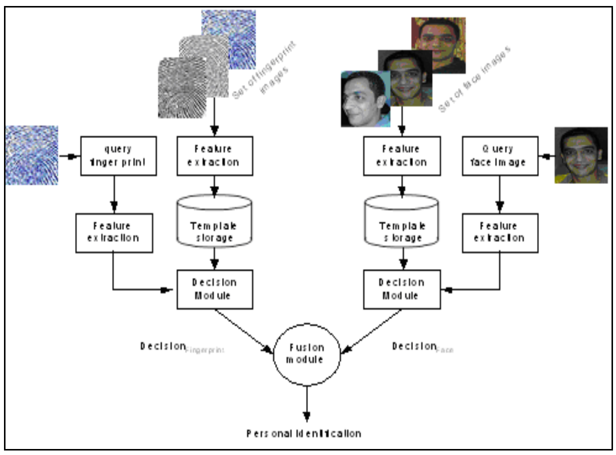


Fig 7: Fingerprint and face images fusion

6. EXPERIMENTAL RESULTS

The performance evaluation of the proposed framework has been performed according to the false acceptance rate (FAR), the false rejection rate (FRR), and genuine acceptance rate

(GAR) for various thresholds. False acceptance occurs when an unauthorized user (impostor) gains access to the system while false rejection occurs when a registered user (genuine) does not gain access to the system. The genuine acceptance rate is the probability of a genuine user being correctly accepted as genuine. Therefore, a perfect biometric authentication system would have a FRR = 0 and a FAR = 0. These measures are calculated as follows [64]:

$$FAR = \frac{\text{The number of false acceptances}}{\text{The number of impostor attempts}} x100 \quad (11)$$

$$FRR = \frac{\text{The number of false rejections}}{\text{The number of enrollee attempts}} x100 \quad (12)$$

$$GAR = 100 - FRR \quad \text{in percentage} \quad (13)$$

If threshold is set to a very high value then FAR of the system may decrease but it may increase FRR. While a low threshold may result in decreasing FRR but it may increase the FAR. So, the threshold is set according to the requirement whether a low FAR or a low FRR is needed. Therefore, the main aim of the proposed framework is to decrease the false acceptance rate and increase the genuine acceptance rate. The given used database consists of 100 persons, for each person 10 face images and 10 fingerprint images were acquired. The face and the fingerprint images were acquired using a digital camera and an optical fingerprint scanner respectively. Therefore, the total face and fingerprint images in a given database are 2000 images. Results of the proposed personal identification framework are explored throughout different phases. The first phase extracts the features' vectors of the face and the fingerprint database to construct the templates storage of face (V_{ij}) and fingerprint images (U_{ik}). The second phase concerns with calculating the matching score, for each person, five face and five fingerprint images are taken as the standard set and the remaining five face and five fingerprint images are taken as the testing set. The similarity between the standard images and the test images was measured using the correlation coefficient. Correlation coefficient classifier uses genuine and imposter score for classification. In order to compute FAR and GAR, first we need to generate all possible genuine and imposter matching scores and then set a threshold for deciding whether to accept or to reject a match. The genuine matching score is generated by calculating the correlation coefficient between the testing set and the standard set of the same individual. Same procedure is followed for all the individuals in the database. Thus, the total count of genuine score is 100 * 5 * 5 = 2500. Imposter matching score is generated by calculating the correlation coefficient between a testing set and the standard set of all other members. It is repeated for all individuals. Then, the total count of imposter score is (100 * 5) * (100 * 5 – 5) = 247500. A threshold is set based on the genuine and imposter scores. If the similarity measure calculated is greater than the threshold, they are recognized as genuine persons. If the score is less than the threshold, the person is recognized as an imposter. In the third phase, the face module and the fingerprint module retrieve the face and fingerprint images which have the highest score with the query face and fingerprint images respectively. Finally, the fusion module shows the user information if the received face and fingerprint images belong to the same user. The performance of the proposed framework can be performed by plotting a receiver operating characteristic (ROC) curve. A ROC curve is a plot of the GAR against each value of FAR for various thresholds as shown in figure 8. Therefore, the performance of the fusion method is improved effectively than face-only based or fingerprint-only based methods. The graphical user interface (GUI) for the proposed framework was implemented using MATLAB 7.1 and the snapshot of this GUI is shown in figure 9 (a-g).

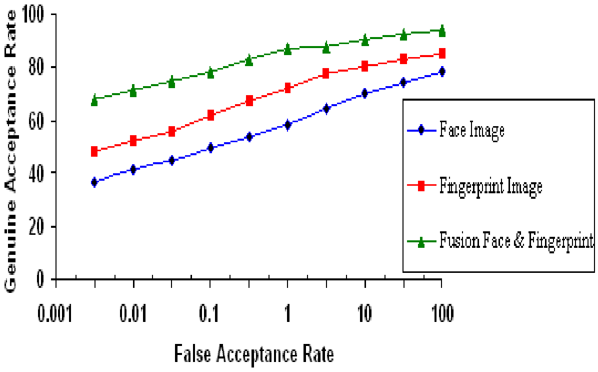
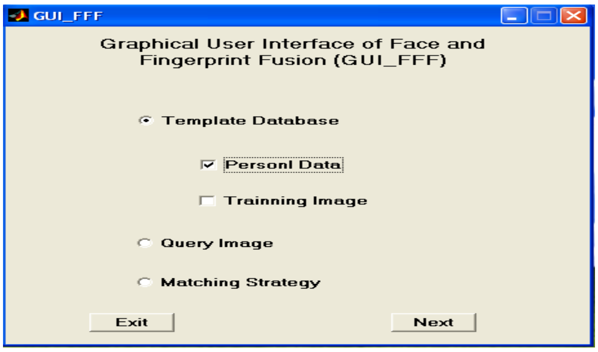
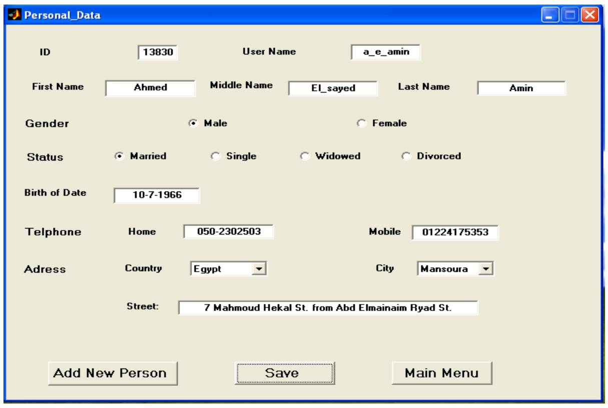


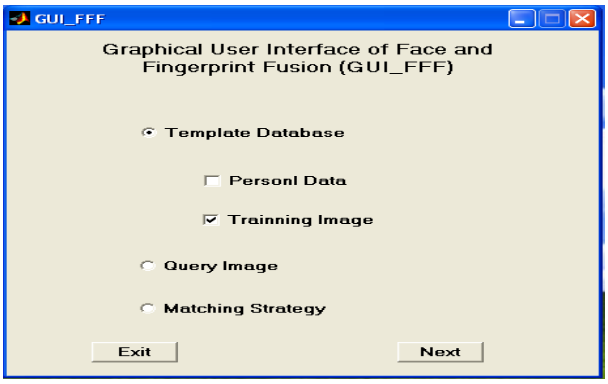
Fig 8: ROC curve for different biometric techniques



(a)



(b)



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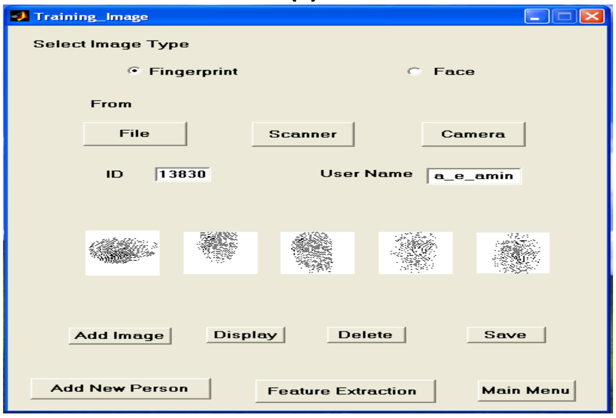

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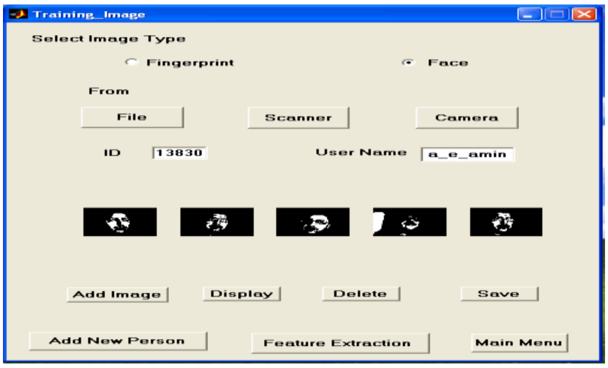

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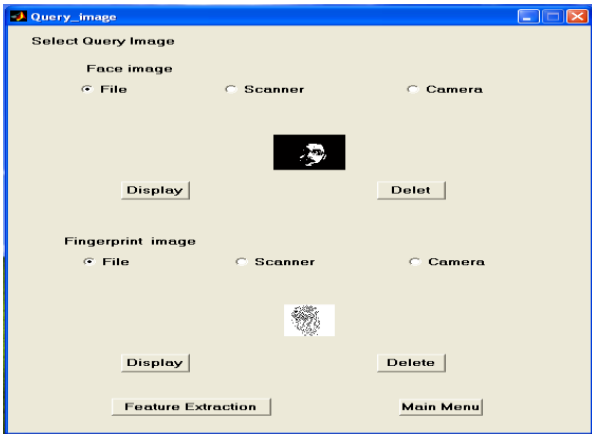

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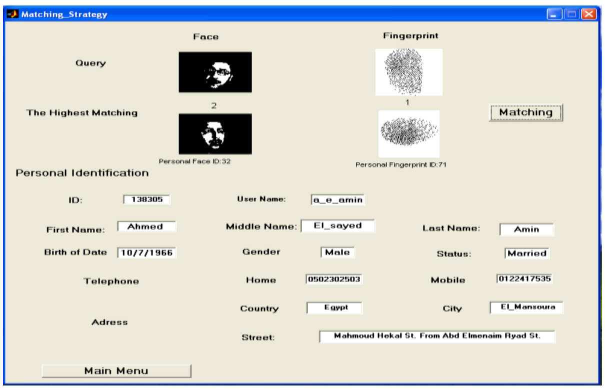

(g)

Fig 9 (a-g) : The GUI of the proposed framework

7. CONCLUSION

Multi-biometrics is a new and exciting area of information science research for accurate and reliable personal information representation for matching. Some of biometrics are more reliable than others. Therefore, the present trend is to find a good combination of multiple biometric to get the optimal identification. The present paper introduced a fusion biometric system which integrates face and fingerprint in authenticating a personal identification. It combines the advantages of different techniques and performs better than face-only or fingerprint-only systems. The experimental results demonstrate that fusing information from independent sources (face and fingerprint) improves the genuine acceptance rate compared with any single mode biometric system. In future, it would be instructive to study other datasets involving a larger number of users with additional biometric indicators such as fingerprint, face, voice and hand geometry to improve the system accuracy.

8. REFERENCES

[1] K. W. Bowyer, K. I. Chang, P. Yan, P. J. Flynn, E. Hansley, and S. Sarkar. “Multi-modal biometrics: An overview”, Second Workshop on Multi-Modal User Authentication, 2006.

[2] N. Ozay, Y. Tong, F.W. Wheeler, and X. Liu, “Improving face recognition with a quality-based probabilistic framework”, In IEEE Computer Society Workshop on Biometrics (in association with CVPR), 2009.

[3] Choonwoo Ryu, Seong G. Kong, Hakil Kim, “Enhancement of feature extraction for low-quality fingerprint images using stochastic resonance”, Pattern Recognition Letters 32, Pages 107–113, 2011.

[4] Kulwinder Singh, Kiranbir Kaur, Ashok Sardana, "Fingerprint Feature Extraction", IJCST Vol. 2, Issue 3, September 2011.

[5] And-elija M. Raiˇcevi´c and Brankica M. Popovi´c, "An Effective and Robust Fingerprint Enhancement by Adaptive Filtering in Frequency Domain", FACTA Universitatis (NI ˇS) SER.: ELEC. ENERG. Vol. 22, No. 1, Pages 91-104, April 2009.

[6] Wei Wang, Jianwei Li, Feifei Huang, and Hailiang Feng, "Design and implementation of Log-Gabor filter in fingerprint image enhancement ", Pattern Recognition Letters, Volume 29, Issue 3, Pages 301-308, 2008.

[7] Jianwei Yang, Lifeng Liu, Tianzi Jiang, and Yong Fan "A modified Gabor filter design method for fingerprint image enhancement", Pattern Recognition Letters, Volume 24, Issue 12, Pages 1805-1817, August 2003.

[8] Xinjian Chen, Jie Tian, Yangyang Zhang and Xin Yang, "Enhancement of Low Quality Fingerprints Based on Anisotropic Filtering", Lecture Notes in Computer Science, Volume 3832/2005, Pages 302-308, 2005.

[9] Zhendong Ye, and Mei Xie "An Effective One-Dimensional Anisotropic Fingerprint Enhancement Algorithm", The 3rd International Conference on Machine Vision (ICMV), 2010.

[10] Tico M, and Kuosmanen P, "A topographic method for fingerprint segmentation", International Conference on

Image Processing (ICIP), Vol. 1, Pages 36 – 40, 24-28 Oct 1999.

[11] Neil Yager and Adnan Amin, "Fingerprint Classification: a Review", Pattern Analysis & Applications 7, Pages 77–93, 2004.

[12] S. Malathi, S. Umamaheswari and C. Meena, “Rolled Fingerprint Segmentation”, Global Journal of Computer Science and Technology, Vol.9, Issue 5, Pages 107-110, 2010.

[13] J. Ravi, K.B Raja and K.R Venugopac, “Fingerprint Recognition Using Minutiae Score Matching”, International Journal of Engineering Science and Technology, Vol.1(2), Pages 35-42, 2009.

[14] R. Seshadri and T.R Trivedi, “Generate a Key MAC Algorithm using Biometric Fingerprint”, International Journal of Ad hoc, Sensor & Ubiquitous Computing Vol.1, No.4, Pages 38-45, 2010.

[15] S. A Daramola and C .N Nwankwo, "Algorithm for Fingerprint Verification System", Journal of Emerging Trends in Engineering and Applied Sciences (JETEAS) 2 (2): Pages 355-359

[16] Chengjun Liu, “Extracting Discriminative Color Features For Face Recognition”, Pattern Recognition Letters, Volume 32, Issue 14, Pages 1796-1804, 2011

[17] Lei Yu, Zhongshi He, and Qi Cao, “Gabor Texture Representation Method For Face Recognition Using The Gamma And Generalized Gaussian Models”, Image and Vision Computing, Volume 28, Issue 1, Pages 177-187, 2010

[18] Xudong Xie, and Kin-Man Lam, “Facial Expression Recognition Based on Shape and Texture”, Pattern Recognition, Volume 42, Issue 5, Pages 1003-1011, 2009

[19] J.F. Vargas, M.A. Ferrer, C.M. Travieso, and J.B. Alonso, "Off-line Signature Verification Based on Grey Level Information Using Texture Features", Pattern Recognition, Volume 44, Issue 2, Pages 375-385, February 2011.

[20] Jinhai Cai, Zhi-Qiang Liu, " Pattern recognition Using Markov Random Field Models", Pattern Recognition, Volume 35, Issue 3, March 2002, Pages 725-733.

[21] Olivier Alata, and Clarisse Ramananjarasoa, "Unsupervised Textured Image Segmentation Using 2-D Quarter Plane Autoregressive Model with Four Prediction Supports", Pattern Recognition Letters, Volume 26, Issue 8, Pages 1069-1081, June 2005.

[22] Wei Wang, Jianwei Li, Feifei Huang, and Hailiang Feng, "Design and Implementation of LOG-Gabor Filter in Fingerprint Image Enhancement", Pattern Recognition Letters, Volume 29, Issue 3, Pages 301-308, 1 February 2008.

[23] Tamás Kovács, "A Fast Classification Based Method for Fractal Image Encoding", Image and Vision Computing, Volume 26, Issue 8, Pages 1129-1136, 1 August 2008.

[24] Xiaohui Cheng, Cuina Zhang, and Maojie Zhou, "Rotation Invariant Texture Spectrum-Based Image Retrieval Algorithm", IEEE 2nd International Conference on Software Engineering and Service Science (ICSESS), Pages: 602 - 605, 2011.

[25] Hui-fang LI, Ning CHANG, and Xiao-ming CHEN, "A Study on Image Digital Watermarking Based on Wavelet Transform", The Journal of China Universities of Posts and Telecommunications, Volume 17, Supplement 1, Pages 122-126, July 2010.

[26] S. Baheerathan, F. Albregtsen, and H.E. Danielsen, "New Texture Features Based on the Complexity Curve", Pattern Recognition, Volume 32, Issue 4, Pages 605-618, April 1999.

[27] Zhongwei He, Wei Sun, Wei Lu, Hongtao Lu, "Digital Image Splicing Detection Based on Approximate Run Length", Pattern Recognition Letters, Volume 32, Issue 12, Pages 1591-1597, 1 September 2011.

[28] Abdulrahman Al-Janobi, "Performance Evaluation of Cross-Diagonal Texture Matrix Method of Texture Analysis", Pattern Recognition, Volume 34, Issue 1, Pages 171-180, January 2001.

[29] R. C. Gonzalez, and R. E. Woods, “Digital Image Processing”, Prentice Hall, Upper Saddle River, New Jersey, 2008

[30] L. Hong and A.K. Jain, “Integrating Faces and Fingerprints for Personal Identification,” IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 20, No. 12, Pages 1295-1307, Dec. 1998.

[31] R. W. Frischholz and U. Dieckmann, "Bioid: A Multimodal Biometric Identification System", IEEE Computer, Vol. 33, No. 2, Pages 64-68, 2000.

[32] A. Ross and A.K. Jain, “Information Fusion in Biometrics”, Pattern Recognition Letters, Vol. 24, No. 13, Pages 2115-2125, 2003.

[33] J. Fierrez-Aguilar, J. Ortega-Garcia, D. Garcia-Romero, and J. Gonzalez Rodriguez “A Comparative Evaluation of Fusion Strategies for Multimodal Biometric Verification”, Proceedings of the 4th international conference on Audio- and video-based biometric person authentication (AVBPA), Springer LNCS-2688, Pages 830–837, 2003

[34] A. Kumar, D. C. M. Wong, H. C.Shen1, and A. K. Jain, “Personal Verification Using Palmprint and Hand Geometry Biometric”, Proceedings of the 4th international conference on Audio- and video-based biometric person authentication (AVBPA), Springer LNCS-2688, Pages 668–678, 2003

[35] K. A. Toh, X. D. Jiang, and W. Y. Yau,”Exploiting Global and Local Decisions for Multi-Modal Biometrics Verification”, IEEE Trans. Signal Process, Vol. 52, No. 10, Pages. 3059–3072, Oct. 2004

[36] G. Feng, K. Dong, D. Hu and D. Zhang, "When Faces Are Combined with Palmprints: A Novel Biometric Fusion Strategy," in Lecture Notes in Computer Science, Springer, 3072, Pages.701-707, 2004

[37] R. Snelick, U. Uludag, A.Mink, M. Indovina, and A. K. Jain, “Large Scale Evaluation of Multimodal Biometric Authentication Using state-of the-art Systems”, IEEE Trans. Pattern Anal. Mach. Intel, Vol. 27, No. 3, Pages. 450– 455, Mar. 2005

[38] Kumar A, Wong DCM, Shen HC, Jain AK, “Personal Authentication Using Hand Images”, Pattern Recognition Letters, 27: Pages 1478-1486, 2006.

[39] Zhou J, Su G, Jiang C, Deng Y, Li C, “A Face and Fingerprint Identity Authentication System Based on Multi-Route Detection”, Neurocomputing, 70: Pages 922-931, 2007.

[40] A. Rattani, D. R. Kisku, M. Bicego and M. Tistarelli, "Feature Level Fusion of Face and Fingerprint Biometrics", in Biometrics: Theory, Applications, and Systems (BTAS), Washington, DC, Pages. 27-29, Sep. 2007.

[41] Shahin MK, Badawi AM, Rasmy ME, “A Multimodal Hand Vein, Hand Geometry and Fingerprint Prototype Design for High Security Biometrics”, Cairo International Biomedical Engineering Conference (CIBEC), Pages 1-6, 18-20 Dec. 2008

[42] Tayal A, Balasubramaniam R, Kumar A, Bhattacharjee A, Saggi M, “A Multimodal Biometric Authentication System Using Decision Theory, Iris and Speach Recognition”, 2nd International Workshop on Nonlinear Dynamics and Synchronization (INDS), Pages 1-8, 20-21 July 2009

[43] Kang BJ, Park K, “Multimodal Biometric Authentication Based on the Fusion of Finger Veins and Finger Geometry”, Optical Eng., Vol. 48, No. 9, Pages 090501-1 – 090501-3, 2009.

[44] M. M. Monwar and M. L. Gavrilova, "Multimodal Biometric System Using Rank-Level Fusion Approach," IEEE Transactions on Systems Man and Cybernetics, Part B (Cybernetics), Vol. 39, Pages. 867-878, 2009.

[45] Darwish, A.A, Zaki, W.M, Saad, O.M, Nassar, N.M and Schaefer, G, “Human Authentication Using Face and Fingerprint Biometrics”, Second International Conference on Computational Intelligence, Communication Systems and Networks (CICSyN), Pages: 274 – 278, 2010

[46] Gargouri Ben Ayed, Masmoudi A.D and Masmoudi D.S, “A New Human Identification Based on Fusion Fingerprints and Faces Biometrics Using LBP and GWN Descriptors”, 8th International Multi-Conference on Systems, Signals and Devices (SSD), Pages 1 – 7, 2011

[47] Jinfeng Yang and Xu Zhang, “Feature-Level Fusion of Fingerprint and Finger-Vein for Personal Identification”, Pattern Recognition Letters 33, Pages 623–628, 2012.

[48] A. Gelzinisa, A. Verikasa, and M. Bacauskienea, “Increasing the Discrimination Power of the Co-occurrence Matrix-Based Features”, Pattern Recognition, vol. 40, Pages 2367–2372, 2004.

[49] N. Jhanwar, S. Chaudhuri, G. Seetharaman, and B. Zavidovique, “Content Based Image Retrieval Using Motif Co-Occurrence Matrix”, Image Vision Computing, Vol. 22, Pages. 1211–1220, 2004.

[50] R.F. Walker, P.T. Jackway, and D. Longstaff, “Genetic Algorithm Optimization of Adaptive Multi-Scale GLCM Features”, International Journal on Pattern Recognition and Artificial Intelligence, Vol. 17, No. 1, Pages.17–39, 2003.

[51] R.M. Haralick, K. Shanmugam, and I. Dinstein, “Textural Features for Image Classification”, IEEE Transactions on Systems, Man, and Cybernetics, Vol. 3, No. 6, Pages 610–621, 1973.

[52] Virginia Espinosa-Duro, “Fingerprints Thinning Algorithm”, Aerospace and Electronic Systems Magazine, IEEE, Vol. 18, Issue: 9, Pages 28-30, Sept 2003.

[53] Emiroglu, I. and Aklan, M. B. “Pre-Processing of Fingerprint Images”, Security and Detection, ECOS 97., European Conference, Pages 147-151, 28 – 30 April 1997.

[54] O. C. Akinyokun and E. O. Adegbeyeni. ‘Scientific Evaluation of the Process of Scanning and Forensic Analysis of Fingerprints on Ballot Papers’, Proceedings of Academy of Legal, Ethical and Regulatory Issues, Vol. 13, Numbers 1, New Orleans, 2009.

[55] L. Hong, Y. Wan and A. K. Jain. ‘Fingerprint Image Enhancement: Algorithm and Performance Evaluation”, IEEE Transactions on Pattern Analysis and Machine Intelligence 20, 8, Pages 777–789, 2001.

[56] J. Tsai-Yang and V Govindaraju. “A Minutia-Based Partial Fingerprint Recognition System”, Center for Unified Biometrics and Sensors, University at Buffalo, State University of New York, Amherst, NY USA 14228, 2004.

[57] M.Kaur, M. Singh, and P.S. Sandhu, “Fingerprint Verification system using Minutiae Verification Technique”, Proceedings of world Academy of Science, Engineering and Technology, Vol. 36, 2008.

[58] L. H. Thai and N. H. Tam, “Fingerprint Recognition Using Standardized Fingerprint Model”, IJSCI International Journal of Computer Science Issues, Vol. 7, Issue 3, No. 7, Pages 11-16, 2010.

[59] A. K. Jain, F. Patrick, and A. Arun, “Handbook of Biometrics”. Springer Science and Business media, I Edition, Pages 1-42, 2008.

[60] T. Raymond, “Fingerprint Image Enhancement and Minutiae Extraction”, PhD Thesis Submitted to School of Computer Science and Software Engineering, University of Western Australia, Pages 21-56, 2003.

[61] N. Sara, D. Sergie and V. Gregory ‘User Interface Design of the Interactive Fingerprint Recognition (INFIR) System, 2004.

[62] Denis Rutovitz, "Pattern Recognition", Journal of the Royal Statistical Society, 129, Pages 504–530, 1966.

[63] Frederick Emory Croxton, Dudley Johnstone Cowden and Sidney Klein; "Applied general statistics", 3d Edition , Published by Prentice-Hall in Englewood Cliffs, N.J, 1967.

[64] Mohammed S. Khalil et al., "Fingerprint Verification Using Statistical Descriptors", Digital Signal Processing 20, Pages 1264–1273, 2010.