Fusion Face and Palmprint for Human Recognition via Spectral Eigenvector

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Abstract

The Biometrics recognition systems act as an efficient method with broad applications in the area of: security access control, personal identification to human-computer communication. From other hand, some biometrics have only little variation over the population, have large intra-variability over time, or/and are not present in all the population. To fill these gaps, a use of multimodal biometrics is a first choice solution [1].

This paper describes a multibiometrics method for human recognition based on new teacher vector identified as spectrum eigenface, and spectrum eigenpalm. The proposed combination scheme exploits parallel mode capabilities of the fusion feature vectors in matching level and invokes certain normalization techniques that increase its robustness to variations in geometry and illumination for face and palmprint. The correlation distance is used as a similarity measure. A threshold value is used to prevent the imposter for being recognized. Experimental results demonstrate the effectiveness of the new method compared to the unimodal biometrics for spectrum eigenface/eigenpalm.

Keywords: Modeling; Ferrocement; Corrosion; Service life; Durability; Metakaolin, Galvanized steel

دمج الوجه مع راحة اليد لتميز الاشخاص بأستعمال المتجهات الطيفية

الخلاصه

أنظمة تميز المقاييس البايولوجية تعمل كوسائل فعالة مع العديد من التطبيقات في مجـالات: سرية سيطرة الوصول، تميز الأشخاص عند الاتصال بين الحاسوب مع الإنسان. من ناحيــة أخـرى بعض المقاييس البايولوجية قد لا تكون متنوعة جدا إذا ما أخذت لحشد من الناس، أو ممكن تتغير مـع مرور الزمن، و/أو غير متوفرة للعديد من الأشخاص. وللتغلب على هـذه المـشاكل تـم اسـتعمال المقاييس البايولوجية المتعددة.

في هذا البحث نستعرض طريقة المقاييس البايولوجية المتعدد لتمييز الأشـخاص و المبنيــة على استخدام متجهات جديدة تدعى محدد الوجه الطيفية ومحدد راحة اليد الطيفية. المخطط المـدموج يستثمر قابليات النموذج المتوازي للدمج في مستوى التطابق ويدخل طريقة تسوية والتــي تزيــد مــن فعاليتها اتجاه التغير بالإضاءة وهندسة الوجه مع راحة اليد. مسافة الارتبــاط اسـتخدمت كمقيــاس للتشابه. تم استعمال حد لمنع المتطفل من أن يميز داخل النظام. نتائج الاختبارات عبرت عــن مــدى فعالية الطريقة الجديدة المطبقة اتجاه استعمال النموذج البايولوجي الواحد للمحــدد الوجــه الطيفــي أو محدد راحة اليد الطيفي.

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Introduction

Unimodal biometric systems, relying on the evidence of a single source of biometric information for recognition, have been successfully used in many different application contexts. However, a single biometric feature sometimes fails to recognize of a person. By combining multiple modalities, enhanced performance reliability could be achieved. Biometric systems have four main components [1]: sensor, feature extraction, matching-score and decision-making modules. Multimodal systems can be designed to operate in five different ways as depicted in Figure (1). From the scenarios described above and the four important components of biometric systems, the combination and the fusion of the information acquired in each stage is possible as depicted in Figure (2)

Furthermore, from an operational aspect, biometric systems can perform in three different modes, as depicted in Figure (3(a-c)), and these are [1]: Parallel mode: This operational mode consists in completing the combination of the modalities simultaneously, Serial mode: This operational mode consists in completing the combination of the modalities one after the others, as it permits to reduce at the start the initial population before the following modality is used. Finally Hierarchical mode: This operational mode consists in completing the combination of the modalities in a hierarchical scheme, like a tree structure, when the number of classifiers is large.

In the matching score level, methods such as simple sum rules, weighted averaging, product rules, k-NN classifiers, decision trees and Bayesian methods can be used to combine scores obtained by biometric systems. Such approaches provide significant performance improvement [1].

Face and palmprint multimodal biometrics are advantageous due to the use of non-invasive and low-cost image acquisition. Face and palmprint images are easily acquired using two touchless sensors simultaneously [1].

This paper, presents a new multimodal biometric recognition method via face and palmprint method. The Effective classifiers based on spectrum eigenface, and spectrum eigenpalm features are constructed for faces and palmprints, respectively. Then, the matching scores from the two classifiers are combined using and fusion strategies. Experimental results demonstrate the effectiveness of the new feature vector to the fusion model compared to the existing unimodal for spectrum eigenface/eigenpalm.

The remaining sections are organized as follows: background in Section 2. The purposed feature extraction is explained in Section 3. The fusion system is given in Section 4. Finally, Section 5 conclusions to the main results

Background

Palmprint Pre-processing

A coordinate system of a palmprint is used, via gaps between the fingers as reference points, next central square part is extracts, as depicted in Figure (4), and the pre-processing algorithm is summarized below:

Input: Palmprint image of 256 gray levels

Output: Central square part of a palmprint

Process:

Step1: Apply a low-pass filter for the input image.

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Step2: binarylized the palmprint image using a threshold method.

Step3: Find the contours of the hand shape.

Step4: Extract the anchor points, which represent the minimum mean radial distance from all the points on the hand contour to the hand centroid.

Step**5**: The origin of the coordinate system is defined as the point between index and middle finger and the point between the middle and pinky finger.

Step6: The slope of the line passing through the anchor points is determined and each hand image is rotated in the direction of the slope around the anchor midpoint.

Step7: Extract a sub-image with the fixed size on the basis of coordinate system, which is located at the certain part of the palmprint.

Discrete Time Fourier Transform

Signals are functions of time that have related to frequency domain interpretation. The importance of being able to transform between time and frequency domains is accordingly palpable. For analog signals the medium for performing the transformation is the Fourier transform (FT), while in DSP it is the Discrete Fourier Transform (DFT) [2]. Once the signal has been acquired and digitized, it can be converted to the frequency domain by using Fast-Fourier-Transformed (FFT). The FFT results can be either real and imaginary, or magnitude and phase, functions of frequency. The transform and inverse transform pair given for vectors of length N by [2]:

$$X(k) = \sum_{j=1}^{N} x(j) y_N^{(j-1)(k-1)} , \ldots\ldots (1)$$

$$x(j) = \frac{1}{N} \sum_{k=1}^{N} X(k) y_N^{-(j-1)(k-1)} , \ldots (2)$$

Where $y_N = e^{(-2pi)/N}$ is an N_{th} root of unity.

Correlation Implementation Using FFT

Let X, and Y be any two data sets such that, correlations based on the FFT is defend using three steps as:

1. By tacking the FFT of X, and the FFT of Y,

2. Next, multiply one resulting transform by the complex conjugate of the other one,

3. and inverse transform the result product such as [3]:

$$Corr(X,Y) = IFFT(FFT(X) * FFT(Y)) , \ (3)$$

Eigenvector

Eigenvector or the Principle Component Analysis (PCA) is a statistical measurement method, which operates in the linear domain and can be used to reduce the dimensionality of an image. An image can be viewed as vectors and represented in matrix form. This method can be described as follows [4]:

Let I denote a $n_1 \times n_2$ gray scale image. Represent I by a means of a vector, $x = n_1 \times n_2$, which can be seen as a point in R^n. When performing PCA on these vectors, the eigenvectors obtained from the sample covariance matrix are called *Eigenvectors*. Here are the steps to compute these Eigenvectors:

1. Obtain an images $I_1, I_2,..., I_M$.
2. Represent every image I_i as a vector x_i.

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3. Compute the average image $y = \frac{1}{M}\sum_{i=1}^{M} x_i$ ………..… (4)

4. Subtract the mean image $j_i = x_i - y_i$,………… (5)

5. Compute the covariance matrix $C = \frac{1}{M}\sum_{n=1}^{M} j\, j_n^{\,T} = AA^T$,...(6)

6. Compute the eigenvectors u_i of AA^T:

    6.1 Consider matrix AA^T as an MxM matrix.

    6.2 Compute the eigenvectors vi of AA^T such that

$$A^T Av_i \Rightarrow m_i v_i \Rightarrow AA^T Av_i = m_i Av_i \Rightarrow Cu_i = m_i u_i$$

      Where $m_i = Av_i$,……(7)

    6.3 Compute the M best eigenvectors of AA^T: $m_i = Av_i$,… ...(8)

7. Keep only K eigenvectors.

Post-processing

A feature is normalized by scaling its values so that they fall within a small-specified range, such as 0 to 1. Min-max normalization performs a linear transformation on the original data. Suppose that mina and max are the minimum and the maximum values for feature A. Min-max normalization maps a value v of A to v′ in the range [new$_{min}$, new$_{max}$] by computing:

$$v' = ((v\text{-}min)/(max\text{-}min)) \times (new_{max}\text{-}new_{min}) + new_{min}, ….(9)$$

Eigenvector Matching

Let X and Y be two spectral eigenvector feature vectors where, $x_i \in$ X, $y_i \in$ Y, i=1,…,n. to calculate the degree of association, a correlation distance is defined as[5]:

$$R = 1 - r, …………………...(10)$$

Where r is the linear correlation coefficient which is given by the formula [5]:

$$r(X,Y) = \frac{\sum_{i=1}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}(x_i - \bar{x})^2}\,\sqrt{\sum_{i=1}(y_i - \bar{y})^2}} ,….(11)$$

Where $\bar{x}$: is the mean of the vector X,

and $\bar{y}$: is the mean of the vector Y.

The correlation distance determines the genuine or forged query sample. It is easy to verify the input pattern by a pre-defined threshold value T. If the value R is smaller than threshold T, then the owner of query sample is claimed to be individual X. Otherwise, the query sample is classified as a forged pattern.

Threshold Selection

In any biometric image recognition system, it is essential to pick a suitable threshold (T), for good performers results. To this end, an approach based on intra-class and inter-class information collected from the Enrolment database. The intra-class (*D*) measures the distances between images of the same individual, therefore it gives an indication of how similar the images of the same individual are. The intra-distance is defined as:

$$d_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{ik'})), \text{ Where } i \in I$$
$$I, k' \in K \text{ ,and, } K \neq K' ….....(12)$$

The inter-class (*P*): The distances between the images of an individual are measured against the images of other individuals in the enrolment database, therefore it gives an indicates how different each image of an individual is when compared to images of other

individuals in the enrolment database. The inter-distance is defined as:

$$p_{ik}^{ik'} = (1 - r(\Omega_{ik}, \Omega_{jl})), \ldots\ldots\ldots\ldots(13)$$

Where $j \in I$, $i \neq j$, and $l, k \in K$

A threshold (T) is then calculated from intra-class and inter-class information as described in [6]. The estimation of threshold (T) depends mainly on the number of images per individual in enrolment, therefore as in [4], every individual should have at least 4 images for enrolment database. The algorithm for the maximum intra-class and the minimum inter-class calculation is described as:

Input: $I = \{1,...I'\}$, where $I' =$ number of individuals, $K = \{1,..., K'\}$, where $K' =$ number of images per individual, $F_{ik} =$ image feature vector i $\in$ I and k $\in$ K

Ω = feature matrices of training images for each image

Output: $D_{max} = Maximum\ intra\text{-}class$, and $P_{min} = minimum$ inter-class

Process:

Step1: Do while the $(F_{ik} \neq 0)$

Step2: Compute the intra distances, and the inter distances

Step3: End of while

Step4: Store the intra-class (D), and the inter-class (P) in ascending order

Step5: Compute D_{max}, and P_{min} .

Step6: End.

Eigenvector Recognition Process

An unknown query image can be represented as a linear combination of the best K Eigenvectors of the obtaining eigenvectors for a given dataset. In image recognition, the eigenvectors are used once again in order to compute a distance from the query in the image space. The algorithm is summarized below:

Input: an unknown image vector x

Output: matching result

Process:

Step1.

Compute j = x - y ,………………..(14)

Step2. Compute

$$j^{\wedge} = \sum_{i=1}^{k} w_i u_i \text{ where } w_i = u_{,i}^T j \ ,...(15)$$

Step3.

Compute $D_e = \left\| j - j^{\wedge} \right\|$,…………..(16)

Step4. If $De < T$, then x is a exact image. De : Is the distance from image space.

The proposed Spectral Eigenvector Feature

The new purposed idea of applying the FFT in the implementation for Eigenvector is by use FFT in the implementation of the correlation, as an alternative of conventional ideas of converting the intensity of the image data into the spectral domain, followed by applying the Eigenvector. The new purposed idea is named as the spectral based eigenvector feature.

The correlations can be computed by using the FFT as follows: FFT the two data sets, multiply one resulting transform by the complex conjugate of the other, and inverse transform the product. The method is implement via the converting the input image into one dimensional vector.

Let I denote a $n_1 \times n_2$ gray scale image. Represent I by means of a vector, $x = n_1 \times n_2$, which can be seen as a point in R^n . Here are the steps to computing these Eigenvectors:

1. Obtain face images $I_1, I_2,., I_M$.
2. Represent every image I_i as a vector x_i,
3. Compute the average image

$$y = \frac{1}{M} \sum_{i=1}^{M} x_i$$

4. Subtract the mean image

$$j_i = x_i - y_i$$

5. Compute the covariance matrix

$$C = IFF(FF(j)FF(j^T)) = AA^T$$

6. Compute the eigenvectors u_i of AA^T:

    6.1 Consider matrix AA^T as a $M \times M$ matrix.

    6.2 Compute the eigenvectors vi of AA^T such that:

$$A^T A v_i \Rightarrow m_i v_i \Rightarrow AA^T A v_i = m_i A v_i \Rightarrow C u_i = m_i u_i$$

Where $m_i = A v_i$

    6.3 Compute the M best eigenvectors of AA^T:

$$m_i = A v_i$$

7. Keep only K eigenvectors.

Fusion System Using Spectrum Eigenvector Features

The proposed multimodal biometric system based on the fusion of face and palmprint at the matching score level as depicted in Figure (5). Firstly, effective face and palmprint spectral eigenvector features are extracted for matching as illustrated in section 4.1.1. By comparing with the templates stored in the database as illustrated in section 4.1.2, the matching scores of each classifier are generated. Then, the scores output from the two classifiers are combined using several fusion strategies to give a unique matching score. Finally, the result class label is presented.

Scheme Phases
Training Phase

A 100 palmprint images and 100 face images are collect from 10 individuals, a sample of the images are depicted in Figure (5(a-f)), 4 of them are female, 6

of them are male. Each of them is asked to provide abut 10 images for their left palm, and 10 images for their faces. Originally, the collect samples of the palm have size, 584×484 pixels with 75dpi resolution. The gathered palmprints samples belong to individuals place their hands freely on the platform of the scanner when scanned. This results in palmprint images with different shifts and rotation. Therefore, some pre-processing operations are required to correct the orientation of the image. Next, a sub-image which represents the central part of the palm is extracted so that the feature extraction process can be performed on a fixed size of image. The size of the central part for each palmprint image is 256× 256 pixels.

A spectrum eigenpalms is applied. A min-max normalization take place to convert the result feature vector to an element between [0,1]. The results normalized feature vector is labeled manually, and 40 samples (4 for each individual) where used to form a database, which named the Enrollment Database EDB1, the other 60 samples where used to perform the recognition. A threshold value T, is computed using the intra-classes and inter-classes, T = 0.755 and stored in the EDB1 for the recognition phase.

Originally, the collected images of the faces are in PGM format, with a size of each image is 112x92, 8-bit grey levels. A spectrum eigenfaces is applied. A min-max normalization take place to convert the result feature vector to an element between [0,1]. The results normalized feature vector is labeled manually, and 40 samples (4 for each individual) where used to form a database, which named the Enrollment Database EDB2, the other 60 samples

where used to perform the recognition. A threshold value T, is computed using the intra-classes and inter-classes, T = 0.81 and stored in the EDB2 for the recognition phase.

Recognition Phase
A comparison based on using the correlation distance for each of the rest 60 query samples for the palm with the other 40 reference in EDB1, also a comparison based on using the correlation distance for each of the rest 60 query samples for the face with the other 40 reference in EDB2.

The output of a recognition system is a list of sorted reference images in descending order by similarity with the testing image. That means, the reference image on the top of the list has the highest similarity (lowest distance) with the testing image. Recognition accuracy is defined as follows:

$$Recognition accuracy = \frac{Number of corrected matches}{Total Number of matches} \times 100\%$$

$$..(17)$$

The corrected matching means that the reference image on the top of the list is the testing image. The results of each classifier are depicted in Table (1), and the results of the combined face and palmprint is depicted in Table (2).

The recognition accuracy is calculated using equation 17 for the palm classifier is find equal 97.5 %, face classifier is find equal 98.3 %, and combined classifier is find equal 99 %.

Conclusions
This paper describes a method of fusion face and palmprint for human recognition based on a new feature vectors identified as spectrum eigenface, and spectrum eigenpalm. The proposed combination scheme exploits parallel mode capabilities of the fusion feature vectors in matching level and invokes certain normalization techniques that increase its robustness to variations in geometry and illumination for face and palmprint. Experimental results demonstrate the effectiveness of the new method compared to the existing unimodal for spectrum eigenface/eigenpalm. The recognition system is implemented using Matlab 7 as programming language and uses of 100 pairs of image one for the palmprint and the other for the face for 10 individuals. The recognition accuracy is calculated for the palm classifier and is find to be equal 97.5 %, face classifier is find to be equal 98.3 %, and combined classifier is find to be equal 99 %.

The multimodality biometrics methods present an appropriate measure to oppose against spoof attacks, as it is hard to counterfeit several modalities at the same time, to circumvent a system. They also present an adapted solution to the limitations of universality, as even if a biometrics is not possessed by an individual, the other(s) modality (ies) can still be used.

The gathered palmprints images belong to individuals place their hands freely on the platform of the scanner when scanned. This results in palmprint images with different shifts and rotation. Therefore, some preprocessing operations are required to correct the orientation of the image. Next, a sub-image which represents the central part of the palm is extracted so that the feature extraction process can be performed on a fixed size.

The min-max normalization helps to prevent features with initially large ranges from outweighing features with initially smaller ranges, and also this

step is necessary for the combination in the matching level. To reduce system complexity, we adopt horizontal projection to obtain 1-D energy profile signal. To exploit the benefits driving from concentrated energy, every column is accumulated as energy signal. The correlation distance is used to calculate the intra-class, and inter-class which is the bass for calculation the threshold value, and find the correct recognition of each individual. The thresholds value is important to prevent the imposter from being recognized.

References

[1]: D. D., J. R., C. C., A. D., "Multimodal Bio-metrics for Identity Documents (MBioID): State-of-the-Art" http://www.europeanbiometrics.info

[2]: S. H., R. F., and P. S., "Comparison of multi-wavelet, wavelet, Haralick, and shape features for micro calcification classification in mammograms", Pattern Recognition, Volume 37, Issue 10, October 2004, Pages 1973-1986

[3]: Min Luo, Yuwapat Panitchob, "Eigenface for Face Recogrition", ECE 533 Final Project Report, fall'03.

[4]: O.O., M.Y., and S. G., "Face Recognition Using PCA Wavelet Decomposition", Electrical & Computer Department, Kuliyyah of Engineering, International Islamic University Malaysia, 2001.

[5]:K. A. and S. H.," Recognition of Palmprints Using Wavelet-based Features", Proc. Intl. Conf. Sys., Cybern, SCI-2002, 2002

[6]: R. T., W. L. and S.V., "Face Recognition based on Ordinal Correlation", Auditing and Performance Evaluation", IEEE, 349- 354 ISBN: 0-7803-9399-6

Table (1): Depict the success recognition for each classified.

	Sample11	Sample12	Sample13	Sample14	Sample15	Sample16	Sample17	Sample18	Sample19	Sample110
Recognition Accuracy Of the palm	12/12	12/12	12/12	12/12	10/12	12/12	12/12	12/12	11/122	12/12
Recognition Accuracy Of the face	12/12	12/12	12/12	12/12	11/12	12/12	12/12	12/12	11/22	12/12

Table (2): Depict the combined recognition results

	Palm1 & Face1	Palm2 & Face2	Palm3 & Face3	Palm4 & Face4	Palm5 & Face5	Palm6 & Face6	Palm7 & Face7	Palm8 & Face8	Palm9 & Face	Palm10 & Face
Recognition Accuracy Using the sum	12/12	12/12	12/12	12/12	1/12	12/12	12/12	12/12	12/122	12/12
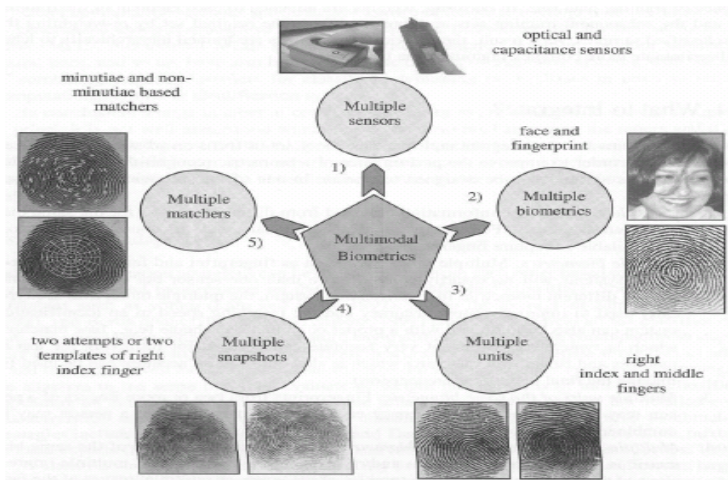
Figure (1): Combination schemes [1].

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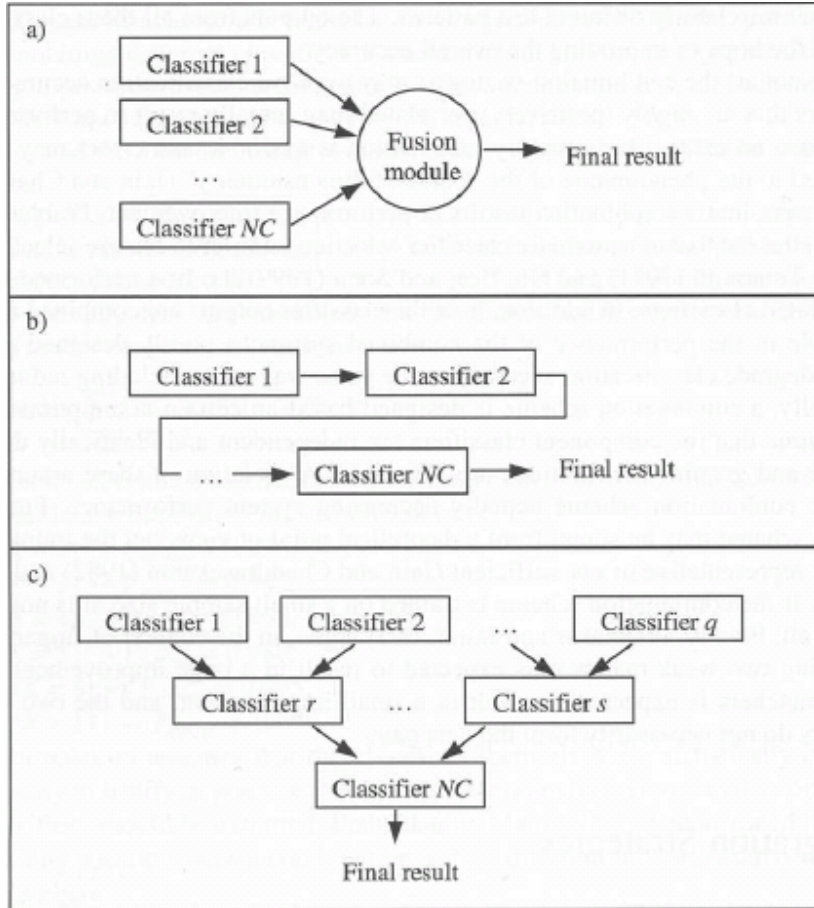
Figure (2): Fusion levels possibilities [1], a: feature level,
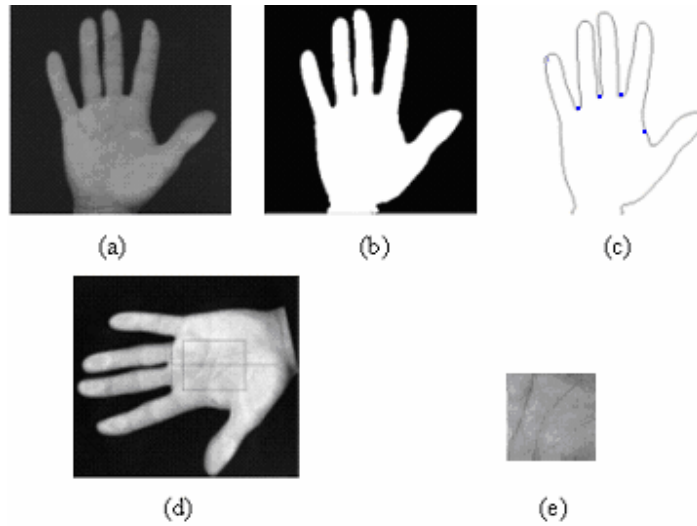
b: matching level, c: decision level
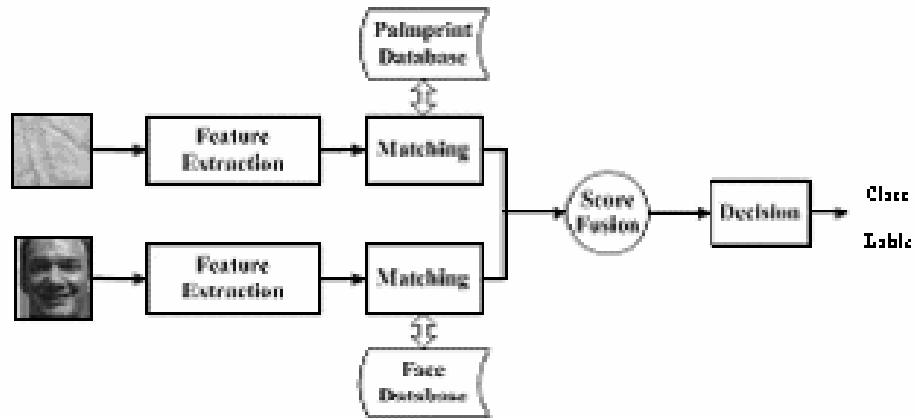
Figure (3(a-e)): the preprocessing steps

Figure (4): The multimodal biometric system of face and palmprint.

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(a)   (b)

(c)   (d)

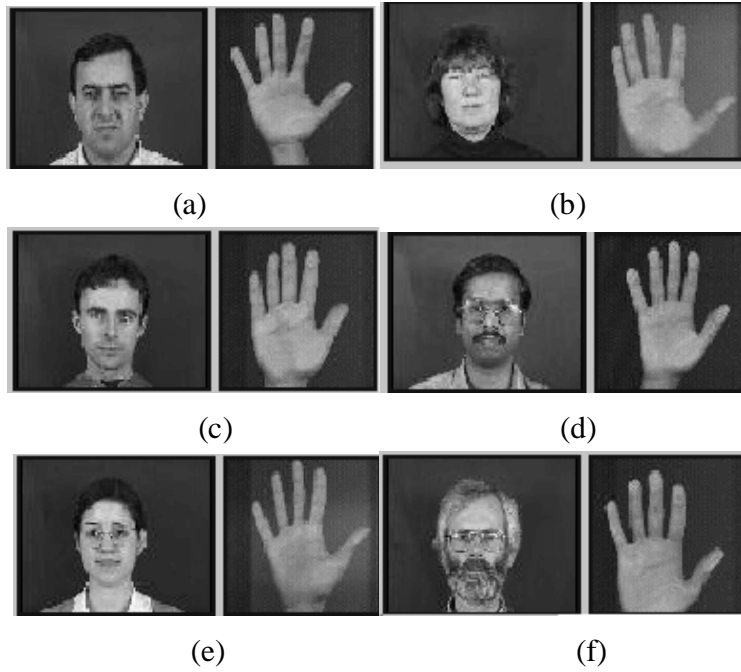(e)   (f)

Figure (5(a-f)): Shows typical images from the databases.