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Palmprint based automated palmprint recognition system based on minutiae

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Abstract:
Many palmprint authentication approaches have been proposed in recent years. Among them, the orientation-based coding approach, in which the dominant orientation features of palmprints are extracted and encoded into bitwise codes, is one of the most promising approaches. The distance between codes created from two palmprint images is calculated in the matching stage. Reliable orientation feature extraction and efficient matching are the two most crucial problems in orientation-based coding approaches. In this paper, an automated scanner-based palmprint recognition system is proposed. The system automatically captures and aligns the palmprint images for further processing. Several linear subspace projection techniques have been tested and compared. In specific, we focus on principal component analysis (PCA), fisher discriminant analysis (FDA) and independent component analysis (ICA). In order to analyze the palmprint images in multi-resolution-multifrequency representation, wavelet transformation is also adopted. The images are decomposed into different frequency sub-bands and the best performing sub-band is selected for further processing.

Keywords: Biometric; Palmprint recognition; Palmprint pre-processing; Subspace projection methods; Similarity matching.

I. Introduction

Recently, a new biometric feature based on palmprint has been introduced. Palmprint recognition refers to the process of determining whether two palmprints are from the same person based on line patterns of the palm. Palmprint is referred to the principal lines, wrinkles and ridges appear on the palm, as showed in figure 1. There are three principal lines on a typical palm, named as heart line, head line and life line, respectively [1]. These lines are clear and they hardly change throughout the life of a person. Wrinkles are lines that are thinner than the principal lines and are more irregular [2]. The lines other than principal lines, as well as wrinkles, are known as ridges, and they exist all over the palm.

Palmprint serves as a reliable human identifier because the print patterns are not duplicated in other people, even in monozygotic twins. More importantly, the details of these patterns are permanent [3]. The rich structures of the palmprint offer plenty of useful information for recognition.

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There are two popular approaches to palmprint recognition. The first approach is based on the palmprint statistical features while the other on structural features [4]. For statistical based palmprint recognition approach, the works that appear in the literature include eigenpalm, fisherpalms, Gabor filters, Fourier Transform, and local texture energy.

Another important feature extraction approach is to extract structural information, like principal lines and creases, from the palm for recognition [5-6]. The devised a minutiae extraction method for palmprints. This idea was inspired by the fact that palmprint also contains minutiae like fingerprints. Determined the datum points derived from the principal lines using the directional projection algorithm [7]. These datum points were location and rotational invariant due to the stability of the principal lines. Unlike the work explicitly extract palm lines, but used only isolated points that lie along palm lines as they deduced that feature point connectivity was not essential for the matching purposes. The recognized palmprint by using creases. Their work was motivated by the finding that some crease patterns are related to some diseases of people. Another structural based method was to implement fuzzy [8].

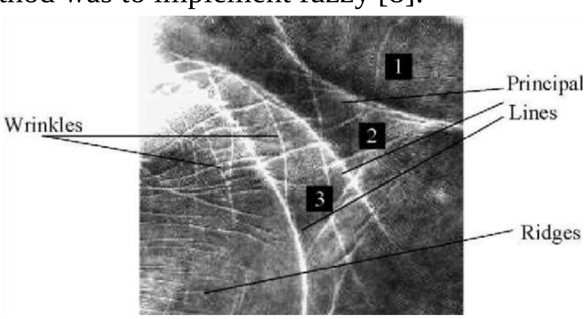

Fig. 1. The line patterns on the palmprint. The three principal lines on a typical palm: 1-heart line, 2-head line and 3-life line.

Fuzzy directional element energy feature (FEDDF) which originated from the idea of a Chinese character recognition method called directional element feature (DEF). On the other hand, the Sobel’s and morphological operations to extract palmprint structural features from the region of interest (ROI).

In the first statistical features based palmprint recognition approach, the palmprint image is treated as a whole for extraction, representation and comparison. Thus, the recognition process is straightforward. However, as abundant textural details are ignored, the natural and structural information of the palmprint cannot be characterized. On the other hand, structural approach can represent the palmprint structural features clearly. Besides, image with lower quality can be used for structural approach as lines can be detected under low-resolution. However, this method is restricted by the complication in determining the primitives and placements of the line structures, and usually more computational power is required to match the line segments with the templates stored in the database [9]. Each approach demonstrates its strengths and weaknesses, and the choice depends on the temperament of application: operational mode, processing speed, memory storage and quality of the image acquired.

In addition to the feature selection process, image capturing method is another important factor to be evaluated. The palmprint recognition methods proposed by utilized inked palmprint images. These approaches are able to provide high-resolution images and are suitable for methods which require fine resolution images to extract lines, datum points and minutiae features. However, these methods are not suitable for online security systems as two steps are required to be performed: ink the palmprint images on papers and then scan them to obtain digital images. Some recent works demonstrated by [9] used CCD based digital camera to capture palmprint images. The digital images acquired could be directly fed into computer for computation. Another approach proposed by [11] used scanner as the acquiring device. The advantage of scanner is that it is equipped with a flat glass that enables the users to flatten their palm properly on the glass to reduce bended ridges and wrinkle errors. Some authors like [10] fixed some guidance pegs on the sensor's platform to limit the palm'sshiftandrotation. Someuserswillfeel uncomfortable when their hands images are acquired. In addition, this approach requires additional peg-removal algorithm to remove the pegs from the hand image.

In this paper, an automated peg-free scanner-based palmprint recognition system is proposed. Two novel components are contained in the proposed system. First, a pre-processing module that automatically aligns palmprint images from peg-free sensor is developed. This module segments hand image from the background and extracts the center region of the palm for recognition. Second, systematic comparison and analysis of three types of subspace projection techniques, namely principal component analysis, fisher discriminant analysis and independent component analysis, using a standard palmprint database is presented. In order to analyze palmprint images in multi-resolution-multi-frequency representation, the wavelet transformation is also adopted.

In the next section, the overview of the proposed palmprint recognition system is provided and each of the system's components is discussed in details. Section 3 presents the experiment setup, as well as the results of this research. In Section 4, we make some concluding remarks. Finally, the review of PCA, FDA, ICA and Wavelet Transform theories are provided in Appendix A for the convenience of readers unfamiliar with these techniques.

2. Overview of system architecture

The proposed system is divided into two phases, namely the enrollment and verification phase, as shown in Fig. 2.

The important tasks contain in the system include the pre-processing, feature extraction as well as feature matching. In the pre-processing stage, the alignment and orientation of the hand images are corrected for use in the successive tasks. In the feature extraction stage, the most discriminating features from the palms are extracted for representation, and finally in the feature matching stage comparison is performed and decision is made whether two palmprint features are from the same person. The details of each of these components are discussed in the subsequent sections.

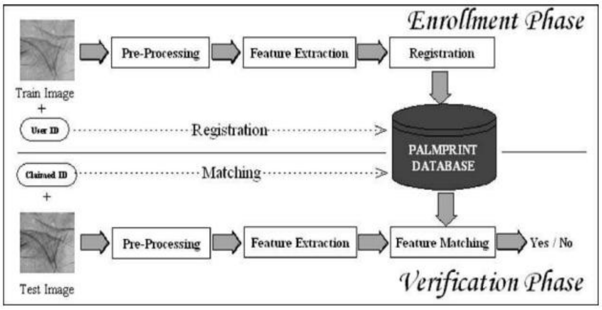

Fig. 2. Block diagram of the proposed palmprint verification system.

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2.1. Pre-processing

In this system, no guidance pegs are fixed on the scanner's platform and the users are allowed to place their hands freely on the platform of the scanner when scanned. Thus, palmprint images with different sizes, shifts and rotations are produced. Therefore, a pre-processing algorithm has been developed to correct the orientation of the images and also convert the palmprints into same size images. Successful pre-processing measure can provide the foundation for both feature extraction and matching.

Before alignment and orientation are performed on the palmprint, a smaller region from the center of the palm, called region of interest (ROI), is automatically extracted. The ROI is defined in square shape and it contains sufficient information to represent the palmprint for further processing. Fig. 3 depicts the appearance of ROI of a palm.

We applied the salient-point detection algorithm proposed to obtain the three crucial points, v_1, v_2 and v_3 as shown in Fig. 3, used to locate the ROI. First, an image thresholding technique is applied to segment the hand image from the background. The proposed technique can also detect fingernails and rings by analyzing the skin color of the hand. The hand image acquired is in 256-RGB colors with stable background in grey. The background can be segmented based on the values of the image's color component r, g, and b which represent red, green and blue, respectively. The image thresholding technique proposed is shown in Eq. (1):

$$C_1(u,v) = \begin{cases} 1 & |r(u,v) - b(u,v)| < T \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Eq. (1) is repeated for setting, j$r(u,v)$Kg(u,v)j, yielding $C_2(u,v)$ and j$b(u,v)$Kg(u,v)j, $C_3(u,v)$. The threshold value T is set to 50 to filter all the grey level color to white and other color to black. The resultant image of binary pixel C_1, C_2 and C_3 are ANDed to obtain the binary image, I:

$$I = \sum_{v=1}^{h} \sum_{u=1}^{w} \bigcap_{i=1}^{3} C_i(u,v) \tag{2}$$

After that, contour of the hand shape is obtained by using eight neighborhood border tracing algorithm. The process starts by scanning the pixels of the binary image from the bottom-left to the right. When the first black pixel is detected the border tracing algorithm is initiated to trace the border of the hand in clockwise directions. During the border tracing process, all the coordinates of the border pixels were recorded in order to represent the signature of the hand, $f(i)$ where i is the array index. The hand signature is blocked into non-overlapping frames of 10 samples, $f(i)$. Every frame is checked for existence of stationary points and in this way the valleys of the fingers, v_1, v_2 and v_3 could be pinpointed. Based on the information of these three crucial points, the outline of the ROI could be obtained as follows:

1. The two valleys beside the middle finger, v_1, v_2, are connected to form a reference line.
2. The reference line is extended to intersect the right-edgeof the hand.
3. The intersection point obtained from step (2) is used tofind the midpoint, m_1, based on the midpoint formula.
4. Steps (1) to (3) are repeated to find the other midpoint, m_2, by using the valleys v_2, v_3.
5. The two midpoints, m_1 and m_2, are connected to form the base line to obtain the ROI.

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6. Based on the principal of geometrical square where allthe four edges having equal length, the other two points, m_3 and m_4, needed to form the square outline of the ROI can be obtained (refer Fig. 3).

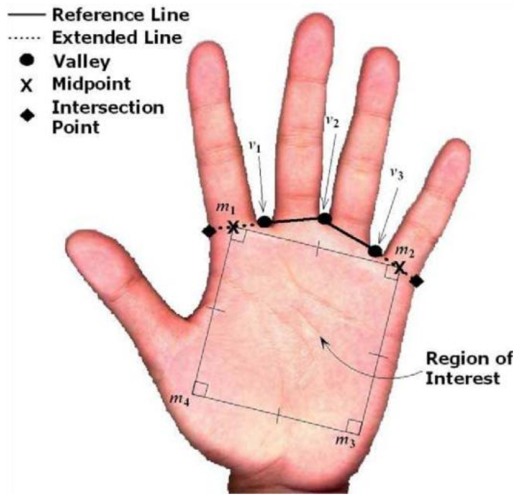

Fig. 3. Outline of the region of interest (ROI) from the palm

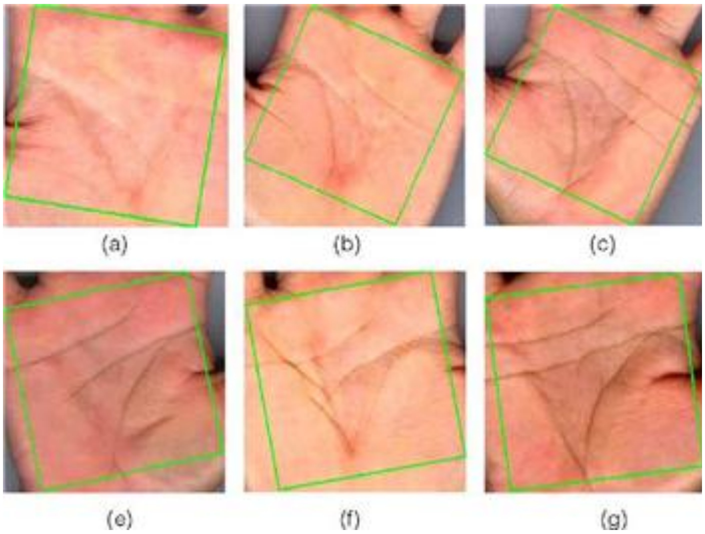

Fig. 4. ROIs obtained from different individuals. They have different sizes and rotations. (a), (b), (c) and (d) depicts ROIs from the right palms from four individuals, while (e), (f), (g) and (h) are ROIs from the left palms from another four individuals.

Fig. 4 shows some examples of the ROIs extracted from different individuals, obtained from both the right and left palms. There are some variances in the locations of the base points, m_1 and m_2, used to obtain the ROI. This variance is caused by the different stretching degree of the hand. Experimental statistic shows that the average standard deviation of the location of the base point is approximately 2.462 pixels. However, the variance in locations of the base points does not cause much effect to the feature extraction process, as it only affects the capturing size of the outline of the ROI. Most of the information significant for the recognition task lies in the center of the ROI, thus small variation in the location of the base points will not jeopardize the system's performance. In fact, experimental result shows that the system performs well using these ROI features.

From Fig. 4, it can be observed that the ROI have different sizes, due to the varying palm's size. Usually, men have larger palms' sizes than the women. For example, the ROI of a man shown in Fig. 4(d) is larger in size than ROI of a lady shown in Fig. 4(c). Besides the differences in size, all the ROIs lie in various directions. Due to these inconsistencies, the pre-processing job is performed to align all the ROIs into the same location in their images.

First, the images are rotated to the right-angle position by using *Y*-axis as the rotation-reference axis. The next step is to convert the RGB ROI into grayscale image. After that, as the sizes of the ROIs vary from hand to hand (depending on the sizes of the palms), they are resized to 150!150 pixels images by using *bicubic* interpolation.

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The last procedure in the pre-processing stage is to normalize the palmprint images in order to smoothen the noise and lighting effect. Let $P(x, y)$ represents the pixel value at the coordinate (x, y), m and n be the image mean and variance, respectively. The normalized image is computed by using the operation below:

$$P'(x,y) = \begin{cases} \mu_t + \beta \text{ if } P(x,y) > \mu \\ \mu_t - \beta \text{ otherwise} \end{cases} \text{ where } \beta = \sqrt{\frac{\nu_t\{P(x,y)-\mu\}^2}{\nu}} \quad (3)$$

where m_t and n_t are the pre-set values for mean and variance for the image. In this experiment, the value of m_t and n_t were set to 10, respectively. Fig. 5(b) depicts the palmprint image after the normalization process.

2.2. Palmprint feature extractions

After the well-aligned ROIs are obtained from the pre-processing stage, we extract important features from the image for recognition task. As discussed in Section 1, there are many approaches to achieve this purpose.

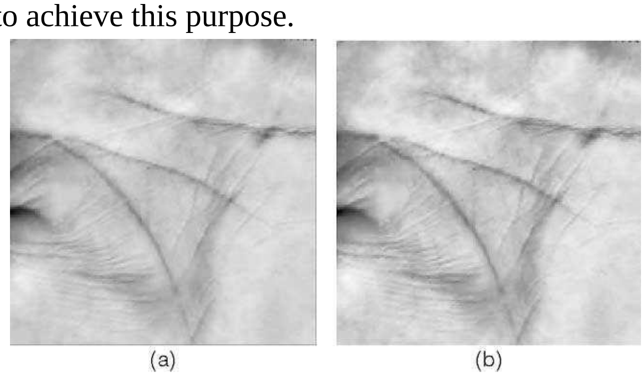

Fig. 5. Extracted ROI from the palm. (a) Palmprint image before normalization. (b) Palmprint after normalization.

In this paper, three subspace projection techniques are experimented and compared. In particular, we use principal component analysis (PCA), fisher discriminant analysis (FDA) and independent component analysis (ICA). The subspace projection technique is performed as a two-step process of constructing the subspace basis followed by projecting the palmprint images into the compressed subspace. New test images are then projected into the same subspace for image matching. It is computationally more efficient to perform image matching in subspaces as the dimensions have been reduced significantly. For example, image with 22, 500 pixels (150!150) might be projected into a subspace with only 20–60 dimensions.

2.2.1. Principal component analysis

PCA has been widely used for dimensionality reduction in computer vision. It finds a set of orthogonal basis vectors which describe the major variations among the training images, and with minimum reconstruction mean square error. This is useful as it helps to decrease the dimensions used to describe the set of images and also scale each variable according to its relative importance in describing the observation. The eigen bases generated from the set of palmprint images are shown in Fig. 6(a). As these bases have the same dimension as the original images and are like palmprint in appearance, they are also called *eigenpalms*.

2.2.2. Fisher discriminant analysis

The successful implementation of PCA in various recognition tasks popularized the idea of matching images in the compressed subspaces FDA is another popular subspace projection technique which computes a subspace that best discriminates among classes. It is different from PCA in the aspect that it deals directly with class separation while PCA treats images in its entirety without considering the underlying class structure. The bases generated using FDA are also known as

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fisherpalms. Some appearances of *fisherpalms* are depicted in Fig. 6(b).

2.2.3. Independent component analysis

While both PCA and FDA only impose independence only up to the second order, there is also a lot of interest to decorrelate higher order statistics from the training images ICA is one such approach that computes the basis components that are statistically independent or as independent as possible. ICA is originally used to solve blind source separation (BSS) problem. When applied in palmprint recognition, the palmprint images are considered as the mixture of an unknown set of statistically independent source images by an unknown mixing matrix. A separating matrix is learnt by ICA to recover a set of statistically independent basis images. The bases generated are spatially localized in various portions in the palmprint image, as shown in Fig. 6(c).

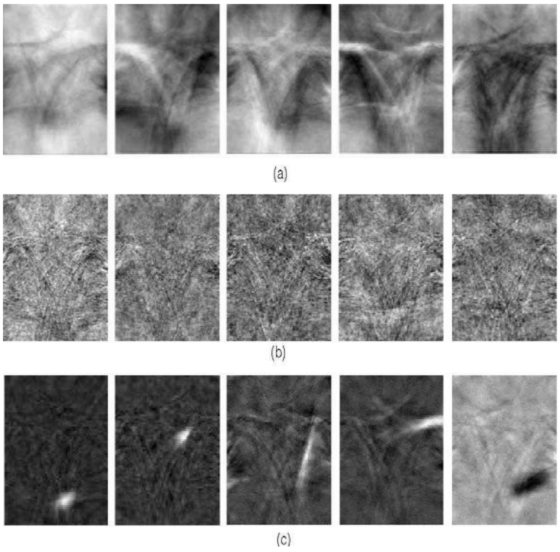

Fig. 6. The first five bases generated by (a) PCA (b) FDA (c) ICA.

2.2.4. Wavelet decomposition

Multiresolution analysis of the images is performed by using wavelet decomposition in this paper, Wavelet Transformation is integrated into the feature extractors as follows:

1. Decompose the palmprint image by using different families of wavelet.
2. Retain the low-frequency sub-band of the approximation coefficients.
3. Feed the reduced images into {PCAjFDAjICA} computation.

According to wavelet theory, it is generally found that most of the energy content is concentrated in the low frequency sub-band, as compared to higher frequency sub-bands. Low frequency sub-band is the smoothed version of the original image and it helps to reduce the influence of noise on one hand, and on the other hand preserves the local edges well which helps to capture the features that is insensitive to small distortion. On the other hand, the higher frequency sub-babds only contain low energy content and their high pass feature tends to enhance the edges detail, including noise and shape distortion.

WT is selected upon other filtering designs as it can decompose the palmprint images into different-frequency multi-resolution sub-band images for analysis. In decomposing the image into lower resolution images, WT can conserve the energy signals and redistribute them into more compact form. Usually, the low frequency sub-bands contain most of the energy content and it is able to preserve local edges well which helps to capture the features that are insensitive to small distortion. In addition, as the sub-band image is only quarter size of the original image, the computational complexity can be reduced by working on a lower resolution image. This makes WT distinguishable from other

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noise/resolution reduction techniques like spatial filters with dyadic down-sampling.

2.3. Feature matching/classification procedures

Identity of an individual can be verified through the feature matching or classification process. The output of each feature extraction algorithm produces a feature vector that is used for classification. The simplest classification method is based on the concept of similarity where samples that are similar are classified to the same class. Some popular similarity measures include the Manhattan (or city block), Euclidean and Mahalanobis distances. As ICA produces basis vectors that are not mutually orthogonal, the cosine distance measure is also employed here. Cosine measure can be used since ICA allows the basis vectors to be non-orthogonal, and the angles and distances between images differ from each other.

Another classification approach is to construct decision boundaries directly by optimizing an error criterion. Artificial neural network (ANN) is one such famous technique. ANN can generalize well on the data it has not seen before and can take into account the subtle differences between the modeled data, without the need to assume the type of relationship and the degree of nonlinearity between the various independent and dependent variables. In this research, the Probabilistic neural network (PNN) is deployed. PNN was first introduced by Specht and it offers several advantages over back-propagation network. Despite its generalization ability, the training speed of PNN is much faster because the learning rule is simple and requires only a single pass through the training data. Most importantly, PNN new training data can be added anytime without the need to retrain the entire network his is an important factor in this research when this system is to be extended to real-time application in the future.

3. Experiment and discussion

3.1. Experiment setup

In our research, a standard PC with Intel Pentium III processor (1 GHz) and 256 MB random access memories is used Our input device is the Hewlett–Packard ScanJet 3500c optical scanner. Resolution of 150 dpi, with color output type in 256 RGB format is adopted when the hand images are scanned. The original size of the hand image is about 600!800 pixels but consequently, only the region of interest (ROI) of the image will be extracted and resized to 150!150 pixels.

The proposed methodology is tested on a modest-sized database containing palm images from 75 individuals. Thirty-seven of them are females, 46 of them are less than 30 years old, and three of them are more than 50 years old. The users come from different ethnic groups: 37 Chinese, followed by 24 Malays, 11 Indian, a Pakistani, an African and an Iranian. Most of them are students and lecturers from Multimedia University. To investigate how well the system can identify unclear or worn palmprints due to labour work, we have also invited ten cleaners to contribute their palmprint images to our system.

The users are asked to present their palms at different directions and stretching degrees when scanned. They do not need to remove rings or other ornaments from their fingers when their hand images are taken. The users are allowed to rotate their palms within G208. If they fail to do so, an error will be detected in the pre-processing module and they will be requested to repeat the hand scanning process again. Fig. 7 illustrates an

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example of an error detected during the image acquiring process when the user's hand exceeds the permitted angle of rotation.

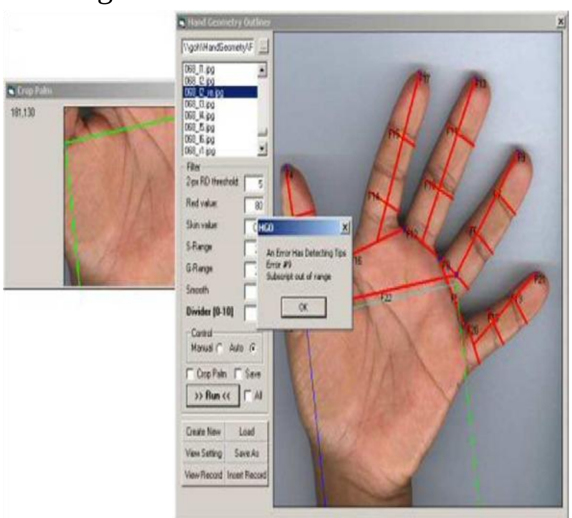

Fig. 7. An example of an error detected during the image acquiring process when the user's hand exceeds the permitted angle of rotation

Each user was requested to provide six images from their right and left hands with different positions in two occasions. The average interval between the two occasions is 21 days. Since the right and left palmprints of each person are different, both of them are captured and treated as palmprints from different user. Therefore, there are altogether 900 (75!6!2) palmprints images in our database. Among the six images from each palm, three are selected for training (enrollment) while the other three are used for testing. Fig. 8 illustrates some palmprint samples in our database.

3.2. Performance evaluation criteria

The results obtained in this paper are evaluated in terms of their: (i) correct recognition rate and (ii) verification rate.

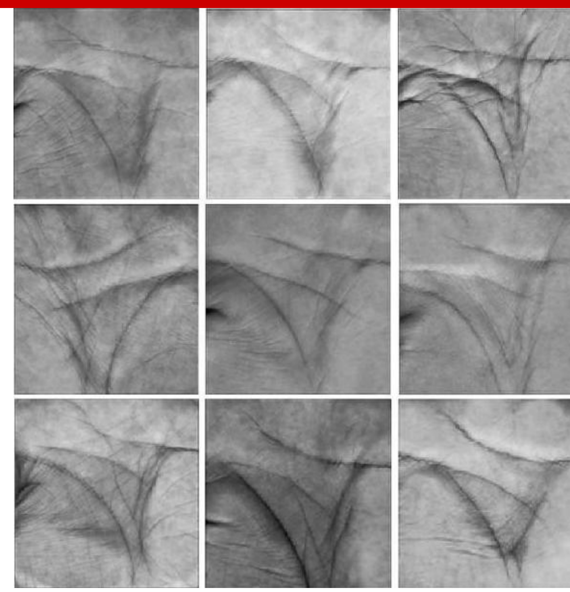

Fig. 8. Palmprint samples in the database.

3.2.1. Principal component analysis

In the first experiment, we investigate the performance of PCA by using different number of principal components (or feature lengths), varying from 30 to 90. Experimental result shows that longer feature length leads to higher recognition rate. Table 1 displays the correct recognition rate of using the principal components that yield significant changes in the result. Several classifiers are used to justify the performance, namely L_1 and L_2 distance measure, cosine measure and Probabilistic Neural Network (PNN).

It is demonstrated by our experiment that as the number of feature lengths/principal components increases, the correct recognition rate also increases. The performance peaks when 55 principal components is used. It is interesting to discover that the performance stabilizes, or even begins to decrease after this point. PNN gives correct recognition rate of 93.1% onwards after 55

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feature lengths, and the other classifiers indicates the performance is deteriorating.

Table 1: Correct recognition rates of using different number of principal components

Number of feature length	L_1 measure (%)	L_2 measure (%)	Cosine measure (%)	Probabilistic neural network (%)
30	89.4	90.7	85.1	91.7
40	90.2	92.2	85.7	92.4
45	90.7	92.9	87.4	92.7
50	90.9	92.9	89.2	93.9
55	92.4	93.1	90.4	94.1
60	92.1	92.9	89.4	94.1
70	91.7	92.4	89.1	94.1
80	91.1	92.4	88.4	94.1
90	91.1	92.2	87.7	94.1

Table 2: Performance evaluation of using different principal components

Feature length	FAR (%)	FRR (%)	TSR (%)	EER (%)
30	3.3	3.3	96.7	3.3
40	3.3	3.3	96.7	3.3
45	3.2	3.3	96.8	3.2
50	2.6	2.6	97.3	2.6
55	2.6	2.6	97.3	2.6
60	3.2	3.3	96.7	3.2
70	3.3	3.3	96.7	3.3
80	3.3	3.3	96.7	3.3
90	3.7	4.0	96.3	3.8

It can be anticipated that the classification accuracy of the methods will improve when a more sophisticated classifier is used. In this research, PNN is used to show how well the result can improve when a sophisticated classifier is used. The verification rates of PCA using the various principal components are shown in Table 2. We use the distance measure that maximized the performance, which is L_2, for this purpose. The palmprint verification method can achieve ideal result with FARZ2.6% and FRRZ2.6%, respectively. Fig. 9 shows the Receiver Operating Characteristic (ROC) curve to serve as a comparison among the performances of the different principal components.

Based on the experimental result, it can be concluded that the first few eigenpalms contain the largest variance direction in the learning set. In this way, we can find directions in which the learning set has the most significant amounts of energy. However, as the principal components increases, it tends to maximize other insignificant information such as noise, which will decrease the performance of the system. In fact, it can be shown from the images generated by using higher-order eigenpalms that they only contain noise, and do not look like palms at all. In this, we deduce that in our palmprint database, 20% of the principal components are attributed to true correlation effects while the rest to small trailing eigenvalues. Therefore, the discarded dimensions are the ones along which the variance in the data distribution is the least, which fail to capture enough information for representation.

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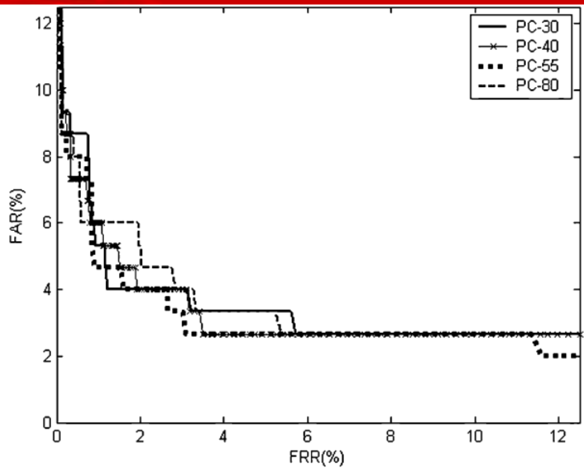

Fig. 9. ROC curve that serves as a comparison among the performance of the different principal components

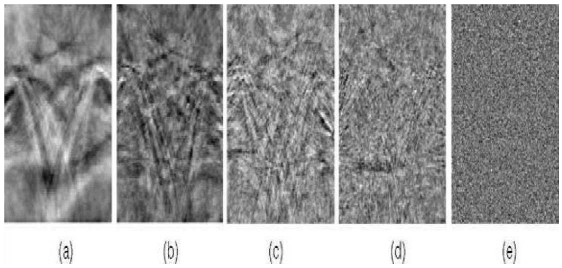

Fig. 10. Eigenpalms generated by using different number of feature lengths. (a) Eigenpalms generated using the 55th principal components. (b) Eigenpalms generated using the 70th principal components. (c) Eigenpalms generated using the 80th principal components. (d) Eigenpalms generated using the 90th principal components. (e) Eigenpalms generated using the 100th principal components.

Conclusion

We have developed a scanner-based palmprint recognition system to automatically authenticate the identity of an individual based on biometric palmprint features. The proposed system is reliable and user friendly as high recognition result is provided and convenient acquiring process is offered.

Our experiments suggest a number of conclusions:

1. Holistic analysis statistical approach is very suitable for palmprint authentication task. This approach is faster, less computationally intensive and less prone to misconceptions in the extraction task used since little a priori assumptions are made on the nature of the palmprint.
2. The position and scaling of the palmprint is critical to the success of palmprint template-based approach, and the alignment of the training images is determinant. We stress that the good performance of the palmprint recognition method depend on the precision of the pre-processing step.
3. For the feature extraction stage, ICA does not provide significant advantage over FDA. Thus, it is not intuitively clear that the palm images comprise of a set of independent basis images for recognition. It also suggests that localized feature basis provided by ICA may not be suitable to represent the crossing and overlapping ridge structures of the palmprint.
4. The intrinsic structure of the modeled data can boost the performance of FDA. Images with low within-class variability and sufficiently high between-class variability have proven to be able to increase FDA's performance.
5. As WT conserves energy and redistribute them into more compact form, performing operations in the wavelet domain and then reconstructing the result is more efficient than performing the same operation in the standard feature space. At the same time, the memory burden can be reduced.

In this paper, systematic testing and analysis have been conducted using a modest palmprint database. We are currently investigating how well the subspace projection techniques perform when extended to large database.

We conjecture that exploration in palmprint recognition is very promising in that it would become an important complement to the existing biometric technology.

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