An Adaptive Biometric System Based on Palm Texture Feature and LVQ Neural Network

Chen-Sen Ouyang, Ming-Yi Ju, and Han-Lin Yang

Abstract. We propose an adaptive biometric system based on the palm texture feature and LVQ2 neural network. The user's palm image is acquired by a scanner and preprocessed to be a labeled palm contour in the binary image format. Then, the positions of 12 feature points are identified speedily and roughly on the contour and refined to be more precise with a proposed correction mechanism. By referring the positions of feature points, six subimages of five fingers and the palm are obtained and transformed into six feature vectors with a modified texture descriptor of LFP (local fuzzy pattern). We employ the LVQ2 to learn the prototypes of feature vectors of each user. Therefore, an unknown user's palm feature vector is compared with prototypes to identify or verify his identity.

1 Introduction

Biometric systems have attracted much of attention in recent years since there have been many applications in many areas, such as security control, entrance control, identity identification and verification, etc. Biometric means using measurable physiological and/or behavioral features to identify or verify a user's identity. Physiological features (e.g. fingerprint, iris, face, etc.) and behavioral features (e.g. voiceprint, handwriting, signature, etc.) have been employed in many biometric systems and

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B.-C. Chien and T.-P. Hong (Eds.): Opportunities and Challenges, SCI 214, pp. 25–30.
springerlink.com

possess high recognition rate. However, most of them encounter the problems of high cost of equipments, high computation complexity, inconvenience for feature acquirement, and personal privacy.

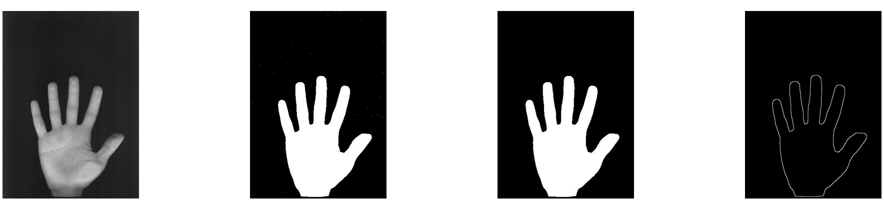
Recently, many researchers have paid their attention to view the palm as the source of feature extraction. The advantages of palm features are high public acceptance, low cost of equipments, and high accuracy level. Therefore, we focus on the approaches based on palm features in this paper. Ribaric et al. [5] proposed a biometric identification system by extracting the eigenpalm and eigenfinger features from subimages of palm and fingers. However, the feature point extraction and K-L transformation used in this approach are not robust enough, especially in the condition that the palm in the image is inclined or illumination change. Wu et al. [7] proposed an approach for palm line extraction and matching with chaining coding. However, the coding method is too sensitive to the extracted palm lines. A hierarchical identification of palmprint using the line-based Hough transform is proposed by Li and Leung [3]. Wu and Qiu [6] proposed a hierarchical palmprint identification method using the hand geometry and gray-scale distribution features. Both of these two approaches are too sensitive to the rotation and position of palm in the image.

From the discussion above, we can conclude that three important problems should be solved. The first one is the palm position and rotation in the image should be automatically detected. The second one is the feature extraction should be robust enough in different conditions. The third one is a leaning mechanism is needed for the feature learning of different users, so as to reduce the stored features and the complexity and computation power in the matching phase.

2 Our Approach

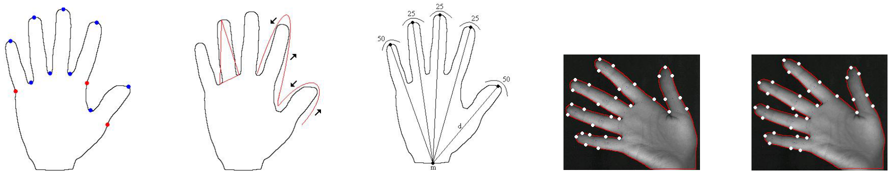
In our system, there are four steps in the user registration phase, i.e., palm image preprocessing, palm feature point extraction, palm feature extraction, and LVQ2 learning. We describe the four steps in detail as follows.

The main purpose of palm image preprocessing is to transform the scanned greyscale palm image into a binary image of palm contour and label the points on the palm contour in order. Firstly, the scanned image are resized into an image with 352×485 size by the bilinear interpolation [1], as shown in figure 1(a). Secondly,



(a) (b) (c) (d)

Fig. 1 Palm image preprocessing: (a) Acquired image; (b) Binary image after thesholding; (c) Image after median filtering; (d) Contour image after Laplacian filtering

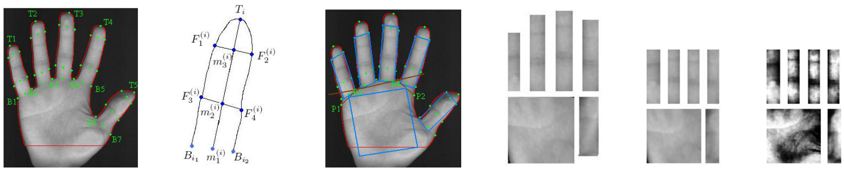


(a) (b) (c) (d) (e)

Fig. 2 Feature Point Extraction: (a) Ideal positions of feature points; (b) The search order for initial feature points; (c) The adopt neighborhoods of initial fingertip feature points; (d) Initial positions of feature points of an inclined palm. (e) Corrected result

we set a threshold of grey level to transform the resized grey-scale image into a binary image, as shown in figure 1(b). The threshold we set is the average of grey values in the whole palm image. Note that there are some wrong classified pixels caused by noise, especially in the background area. Therefore, we employe a 3×3 median filter to cancel these noise points in the third sub-step. Figure 1(c) shows a resultant binary image. Apparently, the noise points in the background area are canceled. Fourthly, the Laplacian filtering for edge detection is employed to find out the contour of the palm, as shown in figure 1(d). Finally, the points on the contour are labeled in order.

The main purpose of palm feature point extraction is to identify the 12 feature points located on the palm contour. The ideal result is shown in the figure 2(a). Note that 9 points are located on the fingertips and the valleys between the fingers, while the other 3 points are located at positions which are symmetric to the points in the valleys of the correspond fingers (thumb finger, index finger, and little finger). The 5 points located on five fingers and 4 points located on the valleys between the fingers are identified by the local minima and maxima, respectively, on the contour according to the y values of the sequence of contour point positions. Figure 2(b) shows the order for searching. To identify the other 3 points, we employ the property that the distance between each of these points and its corresponding fingertip is the same as the distance between the fingertip and the valley-point on the other side of the corresponding finger. Therefore, we have the initial positions of 12 feature points roughly. However, the initial positions may be not so precise, especially when the palm in the acquired image is inclined as shown in figure 2(d). To correct the initial positions to be more precise, we employ a simple property that the distance between the middle contour point at the wrist and each fingertip is the longest by comparing with the neighboring contour points of the fingertip. Therefore, we calculate the distances between the middle contour point at the wrist and all neighboring contour points of each initial fingertip feature point. Then, the corresponding fingertip feature point is corrected to the point with the largest distance. Through our experimental experience, the number of neighboring points are set as 50 for the thumb fingertip and little fingertip, and 25 for the other three fingertips, as shown in figure 2(c). Figure 2(e) shows the correction result of figure 2(d). Apparently, the initial positions of feature points are corrected to be more precise and reasonable.



(a) (b) (c) (d) (e) (f)

Fig. 3 Subimage Extraction: (a) Positions of 12 feature points; (b) Reference points for finger subimage extraction; (c) Reference points for palm subimage extraction; (d) Six obtained subimages; (e) Normalized subimages; (f) Resultant subimages after lighting normalization

In the third step, we focus on the feature extraction from the palm image. Let the 5 fingertip feature points and the other 7 feature points be denoted as $T_1, T_2, \ldots, T_5$ and $B_1, B_2, \ldots, B_7$, respectively. The figure 3(a) shows the 12 feature points. For each finger with the fingertip T_i and the (B_{i_1}, B_{i_2}), we firstly obtain the middle point $m_1^{(i)}$ of the line segment $B_{i_1} - B_{i_2}$. The distance between the middle point $m_1^{(i)}$ and the fingertip T_i is defined as the length d_i of the corresponding finger. As shown in figure 3(b), two additional point pairs $(F_1^{(i)}, F_2^{(i)})$ and $(F_3^{(i)}, F_4^{(i)})$ are determined at the one-third and two-thirds, respectively, of d_i, and the middle points $m_3^{(i)}$ and $m_2^{(i)}$ of $F_1^{(i)} - F_2^{(i)}$ and $F_3^{(i)} - F_4^{(i)}$ are also determined accordingly. The line connecting the middle points $m_2^{(i)}$ and $m_3^{(i)}$ is viewed as the line of symmetry for the sub-image. The length of the subimage is set as five-sixths of the length d_i. The width of the subimage is determined by the distance between the point $F_1^{(i)}$ and the corresponding contour point in the other side of the line of symmetry. Besides, we have to obtain the subimage of the palm which is the inner surface of the hand between the wrist and the fingers. The subimage of the palm is defined as a square region with two of its corners placed on the middle points of the two line segments $P_1 - B_2$ and $B_4 - P_2$. Note that the points P_1 and P_2 are determined by rotating the line segments $B_1 - B_2$ and $B_4 - B_5$ with 30° and 40°, respectively. The obtained six subimages of the five fingers and palm should be resized by bilinear interpolation method for size normalization. The thumb and little finger subimages are resized to 16×64, while the other finger subimages are resized to 14×64. Besides, the palm subimage is resized to 64×64. Then, we perform a procedure of histogram equalization [1] on each subimage for lighting normalization.

To extract the feature vectors for the six subimages, we use a modified version of LFP texture descriptor [4]. In the original version of LFP, a LFP histogram for each pixel should be calculated by aggregating the LFPs of all pixels in the corresponding circular neighborhood. To save the computation power, we aggregate the LFPs of all pixel in each subimage directly. Therefore, each subimage is transformed into a 2^p-dimensional feature vector which describes the texture distribution of the corresponding subimage. Note that P is a parameter related to the LFP.

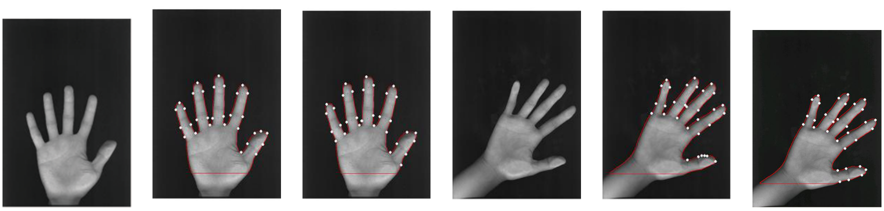
Finally, we use a LVQ2 [2] to obtain representative prototypes of different users. The learned prototypes of different users are stored in a registration database.

3 Experimental Results

To demonstrate the advantages of our proposed system, we present some experimental results in this section. There are 20 users and 15 palm images are acquired from each user by putting his palm on the scanner for scanning in several possible conditions, like normal position, different rotations, illumination change, different positions of fingers, etc. For each user, we randomly choose 5 images for training and the other 10 for testing.

In the first part, we present two experimental results to demonstrate the effectiveness of our correction mechanism. In the first experiment, two palm images are acquired in normal and inclined conditions, respectively. Figure 4 shows the correction results. Apparently, most of finger feature points are identified at incorrect initial positions. After correction, we obtain more precise positions of these feature points. The second experiment tests the rotation tolerance of our correction mechanism. Therefore, we consider different rotation angles from 0° to 50° of the palm. We can see that the correction mechanism still works very well even when the rotation reaches to 40°. However, it is fail when the rotation reaches to 50°. As mentioned earlier, we can improve the problem by choosing more neighboring points for each initial fingertip feature point. However, more computation power is needed.

In the second part, we compar the recognition rates, time of feature extraction, and time of matching on the samples of the test dataset with these two methods, as shown in Table 1. Our method presents a better recognition rate. Besides, the time taken by our method is more in the feature extraction, however, less in the search.

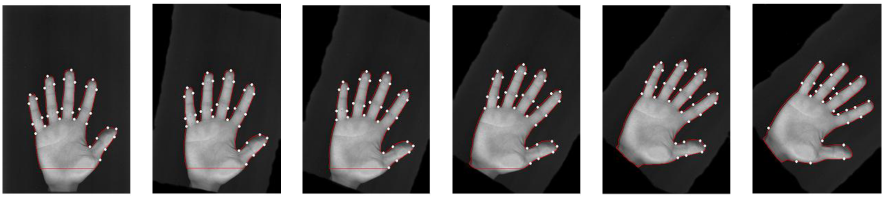


(a) (b) (c) (d) (e) (f)

Fig. 4 Correction results: (a) palm image 1; (b) Initial result 1; (c) Corrected result 1; (d) palm image 2; (e) Initial result 2; (f) Corrected result 2

Table 1 Comparison on recognition rate, time of feature extraction, and time of matching

Recognition rate		Time of feature extraction		Time of matching	
K-L	LFP	K-L	LFP	K-L	LFP
88.50%	91.00%	1.003 (sec.)	1.187 (sec.)	0.070 (sec.)	0.027 (sec.)



(a) (b) (c) (d) (e) (f)

Fig. 5 Results of rotation test with (a) 0°; (b) 10°; (c) 20°; (d) 30°; (e) 40°; (f) 50°

4 Conclusion and Future Works

We have presented an adaptive biometric system based on the palm texture feature and LVQ2 neural network. A correction mechanism is integrated into the feature point extraction to improve the tolerance of palm rotation. A palm feature extraction with a modified version of our proposed LFP texture descriptor is employed to increase the robustness. Besides, we employ a LVQ2 neural network to learn the prototypes of each registered user. Therefore, our proposed system has better performance. In our future works, we consider to extend the feature point extraction to be tolerable for any rotation of the palm. Besides, we will extend our database by collecting more user's palm images.

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