

Using Low-Resolution Palmprint Images and Texture Analysis for Personal Identification

Wai Kin Kong
Biometrics Research Centre
Department of Computing,
The Hong Kong Polytechnic University
Kowloon, Hong Kong
cswkkong@comp.polyu.edu.hk

David Zhang
Biometrics Research Centre
Department of Computing,
The Hong Kong Polytechnic University
Kowloon, Hong Kong
csdzhang@comp.polyu.edu.hk

Abstract

Biometrics identification is an emerging technology for solving security problems in our networked society. A new branch of biometric technology, palmprint recognition, whereby the lines and points can be extracted from our palm for personal identification was proposed several years ago [1-6]. In this paper, we implement the feature extraction technique applied to iris recognition [7] on low – resolution palmprint images. A 2-D Gabor filter is used to obtain the texture information and two palmprint images are compared in term of their hamming distance. The experimental results show that our method is effective.

1. Introduction

Palmprint identification can be divided into two categories, on-line and off-line. For off-line identification, all the palmprint samples are inked, which are then transmitted into a computer with a scanner. For on-line identification, the samples are captured with a palmprint scanner which directly connects to a computer. Off-line palmprint recognition was the main focus in past palmprint research [1-6]. Recently, a CCD camera-based palmprint capture device has been developed [3]. Fig. 1 shows an image captured with the device. Real-time applications of this on-line palmprint recognition device are possible. Because of the relative high-resolution of the off-line palmprint image (350 dpi), some techniques applied to fingerprint recognition can be used for the off-line palmprint recognition, where lines, datum points and singular points are extracted [1, 5-6]. In this paper, we use low-resolution on-line images (65 dpi) so we attempt a new approach to extract texture features from palmprint images.

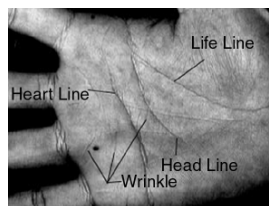


Figure 1. A palmprint image with line definitions.

An on-line palmprint identification system can be examined in terms of five parts functions, summarized below:

- 1) Image acquisition — Capture a palmprint with a palmprint scanner [3].
- 2) Preprocessing — Determine a coordinate system and extract the central part of the palmprint image.
- 3) Feature extraction — Extract some stable and unique features.
- 4) Pattern matching — Decide whether two palmprints are from the same person.
- 5) Data storage — Store the features from the registered images for use in later comparisons.

An on-line palmprint system runs on at least two of three modes — enrollment, identification and verification. In the enrollment mode, a new user's palmprint feature is extracted and then stored in a database for later comparisons. In the identification mode, an input palmprint must pass through image acquisition, preprocessing and feature extraction. The feature extracted is compared with all records in a given database. The difference between the identification and verification modes is that in the verification mode, each user must have a user ID and his/her palmprint can only be

compared with all the features belonging to the same user ID.

This paper is organized as follows: preprocessing is discussed in Section 2; palmprint feature extraction with texture analysis is explained in Section 3; palmprint matching and experimental results are given in Section 4 and Section 5, respectively; finally, some conclusion is provided in Section 6.

2. Palmprint Image Preprocessing

The goal of preprocessing is to obtain a sub palmprint image for feature extraction and to eliminate the variation caused by the rotation and translation. Five main steps are given below (see Fig. 2).

Step 1: Apply a lowpass filter to an original image. Then, using a threshold, T_p , is used to convert this original image to a binary image as shown in Fig. 2(b). Mathematically, this transformation can be represented as

$$B(x, y) = 1 \text{ if } O(x, y) * L(x, y) \geq T_p, \quad (1)$$

$$B(x, y) = 0 \text{ if } O(x, y) * L(x, y) < T_p, \quad (2)$$

where $B(x, y)$ and $O(x, y)$ are the binary image and the original image, respectively; $L(x, y)$ is a lowpass filter such as Gaussian, and “*” represents an operator of convolution.

Step 2: Extract the boundaries of the holes, $(F_i x_j, F_i y_j)$, ($i=1, 2, 3$), between fingers using a boundary tracking algorithm. The start points, (Sx_i, Sy_i) , and end points, (Ex_i, Ey_i) , of the holes are then marked in the process (see Fig. 2(c)).

Step 3: Compute the center of gravity, (Cx_i, Cy_i) , of each hole with the following equations:

$$Cx_i = \frac{\sum_{j=1}^{M(i)} F_i x_j}{M(i)}, \quad (3)$$

$$Cy_i = \frac{\sum_{j=1}^{M(i)} F_i y_j}{M(i)}, \quad (4)$$

where $M(i)$ represents the number of boundary points of the hole, i . Then, construct a line that passes through (Cx_i, Cy_i) and the midpoint of (Sx_i, Sy_i) and (Ex_i, Ey_i) . The line equation is defined as

$$y = x \frac{(Cy_i - My_i)}{(Cx_i - Mx_i)} + \frac{My_i Cx_i - Mx_i Cy_i}{Cx_i - Mx_i}, \quad (5)$$

where (Mx_i, My_i) is the midpoint of (Sx_i, Sy_i) and (Ex_i, Ey_i) . Based on these lines, three key points, (k_1, k_2, k_3) , can easily be detected (see Fig. 2(d)).

Step 4: Line up k_1 and k_3 to get the Y-axis of the palmprint coordinate system, and make a line through k_2 , which is perpendicular to the Y-axis to determine the origin of the palmprint coordinate system (see Fig. 2(e)). This coordinate system can align different palmprint images.

Step 5: Extract a sub image with a fixed size on the basis of the coordination system, which is located at a certain part of the palmprints for feature extraction (see Fig. 2(f)).

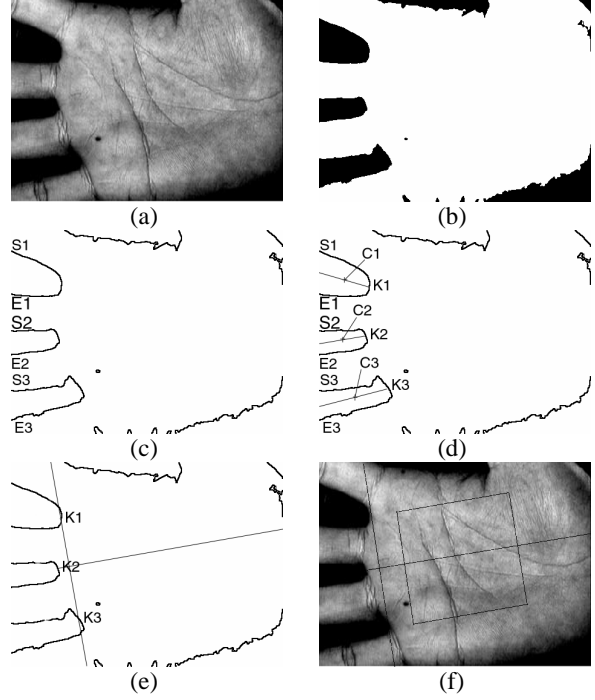


Figure 2. The main steps of preprocessing. (a) Original image, (b) Binary image, (c) Boundary tracking, (d) Key points (k_1, k_2 and k_3) detecting, (e) The coordinate system, and (f) The central part of a palmprint

3. Palmprint Feature Extraction with Texture Analysis

Generally, a palmprint has some principal lines, wrinkles and ridges (see Fig. 1). Some algorithms such as the stack filter [8] can extract the principal lines. However, these principal lines do not contribute adequately to high accuracy because of the similarity of these principal lines between different people. Wrinkles play an important role in palmprint identification but accurately extracting them is a difficult task. This motivates us to apply texture analysis to palmprint recognition. The Gabor filter is an effective tool for texture analysis, and has the following general form,

$$G(x, y, \mathbf{q}, u, \mathbf{s}) = \frac{1}{2ps^2} \exp\left\{-\frac{x^2 + y^2}{2s^2}\right\} \exp\{2\pi i(ux \cos \mathbf{q} + uy \sin \mathbf{q})\}, \quad (6)$$

where $i = \sqrt{-1}$; u is the frequency of the sinusoidal wave; \mathbf{q} controls the orientation of the function and \mathbf{s} is the standard deviation of the Gaussian envelope. Gabor filters are widely used in texture analysis and biometrics [9-12]. In order to provide more robust to brightness, the Gabor filter be turned to zero DC with the application of the following formula:

$$\tilde{G}[x, y, \mathbf{q}, u, \mathbf{s}] = G[x, y, \mathbf{q}, u, \mathbf{s}] - \frac{\sum_{i=-n}^n \sum_{j=-n}^n G[i, j, \mathbf{q}, u, \mathbf{s}]}{(2n+1)^2}, \quad (7)$$

where $(2n+1)^2$ is the size of the filter. In fact, the imaginary part of the Gabor filter automatically has zero DC because of odd symmetry. This adjusted Gabor filter will convolute with the central part of a palmprint. Each point in the resultant image is coded to two bits, (b_r, b_i) , by the following inequalities,

$$b_r=1 \text{ if } \operatorname{Re}[\tilde{G}[x, y, \mathbf{q}, u, \mathbf{s}] * I] \geq 0, \quad (8)$$

$$b_r=0 \text{ if } \operatorname{Re}[\tilde{G}[x, y, \mathbf{q}, u, \mathbf{s}] * I] < 0, \quad (9)$$

$$b_i=1 \text{ if } \operatorname{Im}[\tilde{G}[x, y, \mathbf{q}, u, \mathbf{s}] * I] \geq 0, \quad (10)$$

$$b_i=0 \text{ if } \operatorname{Im}[\tilde{G}[x, y, \mathbf{q}, u, \mathbf{s}] * I] < 0, \quad (11)$$

where I is the central part of a palmprint image. Note that this feature extraction method only stores the phase information in the feature vector.

4. Palmprint Matching

In order to describe clearly the matching process, each feature vector will be considered as two 2-D feature matrixes, real and imaginary. Palmprint matching is based on a normalized hamming distance. Let P and Q be two palmprint feature matrixes. The normalized hamming distance can be described as,

$$D_o = \frac{\sum_{i=1}^N \sum_{j=1}^N (P_R(i, j) \otimes Q_R(i, j) + P_I(i, j) \otimes Q_I(i, j))}{2N^2}, \quad (12)$$

where P_R (Q_R) and P_I (Q_I) are the real part and the imaginary part of P (Q), respectively; the result of Boolean operator, “ \otimes ”, is equal to zero if and only if the two bits, $P_{R(I)}(i, j)$, equal to $Q_{R(I)}(i, j)$, and the size of the feature matrixes is $N \times N$. It is noted that D_o is between 1 and 0. For a perfect matching, the matching score is zero. In order to further reduce the variation of translation, Eq. 12 can be improved to form Eq. 13:

$$D_{\min} = \min_{|s| < S, |t| < T} \frac{\sum_{i=\max(1, 1+s)}^{\min(N, N+s)} \sum_{j=\max(1, 1+t)}^{\min(N, N+t)} (P_R(i+s, j+t) \otimes Q_R(i, j) + P_I(i+s, j+t) \otimes Q_I(i, j))}{2H(s)H(t)}, \quad (13)$$

where $S=6$ and $T=6$ control the range of horizontal and vertical translation of a feature in the matching process, respectively, and

$$H(s) = \min(N, N+s) - \max(1, 1+s). \quad (14)$$

The matching score, D_{\min} , can support translation matching; nevertheless, it still suffers from the variation of rotation of the images. Therefore, all the sub images of the registered images are rotated by some degrees (-6° , -4° , -2° , 0° , 2° , 4° , 6°) and then the features of the images are extracted and stored. As the result, our palmprint matching process can handle different rotation and translation.

5. Experimental Results

The database for testing contains 425 images from 95 persons. The sub images of the palmprint images is 64 by 64. Fig. 3 shows six sub images in our database with various texture features. Fig. 4 illustrates the real and imaginary parts of our features (PalmCode) described in Eq. 12 and the corresponding preprocessed images.

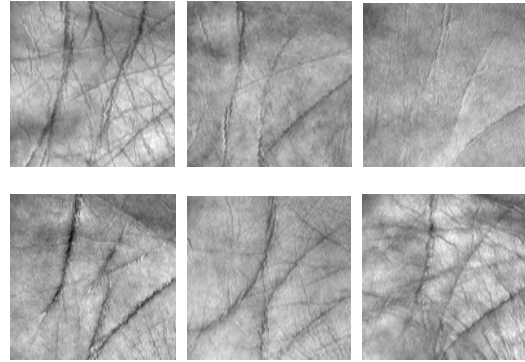


Figure 3. Typical images obtained from our database.

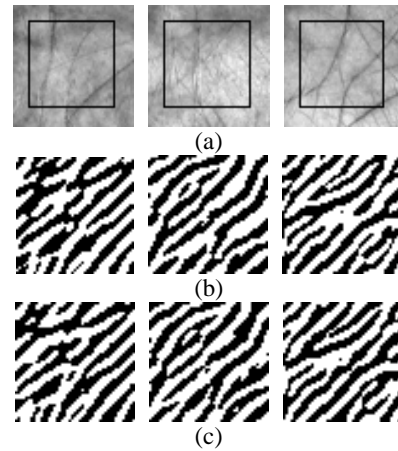


Figure 4. Original images and their features (a) Original images with the effective areas specified, (b) Features

from the real part of the Gabor filter c) Features from the imaginary part of the Gabor filter

The performance of the proposed method under different thresholds that control the false accept rate and false reject rate is shown in Table 1. In this experiment, the imposter distribution and genuine distribution are generated by 1,083 and 769 comparisons, respectively. Fig. 5 shows the two distributions. When the threshold is 0.335, the false reject rate is 0.9% with 0% false accept rate. Some images are still not recognized with the proposed method because of non-linear distortion.

Table 1. Experimental results of the selected thresholds.

Threshold	False accept rate (%)	False reject rate (%)
0.325	0.00	1.56
0.335	0.00	0.91
0.345	0.37	0.65
0.355	0.92	0.65
0.365	2.50	0.39
0.375	5.36	0.13

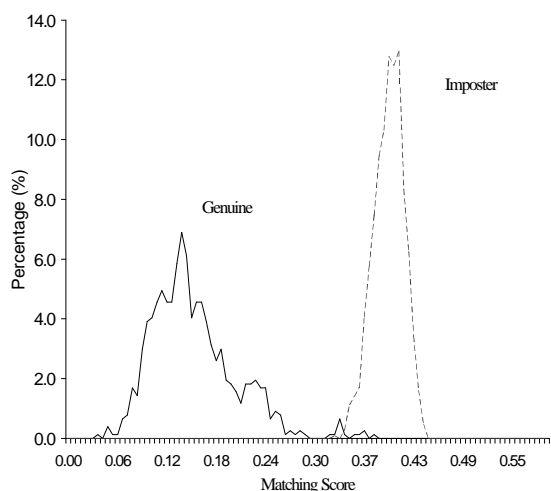


Figure 5. Imposter and genuine distributions of our experiments

6. Conclusion

This paper reports on using low-resolution images and texture-based feature extraction method for palmprint identification. A palmprint is handled as a texture image, and an adjusted Gabor filter is applied to capture the texture information. For the optimal cases in our database,

the false reject rate is 0.91% with 0% false accept rate. The experimental results are encouraging.

Acknowledgments

The authors would like to thank Wenxin Li and Qingyun Dai at Biometrics Research Centre for their palmprint image collection. The work is partially supported with UGC (CRC) fund from the Hong Kong SAR Government and central fund from The Hong Kong Polytechnic University.

References:

- [1] D. Zhang and W. Shu, "Two novel characteristics in palmprint verification: datum point invariance and line feature matching," *Pattern Recognition*, vol. 32, no. 4, pp. 691-702, 1999.
- [2] N. Duta, A. K. Jain, and Kanti V. Mardia, "Matching of Palmprint", *To appear in Pattern Recognition Letters*, 2001.
- [3] D. Zhang, *Automated Biometrics – Technologies and Systems*, Kluwer Academic Publishers, 2000.
- [4] J. You, W. Li and D. Zhang, "Hierarchical palmprint identification via multiple feature extraction". To appear in *Pattern Recognition*
- [5] W. Shu and D. Zhang, "Automated personal identification by palmprint," *Optical Engineering*, vol. 37 no. 8, pp.2,659-2,362, 1998.
- [6] W. Shi and D. Zhang, "Automatic palmprint verification". *International Journal of Image and Graphics*, vol. 1, no. 1, pp. 135-152, 2001
- [7] J. Daugman, "High confidence visual recognition of persons by a test of statistical independence," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp. 1,148-1,161, 1993.
- [8] P.S. Wu and M. Li. "Pyramid edge detection based on stack filter", *Pattern Recognition Letters*, vol. 18, no. 4, pp. 239-248, 1997.
- [9] A. Jain and G. Healey, "A multiscale representation including opponent color features for texture recognition," *IEEE Transactions on Image Processing*, vol. 7, no. 1, pp. 124-128, 1998.
- [10] D. Dunn and W.E. Higgins, "Optimal Gabor filters for texture segmentation," *IEEE Transactions on Image Processing*, vol. 4, no. 4, pp. 947-964, 1995.
- [11] A.K. Jain, S. Prabhakar, L. Hong and S. Pankanti, "Filterbank-based fingerprint matching," *IEEE Transactions on Image Processing*, vol. 9, no. 5, pp. 846-859, 2000.
- [12] B. Duc, S. Fischer and J. Bigun, "Face authentication with Gabor information on deformable graphs," *IEEE Transactions on Image Processing*, vol. 8, no. 4, pp. 504-516, 1999.