A Region-of-Interest Segmentation Algorithm for Palmprint Images

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Abstract

Biometric identification system has high efficiency, high recognition rate and comfortable to the user's operating characteristics. Palmprint recognition is considered the most viable and reliable biometric recognition technique owing to its merits, such as low cost, user friendliness, high speed and high accuracy. Region-of-Interest (ROI) segmentation of palmprint is to automatically and reliably segment a small region from the captured palmprint image; it is considered one of important stages in automatic palmprint recognition system because it greatly influences the overall identification accuracy and processing speed of the whole system. In this paper, we presented a palmprint ROI extraction algorithm which combines Otsu thresholding scheme, morphological openning operation, Sobel edge detector, reference points and line construction, and palmprint image alignment. The performance of the proposed palmprint ROI segmentation scheme is verified using a palmprint image database, PolyU database (version 2). The experimental results show that the proposed algorithm is effective and efficient in palmprint ROI segmentation and is robust for noises surrounding palmprint images.

Keywords: *Biometric identification, Palmprint, Region-of-Interest (ROI).*

1 Introduction

With the rapidly development of the world's economy, the worsening of social order causes destruction and violence around the world [1-6]. They have weighted the importance of security, and raised the growing demand for automatic identification systems [7-12]. On the other hand, many techniques are applied in automatic identification systems such as access controlling, ATM, computer data accessing, etc [3]. For example, a person always uses keys, passwords or access cards for identity verification to access the confidential documents (or personal information), control places or networked societies. But the keys and access cards may be lost by user himself or be unauthority copied by others and the password might be forgotten by user himself or be known by other people [2,3,7]. Therefore, people need an identification system to identify the user's identity without above disadvantages, which is the biometric identification.

Biometric identification system has high efficiency, high recognition rate and comfortable to the user's operating characteristics, it is an automatic recognition process based on a feature vector derived from an individual's behavior or physiological characteristics [3, 8]. The individuals' physiological characteristics include DNA, face, ear, fingerprint, gait, Iris, palmprints, voice, etc [1, 4]. A biometric identification system should meet accuracy, speed, resource requirement, be harmless to the users, be accepted by the intended people and robust to various attacks [9, 11]. A palmprint pattern is so unique that even twins have different palmprint patterns, the pattern remains stable and fixed throughout one's life [8, 12]. Compared to other physiological characteristics, palmprint recognition is considered the most viable and reliable biometric recognition technique owing to its merits, such as low cost, user friendliness, high speed and high accuracy [9, 12].

Similar to other biometric systems, a palmprint identification system includes four stages: image acquisition stage, region of interest (ROI) segmentation stage, feature extraction stage, and pattern identification stage [2, 4]. ROI segmentation of palmprint is to automatically and reliably segment a small region from the captured palmprint image and palmprint extraction is to extract the palmprint from a ROI. This is considered one of important stges in these four stages because it greatly influences the overall identification accuracy and processing speed of the whole system. it is very important that to take the ROI at the same position for different palmprint images to guarantee the stability of the segmented palmprint features to provide reliable recognition rate and fast processing speed. In fact, a palmprint is frequently surrounded by noise, a novel palmprint segmentation scheme must extract the palmprint by removing all of these "noise" features.

There are many schemes were proposed to extract the ROI in palmprint images [13-16]. Han et al. [13] segmented the ROI from a palmprint image by utilizing the central line of medius. C. L. Lina et al. [14] took finger-webs as the datum points to determine the approximate the immovable ROI of a Palmprint image. J. You [15] applied two end points obtained from the intersections of the two sides of the palmprint and principal lines to locate the palmprint ROI. Li et al. [16] conducted the end point of heart line and the orientation of palm outer boundary to overcome the shift and rotation of images to extract the palmprint ROI.

In this paper, we utilize Otsu thresholding scheme to binarize the original palmprint images, use morphological dilation and erosion operations to remove noises, applied Sobel edge detection to detect the palm boundary, took double derivatives on the detected palm boundary to find two reference points located at two valleys between the fingers, alignment the palm to standard pose and segment a square area as the ROI. The performance of the proposed palmprint ROI segmentation scheme is verified using a palmprint image database, PolyU database (version 2) [2- 4]. This database consists of a set of 7752 palmprint images of 386 persons. The experimental results show that the proposed algorithm is effective and efficient in palmprint ROI segmentation. The remainder of this paper is organized as follows: Section 2 illustrates the proposed palmprint ROI segmentation algorithm. Section 3 presents the experiment results. Section 4 gives our conclusions.

2 Proposed palmprint ROI Segmentation

A robust palmprint ROI segmentation scheme for palmprint images must be extremely effective and efficiency. In order to construct an accurate palmprint ROI segmentation algorithm for palmprint images, several schemes are used in this paper to achieve the goal. The overall palmprint ROI segmentation algorithm for palm images is shown in Figure 1. There are three main stages in the presented algorithm for segmenting palmprint ROI from palm images: (i) binarizing the original palmprint images by using Otsu thresholding scheme, (ii) noises deleting by using morphological openning operation, (iii) aligning the palmprint to standard pose and extracting the palmprint ROI. The main steps of the proposed palmprint ROI segmentation algorithm are shown in figure 2 and the details of these stages used in the presented palmprint ROI segmentation algorithm are described in the following subsections.

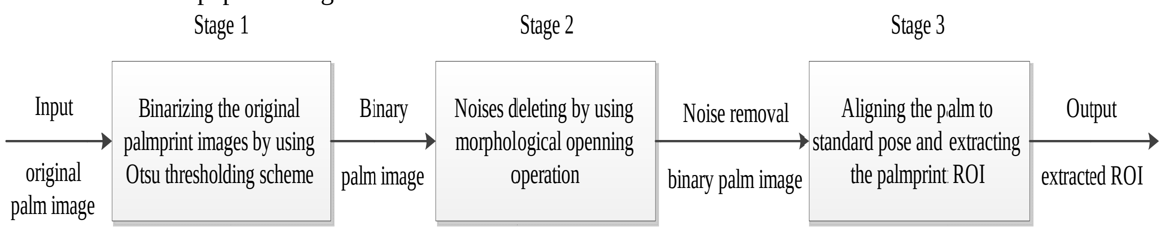

Figure 1. The flow chart of the proposed palmprint ROI extraction algorithm for palmprint images.

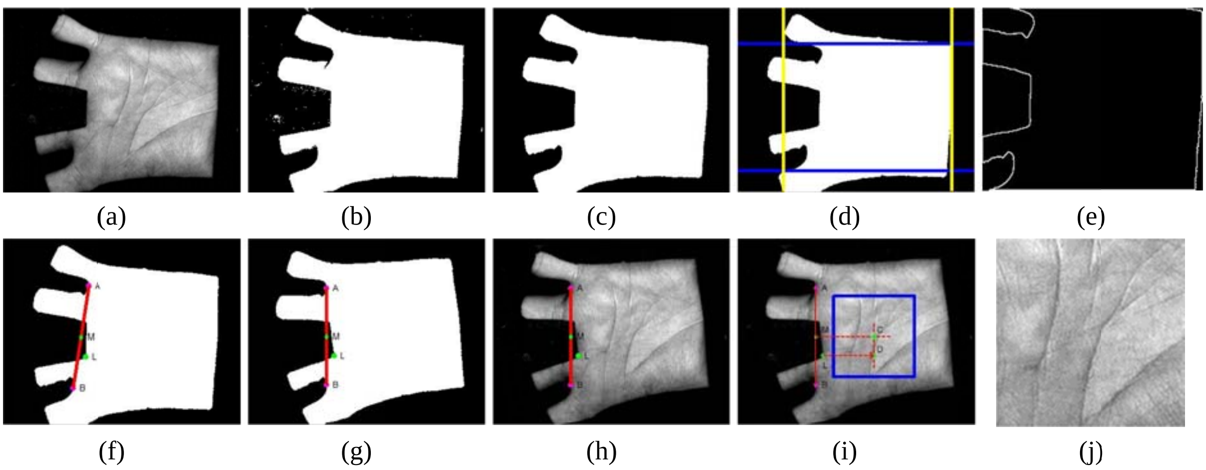

Figure 2. The main steps of the proposed palmprint ROI extraction algorithm for palmprint images; (a) original palmprint image, (b) after binarization, (c) after noise removal, (d) after range shrink, (e) after Sobel edge operation, (f) after reference points and reference line segment structuring, (g) after alignment, (h) after alignment grayscale palmprint image, (i) after ROI location, (j) extracted ROI.

- **Binarization**

The binarization step is used to obtain a rough palmprint area from the palm image. The presented algorithm applies the famous Otsu thresholding scheme to binarize the input palm image to determine the palmprint area. The Otsu thresholding scheme proposed by Otsu (1979) searches an optimal threshold to divide a grayscale image's pixels into two classes [17]. The optimal threshold is evaluated by the discriminated criterion which maximizes the separability between target and background classes. The Otsu thresholding scheme inputs a data set and determines the maximum and minimum values of the input data set, indicated as $L_{\min}$ and $L_{\max}$. The histogram of the data set is normalized as a probability distribution by the following equation.

$$p(l) = n(l)/N\,, p(l) \geq 0, \int_{l=L_{min}}^{L_{max}} p(l) * dl = 1 \tag{1}$$

Here, $n(l)$ is the number of elements with value l and N is the total number of elements of the data set. We suppose that all elements of the set are divided into two classes, C_1 and C_2 by a threshold *k*. The probabilities of occurrence (ω) and mean (μ) of each class are evaluated by the following formulas.

$$\omega_1 = \Pr(C_1) = \frac{1}{N}\int_{l=L_{min}}^{k} n(l) * dl = \omega(k) \tag{2}$$

$$\begin{aligned}\omega_2 &= \Pr(C_2)\\ &= \frac{1}{N}\int_{l=k}^{L_{max}} n(l) * dl = 1 - \omega_1 = 1 - \omega(k)\end{aligned} \tag{3}$$

$$\begin{aligned}\mu_1 &= \int_{l=L_{min}}^{k} l * \Pr(l|C_1) * dl\\ &= \int_{l=L_{min}}^{k} l * p(l) * dl/\omega_1 = \mu(k)/\omega(k)\end{aligned} \tag{4}$$

$$\begin{aligned}\mu_2 &= \int_{l=k}^{L_{max}} l * \Pr(l|C_2) * dl\\ &= \int_{l=k}^{L_{max}} l * p(l) * dl/\omega_2 = (\mu_T - \mu(k))/(1-\omega(k))\end{aligned} \tag{5}$$

Where

$$\mu_T = \mu(L_{max})\int_{l=L_{min}}^{L_{max}} l * p(l) * dl \tag{6}$$

The class variances are evaluated by

$$\begin{aligned}\sigma_1^2 &= \int_{l=L_{min}}^{k} (l-\mu_1)^2 * \Pr(l|C_1) * dl\\ &= \int_{l=L_{min}}^{k} (l-\mu_1)^2 * p(l) * dl/\omega_1\end{aligned} \tag{7}$$

$$\begin{aligned}\sigma_1^2 &= \int_{l=k}^{L_{max}} (l-\mu_2)^2 * \Pr(l|C_2) * dl\\ &= \int_{l=k}^{L_{max}} (l-\mu_2)^2 * p(l) * dl/\omega_2\end{aligned} \tag{8}$$

The within-class variance, the between-class variance and the total variance of element-values are defined as follows.

$$\sigma_w^2 = \omega_1 * \sigma_1^2 + \omega_2 * \sigma_2^2 \tag{9}$$

$$\begin{aligned}\sigma_B^2 &= \omega_1(\mu_{1-}\mu_T)^2 + \omega_2(\mu_{2-}\mu_T)^2\\ &= \omega_1 * \omega_2(\mu_{1-}\mu_T)^2\end{aligned} \tag{10}$$

$$\sigma_T^2 = \sigma_W^2 + \sigma_B^2 = \int_{l=L_{min}}^{L_{max}} (l-\mu_T)^2 * p(l) * dl \tag{11}$$

Otsu introduced the following two measuring functions to get the optimal threshold $\hat{k}$:

$$\begin{aligned}\hat{k} &= \operatorname*{argmin}_{L_{min}\leq k\leq L_{max}} (\sigma_B^2(k))\\ &= \operatorname*{argmin}_{L_{min}\leq k\leq L_{max}} (\omega_1 * \omega_2(\mu_1 - \mu_2)^2)\end{aligned} \tag{12}$$

$$\begin{aligned}\hat{k} &= \operatorname*{argmin}_{L_{min}\leq k\leq L_{max}} (\sigma_W^2(k))\\ &= \operatorname*{argmin}_{L_{min}\leq k\leq L_{max}} (\omega_1 * \sigma_1^2 + \omega_2 * \sigma_2^2)\end{aligned} \tag{13}$$

In this paper, the black region in a palmprint image is the background, and white regions usually contained the palmprint. For obtaining a region as the palmprint, the presented algorithm will apply the morphological operation and connected component scheme on the white regions colored by Otsu thresholding scheme to extract the palmprint area in following processes (see figure 2(b)).

- **Morphological processing**

The morphological opening operation is combined with the morphological erosion and the dilation operations. Where erosion operation is applied to "shrink" or "thinning" the objects and dilation operation is utilized to "enlarge" or "thickening" the objects. In an Otsu binarized palmprint image, white areas are consist of palmprint and some noises such as isolated pixels, spurs and leaks. For obtaining a better and simple binary image of palmprint, the presented algorithm adapts the morphological opening operation to delete the white areas occupied by noises as shown in figure 2(c). The structuring element of the morphological opening operation used in the presented algorithm is a disk with radius 2 pixels.

- **Palm alignment and ROI extraction**

In a palmprint image, palm's location, orientation, rotation angle and degree of stretch will affect the ROI segmentation to bother the feature extraction of the palmprint. Palm alignment is a necessary and crucial step for aligning palm poses to a standard pose to reduce the disturbing of nonlinear factors such as rotation, translation and distortion in sampling process to enhance the robustness of palmprint ROI segmentation. The palm alignment is to find suitable key points from the palm to normalize the position of the palmprint image. The palm alignment and ROI extraction are performed by palm contour detection in the shrink region of palm, reference line construction and palm normalization steps described in the following subsections.

1. Palm contour detection on the shrink region of palmprint image

To reduce the region of operation is necessary for accelerating the processing speed. As shown in figure 2 (d), the shrink region is a rectangular region bounded by four line segments. The upper-bound line is the most upper row whose white pixels is no less than 200, the lower-bound line is the lowest row whose white pixels is no less than 200, the right-bound line is the rightest column whose white pixels is no less than 95 pixels and the left-bound line is the most left column whose white pixels is no less than 95 pixels. For obtaining better and suitable key points to construct the reference line for effectively aligning the palm in a palm image, the presented algorithm applies the Sobel gradient mask on the shrink region of the binary noise-removal palmprint image to acquire the palm contour. The Sobel gradient mask is one of popular edge detection methods. Figure 3 shows the Sobel gradient mask; Figure 3(a) is a mask type, Figure 3(b) and Figure 3(c) are the values of masks that are used for detecting the horizontal and vertical edge, respectively. Figure 2(e) shows the palm contour detected by the Sobel edge detector.

Z1	Z2	Z3
Z4	Z5	Z6
Z7	Z8	Z9

(a)

-1	-2	-1
0	0	0
1	2	1

(b)

-1	0	1
-2	0	2
-1	0	1

(c)

Figure 3. The Sobel gradient mask, (a) the mask pixels (b) $f_x(x, y)$ (c) $f_y(x, y)$

2. Reference points and reference line construction

For extracting the central parts of the palmprint images, this step detects the three reference points between fingers. Two of them are used to construct a reference line segment for aligning the different palmprint images, and another one is used to determine the central position of the ROI. As shown in figure 2(f), there are three curves located on the left half-plane in a palm contour map. On each curve, the rightest pixel is located as the reference points. The line segment AB is created by connected the reference point, A, in the upper curve and the reference point, B, in the lower curve as the reference line for aligning the palmprint image, point, M, is the middle point of the reference line segment, and another reference point, L, located on the middle curve is use to locate the ROI center.

3. Palm normalization and palmprint ROI extraction

Once the Reference points and reference line are defined, the proposed algorithm normalizes the palmprint's pose by taking the middle point as the center of rotation to rotate the palmprint counterclockwise with an angle evaluated by the following equation such that the reference line is in vertical direction (as shown in figure 3(g) and figure 3(h)).

$$\beta = \cot^{-1}\left(\frac{y_B - y_A}{x_B - x_A}\right) \tag{14}$$

Where (x_A, y_A) and (x_A, y_A) are the coordinates of reference points, A, and , B, respectively. On the pose normalized palmprint map, two horizontal lines are drawn with one pass through the middle point of reference line and the other one pass through the third reference point, respectively. A point, D, located on the second horizontal line is taken with the reason that the length of the line segment, LD, is 150 pixels. Then we draw a vertical line that passes through point D, and the intersection, C, of the vertical line and the first horizontal line is taken as the center of the ROI. Finally, a horizontal square area with center, C, and side length 128 pixels is segmented as the extracted ROI, as shown in figure 3(i) and figure 3(j).

3 Experimental Results

The presented palmprint ROI segmentation scheme was applied on the Hong Kong Polytechnic University (PolyU) palmprint database (version 2) using Matlab 7.8 on a 2.8GHz Intel Pentium processor with 512 MB RAM. The PolyU database (version 2) has 7752 grayscale palmprint images corresponding to 386 persons' right and left palms. Each person has 18 to 20 different sample palmprint images taken in two phases. The size of each palmprint image is 384*284 with resolution of 75 dots per inch, and bit-depth of 8 bits ([0, 255]). All the 7752 palmprint images have been tested to find that the proposed algorithm can correctly extract the corresponding ROI of each palmprint image. This result means that the accuracy rate of automatic ROI extracting is 100%. Some experimental results are shown in figures 4, 5, and 6 to illustrate the performance of the proposed palmprint ROI extraction algorithm. Figure 4 shows the extraction result by applying the proposed algorithm on three different left palmprint images, figure 5 shows the extraction result by applying the proposed algorithm on three different right palmprint images, and figure 6 shows the extraction result by applying the proposed algorithm on three noises surrounding palmprint images.

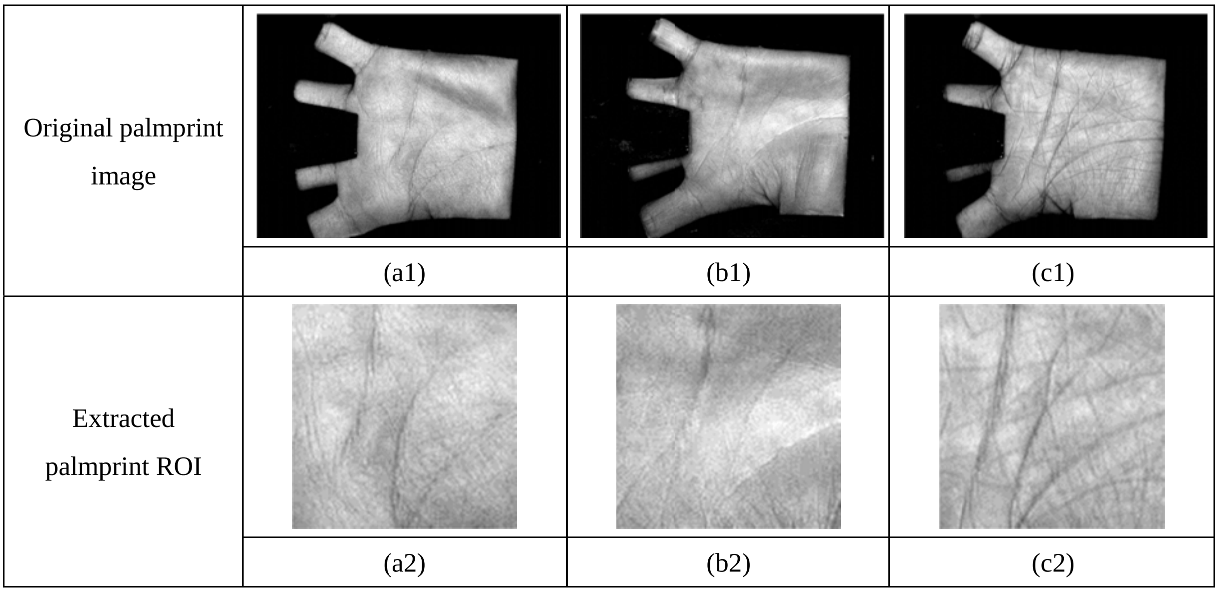

Figure 4. The extraction result by applying the proposed algorithm on three different left palmprint images.

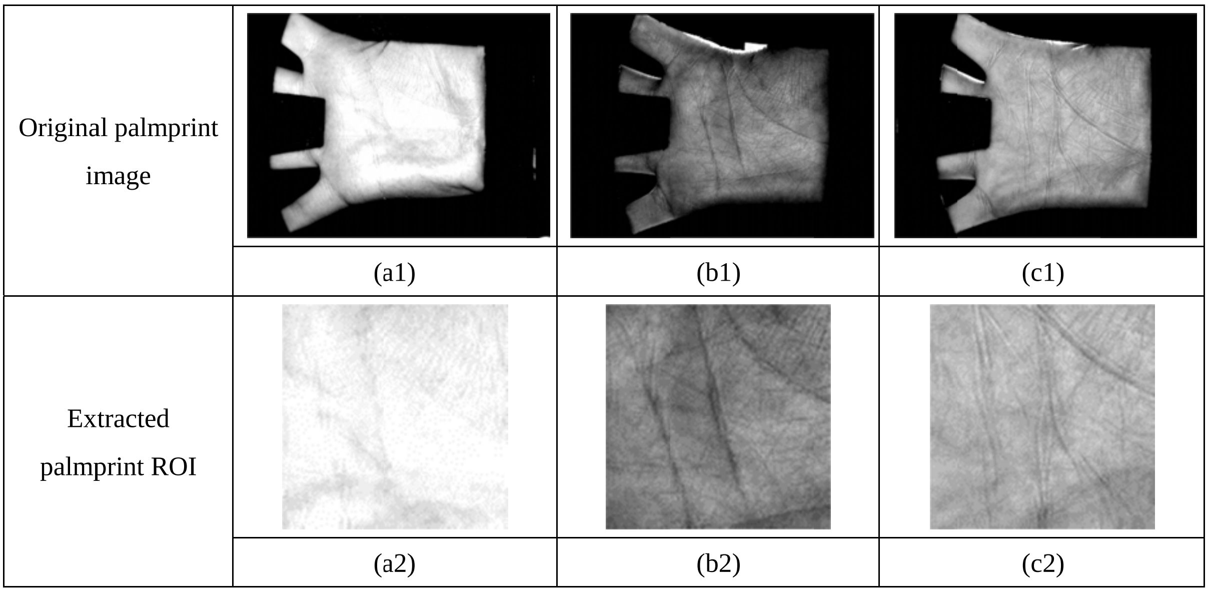

Figure 5. The extraction result by applying the proposed algorithm on three different right palmprint images.

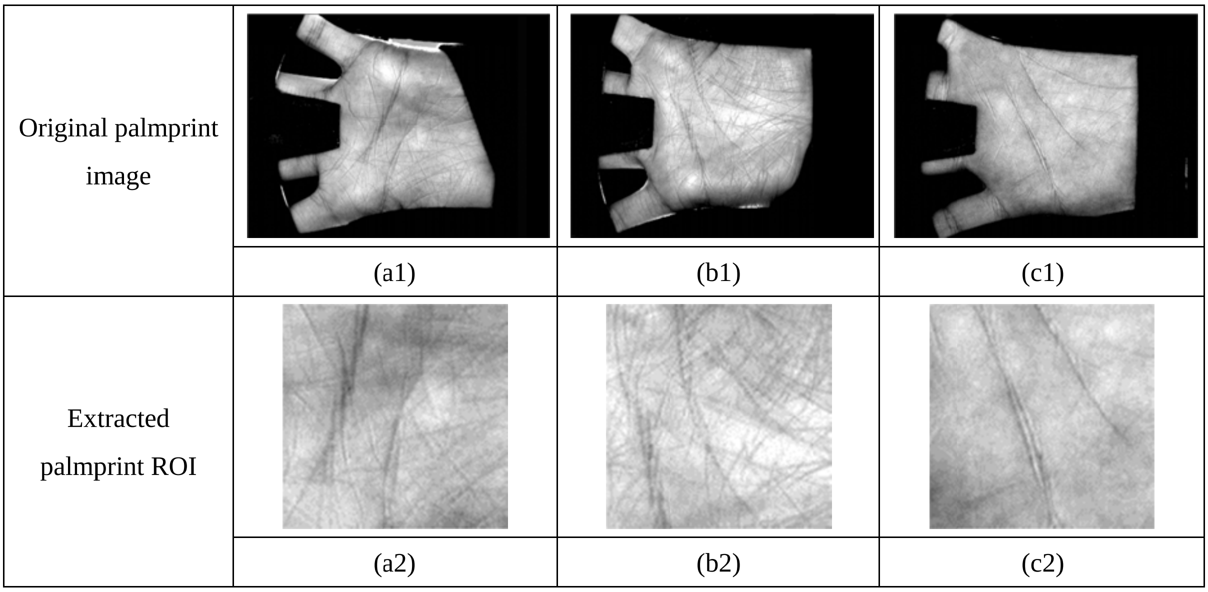

Figure 6. The extraction result by applying the proposed algorithm on three noises surrounding palmprint images.

4 Conclusion

Biometric identification system has high efficiency, high recognition rate and comfortable to the user's operating characteristics. Palmprint recognition is considered the most viable and reliable biometric recognition technique owing to its merits, such as low cost, user friendliness, high speed and high accuracy. ROI segmentation of palm is to automatically and reliably segment a small region from the captured palm image; it is considered one of important stages in automatic palmprint recognition system because it greatly influences the overall identification accuracy and processing speed of the whole system. In this paper, we presented a robust palmprint ROI extraction algorithm which combines Otsu thresholding scheme, morphological openning operation, Sobel edge detector, reference points and line construction, and palmprint image alignment. The performance of the proposed palmprint ROI segmentation scheme is verified using a palmprint image database, PolyU database (version 2). The experimental results show that the proposed algorithm is effective and efficient in palmprint ROI segmentation and is robust for noises surrounding palmprint images. In the future we will develop a high performance palmprint recognition scheme based on the proposed palmprint ROI extraction algorithm to power the automatic palmprint recognition system.

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References

[1] D. Zhang, G. Lu, W. Li, L. Zhang, N. Luo, Palmprint recognition using 3-D Information, IEEE transactions on systems, man, and cybernetics—part c: applications and reviews, 39(5) (2009) 505- 519.

[2] A. W. K. Kong, D. Zhang, M. Kamel, Analysis of brute-force break-ins of a palmprint authentication system, IEEE transactions on systems, man, and cybernetics—part b: cybernetics 36(5) (2006) 1201 – 1025.

[3] W. Jia, D. Huang, D. Zhang, Palmprint verification based on robust line orientation code, Pattern recognition 41 (5) (2008) 1521 – 1530.

[4] J. S. Chen, Y. S. Moon, M. F. Wong, G. Su, Palmprint authentication using a symbolic representation of images, Image and Vision Computing 28 (2010) 343 – 351.

[5] A.K. Jain, J. Feng, Latent palmprint matching, IEEE Transactions on pattern analysis and machine intelligence 31 (6) (2009) 1032 – 1047.

[6] L. Shang, D.-S. Huang, J.-X. Du, C.-H. Zheng, Letters: palmprint recognition using fastica algorithm

and radial basis probabilistic neural network, Neurocomputing 69 (13 – 15) (2006) 1782 – 1786.

[7] G.S. Badrinath, N. Kachhi, P. Gupta, Palmprint based verification system robust to occlusion using low-order zernike moments of sub-images, Telecommunication systems (2010) 1 – 16.

[8] X. Wu, D. Zhang, K. Wang, Fusion of phase and orientation information for palmprint authentication, Pattern analysis and applications 9 (2) (2006) 103 – 111.

[9] T. Connie, A. Teoh, M. Ong, D. Ngo, An automated palmprint recognition system, Image and vision computing 23 (5) (2005) 501 – 515.

[10] J. Wang, W. Yau, A. Suwandy, E. Sung, Person recognition by fusing palmprint and palm vein images based on 'laplacianpalm' representation, Pattern recognition 41 (5) (2008) 1531 – 1544.

[11] A. Kumar, D. Zhang, Personal recognition using hand shape and texture, IEEE transactions on image processing 15 (8) (2006) 2454 – 2461.

[12] G.S. Badrinath, P. Gupta,Palmprint based recognition system using phase-difference information, Future generation computer systems 28 (2012) 287 – 305.

[13] C.C. Han, H.L. Cheng, C.L. Lin, K.C. Fan, Personal authentication using palmprint features, pattern recognition, 36 (2) (2003) 371–381.

[14] C. L. Lina, T. C. Chuang, K. C. Fanc, Palmprint verification using hierarchical decomposition, Pattern recognition 38 (2005) 2639 – 2652.

[15] J. You, W. Li, D. Zhang, Hierarchical palmprint identification via multiple feature extraction, Pattern recognition, 35 (4) (2002) 847–859.

[16] W. Li, D. Zhang, Z. Xu, Image alignment based on invariant features for palmprint identification, Signal process: image communication, 18 (5) (2003) 373–379.

[17] H.B. Kekre, V.A. Bharadi, Fingerprint & palmprint segmentation by automatic thresholding of gabor magnitude, 2nd International conference on emerging trends in engineering and technology (ICETET) , (2009) 235-241.