

## PALMPRINT RECOGNITION USING VALLEY FEATURES

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### Abstract:

This paper presents a novel approach for palmprint recognition based on the valley features. This approach uses the both operation to extract the valleys from a very low-resolution palm image in different directions to form the valley feature, and then define a matching score to measure the similarity of the valley features. The experimental results shows that the proposed approach can effectively discriminate palmprints and can obtain about 98% accuracy in palmprint verification.

### Keywords:

Biometrics; palmprint recognition; valley feature; morphological operator

### 1. Introduction

Computer-aided personal recognition is becoming increasingly important in our information society. Biometrics is one of the most important and reliable methods in this field [1]. The most widely used biometric feature is the fingerprint and the most reliable feature is the iris. However, it is very difficult to extract small unique features (known as minutiae) from unclear fingerprints and the iris input devices are very expensive [1]. Other biometric features, such as the face and voice, are less accurate and they can be mimicked easily. The palmprint, as a relatively new biometric feature, has several advantages compared with other currently available features [2]: palmprints contain more information than fingerprint, so they are more distinctive; palmprint capture devices are much cheaper than iris devices; palmprints also contain additional distinctive features such as principal lines and wrinkles, which can be extracted from low-resolution images; a highly accurate biometrics system can be built by combining all features of palms, such as palm geometry, ridge and valley features, and principal lines and wrinkles, etc. It is for these reasons that palmprint recognition has recently attracted an increasing amount of attention from researchers [3-7].

There are many features in a palmprint such as

geometrical features, principal lines, wrinkles, delta points, minutiae, etc. [1]. However, geometrical features, such as the width of the palm, can be faked easily by making a model of a hand. Delta points and minutiae only can be extracted from the fine-resolution images. Principal lines and wrinkles, called palm-lines [3], are very important to discriminate between different palmprints and they can be extracted from low-resolution images. Therefore, palm-lines are one of the most important features in automated palmprint recognition. The palm-lines in a palm are very irregular and even in the same palm they have quite different directions, shapes and contrast, thus it is a very difficult task to extract these lines. Zhang et al. [3] extracted palm-lines by using twelve templates. Duta et al. [4] binarized the offline palmprint images directly to get the lines by applying an interactively chosen threshold. Both methods were devised for the off-line palmprints, which were created by inked palms. Because of the noise and unexpected disturbance such as the movement of hand, lighting, settings, etc., the online palmprints, which are captured online from palms using some digital devices, have much worse quality than offline images. It is a difficult task to extract the lines from an online palmprint image. Han [6] used Sobel and morphological operations to enhance the lines on a palm and then divided the palmprint into several blocks, after that, the mean of the values of the points in each block is used to form a vector, which are call line-like features. Similarly, for verification, Kumar [7] used other directional masks to extract line-like features from palmprints captured using a digital camera. The line-like features extracted by Han and Kumar are heavy affected by the illuminance. To overcome this problem, this paper proposes a novel approach based on both morphological operations for palmprint recognition.

When palmprints are captured, the position, direction and amount of stretching of a palm may vary so that even palmprints from the same palm may have a little rotation and translation. Furthermore, palms differ in size. Hence palmprint images should be orientated and normalized before feature extraction and matching. The palmprints

used in this paper are from the PolyU Palmprint Database [9]. The samples in this database are captured by a CCD based palmprint capture device [5]. In this device, there are some pegs between fingers to limit the palm's stretching, translation and rotation. These pegs separate the fingers, forming holes between the forefinger and the middle finger, and between the ring finger and the little finger. In this paper, we use the preprocessing technique described in [5] to align the palmprints. In this technique, the tangent of these two holes are computed and used to align the palmprint. The central part of the image, which is  $128 \times 128$ , is then cropped to represent the whole palmprint. Such preprocessing greatly reduces the translation and rotation of the palmprints captured from the same palms. Figure 1 shows a palmprint and its cropped image.

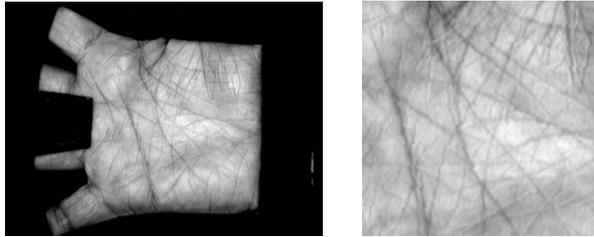


Figure 1. An example of the palmprint and its cropped image: (a) Original palmprint and (b) cropped image

The rest of this paper is organized as follows. Section 2 describes the feature extraction. Section 3 defines the similarity measurement. Section 4 gives some experimental results. Section 5 provides some conclusions.

## 2. Feature Extraction

### 2.1. Morphological Operations

Morphology theory [8] has been successfully used in image processing and feature extraction. In the gray-scale morphology theory, two basic operations, namely *dilation* and *erosion* for image  $f$  are defined as follows:

*Dilation*:

$$(f \oplus b)(s, t) = \max \{ f(s-x, t-y) + b(x, y) \mid (s-x, t-y) \in D_f \text{ and } (x, y) \in D_b \} \quad (1)$$

*Erosion*:

$$(f \ominus b)(s, t) = \min \{ f(s-x, t-y) - b(x, y) \mid (s-x, t-y) \in D_f \text{ and } (x, y) \in D_b \}, \quad (2)$$

where  $D_f$  and  $D_b$  represent the domains of image  $f$

and structuring element  $b$ . Furthermore, two additional operations *opening* and *closing* are defined by combining the dilatation and erosion operations:

*Opening*:

$$f \circ b = (f \ominus b) \oplus b \quad (3)$$

*Closing*:

$$f \bullet b = (f \oplus b) \ominus b \quad (4)$$

And using the opening and closing operation, *bothat* operation is defined as below:

*Bothat*:

$$h = (f \bullet b) - f \quad (5)$$

The bothat operation can be used to detect the valley in an image. Therefore, we use the bothat operation to detect the valleys on a palm.

### 2.2. Valley Detection

Let  $I$  denote a palmprint image. Now we extract the valley in horizontal direction.

First, we define a directional filter  $F_{0^\circ}$  and a directional structuring element  $b_{0^\circ}$ :

$$F_{0^\circ} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 \\ 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 & 3 \\ 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 & 2 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix} \quad (6)$$

$$b_{0^\circ} = [1 \ 1 \ 1 \ 1 \ 1]^T \quad (7)$$

where “ $T$ ” is the transpose operation.

Then the palmprint is smoothed by this filter:

$$I_s = I * F_{0^\circ} \quad (8)$$

where “ $*$ ” is the convolve operation.

After that, the smoothed palmprint  $I_s$  is processed by the bothat operation with the directional element  $b_{0^\circ}$  as below:

$$B_{0^\circ} = (I_s \bullet b_{0^\circ}) - I_s \quad (9)$$

Finally,  $B_{0^\circ}$  is converted to a binary image as below:

$$V_{0^\circ} = \begin{cases} 1, & B_{0^\circ} > 0; \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

$V_{0^\circ}$  is called  $0^\circ$ -valley image of the palmprint  $I$ .

The filter  $F_\theta$  used to enhance the valley in  $\theta$  direction can be obtained by rotating  $F_{0^\circ}$  with Angle  $\theta$  and the corresponding directional structural element  $b_\theta$  can be obtained by rotation  $b_{0^\circ}$  with Angle  $\theta$ . With a similar process, we can get the  $\theta$ -valley image of  $I$  by

using  $F_\theta$  and  $b_\theta$ .

In this paper, we extract the valley images in  $(0^\circ, 45^\circ, 90^\circ \text{ and } 135^\circ)$ , and  $V = \{V_{0^\circ}, V_{45^\circ}, V_{90^\circ}, V_{135^\circ}\}$  is called the *valley feature* of the palmprint and will be used for personal recognition.

The size of the preprocessed palmprint is  $128 \times 128$ . Extra experiments shows that the image with  $32 \times 32$  is enough for the proposed approach. Therefore, before extracting the valleys, we resize the image from  $128 \times 128$  to  $32 \times 32$ . Hence the size of the each valley image is  $32 \times 32$  and the storage requirement of a valley feature is  $(4 \times 32 \times 32) / 8 = 512$  bytes.

Figure 2 shows some examples of valley features. From this figure, the valley features keep the most information of the lines on a palm.

### 3. Similarity Measurement

Let  $V = \{V_{0^\circ}, V_{45^\circ}, V_{90^\circ}, V_{135^\circ}\}$  and  $U = \{U_{0^\circ}, U_{45^\circ}, U_{90^\circ}, U_{135^\circ}\}$  denote the directional valley features of two palmprint images. The total number of the non-zero points in  $V$  and  $U$  (denoted as  $N_V$  and  $N_U$ ) can be computed as below:

$$N_V = \sum_{\theta=0^\circ}^{135^\circ} \sum_{i=1}^{32} \sum_{j=1}^{32} V_\theta(i, j) \quad (11)$$

$$N_U = \sum_{\theta=0^\circ}^{135^\circ} \sum_{i=1}^{32} \sum_{j=1}^{32} U_\theta(i, j) \quad (12)$$

And the number of the non-zero points overlapped between  $V_\theta$  and  $U_\theta$  is computed as below:

$$N_\theta = \sum_{i=1}^{32} \sum_{j=1}^{32} V_\theta(i, j) \wedge U_\theta(i, j) \quad (13)$$

Then we define the matching scores between  $V$  and  $U$  as below:

$$S(V, U) = \frac{2 \times \sum_{\theta=0^\circ}^{135^\circ} N_\theta}{N_V + N_U} \quad (14)$$

Obviously,  $S(U, V)$  is between 0 and 1 and the larger the matching score, the greater the similarity between  $V$  and  $U$ . The matching score of a perfect match is 1. Because of the imperfect of the preprocessing, there may still be a little translation between the palmprints captured from the same palm at different times. To overcome this problem, we vertically and horizontally translate  $U$  a few points, and

then, at each translated position, compute the matching score. Finally, the final matching score is taken to be the maximum matching score of all the translated positions.

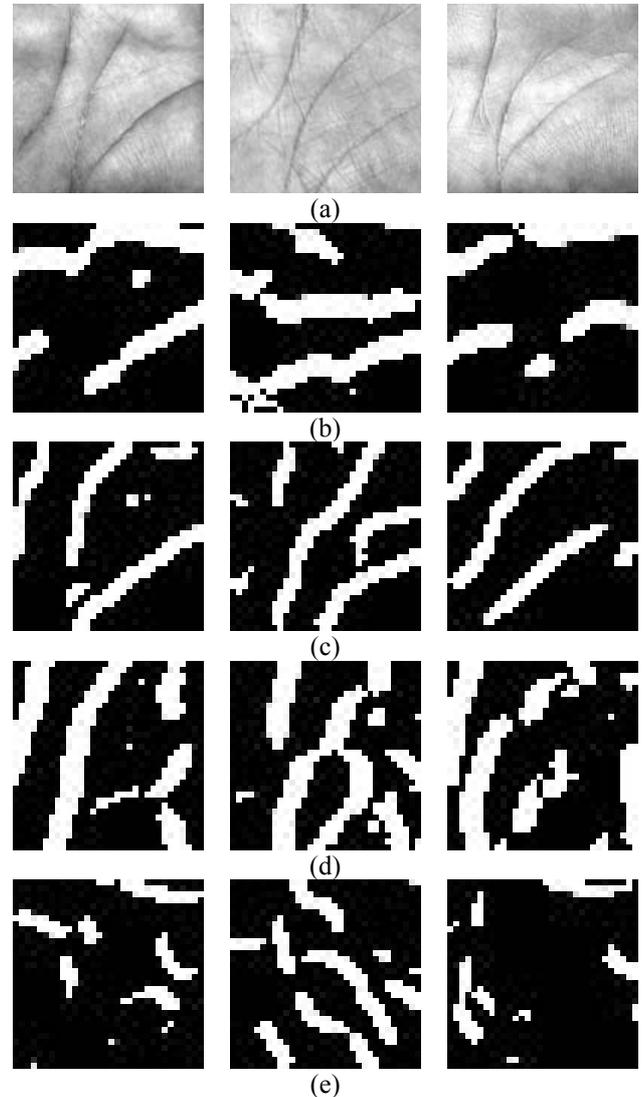


Figure 2. Some examples of valley features. (a) Original palmprints; (b)–(e) the valley images in  $0^\circ, 45^\circ, 90^\circ$  and  $135^\circ$  directions.

## 4. Experimental Results and Analysis

### 4.1. Palmprint Database

We employed the PolyU Palmprint Database [9] to test our approach. This database contains 600 grayscale images

captured from 100 different palms by a CCD-based device. Six samples from each of these palms were collected in two sessions, where three samples were captured in the first session and the other three in the second session. The average interval between the first and the second collection was two months. Some typical samples in this database are shown in Figure 3, in which the last two samples were captured from the same palm at different sessions. According to this figure, the lighting condition in different sessions is very different.

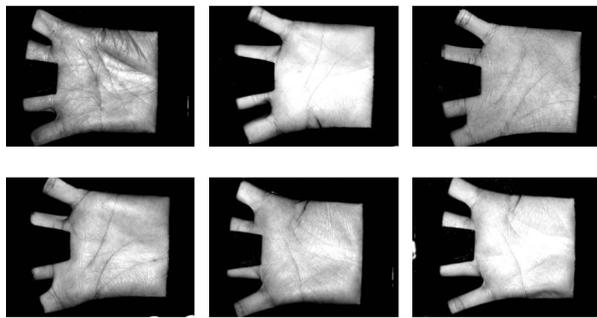


Figure 3. Some typical samples in the PolyU Palmprint Database.

#### 4.2. Palmprint Matching

In order to investigate the performance of the proposed approach, each sample in the database is matched against the other samples. The matching between palmprints which were captured from the same palm is defined as a genuine matching. Otherwise, the matching is defined as an impostor matching. A total of 179,700 ( $600 \times 599/2$ ) matchings have been performed, in which 1500 matchings are genuine matchings. Figure 4 shows the genuine and impostor matching scores distribution. There are two distinct peaks in the distributions of the matching scores. One peak (located around 0.7) corresponds to genuine matching scores while the other peak (located around 0.3) corresponds to impostor matching scores. Therefore, the valley features can effectively distinguish the different palmprints.

#### 4.3. Palmprint Verification

Palmprint verification, also called one-to-one matching, involves answering the question “whether this person is who he or she claims to be” by examining his or her palmprint. In palmprint verification, a user indicates his or her identity and thus the input palmprint is matched only against his or her stored template. To determine the

accuracy of the verification, each sample is matched against the other palmprints in the database. If the matching score of the sample palmprint exceeds a given threshold, it is accepted. If not, it is rejected. The performance of a verification method is often measured by the false accept rate (FAR) and false reject rate (FRR). While it is ideal that these two rates should be as low as possible, they cannot be lowered at the same time. So, depending on the application, it is necessary to make a trade-off: for high security systems, such as some military systems, where security is the primary criterion, we should reduce the FAR, while for low security systems, such as some civil systems, where ease-of-use is also important, we should reduce the FRR. To test the performance of a verification method with respect to the FAR and FRR trade-off, we usually plot the so-called Receiver Operating Characteristic (ROC) curve, which plots the pairs (FAR, FRR) with different thresholds [10]. Fig. 5 shows the ROC curves of the proposed approach and of the Sobel method [6], which were also implemented in the database. The proposed approach's equal error rate (EER), where FAR equals FRR, is about 1.96% while the EER of the Sobel method are about 14.03%. According to this figure, the performance of the proposed approach is much better than that of the Sobel method.

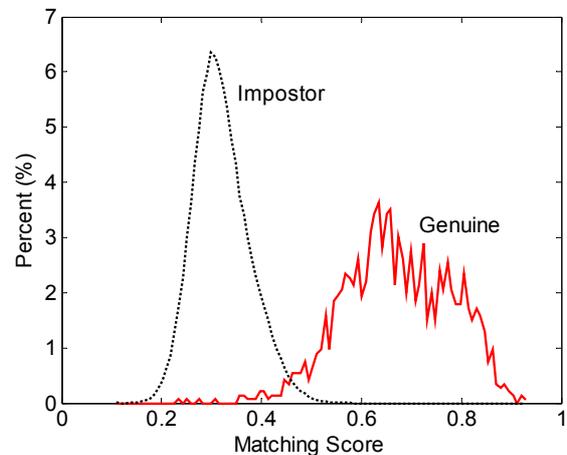


Figure 4. Distributions of genuine and impostor matching scores.

### 5. Conclusion and Future Work

Palmprint recognition is a relative new biometric technique for personal recognition. In this paper, we developed a novel approach to extract and match the valleys on a palm. Four directional smoothing filters and directional structural elements are used to extract the valley

in  $0^\circ$ ,  $45^\circ$ ,  $90^\circ$  and  $135^\circ$  directions. And all of the valley extracted in different directions form the valley feature. And then we define a matching score for measure the similarity between valley features. The experimental results show that the proposed approach is much better than Sobel method.

In future, we will test the proposed approach in a large database and investigate the fusion of the proposed approach and the other available palmprint recognition algorithms.

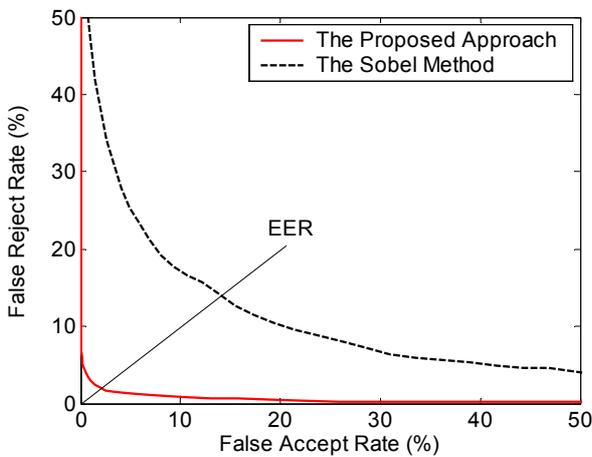


Figure 5. ROC curve of the proposed approach and the Sobel method.

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