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Palmprint Recognition using PCF and SURF

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Abstract - In Biometric Technology, Palm print recognition is one of the most reliable personal identification methods. In the present study an attempt was made to texture based palmprint identification using Phase-Correlation Function (PCF) and Speeded Up Robust Features (SURF). The PCF is an image matching technique using the phase components in 2D DFTs of given images. In SURF, a region of interest (ROI) is cropped for feature extraction and the key points are extracted with fast Hessian detector and an orientation invariant descriptor is constructed for each key point. Among the two methods, the SURF method can significantly achieved less EER without sacrificing recognition performance compared with Phase Correlation function. The implemented features and decision rules yields promising result of EER=6.488 % for verification rate.

Keywords - Phase-Correlation Function; Speeded Up Robust Features; Region of interest; Fast Hessian detector

I. INTRODUCTION

Basically biometric system is a pattern recognition system which generate a personal identification to authenticate the specific physiological or behavioral characteristic possessed by the user. Recently, the biometric system has gained more interest in the security system. A lot of personal identification systems have been establsihed, of which palmprint verification is one of the promising identification system due to its stable, unique characteristics, low-price capture device, fast execution speed also it provides a large area for feature extraction. A palmprint holds many features such as principle lines, ridges, minutiae points, singular points and texture, and is anticipated to be more unique than a fingerprint [1].

First, data acquisition is relatively easy and economical via commercial low-resolution cameras. Second, hand-based access systems are very suitable for indoor and outdoor usage. Finally, human hand-based biometric information is very reliable and it can be successfully used for recognizing people among several populations. A simple palmprint biometric system has a sensor module, for acquiring the palmprint, a feature extraction module, for palmprint representation and a matching module for decision making [2]. Numerous methods have been developed to detect palmprint images such as phase only correlation [3], Gabor feature-based [4], Band-Limited Phase Only Correlation [5], DCT Features [6], Interested directional context matrix [7], Wavelet energy feature extraction [9], Texture Analysis based on Low-Resolution Images [9], principle component analysis (PCA) [10], DCT-based Local Feature Extraction [11], Fisher discriminant analysis (FDA) and independent component analysis (ICA) [12], Fuzzy direction element energy feature extraction [13].

In nature, more than one individuals have similar principal lines, line based algorithms may find solutions for this kind of ambiguous identification. In order to overcome this limitation, the texture-based feature extraction schemes can be used, where the variations existing in either the different blocks of images or the features extracted from those blocks are computed [6, 12]. To over come the ambiguous identification, generally, principal component analysis (PCA) or linear discriminant analysis (LDA) is applied directly on the palm-print image data or Fourier and discrete cosine transforms (DCT), are used for extracting features from the image data. By using (IDCM), characterize an input palmprint with a set of statistical signatures [7]. The problems by this approach are global measurements, and the signatures of some palmprints are very similar. The texture information was obtained by 2-D Gabor filter and the Hamming Distance used for comparing the images [9]. A novel palmprint feature, named wavelet energy features reflect the distribution of principal lines, wrinkles and ridges at different decomposition levels [9].Robustness achieved to some extent in rotation and translation of the images.

Ito et al. [2] and Iitsuka et al. [3] applied Phase-Only Correlation (POC) - an image matching technique using the phase components in 2D Discrete Fourier Transforms (DFTs) for palmprint recognition and obtained efficient recognition performance compared with a Gabor feature-based algorithm.This paper describes the prototype of a biometric recognition system based on a palmprint. For that, we propose to use Phase-Correlation Function (PCF) method and Speeded Up Robust Features (SURF) for matching.

II. BRIEF DESCRIPTION OF THE SCHEME

A typical palm-print recognition system consists of some major steps, namely, input palm-print image collection, preprocessing, feature extraction and matching as illustrated in Fig. 1. The input palmprint image can be collected generally from the Hong Kong Polytechnic University (PolyU database [14]). In the process of capturing palm images, distortions including rotation, shift and translation may be present in the palm images, which make it difficult to locate at the correct position. Pre-processing sets up a coordinate system to align palm-print images and to segment a part of palm-print image for feature extraction. From palm-print images, some characteristic features are extracted for preparing the template. The matching between the verified ROI and registered one in database, for Palmprint is performed. Matching scores from the unimodal biometric recognition systems makes a final decision (the user is identified or rejected).

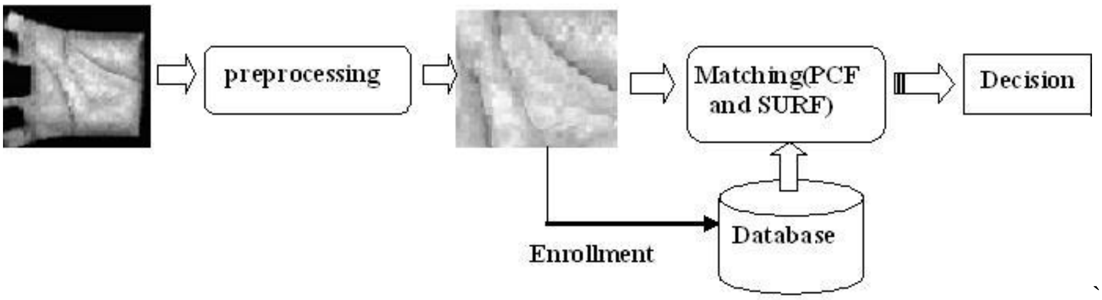

Fig. 1 The block diagram of the palmprint based biometric recognition system

A. PCF Feature Extraction

Frequency-domain palmprint matching is based on the 2D Discrete Fourier Transform (2D DFT) property. It consists of translational displacement in the spatial domain that corresponds to a linear phase shift in the frequency domain [15].Let now N1 × N2 images, the palmprint image to be verified (current), noted by f_v and the registered palmprint image, (reference), noted by f_r. Thus, assuming that these two images are different upon a moving area, which we note it here by A, only due to a translational displacement (τ_1,τ_2).

$$f_v(n_1,n_2) = f_r(n_1+\tau_1, n_2+\tau_2), \qquad (n_1,n_2) \in A \tag{1}$$

By taking the 2D DFT of both sides, with respect to the spatial variables (n_1,n_2), we obtain, in frequency domain, the following equation of the frequency variables (k_1,k_2):

$$F_v(k_1,k_2) = F_r(k_1,k_2)e^{j(-k_1\tau_1-k_2\tau_2)} \tag{2}$$

Where F_v and F_r are the Fourier transform (FT) of the palmprint image to be verified (current) and the registered palmprint image (reference), respectively. If we define $\Delta\text{Ø}(k_1,k_2)$ as the phase difference between the FT of the current image and that of the reference one, then we have:

$$\begin{aligned} e^{j\Delta\text{Ø}(k_1,k_2)} &= e^{j[\text{Ø}_v(k_1,k_2)-\text{Ø}_r(k_1,k_2)]} \\ &= e^{j\text{Ø}_v(k_1,k_2)} \cdot e^{-j\text{Ø}_r(k_1,k_2)} \\ &= \frac{F_v(k_1,k_2)}{|F_v(k_1,k_2)|} \cdot \frac{F_r^*(k_1,k_2)}{|F_r^*(k_1,k_2)|} \end{aligned} \tag{3}$$

Where Ø_v and Ø_r are the phase components of F_v and F_r, respectively, and the superscript * indicates the complex conjugate. If we define $C_{v,r}(n_1,n_2)$ as the inverse DFT of $e^{j\Delta\text{Ø}(k1,k2)}$, this permits to have:

$$\begin{aligned} C_{v,r}(n_1,n_2) &= F^{-1}\{e^{-j\Delta\text{Ø}(k_1,k_2)}\} \\ &= F^{-1}\{e^{j\text{Ø}_v(k_1,k_2)} \cdot e^{-j\text{Ø}_r(k_1,k_2)}\} \\ &= F^{-1}\{e^{j\text{Ø}_v(k_1,k_2)}\} \otimes F^{-1}\{e^{-j\text{Ø}_r(k_1,k_2)}\} \end{aligned} \tag{4}$$

Where $\otimes$, is the 2D convolution operation. In other words, $C_{v,r}(n_1,n_2)$ is the cross-correlation of the inverse 2D Discrete Fourier Transform (F^{-1}= 2D-IDFT) of the phase components of F_v and F_r. For this reason, $C_{v,r}(n_1,n_2)$ is known as the Phase Correlation Function (PCF) [16]. The importance of this function becomes apparent if it is rewritten in terms of the phase difference in equation (2):

$$\begin{aligned} C_{v,r}(n_1,n_2) &= F^{-1}\{e^{j\Delta\text{Ø}(k_1,k_2)}\} \\ &= F^{-1}\{e^{j(-k_1\tau_1-k_2\tau_2)}\} = \delta(n_1-\tau_1, n_2-\tau_2) \end{aligned} \tag{5}$$

Thus, the phase correlation surface has a distinctive impulse at $(\tau_1, \tau2)$. This observation is the basic idea behind the phase correlation matching. In this method, equation (3) is used tocalculate $e^{j\Delta\text{Ø}(k1,k2)}$, the 2D-IDFT is then applied to obtain $C_{v,r}(n_1,n_2)$ and the location of the impulse in this function is detected to estimate (τ_1,τ_2) When the two images are similar, their PCF gives a distinct sharp peak. When the two images are not similar, the peak drops significantly. Thus, the PCF exhibits much discrimination capability than the ordinary correlation function. The height of the peak can be used as a good similarity measure for image matching.

B. Surf Feature Extraction

SURF (Speeded Up Robust Features) is a scale and in-plane rotation-invariant image features. By using integral images for image convolutions it is faster to compute than other state-of-the-art algorithms, yet produces comparable or even better results by means of repeatability, distinctiveness and robustness. This algorithm describes the keypoint detector and descriptor. The detector locates the keypoints in the image, and the descriptor describes the features of the keypoints and constructs the feature vectors of the keypoints.

1) *Keypoint Detector*:

SURF uses the determinant of the approximate Hessian matrix as the base of the detector. To Integral images are used in Hessian matrix approximation, which allows fast evaluation of box filters. The integral representation J of an image I is described as

$$J(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j) \tag{6}$$

Given a point X = (x, y) in an image I, the Hessian matrix $H(X, \sigma)$ in X at scale σ is defined as:

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix} \tag{7}$$

where $L_{xx}(X,\sigma)$, $L_{xy}(X,\sigma)$ and $L_{yy}(X,\sigma)$ refers to the convolution of the second order partial Gaussian derivative with the image I at point X= (x, y) respectively. These derivatives are known as the Laplacian of Gaussians.

To reduce the computation time, a set of 9×9 box filters is used as the approximations of a Gaussian with σ = 1.2 and represents the lowest scale for computing the blob response maps. By using integral image, the convolution of image I with box filter can be realized with high efficiency. In order to localise interest points in the image and over scales, non-maximum suppression in a 3 × 3 × 3 neighbourhood is applied. The key points detected from FKP ROI images with Fast-Hessian.

2) *Keypoint descriptor*:

The SURF used the sum of the Haar wavelet responses to describe the feature of a keypoint. Haar wavelets are used for the integral images to increase robustness and decrease computation time. Fig. 2 shows the Haar wavelets used to compute the responses in the x and y directions respectively. Weights are 1 for black regions and -1 for white regions.

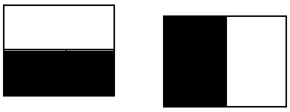

Fig. 2 Left and right filters for computing the response in the x and y directions,

For the descriptor extraction, (i) construct a square region centered at the keypoint and orientation decided by the orientation selection method established in [17]. (ii) The region is split up equally into smaller 4×4 square sub-regions. For each sub-region, the Haar wavelet responses are computed at 5×5 regularly spaced sample points We call d_x the Haar wavelet response in horizontal direction and d_y the Haar wavelet response in vertical direction. The keypoint descriptors are shown in Fig. 3.

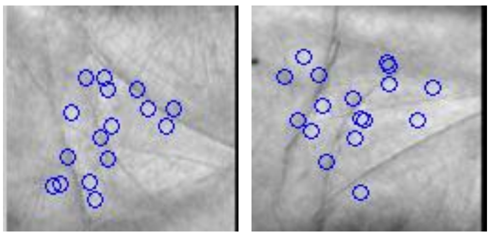

Fig. 3 Keypoint descriptors obtained using SURF.

It fixes a reproducible dominant orientation based on information from a circular region around the interest point. Feature vector of 64 values is computed from the oriented square local image region around key-point. In this paper, based on point matching method suggest in [18], we introduce geometric constraints into point-matching based on SURF features to increase the matching speed and robustness. Because in palm recognition, palm images are usually normalized, the matching points in two images must have the similar locations on the two palms. If the ratio of these two distances is smaller than a pre-defined threshold, the point-pair with the minimum distance is confirmed as a matched pair. Since location information is introduced in search of the minimum-distance point-pair, and the ratio of the minimum distance and next to minimum distance measures the matching reliability of two interest points. Similarity measure, which contains the number of matched points, the average value of the Euclidean distance, and the average distance ratio of all matched points. Fig.4 shows the point matching result. The blue lines indicate the corresponding matched interest points.

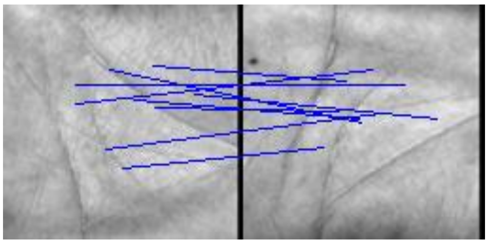

Fig. 4 The point matching result

III. EXPERIMENTAL RESULTS

A. PCF for Palm Recognition

Palmprint images of the experiment database were divided into two parts: 3 of 12 images were randomly selected in the enrolment stage to create the client database; the remaining 9 images were used for testing. Thus, the genuine distribution and impostor distribution are generated for comparisons. At the identification, a threshold T_o is used to regulate the system decision. The system infers that pairs of biometric samples generating scores higher than or equal to T_0 are mate pairs (that is, they belong to the same person). Consequently, pairs of biometric samples generating scores lower than T_o are non-mate pairs (that is, they belong to different persons). The distribution of scores generated from pairs of samples from different persons is called an impostor distribution; the score distribution generated from pairs of samples from the same person is called a genuine distribution.

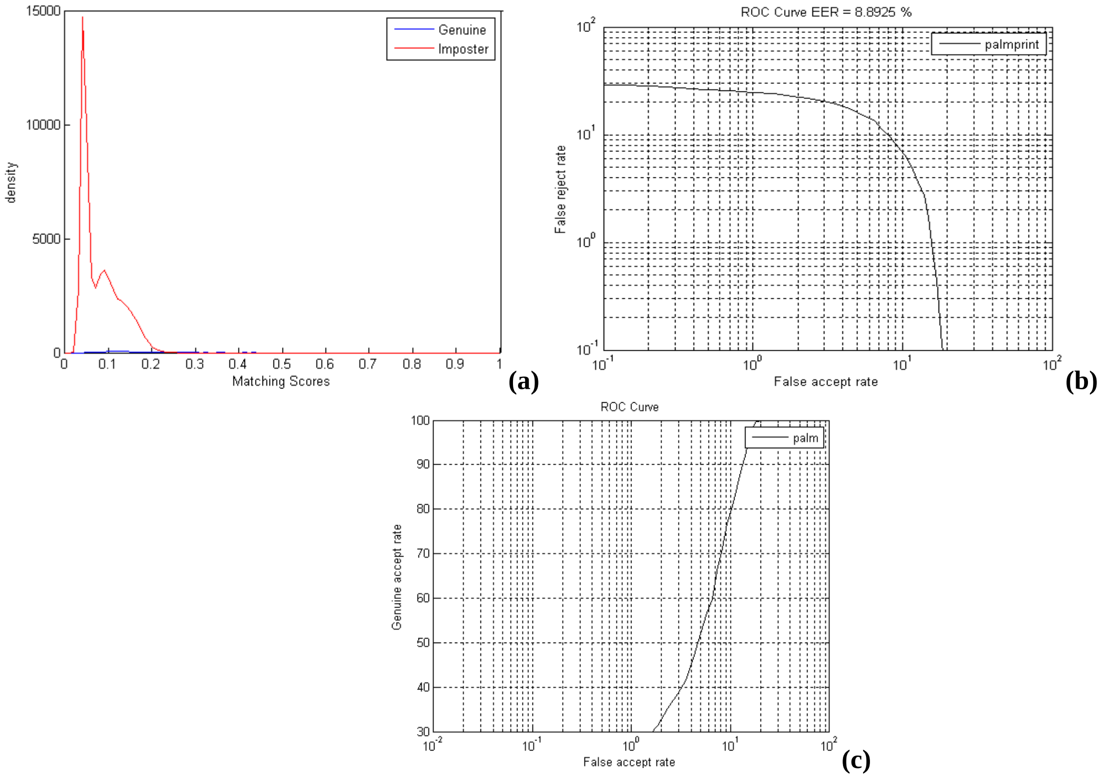

Fig. 5 Verification test for PCF(a) The genuine and impostor distribution (b) The dependency of the FAR and the FRR on the threshold value and (c) The ROC curves for the Palmprint modalities

For the evaluation of the system performance, palmprint as input of biometric data, the genuine and impostor distributions are plotted in Fig. 5a. The results expressed as a FAR and FRR depending on the threshold values is plotted in Fig. 5 b. The system performance at all thresholds can be depicted in the form of a ROC curve Fig. 5(c). The described recognition system can achieves an EER equal to 8.89 % and a maximum Genuine Acceptance Rate (GAR) equal to 98.12 %.

B. SURF for Palm Matching

The FKP images used in this paper are from the PolyU FKP database. We used the middle finger knuckle print images from 165 left fingers to test our algorithm. 12 images are captured from each finger during 2 sessions in which one are used as template and the remaining samples are for testing. Verification means an unknown subject is compared against a specific subject in the database to verify his/her identity, while identification means an unknown subject is compared against all the subjects in the database to establish his/her identity. For the evaluation the genuine and impostor distributions are plotted in Fig. 6a. The results expressed as a FAR and FRR depending on the threshold values is plotted in Fig. 6b. The system performance at all thresholds can be depicted in the form of a ROC curve Fig. 6(c). The described recognition system can achieves an EER equal to 6.488 % and a maximum Genuine Acceptance Rate (GAR equal to 99.65 %.

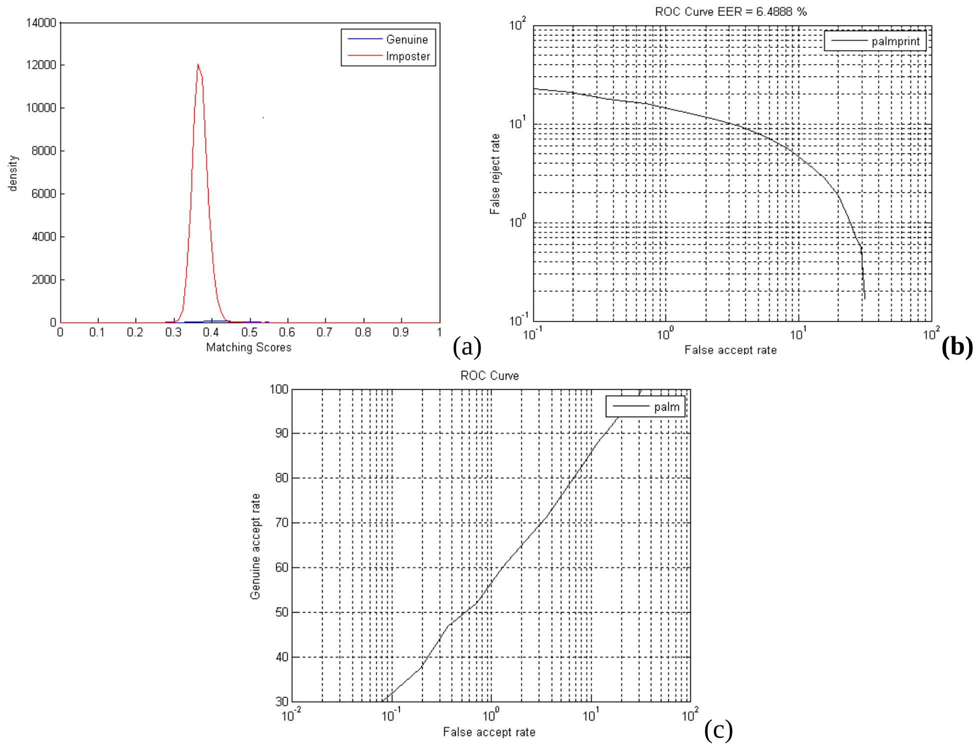

Fig. 6: Verification test for SURF(a) The genuine and impostor distribution (b) The dependency of the FAR and the FRR on the threshold value and (c) The ROC curves for the Palmprint modalities.

IV. CONCLUSION

In this paper, we have designed a biometric recognition system based on the Phase correlation function and Speeded Up Robust Features. The scheme uses the PCF and SURF for matching process. A database of 100 persons was used for testing the system. The performance of the system improves while appling SURF algorithm than PCF. The obtained results showed that the proposed system has the capacity to be used in the environments that require a high security.

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