A PALMPRINT RECOGNITION ALGORITHM USING PHASE-BASED CORRESPONDENCE MATCHING

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ABSTRACT

Palmprint images taken from a camera are distorted due to movement of a hand and fingers. To achieve reliable palmprint recognition, it is necessary to employ a recognition algorithm dealing with nonlinear distortion, while the conventional algorithms only consider the rigid body transformation between palmprint images. This paper proposes a palmprint recognition algorithm using phase-based correspondence matching. In order to handle nonlinear distortion, the proposed algorithm (i) finds corresponding points between two images using phase-based correspondence matching and (ii) evaluates a similarity between local image blocks around the corresponding points. Experimental evaluation using a palmprint image database demonstrates efficient recognition performance of the proposed algorithm compared with conventional algorithms.

Index Terms— image recognition, palmprint recognition, nonlinear distortion, phase-only correlation, biometrics

1. INTRODUCTION

With the need for robust human recognition techniques in various networked applications, biometric authentication has been receiving extensive attention [1]. Biometric authentication (or simply biometrics) is to identify a person based on the physiological or behavior characteristics such as fingerprint, face, iris, voice, signature, etc. Among many biometric techniques, this paper focuses on the palmprint recognition. A palmprint, the large inner surface of a hand, contains many features such as principle lines, ridges, minutia points, singular points and texture, and is expected to be more distinctive than a fingerprint [2, 3].

Conventional algorithms for palmprint recognition are to extract feature vectors corresponding to individual palmprint images and to perform palmprint matching based on some distance metrics [4, 5, 6]. Another algorithm is to employ correlation filters to classify and recognize palmprint images [7]. On the other hand, we have proposed a palmprint recognition algorithm using Phase-Only Correlation (POC) which is an image matching technique using the phase components in 2D Discrete Fourier Transforms (DFTs) of given images [8]. The recognition performance of these algorithms is degraded for palmprint images having nonlinear distortion due to movement of a hand and fingers, since these algorithms consider only the rigid body transformation between palmprint images.

In this paper, we propose a palmprint recognition algorithm using phase-based correspondence matching. The proposed algorithm employs (i) sub-pixel correspondence search technique using POC and (ii) local block matching to deal with nonlinear distortion. Experimental evaluation using the PolyU Palmprint Database [9] demonstrates efficient recognition performance of the proposed algorithm compared with conventional algorithms.

2. PHASE-BASED CORRESPONDENCE MATCHING

2.1. Phase-Only Correlation (POC) function

We briefly introduce a Phase-Only Correlation (POC) function (which is sometimes called the “phase-correlation function”) [10, 11, 12]. The POC function is defined as the inverse DFT of normalized cross-power spectrum. When two images are similar, their POC function gives a distinct sharp peak. When two images are not similar, the peak drops significantly. The height of the peak gives a good similarity measure for image matching, and the location of the peak shows the translational displacement between the images.

We have proposed a high-accuracy translational displacement estimation method, which employs (i) an analytical function fitting technique to estimate the sub-pixel position of the correlation peak, (ii) a windowing technique to eliminate the effect of periodicity in 2D DFT, and (iii) a spectrum weighting technique to reduce the effect of aliasing and noise [11]. Our experimental observation shows that POC-based matching can estimate displacement between two images with 0.01-pixel accuracy when image size is about 100×100 pixels.

For biometric applications, we have developed a similarity evaluation technique using Band-Limited Phase-Only Correlation (BLPOC) function [13]. The idea to improve the similarity evaluation performance is to eliminate meaningless high frequency components in the calculation of cross-phase spectrum depending on the inherent frequency components of images. Our experimental observation shows that the BLPOC function provides the higher correlation peak and better discrimination capability than that of the original POC function.

2.2. Sub-pixel correspondence matching

In order to handle the nonlinear distortion of palmprint images, we employ the sub-pixel correspondence matching [12] using POC, which employs (i) a coarse-to-fine strategy using image pyramids for robust correspondence search and (ii) a sub-pixel window alignment technique for finding a pair of corresponding points with sub-pixel displacement accuracy. Let $\boldsymbol{p}$ be a coordinate vector of a reference pixel in the reference $I(n_1, n_2)$. The problem of sub-pixel correspondence search is to find a real-number coordinate vector $\boldsymbol{q}$ in the input image $J(n_1, n_2)$ that corresponds to the reference pixel $\boldsymbol{p}$ in $I(n_1, n_2)$. We briefly explain the procedure as follows.

Step 1: For $l = 1, 2, \cdots, l_{max} - 1$, create the l-th layer images $I_l(n_1, n_2)$ and $J_l(n_1, n_2)$, i.e., coarser versions of $I_0(n_1, n_2)$ and

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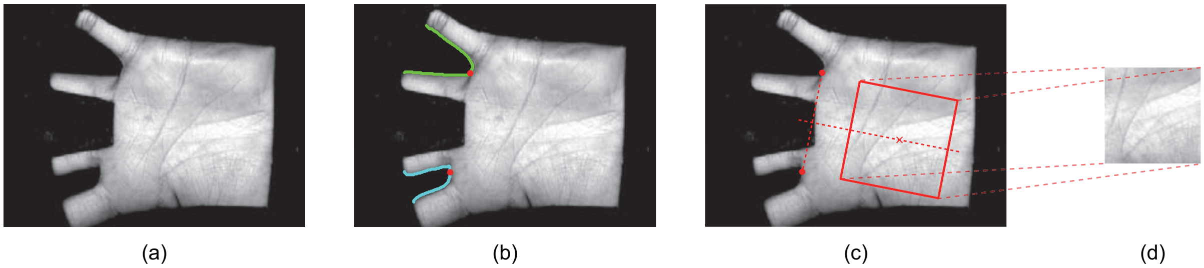
(a)
(b)
(c)
(d)

Fig. 1. Example of palmprint region extraction: (a) palmprint image, (b) gaps between index and middle fingers and between ring and little fingers, (c) palmprint region in the palmprint image and (d) extracted palmprint region.

$J_0(n_1, n_2)$, recursively as follows:

$$I_l(n_1, n_2) = \frac{1}{4} \sum_{i_1=0}^{1} \sum_{i_2=0}^{1} I_{l-1}(2n_1 + i_1, 2n_2 + i_2),$$

$$J_l(n_1, n_2) = \frac{1}{4} \sum_{i_1=0}^{1} \sum_{i_2=0}^{1} J_{l-1}(2n_1 + i_1, 2n_2 + i_2).$$

In this paper, we employ $l_{max} = 3$.
Step 2: For every layer $l = 1, 2, \cdots, l_{max}$, calculate the coordinate $\boldsymbol{p}_l = (p_{l1}, p_{l2})$ corresponding to the original reference point $\boldsymbol{p}_0$ recursively as follows:

$$\boldsymbol{p}_l = \lfloor \tfrac{1}{2}\boldsymbol{p}_{l-1} \rfloor = (\lfloor \tfrac{1}{2} p_{l-1\ 1} \rfloor, \lfloor \tfrac{1}{2} p_{l-1\ 2} \rfloor), \qquad (1)$$

where $\lfloor z \rfloor$ denotes the operation to round the element of z to the nearest integer towards minus infinity.
Step 3: We assume that $\boldsymbol{q}_{l_{max}} = \boldsymbol{p}_{l_{max}}$ in the coarsest layer. Let $l = l_{max} - 1$.
Step 4: From the l-th layer images $I_l(n_1, n_2)$ and $J_l(n_1, n_2)$, extract two sub-images (or image blocks) $f_l(n_1, n_2)$ and $g_l(n_1, n_2)$ with their centers on $\boldsymbol{p}_l$ and $2\boldsymbol{q}_{l+1}$, respectively. The size of image blocks is $W \times W$ pixels. In this paper, we employ $W = 32$.
Step 5: Estimate the displacement between $f_l(n_1, n_2)$ and $g_l(n_1, n_2)$ with pixel accuracy using POC-based image matching. Let the estimated displacement vector be $\boldsymbol{\delta}_l$. The l-th layer correspondence $\boldsymbol{q}_l$ is determined as follows:

$$\boldsymbol{q}_l = 2\boldsymbol{q}_{l+1} + \boldsymbol{\delta}_l. \qquad (2)$$

Step 6: Decrement the counter by 1 as $l = l - 1$ and repeat from Step 4 to Step 6 while $l \geq 0$.
Step 7: From the original images $I_0(n_1, n_2)$ and $J_0(n_1, n_2)$, extract two image blocks with their centers on $\boldsymbol{p}_0$ and $\boldsymbol{q}_0$, respectively. Estimate the displacement between the two blocks with sub-pixel accuracy using POC-based image matching. Let the estimated displacement vector with sub-pixel accuracy be denoted by $\boldsymbol{\delta} = (\delta_1, \delta_2)$. Update the corresponding point as follows:

$$\boldsymbol{q} = \boldsymbol{q}_0 + \boldsymbol{\delta}. \qquad (3)$$

□

Our experimental evaluation shows that the displacement between corresponding points with 0.05-pixel accuracy when using 32×32-pixel matching window.

3. PALMPRINT RECOGNITION ALGORITHM

This section presents a palmprint recognition algorithm proposed in this paper. The proposed algorithm consists of 2 steps: (i) preprocessing and (ii) matching. We describe the details of each step as follows.

3.1. Preprocessing

This step is to extract a palmprint region from an input image. In order to extract the center part of a palmprint for accurate matching, we employ the method described in [5]. This method uses gaps between fingers as reference points to define the palmprint region.
Step 1: Apply the Gaussian low-pass filter to the input image (Fig. 1 (a)) and convert the smoothed image into the binary image by thresholding.
Step 2: Obtain the chain code from boundaries of the binary image using a boundary tracking algorithm and determine the landmarks based on the chain code (red circles in Fig. 1 (b)). In this paper, the landmarks are the bottom of gaps between index and middle fingers and between ring and little fingers.
Step 3: Obtain the perpendicular bisector of the line segment between two landmarks to determine the centroid of the palmprint region (× in Fig. 1 (c)).
Step 4: Extract the palmprint region of fixed size, which is centered at the centroid obtained the previous step, as shown in Fig. 1 (d) to normalize a scaling factor of the region. The upper and lower hems of the palmprint region are parallel to the perpendicular bisector of the line segment between two landmarks to normalize a rotation angle of the region. In this paper, the size of palmprint region is 128×128 pixels.

□

Finally, we obtain the palmprint regions which scaling factor and rotation angle are normalized.

3.2. Matching

This step is to evaluate the similarity between two palmprint regions extracted in Sec. 3.1 taking account of nonlinear distortion. Consider two palmprint regions, $f(n_1, n_2)$ and $g(n_1, n_2)$, as shown in Fig. 2 (a). In local blocks of palmprint regions $f(n_1, n_2)$ and $g(n_1, n_2)$, the nonlinear distortion is approximately represented by the translational displacement between local blocks. Therefore, we find corresponding points between $f(n_1, n_2)$ and $g(n_1, n_2)$ using sub-pixel correspondence matching and evaluate a similarity between local image blocks around the corresponding points.

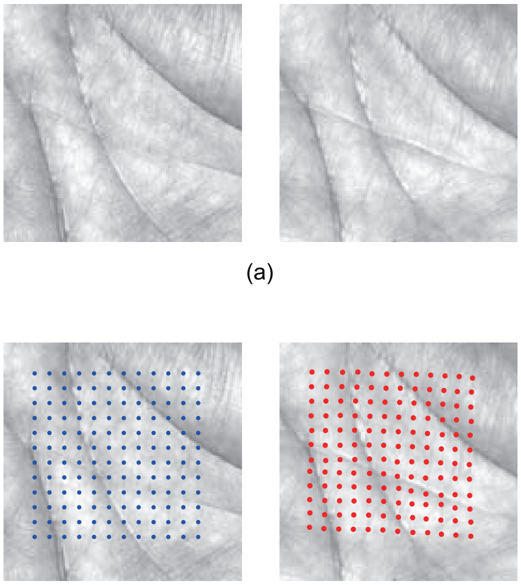

Fig. 2. Example of correspondence matching: (a) palmprint regions $f(n_1, n_2)$ and $g(n_1, n_2)$ and (b) reference points on $f(n_1, n_2)$ and their corresponding points on $g(n_1, n_2)$.

Step 1: Set the reference points on $f(n_1, n_2)$ with a spacing of 8 pixels and obtain the points on $g(n_1, n_2)$, which correspond to the reference points on $f(n_1, n_2)$, using the sub-pixel correspondence matching described in Sec. 2.2 (Fig. 2 (b)).
Step 2: Extract image blocks $f_i(n_1, n_2)$ and $g_i(n_1, n_2)$ from $f(n_1, n_2)$ which centroids are reference points and from $g(n_1, n_2)$ which centroids are corresponding points, respectively, where $i = 1, \cdots, N_{block}$ and N_{block} is the number of image blocks. Compute the BLPOC functions $r_{f_ig_i}^{K_1K_2}(n_1, n_2)$ for every pair of image blocks $f_i(n_1, n_2)$ and $g_i(n_1, n_2)$.
Step 3: Take the average of a set of the BLPOC functions $r_{f_ig_i}^{K_1K_2}(n_1, n_2)$ to improve the PNR (Peak-to-Noise Ratio) as follows [14],

$$r_{ave}(n_1, n_2) = \sum_{i=1}^{N_{block}} r_{f_ig_i}^{K_1K_2}(n_1, n_2)/N_{block}. \tag{4}$$

Figure 3 shows an example of PNR improvement through averaging. Compute the highest peak value of $r_{ave}(n_1, n_2)$ as the matching score between $f(n_1, n_2)$ and $g(n_1, n_2)$.

□

In this paper, the parameters of the BLPOC function are $K_1/M_1 = K_2/M_2 = 0.5$.

4. EXPERIMENTS AND DISCUSSION

This section describes a set of experiments using the PolyU palmprint database [9] for evaluating palmprint recognition performance of the proposed algorithm. This database consists of 600 images (384 × 284 pixels) with 100 subjects and 6 different images of each palmprint. Figure 4 shows some examples of palmprint images in this database. As shown in this figure, palmprint images in the database are captured under different lighting condition and have nonlinear distortion due to movement of a hand and fingers.

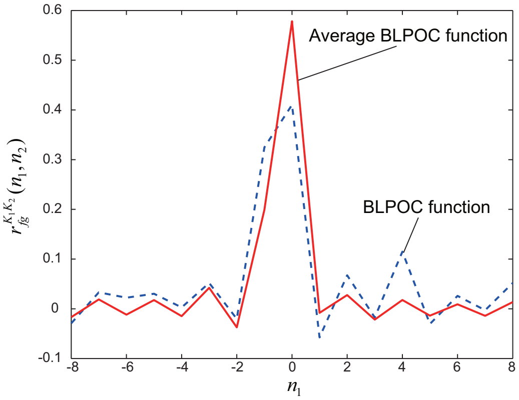

Fig. 3. Average BLPOC function.

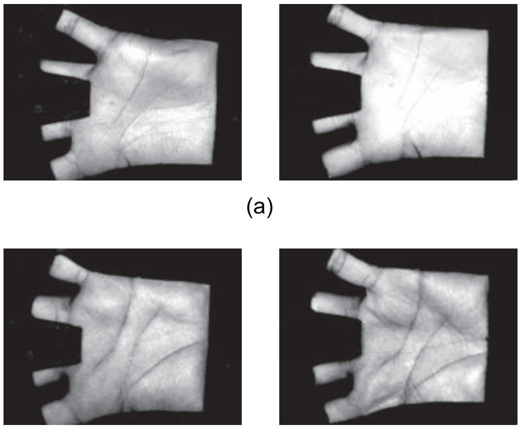

Fig. 4. Examples of palmprint images in the PolyU palmprint database: palmprint image pairs with different lighting condition (a) and nonlinear distortion (b).

The performance of the biometrics-based verification system is evaluated by the Receiver Operating Characteristic (ROC) curve, which illustrates the False Non-Match Rate (FNMR) against the False Match Rate (FMR) at different thresholds on the matching score. We first evaluate the FNMR for all the possible combinations of genuine attempts; the number of attempts is ${}_6C_2 \times 100 = 1,500$. Next, we evaluate the FMR for ${}_{100}C_2 = 4,950$ impostor attempts, where we select a single image (the first image) for each palmprint and make all the possible combinations of impostor attempts. The performance is also evaluated by the Equal Error Rate (EER), which is defined as the error rate where the FNMR and the FMR are equal.

We compare four different matching algorithms: (A) a conventional feature-based matching algorithm [5], (B) conventional POC-based matching algorithm [8], (C) the proposed algorithm without considering nonlinear distortion, and (D) the proposed algorithm. The difference between algorithms (C) and (D) is whether the sub-

Table 1. EER and computation time of each algorithm.

Algorithm	EER [%]	Computation time [sec.]
(A)	0.3919	1.2391
(B)	0.1273	0.5095
(C)	0.7939	0.4992
(D)	0.0000	0.9216

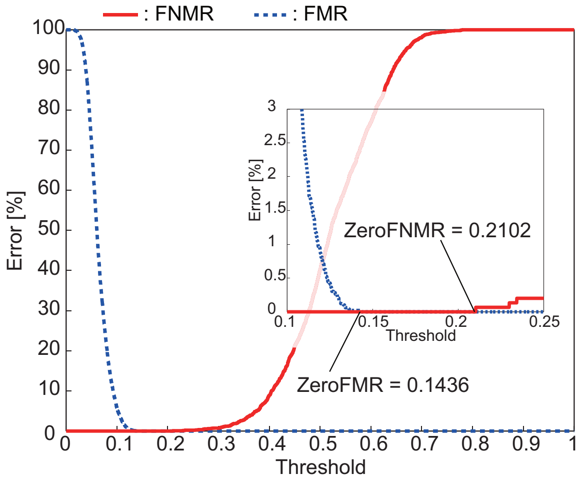

Fig. 5. FNMR and FMR of the algorithm (D)

pixel correspondence matching is employed or not. Hence, in the case of the algorithm (C), the correspondence matching is not employed and the image blocks $g_i(n_1, n_2)$ are extracted from the same location of reference points on $f(n_1, n_2)$. The matching score of the algorithm (A) is normalized and converted to similarity measure, since the matching score is a distance between features.

Table 1 summarizes EER and computation time (preprocessing and matching) of each algorithms. The computation time is evaluated by using MATLAB 7.2.0 on Pentium4 3.2 GHz. The EER of the proposed algorithm (D) is 0.00 %, which means that the score distribution shows a good separation of genuine and impostor matching scores. The computation time of (D) is comparable with that of (B) and (C) and can be drastically reduced by translating the MATLAB code to other implementation-oriented languages such as C/C++.

Figure 5 shows the FNMR and FMR of the proposed algorithm (D). The horizontal axis indicates a threshold (a matching score) to calculate the FNMR and FMR, and the vertical axis indicates the error rate. The threshold of ZeroFNMR, i.e., the minimum matching score of the genuine pairs, is 0.2102, while the threshold of ZeroFMR, i.e., the maximum matching score of the impostor pairs, is 0.1436. The threshold within 0.1436∼0.2102 can be chosen as a separation point, so that if the matching score between any two palmprint images is greater than the separation point, they are deemed to be captured from the same person. If the matching score between two palmprint image is lower than the separation point, then the two are deemed to be from the different person.

As is observed in the above experiments, the proposed algorithm is particularly useful for verifying palmprint images.

5. CONCLUSION

This paper proposed a palmprint recognition algorithm using phase-based correspondence matching. The local block matching using the Phase-Only Correlation (POC) makes it possible to recognize distorted palmprint images and improve recognition performance. In future work, we will implement the proposed algorithm on an embedded system to work toward practical use.

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