FINGER-KNUCKLE-PRINT: A NEW BIOMETRIC IDENTIFIER

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ABSTRACT

This paper presents a new biometric identifier, namely finger-knuckle-print (FKP), for personal authentication. First a specific data acquisition device is constructed to capture the FKP images, and then an efficient FKP recognition algorithm is presented to process the acquired data. The local convex direction map of the FKP image is extracted, based on which a coordinate system is defined to align the images and a region of interest (ROI) is cropped for feature extraction. A competitive coding scheme, which uses 2D Gabor filters to extract the image local orientation information, is employed to extract and represent the FKP features. When matching, the angular distance is used to measure the similarity between two competitive code maps. An FKP database was established to examine the performance of the proposed system, and the experimental results demonstrated the efficiency and effectiveness of this new biometric characteristic.

Index Terms— Biometrics, finger-knuckle-print, personal authentication

1. INTRODUCTION

Personal authentication is a common concern to both industries and academic research due to its numerous applications. Biometrics can be used to distinguish between individuals based on their inherent physical and behavioral characteristics and hence can serve as an ideal solution to this problem. In the past three decades, many biometric characteristics have been investigated, including fingerprint, face, iris, retina, palm-print, hand geometry, voice, gait and signature, etc [1].

Recently, it has been noticed that the textures in the outer finger surface has the potential to do personal authentication. Woodward et al. [2] used the 3D range image of the hand to calculate the curvature surface representation of the index, middle, and ring fingers for similarity comparison. In [3], Ravikanth et al. applied the subspace analysis methods to the finger-back surface images for feature extraction and person classification. The above works made a good effort to validate the uniqueness of biometric features in the outer finger surface; however, they did not provide a practical solution to establishing an

efficient system using the outer finger surface features. In addition, the method [2] mainly exploits the 3D shape information of finger back surface but does not fully use the texture information; while the subspace analysis methods used in [3] may not be able to effectively extract the distinctive line and junction features in finger back surface.

In palmprint recognition [4-6], the features used for matching are the principal lines and wrinkles. Actually, the outer surfaces of finger joints have even more obvious line features than the palm surface, while they have much smaller area than the palm surface. This motivates us to propose a new biometric technique — the finger-knuckle-print (FKP), which refers to the image of the outer surface of the finger phalangeal joint. In this paper, an FKP recognition system, including the specifically designed FKP data acquisition device and the FKP feature extraction and pattern matching algorithms, will be developed. The experimental results demonstrate that the proposed FKP authentication system can verify the personal identity in real time with a high recognition rate.

In the rest of this paper, Section 2 introduces the device used to capture the FKP images. Section 3 describes the ROI extraction algorithm. Section 4 describes the Gabor filter based competitive coding scheme and the angular matching of FKP images. Section 5 reports the experimental results. Finally, conclusions are presented in Section 6.

2. THE FKP RECOGNITION SYSTEM DESIGN

The proposed FKP recognition system is composed of an FKP image acquisition device and a data processing module. The device (referring to Fig. 1) is composed of a finger bracket, a ring LED light source, a lens, a CCD camera and a frame grabber. The captured FKP image is inputted to the data processing module, which comprises three basic steps: ROI (region of interest) extraction, feature extraction and coding, and feature matching. Refer to Fig. 1, a basal block and a triangular block are used to fix the position of the finger joint. Fig. 2-a and 2-d show two sample images acquired by the developed device.

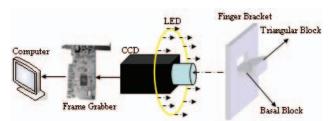


Fig. 1: FKP image acquisition device.

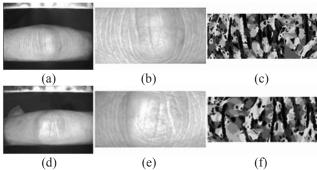


Fig. 2: (a) and (d) are two FKP images; (b) and (e) are the ROI images of (a) and (d); (c) and (f) are the competitive code maps generated from (b) and (e) respectively.

3. ROI EXTRACTION

It is necessary to construct a local coordinate system for each FKP image. With such a coordinate system, an ROI can be cropped from the original image for reliable feature extraction and matching. The detailed steps for setting up such a coordinate system are as follows.

Step 1: determine the *X*-axis of the coordinate system. The bottom boundary of the finger can be easily extracted by a Canny edge detector. Actually, this bottom boundary is nearly consistent to all FKP images because all the fingers are put flatly on the basal block in data acquisition. By fitting this boundary as a straight line, the *X*-axis of the local coordinate system is determined.

Step 2: crop a sub-image I_S . The left and right boundaries of I_S are two fixed values evaluated empirically. The top and bottom boundaries are estimated according to the boundary of real fingers and they can be obtained by a Canny edge detector.

<u>Step 3:</u> Canny edge detection. Apply a Canny edge detection to I_S to obtain the edge map I_E .

Step 4: convex direction coding for I_E . We define an ideal model for FKP "curves". In this model, an FKP "curve" is either convex leftward or convex rightward. We code the pixels on convex leftward curves as "1", pixels on convex rightward curves as "-1", and the other pixels not on any curves as "0".

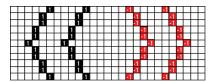


Fig. 3: Illustration for convex direction coding scheme.

Fig. 3 illustrates this convex direction coding scheme and the pseudo codes are presented as follows:

Convex_Direction_Coding (
$$I_E$$
)

Input: I_E Output: I_{CD} (convex direction code map)

 $y_{mid} = \frac{height \ of \ I_E}{2}$;

for each $I_E(i,j)$:

if $I_E(i,j) = 0$
 $I_{CD}(i,j) = 0$;

else if $I_E(i+1,j-1) = 1 \ and \ I_E(i+1,j+1) = 1$
 $I_{CD}(i,j) = 0$;

else if $(I_E(i+1,j-1) = 1 \ and \ i <= y_{mid}) \ or$
 $(I_E(i+1,j+1) = 1 \ and \ i > y_{mid})$
 $I_{CD}(i,j) = 1$;

else if $(I_E(i+1,j+1) = 1 \ and \ i > y_{mid})$
 $I_{CD}(i,j) = -1$;

end if

Step 5: determine the Y-axis of the coordinate system. For an FKP image, "curves" on the left part of phalangeal joint are mostly convex leftward and those on the right part are mostly convex rightward. Meanwhile, "curves" in a small area around the phalangeal joint do not have obvious convex directions. Based on this observation, at a horizontal position x (x represents the column) of an FKP image, we define the "convexity magnitude" as:

$$conMag(x) = abs\left(\sum_{W} I_{CD}\right)$$
 (1)

where W is a window being symmetrical about the axis X = x. W is of the size $d \times h$, where h is the height of I_s . The characteristic of the FKP image suggests that conMag(x) will reach a minimum around the center of the phalangeal joint and this position can be used to set the Y-axis of the coordinate system. Let

$$x'_0 = \arg\min(conMag(x))$$
 (2)

Then $X = x_0'$ is set as the *Y*-axis.

Step 6: crop the ROI image. Now that we have fixed the X-axis and Y-axis, the local coordinate system can then be determined and the ROI sub-image I_{ROI} can be extracted with a fixed size. Fig. 2-b and 2-e show two examples of the extracted ROI images.

4. FKP RECOGNITION

4.1. Feature extraction and coding

The Gabor filter can simultaneously capture spatial and frequency uncertainty information [7]. Since 1980s, it has been widely used as a convolution filter to fulfill the feature extraction job. Recently, Kong [8] evaluated the three basic features—magnitude, phase, and orientation—produced by the Gabor filter for face recognition and concludes that the orientation feature is the most robust and distinctive feature. Therefore, in this paper we employ the Gabor filter based competitive coding scheme [5] to extract orientation information from FKP images for recognition.

The Gabor function has several slightly different forms in the literature and we adopt the one proposed by Lee [9]:

$$G(x, y, \omega, \theta) = \frac{\omega}{\sqrt{2\pi\kappa}} e^{-\frac{\omega^2}{8\kappa^2}(4x'^2 + y'^2)} \left(e^{i\omega x'} - e^{-\frac{\kappa^2}{2}} \right)$$
(3)

where $x = (x - x_0)\cos\theta + (y - y_0)\sin\theta$, $y = -(x - x_0)\sin\theta + (y - y_0)\cos\theta$, (x_0, y_0) is the center of the function, ω is the radial frequency in radians per unit length and θ is the orientation of the Gabor functions in radians. The κ is defined by

$$\kappa = \sqrt{2 \ln 2} \left(\frac{2^{\delta} + 1}{2^{\delta} - 1} \right)$$
, where δ is the half-amplitude bandwidth

of the frequency response. ω can be determined by $\omega = \kappa/\sigma$, where σ is the standard deviation of the Gaussian envelop.

At each pixel $I_{ROI}(x, y)$, we extract the orientation information and represent it as a "competitive code"[5]. With a bank of Gabor filters sharing the same parameters, except the parameter of orientation, the orientation feature can be extracted. We only use the real part of the Gabor filter to perform this job. Mathematically, this competitive coding process can be represented as:

$$compCode(x,y) = \arg\max_{j} \left\{ abs \left(I_{ROI}(x,y) * G_{R}(x,y,\theta_{j}) \right) \right\}$$
 (4)

where symbol * represents the convolution operation, G_R represents the real part of the Gabor function G, and $\theta_j = j\pi/J$, $j = \{0,...,J-1\}$. J represents the number of different orientations. In this paper, we set J as 6 and consequently each competitive code is an integer within $0{\sim}5$. Fig. 2-c and 2-f show two examples for the competitive code maps.

4.2. FKP feature matching

Given two competitive code maps of two FKP images, a matching algorithm determines the degree of similarity between them. In this paper, the angular distance [5] is employed to fulfill this task. Let P and Q be the two feature matrices (competitive codes), and P_M and Q_M be the corresponding masks used for indicating the overlapping

areas when one of the features is translated. The angular distance D(P,Q) is defined by the following equation:

$$D(P,Q) = \frac{\sum_{y=1}^{Rows} \sum_{x=1}^{Cols} (P_M(x,y) \cap Q_M(x,y)) \times G(P(x,y), Q(x,y))}{3 \sum_{y=1}^{Rows} \sum_{x=1}^{Cols} P_M(x,y) \cap Q_M(x,y)}$$
(5)

where \cap denotes the AND logic operator and G(P(x, y), Q(x, y)) =

$$\begin{cases} \min(P(x,y) - Q(x,y), Q(x,y) - P(x,y) + 6), \ P(x,y) \ge Q(x,y) \\ \min(Q(x,y) - P(x,y), P(x,y) - Q(x,y) + 6), \ P(x,y) < Q(x,y) \end{cases}$$
 (6)

Obviously D is between 0 and 1. Taking into account the possible translations in the extracted sub-image, multiple matches are performed by translating one set of features in horizontal and vertical directions. The minimum of the resulting matching distances is considered to be the final distance.

5. EXPERIMENTAL RESULTS

5.1. Database establishment

In order to evaluate the proposed FKP recognition techniques, an FKP database was established. The FKP images were collected from 120 volunteers, including 85 males and 35 females. Among them, 101 subjects are 20~30 years old and the others are 30~50 years old. We collected the images in two separate sessions. In each session, the subject was asked to provide 6 images for each of the left index finger, the left middle finger, the right index finger and the right middle finger. Therefore, 48 images from 4 fingers were collected from each subject. In total, the database contains 5,760 images from 480 different fingers. The average time interval between the first and second sessions was about 25 days. The maximum and minimum time intervals were 76 days and 14 days respectively.

5.2. FKP verification

In this verification experiment, each one of the 5,760 FKP images was matched with all the other FKP images in the database. A match is counted as correct (genuine) if the two FKP images are from the same finger; otherwise, the match is counted as incorrect (imposter). Thus, we got 16,585,920 matches in total, of which 31,680 were correct matches. The distributions for genuine and imposter are calculated by the correct and incorrect matches and they are shown in Fig. 4-a. We can see that the genuine and imposter curves have little overlap, which indicates that inter-class FKPs and intra-class FKPs have good separability. The equal error rate (EER) is 1.09%, which is competitive with other hand-based biometric technologies, such as [2-5, 10-11]. Fig. 4-b depicts the corresponding Receiver Operating Characteristic (ROC) curve as a plot of the genuine acceptance rate against

the false acceptance rate for all the possible operating points. Table 1 lists 4 typical operating states obtained. We can see that our system can operate at a GAR of 97% and an FAR of 0.02%.

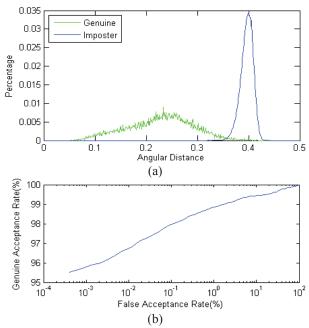


Fig. 4: (a) Distributions of genuine and imposter angular distances. (b) The ROC curve.

Table 1. Typical operating states		
threshold	FAR (%)	GAR (%)
0.350	0.10	97.96
0.348	0.06	97.74
0.341	0.02	96.97
0.340	0.01	96.83

5.3. Real time implementation

The software is implemented using Visual C#.Net 2005 on a Dell Inspiron 530s PC embedded Intel E6550 processor. The execution time for ROI extraction and competitive coding is about 950ms. The time for one angular matching is about 1.8ms. Thus, the total execution time for one verification operation is about 1s in our prototype system.

6. CONCLUSIONS

This paper proposed to use 2D FKP as a new biometric identifier for personal authentication. A cost-effective FKP system, including the image acquisition device and the associated FKP image processing algorithms, was developed. To evaluate the performance of the proposed

system, an FKP database was established, consisting of 5,760 images from 480 different fingers. The FKP verification experiment was performed and an encouraging genuine acceptance rate (97%) and a low false acceptance rate (0.02%) can be reached. The EER is 1.09%, which is very competitive with other hand-based biometric technologies. Meanwhile, the proposed FKP technique has advantages such as user friendliness, no remains, moderate size, cost-effectiveness, etc. It has a great potential to be future improved and employed in real applications.

ACKNOWLEDGEMENT

The work is supported by the Edward Sai Kim Hotung Fund (5-ZH52), the HK-PolyU Internal Competitive Research Grant (G-YH54), and the Hong Kong RGC General Research Fund (PolyU 5351/08E).

7. REFERENCES

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