Competitive Coding Scheme for Palmprint Verification

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Abstract

There is increasing interest in the development of reliable, rapid and non-intrusive security control systems. Among the many approaches, biometrics such as palmprints provide highly effective automatic mechanisms for use in personal identification. This paper presents a new method for extracting features from palmprints using the Competitive Coding Scheme and angular matching. The Competitive Coding Scheme uses multiple 2-D Gabor filters to extract orientation information from palm lines. This information is then stored in a feature vector called the Competitive Code. The angular matching with an effective implementation is then defined for comparing the proposed codes, which can make over 9,000 comparisons within 1s. In our testing database of 7,752 palmprint samples from 386 palms, we can achieve a high genuine acceptance rate of 98.4% and a low false acceptance rate of 3×10^{-6}*%. The execution time for the whole process of verification, including preprocessing, feature extraction and final matching, is 1s.*

1. Introduction

Biometric personal identification is emerging as a powerful means for automatically recognizing identities. It concerns with identifying people by their physiological characteristics such as iris pattern, retina, palmprint, fingerprint, hand geometry and face or some behavioral aspects such as voice, signature and gesture [1]. Automatic fingerprint personal identification has drawn considerable attention over the past 25 years. Recently, voice, face and iris verification/identification have been studied extensively. Consequently, many biometric systems have been developed successfully for various applications, including airport security control, ATM (automatic teller machine) and access control [1]. Nevertheless, compared with other biometric technologies, palmprint research is just in its infancy. Few papers have so far been published in this area [2-6].

A palmprint image contains various features, including principal lines, wrinkles, ridges, minutiae points, singular points and texture. Lines and texture are the most clearly observable features in low-resolution palmprint images (such as 100 dpi). Lines are more appealing than texture for the human vision. When human beings compare two palmprint images, they instinctively compare line features. This action motivates us to develop a coding scheme for the palm lines.

A line contains various information, including 1) type, 2) width, 3) position, 4) magnitude and 5) orientation. There are two types of lines: positive and negative [8]. All the lines in our palmprint images are of the negative lines category. Palm lines do have a certain width. Generally, principal lines are wider than wrinkles but this information was not regarded as a useful feature in the previous palmprint research. On top of types and width, line position is often considered as an important feature, especially for line-based approaches [2]. Magnitude of the lines has also been investigated in a previous palmprint research [5]. It is worthwhile to note that no previous palmprint research has investigated the orientation information of the palm lines for palmprint identification/verification. This paper is the first attempt to fully utilize this information for palmprint verification.

In the paper, we only consider feature extraction and matching. The detailed information about palmprint capture and preprocessing can be referred [6]. The rest of this paper is organized in the following sections. Section 2 highlights the design, properties and implementation of the proposed coding scheme. Section 3 describes the angular matching for comparing the codes and its effective implementation. Section 4 reports experimental results. Section 5 summarizes the main results of this paper and offers concluding remarks.

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2. Coding scheme design

2.1. Neurophysiology-based Gabor function

Some tunable filters are appropriate for capturing the orientation information from palm lines. Gabor filters are a good choice. Based on the neurophysiological evidence from the visual cortex of mammalian brains and wavelet theory, Lee reformed the Gabor functions as the following form [9]:

$$\psi(x,y,\omega,\theta)=\frac{\omega}{\sqrt{2\pi}\kappa}e^{-\frac{\omega^2}{8\kappa^2}(4x'^2+y'^2)}\left(e^{i\omega x'}-e^{-\frac{\kappa^2}{2}}\right) \qquad (1)$$

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, which, according to neurophysiological findings, is between 1 and 1.5 octaves [9]. When σ and δ are fixed, ω can be derived from $\omega=\kappa/\sigma$. These neurophysiology-based Gabor functions are the same as the general Gabor functions but the choices of parameters are limited by neurophysiological findings and the DC (direct current) of the functions are removed. These Gabor functions will be used to extract orientation information from palm lines.

2.2. Competitive rule: winner-take-all

To design an explainable competitive rule for extracting orientation information from palm lines, we have to construct an idea palm line model, whose profile has an upside-down Gaussian shape. It is given by:

$$L(x,y)=A\left[1-\exp\left(-\frac{((x-x_p)\cos\theta_L+(y-y_p)\sin\theta_L)^2}{2\sigma_L^2}\right)\right]+C \qquad (2)$$

where σ_L, the standard deviation of the profile, can be considered as the width of the line; (x_p, y_p) is the center of the line; A, a positive real number, controls the magnitude of the line, which depends on the contrast of the capture device; C is the brightness of the line, which replies on brightness of the capture device and the lighting of the capture environment and θ_L is the orientation of the line. Without loss of generality, we set $x_p=0$ and $y_p=0$ for the following analysis.

To extract the orientation information from the palm lines, we apply the real part of the neurophysiology-based Gabor filters to the idea palm line model. The filter response on the middle of the line, $x\cos\theta_L+y\sin\theta_L=0$, is:

$$R(x,y,\phi,\omega,\kappa,\sigma_L)=-\frac{A\sqrt{8\pi}\kappa\sigma_L}{\sqrt{\omega^2\sigma_L^2+\kappa^2(1+3\sin^2\phi)}}\left\{e^{\frac{-\kappa^2}{2}g}-e^{-\frac{\kappa^2}{2}}\right\} \qquad (3)$$

where $\varnothing=\theta-\theta_L$ and $g=\left(1-\frac{\kappa^2\cos^2\phi}{\omega^2\sigma_L^2+\kappa^2(1+3\sin^2\phi)}\right)$.

According to Eq. 3, we can obtain the following properties.

Property 1: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)$ reaches minimum when $\varnothing=0$

Property 2: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)$ is an increasing function with respect to $\varnothing$ when $0<\varnothing<\pi/2$.

Property 3: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)$ is a symmetry function with respect to $\varnothing$.

Property 4: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)$ is proportional to A, the magnitude of the line.

Property 5: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)$ is independent of C, the brightness of the line.

Property 6: $R(x,y,\varnothing,\omega,\kappa,\sigma_L)=0$ when the orientation the filter is perpendicular to the orientation of the line.

The brightness of the line, C, is removed by the zero DC Gabor filters. However, according to Property 4, the response is sensitive to the contrast of the capture devices. Our goal is to design feature codes, which are completely independent of the contrast and the brightness of the capture devices. The feature codes holding these two properties are more robust to different capturing environments and devices. Thus, we do not directly use the response. Based on the six properties, we can design a competitive rule to extract the orientation information on a palm line. Our competitive rule is a Winner-take-all rule defined as: **arg** $\mathbf{\min_j(I(x,y)*\psi_R(x,y,\omega,\theta_j))}$ where I is a preprocessed image; ψ_R *represents the real part of* ψ; θ_j is the orientation of the filters and $j=\{0,\ldots,J\}$. According to the neurophysiological findings, the simple cells are sensitive to specific orientations with approximate bandwidths of $\pi/6$ [9]. Thus, we choose six orientations, $\theta_j=j\pi/6$, where $j=\{0, 1,\ldots,5\}$ for the competition.

If we only extract the orientation information on the palm lines, we have to face two problems:

1) How do we classify a point that belongs to a palm line?

2) Even though we can have a good technique to classify the points on the palm lines, to design a real-time classifier for the feature points for identifying a palm in a large database is difficult - the number of the extracted feature points may be different, even for two palmprint images belonging to the same palm.

To avoid these two problems and to achieve our goal — real-time palmprint verification – we assume that each point on the palmprint belongs to a palm line. Thus, we apply our competitive rule to code each sample point to obtain feature vectors with the same dimension. The proposed feature is named as *Competitive Code*. An example of Competitive Code is illustrated in Fig. 1. The codes of 0-5 are shown in Figs. 1(c)-(h), respectively. Carefully comparing Fig. 1(a) and Fig. 1(b) (a combination of Figs. 1(c)-(h)), we can observe that the Competitive Code is highly related to the line features, especially for the strong lines, such as the principal lines.

3. Angular matching

To implement a real-time palmprint identification system requires a simple and powerful palmprint matching algorithm. Since the proposed Competitive Code stores the orientation information, we design an angular distance for comparing two codes. Let P and Q be two Competitive Codes and P_M and Q_M be the corresponding masks of P and Q, respectively. The masks are used to indicate the non-palmprint pixels described in [6]. The angular distance is defined as:

$$D(P,Q)=\frac{\sum_{y=0}^{N}\sum_{x=0}^{N}(P_M(x,y)\cap Q_M(x,y))\times G(P(x,y),Q(x,y))}{3\sum_{y=0}^{N}\sum_{x=0}^{N}P_M(x,y)\cap Q_M(x,y)} \tag{4}$$

where

$$G(P(x,y),Q(x,y))=\begin{cases}\min(P(x,y)-Q(x,y),Q(x,y)-(P(x,y)-6))\ if\ P(x,y\geq Q(x,y)\\ \min(Q(x,y)-P(x,y),P(x,y)-(Q(x,y)-6))\ if\ Q(x,y)>P(x,y)\end{cases} \tag{5}$$

and $\cap$ represents an AND operator and the size of the feature matrixes is $N\times N$. Obviously, D is between 0 and 1. For perfect matching, the angular distance is zero. Because of imperfect preprocessing, we need to translate one of the features vertically and horizontally and then perform the matching again. Both the ranges of the vertical and the horizontal translation are –2 to 2. The minimum of the D's obtained by translated matching is regarded as the final angular distance.

However, we find that directly implementing Eqs. 4-5 is ineffective. The elements of Competitive Code are 0, 1, 2, 3, 4 and 5. We can use three bits to represent an element and one bit for the mask. In total, a Competitive Code is constituted by four bit-planes. The bit values among different elements of Competitive Code are shown in Table 1. According to this bit representation of the Competitive Code, a more effective implementation of angular distance can be defined as:

$$D(P,Q)=\frac{\sum_{y=0}^{N}\sum_{x=0}^{N}\sum_{i=0}^{3}(P_M(x,y)\cap Q_M(x,y))\cap(P_i^b(x,y)\otimes Q_i^b(x,y))}{3\sum_{y=0}^{N}\sum_{x=0}^{N}P_M(x,y)\cap Q_M(x,y)} \tag{6}$$

where $P_i^b\left(Q_i^b\right)$ is the i^{th} bit plane of $P(Q)$ and $\otimes$ is bitwise exclusive OR.

Using ASUS notebook embedded Intel Pentium III Mobile processor (933MHz), directly implementing Eqs. 4-5 requires 2.27ms for one matching but Eq. 6 only needs 0.11ms for one matching. This bit representation is not only effective for matching but also effective for storage. In total, three bits are enough to keep the mask and one element of the Competitive Code. If a non-palmprint pixel exits at position *(x,y)*, the corresponding three bits are set to 1, 0 and 1. As a result, the total size of the proposed feature, including the mask and the Competitive Code is 384 bytes.

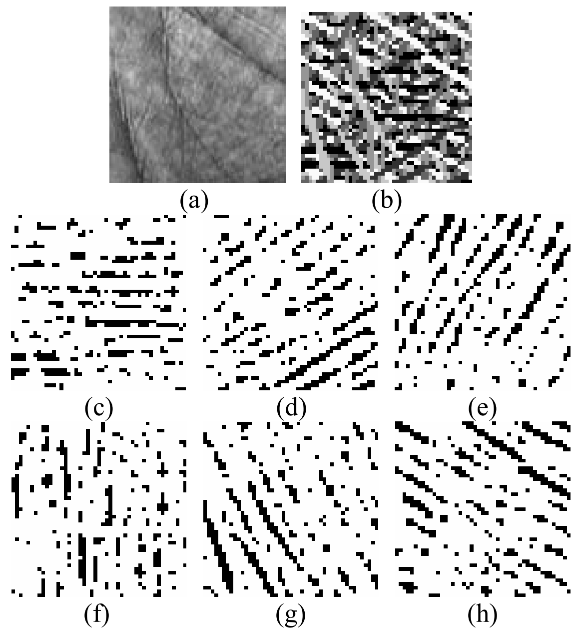

Figure 1. An example of Competitive Code. (a) Preprocessed image. (b) Competitive code. (c)-(h) are the winning Code 0, 1, 2, 3, 4 and 5, respectively.

Table 1. Bit representation of the Competitive Code

Original values	Bit 1	Bit 2	Bit 3
0	0	0	0
1	0	0	1
2	0	1	1
3	1	1	1
4	1	1	0
5	1	0	0

4. Experimental results

We collected palmprint images from 193 individuals using our palmprint scanner. The subjects are mainly students and staff volunteers from The Hong Kong Polytechnic University. In the dataset, 131 people are male, and the age distribution of the subjects is: about 86% are younger than 30, about 3% are older than 50, and about 11% are aged between 30 and 50. We collected the palmprint images in two occasions. Each time, the subjects were asked to provide around 10 images from the left palm and 10 images from the right palm. Altogether, each person provided around 40 images, resulting in a total of 7,752 images from 386 different palms in our database. The average time interval between the first and the second collection is 69 days. The maximum and the minimum time intervals are 162 and 4 days, respectively.

4.1 Verification

To obtain the verification accuracy of our method, each palmprint image is matched with all the other palmprint images in the database. A match is counted as correct if the two palmprint images are from the same palm; otherwise, the match is counted as incorrect. The total number of matches is 30,042,876. None of the angular distances is zero. The number of comparisons that match correctly is 74,068. The rest are incorrect. Fig. 2 depicts the corresponding Receiver Operating Characteristic (ROC) curve as a plot of the genuine acceptance rate against the false acceptance rate for all possible operating points. In Fig. 2 we can see that the proposed method can operate at genuine acceptance rate of 98.4% while the corresponding false acceptance rate is 3×10^{-6}%. In Fig. 2, the other ROC curve is obtained by our previously best method, PalmCode [6]. Comparing these two ROC curves, we ensure that the proposed Competitive Code is much better than PalmCode. The genuine acceptance rate of Competitive Code is about 13.5% higher than that of PalmCode while their false acceptance rates are 3×10^{-6}%. The verification results of Competitive Code are comparable with the previous palmprint approaches and other hand-based biometric technologies, including hand geometry and fingerprint verification [2-7, 10].

5. Conclusions

We have presented a novel feature extraction method, the Competitive Coding Scheme for palmprint identification. This scheme extracts the orientation information from the palm lines and stores it in the Competitive Code. An angular match with an effective implementation is developed for comparing Competitive Codes. Using an ASUS notebook embedded Intel Pentium III Mobile processor (933MHz) and the bit representation of the Competitive Code, angular matching can make over 9,000 comparisons in about 1s. Total execution time for verification is about 1s, which is fast enough for real-time applications. The proposed coding scheme has been evaluated using a database with 7,752 palmprint images from 386 different palms. For verification, the proposed method can operate at a high genuine acceptance rate of 98.4% and a low false acceptance rate of 3×10^{-6}%. In the experiments, we have compared the Competitive Code with the PalmCode, which is our previously best approach [6]. It is no doubt that Competitive Code is more accurate than PalmCode.

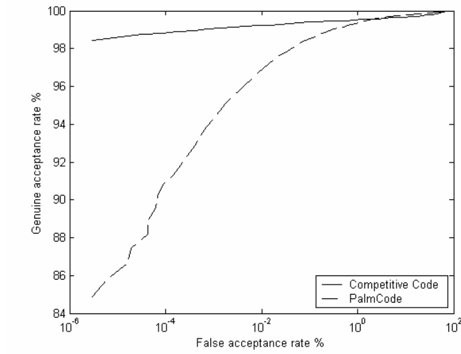

Figure 2 The receiver operator characteristic (ROC) curves of the Competitive Code and the PalmCode.

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