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Palmprint identification using feature-level fusion

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Abstract

In this paper, we propose a feature-level fusion approach for improving the efficiency of palmprint identification. Multiple elliptical Gabor filters with different orientations are employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code. The similarity of two Fusion Codes is measured by their normalized hamming distance. A dynamic threshold is used for the final decisions. A database containing 9599 palmprint images from 488 different palms is used to validate the performance of the proposed method. Comparing our previous non-fusion approach and the proposed method, improvement in verification and identification are ensured.

Keywords: Palmprint; Biometrics; Fusion; Security; Zero-crossing

1. Introduction

Biometric personal identification/verification has long been a widely studied topic. Various technologies have been proposed and implemented, including iris, fingerprint, hand geometry, voice, face, signature and retina identification/verification [1] technologies. Each of these has its own strengths and weaknesses. Currently, hand-based biometric technologies such as fingerprint verification and hand geometry verification most appeal to the biometric identification market, with the International Biometric Group reporting that hand-based biometrics constitute 60% of the total market share as of 2001.

Automatic fingerprint verification is the most mature biometric technology, having been studied for more than 25 years. Currently, fingerprint authentication handles clear fingerprints very well but, because of skin problems or the nature of their work, around 2% of the population are unable to provide clear fingerprint images [2]. Consequently, many researchers continue to develop new scanning technologies, preprocessing algorithms, feature representations, post-processing approaches, and classifiers to resolve problems arising from unclear fingerprint images.

Another popular, hand-based biometric technology is hand geometry [3]. Hand geometry uses geometric information from our hands for personal verification. Simple hand features, however, provide limited information, with the result that hand geometry is not highly accurate. To overcome problems in the hand-based biometric technologies, Zhang and Shu [4] proposed another hand-based biometric for use in personal identification/verification, the palmprint. The palmprint, the large inner surface of a hand, contains many line features such as principal lines, wrinkles, and ridges. Because of the large surface and the abundance of line features, we expect palmprints to be robust to noise and to be highly individual.

1.1. Previous work

Palmprint is a relatively new biometric technology. Previous researchers were mostly interested in inked palmprint images, in which lines and points were considered as useful features for representing palmprints [4,5]. Recently, more researchers have been working on inkless palmprint images

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captured using a special palmprint scanner or a general digital scanner [6–8].

Biometric Research Centre at The Hong Kong Polytechnic University has developed a special palmprint scanner for acquiring high-quality palmprint images. The details of this palmprint scanner have been described in Ref. [7]. In addition to capture device, our group has also implemented various line-, texture-, and component-based approaches [7,9,10]. A promising result was obtained from a texture-based approach called PalmCode, reported in Ref. [7]. This approach exploited zero-crossing information on a palmprint image.

1.2. Motivation

As the proposed method has been developed with reference to PalmCode, we begin with a short review of the concept, in which

1. an adjusted circular Gabor filter is applied to the preprocessed palmprint images,
2. the signs of the filtered images are coded as a feature vector, and
3. two PalmCodes are measured using the normalized hamming distance.

Detailed implementations of PalmCode and the preprocessed palmprint image are discussed in Ref. [7]. Figs. 1(d)–(i) show three PalmCodes derived from the three different palms in Figs. 1(a)–(c). We can observe that the PalmCodes from the different palms are similar, having many 45° streaks. Intuitively, we might conclude that such structural similarities in the PalmCodes of different palms would reduce the individuality of PalmCodes and the performance of the palmprint identification system.

To reduce the correlation between PalmCodes, in this paper, we develop a fusion rule to select one of elliptical Gabor filters for coding the phase information. To further enhance the performance of the system, we replace the fixed threshold used in PalmCode by a dynamic threshold for the final decisions.

1.3. System overview

Our palmprint identification system consists of two parts: a palmprint scanner for on-line palmprint image acquisition and an algorithm for real-time palmprint identification. The system structure is illustrated in Fig. 2. The four main steps in our system are as follows:

(1) Transmit a palmprint image to a computer from our palmprint scanner.
(2) Determine the two key points between the fingers and extract the central parts based on the coordinate system established by the key points. As a result, different palmprint images are aligned.
(3) Convolute the central parts using a number of Gabor filters. Merge the filter outputs, then code the phases as a feature vector called Fusion Code.
(4) Use the normalized hamming distance to measure the similarity of two Fusion Codes and use a dynamic threshold for the final decision.

In this paper, we employ our previous preprocessing algorithm to segment the central parts of palmprints [7]. The proposed method will directly operate on the central parts of palmprints.

This paper is organized as follows. Section 2 presents the step-by-step implementation of Fusion Codes. Section 3 presents the bitwise hamming distance for matching two Fusion Codes and the dynamic threshold for final decision. Section 4 provides a series of experimental results including, verification, identification and computation time. Section 5 discusses the assumption for the development of the dynamic threshold. Section 6 offers our concluding remarks.

2. Implementation of Fusion Code

2.1. Filtering

First, the preprocessed palmprint image is passed to a Gabor filter bank. The filter bank contains a number of Gabor filters, which have the following general formula:

$$G(x, y, \theta, u, \sigma, \beta) = \frac{1}{2\pi\sigma\beta} \exp\left\{-\pi\left(\frac{x'^2}{\sigma^2} + \frac{y'^2}{\beta^2}\right)\right\} \exp(2iux'), \tag{1}$$

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, u is the radial frequency in radians per unit length and θ is the orientation of the Gabor function in radians. σ and β are the standard deviations of the elliptical Gaussian along x and y axes, respectively. As in the implementation of PalmCode, the Gabor filters are adjusted to zero DC (direct current). The parameter θ in the Gabor filters is $j\pi/v$, where $j = 0, 1, \ldots, v-1$ and v is the total number of Gabor filters in the bank. The other parameters are optimized for d' index defined as $d' = |\mu_1 - \mu_2|/\sqrt{(\sigma_1^2 + \sigma_2^2)/2}$, where μ_1 and μ_2 are the means of genuine and impostor distributions, respectively, and σ_1 and σ_2 are their standard deviations. For convenience, we use G_j, to represent the Gabor filters.

2.2. Fusion rule design and feature coding

The filtered images contain two kinds of information: magnitude M_j and phase P_j, which are defined as

$$M_j(x, y) = \sqrt{G_j * I(x, y) \times \overline{G_j * I(x, y)}} \tag{2}$$