Pattern Recognition 61 (2017) 29–46

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/pr

Palmprint recognition with Local Micro-structure Tetra Pattern

Gen Li, Jaihie Kim*

School of Electrical and Electronic Engineering, Yonsei University, Seoul 03722, Republic of Korea

ARTICLE INFO

Article history:
Received 8 January 2016
Received in revised form
28 April 2016
Accepted 28 June 2016
Available online 30 June 2016

Keywords:
Biometrics
Feature extraction
Local descriptor
Palmprint recognition
Subspace learning
Local Tetra Pattern

ABSTRACT

Human palmprint-based biometric solutions have been studied extensively in both controlled and uncontrolled environments. However, the majority of existing methods do not reliably handle variations of translation, rotation, and blurriness of one's palm within the range of acceptable tolerance, which largely degrades the performance. Therefore, this paper presents a unique local descriptor called Local Micro-structure Tetra Pattern (LMTrP) and its application to palmprint recognition. The proposed descriptor takes advantage of local descriptors' direction as well as thickness. In this paper, the palmprint image is first filtered with the line-shaped filter to effectively eliminate unnecessary features. Then, local region histograms of LMTrP are extracted and concatenated into one feature vector to represent the given image. Finally, the kernel linear discriminant analysis is applied on the feature vector for dimension reduction. The experimental results indicate that the proposed methods significantly outperform the state-of-the-art methods without the need to align the palmprint images.

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1. Introduction

Currently, human palmprint-based personal authentication has drawn more and more attention in the biometric information field [1]. Unquestionably, the human palmprint is extracted on the inner surface of the skin between the wrist and fingers of one's hand and contains structurally distinctive features, such as principal lines, wrinkles, creases, ridges, minutiae points and texture patterns [2]. Generally, these features potentially possess discriminative traits and are relatively suitable for identifying an individual from others. Even though monozygotic twins have the same genetic information, their palmprint patterns are distinguishable [3]. Furthermore, compared with other traditional biometric modalities (e.g. face, iris, fingerprint etc.), human palmprint also has the prominent advantage of low computational cost, high accuracy and user-friendliness.

Numerous studies of palmprint recognition have been extensively reported in biometric literature. Comprehensive literature surveys on the recent development are found in [4–6]. The existing approaches broadly fall into three main categories: holistic, structural and hybrid based. The holistic or global feature approach uses each whole palmprint image as a feature set in conjunction with some popular statistical techniques such as Principal Component Analysis (PCA) [7], Linear Discriminant Analysis (LDA) [8], Independent Component Analysis (ICA) [9,10], and Kernel Fisher Discriminant Analysis (KFDA) [11]. In addition, the well-known 2D matrices-based subspace analysis is also used in palmprint feature representation including 2D PCA, 2D LDA [12], 2D PCA+PCA [13], and 2D locality preserving projecting (2D LPP) [14]. Furthermore, in order to enhance the discriminative capability, the Fourier Transform [15,16], Discrete Cosine Transform (DCT) [17], Wavelet Transform [18], and Gabor Transform [19,20] were performed along with aforementioned statistical techniques on the palmprint images to extract palm features. However, these approaches require well-aligned palmprint images, and are very sensitive to illumination, distortion, translation, and rotation variances.

In contrast, the structural or local feature approaches used stable palmprint features such as palm lines and texture. These approaches can be further divided into three main categories: (1) line based, (2) coding based and (3) texture based. The first category extracts the palm lines via several line detection algorithms. Han et al. extracted line-like features using Sobel and morphological operations to the palmprint image [21]. Wu et al. addressed directional line detectors to extract palm lines with different specific directions [22]. Huang et al. proposed a unique principal line detector with Modified Finite Radon Transform (MFRAT) [23]. However, these methods are computationally expensive to apply on palmprint feature extraction and matching. Furthermore, it is very difficult to occasionally extract the stable palm lines. The second category encodes the palmprint features into bitwise codes by using the responses of a bank of phase or directional filters. The well-known representative methods include the PalmCode [24], Competitive Code (Comp Code) [25], Ordinal code [26], Fusion Code [27], etc. In addition, Jia et al. propose Robust Line Orientation Code (RLOC) that extracts the

* Corresponding author.
E-mail addresses: leegeun@yonsei.ac.kr (G. Li), jhkim@yonsei.ac.kr (J. Kim).

http://dx.doi.org/10.1016/j.patcog.2016.06.025
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local orientation information of palmprint with the MFRAT [28]. Yue et al. utilize a modified fuzzy C-means cluster technique into the Comp Code and a better performance was reported [29]. Guo et al. encode the responses of real Gabor filters along with six different orientations for palmprint images, namely Binary Orientation Co-occurrence Vector (BOCV) [30]. Zhang, et al. further improve the verification performance of BOCV by masking out the fragile bits, which is called E-BOCV [31]. Thanks to bitwise code, these methods usually have the advantages of high accuracy and low computational cost. The last category basically extracts the palm features in the local regions of palmprint images either in the overlapped or non-overlapped sub-blocks. Michael et al. apply local binary pattern (LBP) [48] and Sobel directional operator via modified probabilistic neural network (PNN) [32]. Nanni et al. fuse the matching scores of Discrete Cosine Coefficient, invariant LBP, and Gabor filter for the palmprint images [53]. Tamrakar et al. utilize the histograms of Uniform LBP and Entropy for the non-occluded sub-blocks of the palmprint images. Then, the matching scores of non-occluded sub-blocks are fused through the sum rule [54]. Lu et al. propose the Enhanced Gabor-based Region Covariance Matrices features by using the response of both Gabor magnitude and Gabor phase along with eigenvalue-based distance [33]. Guo et al. address a hierarchical multi-scale LBP histogram for palmprint feature representation. Then, chi-square distance is used for feature matching [34]. Mu et al. use the shiftable complex directional filter bank (CDFB) transform and uniform LBP to extract palmprint features with Fisher linear discriminant (FLD) [35]. Hong et al. extract Block Dominant Orientation Code and Block-based Histogram of Oriented Gradient as the fine palmprint features [36]. Recently, Luo et al. have successfully adopted the local line directional pattern (LLDP) descriptor to the palmprint recognition [42]. Therefore, these methods achieve high performance in small changes of misalignment due to usage of local region descriptors' information.

The hybrid based approach utilizes both holistic and structural features to represent palmprint images. Kumar et al. integrate the holistic, line and texture based methods to extract palmprint features by the score and decision level [37]. Morles et al. combine the Scale Invariant Feature Transform (SIFT) and Orthogonal Line Ordinal Features (OLOF) for the contactless palmprint identification [38]. Kumar et al. also propose a new nonlinear rank-level fusion approach for multiple palmprint representation [39]. Recently, Xu et al. propose a new framework that integrates three kinds of similarity scores from left, right and between left (reverse of left) and reverse of right (right) palmprint features with weighted fusion scheme [40]. However, these methods generally require more computational time.

To our knowledge, although various related works have been reported, only a few studies are devoted to slight misalignment issues without the need to align the palmprint images. More recently, Jia et al. investigate the histogram of oriented lines (HOL) and the line-shaped filter with several dimension reduction techniques [41]. It is stable in small changes of illumination, translation and rotation. However, HOL has become the blockage in producing high performance. To overcome these limitations, this paper proposes a unique palmprint recognition method using line-shape filters (i.e. real response of Gabor filter or Modified finite radon transform) in conjunction with the LMTrP descriptor, and achieves better performance than several state-of-the-art methods. Meanwhile, the key contributions of this paper can be listed as follows.

- A unique local micro-structure descriptor, called Local Micro-structure Tetra Pattern (LMTrP), is proposed. Thanks to both the descriptor's direction and thickness information, the proposed descriptor outperforms Local Tetra Pattern (LTrP).
- An effective feature representation method for palmprint images is derived. The experiments were conducted on several palmprint databases either in controlled or uncontrolled environments. It achieves better performance than other related approaches (i.e. Comp code, Ordinal code, LLDP, HOL, etc.).
- In particular, the proposed method for palmprint image is the least sensitive to slight misalignment in almost all cases such as variations of rotation, translation and blurriness.

The remainder of this paper is organized as follows. Section 2 presents some fundamental concepts about the Gabor wavelet filter, MFRAT and LTrP descriptor while the proposed descriptor and our palmprint recognition method are presented in Section 3. Experimental results are shown in Section 4 along with detailed discussions. Finally, Section 5 presents conclusions and possible research topics for future studies.

2. Preliminaries

2.1. Line-shape based Filters

This section briefly reviews the most commonly used line-shape based filters. The line-shape based filters have been successfully applied to palmprint recognition to extract the specific orientation and palm line features on the palmprint images. Moreover, it can effectively eliminate unnecessary palm line features on the palmprint images, such as signal noise, small scars, and unstable palm line features. Kong et al. propose Comp code that utilizes the real part of the Gabor wavelet filter [25]. More recently, inspired by Finite Radon Transform [49], Jia et al. address RLOC that utilizes the MFRAT [28]. In this section, both line-shape filters will be introduced. Then in order to have better understanding for the proposed LMTrP descriptor, the LTrP descriptor is briefly reviewed [43,44,56].

2.1.1. Gabor wavelet filter

In the spatial domain, the Gabor wavelet is a linear filter which is generated by multiplying a 2D Gaussian function and an oriented complex exponential. The general form is usually expressed as follows:

$$G(x,y,\theta_m)=\frac{1}{2\pi\sigma^2}\exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\}\times\exp\left\{2\pi ju\left(x\,\mathrm{Cos}(\theta_m)+y\,\mathrm{Sin}(\theta_m)\right)\right\} \tag{1}$$

where (x, y) denotes the pixel position in the spatial domain and $j^2=-1$, μ is the frequency of the sinusoidal wave and σ is the standard deviation of the 2D Gaussian envelop, respectively. When the number of orientations κ is fixed, the orientation of the sinusoidal wave θ_m can be derived from $\theta_m=\frac{\pi(m-1)}{\kappa}$, where $m\in[1,2,\cdots,\kappa]$.

As in [25,41], this paper also utilizes the real part of Gabor wavelet filter to extract the palm line features from palmprint images. The examples of the real part of Gabor wavelet filter at six orientations are illustrated in Fig. 1. Let $G_R(x,y,\theta_m)$ be the real part of Gabor wavelet filter at the angle of θ_m and $I_{ROI}(x,y)$ be the palmprint Region of Interest (ROI) images. Thus, the magnitude $Mag(x,y)_G$ and the orientation $\mathrm{Orient}(x,y)_G$ can be extracted by convoluting $I_{ROI}(x,y)$ using a family of $G_R(x,y,\theta_m)$.

$$Mag(x,y)_G=min\left(I_{ROI}(x,y)\otimes G_R(x,y,\theta_m)\right) \tag{2}$$

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