Combine Hierarchical Appearance Statistics for Accurate Palmprint Recognition

Yufei Han, Zhenan Sun,Tieniu Tan

Center for Biometrics and Security Research, National Laboratory of Pattern Recognition

Institute of Automation, Chinese Academy of Sciences

{yfhan,znsun,tnt}@nlpr.ia.ac.cn

Abstract

Palmprint recognition is an active member of biometrics in recent years. State-of-the-art algorithms of palmprint recognition describe appearances of palmprints efficiently through local texture analysis. Following this framework, we propose a novel approach of palmprint recognition in this paper, which represents palmprint images based on statistics and spatial arrangement of appearance descriptors within local image areas. In this method, we firstly design a robust descriptor to encode properties of palmprint appearances of local regions. The whole image is divided into non-overlapped blocks at increasingly fine resolutions successively, so as to describe the spatial layout in hierarchical scales. For a specific spatial resolution, local distributions of the proposed descriptors in the blocks are concatenated to represent structures of palmprint structures. Finally, distribution information of different resolutions is combined to provide complementary descriptive power. Promising experimental results demonstrate that the proposed method achieves even better performances than the state-of-the-art approaches.

1. Introduction

Palmprint recognition has attracted much attention from researchers in recent years. Large regions of human palm contain enough discriminative texture patterns, which can be captured with low-resolution CCD cameras [1]. Thanks to its high recognition accuracy and convenience for practical use, palmprint recognition provides an efficient way for personal identification.

It is an important problem for palmprint analysis to describe line-like patterns of palmprints [2]. In the state-of-art algorithms, researchers describe palmprints by utilizing kinds of local texture descriptors and compare the descriptors with exact geometric correspondences for efficient recognition. Nevertheless, this kind of local texture description can be affected easily by variations of local appearances, which is caused by contrast variations or deformation of skin surface. It leads to declination of similarities between intra-class samples and limits further improvement of recognition accuracy.

In our work, we propose a novel Gaussian derivative based descriptor to describe structures of line-like patterns. Instead of using it directly, we describe statistical properties of palmprint appearances with occurrence frequencies of the descriptors in local regions, named appearance statistics. Furthermore, we divide the whole image into blocks with gradually finer spatial resolutions and integrate appearance statistics of different scales into a hierarchical structure. The hierarchical representation provides comprehensive statistical description of palmprint appearances and their spatial layouts.

In rest of the paper, Section 2 illustrates definitions of the proposed palmprint descriptors and hierarchical appearance statistics. In Section 3, we propose a classification oriented combination scheme of the proposed hierarchical descriptions. Section 4 tests the proposed method on a large-scale palmprint database. Finally, we conclude the paper in Section 5.

2. Hierarchical Appearance Statistics for Palmprint Representation

2.1. Gaussian derivative based descriptor

In our work, we propose to use a computational efficient Gaussian derivative based descriptor to describe oriented palm line segments. Directional second order Gaussian derivative filter is close to optimal for detecting orientation, strength and scale of line patterns [3]. Fig.1 shows one example of the filter.

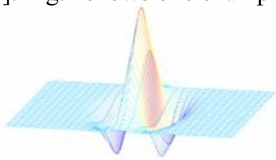

Fig.1 The second order Gaussian derivative filter

The proposed Gaussian derivate filter is defined as product of a second-order Hermite function and a directional Gaussian kernel (see Eq.1). θ is orientation of the filter. $x_1 = x\cos\theta + y\sin\theta$, $y_1 = -x\sin\theta + y\cos\theta$

$$G^{\theta} = \{4\frac{x_1^2}{\delta_x^3} - \frac{2}{\delta_x}\} exp(-(\frac{x_1}{\delta_x})^2 - (\frac{y_1}{\delta_y})^2) \qquad (1)$$

This directional filter is testified to provide noise suppression and precise visual localization capability, like Gabor filter [3]. Furthermore, due to its steerable property [4], we can obtain responses at any other orientations by combining filtering results at only three orientations. This property can save much computation cost during filtering in multiple orientations.

We extract low level appearance features at six orientations $\{ {}^{i\pi}\!/_6 \; (i = 0,1\ldots5)\}$ using the Gaussian derivative filters with zero DC. We set ${}^{\delta_y}\!/_{\delta_x}$ >3 to approximate elongated shape of palm lines. The size of the filter is 35×35. Our empirical results testify that this setting is suitable for describing palm lines. According to steerable property [4], we only perform convolutions at 0, ${}^{\pi}\!/_3$ and ${}^{2\pi}\!/_3$. Filtering results F^{θ} of the other three orientations are then derived based on the three responses following Eq.2.

$$F^{\theta} = k_1(\theta)F^{0} + k_2(\theta)F^{\pi/3} + k_3(\theta)F^{2\pi/3} \qquad (2)$$

where $k_j(\theta) = \frac{1}{3}[1 + 2cos(2(\theta - \frac{\pi(j-1)}{3}))]$ [4]. As a result, time cost is reduced to half of that using Gabor filters with same settings, while experiments denote that recognition using the proposed steerable filter obtain similarly performance. Responses $\{Fi\}$ (i=1,2…6) are encoded into 1 or 0 according to whether they are positive or not [3]. As a result, the obtained quantized 6D binary code vector $\{Ri\}$ is treated as a robust palmprint descriptor which improves robustness to variations of illumination settings and reflects intrinsic image structures qualitatively.

2.2. Hierarchical appearance statistics

In our application, we utilize histograms counting occurrence frequencies of the quantized descriptors to represent palmprint appearances. A plamprint image is divided into non-overlapping blocks. The quantized descriptors within each block represent specific appearance patterns. Different distributions of the patterns denote that different texture structures present in local regions. Thus, the occurrence frequency based representation provides a statistical description of local appearance structure [8]. Each bin in the histogram corresponds to each pattern indexed by Eq.3.

$$Index = \sum_{i=1}^{6} 2^{i-1} R_i \qquad (3)$$

Compared with using the descriptors directly, procedure of constructing histograms improves robustness of texture description against local appearance changes in palmprint images. As shown in Fig.2, to integrate spatial information of local features, histograms of all blocks are concatenated into a spatial enhanced histogram sequence, namely appearance statistics, which encodes both statistical texture description of local regions and spatial layout between them.

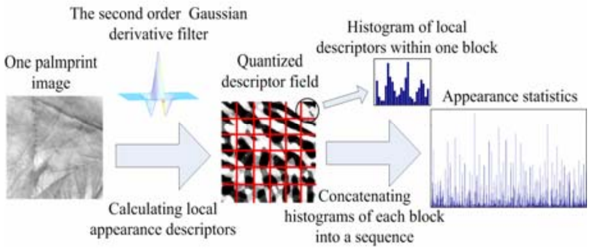

Fig.2 Construction of appearance statistics

In our method, we represent the whole image by dividing it with different spatial resolutions and arranging appearance statistics of each resolution hierarchically, as shown in Fig.3. On one hand, top layers partition images with coarse grids. They describe relatively global structures of the appearance patterns, which is robust enough to appearance variations but can not distinguish details. On the other hand, bottom layers focus on textures in fine local areas and their spatial layout, which are accurate representation of texture patterns but more sensitive to variations of appearances. Those hierarchical arranged layers are combined in a principled way, in order to complement each other in achieving comprehensive geometric matching between palmprint images. In our work, we divide the whole image into non-overlapped blocks with size of 8×8, 16×16 and 32×32, which corresponds to three different layers of the proposed hierarchical representation respectively. Further coarser or finer division leads to much loss of spatial information or much higher dimension of the feature representation, which is neither suitable for efficient recognition.

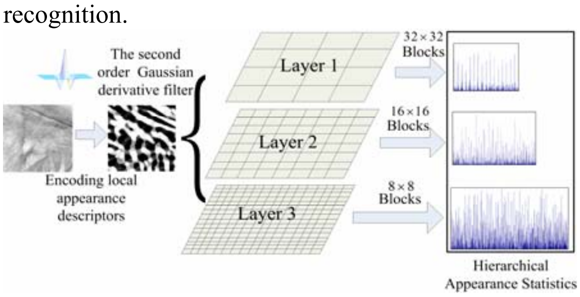

Fig.3. Illustration of hierarchical appearance statistics

3. Combination of hierarchical appearance statistics for palmprint matching

Assuming the hierarchical appearance statistics (HAS) of two palmprint images are $\{A_i\}$ and $\{B_i\}$ (i = 1,2,3) respectively. We utilize chi-square distance to measure similarity between appearance statistics in corresponding layers, as shown in Eq.4.

$$d_i = \sum_k \frac{(A_i^k - B_i^k)^2}{A_i^k + B_i^k} \tag{4}$$

Distance vector $\{d1, d2, d3\}$ measure appearance differences at three different spatial resolutions. Combination of the distances measure provides distribution similarity of palmprint patterns in a coarse-to-fine manner.

In our work, we adopt linear discriminate analysis (LDA) approach to fusion the distance measures [10]. LDA approach assumes that outputs of layers are statistical dependent and projects three-dimensional vectors $\{d_i\}$ into a scalar value d which achieves optimal between-class separation in the sense of fisher criterion, as shown in Eq.5. We use the weighted distance d as the similarity measure between two palmprint images. Weights $\{w_i\}$ are determined by projection coefficients of corresponding layers. Obtained weights vary from each other. It is consistent with the fact that different layers in the proposed representation aren't equally powerful in descriptive power of palmprints. Weights derived using LDA are not necessarily positive. Negative weights are helpful to reduce information redundancy in the hierarchical representation [10].

$$d = w_1 d_1 + w_2 d_2 + w_3 d_3 \tag{5}$$

4. Experimental results

We test performances of the proposed hierarchical representation on PolyU Palmprint Database [11]. This large scale database contains 7,752 palmprint images from 386 palms. Images from the same palm contain contraction and stretching of skin surface, which leads to local changes of appearances in palmprint images. This database is challengeable to discriminating power of recognition algorithms. After normalization, regions of interests with the size of 128×128 are obtained. In our experiment, we select five images randomly from each of the first 100 palms to construct a training data set, so as to choose a proper weight setting. Left 7,252 images form a validation set to test performances of the proposed method. The experiments comprise two parts. Firstly we test efficiency of the proposed method by comparing it with the other state-of-art approaches, namely, fusion code [5], competitive code [6] and ordinal code [7]. We also use Gabor filters with same settings to extract low-level features in proposed the HAS, named "HAS using Gabor filters". In the second part, we test performance of the proposed combination scheme in the proposed HAS representation.

As shown by EER [9] in Table.1 and ROC curves in Fig.4, the hierarchical representation achieves better performance than the other state-of-the-art algorithms. Benefited from the statistical texture descriptions and multi-scale geometric correspondences, the proposed method indicates robustness against local appearance deformation and describes texture details accurately. Furthermore, as illustrated in Table.1, using the Gaussian derivative filter, the proposed HAS achieves slightly better performance than that using Gabor filters, while the former feature extraction scheme could be more computationally efficient than using Gabor filters due to steerable property [4], which has been denoted in Section.2. This experimental result testifies efficiency of the proposed Gaussian derivative based filter in palmprint analysis. Table.2 and Fig.5 compare recognition accuracy of each single layer in the proposed HAS and combinations of three layers in the HAS on the validation set. As expected, descriptive power of individual layers varies a lot. Generally, coarser layers, like layer 1 and 2, focus on global distribution of texture patterns. They lack descriptive ability of spatial structure of local details, while layer 3 becomes sensitive to appearance deformation of fine texture structures. Combination of the complementary layers makes good trade-off between robustness and descriptive ability.

Table.1 Performance comparison on the validation set

Algorithm	EER [9]	d' [9]
Layer 1 in proposed HAS	1.48%	3.94
Layer 2 in proposed HAS	0.13%	5.07
Layer 3 in proposed HAS	0.04%	5.45
Combination of all layers	0.02%	5.47

Table.2 Evaluation of the combination scheme

Algorithms	EER [9]	d' [9]
Fusion code [5]	0.21%	5.40
Competitive code [6]	0.04%	5.84
Ordinal code [7]	0.05%	6.90
The proposed HAS	0.02%	5.47
The proposed HAS using Gabor filters	0.03%	4.41

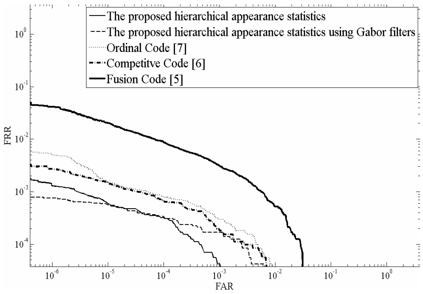

Fig. 4 ROC curves of all compared algorithms

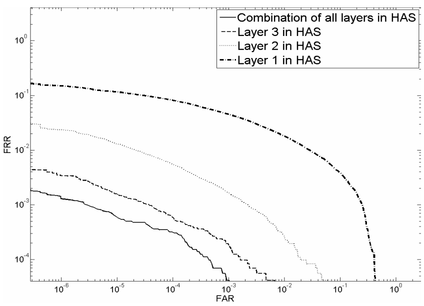

Fig.5.Performance evaluation of the combination

5. Conclusion

In our work, we propose a novel palmprint recognition algorithm based on multi-layer statistical palmprint representation. This approach consists of three main components, which are image division at successive multiple spatial resolutions, concatenating the proposed appearance statistics of palmprint patterns at each spatial resolution into a hierarchical structure and combination of similarity measures between appearance statistics in corresponding layers of the proposed representation. By constructing the spatial enhanced statistics, we obtain robust and discriminative distribution information of palmprint patterns. The hierarchical structure of the proposed representation can capture complementary statistical properties at multiple spatial resolutions. Furthermore, LDA based fusion scheme then seeks an optimal separation between intra-class and inter-class samples. This scheme makes full use of comprehensive descriptions of palmprint texture structures in the proposed representation. Thus, our approach achieves high recognition accuracy, better than state-of-the-art recognition algorithms.

Acknowledgement

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