Robust Palmprint Recognition based on Directional Representations

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Abstract. In this paper, we consider the common problem of automatically recognizing palmprint with varying illumination and image noise. Gabor wavelets can be well represented for biometric image for their similar characteristics to human visual system. However, these Gabor-based algorithms are not robust for image recognition under non-uniform illumination and noise corruption. To improve the recognition performance under the low quality conditions, we propose novel palmprint recognition approach using directional representations. Firstly, the directional representation for palmprint appearance is obtained by the anisotropy filter, which is robust to drastic illumination changes and preserves important discriminative information. Then, the PCA is employed to reduce the dimension of image feature. At last, based on a sparse representation on palmprint feature, the compressed sensing is used to distinguish palms from different hands. Experimental results on the PolyU palprint database show the proposed algorithm have better performance. And the proposed scheme is robust to varying illumination and noise corruption.

Keywords. palmprint recognition; directional representation; compressed sensing; noise corruption; illumination changes

1 Introduction

Biometrics is the automated method of recognizing a person based on a physiological or behavioral characteristic. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. Among different biometric authentication, palmprint recognition is one of the most promising approaches since it has several special advantages such as stable line features, rich texture features, low-resolution imaging, low-cost capturing devices, easy self positioning, and user-friendly interface[1]. And various palmprint high performance recognition algorithms have been to proposed to improve the recognition rate[2]. For example, in early times, Lu et al. [3] and Wu et al. [4] proposed two methods based on Principal Components Analysis (PCA) and Linear Discriminant Analysis (LDA), respectively. Ekinci et al, proposed Kernel PCA to improve the palmprint recognition performance and proposed a palmprint recognition approach integrating the Gabor wavelet representation and kernel PCA[5-6]. However, because of the illumination influence, the recognition performance of appearance based approaches mentioned above is not very satisfying in some aspects.

Orientation based approaches are deemed to have the best performance in palmprint recognition field, because orientation in palmprint contains more discriminative information than other features, and is insensitive to illumination changes. A.Kong and D.Zhang were the first authors who investigated the orientation information of the palm lines for palmprint verification and extracted the orientations of the palm lines by using the Winner-take-all Rule, which was defined as Competitive Code (CompC) [7]. W.Jia designed a matching algorithm based on pixel-to-area comparison, which improve the palmprint performance via reducing the Equal Error Rate(EER)[8]. However, by using only one dominant orientation to represent a local region, we may lose some valuable information because there are cross lines in the palmprint. By directly using multiple orientation features, H.Li used a the matching score level fusion strategy to fuse of different directional Palm-Codes to obtain the high performance[9]. Those above palmprint recognition algorithms imply that directional representations have certain robustness.

Traditional Gabor-based image representation it has got two important drawbacks. First, it is computationally very complex. Second, a lot of memory is needed to store Gabor features [10]. And what is important, Gabor-based image representation is not robust to varying illumination and noise corruption. To improve the implemented efficiently and robustness in the palmprint recognition, we propose novel palmprint recognition approach using directional representations and compressed sensing in this paper. The novel proposed approach can effectively overcome the Gabor-based shortcoming and can significantly improve the performance of appearance based approaches. Perhaps, the simplest classification scheme is a nearest neighbor (NN)classifier to distinguish different biometric traits using Subspace-based features [11]. Under this classifier, an image in the test set is recognized (classified) by assigning to it the label of the closest point in the learning set, where distances are measured in the image space. However, it does not work well under varying lighting conditions. Based on a sparse representation computed by l1-minimization, J. Wright et al propose a general classification algorithm for face object recognition. In this classification, the testing image is coded as a sparse linear combination of the training samples. Compared with the traditional recognition algorithm, a sparse representation provides deep insights into feature classification and has proven its superior performance [12].

The rest of this paper is organized in the following. In Section 2, the directional representations of palmprint images using multiple anisotropy filters will be introduced. Feature extraction and dimension reduction using PCA and classification using compressed sensing will be proposed in Section 3. Experimental results on PolyU Palmprint Database are given in Section 4. Finally, conclusions are made in Section 5.

2 The directional representations

From some literatures, it can be seen that different representations of palmprint can be adopted for Subspace-based approaches. These representation algorithms include

Gabor, wavelet transform[5], dual-tree complex wavelet transform[13] et,al. Generally speaking, the commonly used strategy is applying the corresponding filter to convolute with the original palmprint image. However, these mentioned above still have some drawbacks. Let us take the most popular Gabor filters as an example. The Gabor filters, which could effectively extract the image local directional features at multiple scales, have been successfully and prevalently used in palmprint recognition, leading to better results. Since the Gabor features are extracted in local regions, they are less sensitive to variations of illumination. Also, the computational burden of Gabor-based representations is very heavy.

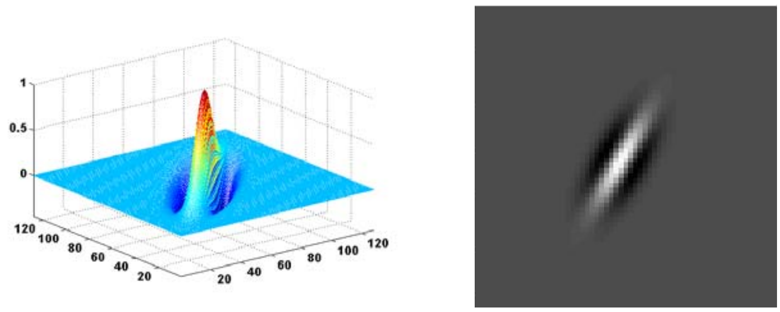
An image can be modeled as a piecewise smooth 2D signal with singularities. These properties need anisotropic refinement representations. However, the traditional Gabor isotropic refinement can't efficiently represent the palmprint structure. The Anisotropic Filter (AF) is to obtain sparse representation by the idea of efficiently approximating contour-like singularities in 2-D images. The AF is a smooth low resolution function in the direction of the contour, and behaves like a wavelet in the orthogonal (singular) direction. That is, the AF is built on Gaussian functions along one direction, and on second derivative of Gaussian functions in the orthogonal direction. The structure of AF is very special for capturing the orientation of palmprint image[14]. The AF has the following general form

$$G(u,v) = (4u^2 - 2)\exp(-(u^2 + v^2)) \tag{1}$$

where (u,v) is, in this case, the plane coordinate and can be obtained in the following way.

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 1/\alpha & 0 \\ 0 & 1/\beta \end{bmatrix} \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x - x_0 \\ y - y_0 \end{bmatrix} \tag{2}$$

Where $[x_0, y_0]$ is the center of the filter, the rotation θ, to locally orient the filter along palm contours and α and β are to adapt to contour type.



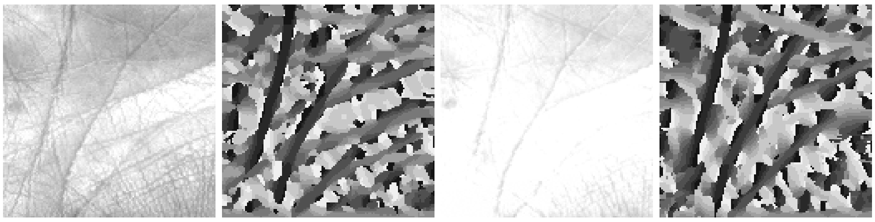
(a) (b)

Fig. 1. (a)Appearance of anisotropic filter(2D);(b) Sample anisotropic filter with a rotation of 2*pi/3 radians and scales of 3 and 9

The choice of the Gaussian envelope is motivated by the optimal joint spatial and frequency localization of this kernel and by the presence of second derivative-like filtering in the early stages of the human visual system. It is also motivated by the presence of second derivative-like filtering in the early stages of the human visual system. Usually, $\beta > \alpha$ is set to better obtain the line orientation of palmprints. A 3D visualization of an AF can be seen in Fig.1. The competitive rule is a Winner-take-all rule defined as:

$$j = \arg\min_{p} \iint I * G\left(\theta_p\right) dxdy \qquad (3)$$

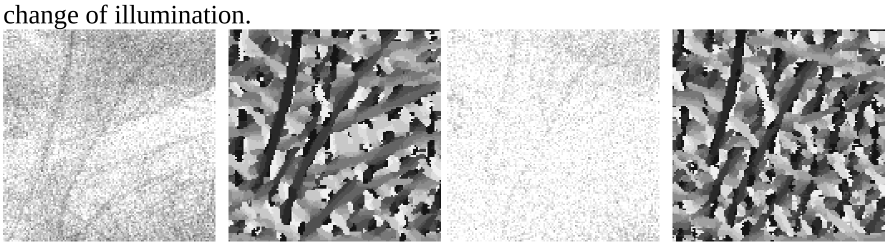
where j is called the winning index. The orientations of the six filters, θ_p are $p\pi / 12$, where p=0,1,2,…11.



(a) (b) (c) (d)

Fig. 2. Plmprint images and their directional representation and directional representation s are robust for illumination changes

Fig. 2 shows three palmprint images and their directional representations. Among them, Fig 2(a) and (c) come from the same palm, but were captured in different illumination conditions. Although the illumination conditions changed drastically, their directional representations are still very similar (see Fig 2(b) and (d)). From this example, it can be concluded that the directional representations is also robust for the change of illumination.



(a) (b) (c) (d)

Fig. 3. Plmprint images and their directional representation and directional representation s are robust for noise corruption

Fig. 3 shows three palmprint images and their directional representations. Among them, Fig 3(a) comes from Fig 2(a) which adds Gaussian white noise(noise level is 25) . Fig 3(c) comes from Fig 2(c) which adds Gaussian white noise(noise level is 25) .Although the noise made the image quality and understandability worse, their directional representations are still very similar. From this example, it can be concluded that the directional representations is also robust for the noise corruption.

3 The proposed robust recognition algorithm

This section describes the proposed palmprint verification algorithm using a compressed sensing as a classifier. We first extract from the original palmprint images a region of interest (ROI), as illustrated in Fig.4. The directional representations using multiple anisotropic filter will be obtained on the ROIs of palmprint images via winner-take-all rule. The PCA is used to extract the feature and reduce dimension of At last, the compressed sensing is used to classify the palms from different hands.

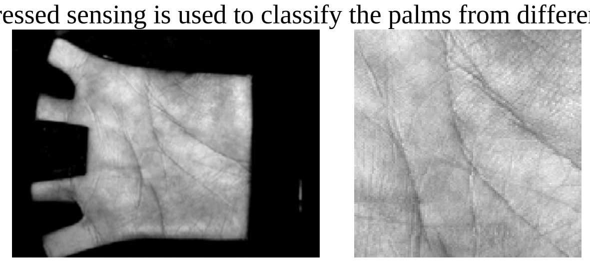


Fig. 4. (a) The determination of ROI. (b) A cropped ROI image of the palmprint image in (a).

PCA has been widely used as linear feature extraction in computer vision. It computes the basis of a pace which is a space which is represented by its training vectors yields projection directions that maximize the total scatter across all classes. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. PCA is one of the most successful techniques that have been used in biometric recognition. The 2-DPCA is introduced to generate a projection space while extracting the projected feature of each image on the space. In classical PCA technique, an image matrix should be mapped into 1-D vector in advance. 2-DPCA method can directly extract feature matrix from the original image matrix, which can reduce the size of the image covariance matrix[15].

3.1 Classification based on sparse representation

Sparse representation, which indicates that account for most information with a linear combination of a small number of elementary signals, has proven to be an extremely powerful tool for pattern classification. Finding a sparse representation can be solved as the following optimizing problem:

$$\hat{x}_0 = \arg\min \|x\|_0 \text{ s. t. } Dx = y \tag{4}$$

Where $\|.\|_0$ denotes the l^0-norm, which counts the number of nonzero entries in a vector. Seeking the sparsest solution to $Dx = y$ is a NP-hard problem. The theory of sparse representation and compressed sensing reveals that if the solution x_0 sought is sparse enough, the solution of the l^0-minimization problem is equal to the solution to the l^1-minimization problem[16].

Given sufficient training palmprint samples of the *i*-th object hand class, $D_i = [d_{i,1}, d_{i,2}, ..., d_{i,n_i}] \in \mathbb{R}^{m \times n_i}$, a test palmprint sample $y \in \mathbb{R}^m$ from the same hand will approximately lie in the linear span of the training palmprint samples associated with object i $y = D_i x_i$ for some coefficient vector $x_i \in \mathbb{R}^{n_i}$ .Usually, the small nonzero entries in the estimation associated with the columns of *D* from a single object class *I*, and can easily assign the test palmprint feature *y* to that class. Based on the prior sparse representation of palmprint images, one can treat the test feature can be treated as a linear combination of all training features of each object. And, one can identify the right class from multiple possible classes.

Therefore, given a new test palmprint template *y* from one of the classes in the training template set, we first compute its sparse representation via basis pursuit. And then, we compute the coding residual.It can be computed as follows: For each class *i*, let $\lambda_i : \mathbb{R}^n \to \mathbb{R}^n$ be the characteristic function which selects the coefficients associated with the *i*-th class, one can obtain the approximate representation $\hat{y}_i = D\lambda_i(\hat{x}_1)$ for the given test sample y. We then classify y based on the approximations by assigning it to the object class that minimizes the residual between y and $\hat{y}_i : \min r_i(y) = \left\| y - D\lambda_i(\hat{x}_1) \right\|$ [12].

3.2 Palmprint Recognition using directional representation and compresses sensing

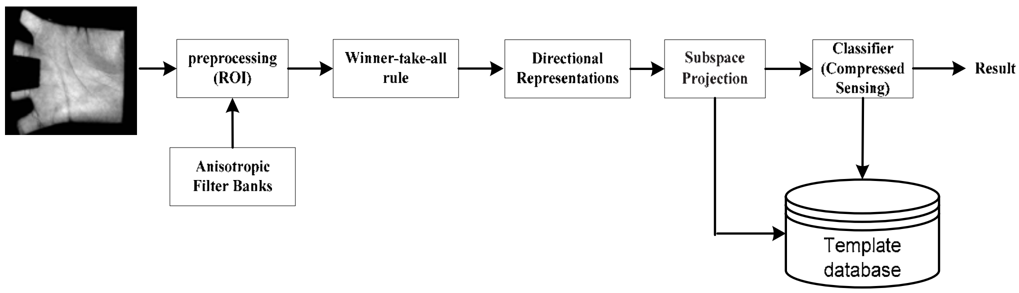


Fig. 5. The flowchart of the proposed palmprint recognition system

From discussion above, as illustrated in Fig.5, the proposed framework can be briefly summarized as follows:

Step 1: For reliable feature measurements, the gaps between the fingers as reference points to determine a coordinate system is used to extract the region part of a palmprint image. Fig.4 is an example.

Step 2: The ROI parts of palmprint image are further processed to obtain the directional representations. To be specific, the directional representations using multiple anisotropic filters will be obtained on the ROIs via winner-take-all rule.

Step 3: The PCA is employed to reduce dimension to reduce redundancy efficiently and extract the palmprint feature of the directional presentations for next match stage.

Step 4: By computing the coding residual, the minimum residual is identified as for recognition. Then recognition rates for the compressed sensing in a palmprint database are used to evaluate the performance.

4 Experimental results and analysis

In this section, we present experiments on PolyU publicly available databases for palmprint recognition, which demonstrate the efficacy of the proposed directional representations and validate the claims of the proposed sections. We will first examine the role of feature extraction within our framework, comparing performance across various feature spaces and feature dimensions. We will demonstrate the robustness of the proposed algorithm to noise corruption. Also, we test the speed of the proposed algorithm and compare with the traditional algorithms.

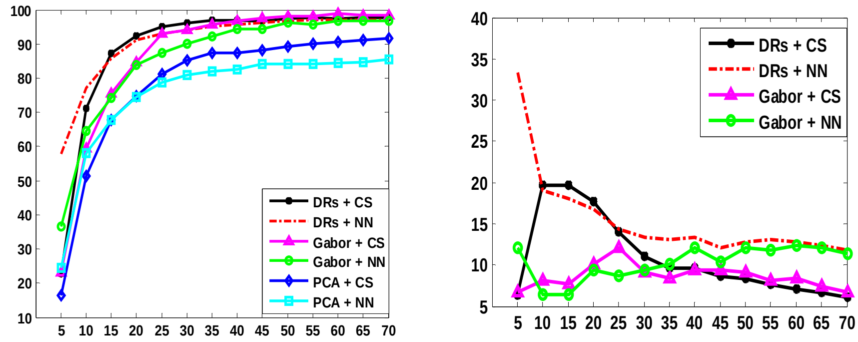
4.1 Experimental settings

In PolyU Palmprint Database, there are 600 gray scale images captured from 100 different palms by a CCD-based device(http://www.comp.polyu.edu.hk/ biometrics). Six samples from each palm are collected in two sessions: the first three samples were captured in the first session and the other three were captured in the second session. The average time interval between these two sessions was two months. The size of all the images in the database was 384 × 284 with a resolution of 75dpi. In our experiments, a central part (128×128) of each image is extracted for further processing. The results have been generated on a PC with an Intel Pentium 2 processor (2.66GHz) and 3GB RAM configured with Microsoft Windows 7 professional operating system and Matlab 7.10.0(R2010a). In all of our experiments, we employed a highly efficient algorithm suitable for large scale applications, known as the Spectral Projected Gradient (SPGL1) algorithm, to solve the BP problems[17].

4.2 Recognition performance

The first three samples of each palm are selected for training, and the remaining three samples are used for testing. The feature vector of the input palmprint is matched against all the stored templates and the most similar one is obtained as the matching result. In the implementation of Gabor filters, the parameters are set as $k\max = \pi / 2$, $\sigma = 2\pi$, $f = \sqrt{2}$, $u = \{0,1,...11\}$, $v = \{0,1,2\}$. For the anisotropic filter banks, the number of orientation is 12, and the scales of x-axis and y-axis are 3 and 9.

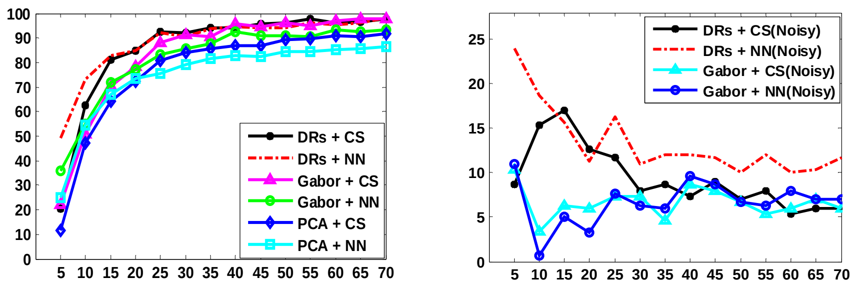
Following these schemes, we have calculated recognition rates with the dimensions ranging from 5 to 70. The experimental results are shown in Fig.6(a). As we can see from this Fig.6(a), the correct recognition rate increases with the increasing of the dimension of features, and it surpasses 90% when the dimension equals with or exceeds 25. In general, the compressed sensing(CS) classifier has superior performance than the NN. In the lower dimension, such as 10, the feature cannot be represent the intrinsic the palmprint image, therefore, the NN seems better. The Fig.6(a) also suggests that the recognition rate of Ours has better performance than all the other approaches under the same condition. For the feature dimension is lower than 45, the directional representations based approaches has better performance than Gabor methods. When the feature dimension is larger than 45, the performance of directional representation and Gabor are nearly the same. This is also been illustrated in Fig.6(b), in which PCA as a reference baseline(the same classification algorithm).



(a) (b)

Fig. 6. Performance Original palmprint database (a) Recognition performance of different approaches with varying feature dimension (b)Performance comparison between directional representations, Gabor-based and the results obtained by PCA as a reference baseline.

To test the performance under the noisy circumstances, we add the Gaussian white noise to each train samples and test samples. In the following experiments, the noise level is 25. As shown in Fig.7, we have calculated recognition rates with the dimensions ranging from 5 to 70. The Fig.7 also suggests that the recognition rate of our proposed method (Ours) has better performance than all the other approaches under the same condition. From the Fig.7(a), the CS classification is better than NN for the same features. If PCA is acted as a reference baseline, we will find we find the directional representation and NN based algorithm is drastically improved compared with original PCA algorithm, as illustrated in Fig.7(b). Compared with the original palmprint database (without adding the Gaussian noise), The superior performance of directional representations means that our proposed algorithm is robust illumination changes and noise corruption.



(a) (b)

Fig. 7. Performance Original palmprint database under noise corruption (a) Recognition performance of different approaches with varying feature dimension (b)Performance comparison between directional representations, Gabor-based and the results obtained by PCA as a reference baseline.

4.3 Computational speed

The proposed algorithm consists of three parts: (1)directional representations (2)PCA-dimension reduction method(3)CS classifier. Compared with the traditional Gabor-based algorithm, the dimension of directional representation is the same with original palmprint image, that is 64×64(we use the downsample strategy in the implemented process), which is much smaller the 9600 dimension of Gabor–based. The lower dimension can speed up the PCA operation. Tab.1 illustrates the computing time of the proposed approach and other approaches. Form the Tab.1, the computational running time of the proposed approach for feature extraction and classification is shorter than the Gabor based approaches. The performance of approaches based on directional representations is a little better than the Gabor-based. However, the running time of Gabor based palmprint recognition algorithms is 1.5 times of that Directional Representations based algorithms.

Table 1. Running time with different approaches(feature dimensions: 40)

Algorithms	PCA+NN	PCA+CS	Gabor+NN	Gabor+CS	DRs+NN	DRs+CS
Recognition rate	82.33%	87.33%	94.33%	96.67%	95.67%	97.00%
Time (s)	6.52	14.08	54.63	61.78	33.49	43.27

5 Conclusions

In this paper, a novel image representation approach, named directional presentations for palmprint recognition is proposed. Firstly, a new representation for appearance based approach using the multiple anisotropy filters for palmprint recognition is presented. Compared with original spatial and Gabor representation, the proposed directional representation contains stronger discriminative information, and is insensitive to illumination changes and noise corruption. Then, subspace based approaches, such as PCA, is used to extract the palmprint features and reduce the dimension. Finally, a compressed sensing classification is employed to distinguish different palms from different hands. Experimental results show that the proposed algorithm have better performance and is robust illumination changes and noise corruption.

Acknowledges

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