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Palmprint Recognition Using Directional Representation and Compresses Sensing

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Abstract: In this study, based on directional representation for palmprint images and compressed sensing, we propose a novel approach for palmprint recognition. Firstly, the directional representation for appearance based approaches is obtained by the anisotropy filter to efficiently capture the main palmprint image characters. Compared with the traditional Gabor representations, the new representations is robust to drastic illumination changes and preserves important discriminative information for classification. Then, in order to improve the robustness of palmprint identification, the compressed sensing is used to distinguish different palms from different hands. As a result, the palmprint recognition performance of representative appearance based approaches can be improved. Experimental results on the PolyU palprint database show that the proposed algorithm has better performance and with good robustness.

Keywords: Compressed sensing, directional representation, image processing, palmprint recognition

INTRODUCTION

With the development of information and networked society, the application of biometric recognition systems will be wilder and brings much challenge to the researchers. Recently years, palmprint recognition has drawn wide attention from researchers for its special advantages such as stable line features, rich texture features, low-resolution imaging, low-cost capturing devices, easy self positioning and user-friendly interface (Zhang *et al*., 2003). At present, various palmprint recognition algorithms have been proposed to improve the recognition performance (Kong *et al*., 2009).

In biometric recognition research areas, the research on appearance based approaches were firstly proposed to be used in face recognition and had been attracted a lot of researchers (Belhumeur *et al*., 1997). Also, they were also successfully applied to palmprint recognition. For example, Based on Principal Components Analysis (PCA) and Linear Discriminant Analysis (LDA) and their versions, has been efficiently exacted the palmprint features (Lu *et al*., 2003; Wu *et al*., 2003). Gabor wavelets are extensively employed to extract face feature for biometric recognition and have obtained better performance than the original image samples for their similar characteristics to those of human visual system (Lee, 1996). However, in one way, the Gabor wavelet representation has two unavoidable drawbacks. First, it is computationally very complex. Second, memory requirements for storing Gabor features are very high (Shen and Bai, 2006). In the other ways, different from other biometric traits, such as the projection features in face images and the texture information in iris images (Daugman, 2004), the orientation information in palmprint is the fundamental character and the Gabor representations cannot express the line orientation very well. However, multi-orientation based approaches are deemed to have the best performance in palmprint recognition field (Yue *et al*., 2009; Li *et al*., 2010), because orientation feature contains more discriminative information than other features and is insensitive to illumination changes. The simplest classification scheme is a nearest neighbor classifier to distinguish different biometric image traits (Hu *et al*., 2008). However, it does not work well under varying lighting conditions. Based on a sparse representation computed by l1-minimization, a general superior performance classification algorithm for biometric recognition field (Wright *et al*., 2009; Wright *et al*., 2010).

In this study, to improve the robustness of extracted features, therefore, the directional representations of palmprint images using an anisotropy filter is proposed to improve the directional representations of palmprint images. Then, feature extraction and dimension reduction using PCA and classification using compressed sensing. At last, experimental results on PolyU Palmprint Database

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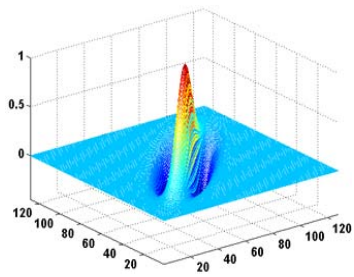


Fig. 1: Appearance of anisotropic filter

are given to demonstrate the effectiveness of proposed approach.

METHODOLOGY

The directional representation for palmprint images: The Anisotropic Filter (AF) is firstly used in building over-complete dictionary 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 (Li and Wang, 2012). The AF has the following general form:

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

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. 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 orientation of a pixel can be calculated by the formula:

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

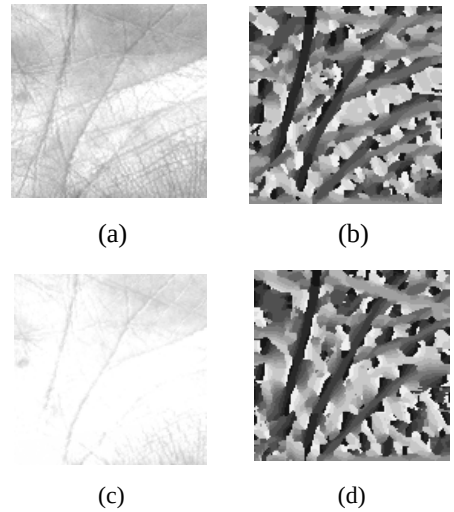


Fig. 2: Plmprint images and their directional representation. (a) and (c) come from the same palmprint, but were captured in different illumination conditions. (b) and (d) are their corresponding directional represention

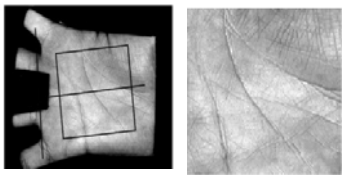
where, j is called the directional index, "*" represent convolution operation. The orientations of the twelve filters, θ_p are $p/\pi 12$, where p = 0, 1, 2, …11.

By this means, the directions of every pixels can be computed if the center of AF moves through out an image pixel by pixel. If an image is m n, the directional representations of an image can be obtained by their index values of directions.

Figure 2 shows three palmprint images and their directional representations, it corresponding parameters are $(\alpha, \beta, x_0, y_0)$ = (5, 23, 12, 12). Among them, Fig. 2a and c come from the same palmprint, but were captured in different illumination conditions. Although the illumination conditions changed drastically, however, their directional representations are still very similar (Fig. 2b and d). From this example, it can be concluded that the proposed pamprint directional representation is also robust for the change of illumination.

The proposed algorithm: Usually, Region of Interest (ROI) from the original palmprint images are extracted to align different palmprint images for matching. Compared with the heaven computational burden in the Gabor representations, here we used the directional palmprint representations instead, which can extract orientation and line feature effectively. At the next stage, the PCA is used to extract the feature and reduce dimension of palmprint images. At last, the compressed sensing is used to classify the palms from different hands, which is rubost to imperfect image captured and preprocessed.

ROI parts of palmprint image: Once the palmprint is captured, it is processed to get the Region of Interest



(a) (b)

Fig. 3: (a) The determination of ROI, (b) A cropped ROI image of the palmprint image in, (a)

(ROI), which is a 128×128 area. The ROI parts are employed for feature extraction and identity recognition. This process will also reduce, to some extent, the effect of rotation and translation of the hand via defining a coordinate system, which can be found in Zhang *et al*., (2003) for the detailed. Figure 3 illustrates a ROI image cropped from the original palmprint image. The ROI parts contain the most part of information and are used in the following recognition stage.

Principle component analysis: PCA has been widely used for dimensionality reduction and as linear feature extraction in computer vision. PCA, also known as Karhunen-Loeve methods, 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. The intrinsic dimensionality of eigenvectors is smaller than the original image data space. The economical data representations of PCA show that it can performs well in various recognition tasks. And PCA is one of the most successful techniques that have been used in image recognition(Brunelli and Poggio,1993).

More formally, let us consider a set of N sample images $\{x_1, x_2, ..., x_N\}$ taking values in an n-dimensional image space and assume that each image belongs to one of c classes $\{X_1, X_2, \ldots, X_c\}$. Let us also consider a linear transformation mapping the original n-dimensional image space into m-dimensional feature space, where m<n. The new feature vectors $y_k \epsilon^m$ are defined by the following linear transformation:

$$y_k = W^{T_{x_k}} \quad k = 1,2,\ldots N \tag{4}$$

where, $W\epsilon^{n\times m}$ is a matrix with orthonormal columns. If the total scatter matrix S_T is defined as:

$$S_T = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T \tag{5}$$

where, n is the number of sample images and $\mu = \epsilon^m$ is the mean image of all samples, then after applying the linear transformation W^T, the scatter of the transformed feature vectors $\{y_1, y_2\ldots, y_N\}$ is $W^T S_T W$. In PCA, the projection W_{opt} is chosen to maximize the determinant of the total scatter of the projected samples, i.e.:

$$W_{opt} = \arg\max_W \left|W^T S_T W\right| = \left[w_1, w_2, \ldots w_m\right] \tag{6}$$

where, $\{w_i \mid i = 1, 2\ldots, m\}$ is the set of *n*-dimensional eigenvectors of S_T corresponding to the *m* largest eigenvalues. These eigenvectors have the same dimension as the original images.

Compressed sensing for classification: Sparse representation, which are representations that account for most or all information of a signal with a linear combination of a small number of elementary signals, has proven to be an extremely powerful tool for representing natural images. Finding a representation with a small number of significant coefficients can be solved as the following optimizing problem:

$$\hat{x}_0 = \arg\min \|x\|_0 \text{ subject to Dx = y} \tag{7}$$

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 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.

Given sufficient training palmprint samples of the *i*-th object hand class, $D_i = \left[d_{i,1}, d_{i,2}, \ldots, d_{i,n_i}\right] \in^{m\times n_i}$, a test palmprint sample $y\epsilon^m$ 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 $x_i \in^{n_i}$.

Therefore, given a new test palmprint sample feature *y* from one of the classes in the training feature set, we first compute its sparse representation via basis pursuit. 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. It can be computed as follows:

For each class *i*, let λ_i: $^n \rightarrow {}^n$ 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 $\hat{y}_i$: $r_i(y) = \left\|y - D\lambda_i(\hat{x}_1)\right\|$ (Wright *et al*., 2009). The

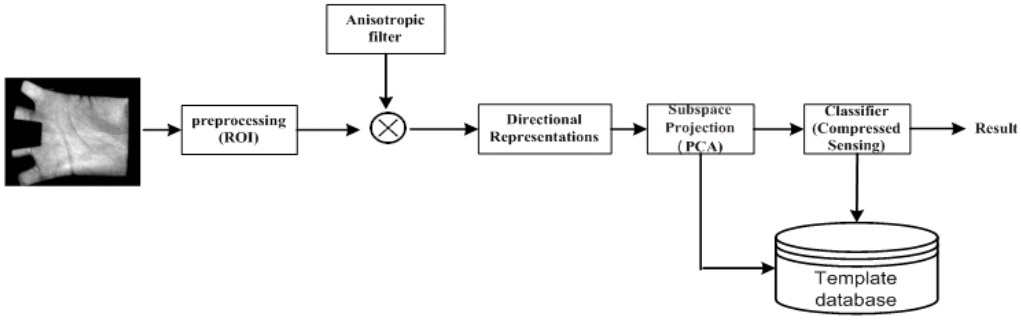


Fig. 4: The flowchart of the proposed palmprint recognition

empirical complexity of the commonly used l_1-regularized sparse coding methods (Kim *et al.*, 2007; Berg and Friedlander, 2008).

Palmprint recognition using directional representation and compresses sensing: From the above discussion, based on directional representations and compressed sensing, we proposed a light computational burden and robustness palmprint recognition. As illustrated in Fig. 4, the recognition system can be briefly summarized as follows:

Step 1: For convenience during in the feature extracting, the gaps between the fingers as reference points to determine a coordinate system is used to extract the region part of a palmprint image.

Step 2: The directional representations of the preprocessed palmprint image are obtained via a bank of anisotropic filter with twelve orientations on the ROI part of palmprint images.

Step 3: The PCA is employed to reduce dimension and extract the feature of the directional representations of palmprint images efficiently. PCA uses the eigenvectors of the covariance matrix.

Step 4: The eigenvectors as the feature is calculated by compressed sensing and employed to measure the similarity of two palmprints from different hands.

EXPERIMENTAL RESULTS AND ANALYSIS

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 75 dpi. In our experiments, a central part (128×128) of each

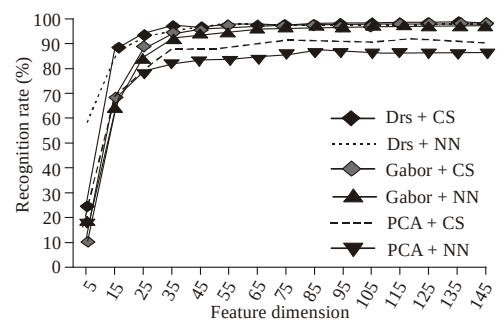


Fig. 5: Recognition performance of different approaches with varying feature dimension

image is extracted for further processing. The results have been generated on a PC with an Intel Pentium 2 processor (2.66 GHz) and 3 GB RAM configured with Microsoft Windows 7 professional operating system and Matlab 7.10.0 (R2010a). In our experiments, a highly efficient algorithm suitable for large scale applications, known as the Spectral Projected Gradient (SPGL1) algorithm (Berg and Friedlander, 2008), is employed to solve the BP and BPDN problems. 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}.

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. The first three samples of each palm are selected for training and the remaining three samples are used for testing. Following these schemes, we have calculated recognition rates with the dimensions ranging from 5 to 145.

The experimental results are shown in Fig. 5. As we can see from this Fig. 5, the correct recognition rate increases with the increasing of the dimension of features and it surpasses 90% when the dimension equals to or exceeds 25. The Fig. 5 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. 5, the CS classification methods is better than NN (Nearest Neighbour) for the same features. For the feature dimension is lower than 45, the

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%	88.00%	93.67%	95.67%	95.67%	97.00%
Time consumed (sec)	6.52	14.08	54.63	61.78	33.49	43.27

directional representations based approaches has better performance than Gabor methods. When the feature dimension is lager than 45, the performance of directional representation and Gabor are nearly the same.

Table 1 illustrates the computing time of the proposed approach and other approaches. Form the Table 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.

CONCLUSION

In this study, a novel approach for palmprint recognition is proposed. Firstly, a new directional representation for appearance based approach using the anisotropy filter for palmprint recognition is presented. Compared with original representation, the designed directional representation contains stronger discriminative information and is insensitive to illumination changes. Then, appearance based approaches, such as PCA, is used to extract the palmprint features. Finally, a compressed sensing classification is employed to distinguish different palms from different hands. The experimental results clearly demonstrated that the proposed algorithm has much better performance than Gabor-based algorithm and the traditional NN classifier.

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