Multimed Tools Appl (2014) 70:2331–2345
DOI 10.1007/s11042-012-1240-8

Robust palmprint identification based on directional representations and compressed sensing

Hengjian Li · Jiashu Zhang · Lianhai Wang

Published online: 28 September 2012

Abstract In this paper, we propose a novel approach for palmprint recognition, which contains two interesting components: directional representation and compressed sensing. 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 suffer from the heavy computational burden. To improve the recognition performance under the low quality conditions with a fast operation speed, 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 principal component analysis (PCA) is used for feature extraction to reduce the dimensions of the palmprint images. At last, based on a sparse representation on PCA feature, the compressed sensing is used to distinguish palms from different hands. Experimental results on the PolyU palmprint database show the proposed algorithm have better performance than that of the Gabor based methods.

Keywords Palmprint recognition · Directional representation · Compressed sensing · Image processing

1 Introduction

The rapid growth in the use of Internet applications and the great concern of security require reliable and automatic personal identification. Traditional knowledge-based and token-based automatic personal identification schemes have forgotten or stolen limitations. Biometrics is

H. Li (✉) · L. Wang
Shandong Provincial Key Laboratory of computer Network, Shandong Computer Science Center, Jinan 250014, China
e-mail: hengjianli@gmail.com

J. Zhang
Sichuan Province Key Lab of Signal and Information Processing, Southwest Jiaotong University, Chengdu 610031, China

an automated method of recognizing an individual based on a physiological or behavioral characteristic, such as face, fingerprint, iris, palmprint etc. Biometric recognition technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. Many large-scale human identity management projects such as US-visit program, EU biometric passport and Hong Kong identity card involve biometrics. And it is also applied to many other applications including access control, computer login and financial transactions authentication. Among different biometric authentications, 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 [27].

Palmprint recognition has been investigated over the past several years. During this period, many different problems related to palmprint recognition have been addressed. Researchers have focused on developing accurate verification algorithms. Various feature extraction and matching algorithms have been proposed to improve the speed of implement and recognition rate [13]. For example, in early times, Lu et al. [18] and Wu et al. [24] 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 [4, 5]. However, because of the illumination influence, the recognition performance of appearance based approaches mentioned above is not very satisfying in some aspects. Inspired by the face recognition algorithms, the Gabor based appearance algorithms are proposed on palmprint biometric traits [5, 25]. However, traditional Gabor-based image representation it has got two important drawbacks [20]. First, the computation burden is very heavy. Second, a lot of memory is needed to store Gabor features. And what is important, Gabor-based image representation is not robust to varying illumination. There are usuallythree principal lines in a palmprint: the heart line, the head line, and the life line. The Gabor-based image representation can't represent the lines very well [10]. Other wavelets also are employed to represent the biometric traits, such as DT-CWT. It cannot represent the palmprint images well [15] though it has better performance than of Gabor based on face images [6].

Orientation based approaches are deemed to have the best performance in palmprint recognition field, because orientation in palmprint contains more discriminative principal line information than other features. 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) [12]. Inspired by CompC, W.Jia used a modified FRAT to extract every orientations of palmprint pixels which was defined as Robust Line Orientation Code (RLOC) [11]. And also designed a matching algorithm based on pixel-to-area comparison, which improve the palmprint performance and reduce the Equal Error Rate (EER). Yue use modified FCM based clustering method to find the orientations of Gabor filters in CompC [26]. However, by using only one dominant orientation to represent a local region, it may lose some valuable information because there are cross lines in the palmprint. To better describe the local orientation features and be more robust to image rotation, Z.Guo proposed binary orientation co-occurrence vector (BOCV) to represent multiple orientations for a local region [7]. Compared with RLOC, the EER of BOCV was reduced significantly. 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 [17]. Those above palmprint recognition algorithms imply that directional representations have certain robustness and can represent the main characters of palmprint.

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. Based on the principle of structural risk minimization, Support Vector Machines (SVMs) are a set of supervised learning methods for linear classification and regression of data [2]. SVM classifier has good performance in biometric recognition. Compared with SVM and other classification algorithms, perhaps, the simplest classification scheme is a nearest neighbor (NN) classifier to distinguish different biometric traits using Subspace-based features [9]. 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. A sparse representation provides deep insights into feature classification. Based on a sparse representation, J. Wright et al propose a general classification algorithm [23]. Usually, a sparse representation computed by l1-minimization [21] and has proven its superior performance on pattern recognition [22, 28].

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 proposed. Feature extraction and dimension reduction using PCA and classification using compressed sensing will be presented in Section 3. Experimental results on PolyU Palmprint Database are given in Section 4. Finally, conclusions are made in Section 5.

2 Image representations using directional representations

Based on physiological constraints and the wavelet theory, a family of 2D Gabor wavelets which model the receptive fields of the simple cells in the brain's primary visual cortex has been derived in [14]. And Gabor is extensively employed to extract biometric image features and has improved its performance in the biometric trait recognition system for its characteristics to those of human visual system. From some literatures, it can be seen that different representations of palmprint can be adopted for Subspace-based approaches. These representation algorithms include Gabor [4], wavelet transform [5], dual-tree complex wavelet transform [15] 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. However, the Computation burden of Gabor is very heavy due to the filtering of the biometric image with a bank of Gabor filtering at many scales and orientations.

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 initially 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 good at capturing the orientation of palmprint image [16]. 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 anisotropic filter, the rotation θ is to locally orientation the filter along palm contours and α and β are to adapt to contour type. Parameters α, β are the anisotropic scaling factors along X-axis and Y-axis. These parameters are adjusted to adapt to contour smoothness, which is helpful for extraction local orientation of palmprint images.

A line in palmprint contains various information including type, width, position and orientation. These properties can used to compare two palmprint images by discriminating different line features. All the lines in palmprints belong to the negative lines (darker pixels in the center of the line) category. Palm lines do have a certain width for principal lines are wider(about 2-6 pixels). On top of types and width, line position is often considered as an important feature. It is worthwhile to note that lots of research results show that the orientation information is most discriminative features. And various of filters are designed to extract the palmprint orientation [7, 11, 12, 17, 26].

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 palmprint images. A 3D visualization of an AF can be seen in Fig. 1. The orientation information of a local region is calculated by the competitive rule(winner-take-all rule):

$$j = \arg\min_{p} \iint I(x,y)G(x,y,\alpha,\beta,\theta_p)dxdy \tag{3}$$

Where I represent a preprocessed palmprint image and j is called the winning index. The orientations of the twelve filters are employed, in particular, θ_p is $p\pi/12$, where $p \in \{0,1,2,\ldots,11\}$. Based on the competitive rule is introduced (3), we can extract the orientation information on a palm line, which is the palmprint intrinsic features and very

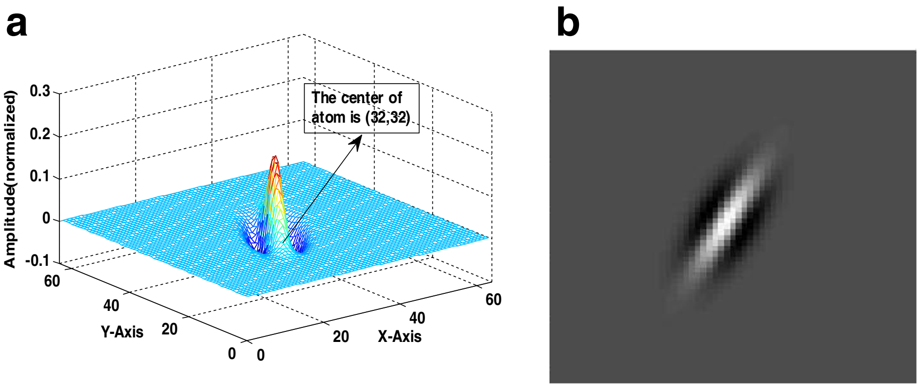

Fig. 1 **a** Appearance of anisotropic filter(3D);(**b**) Sample anisotropic filter with a rotation of 2*pi/3 radians and scales of 3 and 9

important to distinguish different hands. The winning indexes are integer representations of the local orientations of palmprints.

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

Figure 3 shows three palmprint images and their directional representations. Among them, Fig. 3a comes from Fig. 2a 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. It also indicates that it has robust nessto different capturing environments and devices.

In a word, different orientations are employed to calculate the sum of product of pixel values in local area and anisotropic filters(also it is the same as the “convention” operation). And the orientation which is corresponding to the smallest amplitude response (via the competitive rule) is regarded as the pixel orientation. All the pixel orientations are called the directional representations. Also the direction representations can well reflect the essence feature of palmprint images properly. The Sum operation can be implemented very fast and the number of anisotropic filter banks is less than Gabor.

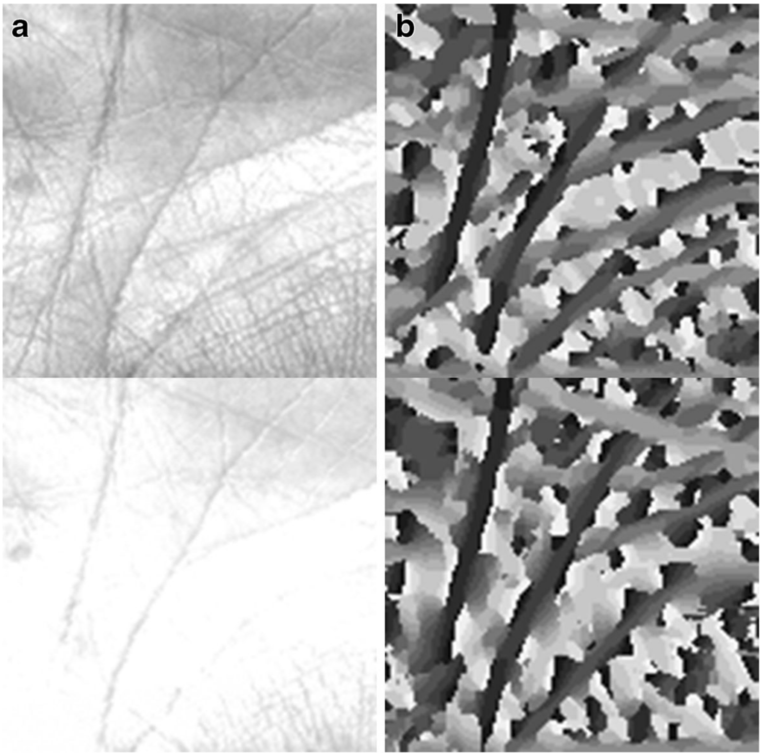

Fig. 2 Examples of palmprint directional representations (**a**) Preprocessed images. (**b**) directional representations

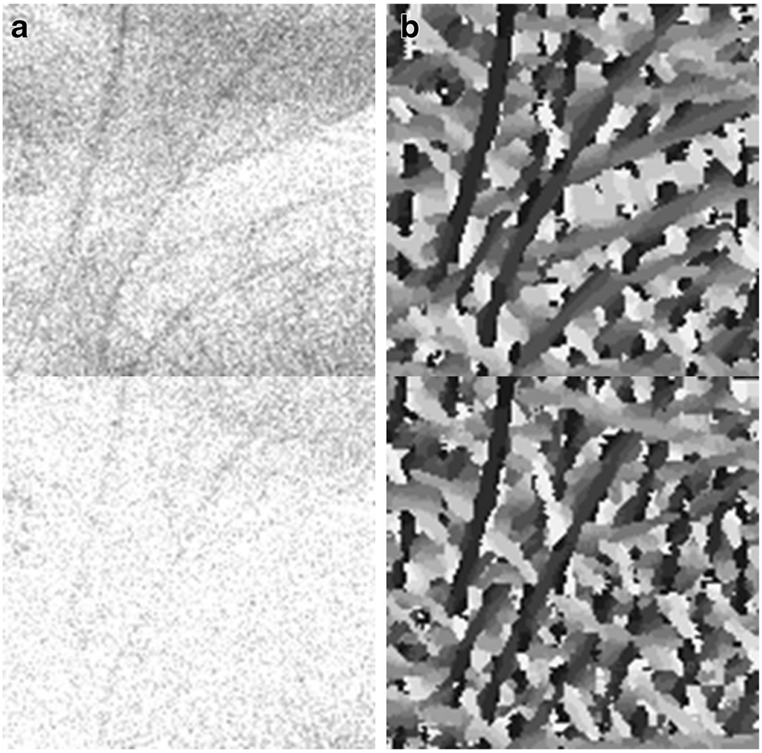

Fig. 3 Plmprint images and their directional representation and directional representation s are robust for noise corruption(**a**) Preprocessed images. (**b**) directional representations

3 Feature extraction and classification methods

PCA, which it to reduce the large dimensionality of the data space to the smaller intrinsic dimensionality of feature space, has been widely used as linear feature extraction in computer vision [1]. It computes the basis of a space 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 image recognition. PCA computes the basis of a space which is a space which is represented by its training vectors. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. PCA techniques, also known as Karhunen-Loeve methods, choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples.

More formally, let us consider a set of N sample images $\{x_1, x_2, \ldots, x_N\}$ 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 $y_k \in \mathbb{R}^m$ are defined by the following linear transformation:

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

Where $W \in \mathbb{R}^{n \times m}$ is a matrix with orthonormal column.

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 $\mu \in \mathbb{R}^n$ 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.,

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

Where $\{w_i | i = 1, 2 \ldots, m\}$ 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.

Sparse representation, which indicates 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:

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

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. The optimizing problem can be solved as the following:

$$\widehat{x}_1 = \arg\min \|x\|_1 \text{ subject to } Dx = y \tag{8}$$

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

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

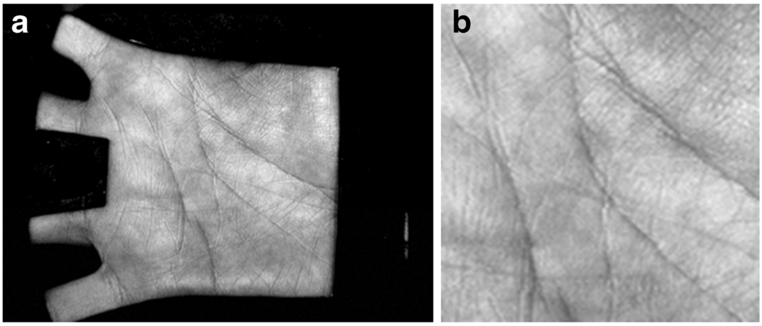

Fig. 4 **a** The determination of ROI. (**b**) A cropped ROI image of the palmprint image in (**a**)

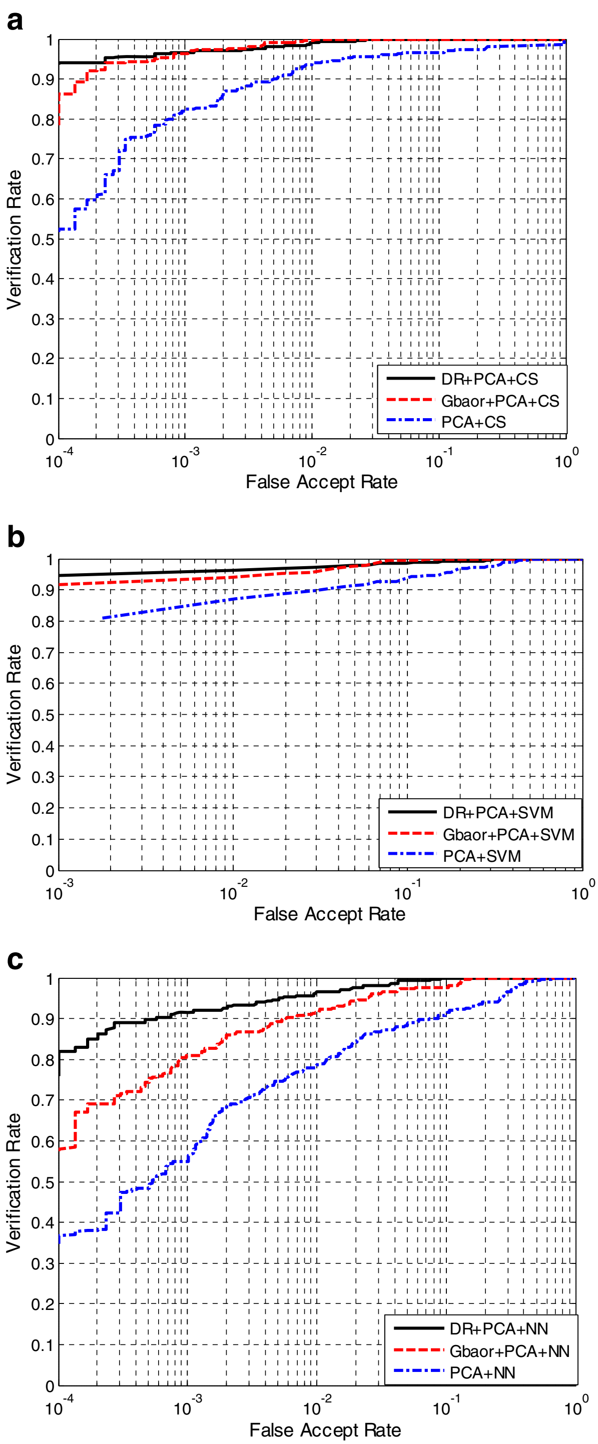

Fig. 5 Verification test results, the receiver operator characteristic curves of different approaches

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 $\lambda_i : \mathbb{R}^n \to \mathbb{R}^n$ be the characteristic function which selects the coefficients associated with the i-th class, one can obtain the approximate representation $\widehat{y}_i = D\lambda_i(\widehat{x}_1)$ 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 $\widehat{y}_i$: $\min r_i(y) = \|y - D\lambda_i(\widehat{x}_1)\|$ [23].

4 Experimental results and analysis

4.1 Experimental settings and methods

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 CS. In PolyU Palmprint Database, there are 600 gray scale images captured from 100 different palms by a CCD-based device [8]. 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 2 months. The size of all the images in the database was 384×284 with a resolution of 75dpi. By using the similar preprocessing approach described in literature [27], a central part (128×128) of each image is extracted for further processing. Figure 4 illustrates a ROI image cropped from the original palmprint image. 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.

The experimental 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 the implementation of Gabor filters, the parameters are set as $k$max=π/2, σ=2π, $f = \sqrt{2}$, u={0,1,…11}, v={0,1,2}. For the anisotropic filter banks, the orientations of the twelve filters are employed, in particular, θ_p is $p\pi/12$, where $p \in \{0, 1, 2, \ldots, 11\}$ .and the scales of x-axis and y-axis are 7 and 21, the size of anisotropic filter is 23×23.

The Nearest Neighbor (NN) classifier employed minimum Euclidean distancebetween the query feature vector and all the prototype training data. The Support Vector Machine (SVM) classifier employed linear kernel as it gave us the best results [19]. A highly efficient algorithm suitable for large scale applications, known as the Spectral Projected Gradient (SPGL1) algorithm [3, 21], is employed to solve the BP problems. The performance of a verification method is often measured by the FAR(false accept rate), FRR (false reject rate)and EER(equal error rate) and also ROC(receiver operating characteristic) curve is plotted. To demonstrate the effectiveness of the proposed approach, the following series of

Table 1 EERs of different approaches(feature dimensions: 30)

Algorithms	PCA			Gabor+PCA			DR+PCA		
	NN	SVM	CS	NN	SVM	CS	NN	SVM	CS
EER	0.257	0.091	0.053	0.212	0.090	0.026	0.163	0.045	0.024

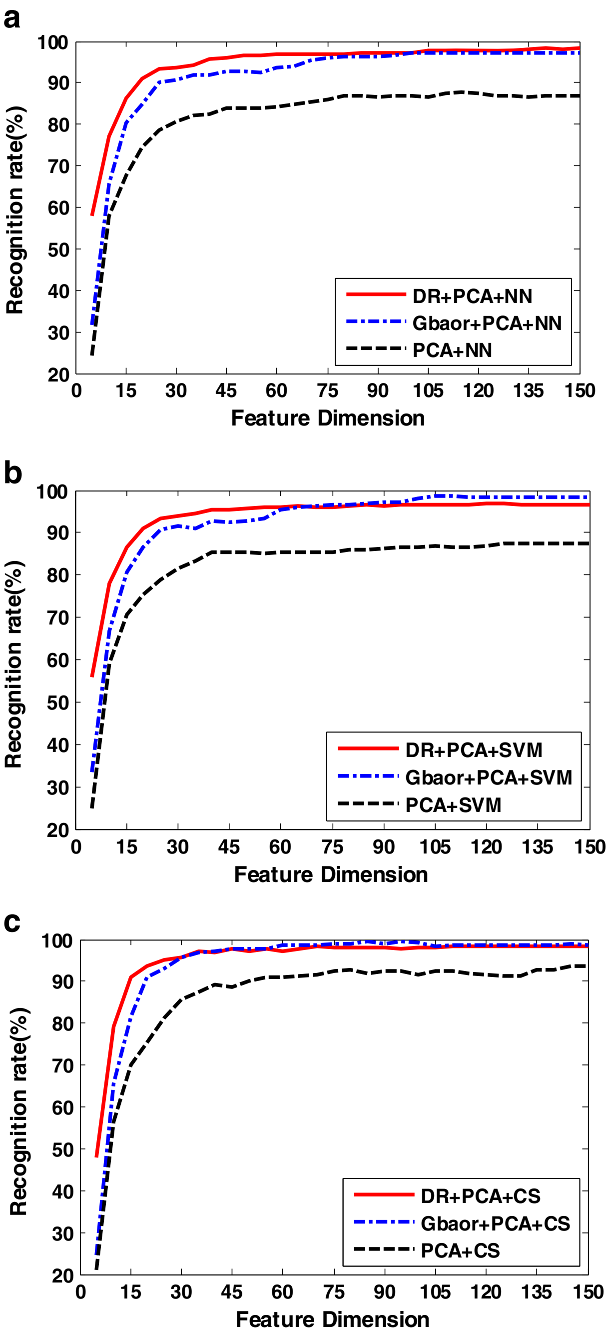

Fig. 6 Recognition Performance (**a**) Recognition performance of different approaches with NN classifier (**b**) Recognition performance of different approaches with linear SVM classifier. (**c**) Recognition performance of different approaches with CS classifier

comparison experiments were carried out. Additionally, the speed for every part of the proposed algorithm is compared with the traditional algorithms in the last subsection.

4.2 Palmprint verification performance

Verification, also known as one against one matching, is defined as deciding if a person is whom he claims to be by examining his palmprint. To obtain the verification accuracy of our palmprint system, each of the palmprint images was matched with all of the palmprint images in the database. A matching is noted as a correct matching if two palmprint images are from the same palm. 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 total match is 30,000. The failure to enroll rate is zero. The test palmprint images is 300, and each sample is match the three training samples with the same class, the mean value of the three matching scores is acted as the final score. Therefore, the number of comparisons that have correct matching is 300, and the rest are incorrect matchings. The feature dimension is 30 in the experiments.

Figure 5 depicts the corresponding Receiver Operating Characteristic (ROC) curve, which is a plot of genuine acceptance rate against false acceptance rate for all possible operating points. From Fig. 5a illustrated the CS classifier algorithms, we can see that the PCA approach can operate at about 52 % genuine acceptance rate(GAR) and a 1×10^{-2}% false acceptance rate (FAR). At the same FAR, the GAR of Gabor approach is about 34 % higher than that of PCA and the GAR of our system is about 42 % higher than that of PCA. From Fig. 5b illustrated the SVM classifier algorithms, we can see that the PCA approach can operate at about 81 % genuine acceptance rate(GAR) and a 0.2 % false acceptance rate(FAR). At the same FAR, the GAR of Gabor approach is about 11 % higher than that of PCA and the GAR of our system is about 14 % higher than that of PCA. From Fig. 5c illustrated the NN classifier algorithms, we can see that the PCA approach can operate at about 36 % genuine acceptance rate(GAR) and a 1×10^{-2}% false acceptance rate(FAR). At the same FAR, the GAR of Gabor approach is about 22 % higher than that of PCA and the GAR of our system is about 46 % higher than that of PCA. This results show that the proposed directional representation and CS approach is comparable with previous Gabor based palmprint approaches.

Results come from different approaches, such as spatial image representations, Gabor based approach and DR(directional representations) approach, and also different classification algorithms, such as NN, SVM and CS, are compared in Table 1. From Table 1, we can see that the results of our approach are better than that of other approaches. From the Fig. 5 ROC curves and Table 1 EERs, the proposed system obtains a better performance than the traditional Gabor approaches.

4.3 Palmprint identification performance

Identification is defined as deciding whom a person is according to his/her palmprint. The feature vector of the input palmprint is matched against all the stored templates and the most

Table 2 Recognition performance under different approaches with 40 dimensional features

Algorithms	PCA			Gabor+PCA			DR+PCA		
	NN	SVM	CS	NN	SVM	CS	NN	SVM	CS
Recognition rate	82.3 %	85.3 %	89.3 %	92.0 %	92.7 %	97.3 %	95.7 %	95.3 %	97.0 %

Table 3 Running time under different feature exaction approaches with 40 dimensional features

Algorithms	PCA	Gabor+PCA	DR+PCA
Time consumed(second)	6.74	61.7	32.02

similar one is obtained as the matching result. Following these schemes, we have calculated recognition rates with the dimensions ranging from 5 to 150. Figure 6 shows the recognition rates for this experiment. As we can see from this Fig. 6, 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. With the increasing of the feature dimension, most of the palmprint image has been extracted. Therefore, the recognition performance trends to stable when the dimension of feature is more than 45. In general, the compressed sensing (CS) classifier has superior performance than the linear SVM and NN.

In the lower dimension, such as 10, the feature cannot represent the intrinsic the palmprint image, therefore, the NN seems better. The Fig. 6 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. As the dimension of the feature space increases, most of the palmprint image has been extracted. Therefore, the recognition performance trends to stable.

As illustrated in Table 2, with 40 dimensional features, CS achieves a recognition rate between 89.3 % and 97.0 % and . One the other hand, the best recognition rates achieved by NN and linear SVM are 95.7 % and 95.3 %, respectively. In general, for the same dimensional feature, the CS classifier achieves maximum recognition rate of the three classifiers. For the same classifier, the directional representation achieves a better recognition performance.

4.4 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(downsample strategy is employed in the implemented process), which is much smaller the 9600 dimension of Gabor–based. The lower dimension can speed up the PCA operation. The Sum operation can be implemented very fast and the number of anisotropic filter banks is less than Gabor. From above discussion, we can infer that the time of DR implemented is less that of Gabor. Table 3 illustrates the computing time of the proposed feature exaction approach and other approaches. Form the Table 3, the computational running time of the proposed directional representations for feature extraction is nearly half of the Gabor representational approaches. Of course, they are both longer than that of PCA approach.

Table 4 Running time under different feature classifiers with dimensional features

Algorithms	NN	SVM	CS
Time consumed(second)	0.37	0.14	48.59

Table 4 illustrates the computing time under different feature classifiers with 40 dimensional features. Form the Table 4, the computational running time of the CS classification is much longer than then and linear SVM approaches. In the libsvm toolbox(libsvm-mat-3.0-1) [19], the SVM algorithm is implemented using compiled VC++ and Matlab mixed programming, therefore, the speed of SVM is faster than that of NN in our experiments. From Table 3 and Table 4, we can get that the total computational running time of the proposed approach for feature extraction and classification is 80.61 s. It should be noted that in samples in the palmprint Database is 600, therefore, the mean time of one user is about 0.13, which can meet the real time applications.

The performance of approaches based on directional representations is a little better than the Gabor-based. What is important, the running time of Gabor based palmprint recognition algorithms is 1.5 times of that Directional Representations based algorithms. As the dimension of the feature space increases, directional representation has the similar performance. However, the computation burden on the directional representations is less than that of the Gabor based approach.

5 Conclusions

In this paper, a novel image representation approach, named directional representations for expressing palmprint images efficiently, is proposed. Firstly, a new representation for appearance based approach using competitive rule on the multiple anisotropy filters is presented. Compared with the Gabor representation, the proposed directional representation contains stronger discriminative information with lower computational burden, and is insensitive to illumination changes. 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 with a real-time implementation speed.

Acknowledgments This work is supported by grants by National Natural Science Foundation of China (Grant No. 51175443 and 61070163), by the Shandong Province Outstanding Research Award Fund for Young Scientists of China (Grant No. BS2011DX034) and the Shandong Natural Science Foundation (Grant No. ZR2011FQ030 and ZR2011FM023).

References

1. Belhumeur PN, Hespanha JP, Kriegman DJ (1997) Eigenfaces vs.Fisherfaces: recognition using class specific linear projection. IEEE Trans Pattern Anal Mach Intell 19(7):711–720
2. Burges C (1998) A tutorial on support vector machines for pattern recognition. Data Min Knowl Discov 2 (2):121–167
3. Chang C and Lin C (2001) LIBSVM: a library for support vector machines. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm/
4. Ekinci M, Aykut M (2007) Palmprint recognition by applying wavelet subband representation and kernel PCA. Lect Notes Artifi Intell: 628–642
5. Ekinci M, Aykut M (2007) Gabor based kernel PCA for palmprint recognition. Electron Lett 43 (20):1077–1079
6. Eleyan A, Ozkaramanli H and Demirel H. Complex Wavelet Transform-Based Face Recognition. EURASIP J Adv Signal Process 2008: 13, Article ID 185281
7. Guo ZH, Zhang D, Zhang L, Zuo WM (2009) Palmprint verification using binary orientation co-occurrence vector. Pattern Recognit Lett 30:1219–1227
8. http://www.comp.polyu.edu.hk/ biometrics

9. Hu Q, Yu D, Xie Z (2008) Neighborhood classifiers. Expert Syst Appl 34:866–876
10. Huang DS, Jia W, Zhang D (2008) Palmprint verification based on principal lines. Pattern Recogn 41 (4):1316–1328
11. Jia W, Huang DS, Zhang D (2008) Palmprint verification based on robust line orientation code. Pattern Recogn 41(5):1504–1513
12. Kong AWK and Zhang D (2004) Competitive Coding Scheme for Palmprint Verification. Proc Int Conf Pattern Recog 520–523
13. Kong A, David Z, Mohamed K (2009) A survey of palmprint recognition. Pattern Recogn 42(7):1408–1418
14. Lee TS (1996) Image representation using 2D Gabor wavelets. IEEE Trans Pattern Anal Mach Intell 18 (10):959–971
15. Li H, Wang LH (2012) Palmprint recognition using dual-tree complex wavelet transform and compressed sensing. IEEE MIC2012: Int Conf Meas Inf Control 63~56
16. Li H, Wang LH (2012) Chaos-based cancelable palmprint authentication system. Procedia Eng 29:1239–1245
17. Li H, Zahng J, Zhang Z (2010) Generating cancelable palmprint templates via coupled nonlinear dynamic filters and multiple orientation palmcodes. Inform Sci 180(20):3876–3893
18. Lu G, Zhang D, Wang K (2003) Palmprint recognition using eigenpalms features. Pattern Recognit Lett 24(9–10):1463–1467
19. SGPL1: A solver for large-scale sparse reconstruction http://www.cs.ubc.ca/~mpf/spgl1/
20. Shen LL, Bai L (2006) A review on Gabor wavelets for face recognition. Pattern Anal Appl 9:273–292
21. van den Berg E, Friedlander MP (2008) Probing the Pareto frontier for basis pursuit solutions. SIAM J Sci Comp 31(2):890–912
22. Wright J, Ma Y, Mairal J, Sapiro G, Huang TS, Yan S (2010) Sparse representation for computer vision and pattern recognition. Proc IEEE 98(6):1031–1044
23. Wright J, Yang J, Ganesh AY, Sastry A, Yi Ma SS (2009) Robust face recognition via sparse representation. IEEE Trans Pattern Anal Mach Intell 31:210–227
24. Wu XQ, Zhang D, Wang KQ (2003) Fisherpalms based palmprint recognition. Pattern Recognit Lett 24 (15):2829–2838
25. Xin Pana, Qiu-Qi Ruan (2008) Neurocomputing, Palmprint recognition using Gabor feature-based (2D)2PCA. 71(13–15): 3032–3036
26. Yue F, Zuo WM, Zhang D, Wang KQ (2009) Orientation selection using modified FCM for competitive code-based palmprint recognition. Pattern Recogn 42(11):2841–2849
27. Zhang D, Kong A, You J, Wong M (2003) Online palm print identification. IEEE Trans Pattern Anal Mach Intell 25(9):1041–1050
28. Zhang L, Yang M, Feng XC (2011) Sparse representation or collaborative representation: Which helps face recognition. IEEE Int Conf Comput Vis (ICCV) 471–478

Hengjian Li received the B.S. and Ph.D. degrees from Southwest Jiaotong University, Chengdou, Sichuan Province, P.R.China in 2004 and 2010 respectively.

Currently, he is an assistant researcher in theShandong Provincial Key Laboratory of computer Network, Shandong Computer Science Center,Jinan, Shandong Province, P.R.China. His research interests involve biometric recognition, image forensics, information security and computer forensics.

Jiashu Zhang received his B. S. and Ph. D degree from university of Electronic Science and Technology of China, in 1987 and 2001, respectively. In 2001 he joined the school of Information Science and Technology at Southwest Jiaotong University, Chengdu, Sichuan, China, where he is a professor and director of the SiChuan province Key Lab of Signal and Information processing. His research interests focus on digital signal processing, information forensic and data hiding, biometrics & security, and chaos theory with application to electronic engineering.

Lianhai Wang, professor at Shandong computer Science center, Supervisor of master. He is an outstanding contributions expert of Shandong province and was awarded with special allowance from the national government. His research interests involve pattern recognition, information security live forensics and memory analysis.