Kernel Principal Component Analysis of Gabor Features for Palmprint Recognition*

Murat Aykut and Murat Ekinci

Computer Vision & Pattern Recognition Lab.
Department of Computer Engineering, Karadeniz Technical University
61080 Trabzon, Turkey
{murat_aykut,ekinci}@ktu.edu.tr

Abstract. This paper presents Gabor-based kernel Principal Component Analysis (KPCA) method by integrating the Gabor wavelet and the KPCA methods for palmprint recognition. The intensity values of the palmprint images extracted by using an image preprocessing method are first normalized. Then Gabor wavelets are applied to derive desirable palmprint features. The transformed palm images exhibit strong characteristics of spatial locality, scale, and orientation selectivity. The KPCA method nonlinearly maps the Gabor wavelet image into a high-dimensional feature space and the matching is realized by weighted Euclidean distance. The proposed algorithm has been successfully tested on the PolyU palmprint database which the samples were collected in two different sessions. Experimental results show that this method achieves 97.22% accuracy for PolyU dataset using 3850 images from 385 different palms captured in the first session as train set and the second session im0061ges as test set.

Keywords: Palmprint recognition, Biometrics, Gabor-wavelet, Kernel PCA.

1 Introduction

Over the last decade, palmprint recognition has attracted growing attention in biometrics [1]. The palmprint is a relatively new biometric feature, and can be used to recognize a person based on unique features in his palm, such as the principal lines, wrinkles, ridges, and texture etc. Furthermore, the several advantages of the palmprint identification can be (1) low-resolution imaging; (2) low-cost capture devices; (3) low intrusiveness; (4) difficulties to a fake palmprint; (5) stable line features, and so forth. In the literature, various techniques have been proposed for palmprint recognition. These techniques have focused on the extraction of structural [2], statistical [3], textural [4], algebraic [1] and multiple biometrics features [5].

In this paper, a novel Gabor-based kernel PCA method, by integrating the Gabor wavelet and the kernel PCA is presented for palmprint recognition. In the proposed method, Gabor wavelets first derive desirable palm features characterized by spatial frequency, spatial locality, and orientation selectivity to cope with the variations of

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illumination and location. The kernel PCA method [9] is then applied to project palmprints from the high dimensional palmprint space to a significantly lower-dimensional feature space, in which the palmprints can be discriminated much more efficiently. Finally, weighted Euclidean distance (WED) and the nearest neighbor classifier are used for feature matching and classification.

This paper also expands on [10] by including new experimental studies. The feasibility of the proposed method has been successfully tested on PolyU palmprint dataset that contains 7,752 images corresponding to 386 different palms. In the dataset, the images were acquired under variable illumination conditions and collected on two separate occasions. A large number of papers in the literature reported their recognition results on either the earlier or new version of PolyU databases, but least of them made informed comparisons among different algorithms. Here, we provide some comparative experiments to examine the performance of the proposed algorithm.

This paper is organized as follows. Section 2 introduces briefly Gabor wavelets and Gaborpalm extraction. Description of recently popular feature extraction method kernel PCA is given in Section 3. Experimental studies and results on palmprint database are summarized in Section 4, followed by conclusions in Section 5.

2 Gabor Feature Representation

Gabor (wavelet, kernel, or filters) functions are Gaussian modulated by complex sinusoids. The Gabor wavelets-based features were introduced to image analysis due to their biological relevance, performance of capturing salient visual properties [12] and computational properties [11]. The Gabor wavelets have been widely applied to texture segmentation [13], fingerprint recognition [15] and face recognition [8].

In the Gabor wavelets, basis function is the Gabor function defined as:

$$g(x,y)=\left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \tag{1}$$

where σ_x and σ_y are the horizontal and vertical standard deviation. Then Gabor wavelets can be obtained with dilations and rotations of this function like this:

$$\begin{aligned} &g_{mn}(x,y)=a^{-m}g(x',y'),\ \ a>1,\\ &x'=a^{-m}(x\cos\theta+y\sin\theta),\ \ and\ \ \ y'=a^{-m}(-x\sin\theta+y\cos\theta), \end{aligned} \tag{2}$$

where $\theta = n\pi/K$, a^{-m} is the scale factor, and K is the total number of orientations. Because Gabor functions form a non-orthogonal basis set, filtered images has redundant information. For this purpose, Manjunath and Ma [14] developed a strategy to reduce this redundancy. In this strategy, horizontal and vertical standard deviation values are computed according to lower and upper center frequencies of interest.

The Gabor feature representation of a palm image is obtained by convolving the family of Gabor kernels which can be produced by selecting different orientations and scales, with the palm image. Therefore, the Gabor wavelet representation formed by the set $S=\{P_{mn}(x,y): m\in\{0,\cdots,7\},\ n\in\{0,\cdots,4\}\}$.

In our approach, to reduce the computational costs of calculation for palmprint representation, five different scales and four orientations of Gabor wavelets are used. Parameters of the Gabor function are selected as U_{low}=0.2, and U_{high}=0.5, empirically.

3 Kernel PCA

The KPCA is a technique for non-linear feature extraction [9]. It is used to nonlinearly transform an input space into a high-dimensional feature space to achieve linearly separable with high probability for nonlinearly separable patterns in the input space.

Let $x_1, x_2, \cdots, x_M \in \mathbb{R}^N$ be the data in the input space (Gabor coefficients in this work), and let Φ be a nonlinear mapping between the input space and the feature space: $\Phi : \mathbb{R}^N \to F$, and then performing a linear PCA in F.

Assuming the mapped data is centered on the feature space, kernel PCA diagonalizes the estimate of the covariance matrix of the mapped data, defined as:

$$C = \frac{1}{M}\sum_{i=1}^{M}\Phi(x_i)\cdot\Phi(x_i)^T \tag{3}$$

For KPCA, the nonlinear mapping, Φ, usually defines a kernel function. The most often used kernel functions are polynomial, Gaussian and sigmoid kernels [9]. Gaussian kernel was used for the experiments in this work, and it is defined as:

$$k(x_i, x_j) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right), \tag{4}$$

The eigenvalues, $\lambda_1, \lambda_2, \cdots, \lambda_M$, and the eigenvectors, $V_1, V_2, \cdots, V_M$ of kernel PCA can then be derived by solving the following eigenvalue equation as given in [9]:

$$MA\Lambda = KA, \tag{5}$$

where $A = (\alpha_1, \cdots, \alpha_M)$ is an M x M orthogonal eigenvector matrix, Λ is a diagonal eigenvalue matrix and M is the number of training samples. $K \in \mathbb{R}^{M\times M}$ define a kernel matrix by means of dot product in the feature space. Since the eigenvalue equation is solved for A, we will have to normalize A to ensure that eigenvalues of kernel PCA have unit norm in the feature space, therefore $\alpha_j = \alpha_j \big/ \sqrt{\lambda_j}$. After the normalization, the eigenvector matrix, V, of kernel PCA is computed as follows:

$$V = DA, \quad D = \left[\Phi(x_1)\Phi(x_2)\cdots\Phi(x_M)\right] \tag{6}$$

where D is the data matrix in the feature space. Now let x be a test example whose map in the higher dimensional feature space is $\Phi(x)$. The kernel PCA features for this example are derived as follows:

$$F = V^T\Phi(x) = A^T B, \quad B = \left[\Phi(x_1)\cdot\Phi(x) \quad \Phi(x_2)\cdot\Phi(x) \quad \cdots \quad \Phi(x_M)\cdot\Phi(x)\right] \tag{7}$$

4 Experiments

4.1 PolyU Palmprint Database

The performance of the proposed method is evaluated on PolyU [3] palmprint database. In the literature, PolyU database is most-well known palmprint database which includes palm samples captured from different sessions. PolyU palmprint database was obtained by collecting palmprint images from 193 individuals using a palmprint capture device. This database contains 7752 gray scale images corresponding to 386 different palms. The samples were collected in two sessions, where ten samples were captured in each session. In addition, they changed the light source and adjusted the focus of the CCD camera so that the images collected on the first and second occasions could be regarded as being captured by two different palmprint devices [3].

At the experiments, we use the preprocessing technique described in [3] to align the palmprints. In this technique, the tangent of the two holes (they are between the fore and the middle finger, and between the ring and the little finger) are computed and used to align the palmprint. The central part of the image, which is 128 x 128, is then cropped to represent the whole palmprint. Such preprocessing greatly reduces the translation and rotation of the palmprints captured from the same palms. We then use z-score normalization on the gray-level distribution of the image. After the discrete transforms and feature extraction stages the WED is used to cluster the features [16].

4.2 Palmprint Identification

Palmprint identification searchs to answer the question “who is the person?”. In identification the image is matched against each template and, finally, the most similar template is obtained as the identification result.

In our experiments, firstly region of interest is cropped from the palm images. In order to reduce the computational cost of the Gabor wavelet, each subimage is reduced to 32 x 32 for Gabor-based experiments. We then obtain the Gabor feature representation of the palm images. Then kernel PCA works and nonlinearly derives low-dimensional features. WED-based matching is finally used to cluster those features. In our recognition experiments, first session samples are selected as training, and the second session samples are selected as test set. In the experiments, different feature lengths (50, 100, 200, 300, and 380) are used for comparative results.

The most well-known discrete transforms, such as FFT, DCT and DWT are alternatively employed in the proposed algorithm in order to examine the effects of these transform. In the FFT, the coefficients correspond to the lower frequencies than 3 x 3, and higher frequencies than 16 x 16, are discarded by filtering. In DCT, lower frequencies correspond to the 12.5% coefficients are also selected as useful features. In DWT, the wavelet transform of the palm image is extended to the fourth level. We then choose lowest frequency subimage with a matrix of 16 x 16 as the feature vectors obtained by Daubechies-8 filter banks [17]. In discrete transforms, parameters were empirically determined to achieve highest accuracies for palmprint recognition.

The experimental results are also summarized in Table 1. The number given in Table 1 represents the correct recognition rates. As can be seen from Table 1, the presented approach has achieved highest recognition rate. To improve the experimental

results by doing more experiments, the image size 64 x 64 has not been able to choosen because of the memory limitation constrained by the operating system. Hence, 32 x 32 image size will be used for Gabor based approach. The other important point summarized in Table 1 is that, kernel PCA gives higher performance than PCA for all feature lengths used.

Table 1. Comparative performance evaluation for different methods on the PolyU database with different feature lengths

Method	Feature Length (Eigenvectors)				
	50	75	100	200	300
PCA	88.597%	90.311%	90.857%	91.246%	91.246%
KPCA	88.597%	90.415%	90.857%	91.116%	91.168%
DCT+KPCA	89.74%	91.636%	92.311%	93.376%	93.454%
FFT+KPCA	71.324%	76.181%	78.805%	82.411%	84.493%
DWT+KPCA	89.376%	91.324%	92.493%	93.428%	93.584%
Gabor+PCA	82.597%	88.025%	90.701%	93.61%	94.311%
Gabor+KPCA	83.038%	88.285%	90.987%	93.714%	94.415%
Gabor+KPCA (64 x 64)	86.103%	90.259%	92.051%	94.259%	94.805%

Table 2. Comparison of correct recognition rates (%) of different methods with the different number of the samples per palm in the kernel matrix calculation

Method	Number of samples in each class									
	1	2	3	4	5	6	7	8	9	10
DWT+KPCA	93.58	93.69	93.77	94.0	94.05	94.23	94.36	94.47	94.52	94.60
Gabor+PCA	94.41	94.65	94.78	94.78	95.84	96.0	96.36	96.57	96.86	96.91
Gabor+KPCA	94.57	94.65	95.58	96.54	96.57	96.75	96.88	97.09	97.12	97.22

The results presented so far are for the kernel matrix, calculated by using only one sample for each palm. To make further improving on the recognition accuracies, the different number of the samples for each palm are used in the following experiment. This is also one of the contribution in this paper. In this experiment we will discuss results for only 32 x 32 image sizes. As mentioned above, while the image size is reduced to 64 x 64 instead of 32 x 32, the application of the presented approach was not successful for the all samples used for per palm due to typical constraints on the memory available in term of the operating system. Operating systems based Microsoft Windows NT provide applications with a 4GB virtual address space. The virtual address space is divided such that 2GB is available to the application and the other 2GB is available only to the system [20]. Table 2 presents the comparison of correct recognition rates using KPCA on DWT features, PCA and KPCA on gabor-wavelet features. A high recognition rate (97.22%) was achieved for the proposed method,

with the all samples usage in calculation of the kernel matrix. It is evident that the number of the samples for each class play an important role in the kernel trick. In the experiments given in Table 2, the feature dimensions of the samples were dynamically determined with PCA or KPCA method by ratio of the sum of chosen largest eigenvalues to all (about 98%).

When the palmprints are collected in different sessions, direction and amount of stretching of a palm may vary so that even palmprints from the same palm may have a little rotation and translation. Furthermore, the lighting, translation, and orientation conditions in both sessions are very different. Hence they will effect the accuracy. As conclusion, the experiments achieved on the training and test images collected in different sessions are becoming more realistic. Figure 1 shows typical samples and problems in the database. The palms shown in the first column were used as the train set, and the corresponding to the last two samples were also employed as test set.

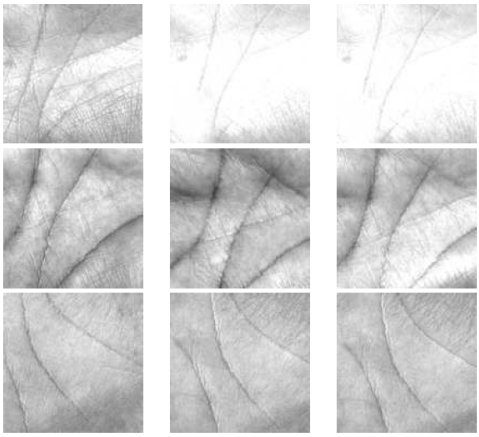

Fig. 1. Experimental results by different lighting (top), orientation (middle) and rotation (bottom) conditions

In biometric systems, the recognition accuracy will decrease dramatically when the number of image classes increase [1]. In our previous work [10], we have achieved 100% accuracy for the earlier version of PolyU palmprint database which contains 600 images from 100 different palms. 300 images collected in the first session were selected for training, the rest samples were also used as test set.

4.2.1 Comparisons

Most published papers in the literature has presented their experimental results on the samples collected in the same session. For instance, the presented results in the published papers [6][7][18] were achieved by using training and test sets contain the palmprint images collected from one session only. In the other paper [4], they selected some of the images collected in the first session as training set, and then used the rest images as test set. As different from them, in our experiments, given in Table 1 and 2, first session palm images were chosen as training set and the second session palm images were used as the test set.

To compare the performance of the proposed algorithm, the experimental results given in Table 3 were obtained from the first session samples only. We took the four samples of each person as training set, and the remaining six samples as test set. In this test before the Gabor transform images are sampled to 64 x 64 resolution. The numbers given in Table 3 represent the corresponding recognition rate. A high recognition rate (99.697%) was achieved for kernel PCA with Gabor-wavelet and WED-based classifier approach. The experimental results of different discrete transforms are also summarized in Table 3 to show their performance.

Table 3. Testing results of different approaches with different feature lengths

Method	Feature Length				
	50	100	200	300	380
PCA	98.747%	99.179%	99.093%	99.05%	98.963%
KPCA	98.877%	99.222%	99.05%	99.006%	98.92%
DWT+PCA	98.834%	99.309%	99.352%	99.352%	99.395%
Gabor+PCA	98.056%	99.222%	99.438%	99.438%	82.728%
DWT+KPCA	98.747%	99.309%	99.568%	99.654%	99.654%
Gabor+KPCA	98.1%	99.265%	99.525%	99.697%	99.697%

Table 4 comparatively presents the experimental results achieved by different palmprint recognition approaches. The works in [6][7][18][4] used the early versions or some samples of the PolyU palmprint database. In other works [5][19], they also collected their palmprint images on one occasion only.

Table 4. Comparisons of different palmprint recognition methods

	The approaches						
	This paper	In [6]	In [7]	In [18]	In [4]	In [5]	In [19]
Different palms	386	300	382	50	190	100	160
Total samples	3860	3000	3056	200	3040	1000	1600
Recog. Rate (%)	99.697	99.2	99.149	98.0	98.13	95.8	97.25

In the work [6], a linear projection-based on Fisher's linear discriminant was used. Then a nearest-neighbor classifier was employed for classification. In [7], they proposed an eigenpalm method and applied to recognition with an Euclidean distance. In another work [18], they use the wavelet transform and identify the predominant structures using context modeling. The work in [4] proposed an approach based on DCT and linear discriminant technique. In their experiments, they used five images of each person as the training samples, and the remainder (11 images of each person) as the test samples. Kumar and Zhang [5] proposed a method of hand-shape and palmprint image segmentation, and the combination of features from these images.

Their approach uses DCT and some classification algorithms to evaluate the performance. In the study [19], kernel FDA is proposed for palmprint recognition. Although our proposed method is tested on the public database includes more different palms, the proposed approach achieves highly competitive performance with respect to the other published papers.

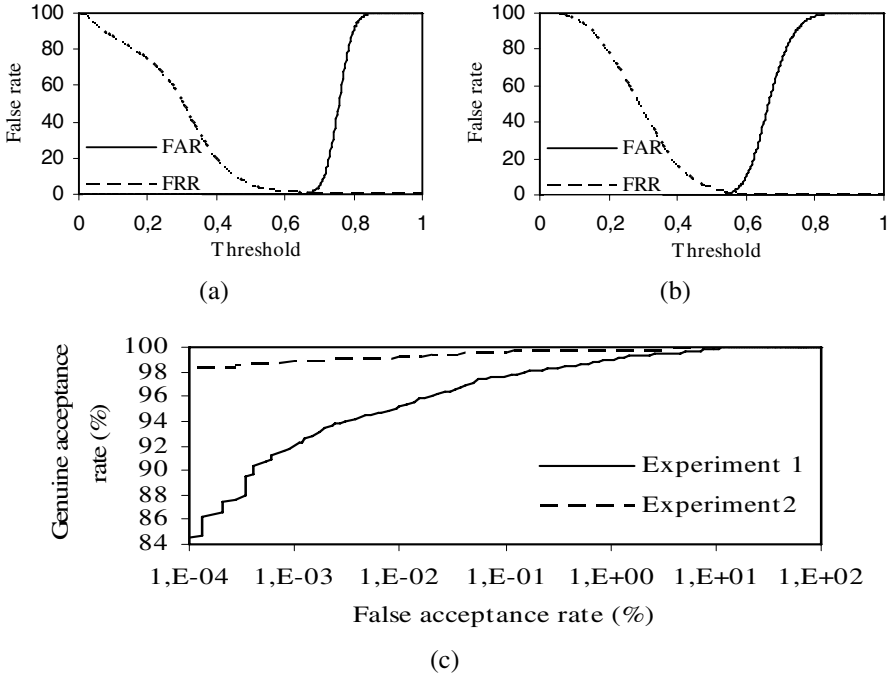

Fig. 2. Verification results of the proposed method (a) FAR-FRR curves of first experiment (b) FAR-FRR curves of second experiment (c) ROC curves of the experiments

Table 5. Experimental results near cross-over points of the FAR and FRR curves

First verification experiment			Second verification experiment		
Threshold	FAR (%)	FRR (%)	Threshold	FAR (%)	FRR (%)
0.737	27.866	0	0.609	13.915	0
0.721	14.282	0.051	0.591	7.166	0.285
0.705	6.255	0.129	0.573	3.188	0.467
0.673	0.804	0.337	0.551	0.960	0.987
0.661	0.337	0.337	0.533	0.321	1.636
0.645	0.102	0.441	0.515	0.099	2.337
0.613	0.009	0.909	0.478	0.009	4.909
0.579	4.7×10^{-4}	1.428	0.434	4.05×10^{-4}	9.610
0.561	6.7×10^{-5}	1.844	0.398	6.76×10^{-5}	15.662
0.553	0	2.155	0.396	0	16.103

4.3 Palmprint Verification

Biometric verification answers the question of "whether the person is whom he claims to be" by examining his biometric features. To obtain the verification accuracy, we perform two experiments which research impact of the time lag. In both of them, Gabor wavelet transform is applied for the palmprint images at 32 x 32 resolutions. Feature extraction and matching procedures are achieved by using KPCA and WED. In the KPCA, kernel space is formed using 10 first session samples for each class.

In the first experiment on the verification, the palm images in the first session only were used as database. Each palmprint image is then matched with all the other palmprint images in the database. The total number of comparisons is 14,818,650, where the number of intra-class comparisons is 34,650 and the number of inter-class comparisons is 14,784,000. In the verification system, the performance of the system is often measured by the false accept rate (FAR) and false reject rate (FRR). Fig. 2.a and Fig. 2.c show the FAR and FRR curves and corresponding Receiver Operating Characteristic (ROC) curve, which is a plot of genuine acceptance rate against false acceptance rate for all possible operating points, respectively. The experimental results near the cross-over point of the FAR and FRR curves are tabulated in Table 5. From Fig. 2 and Table 5, it can be seen that EER of this experiment is 0.338% and genuine acceptance rate is 98.16% while FAR is about 6×10^{-5} %.

In the second experiment, the palm images collected in the first session were used as training set; the images accumulated in the second session were used as test set. Each palmprint image in the training set is matched with all the palmprint images in the test set. The total number of comparisons is 14,822,500, where the number of intra-class comparisons is 38,500 and the rest are inter-class comparisons. Fig. 2.b and Fig. 2.c show the FAR and FRR curves of this experiment and corresponding ROC curve, respectively. The experimental results near the cross-over point of the FAR and FRR curves are finally tabulated in Table 5. From Fig. 2.b and Table 5, it can be seen that EER of this experiment is 0.982% and genuine acceptance rate is 90.39% while FAR is about 5×10^{-4} %.

5 Conclusions

In this paper, Gabor-based KPCA method by integrating the Gabor wavelet representation of palm images and the kernel PCA method are proposed for palmprint recognition. The Gabor wavelets are particularly aggressive at capturing the features of the local structures corresponding to spatial frequency, spatial localization, and orientation selectively and Gaborpalms can be robust against variations due to illumination and pose changes. The kernel PCA overcomes many limitations of its linear counterpart by nonlinearly mapping the input space to a high-dimensional feature space. The proposed algorithm has been successfully tested on public data set from the PolyU palmprint database for which the samples were collected in two different sessions. In the experiments, the samples captured in the first session were used as training set, the others collected in the second session were chosen as test set. Experimental results show that 1) Gabor-wavelet is an effective and efficient palmprint representation, and 2) the proposed recognition approach achieves highly competitive performance with respect to the published major palmprint recognition approaches.

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