Palmprint Recognition by Applying Wavelet Subband Representation and Kernel PCA

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Abstract. This paper presents a novel Daubechies-based kernel Principal Component Analysis (PCA) method by integrating the Daubechies wavelet representation of palm images and the kernel PCA method for palmprint recognition. The palmprint is first transformed into the wavelet domain to decompose palm images and the lowest resolution subband coefficients are chosen for palm representation. The kernel PCA method is then applied to extract non-linear features from the subband coefficients. Finally, weighted Euclidean linear distance based NN classifier and support vector machine (SVM) are comparatively performed for similarity measurement. Experimental results on PolyU Palmprint Databases demonstrate that the proposed approach achieves highly competitive performance with respect to the published palmprint recognition approaches.

1 Introduction

Biometric approaches utilize the identity of a person with certain physiological or behavioral characteristics [1]. Palmprint is a relatively new biometric feature, and is regarded as one of the most unique, reliable, and stable personal characteristics [1]. Compared with other biometrics, the palmprints has several advantages: low-resolution imaging can be employed; low-cost capture devices can be used; it is difficult to fake a palmprint; the line features of the palmprints are stable, etc. [1]-[11]. It is for these reasons that palmprint recognition has recently attracted an increasing amount of attention from researchers.

There are many approaches for palmprint recognition based on line-based [6][4][5], texture-based [11][5], and appearance-based methods [3][10][9][8] in various literature. In the line-based approach, the features used such as principal lines, wrinkles, delta points, minutiae [6], feature points [4] and interesting points [5], are sometimes difficult to extract directly from a given palmprint image with low resolution. The recognition rates and computational efficiency are not strong enough for palmprint recognition. In the texture-based approach, the texture features [5][1] are not sufficient and the extracted features are greatly affected by the lighting conditions. From that disadvantages, researches have developed the appearance-based approaches.

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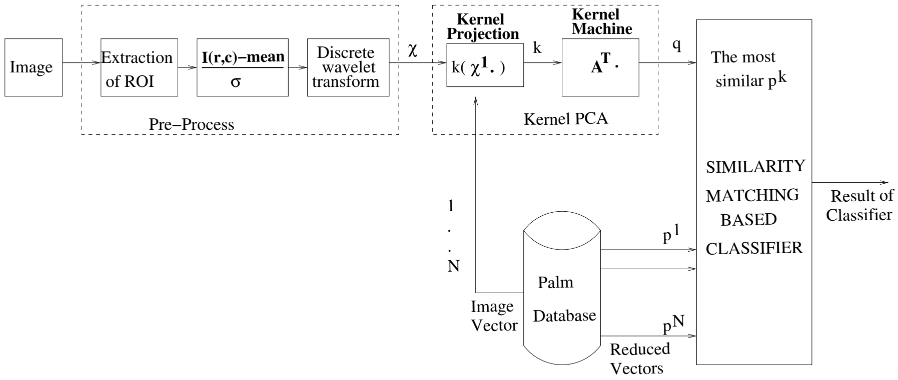

Fig. 1. Main steps in the proposed algorithm

The appearance-based approaches only use a small quantity of samples in each palmprint class randomly selected as training samples to extract the appearance features (commonly called algebraic features) of palmprints and form feature vector. Eigenpalms method [10], fisherpalms method [3], and eigen-and-fisher palms [9] are presented as the appearance-based approaches for palmprint recognition in literature. Basically, their representations only encode second-order statistics, namely, the variance and the covariance. As these second order statistics provide only partial information on the statistics both natural images and palm images, it might become necessary to incorporate higher order statistics as well. In other words, they are not sensitive to higher order statistics of features. A kernel fisherpalm [8] is presented as another work to resolve that problem. In addition, for palmprint recognition, the pixel wise covariance among the pixels may not be sufficient for recognition. The appearance of a palm image is also severely affected by illumination conditions that hinder the automatic palmprint recognition process.

Converging evidence in neurophysiology and psychology is consistent with the notion that the visual system analyses input at several spatial resolution scales [26]. Thus, spatial frequency preprocessing of palms is justified by what is known about early visual processing. By spatial frequency analysis, an image is represented as a weighted combination of basis functions, in which high frequencies carry finely detailed information and low frequencies carry coarse, shape-based information. Recently, there have been renewed interests in applying discrete transform techniques to solve some problems in face recognition [18][19][24], in palmprint recognition [2][24][25] and many real world problems. An appropriate wavelet transform can result in robust representations with regard to lighting changes and be capable of capturing substantial palm features while keeping computational complexity low.

From the considerations briefly explained above, we propose to use discrete wavelet transform (DWT) to decompose palm images and choose the lowest resolution subband coefficients for palm representation. We then apply kernel PCA as a nonlinear method to project palmprints from the high-dimensional palmprint space to a significantly lower-dimensional feature space, in which the palmprints from the different palms can be discriminated much more efficiently.

The block diagram of the main steps involved in developing the proposed palmprint algorithm is illustrated in Figure 1. The palm images are read from the digital system and used to extract a gray-level region of interest (ROI) depicting palmprint texture. The palm images are resized to 128 by 128 pixels, converted into column vector form and made zero mean and unit variance. In the process of feature extraction, the palmprint images are then decomposed into multi resolution representation by discrete wavelet transform (DWT). Then, the decomposed images in the lowest resolution subband coefficients are selected and are fed into a nonlinear method, Kernel PCA, computation. Therefore, we get the feature matrix of all training palmprint samples. The main contributions and novelties of the current paper are summarized as follows:

– To reliably extract palmprint representation, we adopt a template matching approach where the feature vector of a palm image is obtained through a multilevel two-dimensional discrete wavelet transform (DWT). The dimensionality of a palm image is greatly reduced to produce the *waveletpalm*.
– A nonlinear machine learning method, kernel PCA, is applied to extract palmprint features from the waveletpalm.
– The proposed algorithm is tested on two public palmprint databases, we called as PolyU-I and PolyU-II databases. We provide some quantitative comparative experiments to examine the performance of the proposed algorithm and different combinations of the proposed algorithm. Comparison between the proposed algorithm and other recent approaches is also given.

2 Discrete Wavelet Transform

The DWT was applied for different applications given in the literature e.g. texture classification [16], image compression [17], face recognition [18][19], because of its powerful capability for multi resolution decomposition analysis. The wavelet transform breaks an image down into four sub-sampled, or decimated, images. They are subsampled by keeping every other pixel. The results consist of one image that has been high pass filtered in both the horizontal and vertical directions, one that has been high pass filtered in the vertical and low pass filtered in the horizontal, one that has been lowpassed in the vertical and highpassed in the horizontal, and one that has been low pass filtered in both directions.

So, the wavelet transform is created by passing the image through a series of 2D filter bank stages. One stage is shown in Fig. 2, in which an image is first filtered in the horizontal direction. The filtered outputs are then down sampled by a factor of 2 in the horizontal direction. These signals are then each filtered by an identical filter pair in the vertical direction. Decomposed image into 4 subbands is also shown in Fig. 2. Here, H and L represent the high pass and low pass filters, respectively, and $\boxed{\downarrow 2}$ denotes the subsampling by 2. Second-level decomposition can then be conducted on the LL subband. Second-level structure

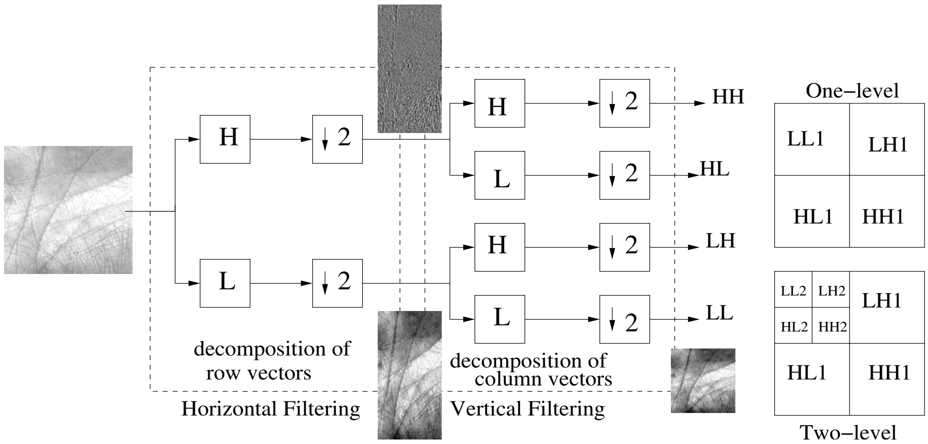

Fig. 2. One-level 2-D filter bank for wavelet decomposition and multi-resolution structure of wavelet decomposition of an image

of wavelet decomposition of an image is also shown in Fig. 2. This decomposition can be repeated for n-levels.

The proposed work based on the DWT addresses the four-level and six-level decomposition of images in Database I and Database II, respectively. Daubechies-4 and -8 low pass and high pass filters are also implemented [14]. Additionally, four- and six-levels of decompositions are produced, then 32 x 32 and 16 x 16 sub-images of 128 x 128 images in the wavelet is processed as useful features in the palmprint images. Reducing of the image resolution helps to decrease the computation load of the feature extraction process.

2.1 FFT and DCT

$F(u, v)$ and $C(u, v)$ are 2-D FFT and DCT coefficients of an W x H image $I(x, y)$, respectively. The feature sequence for each one is independently generated using the 2D-FFT and 2D-DCT techniques. The palmprint image (128 x 128) in the spatial domain is not divided into any blocks. The FFT and DCT coefficients for the palmprint image are first computed. In the FFT, the coefficients correspond to the lower frequencies than 3 x 3, and correspond to the higher frequencies than 16 x 16 in the FFT, are discarded by filtering. In other words, 247 coefficients correspond to the 6% coefficients in the frequency domain, are only implemented. These data are empirically determined to achieve best performance. Therefore, the palmprint image in the spatial domain is represented with a few coefficients, which is corresponding to 1.5% of the original size of image (128 x 128), by using filtered FFT based image representation. In DCT, low frequencies correspond to the 12.5% coefficients are also selected as useful features. Finally, $N = \mu$ x ν features form a vector $\chi \in \Re^N$, $\chi = (F_{0,0}, F_{0,1}, ...F_{\mu,\nu})$ for FFT, and form a vector $\chi = (C_{0,0}, C_{0,1}, ...C_{\mu,\nu})$ for DCT.

3 Kernel PCA

The kernel PCA (KPCA) is a technique for nonlinear dimension reduction of data with an underlying nonlinear spatial structure. A key insight behind KPCA is to transform the input data into a higher-dimensional **feature space** [12]. The feature space is constructed such that a nonlinear operation can be applied in the input space by applying a linear operation in the feature space. Consequently, standard PCA can be applied in feature space to perform nonlinear PCA in the input space.

Let $\chi_1, \chi_2, ..., \chi_M \in \Re^N$ be the data in the input space (the input space is 2D-DWT coefficients in this work), and let Φ be a nonlinear mapping between the input space and the feature space i.e. using a map $\Phi : \Re^N \rightarrow F$, and then performing a linear PCA in F. Note that, for kernel PCA, the nonlinear mapping, Φ, usually defines a kernel function [12]. The most often used kernel functions are polynomial kernels, Gaussian kernels, and sigmoid kernels [12]:

$$k(\chi_i, \chi_j) = \langle \chi_i, \chi_j \rangle^d, \tag{1}$$

$$k(\chi_i, \chi_j) = exp\left(-\frac{\|\chi_i - \chi_j\|^2}{2\sigma^2}\right), \tag{2}$$

$$k(\chi_i, \chi_j) = tanh(\kappa\langle \chi_i, \chi_j \rangle + \vartheta), \tag{3}$$

where d is a number in the set of natural numbers, e.g. $\{1,2,\ldots\}$, $\sigma > 0$, $\kappa > 0$, and $\vartheta < 0$.

The mapped data is centered, i.e. $\sum_{i=1}^{M} \Phi(\chi_i) = 0$ (for details see [12]), and let D represents the data matrix in the feature space: $D = [\Phi(\chi_1)\Phi(\chi_2)\cdots\Phi(\chi_M)]$. Let $K \in \Re^{MxM}$ define a kernel matrix by means of dot product in the feature space:

$$K_{ij} = (\Phi(\chi_i) \cdot \Phi(\chi_j)) \,. \tag{4}$$

The work in [12] shows that the eigenvalues, $\lambda_1, \lambda_2, \ldots, \lambda_M$, and the eigenvectors, $V_1, V_2, \ldots, V_M$, of kernel PCA can be derived by solving the following eigenvalue equation:

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

with $A = [\alpha_1, \alpha_2, \ldots, \alpha_M]$ and $\Lambda = diag\{\lambda_1, \lambda_2, \ldots, \lambda_M\}$. A is MXM orthogonal eigenvector matrix, Λ is a diagonal eigenvalue matrix with diagonal elements in decreasing order ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_M$), and M is a constant corresponds to the number of training samples. Since the eigenvalue equation is solved for α's instead of eigenvectors, $V = [V_1, V_2 \ldots V_M]$, of kernel PCA, first, A should be normalized to ensure that eigenvalues of kernel PCA have unit norm in the feature space, therefore $\lambda_i\|\alpha_i\|^2 = 1, i = 1, 2, \ldots, M$. After normalization the eigenvector matrix, V, of kernel PCA is then computed as follows:

$$V = DA \tag{6}$$

Now let χ be a test sample whose map in the higher dimensional feature space is $\Phi(\chi)$. The kernel PCA features of χ are derived as follows:

$$F = V^T \Phi(\chi) = A^T B \tag{7}$$

where $B = [\Phi(\chi_1) \cdot \Phi(\chi)\Phi(\chi_2) \cdot \Phi(\chi) \cdots \Phi(\chi_M) \cdot \Phi(\chi)]^T$.

4 Similarity Measurement

When a palm image is presented to the wavelet-based kernel PCA classifier, the wavelet feature of the image is first calculated as detailed in Section 2, and the low-dimensional wavelet-based kernel PCA features, F, are derived using the equation 7. Let $M_k^0, k = 1, 2, .., L$, be the mean of the training samples for class w_k. The classifier applies, then, the nearest neighbor rule for classification using some similarity (distance) measure δ:

$$\delta(F, M_k^0) = min_j \delta(F, M_j^0) \longrightarrow F \in w_k, \tag{8}$$

The wavelet-based kernel PCA feature vector, F, is classified as belong to the class of the closest mean, M_k^0, using the similarity measure δ.

Popular similarity measures include the Weighted Euclidean Distance (WED) [13] and Linear Euclidean Distance (LED) which are defined as follows:

$$WED : d_k = \sum_{i=1}^{N} \frac{(f(i) - f_k(i))^2}{(s_k)^2} \tag{9}$$

where f is the feature vector of the unknown palmprint, f_k and s_k denote the kth feature vector and its standard deviation, and N is the feature length.

$$LED : d_{ij}(\mathbf{x}) = d_i(\mathbf{x}) - d_j(\mathbf{x}) = 0 \tag{10}$$

where $d_{i,j}$ is the decision boundary separating class w_i from w_j. Thus $d_{ij} > 0$ for pattern of class w_i and $d_{ij} < 0$ for patterns of class w_j.

$$d_j(\mathbf{x}) = \mathbf{x}^T \mathbf{m}_j - \frac{1}{2} \mathbf{m}_j^T \mathbf{m}_j, \quad j = 1, 2, ...M \tag{11}$$

$$\mathbf{m}_j = \frac{1}{N_j} \sum_{\mathbf{x} \in w_j} \mathbf{x}, \qquad j = 1, 2, ..., M \tag{12}$$

where M is the number of pattern classes, N_j is the number of pattern vectors from class w_j and the summation is taken over these vectors.

Support Vector Machines (SVMs) have recently been known to be successful in a wide variety of applications [12][20]. SVM-based and WED-based classifier are also compared in this work. In SVM, we first have a training data set, like, $D = \{(x_i, y_i) | x_i \in X, y_i \in Y, i = 1, ..., m\}$. Where X is a vector space of dimension d and $Y = \{+1, -1\}$. The basic idea of SVM consists in first mapping

x into a high dimension space via a function, then maximizing the margin around the separating hyper lane between two classes, which can be formulated as the following convex quadratic programming problem:

$$maximize \quad W(\alpha) = \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{m} \alpha_i \alpha_j y_i y_j (K(x_i, x_j) + \frac{1}{C}\delta_{i,j}) \tag{13}$$

$$subject \quad to \qquad 0 \leq \alpha_i \leq C, \forall_i, \tag{14}$$

$$and \qquad \sum_{i}^{m} y_i \alpha_i = 0 \tag{15}$$

where $\alpha_i (\geq 0)$ are Lagrange multipliers. C is a parameter that assigns penalty cost to misclassification of samples. $\delta_{i,j}$ is the Kronecker symbol and $K(x_i, x_j) = \langle \phi(x_i) \cdot \phi(x_j) \rangle$ is the Gram matrix of the training examples. The form of decision function can be described as

$$f(x) = \langle w, \Phi(x) \rangle + b \tag{16}$$

where, $w = \sum_{i=1}^{m} \alpha_j^* y_i \Phi(x_i)$, and b is a bias term.

5 Experiments

The performance of the proposed method is evaluated with PolyU-I database [15] and PolyU-II database [11].

5.1 Database I

The samples in PolyU-I palmprint database were captured by a CCD based palmprint capture device [15]. The PolyU-I database contains 600 gray scale images of 100 different palms with six samples for each palm. Six samples from each of these palms were collected in two sessions, where the first three samples were captured in the first session, and the other three in the second session. The average interval between the first and the second session was two months. In our experiments, sub-image of each original palmprints was firstly cropped to the size of 128 x 128 by finger gaps using an algorithm similar to [21]. Figure 3 shows typical samples in the database in which the last two samples were captured from the same palm at different sessions. When 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, palms differ in size and the lighting, translation, and orientation conditions in both sessions are very different. Hence they will effect the accuracy, if palmprint images are oriented and normalized before feature extractions and matching. But no any preprocessing step was done. It is directly processed to achieve recognition performances given in this paper. For instance, the palms

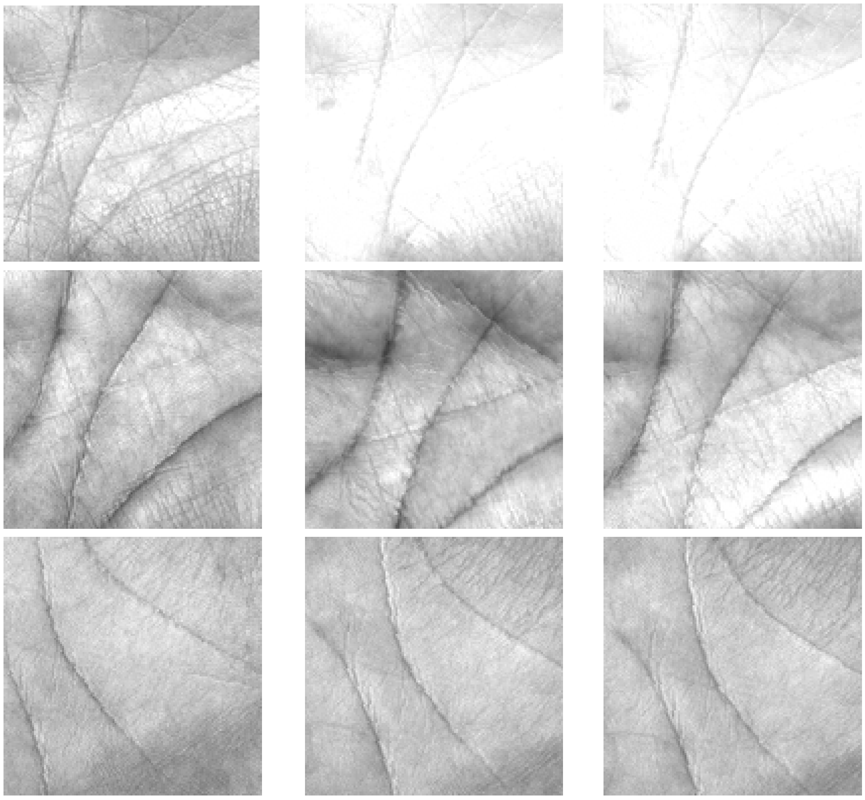

Fig. 3. Some typical restrictions in the the PolyU-I database. Left samples were cropped at first session. Last two samples were cropped from the same palm at second session. The restrictions are reported in this work as the different lighting (Top), orientation (Middle), and translation (Bottom) conditions.

shown in the first column in Figure 3 are used as training set, and the corresponding to the last two samples are also employed as testing set. In order to reduce the computation complexity, we independently adopted three different 2D discrete transforms (FFT, DCT, WT) to decompose the palm print image into lower resolution.

Two different experiments on this PolyU-I database were done to show the recognition performance of the proposed algorithm. The first experiment is the most challenging experiment which is in the case of that the palm images captured in the first session are chosen as training set, the other palms captured in the second session are selected as testing set. This is more realistic experiment and there are also more various problems such as lighting, orientation, and translation conditions because the training and test images were not obtained in the same session, which is always the case in a real world applications. During the experiments, the features are extracted by using the proposed method with

Table 1. Database I: Comparative performance evaluation for the different matching schemes with different feature lengths

Method	Feature length				
	25	75	125	200	300
PCA	212 (70.667)	231 (77.0)	229 (76.333)	227 (75.66)	231 (77.0)
KPCA	149 (49.67)	186 (62.0)	224 (74.667)	221 (73.667)	233 (77.667)
DCT+KPCA	218 (72.667)	231 (77.0)	240 (80.0)	240 (80.0)	242 (80.767)
FFT+KPCA	194 (64.667)	226 (75.333)	240 (80.0)	244 (81.333)	242 (80.667)
DWT+KPCA	215 (71.667)	234 (78.0)	237 (79.0)	242 (80.667)	244 (81.333)

length 25, 75, 125, 200, and 300. The WED is first used to cluster those features. The matching is separately conducted and the results are listed in Table 1. The numbers given in Table 1 show the correct recognition from 300 test samples. The entries in the brackets indicate the corresponding recognition accuracies. Kernel PCA gives higher performance than PCA when long feature lengths is used. A high recognition rate (81.333%) was achieved for the DCT+KPCA and DWT+KPCA, with feature lengths of 200 and 300, respectively.

Figure 4 shows the performance variation for WED and SVM classifiers with the increase in number of features produced by wavelet-based kernel PCA. The parameters of SVM employed in the experiments were empirically selected. The SVM using the radial basis function was implemented. The SVM training was achieved with C-SVM, a commonly used SVM classification algorithm [22]. The training parameter γ, ϵ and C were empirically fixed at 0.5, 0.1, and 100, respectively. When the number of features is less than about 60, the SVM-based classifier gives higher recognition rate. But while the number of features is higher than about 60, WED-based classifier gives higher accurate results.

The recognition accuracy (81.333%) in the first experiment may not be very encouraging. When the database is carefully investigated, there are translation,

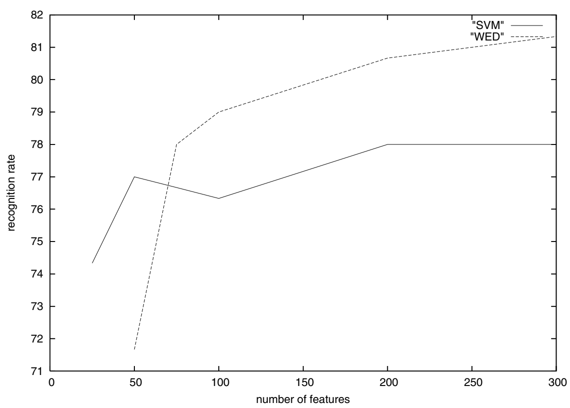

Fig. 4. Performance analysis of classifier with the number of features: DWT+ KPCA method using the SVM- and WED-based classifiers

Table 2. Database I: Recognition rate of different number of training samples(%)

Train	PCA		KPCA		FFT+KPCA		DCT+KPCA		DWT+KPCA	
Samples	LED	WED	LED	WED	LED	WED	LED	WED	LED	WED
1	66.0	80.2	73.6	80.6	82.0	82.8	80.0	82.4	82.8	82.0
2	74.25	93.5	83.75	94.0	92.25	98.0	89.5	95.75	89.5	95.75
3	77.3	95.0	84.0	96.67	90.6	98.67	90.0	97.33	90.3	97.67
4	70.0	97.5	82.0	98.0	92.0	**99.5**	90.5	98.0	91.0	98.0

rotation, or illumination changes in the input images at least 42 samples correspond to 14 persons (the database includes 100 persons). This is one of the main problem to obtain lower recognition rate than expected. We did not do more works in the pre-processing and at the palm image alignment for PolyU-I database, because we focused to another palmprint database which is developed by the PolyU [11] and includes more samples and persons, and we called PolyU-II to this database. However, we designed a second experiment for PolyU-I database to clarify the efficiency of the proposed algorithm. The experiments on the PolyU-II database will also be given in the next section.

The performance of the second experiment on the PolyU-I database is summarized in Table 2. Table 2 shows the different recognition rate with different number of training samples. Four kind of experiment schemes were designed: one (two, three, or four) sample(s) of each person was randomly selected for training, and other samples were used for authentication, respectively. Kernel PCA has given higher recognition rate than PCA. Discrete transform-based kernel PCA has increased the recognition rate. High recognition rates (99.5%) and (98.0%) were achieved by FFT+KPCA and DWT+KPCA, respectively, when the four samples were used as training. WED-based classifier has also given higher matching results than LED-based classifier.

5.2 Database II

The PolyU-II palmprint database [11] was also obtained by collecting palmprint images from 193 individuals using a palmprint capture device. People was asked to provide about 10 images, each of the left and right palm. Therefore, each person provided around 40 images, so that this PolyU database contained a total of 7,752 gray scale images from 386 different palms. The samples were collected in two sessions, where the first ten samples were captured in the first session and other ten in the second session. The average interval between the first and second collection was 69 days. The resolution of all original palmprint images is 384 x 284 pixels at 75 dpi. 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. Typical samples captured under different lighting conditions on the second sessions of image capture could not be shown in this paper because of paper limitation, but they can be seen from [11]. Although the lighting conditions in the second collection of palm images are quite different from the first collection, the proposed method can still easily recognize the same palm.

At the experiments for PolyU-II database, we use the preprocessing technique described in [11] to align the palmprints. In this technique, the tangent of the two holes (they are between the forefinger and the middle finger, and between the ring finger 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. An example of the palmprint and its cropped image is shown in Figure 5.

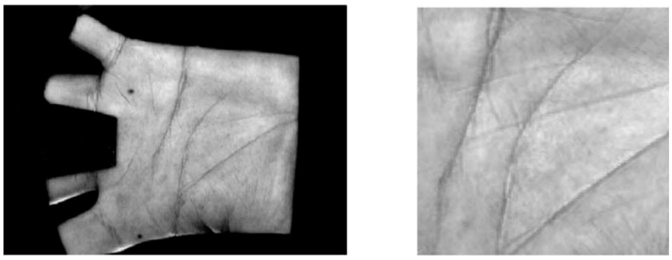

Fig. 5. Original palmprint and it's cropped image

Two different experiments were done on the PolyU-II database. In the first experiment, the first session was used as training set, second session includes 3850 samples of 386 different palms was also used as testing set. In this experiment, the features are extracted by using the proposed kernel based eigenspace method with length 50, 100, 200, 300, and 380. WED- and LED-based matching were independently used to cluster those features. The matching is separately conducted and the results are listed in Table 3. The number given in Table 3 represents the correct recognition samples in all test samples (3850). The entries in brackets also represent corresponding the recognition rate. High recognition rates **93.454%** and **93.168%** were achieved for the FFT+KPCA and DWT+KPCA, with feature length of 300, respectively. A nearest-neighbor classifier based on

Table 3. Database II: Comparative performance evaluation for the different matching schemes with different feature lengths. Train is first session, test is second session.

Method	Feature length				
	50	75	100	200	300
PCA	3411 (88.597)	3477 (90.311)	3498 (90.857)	3513 (91.246)	3513 (91.246)
DWT+PCA	3444 (89.454)	3513 (91.246)	3546 (92.103)	3570 (92.727)	3568 (92.675)
KPCA	3411 (88.597)	3481 (90.415)	3498 (90.857)	3508 (91.116)	3510 (91.168)
DCT+KPCA	3455 (89.74)	3528 (91.636)	3554 (92.311)	3595 (93.376)	3598 (93.454)
FFT+KPCA	2746 (71.324)	2933 (76.181)	3034 (78.805)	3174 (82.441)	3253 (84.493)
DWT+KPCA	3457 (89.792)	3531 (91.714)	3558 (92.415)	3584 (93.09)	3587 (93.168)

the weighted Euclidean distance (WED) is employed. It is evident that feature length can play an important role in the matching process. Long feature lengths lead to a high recognition rate.

The another interesting point, DCT+KPCA based method achieved highest recognition rate (93.454%) with feature length of 300, while it gave lowest accuracy for the first database as explained in previous section (see to the Table 1). Although FFT+KPCA based method achieved highest recognition rate for the first database, but it has given lowest recognition rate (84.493%) for the second database, with feature length of 300. DWT+KPCA based method has also achieved very close recognition rate to the highest recognition rates for both databases. For instance, at the experiments given in Table 3, although DWT+KPCA achieved the better performance than others for the feature lengths less than 300, but DCT+KPCA achieved higher recognition rate than DWT+KPCA for feature length of 300. Consequently, we propose DWT+KPCA based method for palmprint recognition because it has given stable experimental results on both databases.

The performance variation for WED-based nearest-neighbor (NN) and SVM classifiers with the increase in number of features are shown in Figure 6. The SVM using radial basis function was employed in the experiments and the parameters of SVM were empirically selected. The training parameter γ, ϵ and C were empirically fixed at 0.55, 0.001, and 100, respectively. As shown in Figure 6, the SVM classifier achieved higher recognition when 50 features were only implemented. For the feature lengths longer than 50, the WED-based NN classifier has achieved better performance.

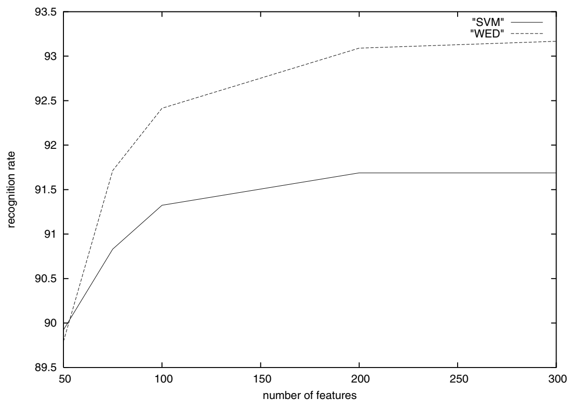

Fig. 6. Performance analysis of classifier with the number of features: DWT+ KPCA method using the SVM- and WED-based classifiers

In the literature by today, PolyU-I and PolyU-II databases are only published and public palmprint databases which include palm samples captured from the different sessions. The experimental results given in Table 3 are first candidate

Table 4. Testing results of the eight matching schemes with different feature lengths

Method		Feature length				
		50	100	200	300	380
PCA	LED	60.664 %	71.804 %	74.568 %	74.395 %	74.136 % (1717)
	WED	98.747 %	99.179 %	99.093 %	99.05 %	98.963 % (2292)
DWT+PCA	LED	59.542 %	71.459 %	87.305 %	87.737 %	87.737 % (2032)
	WED	98.834 %	99.309 %	99.352 %	99.352 %	99.395 % (2302)
KPCA	LED	63.557 %	73.661 %	75.82 %	74.697 %	73.92 % (1712)
	WED	98.877 %	99.222 %	99.05 %	99.006 %	98.92 % (2291)
DWT+KPCA	LED	83.462 %	86.01 %	86.01 %	87.435 %	88.039 % (2039)
	WED	98.747 %	99.309 %	99.568 %	**99.654** %	**99.654** % (2308)

experimental results to be published in the literature, as we have followed the published papers in the literature. The published papers by [1][3][7] only worked on the palm samples collected from the one of the session. They used four samples as training set, and used remainder six samples as testing set. To compare the performance of the proposed algorithm with the published algorithms, a second experiment was designed in this section. In the second experiment which is same scenario to the experiments published in the literature, the palm images collected from the first session were only used to test the proposed algorithm. We use the first four palmprint images of each person as training samples and the remaining six palmprint images as the test samples. So, the numbers of training and test samples are 1544 and 2316. We also test the 8 approaches against conventional PCA method using different test strategies. Based on these schemes, the matching is separately conducted and the results are listed in Table 4. The meaning of LED and WED in Table 4 is linear Euclidean discriminant and the weighted Euclidean distance based nearest neighbor classifier, respectively. The entries in the brackets (in the last column) given in Table 4 indicate the number of the correct recognition samples in all 2316 palms used as test samples. A high recognition rate **(99.654 %)** was achieved for kernel PCA with 2D-DWT (abbreviated as DWT+KPCA) and WED-based classifier approach, with feature length of 300. One of the important conclusion from Table 4 is that, long feature lengths still lead to a high recognition rate. However, this principle only holds to a certain point, as the experimental results summarized in Table 4 show that the recognition rate remain unchanged, or even become worse, when the feature length is extended further.

A comparison has been finally conducted among our method and other methods published in the literature, and is illustrated in Table 5. The databases given in the Table 5 are defined as the numbers of the different palms and whole samples tested. The data represent the recognition rates and given in Table 5 is taken from experimental results in the cited papers. In biometric systems, the recognition accuracy will decrease dramatically when the number of image classes increase [1]. Although the proposed method is tested on the public database includes highest number of different palms and samples, the recognition rate of our method is more efficient, as illustrated in Table 5.

Table 5. Comparison of different palmprint recognition methods

		Method									
		Proposed	In [4]	In [5]	In [3]	In [10]	In [8]	In [9]	In [23]	In [24]	In [25]
Data base	palms	386	3	100	300	382	160	100	100	190	50
	samples	3860	30	200	3000	3056	1600	600	1000	3040	200
Recog. Rate(%)		**99.654**	95	91	99.2	99.149	97.25	97.5	95.8	98.13	98

6 Conclusion

This paper presents a new appearance-based non-linear feature extraction (kernel PCA) approach to palmprint identification that uses low-resolution images. We first transform the palmprints into wavelet domain to decompose the original palm images. The kernel PCA method is then used to project the palmprint image from the very high-dimensional space to a significantly lower-dimensional feature space, in which the palmprints from the different palms can be discriminated much more efficiently. WED based NN classifier is finally used for matching. The feasibility of the wavelet-based kernel PCA method has been successfully tested on two data sets from the PolyU-I and PolyU-II databases, respectively. The first data set contains 600 images of 100 subjects, while the second data set consists of 7752 images of 386 subjects. Experimental results demonstrate the effectiveness of the proposed algorithm for the automatic palmprint recognition.

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