PALMPRINT RECOGNITION USING 2-D WAVELET, RIDGELET, CURVELET AND CONTOURLET

By

HATEM ELAYDI * MOHAMMED ALHANJOURI ** MOHANAD A. M. ABUKMEIL ***

* Associate Professor, Department of Electrical Engineering, Islamic University-Gaza, Palestine.
** Associate Professor of AI & DSP, Director of Excellence and E-learning Center / Academic Affairs, IUG.
*** ICT System Engineer, Department of Electrical Engineering-Communication Field, Islamic University-Gaza, Palestine.

ABSTRACT

Palmprint recognition is a promising biometric field which is used for forensic and commercial applications. This paper provides a comparative palmprint recognition approach using multi-scale transforms: 2D wavelets, ridgelets, curvelets, and contourlets for feature extraction phase, 2-D Principal Component Analysis (2-D PCA) for dimensionality reduction and artificial neural network for recognition phase. Finally, a comparative analysis has been done. The algorithms have been tested using PolyU hyperspectral palmprint database. The recognition rate accuracy was very good and is listed in this order curvelets, contourlets, ridgelets, and 2D discrete wavelets where the curvelets outperformed the others.

Keywords: Palmprint Identification, 2-D Discrete Wavelet, Ridgelets, Curvelets, Contourlets, 2-DPCA, Back Propagation Neural Network.

INTRODUCTION

A biometric system is a personal identification system which plays a significant part in daily life. There are two approaches of personal identification: the first method is token-based such as a passport, a physical key and an ID card, the second method is based on knowledge such as a password. However, these approaches have some limitations [1]. In token-based "token" can be stolen or lost easily while in a knowledge-base a certain degree knowledge can be forgotten or guessed.

The biometric personal identification systems are concerned with identifying persons by either physiological characteristics such as fingerprints, palmprint, iris and face or by using some aspects such as the signature or the voice [1]. Fingerprint-based personal identification has drawn considerable attention over the last 25 years [2]. However, workers and old people may not provide clear fingerprints because of their problematic skin caused by physical work. Recently, voice, face, and iris-based verifications have been studied extensively [3].

Palmprint recognition system is a promising technology which received considerable interest. Among various Biometric identification technologies palmprint recognition system has been successful due to its simplicity, feature extraction, matching feature, small size, high precision and real time computation.

Palmprint identification has emerged as one of the popular biometric modalities for forensic and commercial applications [4]. Palmprint features are considered promising features to identify people. There are two types of Palmprint features with reference to the field at which palmprint systems are used.

The first type of features are the principal lines and wrinkles which could be extracted from low resolution images (<100 dpi) and used for identification in the commercial applications. The second type of features are the singular point, ridges and minutiae point which could be extracted from high resolution images (>100 dpi) and used for forensic applications such as law enforcement application [4].

Both high and low resolutions images feature in palmprints are shown in Figure 1 [4].

The paper uses contourlets in palmprint recognition system for feature extraction as a benchmark and compare the results with 2-D wavelets, ridgelets and curvelets. It also uses 2-D PCA for dimensionality reduction

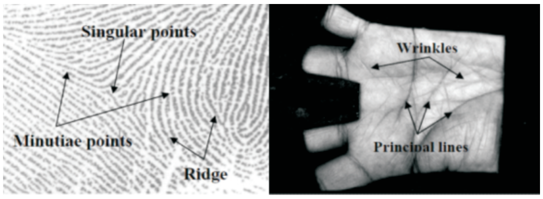

Figure 1. Palmprint Features

and artificial neural network for recognition.

The rest of this paper is organized as follows. Section 1 gives a brief description of related work. Multiscale image transform, dimensionality reduction by 2-D PCA in addition to feed-forward back propagation neural network will be highlighted in section 2. Section 3 reports feature extraction and recognition results for each multiscale image transform. Finally, the conclusion and future work are presented in last section.

1. Background and Related Work

Valuable researches have been presented in literature for the identification of people using palmprint features. Recently, a lot of techniques used to extract features from palmprint images have been attracting much research interest.

Jiwen, et.al. (2006), [5], proposed a novel method using wavelet decomposition and 2D Principal Component Analysis (2DPCA) for palmprint recognition. 2D wavelet transform was adopted to obtain different levels of wavelet coefficients of the original palmprint image; secondly 2DPCA was applied on the low-frequency. The algorithm was tested on the Poly palmprint image database and the experimental result was encouraging and achieved comparatively high recognition independent component analysis. The major limitation of this paper in database consists of only 100 palmprints and six samples for each palm. In addition, the number of training and testing palms where inconsistent. Another limitation is comparison with other projection techniques, the comparison was done with PCA and ICA which has limitations on 2-D domain. 10 projection vectors were used as a classifier input so it is important limitation, because it make the time complexity when making the prediction.

Masood, et.al. (2009), [6], suggested a novel palmprint based identification approach based on the textural information available on the palmprint by utilizing a combination of Contourlet and Non-Subsampled Contourlet transforms. Algorithm was tested on a total of 500 palm images of GPDS Hand database. Different measures of effectiveness of the proposed algorithm were computed and compared with reported results in literature; the proposed algorithm outperforms reported methods of palmprint matching in Equal Error Rate (EER). ROI were 256 x 256 which may increase the complexity in some phases and the comparison with other sophisticated techniques was not clear. The features may be inadequate to distinguish the different classes, features could be highly correlated and features space may simply be too complex which were the limitations of Euclidean distance classifier that is used in Masood, et.al search.

Sharkas, et.al. (2010), [7], suggested and compared two techniques for palmprint recognition. The first technique extracted the edges from the palm images; then, performed the CT or the Discrete Wavelet Transform (DWT) on the edge extracted images. The second technique employed the principal component analysis PCA. Features extracted from both techniques were tested and compared where it was found that the best achieved recognition rate was about 94%. ROI in this paper is not clear, the minimum distance classifier was used and this means that insensitive to differences in variance among categories problem might have occurred. Five palmprint images were trained and the recognition depend on the number of eigenvectors are insufficient in this paper.

Kekre, et.al. (2012), [8], suggested the use of a hybrid wavelet, generated by using Kronecker product of two existing orthogonal transforms, Walsh and DCT, to identify multi-spectral palmprints. One-to-many identification on a large database containing 3 sets of 6000 multi-spectral palmprint images from 500 different palms was used to validate the performance. The matching accuracy of the proposed method in terms of genuine acceptance ratio of 99.979% using score level fusion has been obtained. Selection feature vectors was depended on highly energy components and was insufficient to select the most discriminative feature. Algorithm that started from transformed domain toward recognition phase were complex and time consuming because Kronecker and hybrid wavelets have been applied.

The major disadvantages of existing works are high implementation complexity, execution time, cost, etc, because the existing methods depend on some approaches which are less accurate when compared with our work. In order to overcome the disadvantages of existing techniques a new palmprint recognition system based on the combinations between multiscale image transform, dimensionality reduction by 2D PCA and backpropagations neural networks that require less formal statistical training for feature extraction is suggested.

2. Multiscale Transform

The term multiscale is intended to describe a system with a passband whose spatial scale is controlled by a single parameter. For example, in the context of linear filters the parameter is wavelength. Here wavelength is closely related to resolution as short wavelengths are needed to describe small sized objects associated with fine resolution [9].

2.1 2D wavelet Transform

The 2D DWT [10,11] is a very modern mathematical tool. It is used in compression (JPEG 2000), denoising, and watermarking applications. It is built with separable orthogonal mother wavelets, having a given regularity. At every iteration of the DWT, the lines of the input image (obtained at the end of the previous iteration) are low-pass filtered with a filter having the impulse response m_0 and high-pass filtered with the filter m_1 Then the lines of the two images obtained at the output of the two filters are decimated with a factor of 2.

The columns of those four new sub-images (representing the result of the current iteration) are generated. The first one is obtained after two low – pass filtering; it is named approximation sub-image (or LL image), the other three are named detail sub-images: LH, HL and HH. The LL image represents the input for the next iteration. In the following, the coefficients of the DWT will be noted with xDm k, where x represents the image who's DWT is computed, m represents the iteration index (the resolution level) and k = 1,2,3 and 4 where k = 1, for the HH image, k = 2, for the HL image, k = 3, for LH image and k = 4 for the LL image. These coefficients are computed using the following relation:

$$xD_m^k[n,p] = \left\langle x(\tau_1,\tau_2), \psi_{m,n,p}^k(\tau_1,\tau_2) \right\rangle \quad (1)$$

Where the wavelets can be factorized:

$$\psi_{m,n,p}^k(\tau_1,\tau_2) = \alpha_{m,n,p}^k(\tau_1).\beta_{m,n,p}^k(\tau_2) \quad (2)$$

and the two factors can be computed using the scale function $\varphi(\tau)$ and the mother wavelets $\psi(\tau)$ with the aid of the following relations:

$$\alpha_{m,n,p}^k(\tau) = \begin{cases} \varphi_{m,n}(\tau), k = 1,4 \\ \psi_{m,n}(\tau), k = 2,3 \end{cases} \quad (3)$$

$$\beta_{m,n,p}^k(\tau) = \begin{cases} \varphi_{m,n}(\tau), k = 1,4 \\ \psi_{m,n}(\tau), k = 2,3 \end{cases} \quad (4)$$

Where,

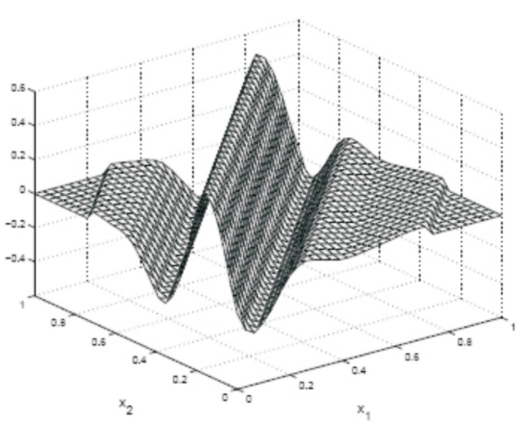

Figure 2. An example ridgelet function $\psi_{a,b,\theta}(x_1, x_2)$.

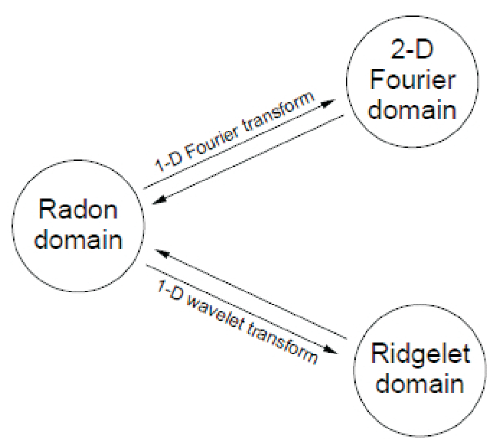

Figure 3. Relations between transforms

$$\varphi_{m,n}(\tau)=2^{\frac{-m}{2}}\varphi\left(2^{-m}\tau-n\right) \quad (5)$$

$$\psi_{m,n}(\tau)=2^{\frac{-m}{2}}\psi\left(2^{-m}\tau-n\right)2 \quad (6)$$

Despite the huge success of wavelets in the domain of image compression, the failure of two-dimensional multiresolution wavelets when dealing with images of the cartoon class, i.e., images consisting of domains of smoothly varying grey values, separated by smooth boundaries, has been noted repeatedly.

2.2 Continuous Ridgelet Transform

Given an integrable bivariate function f(x), its Continuous Ridgelet Transform (CRT) in $\mathbb{R}^2$ is defined by

$$CRT_f(a,b,\theta)=\int_{\mathbb{R}^2}\psi_{a,b,\theta}(x)f(x)dx, \quad (7)$$

where the ridgelets, $\psi_{a,b,\theta}(x)$ in 2-D are defined from a wavelet-type function in 1-D $\psi(x)$ as

$$\psi_{a,b,\theta}(x)=a^{-1/2}\psi((x_1\cos\theta+x_2\sin\theta-b)/a). \quad (8)$$

Figure 2 shows an example ridgelet function, which is oriented at an angle θ and is constant along the lines

$$x_1\cos\theta+x_2\sin\theta=const$$

As can be seen, the CRT is similar to the 2-D continuous wavelet transform except that the point parameters $v:[-\pi,\pi]\rightarrow\mathbb{C}$, $w:\mathbb{R}^+\rightarrow\mathbb{C}$ ne parameters (b,θ). In other words, these 2-D multiscale transform are related by:

Wavelet: $\rightarrow\psi_{scal,point\_Position,}$

Ridgelets: $\rightarrow\psi_{scal,point\_Position,}$

As a consequence, wavelets are very effective in representing objects with isolated point singularities, while ridgelets are very effective in representing objects with singularities along lines. In fact, one can think of ridgelets as a way of concatenating 1-D wavelets along lines. Hence, the motivation for using ridgelets in image processing tasks are appealing since singularities are often joined together along edges or contours in images.

In 2-D, points and lines are related via the Radon transform; thus, the wavelet and ridgelet transforms are linked via the Radon transform. More precisely, denote the Radon transform as

$$Rf(\theta,t)=\int_{\mathbb{R}^2}f(x)\,2\delta(x_1\cos\theta+x_2\sin\theta-t)dt, \quad (9)$$

Then, the ridgelet transform is the application of a 1-D wavelet transform to the slices (also referred to as projections) of the Radon transform,

$$CRT_f(a,b,\theta)=\int\psi_{a,b}\mathbb{Z}(t)R_f(\theta,t)dt \quad (9)$$

It is instructive to note that if in (10) instead of taking a 1-D wavelet transform, the application of a 1-D Fourier transform along t would result in the 2-D Fourier transform. More specifically, let $F_f(\omega)$ be the 2-D Fourier transform of f(x), then we have

$$F_f(\xi\cos\theta,\xi\sin\theta)=\int_{\mathbb{R}}e^{-j\xi}R_f(\theta,t)dt \quad (10)$$

This is the famous projection-slice theorem and is commonly used in image reconstruction from projection methods [14 ,15] The relations between the various transforms are depicted in Figure 3.

2.3. Curvelets

Curvelet [16] approximation is based on the decomposition of the image into a fixed system of components, prescribed without prior knowledge of the image. The curvelet system is a family of functions $\gamma_{j,l,k}$ indexed by a scale parameter , an orientation parameter and a position parameter $k\in\mathbb{R}$, yielding a normalized tight frame of the image space. The latter property amounts to postulating for all $f\in L^2(\mathbb{R}^2)$

$$\|f\|_2^2=\Sigma_{j,k,l}|<f,\gamma_{j,k,l}>|^2 \quad (11)$$

In the curvelet setting, image approximation is performed by expanding the input in the curvelet frame and quantizing the coefficients, just as in the wavelet setting. However, the effectiveness of the approximation scheme critically depends on the type of scaling, and the sampling of the various parameters. A comparison of the two types of curvelets is contained in [17].

Both curvelets constructions are different realisations of a core idea which may be summarized by the catchphrase that the curvelet system corresponds to a critically

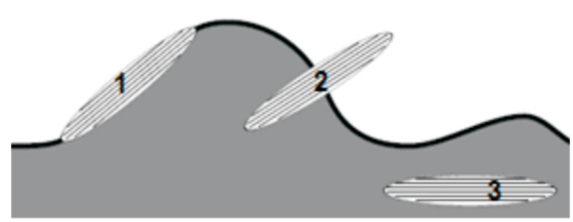

Figure 4. An illustration of the three types of curvelet coefficients

sampled, multiscale directional filterbank, with angular resolution behaving like $1/\sqrt{scale}$.

As the filterbank view suggests, curvelets are most conveniently constructed on the frequency side. The basic idea is to cut the frequency plane into subsets that are cylinders in polar coordinates. The cutting needs to be done in a smooth way; however, in order to ensure that the resulting curvelets are rapidly decreasing.

For this purpose, two window functions have been fixed.

$$v: [-\pi, \pi] \to \mathbb{C} \quad , \quad w: \mathbb{R}^+ \to \mathbb{C}$$

Both v and w are assumed smooth in addition, for v we require that its 2π periodic extension v_{per} is smooth as well. In addition, w picked is to be compactly supported. v act as angular window; in order to guarantee that the functions constructed from v are even.

To obtain estimates for the scalar products $\langle f, \lambda_{j,k,l} \rangle$ depending on the position of the curvelet relative to the boundary, recall that $\lambda_{j,k,l}$ is a function that has elongated essential support of size $2^{-\lfloor j/2 \rfloor} \times 2^{-j}$. In the appropriately rotated coordinate system, it oscillates in the "short" direction.

Then there are basically three cases to consider, sketched in Figure 4.

- *Tangential*: The essential support of $\lambda_{j,k,l}$ is close in position and orientation to one of the covering boxes, i.e., it is tangent to the boundary.
- *Transversal*: The essential support is close in position to one of the covering boxes, but not in orientation. Put differently, the support intersects the boundary at a significant angle.

Disjoint: The essential support does not intersect the boundary.

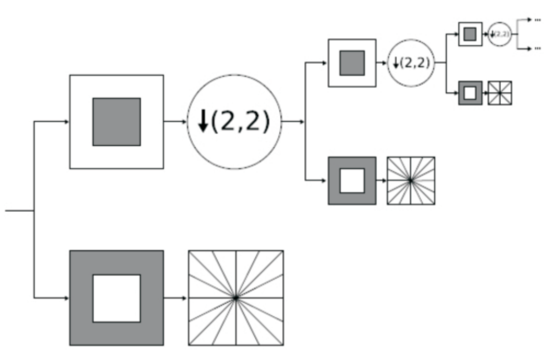

Figure 5. Structure of the contourlet decomposition.

The essential supports of the curvelets are shown as ellipses, with indicated oscillatory behavior. From left to right tangential, transversal and disjoint case.

2.4 Digital curvelets: Contourlets

The curvelet construction [16] relies on features that are hard to transfer to the discrete setting, such as polar coordinates and rotation. Several approaches to digital implementation have been developed since the first inception of curvelets, see example [18, 19 ,20]. The approach introduced by Do and Vetterli [20], are the most promising among the currently available implementations, for several reasons: It is based on fast filter bank algorithms with perfect reconstruction; i.e., the tight frame property of curvelets is fully retained, in an algorithmically efficient manner. Moreover, the redundancy of the transform is 1.333, which is by far better than the factor $16j+1$ ($j=$ number of dyadic scales in the decomposition) reported in [18].

The discrete implementation follows an analogous structure, shown in Figure 5.

- The image is passed through a pyramid filterbank, yielding a sequence of bandpassed and subsampled images.
- Directional filter banks [19, 21], are applied to the difference images in the pyramid, yielding directionally filtered and critically subsampled different images.
- The directional filter banks have an inherent subsampling scheme that makes them orthogonal when employed with perfect reconstruction filters.

The filter bank uses time-domain filtering, leading to linear complexity decomposition and reconstruction algorithms. In the curvelet/contourlet case, the anisotropic scaling amounts to increasing the angular resolution for large frequencies, which cannot be carried out indefinitely for the discrete domain.

2.5 Principal Component Analysis

Principal Components Analysis (PCA) is one of a family of techniques for taking high-dimensional data and using the dependencies between the variables to represent it in a more tractable, lower-dimensional form, without losing too much information. PCA is one of the simplest, oldest and most robust ways of doing such dimensionality reduction.

Consider an M by N image as M x N random matrix denoted by A. Let x be an N-dimensional unit column vector. Projecting A onto x yields an M-dimensional vector y [23].

$$y = Ax$$

The purpose of 2D PCA is to select a good projection vector x. To evaluate the goodness of a projection vector, the authors in [23] suggests that the use of the total scatter of the projected samples, which can be characterized by the trace of the covariance matrix of the projected feature vectors. Thus, the criterion is to maximize the following:

$$J(x)=tr(s_x) \quad (10)$$

Where s_x is the covariance matrix of the projected feature vectors, written by

$$S_x = E(y - E_y)(y - E_y)^T = E[(A - EA)X(A - EA)X]^T \quad (11)$$

Hence

$$J(x) = tr(S_x) = x^T E[(A - EA)(A - EA)^T]x \quad (12)$$

Where tr is trace of covariance matrix

Given a set of training images A(1), A(2), ..., A(n), the criterion (21) becomes

$$J(x) = x^T[\frac{1}{n}\sum_{i=1}^{n}(A(i) - \overline{A})^T(A(i) - \overline{A}]x \quad (13)$$

Where $\overline{A}$ is the average of all training images

$G = \sum_{i=i}^{n}(A(i) - \overline{A}]$, the optimal axis x_{opt} is the unit vector maximizing J(x), i.e. the eigenvector of G corresponding to the largest eigenvalue. Of course, one can compute m best projection axes, which are the m leading eigenvectors of G.

Without loss of generality, all the images have been shifted so that they have zero mean, i.e. $\overline{A} = \frac{1}{n}\sum_{i=1}^{n} A(i) = (0)_{M\times N}$

Thus (13) become

$$J(x) = x^T \sum_{i=1}^{n} A(i)^T A(i)]x \quad (14)$$

2.6 Feed forward Back propagation Neural Network

A successful Palmprint recognition methodology depends heavily on the particular choice of the features used by the pattern classifier .The Back-Propagation is the best known and widely used learning algorithm in training multilayer perceptron (MLP) [24].

Back propagation is a multi-layer feed forward, supervised learning network based on gradient descent learning rule. This BPNN provides a computationally efficient method for changing the weights in feed forward network, with differentiable activation function units, to learn a training set of input-output data[24].

A typical back propagation network [25] with Multi-layer, feed-forward supervised learning is as shown in Figure 6. Here learning process in back propagation requires pairs of input $(x_1, x_2, etc.)$ and target vectors. The output vector 'o' is compared with target vector 't'. In case of difference of 'o' and 't' vectors, the weights are adjusted to minimize the difference. Initially random weights and thresholds are assigned to the network. These weights are updated every iteration in order to minimize the mean square error between the output vector and the target vector [24].

For the efficient operation of the back propagation neural network it is necessary for the appropriate selection of the parameters used for training. The initial weight will influence whether the net reaches a global or local minima of the error and if so how rapidly it converges. To get the best result the initial weights are set to random numbers between -1 and 1[24, 25].

Training a net; the motivation for applying back

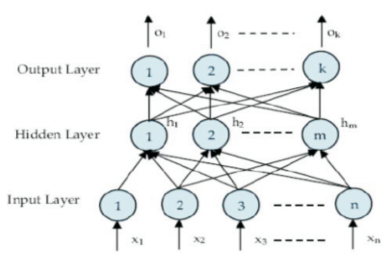

Figure 6. Basic block of Back propagation neural networks.

Figure 7. Palmprint image

propagation net is to achieve a balance between memorization and generalization. It is not necessarily advantageous to continue training until the error reaches a minimum value. The weight adjustments are based on the training patterns. As along as the error for validation decreases training continues. Whenever the error begins to increase, the net is starting to memorize the training patterns. At this point training is terminated. If the activation function can vary with the function, then it can be seen that an input, m output function requires at most 2n+1 hidden units. feature Extraction and experimental results

3. Database

Hyperspectral palmprints database which were developed by The Biometric Research Centre (UGC/CRC) at The Hong Kong Polytechnic University has been used. Hyperspectral palmprint [26] images were collected from 190 volunteers. The age distribution is from 20 to 60 years old. The samples have been collected in two separate sessions. In each session, the subject was asked to provide around 7 images for each palmprint for each wavelength and the size for each palmprint is 128x128 pixels. Zhenhua, et.al [27] suggest using spectral band at 700nm

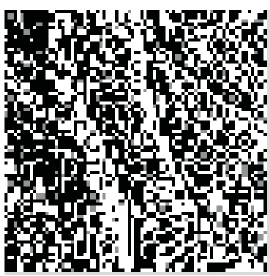

Figure 8. Vertical Coefficients

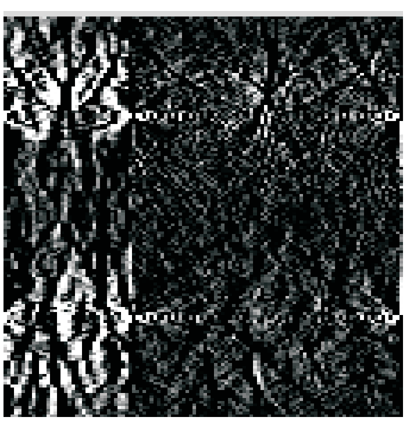

Figure 9. Ridgelets feature

because it contains more discriminative information so it used in our experimental phase.

4. Features Extraction

A palmprint can be represented by some line features from low resolution image. Algorithms such as the stack filter are able to extract the principal lines. However, these principal lines are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines in their palmprints [1]. In addition, some palmprint images do not have clear wrinkles. Several techniques have been implemented to extract features from palmprint image such as wavelets, ridgelets, and other but these methods are unable to detect smooth edges which result from the conjunctions of principal lines and wrinkles. In the following the wavelets, ridgelets, curvelets and contourlets features have been extracted. These features have been projected in order to reduce the dimensionality by using 2D PCA. Finally, a vector which is a projection resultant is passed to the feed-forward neural network for training and testing phases.

2D Wavelet features; Applying wavelet transformation leading to different band of wavelet coefficient of the original palmprint images. High frequency components contribute to details and low frequency components contribute to approximation (global description in palmprint) image. A large variation of palmprint image in high frequency components and small effect in low frequency components. Each level of wavelet decomposition divide original palmprint image into four subband leading to multi-resolution analysis. Each subband can be used to extract feature. In our

Figure 10. Curvelets Discriminative Coefficients

experiment 1st level of 2D discreet wavelet is applied, Figure 8 shows the vertical coefficients of 1st 2D discreet wavelet decomposition level which taken as a palmprint features. 2D PCA has been applied to vertical coefficients leading to single vector which passed to feed- forward back propagation neural network to be trained or tested. Figure 7 shows the original palmprint image.

The unique coefficients which were used as discriminated features are obtained in our work from vertical coefficients only.

Ridgelet features; Ridgelet transform offers a mathematical framework in order to organize the liner information at different scale and resolution.

Firstly, the ridgelet transform is applied to palmprint images in order to convert palmprint images into time-frequency domain leading to ridgelet coefficients. Figure 9 shows ridgelet transform of palmprint image which is illustrated in Figure 7.

When the palmprints have been transformed by ridgelet transform, 2D PCA is applied in order to reduce the dimensionally and to get a vector which is a projection resultant. Then the resulted vector is passed to feed-forward back propagations neural network for recognition phase.

Curvelet features; The combinations between 2D wavelets transform and ridgelets transform lead to curvelet transform. Each curvelet decomposition level lead to high number of curvelet co-efficients. According to the evidence, passing all curvelet co-efficients to neural network classifier is not suitable. The most discriminative features could be obtained as shown in Figure 10.

Curvelab [28] which is a Matlab toolbox that includes the mirror extended curvelets has been used to extract curvelet co-efficients. 2D PCA has been used to reduce the dimensionality in order to pass the most discriminative features to the back propagations neural networks.

Contourlets Features; The contourlet transform can address the features extraction by providing two additional properties, directionality and anisotropy which provides contourlets transform with more efficient representation of the object [20].

To apply contourlet to palmprint image by two different steps: In the first step Laplacian pyramid applies to decompose the image into two subbands or (cells) the first one is low pass filter and other is high pass filter for edge detection.

The next step is to apply Directional Filter Bank (DFB). The most discriminative contourlets coefficients which related to palmprint image in Figure 8 appears in Figure 11.

The contourlets co-efficients are reduced by using 2d PCA in order to get a resultant discriminate vector to be passed into feed-forward back propagation neural network classifier.

5. Recognition Phase

A test samples of 30 persons have been taken, the total palmprint images which were taken were 360 palmprints divided as: 240 palmprints for training phase and 120 palmprints for testing phase. The palmprints images were transformed by using multiscale transforms of images: 2D discrete wavelets, Ridgelets, Curvelets and Contourlets in order to extract the individual's discriminative features. 2D PCA was used for projection in order to reduce the features size and to get a vector which contains the most discriminative features. The resulted vector which constituted from projection by 2D PCA has been used as input for feed-forward back propagation neural network.

In recognition phase, the palmprints were divided into two groups the first group is used for training the network and the other one is testing group to test the accuracy of the network.

In our experiment, the sample is verified by using feed-

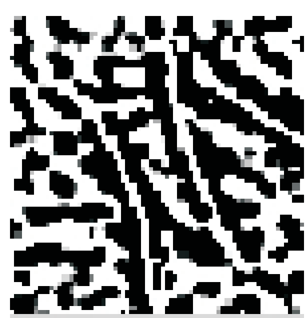

Figure 11. Contourlets coefficients

forward back propagation neural network algorithm. The accuracy was a function of images multiscale transforms which means features reduction and classifier were constant.

The recognition accuracy for each multiscale transforms illustrated in Table 1. By comparing the work with similar works: in [5] wavelets and 2D PCA in addition to PolyU palmprints database were used. The recognition accuracy was 97%.

In [6] the combination between contourlet and sub-sampled contourlet was used and Euclidean distance classifier has been used and different levels of accuracy were achieved.

The contourlet transform, PCA and minimum distance classifier were used for transformation in [7] and the accuracy was 94%. In [8] the Kronecker product and hybrid wavelets have been applied and the accuracy was 99.9%.

The recognition phase in the work has been divided into two stages; the first one is called training stage. Each feature vector which resulted from multiscale transformation and projected by 2D PCA is passed to feed-forward back propagation neural network and trained by using gradient function. The same transformation has been applied to palmprint image which is used in test stage but the resultant feature vector doesn't train.

The learning rate was 0.005. All trained and tested palmprints which identify 30 persons have been used from PolyU hyperspectral palmprint database. Eight palmprints have been used in training stage and four palmprints have been used for test stage. The comparable result was shown in Table 1.

Conclusion and Future Work

Image transformation technique	Recognition rate
2D wavelets	87.5%
Ridgelets	91.3%
Curvelets	97.5%
Contoulets	95.83%

Table 1. Recognition results

This paper proposed a novel approach to identify the individuals based on their palmprints. The approach novelty could be found in the combinations between palmprints images transform techniques, features reduction technique and feed- forward neural network classifier. PolyU pre-processed hyperspectral database and Matlab version 7.11 R 2010b with supporting toolboxes were used in our experiment work. The recognition accuracy were 87.5%, 91.3%, 97.5%, and 95.83% when 2D discrete wavelets, ridgelets, curvelets, and contourlets applied respectively. The results shows the curvelets transform outperformed the other multiscale transform.

For future work, the combinations between another image transformations such as shaplet, bandlet, platlet and others will be taken in addition to use another features reduction techniques such as Independent Component Analysis (2D ICA), Linear Discriminant Analysis (2D LDA), kernel PCA and other modern techniques are suggested to be used. In addition, the classifier type is suggested to change to show how the recognition accuracy could be improved.

References

[1]. D. Zhang, Wai-Kin Kong, J. You and Michael Wong, (2003). "Online palmprint identification," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 25, pp. 1041-1050, Sept. .

[2]. A. Jain, R. Bolle and S. Pankanti (eds.), (1999). *Biometrics: Personal Identification in Networked Society,* Boston, Mass: Kluwer Academic Publishers.

[3]. A. Morales, M. Ferrer and A. Kumar, (2010). "Improved palmprint authentication using contactless imaging," *4th IEEE International Conference on Biometrics: Theory Applications and Systems (BTAS),* pp. 1-6, Sep..

[4]. A. Kong, D. Zhang and M. Kamel, (2009). "A survey of palmprint recognition," *Journal of Pattern Recognition,* vol. 42, pp. 1408-1418, July..

[5]. Jiwen Lu, Erhu Zhang, Xiaobin Kang and Yanxue Xue, (2006). "Palmprint recognition using wavelet decomposition and 2D principal component analysis, "*International conference on Communications, Circuits*

*and Systems Proceedings, v*ol. 3, pp. 2133-2136, June. .

[6]. H. Masood, M. Asim, M. Mumtaz and A. Mansoor, (2009). "Combined contourlet and non-subsampled contourlet transforms based approach for personal identification using palmprint," *Digital Image Computing: Techniques and Applications, DICTA '09,* pp.408-415, Dec.

[7]. M. Sharkas, I. El-Rube and M.A. Mostafa, (2010). "The Contourlet transform with the principal component analysis for palmprint recognition," International Conference on Computational Intelligence, *Communication Systems and Networks (CICSyN),* pp. 262-267, July .

[8]. H.B. Kekre, R. Vig and S. Bisani, (2012). "Identification of multi-spectral palmprints using energy compaction by hybrid wavelet," *International Conference on Biometric (ICB),* pp. 433-438, March.

[9]. J. Andrew Bangham and Richard V.Aldridge, (1993). "Multiscale decomposition using median and morphological filters," *IEEE Winter Workshop on Nonlinear Digital Signal Processing,* 6.1_1.1 - 6.1_1.4.

[10]. Alexandru Isar, Sorin Moga, and Xavier Lurton, (2005). "A statistical analysis of the 2d discrete wavelet transform," *Proceedings of the International Conference AMSDA,* 17-20 May, 2005, 1275-1281.

[11]. Samuel Foucher, Goz´e Bertin B´eni´e and Jean-Marc Boucher, (2001). "Multiscale map filtering of sar images," *IEEE Transactions on Image Processing,* vol. 10, no.1, 49-60, January.

[12]. E.J. Candues, Ridgelets: (1998). *Theory and Applications*, Ph.D. thesis, Department of Statistics, Stanford University.

[13]. E. J. Candues and D. L. Donoho, (1999). "Ridgelets: a key to higher- dimensional intermittency?" Phil. *Trans. R. Soc. Lond. A.* pp. 2495-2509.

[14]. G.T. Herman, Image Reconstruction from Projections: (1980). *The Fundamentals of Computerized Tomography,* Academic Press.

[15]. A. Rosenfeld and A. C. Kak, (1982). *Digital Picture Processing*, Aca- demic Press, 2nd edition.

[16]. H. Führ, L. Demaret and F. Friedrich, Beyond wavelets: (2006). New image representation paradigms. Book chapter. In: M. Barni and F. Bartolini (Eds.), *Document and Image Compression*, *CRC Press, Boca Raton,* FL, 2006.

[17]. E. Candes and D. Donoho. (2004). "New tight frames of curvelets and optimal representations of objects with C2 singularities," *Commun. Pure Appl. Math.* 57, pp. 219–266.

[18]. J. Starck, E. Candes and D. Donoho, (2002). "The curvelet transform for image denoising," *IEEE Transactions on Image Processing,* 11, pp. 670–684.

[19]. M. Do, (2001). *Directional multiresolution image representation*, Thesis, Swiss Federal Institute of Technology.

[20]. M. Do and M. Vetterli. (2001). "The contourlet transform: an efficient directional multiresolution image representation," *IEEE Transactions on Image Processing,* 14 (12), pp. 2091-2106, Dec .

[21]. R. Bamberger and M. Smith. (1992). "A filter bank for the directional decomposition of images: Theory and design," *IEEE Trans. Signal Proc.* 40, pp. 882-893, 1992.

[22]. Liwei Wang, Xiao Wang, Xuerong Zhang and Jufu Feng, (2005). "The equivalence of two-dimensional PCA to line-based PCA," *Pattern Recognition Letters,* 26 (1), pp. 57-60, Jan .

[23]. J. Yang and D. Zhang, (2004). "Two-dimensional PCA: A new approach to appearance-based face representation and recognition," *IEEE Trans. Pattern Anal. Machine Intell. PAMI*-26 (1), 131-137.

[24]. P. Latha, L.Ganesan and S. Annadurai, (2009). "Face Recognition using neural networks," *Signal Processing: An International Journal (SPIJ)*, 3 (5), 153-160, Nov .

[25]. S. Lawrence, C.L. Giles, A.C. Tsoi, and A.d. Back, (1993). "Face recognition: a convolutional neural network approach," *IEEE Transactions of Neural Networks.* Vol.8, No.1, pp.98-113 .

[26]. Department of Computing, The Hong Kong Polytechnic University (PolyU), *Hyperspectra Palmprint database*, Polyu, accessed on Aug. 22, 2013, available at:http://www4.comp.polyu.edu.hk/~biometrics/Hyperspectral Palmprint/HSP.htm.

[27]. **Zhenhua Guo, Lei Zhang, and David Zhang, (2010).** "Feature band selection for multispectral palmprint recognition," *International Conference on Pattern Recognition*, pp. 1136-1139 .

[28]. **Curvelet.org,** accessed on July 14, 2013, available at: http://www.curvelet.org/.

ABOUT THE AUTHORS

Hatem A. Elaydi is currently working as an Assistant Professor at the Electrical Engineering Department, the Islamic University of Gaza and the Director of Administrative Quality Assurance and also a member of IEEE, SIAM, Tau Alpha Pi, AMS, Palestine Engineering Association, and Palestine Mathematic Society. He has received his B.S. degree in Electrical Engineering from Colorado Technical University, ColoSprgs, CO in 1990 and M.S. and Ph.D. degrees in Electrical Engineering from New Mexico State University, Las Cruces, NM in 1992 and 1997. He held several positions such as Department Head, Assistant Dean, Head of the Resources Development Center, & Director of Quality Assurance. He has over 20 years of teaching experience and has published many papers in National and International Journals. He has conducted several studies and consultations in Palestine and the region. He is certified as a regional subject and institutional reviewer. He served as editor board member, member of technical council, member of scientific committees for several local, regional and international journals and conferences. His research interest includes control systems, digital image processing, and quality assurance with concentration on optimal control, robust systems, convex optimization and quality assurance in higher education.

Dr. Mohammed Ahmed Alhanjouri is currently working as an Associate Professor, Director of Excellence and eLearning Center at Islamic University of Gaza. Also he worked at University of Palestine as Dean of library, then as Head of Software Eng. Dept. Currently, he is serving as Associate Professor, Director of Excellence and eLearning Center at Islamic University of Gaza. He has received Bachelor of Electrical and Communications Engineering (honor) (1998), Master of Electronics Engineering (excellent) (2002), and Ph.D. in 2006. He worked as Assistant Professor, Director of projects and research center, and Head of computer Engineering department at Islamic University of Gaza, Palestine. Also he worked at University of Palestine as Dean of library, then as head of Software Eng. Dept. His primary research interest is in the area of Artificial Intelligence. His research interest includes Advanced digital signal processing, Pattern recognition (Image and Speech), modern classification techniques (neural networks, Hidden Markov Models, Ant colony, Swarm Optimization and Genetic Algorithm.

Mohanad A Abukmeil is currently working as an ICT System Engineer in Palestinian Pension authority. He has received his Bachelor of Mechatronics Engineering (2010), Master of Electrical engineering (2011),and pursuing his PhD. He has recognized by Microsoft as Microsoft Certified Technology Specialist (MCTS) in Windows server 2008 Network Infrastructure Configuring. He has worked as a Mechatronics Engineer in several companies in private sector. His primary research interest includes Biometric systems, Palmprint identifications, Features Extraction and also Image Processing and Neural Networks in classification.