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Palmprint Recognition by using Bandlet, Ridgelet, Wavelet and Neural Network

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Abstract— **Palmprint recognition has emerged as a substantial biometric based personal identification. Tow types of biometrics palmprint feature. high resolution feature that includes: minutia points, ridges and singular points that could be extracted for forensic applications. Moreover, low resolution feature such as wrinkles and principal lines which could be extracted for commercial applications. This paper uses 700nm spectral band PolyU hyperspectral palmprint database. Multiscale image transform: bandlet, ridgelet and 2D discrete wavelet have been applied to extract feature. The size of features are reduced by using principle component analysis and linear discriminate analysis. Feed-forward Back-propagation neural network is used as a classifier. The recognition rate accuracy shows that bandlet transform outperforms others.**

Keywords; Palmprint recognition, 2D discrete Wavele; Ridgelet; Bandlet; Neural network.

I. Introduction

A biometric system can be used for personal identification instead of token-based methods such as passports, physical keys and ID cards or Knowledge-based methods such as passwords. In the token-based, "token" can be stolen or lost easily while knowledge can be forgotten or guessed in knowledge-based systems[1].

Palmprint identification has emerged as one of the leading and promising biometric modalities for forensic and commercial applications [2.3] . Palmprint features are considered unique and have a real potential in identify people. Palmprint features can be classified into two groups with reference to the field at which palmprint systems are used. The first group of features are the principal lines and wrinkles which could be extracted from low resolution images (<100 dpi) and may be used in commercial applications. The second group of features are singular points, ridges and minutiae points which could be extracted from high resolution images (>100dpi) and may be used for forensic applications such as law enforcement applications [3]. Both high and low resolution image features in a palmprint image are shown in Fig. 1.

This article uses multiscale image transforms such as, bandlet, ridgelet, 2D discrete wavelet for feature extractions from palmprint images. It also uses 2D PCA and 2D LDA for dimensionality reduction and compares their results. Feed-forward back-propagation neural network has been used for recognition.

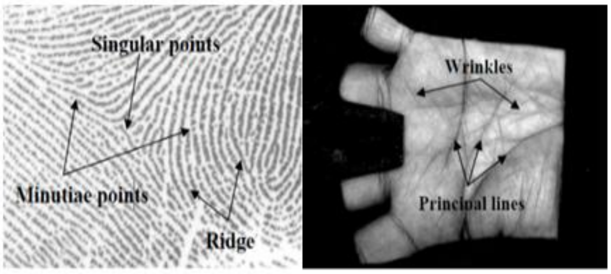

Fig 1. Palmprint features

The rest of this paper is organized as follows: Section 2 gives a brief description of related work. Multiscale image transforms, dimensionality reductions 2D PCA and 2D LDA; in addition to, feed-forward back-propagation neural network are highlighted in section 3. Section 4 reports feature extraction and recognition results for each multiscale image transform. Finally, the conclusion and future work are presented in section 5.

II. Related Work

The development of multiscale image transform together with dimensionality reduction technique leads to valuable research for the identifications of people using palmprint features. Various techniques have gained popularity and attracting much interest to extract features from palmprint images.

Kekre, et.al. (2012) [4], suggested the use of a hybrid wavelet generated by Kronecker product of two existing orthogonal transforms, Walsh and DCT, to identify multi-spectral palmprints. One-to-many identification on a large database containing three sets of 6000 multi-spectral palmprint images from 500 different palms was used to validate the performance. The matching accuracy of the proposed method of genuine acceptance ratio of 99.979% using score level fusion was obtained. Selection feature vectors depended on high energy components and was insufficient to select the most discriminative feature. However, the recognition phase was complex and time consuming.

Sharkas, et.al. (2010) [5], 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%. However, ROI in this paper was not clear; the minimum distance classifier used was insensitive to differences in variance. Five palmprint images were trained and the recognition depended on the number of eigenvectors which was insufficient.

Masood, et.al. (2009) [6], suggested a palmprint based identification approach that drew on the textural information available on the palmprint by utilizing a combination of contourlet and non-subsampled contourlet transforms. The algorithm was tested on a 500 palm images of GPDS hand database. The results of the proposed algorithm were compared with reported results in literature. The proposed algorithm outperformed other reported methods of palmprint matching using equal error rate (EER). ROI was 256×256 pixels which may increase the complexity in some phases. The selected features may be inadequate to distinguish the different classes. The selected features could also be highly correlated and features space may simply be too complex with the limitations of Euclidean distance classifier.

Jiwen, et.al. (2006) [7], proposed using wavelet decomposition and 2D principal component analysis (2DPCA) for palmprint recognition. 2D wavelet transform and 2DPCA were applied to the low-frequency components. The algorithm used the Poly palmprint image database and the experimental results were encouraging and achieved comparatively high recognition. The major limitation consists of using only 100 palmprints and six samples for each palm. In addition, the number of training and testing palms where inconsistent. Another limitation in comparison with other projection techniques, the comparison was done with PCA and ICA while used images require 2-D domain. Ten projection vectors were used as classifier input resulting in time consuming and high complexity.

The major disadvantages of presented works are the high implementation complexity, execution time, cost, etc. The classifier type in some work may be time consuming and has reliability issue when it compared with neural network classifier. The number of vectors that used as a classifier input in some researches is more than one vector meaning that recognition may consume more time. The projection technique may not supports 2D domain and the combination between the classifier and image transform technique may be inconsistent [8,9]. In order to overcome the disadvantages of existing techniques, a new palmprint recognition based on the combinations between multiscale image transforms, dimensionality reduction by 2D PCA and 2D LDA, and back-propagations neural networks that require less formal statistical training and fast in testing for recognition was proposed.

Our proposed work is use palmprint images from PolyU hyperspectral palmprint database, these images were considered as input images to our proposed biometrics palmprint. The feature from palmprint images are extracted by using multiscae image transform techniques and the size of whole feature size is reduced by applying dimensionality reduction techniques that will be discuss in the following section. The performance evaluation of our poroposed work is measured by using back-popagation neural network which is the best classification modality in testing stage.

III. MULTISCALE AND CLASSIFIER

Multiscale transform describes a passband system with a spatial scale controlled by a single parameter such as linear filters with the wavelength as a parameter. In this case, the wavelength is closely related to resolution such that short wavelengths are needed to describe small sized objects associated with fine resolution [10].

A. Image Transfoms

1) 2D Discrete Wavelet: The 2D DWT [11 , 12] is used in compression, denoising and watermarking applications. It is built with separable orthogonal mother wavelets (ψ) with 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. Next, the columns of the two images obtained are low- pass filtered with m_0 and high-pass filtered with m_1. The columns of those four images are also decimated with a factor of 2.

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 others 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 xD_m^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:

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

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 ψ (τ).

2) Continous Ridgelet Transform: Given an integrable bivariate function $f(x)$, its Continuous Ridgelet Transform (CRT) in $\mathbb{R}^2$ is defined by [13 , 14].

$$\mathrm{CRT_f}(a,b,\theta) = \int_{\mathbb{R}^2} \psi_{a,b,\theta}(x) f(x) dx, \qquad (3)$$

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

$$\psi_{a,b,\theta}(x) = a^{-\frac{1}{2}}\psi((x_1\cos\theta + x_2\sin\theta - b)/a) \qquad (4)$$

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

$$x_1\cos\theta + x_2\sin\theta = \mathrm{const} \qquad (5)$$

The CRT is similar to the 2-D continuous wavelet transform except that the point parameters (b_1, b_2) are replaced by the line parameters (b, θ). In other words, these 2-D multiscale transform are related by:

Wavelet: $\rightarrow \psi_{\mathrm{Scale,point\_position,}}$

Ridgelet: $\rightarrow \psi_{\mathrm{Scale,line\_ position,}}$

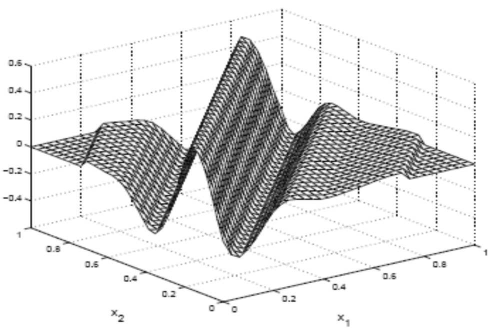

Fig 2. Ridgelet function

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 such as 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 is appealing since singularities are often joined together along edges or contours in images [15 , 16].

3) Bandlet Transform: Orthogonal bandlets using an adaptive segmentation and a local geometric flow are well suited to capture the anisotropic regularity of edge structures. They are constructed with a "bandletization" which is a local orthogonal transformation applied to wavelet coefficients. The approximation in these bandlet bases exhibits an asymptotically optimal decay for images that are regular outside a set of regular edges. These bandlets can be used to perform image compression and noise removal [17].

Each orthogonal bandlet basis $\beta(\lambda) = \{b_v\}_v$ is parameterized using a geometry $\lambda \in \Lambda$ that specifies, for each scale 2^j and each orientation k of the wavelet transform,

- a dyadic segmentation of the corresponding wavelet coefficients,
- a flow, that indicates the approximate geometric direction over each square of the segmentation that contains an edge.[18]

The bandlets are obtained through an orthogonal retransformation of the wavelet coefficients inside each square that contains an edge. This retransformation is the decomposition of each set of wavelet coefficients on an orthogonal basis of Alpert multi-wavelets [19].

Bandlet bases are gathered in a dictionary of orthogonal bandlet bases indexed by a geometry. The efficiency of these bases is linked to the use of two fast algorithms. The first one performs the analysis (decomposition) and synthesis (reconstruction) of a function f in some given basis $\beta(\lambda)$. The second algorithm searches in the whole dictionary of B $\beta(\lambda)$. for a best basis $\beta(\lambda^*)$. adapted to some function f one wishes to approximate.

B. Dimentionality Reduction

When the palmprint image has transformed from time to frequency domain then a matrix out as a result from the transformation, meaning that each image pixel is represents by number. In our experimental work we used palmprint with size 128×128 pixels. It's unfeasible to use the matrix which represents image directly without reduce its size, so the recognition process can meet commercial requirements. Two powerful dimensionality reduction technique have used in the experimental phase.

1) 2D 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.

The purpose of 2D PCA is to select a good projection vector x. To evaluate the goodness of a projection vector, the authors in [20] 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:

$$J(x) = \mathrm{tr}(S_x) \qquad (6)$$

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

$$S_x = E(y - E_y)(y - E_y)^T = E[(A - EA)X(A - EA)X]^T \qquad (7)$$

Hence

$$J(x) = tr(S_x) = x^T E[(A - EA)(A - EA)^T]x \quad (8)$$

Where tr is trace of covariance matrix

Given a set of training images $A(1), A(2), \ldots, A(n)$, the criterion (8) becomes

$$J(x) = x^T[\frac{1}{n}\sum_{i=1}^{n}(A(i) - \overline{A})^T(A(i) - \overline{A}] \quad (9)$$

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

2) 2D linear Discriminate Analysis: Linear discriminate analysis is based on linear combinations between vectors.

2D LDA [21] directly performs discriminate feature analysis on an image matrix rather than on a vector. 2D LDA tries to find the optimal vector W_{opt}^{2d}

$$W_{opt}^{2d} = \text{argmax}_{W^{2d}} \frac{{W^{2d}}^T S_b^{2d} W^{2d}}{{W^{2d}}^T S_w^{2d} W^{2d}} \quad (10)$$

Where $S_b^{2d} = \sum_{k=1}^{L} \frac{N_K}{N}(U_K - U)(U_K - U)^T$ and $S_w^{2d} = \frac{1}{N}\sum_{K=1}^{L}\sum_{i=1}^{N_K}(X_i^K - U_k)(X_i^K - U_K)^T$ are between-class scatter matrix and within-class scatter matrix respectively.

C. Feed-Forward Back-Propagation Neural Network

The back-propagation neural network (BPNN) is the best known and widely used learning algorithm in training multilayer perceptron (MLP) [22]. 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[22].

A typical back propagation network [23] with multi-layer, feed-forward supervised learning is shown in Fig. 3. Here learning process in back-propagation requires pairs of input $(x_1, x_2, \text{etc.})$ 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 [22].

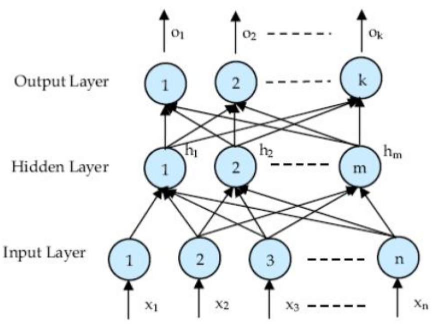

Fig 3. Basic block of Back-propagation neural networks

Appropriate selection of the parameters used for training to ensure efficient operation. 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[22,23].

Training a net is performed in order 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 long 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.

D. Palmprint Database

Hyperspectral palmprints database which is developed by the Biometric Research Centre at Department of Computing in Hong Kong Polytechnic University has been used [24]. Hyperspectral palmprint 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 [25] suggested using spectral band at 700nm because it contains more discriminative information; thus, it is used in our experimental phase. An example of Region on interest (ROI) palmprint 700nm hyperspectral depict in Fig 4.

Fig 4. ROI of Palmprint

IV. Feature Extraction and Recognition Results

A. Feature Extraction

Biometric based commercial application requires fast and effective pattern recognizer. Low resolution palmprint images might be meets commercial requirements, these palmprint can be represented by some line features. The principle lines can be extracted using stack filters or other filters. 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; moreover, 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 bandlet, ridgelets, and 2D discrete wavelet features have been extracted. These features have been projected in order to reduce the dimensionality by using 2D PCA and 2D LDA. Finally, a vector which is a projection resultant is passed to the feed-forward back-propagation neural network for training and testing phases.

Bandlet features; Bandlet transform based on adaptive segmentation and local geometric flow. Applying local orthogonal transformation of wavelets coefficients leading to bandlet coefficients. Applying wavelet in palmprint can capture isotropic regularity of edges in square domain of varying size but geometric regularity that offered by bandlet can capture anisotropic regularity of edges in palmprint. bandlet transform can exploit such anisotropic regularity by construction orthogonal vectors in the direction where the function have the maximum regularity.

Although the principal lines and wrinkles are discontinuous in some images, by bandlet the image can be differentiable in the parallel direction of edge curve. Geometric representation of bandlet as illustrated in Fig 5.

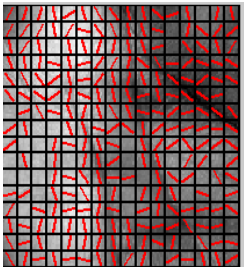

Fig 5. Geometric representation of bandlet

Bandlet toolbos which is a Matlab package that developed by [26] Research Center of Magnetic Resonance and Medical Imaging at Xiamen University has used to extract Bandlets coefficients which reduced by applying 2D PCA and 2D LDA to get the most discriminate vector to be passed into feed-forward back propagation classifier.

Ridgelet features; Ridgelet transform offers a mathematical framework in order to organize the liner information at different scale and resolution. First, the ridgelet transform is applied to palmprint images in order to convert them into time-frequency domain leading to ridgelet coefficients. Fig. 6 shows ridgelet transform features of palmprint image which was illustrated in Fig. 4.

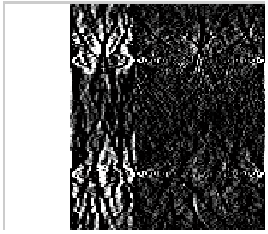

Fig6. Ridgelet features

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

2D Wavelet features; applying wavelet transformation leads to different band of wavelet coefficient of the original palmprint images. While high frequency components contribute to details, low frequency components contribute to approximation (general form of palmprint) image. A large variation of palmprint image is present in high frequency components and small effect in low frequency component. Each level of wavelet decomposition divides original palmprint image into four subbands leading to multiresolution analysis. Each subband can be used to extract feature. In this paper, 2nd level of 2D discreet wavelet is applied, Fig. 6 shows the vertical coefficients of 2nd 2D discreet wavelet decomposition level which is taken as a palmprint features. 2D PCA and 2D LDA have been applied to vertical coefficients leading to single vector which is passed to feed- forward back-propagation neural network for training or testing.

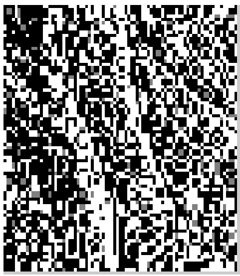

Fig 7. Vertical Coefficients

B. Recognition Result

Table 1. *Recognition Results*

Multiscale Transform	Dimensionality reduction 2D PCA	Dimensionality reduction 2D LDA
Bandlet	78%	96.5%
Ridgelet	91.3%	95.8%
2D discrete wavelet	87.5%	93.3%

A test sample of 30 persons have been taken into account with a total of 360 palmprint images divided as: 240 palmprints for training phase and 120 palmprints for testing phase. For each person 8 palmprint images have been used as a training set and four images have been used as a testing set. The palmprint images were transformed by using multiscale image transforms: Bandlet, Ridgelet and 2D discrete wavelets in order to extract the principal lines and wrinkles. 2D PCA and 2D LDA were used for dimensionality reduction of features matrix in order to reduce the features size and to get a vector which contains the most discriminative features. The resulted vector is used as input to a feed forward back-propagation neural network classifier.

The higher recognition accuracy with reference to Table 1 is 96.5% that obtained using bandlet transform for features extraction and 2D LDA for dimensionality reduction, Because, bandlet transform based on adaptive segmentation and a local geometric flow which suited to capture the anisotropic regularity of principal lines and winkles structures. By considering recognition accuracy as a function of dimensionality reduction 2D LDA outperform 2D PCA.

2D LDA tries to identify attributes that account for the most variance between classes; thus, the 2D LDA is a supervised method, using known class labels. The class labels field is also called target field. But, in 2D PCA definition there is no mention of class label and keeping the dimensions of largest energy (variance) is good but not always enough.

The recognition phase in this 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 LDA or 2D LDA is passed to feed-forward back propagation neural network and trained using gradient function. The same transformation has been applied to palmprint images which are used in test stage but the resultant feature vector didn't trained. The learning rate was 0.05.

The recognition accuracy for each multiscale transforms illustrated in Table 1. By comparing our work with similar works, we can see: In [4] the accuracy was 99.9%. The dependency on highly energy components was insufficient to select the most discriminative feature and the whole recognition algorithm was time consuming and unreliable. The contourlet transform, PCA, and minimum distance classifier were used for transformation in [5] and the accuracy was 94% but the limitations in the classifier and database made the result inconsistent. In [6] the combination between contourlet and sub-sampled contourlet was used where Euclidean distance classifier was used. Different levels of accuracy were achieved but the classifier type, image size, and comparison were inadequate. In [7] wavelets and 2D PCA and the recognition accuracy was 97% but different limitations appear in this work such as the sample size was inconsistent, comparison with 1D projection techniques and 10 projection vectors were used in recognition, but our experimental work used only one projection vector.

V. CONCLUSION

This paper proposed a novel recognition approach of individuals based on their palmprints. The novelty of the approach is in the combinations of images transform techniques, 2D LDA and 2DPCA features reduction techniques and feed- forward NN classifier. PolyU pre-processed 700nm hyperspectral database was used and the recognition accuracy were 78%, 91.3%, and 87.5% when 2D PCA used to reduce features size, but the accuracy were 96.5%, 95.8% and 93.3% when 2D LDA were used to reduce features size where bandlet, ridgelet, 2D discrete wavelet applied respectively. The best result was obtained using bandlet with 2D LDA.

For future work, the combinations between another multiscale image transformations such as shaplet, platlet, surfacelet, beamlet, and other modern techniques in addition to use another features reduction techniques such as independent component analysis (2D ICA), kernel PCA and other modern techniques are suggested to be used. Swarm optimization such as pee colony practical swarm bacteria foraging etc. may be used to enhance classification.

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