Palmprint Recognition by Wavelet Transform with Competitive Index and PCA

Deepti Tamrakar, Pritee Khanna

Abstract—This manuscript presents, palmprint recognition by combining different texture extraction approaches with high accuracy. The Region of Interest (ROI) is decomposed into different frequency-time sub-bands by wavelet transform up-to two levels and only the approximate image of two levels is selected, which is known as Approximate Image ROI (AIROI). This AIROI has information of principal lines of the palm. The Competitive Index is used as the features of the palmprint, in which six Gabor filters of different orientations convolve with the palmprint image to extract the orientation information from the image. The winner-take-all strategy is used to select dominant orientation for each pixel, which is known as Competitive Index. Further, PCA is applied to select highly uncorrelated Competitive Index features, to reduce the dimensions of the feature vector, and to project the features on Eigen space. The similarity of two palmprints is measured by the Euclidean distance metrics. The algorithm is tested on Hong Kong PolyU palmprint database. Different AIROI of different wavelet filter families are also tested with the Competitive Index and PCA. AIROI of db7 wavelet filter achievs Equal Error Rate (EER) of 0.0152% and Genuine Acceptance Rate (GAR) of 99.67% on the palm database of Hong Kong PolyU.

Keywords—DWT, EER, Euclidean Distance, Gabor filter, PCA, ROI.

I. INTRODUCTION

Palmprint based personal recognition has become an active research topic in recent years. Compared with the other currently available biometric features, palmprints contain more distinctive information than fingerprints; palmprints acquisition devices are much cheaper than iris devices; palmprints can build highly accurate biometrics system than face and voice. Palmprint has several advantages such as stable line features, low-resolution images, low cost acquisition device, very difficult to fake, and easy to user acceptation etc. Palmprint has features like texture, wrinkles, principal lines, ridges, and minutiae points that can be used for its representation [1].

Texture and palm lines are the most clearly observable palmprint features in low resolution (such as 100 dpi) images [1], and thus have attracted most research efforts. Therefore texture based approaches are adopted for palmprint recognition. Typically, texture features are extracted by filtering the palmprint images using filters such as the Gabor filter [2], [3], [4], [6], [7], [8], [10], Guassian filter [9], Radon filter [11], and wavelet transform (WT) [12], [10], [13]. The common tasks in texture-based approaches are to extract palm line orientation and compare similarity between different images. The WT has been widely used for palmprint recognition in different forms. The local or global statistical features (energy, entropy)

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of the sub bands of multi resolution analysis are used for palmprint recognition [3], [4], [6], [10]. A different form of Gabor filter is widely used for palmprint recognition. Several coding methods have been developed using Gabor filter such as Competitive Code [8], [9], [11], [12], [5], Fusion Code[12], Binary Co-occurrence Vector[14] and Palm Code [10]. Coding based methods are seemed to be the most promising due to the strengths of small feature size and high recognition accuracy [8]. The orientation and phase information of palm lines are typically encoded as binary or integer numbers, which are robust to illumination variations [8], [10]. However, the number of features in the coding method is equal to the size of image and each feature is represented by binary code. Phase information of the palmprint gives the efficient results without binary coding. But problem is the dimension of the feature vector, which is very large and needs to be reduced. Several statistical subspace approaches exists for reduction of the size of feature vector without loss of any potential information. These approaches can find the uncorrelated features which can discriminate the different classes of the images more accurately. Some Subspace-based approaches of dimensional reduction and discrimination analysis are also used for the palmprint recognition such as Principal Component Analysis (PCA) [16], [17], [18], Fisher Discriminant Analysis [19], Linear Discrimination Analysis (LDA), Locality Preserving Projections (LPP) [20] and Independent Component Analysis (ICA). In literature, Subspace-based approaches are directly applied to palmprint images or combined with other techniques. Instead of taking original ROI, the proposed work is concentrated on the low resolution approximation ROI using DWT. Approximation ROI (AIROI) can reflect sufficient information of nearly all features of palmprints, so that palmprint can quite discriminate by approximation coefficients (without scalable detailed coefficients) [13]. In this works, Gabor filters based competitive index method is used which applied six Gabor filters of different orientation on the AIROI. The index of filtered image which has minimum value corresponding to each pixel is selected. The PCA is further applied to reduce the feature size and to select uncorrelated features.

Rest of the paper is organized as follows; Section 2 explains the preprocessing for extraction of the region of the interest. Section 3 describes the extraction of AIROI by the DWT. Section 4 describes the Competitive index approach. Section 5 explains the Comp Index with PCA. Section 6 gives distance metrics for matching of the two palmprint images. Section 7 describes the experimental setup for proposed technique. Results of the proposed technique and its comparision with other existing methods of palmprint recognition are given in
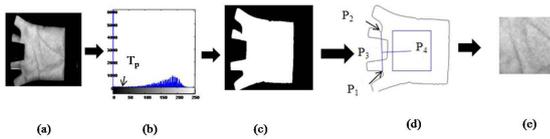
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Fig. 1. Palmprint image preprocessing: alignment and ROI extraction

Section 8. Finally, the work is concluded in Section 9.

II. PREPROCESSING

Before the feature extraction, palmprint image should be aligned to a predefined universal coordinate to facilitate consistent ROI extraction. The following steps are performed for the palmprint alignment, which is shown in "Fig. 1"[4]:

- Convert gray image into binary image using a threshold.
- Trace the boundary of binary image.
- Find the gap points P_1 and P_2 between two fingers.
- Find the center point P_4 of palmprint corresponding to P_1 and P_2.
- A square of 128×128 pixels is extracted with P_4 as its center that is known as the ROI.

III. AIROI

In this work, Discrete Wavelet Transform (DWT) is used to decompose the ROI into lower resolution representation. Multi-resolution analysis using DWT gives the line information of the palmprint in different time and frequency domains. DWT provides localization and representation of different frequencies in the image at different scales. At each level, the high pass filter produces detail coefficients, while the low pass filter associated with scaling function produces coarse approximations coefficients. Detail coefficients give good time resolution and poor frequency resolution while approximation coefficients give good frequency resolution and poor time resolution. The compaction of energy describes how much energy has been compacted into the approximation image during wavelet analysis. The energy compaction is more into the approximation coefficients as compared to detail coefficients. The effect of dropping high frequencies gives the sharp edges in the approximation image. In approximation sub band, palmprint image does not lose the basic appearance of the principal line [6]. So that, ROI is decomposed into two levels by DWT and approximation image ROI (AIROI) is further used for feature extraction. This helps to reduce the size of ROI (16 times approx) as well as increases the accuracy and speed of the palmprint recognition. The proposed work is tested on AIROI of db1, db4, sym4, coif4, bior4.4 and db7 wavelet filters, which are shown in "Fig. 2". It is observed that only principal lines are easily visible and irrelevant small lines are omitted.

IV. COMPETITIVE INDEX

Some tunable filters are appropriate for capturing the orientation information from palmprints. Gabor filters are a good choice. Gabor filters are extremely useful for texture analysis because of the 2-D spectral specificity of texture as well as

its variation with 2-D spatial position. In addition to accurate time-frequency location, they also provide robustness against varying brightness and contrast of images. For the case of the two dimensional (2D) signal or image, the Gabor filter modulation of the 2D sinusoidal plane and 2D Gaussian function is given by Eq. 1.

$$\psi(x,y,\sigma,f,\theta) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{ -\left(\frac{x'^2 + y'^2}{\sigma^2} \right) \right\} \exp\left(2\pi i f x' \right).$$
$$(1)$$

where $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$. $\psi(x,y,\sigma,f,\theta)$ is the Gabor filter with σ standard deviation, f frequency, and θ_p orientation. The parameters of the Gabor filter which are used for Comp Index scheme are given in "Table I". The competitive rule is defined as

$$J = arg \min_{p} \left(I(x,y) * \psi_r(x,y,\sigma,f,\theta_p) \right),$$

where I(x,y) denotes the preprocessed image and J is called the Comp Index, which is an integer representation of the orientation [3]. $*$ denotes image convolution operator. Some of the researchers have coded Comp Index into 3 bits. The present approach does not code Comp Index into bits but uses it as palmprint features. According to the neurophysiology findings, the simple cells are sensitive to specific orientation with approximate bandwidth of $\pi/6$. The overview of the Comp Index scheme is shown in "Fig. 3".

TABLE I
PARAMETERS OF THE GABOR FILTER FOR COMP CODE

Size	f	σ	θ
31×31	0.0916	5.791	$p\frac{\pi}{6}, p = 0, 1, 2, 3, 4, 5$

V. COMP INDEX WITH PCA

Principal Component Analysis (PCA) is a popular technique for data compression and has been successfully used as an initial step in many computer vision tasks, including palmprint and object recognition [16], [17], [19], [20]. In this work, PCA is used for dimensional reduction of Comp Index features of
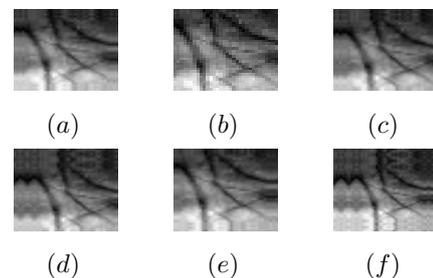

Fig. 2. The approximation coefficients using (a) bior4.4, (b) db1, (c) db4, (d) db7, (e) sym4, and (f) coif4 Wavelet Filters
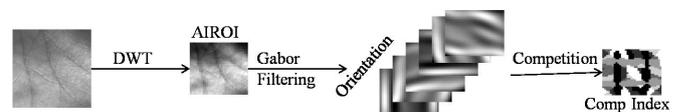

Fig. 3. Overview of Comp Index scheme

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the palmprints. Principal Components (PCs) are uncorrelated variables converted from a set of observations of possibly correlated variables. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has highest variance.

1) The mean Comp Index vector M of training images is computed as

$$M = \frac{1}{n} \sum_{n}^{i=1} C_i.$$

2) Image difference vectors, D_i are obtained by subtracting each Comp Index vector by the Mean Comp Index vector M to make the feature vector centered to the zero mean.

$$D_i = C_i - M.$$

3) The covariance matrix, Cov is obtained from image difference D_i vectors as

$$Cov = \frac{1}{n} \sum_{i=1}^{n} D_i' D_i,$$

where D_i' is the transpose of D_i.

The eigen vectors of the covariance matrix (Cov) are the Principal Components (PC). The eigen values represent the distribution of the source image energy among each of the eigen vectors, so that eigen vector corresponding to the higher eigen value has more energy.

Matrix E of eigen vectors is calculated corresponding to h highest eigen values of covariance matrix (Cov), where $h \leq x \times y$. Matrix E projects the training palmprint into eigenspace, so it is also called projection matrix. The Comp Index image C_i is projected into eigen space using E, which is defined as

$$Ces = (C_i - A)E.$$

Now, Ces is the new training set with the size of $h \times n$. Comp Index of tested palmprint is multiplied with the projection matrix E, so the size of the test Comp Index is also reduced from $1 \times x \times y$ to $1 \times h$.

VI. EUCLIDEAN DISTANCE METRICS

Features of two palmprints that are obtained by the above procedure are compared by using Euclidean Distance.

$$D_{\text{Euc}}(P,Q) = \frac{\sqrt{\sum_{y=1}^{M} \sum_{x=1}^{N} (P(x,y) - Q(x,y))^2}}{M \times N}, \qquad (2)$$

where P and Q are two Comp Index features of size $M \times N$.

VII. EXPERIMENTAL SETUP

All experiments are performed on the Hong Kong PolyU palmprint database, which consists of 7960 images captured from 199 individuals, 398 palms. It consists of 20 images of each palm and it is the largest palmprint database publicly available [22]. The palmprint images were collected, on two different occasions, at an interval of around two months. On

each occasion, the subject was asked to provide about 10 images each of the left palm and the right palm. Therefore, each person has provided around 40 images. The size of all the test images used in the following experiments is 384×284 with a resolution of 75 dpi. The size of extracted ROI from the palmprint image is 128×128 and after applying DWT the size of AIROI reduced to 32×32 approximately. Performances are measured on the AIROI of different wavelet filters (db1, db4, sym4, coif4, db7 and bior4.4). The database is divided into training and testing sets. Five palmprint templates of the first session and five palmprint templates of the second session of each palm are enrolled in the training database.

The rest of the five palmprint templates of the first session and five palmprint templates of the second session of each palm are stored in testing database. The projection matrix is calculated from training palmprint templates. Each palmprint template of the testing database is matched with each palmprint template of training database. The number of genuine and impostor matching are 39800 and 15,800,600 respectively.

All the experiments are tested with the MATLAB 7.1 tools on the standard PC processor (2.83 GHZ) and 4GB RAM. The False Acceptance Rate (FAR) and False Rejection Rate (FRR) are calculated for each threshold value [21] and both are plotted together for different threshold. The performance of the verification system is measured on the basis of the Equal Error Rate (EER), which is a crossover point of the FAR and FRR. The performance of identification system can be measured on the basis of the Genuine Acceptance Rate (GAR), which is the rate of the identification of the genuine user. The proposed scheme is compared with the original Comp Code scheme. The proposed scheme is also tested on the approximation coefficient of the different wavelet filters. The performance of the scheme is tested for different number of PCs.

VIII. EXPERIMENTAL RESULTS

"Fig. 4" (a) and (b) the show ROC curves for Comp Index with PCA and Comp Code respectively. It is observed that EER obtained from Comp Index with PCA is 0.0152% and that for Comp Code is 0.033%. It is clear that on the basis of EER, Comp Index with PCA outperforms Comp Code.
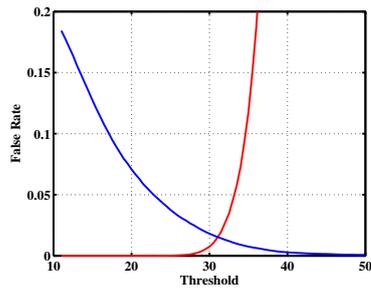
"Fig. 5" (a) and (b) show distribution of genuine and impostor users for Comp Index with PCA, and for Comp Code. The distribution curves separate genuine users and importer. It is observed that the FAR and FRR values are less for Comp Index with PCA as compared to Comp Code.

The proposed approach, Comp Index with PCA for palmprint recognition is compared with other techniques of palmprint recognition and results are shown in the "Table II".
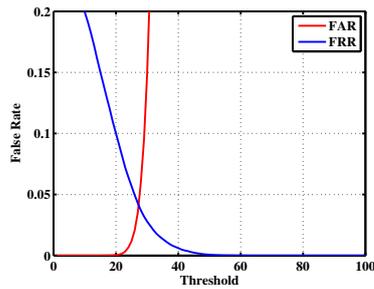
TABLE II
EER AND GAR FOR COMP INDEX WITH PCA WITH OTHER METHOD

Palmprint Recognition	CCR	EER
Palm Code	96.500	0.5450
Fusion Code	97.000	0.336
Competitive Code	99.370	0.0379
Competitive Index with PCA	**99.6734**	**0.017**

"Table III" shows the performance of Comp Index with PCA for various wavelet filters in terms of the EER, GAR

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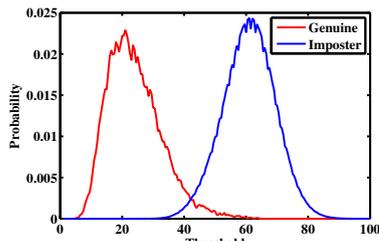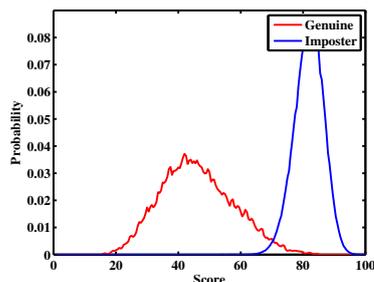Vol:5, No:12, 2011

(a)

(b)

Fig. 4. ROC Curves for (a) Comp Index with PCA, and (b) Comp Code

(a)

(b)

Fig. 5. Distribution Curves for (a) Comp Index with PCA, and (b) Comp Code

TABLE III
EER AND GAR FOR COMP INDEX WITH PCA WITH DIFFERENT WAVELET
FILTERS

Wavelet filter	No. of PC	EER	GAR
db1	90	0.0278	99.4472
db4	90	0.0206	99.6985
db7	**60**	**0.0152**	**99.5226**
bior4.4	60	0.0157	99.6482
coif4	80	0.0215	99.6734
sym4	90	0.0265	99.54

shows that optimum number of required features for palmprint verification is around 60-90. Features less than this range will give errors in the system while higher features will cause deceleration of error in the system.
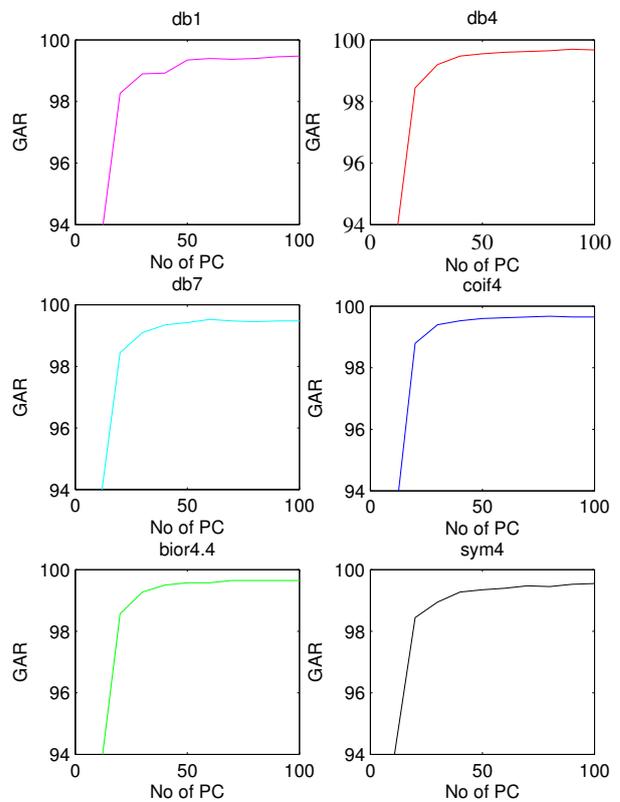

Fig. 6. GAR for Competitive Index with PCA for (a) db1, (b) db4, (c) db7, (d) coif4, (e) sym4, and (f) bior4 Wavelet Filters

and the number of PCs. It can be observed that wavelet and PCA help to improve the accuracy and to reduce the size of templates of palmprint from 6KB to 1 KB (approx). Wavelet filter db7 gives the best performance with the lowest features. "Fig. 6" shows the graphs between GAR and the number of features of the Comp Index with PCA for different wavelet filters. "Fig. 6" shows that the GAR value increase logarithmically continuously up to 80 number of PC with all six wavelet filters. Thereafter, GAR remains constant. This

IX. CONCLUSION

This manuscript presents approach with three different techniques used in cascaded order, which achieves very less EER. AIROI is used to compress ROI, which has important information and makes the system invarient to illumination and translation. PCA helps to reduce the dimension of competitive index features of palmprint. Use of Wavelet filter, Competitive Index and PCA in cascaded order gives better results and the size of templates is also reduced by 80 % (approx).

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