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# Palm Print Recognition Based on Subspace Approaches

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**Abstract—***In todays world, automatic personal recognition is a crucial problem that needs to be solved properly. Palm print recognition is one of the most reliable and successful biometric solutions due to its numerous advantages such as stable line features, low resolution imaging, low cost capturing device, and user friendly. In this article, performance comparisons of palm print recognition techniques based on subspace approaches (PCA and 2DPCA) have presented. The experimental results are evaluated on three benchmark databases (CASIA, Cropped palm images and IIT Delhi) in terms of recognition rate and computation time.*

## 1. INTRODUCTION

Generally, passwords or ID cards have been used for border and airport security, time and attendance control, access to restricted areas, online banking and in office for entering path etc. These types of identity recognition methods have serious disadvantages, like less secure, stolen, manipulated etc. To overcome these limitations biometrics based identity systems play an important role.

Palmprint recognition refers to the process of determining whether two palmprints are from the same persons on line patterns of the palm. A Palm is having principal lines, wrinkles and ridges. There are three principal lines. In general, biometric systems identify a person using physical characteristics, such as fin- gerprint, iris, face, palmprint and ear, or behavioral characteristics, such as signature, gait and keystroke . Among them, palmprint based biometric recognition methods have currently been attracting more attention. Palm print is the inner part of hand which consist lines and points such as heart line, head line and life line respectively. Wrinkles are more irregular than the principal lines. The lines which are not principal lines or wrinkles, are called as ridges and they exist all over the palm. These line and point patterns are always unique, even in the monozygotic twins. The interesting part is that the ridge structure is permanent. This ridge structure is unique and having the low dimensional features. The palmprint recognition system has advantages over the other physiological biometric systems. Some of the advantages are fixed line structure, low intrusiveness, low cost capturing device, low resolution imaging. Thus palmprint recognition is a very interesting research area. A lot of work has already been done in this area, but there is still a lot of scope to make the systems more efficient.

In this paper, the most popular PCA and 2D-PCA approaches are used to extract the palm features from two standard palmprints datasets (CASIA [20] and PolyU cropped [22]. The extracted features are classified using Euclidean distance to evaluate the performance in terms of recognition rate and computation time.

The rest of the paper organised as follow. In section 2 Literature review has been introduced. In section 3 of paper, discussed about the proposed subspace approaches contains methodology of PCA, 2D-PCA and Euclidean distance. Section 4 and section 5 contain the results, discussion and conclusion respectively. At last acknowledgement in section 6 has been introduced and in 7$^{th}$ section references has been given.

## 2. LITERATURE REVIEW

In order to provide an accurate and efficient authentication system, there has been research in the area of palmprint recognition system. For this, a number of relevant papers have been reviewed.

Generally, palmprint based recognition approaches can be categorized into three types: line-based, subspace-based and texture- based approaches. Line based approaches, which also called structural based approaches, employ a set of structural features of palmprints such as principle lines, wrinkles, datum points, ridges and crease points. These approaches either develop edge detectors or use the existing edge detection methods to extract palm lines [1].Wu et al. used Sobel masks to compute the magnitude of palm lines [2]. In [3], datum points of the palmprints are used as features. Datum points are defined as end points of the principle lines. Han et al. proposed a palmprint based system which uses Sobel masks and morphologic operators to extract the structural features of palmprint [4]. In[5], Canny edge operator is used to extract the palm lines. In general, line-based approaches can successfully extracts the majority of lines and ridges correctly. However, the high complexity of these methods is the main drawback in using line based approaches. Besides, a significant computational power is required to determine and match the line segments. Subspace-based approaches utilize numerous techniques such as principle component analysis (PCA) [6], Fisherpalm [7], and independent component analysis (ICA) [8] to extract the palmprint features. These approaches also called appearance-based approach in the literature of face recognition [1]. Subspace-based approaches do not make use of any prior knowledge of palmprints. Lu et al. pro- posed an approach based on the PCA to extract the palm features [6]. They used the Karhunen-loeve transform to project the original image into a small set of feature space called 'eigenpalms'. In [7], Fisher linear discriminant (FLD) is used to project the original palmprint images into the lower dimensional feature space called 'Fisherpalm space'. In another approach, ICA is employed to extract the palm features [8]. In general, these approaches are more computational effective but suffer from dependency to the training data sets. In texture based approaches, texture can be defined as the spatial relationship of pixel values in an image region [9]. Some interesting techniques to analyze the palmprint texture are Gabor filters [10,11], discrete cosines transform (DCT) [12,13], morphological techniques [14], Fourier Transform [17] and wavelet Transforms [16–20]. Zhang et al. used Gabor filters to extract the palm features [10]. They called these features as Palm codes. In [11], Palm codes in varying direction are fused to present the features which are called Fusion code. In [12], DCT is used to extract the palmprint and face features. Meraoumia et al. proposed a method to use two dimensional Block based Discrete Cosine Transform (2D-BDCT) [13]. They divided a palmprint into overlapping and equal-sized blocks and applied DCT over each block. Han et al. pro- posed a method based on the morphological operator to extract the palmprint features [14]. In [16–20], palmprint features are extracted by using various families of Wavelet transform. In general, texture based methods have strong mathematical foundations and fast implementations which make them suitable for palmprint authentication applications. In [16], the wavelet energy features are defined for palm- print representation and the performance of the proposed system has been analyzed for different wavelets. Zhang et al. defined a set of statistical signatures for palmprint classification [17]. Accordingly, wavelet transform is applied to palmprint image and the directional context of each wavelet sub-band is computed. Then, a set of statistical signatures, which includes density, spatial dispersivity, gravity center and energy, is defined to characterize the palmprint. In [18], sequential modified haar transform is applied to palmprint image to compute the modified haar energy features. Zhang et al. pro- posed an image similarity metric called 'complex wavelet structural similarity index' for palmprint classification . In the information extracted from multiple wavelets is combined using the fusion at feature level. On the other hand, some other approaches utilized wavelet transform for extracting the palmprint and fingerprint features. Yang et al. introduced a biometric verification system based on fingerprint, palmprint and hand geometry. In this system, palmprint and fingerprint features are extracted by using the discrete wavelet transform and integrated by fusion at feature level. Then, the integrated textural features are combined with hand geometry features by means of the fusion at matching score level. In Lu et al. applied wavelet zero-crossing for representing the 1D fingerprint and palmprint features. Although, these approaches employed wavelet based techniques for efficient authentication systems, their performance are highly dependent on the type of wavelet transform. Therefore, how to choose the suitable wavelet transform is a critical issue in some wavelet based approaches [16].

## 3. METHODOLOGY USED

The feature extraction and classification are the two major steps in any recognition process. In this work the performance evaluation of feature extraction and classification algorithm are tested on two different sets of palm print images. PCA and 2D-PCA are used as a feature extractor separately in combination with Euclidean distance.

### (1) Principal component analysis

PCA is a well-known feature extraction and data representation technique widely used in the areas of pattern recognition, computer vision and signal processing, etc. In this work, PCA transforms the 2D palm image matrices into 1D image vectors column by column or row by row. It is described is as follows.

Let us consider a set of M palmprint images, $i_1, i_2, \ldots, i_M$ the average palm of the set is defined as:

$$\mathrm{i} = \frac{1}{M}\sum_{j=1}^{M} i_j \qquad (1)$$

Each palmprint image differs from the average palm $\bar{i}$ ,by the vector . A covariance matrix is constructed where:

$$C = \sum_{j=1}^{M} \Phi_i \Phi_i^T \qquad (2)$$

Then, eigenvectors, $V_k$ and eigenvalues, $\lambda_k$ with symmetric matrix C are calculated. $V_k$ determine the linear combination of M difference images with φ to form the eigenpalms:

$$b_i = \sum_{k=i}^{M} V_{lk} \Phi_k \qquad (3)$$

From these eigenpalms, K(<M) eigenpalms are selected to correspond to the K highest eigenvalues. The set of palmprint

images, {i} is transformed into its eigenpalm components (projected into the palm space) by the operation:

$$\omega_{nk} = b_k(i_n - \bar{i}) \tag{4}$$

where n = 1, … ,M and k=1, … ,K.

$$\Omega_n = [\omega_{n1}, \omega_{n2}, \ldots\ldots\ldots, \omega_{nk}]$$

The weights obtained form a vector that describes the contribution of each eigenpalm in representing the input palm image, treating eigenpalms as a basis set for palm images.

**(i) 2D-PCA-**

2D-PCA is based on two dimensional matrices as opposed to the standard PCA, which is based on 1D vectors. In this paper, we first indicate that 2D-PCA is essentially working in the row or column direction of palm images.

Consider an m by n random image matrix **A**. Let XϵR be a matrix with orthonormal columns, $n \geq d$ Projecting **A** onto X yields an m by d matrix. **Y=A**X. In 2DPCA, the total scatter of the projected samples was used to determine a good projection matrix X. The method used is :

$$J(X) = \text{trace } \{E[(Y\text{-}EY)(Y - EY)^T]\}$$

$$= \text{trace}\{E[(AX\text{-}E(AX))(AX - E(AX))^T]\} \tag{5}$$

$$= \text{trace } \{X^T E[(A - EA)^T (A\text{-}EA)]X\}$$

Eq.(5) results from *trace*(RS)=*trace*(SR)

Eq.[5]. Now defines the palm image covariance matrix $K=[(A - EA)^T(A\text{-}EA)]$, which is an n*n nonnegative definite matrix. Let us consider M training palm images, denoted by m*n matrices $A_r$(r=1,2,3,……..M),and denote the average image as $\bar{A} = \frac{1}{M}\sum_r A_r$. Then K can be solved by

$$K = \frac{1}{M}\sum_{k-1}^{M}[(A_r - \bar{A})^T(A_r - \bar{A})] \tag{6}$$

It has been shown that the optimal value for the projection matrix $X_{opt}$ is composed by the orthonormal eigenvectors $X_1 \ldots\ldots X_d$ of K corresponding to the d largest eigenvalues, i.e. Because the size of is only n*n, computing its eigenvectors is very relevant. Also, as in PCA the value of d can be controlled by setting a threshold as follows:

$$\frac{\sum_{i=1}^{d}\lambda_i}{\sum_{i=1}^{n}\lambda_i} \geq \theta_i \tag{7}$$

Where $\lambda_1, \lambda_2, \lambda_3, \ldots\ldots.\lambda_n$ is the biggest eigen values of K and θ is the preset threshold set.

## (ii) Euclidean Distance

Euclidean distance is the distance between two points in Euclidean space. Now the procedure of calculation of Euclidean distance is as follows:The distance between two points in one dimension is simply the absolute value of the difference between their coordinates. Mathematically, this is shown as $|p_1 - q_1|$ where $p_1$ is the first coordinate of the first point and $q_1$ is the first coordinate of the second point.

Generalized, the distance between two points P = ($p_1$, $p_2$, ..., $p_n$) and Q = ($q_1$,$q_2$, ..., $q_n$) in n dimensions. This general solution can be given as (($p_1$-$q_1$)^2 + ($p_2$-$q_2$)^2 + ... + ($p_n$ - $q_n$)^2)^(1/2).

## 4. RESULTS AND DISCUSSIONS

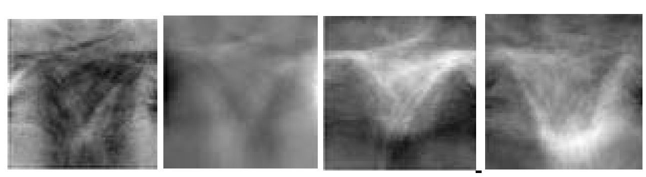
Although 2D-PCA obtains higher recognition accuracy than PCA, a vital unresolved problem of 2D-PCA is that it needs many more coefficients for palm image representation than PCA. The percentage recognition rates of PCA and 2D-PCA are shown in Table 1 and Table 2 respectively. Classifier is tested, namely Euclidean distance. Euclidean distance is the simplest distance matching algorithm among all. Cosine measure can be used since 2D-PCA allows the columns vectors to be non-orthogonal, and the angles and distances between images differ from each other. Table 1 shows the performance recognition rates of PCA using :

**Table 1: PRR by PCA**

| No. of training images | No. of testing images | In PolyU (cropped images) database PRR in % | In CASIA database PRR |
|---|---|---|---|
| 2 | 6 | 81.6 | 67.9 |
| 3 | 5 | 83.2 | 71.1 |
| 4 | 4 | 86.4 | 77.5 |
| 5 | 3 | 89.6 | 80.3 |
| 6 | 2 | 90.1 | 83.1 |
| 7 | 1 | 90.9 | 84.2 |

these distance metrics.

(i) PCA (after applying pca gives this type of images)



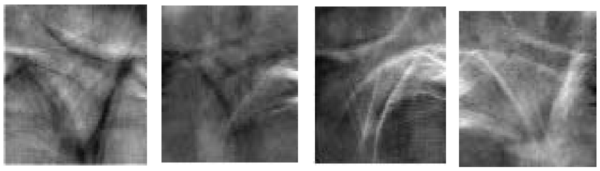
The percentage recognition rate by 2D-PCA is shown in Table 2 as follows:

**Table 2: PRR by 2D-PCA**

| No. of training images | No. of testing images | In PolyU (cropped images) the PRR in % | In CASIA images the PRR in % |
|---|---|---|---|
| 2 | 6 | 85.6 | 70.6 |
| 3 | 5 | 88.7 | 75.7 |
| 4 | 4 | 90.2 | 79.8 |

| | | | |
|---|---|---|---|
| 5 | 3 | 93.3 | 83.4 |
| 6 | 2 | 97.1 | 85.6 |
| 7 | 1 | 98.9 | 89.6 |

(ii) 2D-PCA (after applying the 2D-PCA)



## 5. CONCLUSION

Palm print identification systems measure and compare ridges, lines and Minutiae found on the palm. Palm print is a unique and reliable biometric characteristic with high usability. The 2D-PCA gives more better results than PCA because its computational time is less than computational time in PCA. So 2D-PCA is more convenient than PCA. If we apply PCA in cropped palm images then it gives more better result than CASIA database. In 2D-PCA CASIA database gives better results.

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## REFERENCES

[1] A. Kong, D. Zhang, M. Kamel, A survey of palmprint recognition, Pattern Recogn. 42 (7) (2009) 1408–1418.
[2] X. Wu, K.Wang, D. Zhang, HMMsbased palmprint identification, LCNS Springer 3072 (2004) 775–781.
[3] D. Zhang, W. Shu, Two novel characteristics in palmprint verification: datum point invariance and line feature matching, Pattern Recogn. 32 (4) (1999) 691–702.
[4] C. Han, H. Cheng, C. Lin, K. Fan, Personal authentication using palm-print features, Pattern Recogn. 36 (2) (2003) 371–381.
[5] X. Wu, K. Wang, D. Zhang, Fuzzy direction element energy feature (FDEEF) based palmprint identification, in: Proceedings of International Conference on Pattern Recognition, vol. 1, 2002, pp. 95–98.
[6] G. Lu, D. Zhang, K. Wang, Palmprint recognition using Eigenpalms features, Pattern Recogn. Lett. 24 (9–10) (2003) 1473–1477.
[7] X. Wu, D. Zhang, K. Wang, Fisherpalms based palmprint recognition, Pattern Recogn. Lett. 24 (2003) 2829–2838.
[8] L. Shang, D.S. Huang, J.X. Du, Z.K. Huang, Palmprint recognition using ICA based on winner-take-all network and radial basis probabilistic neural network, LCNS 3972 (2006) 216–221.
[9] S. Drabycz, R. Stockwell, J. Mitchell, Image texture characterization using the discrete orthonormal S-Transform, J. Digit. Imaging 22 (6) (2009) 696–708.
[10] D. Zhang, J. You, Online Palmprint identification, IEEE Trans. Pattern Anal. Matching Intell. 25 (9) (2003) 1041–1050.
[11] W.K. Kong, D. Zhang, Competitive coding scheme for palm print verification, in: Proceedings of the 17th International Conference on Pattern Recognition, 2004, pp. 520–523.
[12] X.Y. Jing, D. Zhang, A face and palmprint recognition approach based on discriminant DCT feature extraction, IEEE Trans, Syst. Man Cybern. Part B 34 (6) (2004) 2405–2415.
[13] A. Meraoumia, S. Chitroub, A. Bouridane, Gaussian modeling and discrete Cosine transform for efficient and automatic palmprint identification, in: Inter- national Conference on Machine and Web Intelligence (ICMWI), 2010, pp. 121–125.
[14] C.C. Han, H.L. Cheng, K.C. Fan, C.L. Lin, Personal authentication using palmprint features, Pattern Recogn. 36 (2) (2003) 371–381.
[15] W. Li, D. Zhang, Z. Xu, Palmprint identification by Fourier transform, Int. J. Pattern Recogn. Artif. Intell. 16 (4) (2002) 417–432.
[16] X.Q. Wu, K.Q. Wang, D. Zhang, Wavelet based palmprint recognition, in: Proceedings of the First International Conference on Machine Learning and Cybernetics 3, 2002, pp. 1253–1257.
[17] L. Zhang, D. Zhang, Characterization of palmprints by wavelet signatures via directional context modeling, IEEE Trans. Syst. Man Cybern. Part B 34 (3) (2004) 1335–1347.
[18] E.W.K. Yih, G. Sainarayanan, A.N.G. Chekima, Palmprint identification using sequential modified Haar wavelet energy, in: International Conference on Sig- nal Processing, Communications and Networking, 2008, pp. 411–416.
[19] Lu, G., David, Z., Wang, K., "Palmprint recognition using eigenpalms features", Pattern Recognition Letters, 24(9-10), pp 1473-1477 (2003).
[20] J. Yang, D. Zhang, A.F. Frangi, and J.Y. Yang, "Two-dimensional PCA: a new approach to appearance-based face representation and recognition," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 26, no. 1, pp. 131-137, Jan. 2004.
[21] CASIA Palmprint Database, (http://biometrics.idealtest.org/dbDetailForUser.do?id=5)
[22] A. Jain, R. Bolle, S. Pankanti, Biometrics: Personal Identification in Networked Society, Kluwer Academic Publishers, Dordrecht, 1999.
[23] PolyU (http://www.comp.polyu.edu.hk/biometrics) Palmprint database.