# An Advance Subspace Method for Implementing Palm Print Recognition

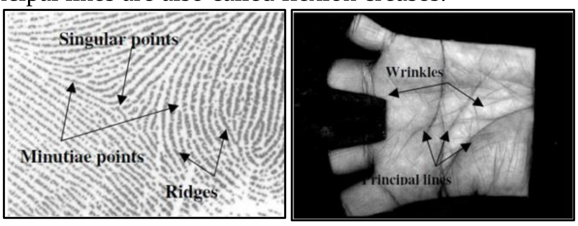
**Abhishek Singhal[1] Manish Mukhija[2]**
[1]M. Tech. Student
[1,2]Department of Computer Engineering
[1,2]MITRC, Alwar, Rajasthan, India

*Abstract*— Biometrics are very useful to identify individuals based on their behavioural and physiological features, that can be used for their personal authorization. Various physical features like, iris patterns, retina patterns, palm print patterns, fingerprint patterns, facial features etc. are used for such purposes. Palm print identification involves recognizing an specific by matching the various wrinkles, principal lines and creases on the surface of the palm of the hand. The base for using the palm prints lies in the fact that since palm print patterns are generated by random orientations of tissues and muscles of the hand during birth, no two individuals have exactly the same palm print pattern. Research of Palm print can be possible with both low resolution and high resolution images. Low resolution images are more appropriate for commercial and civil applications such as financial transaction, access control, etc. while High resolution images are appropriate for forensic applications such as criminal detection. Generally speaking, high resolution rises to four hundred dpi or more while low resolution rises to one hundred and fifty dpi or less. Researchers can extract generally principal lines, wrinkles and texture in low resolution while from high resolution images features are extracted as ridges, singular points and minutia points. In this paper a comparative study for palm print features of different subspace methods have been projected. Where the different subspace methods are separately exploited by using a classifier-Euclidean distance to find the algorithm performance. The experiment results by using two palm print databases determine that the proposed method of class specific information with 2D-PCA, alternate 2DPCA, Kernel PCA and (2D*2D) PCA, Where in comparison to other algorithm (2D*2D) PCA method provides the better results and the recognition rate by this method is given around 87 percent.

***Key words:*** Palm Print Recognition, 2DPCA, Alternate 2DPCA, Kernel 2DPCA, (2D*2D) PCA

## I. INTRODUCTION

The Palm print recognition system recognizes on the base of the palm print of a individual. The print patterns are always unique due to the fact It is trustworthy, even in the monozygotic twins. Three principle lines, wrinkles and ridges normally contain in the inner surface of the palm. Where the wrinkles are called secondary creases and the principal lines are also called flexion creases.




(a) (b)

Fig. 1: Palm print features in (a) A high resolution image and (b) A low resolution image

The lines that are neither principal lines nor wrinkles are called as ridges and they exist all over the palm. The motivating part is that the structure of ridge is permanent. Structure of ridge is formed at about the starting of fifth month of the embryonic development. The completion of this formation is done at the mid of sixth month of pregnancy. There are some advantages of palm print identification system over the other Physiological biometric systems which are low cost capturing device, low intrusiveness, low resolution imaging, fixed line structure.

Thus, palm print recognition is a very interesting research field. A lot of work has already been done in this particular field, but there is still a scope to make the systems more effective. Here, we have tried to examine the already existing systems and thereby propose a new method.

This paper proposes an method in which we have two slandered datasets (POLYU cropped [23] and CASIA [21] . On these dataset we apply most popular approach 2DPCA and (2D*2D) PCA to extract and classify the palm features. Then we use Euclidean distance process to evaluate the performance in terms of correct recognition rate.

The rest of the paper organized as follow. In section 2 Literature review has been introduced. In section 3 of paper, discussed about the proposed subspace approaches contains methodology of 2D-PCA, Alternate 2DPCA, Kernel PCA, (2D*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 7th section references has been given.

## II. LITERATURE REVIEW

In order to provide an effective and efficient authentication system, in the area of palm print identification system, a number of relevant papers have been reviewed.

Generally, palm print based identification 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 palm prints 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].Fisher palm [2], and independent component analysis (ICA) [4] to extract the palm print features. These approaches also called appearance-based approach in the literature of face recognition [1].Han et al. proposed a palm print based system which uses Sobel masks and morphologic operators to extract the structural features of palm print [3]. In [2], Fisher linear discriminate (FLD) is used to project the original palm print images into the lower dimensional feature space called ‘Fisher palm space’. In another approach, ICA is employed to extract the palm features [4]. Some interesting techniques to analyze the palm print texture are Gabor filters [6, 19], discrete cosines transform (DCT) [8, 22], and morphological techniques [18], Fourier Transform [7] and wavelet Transforms [7, 12, 14, 15 and 17] .Zhang et al. defined a set of statistical signatures for palm print classification [7]. Accordingly, wavelet transform is applied to palm print 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 palm print. In [8], DCT is used to extract the palm print and face features. In[9], 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. In [10], datum points of the palm prints are used as features. Datum points are defined as end points of the principle lines. Wu et al. used Sobel masks to compute the magnitude of palm lines [13].In [7, 12, 14, 15, and 17], palm print 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 palm print authentication applications. In [14], the wavelet energy features are defined for palm- print representation and the performance of the proposed system has been analyzed for different wavelets. In [15], sequential modified haar transform is applied to palm print image to compute the modified haarenergy features. Zhang et al. pro- posed an image similarity metric called 'complex wavelet structural similarity index' for palm print 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 palm print and fingerprint features. Yang et al. introduced a biometric verification system based on fingerprint, palm print and hand geometry. In this system, palm print 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 palm print 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 [14]. Subspace-based approaches utilize numerous techniques such as principle component analysis (PCA) [16], Subspace-based approaches do not make use of any prior knowledge of palm prints. Lu et al. proposed an approach based on the PCA to extract the palm features [16].Han et al. proposed a method based on the morphological operator to extract the palm print features [18]. In [19], Palm codes in varying direction are fused to present the features which are called Fusion code. 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 [20]. Meraoumia et al. proposed a method to use two dimensional Block based Discrete Cosine Transform (2D-BDCT) [13]. They divided a palm print into overlapping and equal-sized blocks and applied DCT over each block. 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. They used the Karhunen-loeve transform to project the original image into a small set of feature space called 'Eigen palms'. Zhang et al. used Gabor filters to extract the palm features [6]. They called these features as Palm codes.

## III. METHODOLOGY USED

The feature extraction and classification are the two main steps in any recognition process. In this effort the performance evaluation of feature extraction and classification algorithm are tested on two different sets of palm print images. 2DPCA, Kernel PCA, Alternate 2DPCA and (2D*2D) PCA are used as a feature extractor separately in grouping with Euclidean distance.

### A. Kernel PCA

Kernel PCA is a method which is used for nonlinear dimension reduction and feature extraction. This method basically permits to standard PCA to perform on high dimensional kernel feature space. Since, this is a nonlinear function by which wavelet palm's coefficients are mapped into high dimension feature space where If in high feature space PCA is applied, expensive computation is required in that space. So to simplify the computation Kernel based PCA can be easily applied on such high dimensional space [24]. To execute KPCA, the following steps are carried out:

First of all, calculate k, the dot product matrix where dot products of the form in space F (infinite dimension feature space), which is correlated to input space by a nonlinear map,

$$k_{ij} = \left(k\left(x_i, x_j\right)\right) \quad (1)$$

Then, solve k which contain eigenvectors set and normalize the eigenvector expansion coefficient in F.

$$1 = \lambda_n(\alpha^n . \alpha^n) \quad (2)$$

Where α is the corresponding eigenvectors of k and λ is the eigenvalues.

Now to extract the principal components corresponding to kernel of a test point namely, the projections are calculated onto the eigenvectors in F

$$(kPC)_n(\mathrm{x}) = (\mathrm{V}^n . \Phi(x)) = \sum_{i=1}^{M} \alpha_i^n k(\mathrm{x}_i, \mathrm{x}) \quad (3)$$

The equation (3) can be called nonlinear principal components corresponding to φ. If a kernel function satisfies the eq. (3), it means PCA is performed in M (high dimension) feature space. The kernel which is used in this paper is Gaussian function as follows:

$$k\left(X_i, X_j\right) = \exp\left[-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}\right] \quad (4)$$

The commonly used kernels in literature are Gaussian function, polynomial function and sigmoid function. Therefore, the low dimensional 2D DWT based KPCA features are obtained using eq. (3) and finally to check similarity between training and test images are compared using Euclidean distance as classifier.

*B. Two Dimensional Principal Component Analysis (2DPCA)*

There is an problem in PCA-based palm representation and recognition approach, that the 2D palm image matrices must be previously converted into 1D image vectors row by row or column by column. However, it usually leads to a high-dimensional vector space when concatenating 2 dimensional matrices into 1 dimensional vector, where evaluation is too much difficult of the covariance matrix accurately due to its very large size and the relatively small number of training samples [24]. Furthermore, to compute the eigenvectors of a large size covariance matrix is time-consuming process.

To overcome these problems, a method was proposed named 2-dimensional principal component analysis (2DPCA), this method directly computes eigenvectors from original image matrix, so- this is also named image covariance matrix without matrix-to-vector conversion. We can also say, image matrices can be directly processed and there is no need to transform images matrices into Column or row vectors, Because size of image covariance matrix is equal to or less then with the size of original images, and the size obtained in 2DPCA of image covariance matrix is very small compared with the size of a covariance matrix in PCA.

Consider C an p by q random image matrix.

Let $X \in R^n$ be a matrix with orthonormal columns, $n \geq d$. Image matrix

$$C_k = [C_k^1\, C_k^2 \ldots C_k^m]$$

And image matrix's average be

$$\bar{C} = [\overline{C^1}\, \overline{C^2} \ldots \overline{C^m}]$$

Plotting C onto X yields an p by d matrix Y=CX. In this technique, the total scatter of the plotted samples is used to conclude a better projection matrix X.

The image covariance matrix G which is an q by q matrix is definite nonnegative matrix. Let there are M training palm images, denoted by t by u matrices

$C_k(k = 1,2,\ldots M)$ and $\bar{C}$ denote the average image as $\bar{C} = \frac{1}{M}\sum_{k=1}^{M} C_k$

Then G can be evaluated by

$$G = \frac{1}{M}\sum_{k=1}^{M}(C_k - \bar{C})^T(C_k - \bar{C}) \qquad (5)$$

It has been observed that the optimal value $X_{opt}$ for the projection matrix is composed by the orthonormal eigenvectors $X_1\, X_2 \ldots\ldots X_d$ of G corresponding to the d largest eigenvalues, i.e. $X_{opt} = [X_1 \ldots\ldots X_d]$ Because the size of G is only q by q, computation of its eigenvectors is very efficient.

As 2DPCA works in row direction, it reduces dimensions in row direction.

*C. Alternate 2DPCA*

As 2DPCA reduces and whiten diamensions from row direction, here a procedure named alternate 2DPCA is given that and reduce and whiten diamension of the images in column direction and optimal projection is found in column direction by applying transpose on space matrix.

Let $C_k = [(C_k^1)^T\, (C_k^2)^T \ldots.\ (C_k^m)^T]^T$ and $\bar{C} = [(\overline{C_k^1})^T\, (\overline{C_k^2})^T \ldots.(\overline{C_k^m})^T]^T$ Be the image column matrix. Alternative 2DPCA and 2DPCA only works in the column and row direction of images respectively.as, 2DPCA studies an optimal matrix X from a set of loading images(training images) as information is revealed between rows of images, and then plots an m by n image C onto X, that is an m by d matrix Y=CX. Likewise, the alternative 2DPCA studies optimal matrix Z in which information is revealed between columns of images, and then plots C onto Z, yielding a q by n matrix $D = Z^T X$.

The image covariance matrix **G** from the outer product of row vectors of images, considering the loading images at the training time have the zero mean, i.e. $\bar{C} = (0)_{mxn}$. For that reason, we claim that original 2DPCA is working in the row direction of images. Then the evaluation of alternative covariance matrix **G** can be given by

$$G = \frac{1}{M}\sum_{k=1}^{M}(C_k - \bar{C})(C_k - \bar{C})^T \qquad (6)$$

Likewise, the optimal plot matrix can be gained by computing the eigenvectors $Z_1\, Z_2 \ldots. Z_q$ corresponding to the $q$ largest eigenvalues, i.e. $Z_{opt} = [Z_1 \ldots\ldots Z_q]$.As the information is only revealed between columns of images by eigenvectors, we say that the functioning of alternative 2DPCA is in the column direction of images

*D. Two Directional Two Dimensional PCA, (2D*2D) PCA*

As we have seen a better recognition performance and time consumption 2DPCA and alternate 2DPCA directly process original image matrices. As by using 2DPCA optimal projection is given in row direction because it works in row direction only, similarly, by using alternate 2DPCA the optimal projection is given in column direction. However the chief drawback of 2DPCA and alternate 2DPCA is that they both required too much coefficients for image representation. Solution of this problem can be given if there is a procedure which project image feature matrix both in column and row directions simultaneously.(2D*2D)PCA is a simultaneous way of presenting Alternate 2DPCA and 2DPCA. In 2DPCA, the covariance matrix G can be obtained by

$$G = \frac{1}{M}\sum_{k=1}^{M}(C_k - \bar{C})^T(C_k - \bar{C})$$

Where

$$\bar{C} = \frac{1}{M}\sum_{k=1}^{M} C_k$$

Consider the size of Ci is 900*30, G has a dimension of 30*30. Then for optimal projection matrix orthonormal eigenvectors of image covariance matrix (G) corresponding to the largest optimal value (d) is proved.

$$X_{opt} = [X_1 \ldots \ldots X_d]$$

The value of d can be determined by the ratio of sum of chosen d largest eigenvalues to all.

Likewise, the optimal projection in column direction $Z_{opt} = [Z_1 \ldots\ldots Z_q]$ is determined by transpose space matrix. Now the feature matrix $C_k$ is projected by (2D*2D) PCA both in column and column directions simultaneously by projecting the original feature matrix onto Xopt and Zopt.

$$C_{trn} = Z^T optCX_{opt}$$

Here to represent palm print image Ci Ctrn is a coefficient matrix .As Ci is composed of 30(30*30) matrices in row direction, Ctrn can be achieved by projecting all these 30*30 blocks in Ci onto Xopt and Zopt, respectively and arranging them in same order. Consider the dimensions of Xopt and Zopt are 30*5 and 30*11, the ultimate dimension of feature vector is whiten from 30*30*30=9000 to 5*30*11=1650, means (2D*2D) PCA reserves the precision of 2DPCA but disregards the large number of coefficient requirement of 2DPCA [10]. Thus we obtain the training feature matrices $C_{trn}(trn = 1,2, \ldots.. M)$. Repeating the same for test image $C_{test}$ we get the test feature matrix $C_{test}$. Then the nearest neighbor classifier is used for classification. Here the distance between $C_{trn}$ and $C_{test}$ is defined by

$$d(C_{trn}, C_{test}) = \|C_{trn} - C_{test}\| = \sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(C_{trn}^{(i,j)} - C_{test}^{(i,j)})^2} \quad (7)$$

### *E. Euclidean Distance*

Distance between two points in Euclidean space is Euclidean distance. Now the method of computing of Euclidean distance is as follows: The absolute value between two points is the distance which is simply given by difference between their coordinates in one dimension. Mathematically, that is presented as |r1 – s1| where first coordinate of the first point is r1 and first coordinate of the second point is s1.

Generalized, the distance between these two points r = (r1, r2, ..., rn) and S = (s1,s2, ..., sn) in n dimensions. This general solution can be given as (r1-s1)^2 + (r2-s2)^2 + ... + (rn - sn)^2)^(1/2).

In this case, where the variances of the population classes are given different to each other, Euclidean distance is used. Theoretically the Euclidean distance is identical to the similarity index. We can define a simple similarity score S.S(R1,S1)based on “inverse Euclidean distance”:

$$S.S(R1 - S1) = 1/1 + |r1 - s1| \quad (8)$$

To perform palm print identification, the similarity score is calculated between an testing palm image (input palm) and each of the training images.

## IV. RESULTS AND DISCUSSION

In this session using subspace methods on the two databases results are performed. All algorithms are simulated with MATLAB version R2013 using core i5 processor. The experiments are performed on two different sets of data. First one is standard database i.e. CASIA database, after that on cropped palm images database. In CASIA database, there are hundred and ten subjects that have eight different poses in each subject. In cropped palm images, same records of data has been used but that data has been cropped and having only region of interest part. It has been performed on two dataset as follows:

| Feature vector size | 5 | 10 | 15 | 20 | 25 |
|---|---|---|---|---|---|
| CASIA Dataset | 40 | 45 | 55 | 80 | 75 |
| Cropped images | 40 | 40 | 80 | 100 | 75 |

Table 1: Performance of 2D-PCA algorithm

Correct recognition rate by 2DPCA is given below on different feature vector size:

| Feature vector size | 5 | 10 | 15 | 20 | 25 |
|---|---|---|---|---|---|
| CASIA Dataset | 54.28 | 60 | 72 | 70 | 86.66 |
| Cropped images | 77.14 | 76.66 | 100 | 100 | 100 |

Table 2: Performance of (2D*2D)PCA Algorithm

Correct recognition rate by (2D*2D)PCA is given below on different feature vector size:

## V. CONCLUSION

In this paper, presentation of a novel method is given to authenticate individuals by using their palm-print features. HP scanner is used to capture the hand images and a camera without any fixed peg. This tool is very appropriate and comfortable for all users. The proposed system is providing satisfactory recognition result so this is reliable and user friendly as convenient acquiring process is offered. The Palm print identification system has been implemented using subspace approach. Scaling the position and of the palm print is critical for success of palm print template-based approach, and loading training images is determinant for the alignment. It has been noticeable there should be well alignment of the palm print image for good performance of the palm print verification. First of all preprocessing of image (histogram equalized, resized, and thresholded) is processed and to extract the palm feature Gaussian and Sobel filters are used. They extract features like principle lines, ridges, edges etc. In the template-matching method, as the metric measurement the linear association function is adopted. Using (2D*2D) PCA technique, nearly 87% accuracy recognition rate has been achieved.

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## REFERENCES

[1] A. Kong, D. Zhang, M. Kamel, A survey of palm print recognition, Pattern Recogn. 42 (7) (2009) 1408–1418.
[2] X. Wu, D. Zhang, K. Wang, Fisherpalms based palm print recognition, Pattern Recogn. Lett. 24 (2003) 2829–2838.
[3] C. Han, H. Cheng, C. Lin, K. Fan, Personal authentication using palm-print features, Pattern Recogn. 36 (2) (2003) 371–381.
[4] L. Shang, D.S. Huang, J.X. Du, Z.K. Huang, Palm print recognition using ICA based on winner-take-all network and radial basis probabilistic neural network, LCNS 3972 (2006) 216–221.
[5] A. Jain, R. Bolle, S. Pankanti, Biometrics: Personal Identification in Networked Society, Kluwer Academic Publishers, Dordrecht, 1999.
[6] D. Zhang, J. You, Online Palm print identification, IEEE Trans. Pattern Anal.Matching Intell. 25 (9) (2003) 1041–1050.
[7] 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.
[8] X.Y. Jing, D. Zhang, A face and palm print recognition approach based on discriminate DCT feature extraction, IEEE Trans, Syst. Man Cybern. Part B 34 (6) (2004) 2405–2415.
[9] X. Wu, K. Wang, D. Zhang, Fuzzy direction element energy feature (FDEEF) based palm print identification, in: Proceedings of International Conference on Pattern Recognition, vol. 1, 2002, pp. 95–98.

[10] D. Zhang, W. Shu, Two novel characteristics in palm print verification: datum point invariance and line feature matching, Pattern Recogn. 32 (4) (1999) 691–702.
[11] W. Li, D. Zhang, Z. Xu, Palm print identification by Fourier transform, Int. J. Pattern Recogn. Artif. Intell. 16 (4) (2002) 417–432.
[12] Lu, G., David, Z., Wang, K., "Palm print recognition using Eigen palms features", Pattern Recognition Letters, 24(9-10), pp1473-1477 (2003).
[13] X. Wu, K.Wang, D. Zhang, HMMs based palm print identification, LCNS Springer 3072 (2004) 775–781.
[14] X.Q. Wu, K.Q. Wang, D. Zhang, Wavelet based palm print recognition, in: Proceedings of the First International Conference on Machine Learning and Cybernetics 3, 2002, pp. 1253–1257.
[15] E.W.K. Yih, G. Sainarayanan, A.N.G. Chekima, Palm print identification using sequential modified Haar wavelet energy, in: International Conference on Signal Processing,
[16] G. Lu, D. Zhang, K. Wang, Palmprint recognition using Eigen palms features, Pattern Recogn. Lett. 24 (9–10) (2003) 1473–1477.
[17] 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.
[18] C.C. Han, H.L. Cheng, K.C. Fan, C.L. Lin, Personal authentication using palm print features, Pattern Recogn. 36 (2) (2003) 371–381.
[19] 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.
[20] S. Drabycz, R. Stockwell, J. Mitchell, Image texture characterization using the discrete orthonormal S-Transform, J. Digit. Imaging 22 (6) (2009) 696–708.
[21] CASIA Palm print Database, (http://biometrics.idealtest.org/dbDetailForUser.do?id=5).
[22] A. Meraoumia, S. Chitroub, A. Bouridane, Gaussian modeling and discrete Cosine transform for efficient and automatic palm print identification, in: International Conference on Machine and Web Intelligence (ICMWI), 2010, pp. 121–125.
[23] PolyU(http://www.comp.polyu.edu.hk/biometrics)Palm printdatabase.
[24] W. Zuo, K. Wang and D. Zhang, "Bi-directional PCA with assembled matrix distance metric", in Proceeding of IEEE International Conference on Image Processing, vol. 2, pp. 958-961, 2005.