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Palm Print Identification by using PCA and Advance Variants

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Abstract— In present era, automatic personal identification is a serious problem that needs to be overwhelm properly. This can be resolve by biometrics systems. One often most successful biometric systems is the palm print identification system. Palm print identification algorithms are useful in a wide range of applications like crime investigation, security control, and access control in computer system, entrance control in buildings, access control at automatic teller machines, document verification for identifying the individuals in a given databases. In this article performance comparisons of palm print identification techniques based on sub-space approaches (PCA, LDA and 2DPCA).

Key words: Palm Print Identification, PCA, LDA, 2DPCA

I. INTRODUCTION

The Palm print identification system identifies on the basis of the palm print of a person. It is reliable due to the fact that the print patterns are always unique, even in the monozygotic twins. The inner surface of the palm normally contains three principle lines, wrinkles and ridges. The principal lines are also called flexion creases and the wrinkles are called secondary creases. The lines which are not principal lines or wrinkles are called as ridges and they exist all over the palm. The interesting part is that the ridge structure is permanent. This ridge structure is formed at about the starting of fifth month of the embryonic development. This formation gets completed at the mid of sixth month of pregnancy. The palm print identification system has advantages over the other Physiological biometric systems. Some of the advantages are low intrusiveness, low cost capturing device; fixed line structure, low resolution imaging.

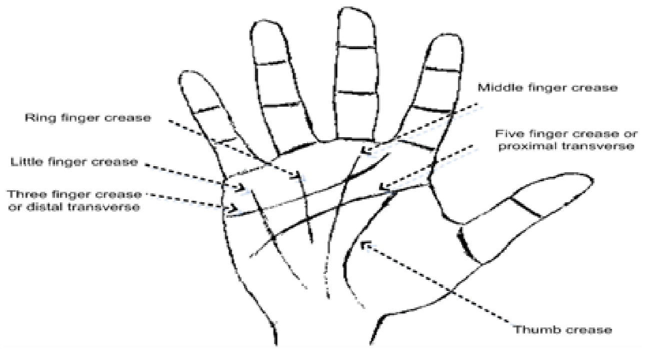

Fig. 1:

Thus, palm print identification is a very interesting research area. A lot of research has already been done in this particular field, but there is still a scope to make the systems more efficient. Here, we have tried to analyze the already existing systems and thereby propose a new approach.

This paper proposes an approach in which we have two slandered datasets (POLYU cropped [21] and CASIA [23] and a self-made data set named NITH. On these dataset we apply most popular approach PCA and 2DPCA to extract and classify the palm features. Then we use Euclidean distance process to evaluate the performance in terms of identification rate and computation time.

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 PCA, LDA, 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 accurate and better authentication system, there has been research in the area of palm print identification system. For this, 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. pro- posed an approach based on the PCA to extract the palm features [16].Han et al. pro- posed 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 identification process. In this effort the performance evaluation of feature extraction and classification algorithm are tested on three different sets of palm print images. PCA, LDA and 2D-PCA are used as a feature extractor separately in grouping with Euclidean distance.

A. Principal Component Analysis

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

Let us consider a set of M palm print images, n1, n2, … ,nM the average palm of set is defined as:

$$i = 1/M\sum mj = 1\ nj\ 1)$$

Each palm print image differs from the average palm̅n ,by the vector . A covariance matrix is constructed where:

$$C = \sum mj = 1\alpha n\alpha nT \qquad (2)$$

Then, eigenvectors, Vk and Eigen values, λk with symmetric matrix C are calculated. Vk determine the linear combination of M difference images with α to form the Eigen palms:

$$dn = \sum mk = n\ vnk\alpha k \qquad (3)$$

From these Eigen palms, K(<M) Eigen palms are selected to correspond to the K highest Eigen values. The set of palm print images, {i} is transformed into its Eigen palm components (projected into the palm space) by the operation:

$$\omega pk = dk(np - \tilde{N}) \quad (4)$$

Where p=1…..,m and k=1,..,k

$$\Omega n = [\omega p1, \omega n2, \dots \dots \dots, \omega pk]$$

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

B. Linear Discriminate Analysis

This method is an enhancement of PCA method, that it uses Fisher's Linear Discriminate Analysis (LDA) for the dimensionality reduction.

Between-class variance is defined by:

$$S_B = \frac{1}{N_C}\sum_{i=1}^{N_C}(\overline{m_\iota} - \overline{m})(\overline{m_\iota} - \overline{m})^T$$

Within- class variance is defined by:

$$S_W = \frac{1}{N_C}\sum_{i=1}^{N_C}\left(\frac{1}{N}\sum_{i=1}^{N_C}(\overline{x_{\iota J}} - \overline{m})(\overline{x_{\iota J}} - \overline{m})^T\right) \qquad (1)$$

Where N_C is the number of class and $\overline{m_\iota}$ is the mean vector of the it h class.

The Goal of LDA method is to maximize the ratio of between-class variance and within-class variance with respective to Eigen vector $\underset{w}{\rightarrow}$.

$$J(\overline{w}) = \frac{\overline{w^T} S_B \overline{w}}{\overline{w^T} S_W \overline{w}} \qquad (2)$$

Since the global mean is from by summing all class mean, only $N_C - 1$ and N_C matrices that go into S_B are linearly independent. The rank of $S_B$is at most $N_C - 1$.

The following procedure described here is to avoid the problem that S_W may be singular.

Step1: Use regular Eigen- decomposition to diagonalizableS_B. This will yield a matrix V of eigenvectors such that $V^T S_B V = \Lambda$

Where $V^T V = I$ and Λ is a diagonal matrix of eigenvalues in a descending order.

Step2: Discard Eigen values that are close to 0 in Λ(no inter-class discriminations), and retain only M eigenvalues. Let Y be the matrix formed by the first M eigenvectors in V.

$$Y^T S_B Y = D_B \quad (21)$$

Where D_B is the upper-left M*M sub-matrix of Λ.

Step3: Construct a matrix Z as follows: $Z = Y D_B^{-1/2}$

Step4: Now diagonalizable$Z^T S_W Z$ by regular eigen decomposition. This will yield a matrix U of eigenvectors such that

$$U^T Z^T S_W Z U = D_W, \quad (22)$$

Where $U^T U = I$.

Step 5: Since the goal is to maximize the ratio of between-class scatter to within-class scatter the since much inter-class discriminatory information is contained in the smallest eigenvectors of S_W, the largest eigenvalues of D_W and the corresponding eigenvectors are discarded.

Step 6: Let$\widehat{U}$ denotes the matrix consists of p (p<M) eigenvectors retained from U. Then matrix of the LDA eigenvectors that maximize the fisher equation is given by

$$W = \widehat{U}^T Z^T$$

1) Comparison of PCA and LDA

The following figure shows a comparison of PCA and LDA results.

- LDA achieve 100% accuracy rate after using 9 eigenvectors as feature space. PCA achieve 100% accuracy after using 13 eigenvectors.
- The PCA projections are optimal for representation in a low dimensional basis, but they may not be optional from a discrimination standpoint.
- The LDA maximizes the ratio of between-class variance to that of within-class variance. It works better than PCA for purpose of discrimination.

In sum, LDA outperformed the PCA method. Both have good performance under varying illumination.

C. Two Dimensional Principal Component Analysis (2DPCA)

In the PCA-based Palm print representation and recognition methods, the 2D palm image matrices must be previously transformed into 1D image vectors column by column or row by row. However, concatenating 2D matrices into 1D vectors often leads to a high-dimensional vector space, where it is difficult to evaluate the covariance matrix accurately due to its large size and the relatively small number of training samples. Furthermore, computing the eigenvectors of a large size covariance matrix is very time-consuming.

To overcome those problems, a new technique called 2-dimensional principal component analysis (2DPCA) was recently proposed, which directly computes eigenvectors of the so-called image covariance matrix without matrix-to-vector conversion. Because the size of the image covariance matrix is equal to the width of images, which is quite small compared with the size of a covariance matrix in PCA; 2DPCA evaluates the image covariance matrix more accurately and computes the corresponding eigenvectors more efficiently than PCA.

$$J(Z) = trace\,\{E[(V-EV)(V-EV)P]\}$$
$$= trace\{E[(DZ-E(DZ))(AZ-E(DZ))P]\} \quad (1)$$
$$= trace\,\{ZPE[(D-ED)P\,(D-ED)]Z\}$$
$$Eq.(1)\ results\ from$$
$$trace(BA) = trace(AB)$$

Eq.[1]. Now defines the palm image covariance matrix K=[(D−ED)P(D-ED)], which is an n*n nonnegative definite matrix. Let us consider M training palm images, denoted by m*n matrices $D_r(r = 1,2,3,\ldots\ldots, M)$,and denote the average image as $\bar{D} = 1/M \sum D_r$. Then K can be solved by

$$K = 1/M \sum k - 1[(D_r - \bar{D})P(D_r - \bar{D})] \ (2)$$

It has been shown that the optimal value for the projection matrix Z_{opt} is composed by the orthogonal eigenvectors of K corresponding to the d largest Eigen values, 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:

$$\sum i = 1d\lambda i / \sum ni = 1 = 1\lambda i \geq \theta i \ (3)$$

Where $\lambda 1, \lambda 2, \lambda 3\ \ldots.\lambda n$ is the biggest Eigen values of K and θ is the preset threshold set.

D. 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 = $(p1, p2, \ldots, pn)$ and $Q = (q1, q2, \ldots, qn)$ in n dimensions. This general solution can be given as $((p1-q1)^2 + (p2-q2)^2 + \ldots + (pn-qn)^2)^(1/2)$.

In this case, Euclidean distance is used where the variances of the population classes are different to each other. The Euclidean distance is theoretically identical to the similarity index.

$$d_k^2 = (X - \mu_k)^T (X - \mu_k)$$

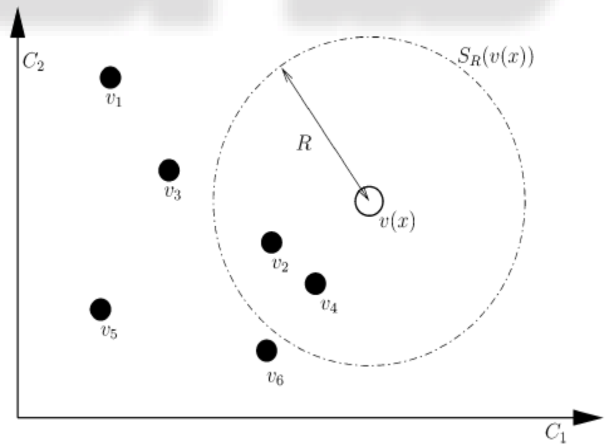

Fig. 2: Comparison of a pixel value with a set of sample in Euclidean colour

E. Results and Discussion

All the algorithms are simulated with MATLAB version R2013 using core i5 processor. The experiments are performed on three different sets of data. First one is standard dataset i.e. CASIA dataset, after that on cropped palm images dataset and at the last self-collected NITH dataset. In CASIA dataset, hundred individuals having eight different pose in each individual. In cropped palm images, same records of data has been used but that data has been cropped and having only region of interest part. Third one, self- made NITH dataset, having fifty individuals with same no. of different pose each individual i.e .eight. It has been performed on three dataset as follows:

The percentage Identification Rate by PCA is given below:

PIR (%)							
Feature vector size	50	100	150	200	250	300	350
NITH	50.14	56.10	57.20	59.50	63.10	64.30	67.12
CASIA	54.20	57.30	60.20	62.50	64.10	65.20	68.90
Cropped images	63.10	65.30	67.10	69.50	70.40	72.18	73.5

Table 1: PIR by PCA

The percentage Identification rate by LDA is given below:

PIR (%)							
Feature vector size	50	100	150	200	250	300	350
NITH	58.00	58.20	62.00	68.30	69.50	71.90	75.20
CASIA	56.20	60.20	64.40	67.30	70.20	76.20	78.60
Cropped images	70.12	74.50	76.30	80.20	82.30	85.60	88.20

Table 2: PIR by LDA

The percentage identification by 2DPCA is given below:

PIR (%)							
Feature vector size	50	100	150	200	250	300	350
NITH	56.20	57.24	61.20	65.10	68.40	70.90	73.42
CASIA	58.60	62.40	66.30	68.30	70.20	73.20	78.20
Cropped images	69.20	72.10	74.50	78.30	80.14	83.20	85.20

Table 3: PIR BY 2DPCA

IV. CONCLUSION

Palm print identification system has been implemented using subspace methodology. These systems measure and compare lines, ridges which are found on the palm. In this approach the observations are expressed using different feature length i.e. 50 to 350, that the PCA provides the less accuracy when feature length is less, when it becomes large then its accuracy become some better than before. but in case of LDA and 2DPCA , both the approaches provide good accuracy when feature length is less compare to PCA, when it becomes large then its accuracy become some better than before. So in compare to PCA technique LDA and 2DPCA are better techniques. It can also observe from the results that cropped images provide better results than that of other two databases for all the techniques.

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