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Palm Print Recognition Using PCA and its Modern Variants

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Abstract
Automatic personal recognition is a critical issue in today's environment that requires correct resolution. Due to its multiple benefits, including steady line characteristics, low-resolution imaging, conviniet cost capturing equipment, and user-friendliness, palm print identification is one of the most effective and successful biometric systems. This paper presents performance comparisons of PCA and 2DPCA-based subspace algorithms for palm print identification techniques. On three benchmark datasets (CASIA, Cropped palm pictures, and IIT Delhi), the experimental outcomes are assessed in terms of recognition rate and calculation time.

Keywords: Security, Euclidien Distance, Two Dimensional principal component analysis etc.

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I. INTRODUCTION

Passwords or ID cards are typically used for workplace entryways, online banking, controlling access to restricted areas, border and airport security, time and attendance monitoring, etc. These identity recognition techniques have significant drawbacks, such as being less secure, stolen, manipulated, etc. Identity systems based on biometrics are crucial in overcoming these constraints.

The method of evaluating whether two palmprints are from the same individual based on the line patterns of the palm is known as palmprint recognition [24]. A palm has prominent ridges, creases, and lines. Three main lines are present. In general, biometric systems use a person's fingerprint, iris, face, palmprint, and ear to identify them, as well as behavioural traits like signature, stride, and keystrokes. Palmprint-based biometric recognition techniques are one of them that has recently gained popularity. The palm print is a pattern on the inside of the hand that consists of several lines and points, including the heart line, head line, and lifeline. The major lines are more regular than wrinkles.

There are ridges all over the palm, which are lines that are not primary lines or wrinkles. Even in monozygotic twins, these line and point patterns are always distinct. The ridge structure's permanence is what makes it intriguing. This ridge structure is distinct and has minimal dimensional characteristics. Comparing the palmprint identification system to other physiological biometric systems, there are benefits. The fixed line structure, low intrusiveness, inexpensive cost of the capturing equipment, and low-resolution images are some of the benefits. Palmprint identification is a very intriguing field of study. Although a lot of work has already been done in this area, there is still plenty of room to improve the systems.

In this study, two common datasets of palmprints—CASIA [20] and PolyU cropped [22]—were utilized to extract the palm characteristics using the most well-liked PCA and 2D-PCA techniques. The classification of the collected features using Euclidean distance allows for an evaluation of the performance in terms of computation time and recognition rate. Following is an organization of the remaining paper. The introduction of the literature review is in section 2. Section 3 of the study discusses the suggested subspace techniques, which include the PCA, 2D-PCA, and Euclidean distance methodologies.

II. LITERATURE REVIEW

There has been a study in the field of palmprint recognition systems to develop an accurate and effective authentication system. A lot of pertinent publications have been reviewed for this.In general, there are three different types of palmprint-based recognition methods: line-based, subspace-based, and texture-based methods. Line-based methods, also known as structural-based methods, make use of a variety of structural elements seen in palm prints, including principal lines, wrinkles, datum points, ridges, and crease points. These methods either create edge detectors from scratch or extract palm lines using existing edge detection techniques [1]. To calculate the magnitude of palm lines, Wu et al. employed Sobel masks [2]. The datum points of the palmprints are characteristics in [3].

A datum point is a place at which a principal line terminates. Han et al. suggested a palmprint-based system that extracts the structural elements of the palmprint using Sobel masks and morphologic operators [4]. To extract the palm lines, [5] use the Canny edge operator. In general, line-based methods can accurately extract the vast majority of lines and ridges. However, the fundamental disadvantage of employing line-based systems is their high level of complexity. Additionally, finding and matching the line segments requires a large amount of processing effort. To extract the palmprint characteristics, subspace-based algorithms employ a variety of methods, including independent component analysis (ICA) [8], Fisherpalm [7], and principal component analysis (PCA) [6]. In the face recognition literature, these strategies are often known as appearance-based strategies [1]. It is not necessary to have any prior understanding of palmprints to employ subspace-based methods.

To extract the characteristics of the palm, Lu et al. proposed a method based on the PCA [6]. To project the original image onto a tiny collection of feature space known as "eigenpalms," they employed the Karhunen-Loeve transform. The original palmprint pictures in [7] are projected onto the lower-dimensional feature space known as "Fisherpalm space" using the Fisher linear discriminant (FLD). Another method uses ICA to extract the characteristics of the palm [8]. These methods often have better computing efficiency but suffer from dependence on training data sets. Texture is characterised by the spatial connection of pixel values in an image area in texture-based techniques [9].

Gabor filters [10, 11], discrete cosines transform (DCT) [12, 13], morphological approaches [14], the Fourier transform [17], and wavelet transforms [16–20] are a few intriguing methods to analyse the palmprint texture. To extract the characteristics of the palm, Zhang et al. employed Gabor filters [10]. They referred to these functions as Palm codes. [11] presents the characteristics known as Fusion code by fusing Palm codes in several directions. DCT is used in [12] to extract the facial and palmprint features. Using the two-dimensional Block based Discrete Cosine Transform (2D-BDCT) is a technique that Meraoumia et al. suggested [13].

They separated a palmprint into blocks of identical size and overlap, then they applied DCT to each block. To extract the characteristics of the palmprint, Han et al. proposed a technique based on the morphological operator [14]. The extraction of palmprint characteristics for palmprint categorization in [16–20] uses a variety of similarity indices. The fusion at feature level is used to merge the data that has been taken from several wavelets. Other methods, on the other hand, used wavelet transform to extract the characteristics of the fingerprint and palmprint. Using fingerprint, palmprint, and hand geometry as the basis, Yang et al. proposed a biometric verification method.

The discrete wavelet transform is used in this method to extract the characteristics of the palmprint and fingerprint, which are then fused at the feature level. Then, using fusion at matching score level, the integrated textural information are coupled with hand geometrical features. For expressing the 1D fingerprint and palmprint characteristics, Lu et al. employed wavelet zero-crossing. Although these methods used wavelet-based techniques for effective authentication systems, the kind of wavelet transform had a significant impact on how well they performed. Therefore, in certain wavelet-based techniques, how to select the appropriate wavelet transform is a crucial problem [16].

III. METHODOLOGY USED

The two key processes in any recognition process are feature extraction and classification. In this study, two independent sets of palm print photos are used to examine the effectiveness of feature extraction and classification algorithms. Separately, PCA and 2D-PCA are employed in conjunction with Euclidean distance as feature extractors.

1.1.1 Principal component analysis

Pattern recognition, computer vision, signal processing, and other fields use PCA, a well-known feature extraction and data representation approach. Column by column or row by row, PCA converts the 2D palm image matrices into 1D image vectors in this study. The following is how it is explained.

Let us consider a set of M palmprint images, i1, i2, … , iM the average palm of the set is defined as:

$$\mathbf{i} = \frac{1}{M}\sum_{j=1}^{M} \mathbf{i}_j \qquad (1)$$

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

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

Then, eigenvectors, Vk and eigenvalues, λk with symmetric matrix C are calculated. Vk 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.

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

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.

1.1.2 2D-PCA

In contrast to normal PCA, which is based on 1D vectors, 2D-PCA is based on two dimensional matrices. In this research, we first show that 2D-PCA essentially analyses palm picture data in the row or column direction. Consider an m by n random image matrix A. Let XϵR be a matrix with orthonormal columns, n≥d Projecting A onto X yields an m by d matrix. Y=AX. In 2DPCA, the total scatter of the projected samples was used to determine a good projection matrix X. The method used is :

$$\begin{aligned} J(X) &= \text{trace } \{E[(Y\text{-}EY)(Y - EY)^T]\} \\ &= \text{trace}\{E[(AX\text{-}E(AX))(AX - E(AX))^T]\} \\ &= \text{trace } \{X^T E[(A - EA)^T (A\text{-}EA)]X\} \end{aligned} \tag{5}$$

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,

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

It has been shown that the optimal value for the projection matrix Xopt is composed by the orthonormal eigenvectors X1……Xd 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, $\lambda_1, \lambda_2, \lambda_3, \dots\dots\lambda_n$ is the biggest eigen values of K and θ is the preset threshold set.

1.1.3 2D^2-PCA

A simultaneously way of presenting 2DPCA and Alternate 2DPCA is $(2D)^2$PCA which uses the projection matrices X and Z of 2DPCA and Alternate 2DPCA respectively. $(2D)^2$PCA Preserves the accuracy of 2DPCA but eliminates the large number of coefficient requirement of 2DPCA [10]. Suppose we have obtained the projection matrices X and Z, projecting the m by n image A onto X and Z simultaneously, yielding a q by d matrix C_{trn}

$$C_{trn} = Z^T AX$$

The matrix C_{trn} is also called the coefficient matrix in image representation, which can be used to reconstruct the original image A. When used for face recognition, the matrix C_{trn} is also called the feature matrix. After projecting each training image $A_{trn}(trn = 1,2,\dots..M)$ onto X and Z, we obtain the training feature matrices $C_{trn}(trn = 1,2,\dots..M)$. Repeating the same for test image A_{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

$$d(C_{trn}, C_{test}) = \|C_{trn} - C_{test}\| = \sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(C_{trn}^{(i,j)} - C_{test}^{(i,j)})^2} \tag{8}$$

1.1.4 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.

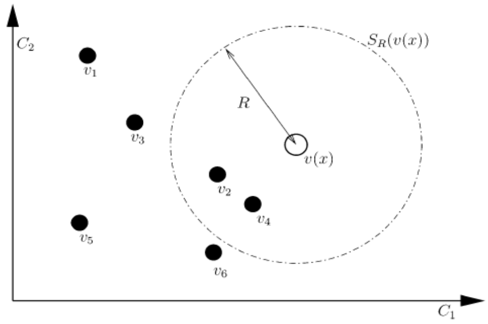

Figure. 1 Comparison of a pixel value with a set of samples in Euclidean colour

Mathematically, this is shown as |p1 – q1| where p1 is the first coordinate of the first point and q1 is the first coordinate of the second point. Generalized, the distance between two points P = (p1, p2, ..., pn) and Q = (q1,q2, ..., qn) in n dimensions. This general solution can be given as ((p1-q1)^2 + (p2-q2)^2 + ... + (pn - qn)^2)^(1/2).

IV. RESULTS AND DISCUSSIONS

A significant unresolved issue with 2D-PCA and 2D2-PCA is that they require significantly more coefficients for palm picture representation than PCA, yet achieving higher recognition accuracy than PCA. Tables 1, 2, and 3 present the percentage recognition rates of PCA, 2D-PCA, and 2D2-PCA, respectively. Euclidean distance is tested as a classifier. The simplest distance-matching algorithm is Euclidean distance. Since 2D-PCA permits non-orthogonal column vectors and allows for different angles and separations between images, the cosine measure can be applied. The performance recognition rates of PCA utilising these distance measurements are displayed in Table 1. The percentage recognition rate by 2D-PCA is shown in Table 2.

Table 1. PRR by PCA

PRR (%)							
Feature vector size	50	100	150	200	250	300	350
GP Jhansi	50.1	56.1	57.2	59.5	63.1	64.3	67.1
CASIA	54.2	57.3	60.2	62.5	64.1	65.2	68.9
Cropped images	63.1	65.3	67.1	69.5	70.4	72.18	73.5

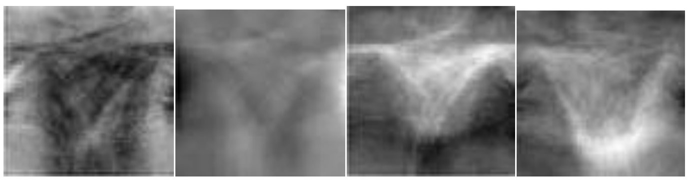

Figure. 2 PCA (after applying pca gives this type of images)

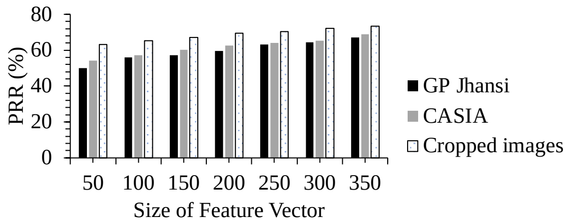

Figure. 3 Graph Representation of PCA results

Table 2. PRR by 2D-PCA

CRR (%)							
Feature vector size	50	100	150	200	250	300	350
GP Jhansi	56.2	57.2	61.2	65.1	68.4	70.9	73.4
CASIA	58.6	62.4	66.3	68.3	70.2	73.2	78.
Cropped images	69.2	72.1	74.5	78.3	80.1	83.2	85.2

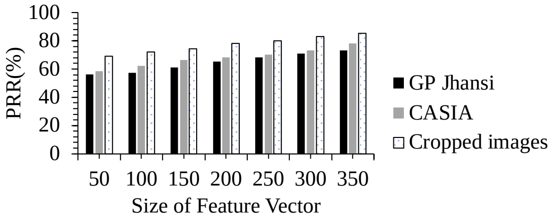

Figure. 4 Graph Representation of 2D-PCA

Figure. 5 2D-PCA (after applying the 2D-PCA)

Table 3. PRR by 2D²-PCA

CRR (%)							
Feature vector size	50	100	150	200	250	300	350
GP Jhansi	57.3	57.6	62.2	67.2	69.3	71.3	74.4
CASIA	60.1	63.4	66.8	69.4	71.2	74.2	79.3
Cropped images	69.4	73.2	75.5	79.3	83.2	85.2	87.5

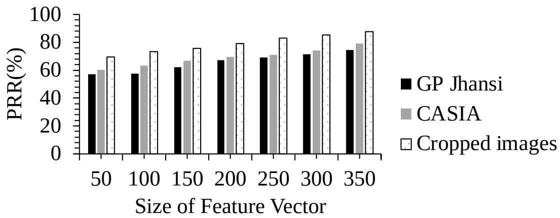

Figure. 6 Graph Representation of 2D²-PCA

V. CONCLUSION

Systems used to identify palm prints assess and compare the ridges, lines, and minutiae on the palm. A distinctive and trustworthy biometric feature with great utility is the palm print. Due to its faster computation times than PCA, 2D-PCA and 2D2-PCA produce results that are superior to PCA. Consequently, 2D-PCA and 2D2-PCA are more practical than PCA. Cropped palm image analysis using PCA yields superior results than CASIA database. 2D2-PCA CASIA database produces superior results in 2D-PCA.

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