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Palm print Authentication Using PCA Technique

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Abstract: **Palmprint recognition algorithms are useful in a wide range of applications like security control, crime investigation, and entrance control in buildings, access control in computer system, access control at automatic teller machines, passport verification, identifying the individuals in a given databases. Personal authentication using palmprint is a promising approach suggested by various researchers. However, most of the techniques suffer from high computational requirements and cost. This paper proposes an approach that makes use PCA (Principal Component Analysis) with reduced dimensionality based feature extraction and the use of Eigen palmprints in the experimentation. The PCA based features significantly minimize the noise, minimizes the memory usage and computational time of authentication. The proposed approach provides better performances in terms of sensitivity, specificity and accuracy.**

I. INTRODUCTION

The widespread use of information technology in our daily lives demands reliable, stable and user friendly mechanism to authenticate individuals. Personal authentication using palmprint has emerged as a promising biometric approach [1], [2], [3], [4], [5], [6], [7]. However, most of the multi-biometrics approaches impose burden on capturing hardware, computation, and cost [8], [9]. Palmprint images with an abundance of features such as principal lines, wrinkles, ridges and minutiae provide good discriminating ability for accurate authentication. PCA features encompass the discriminating capabilities of these multiple features, hence, PCA feature extraction is a promising choice for palmprint recognition [10].

PCA is a method [11], [12], [13] of transforming a number of correlated variables into a smaller number of uncorrelated variables. Similar to how Fourier analysis is used to decompose a signal into a set of additive orthogonal sinusoids of varying frequency, PCA decomposes a signal (or image) into a set of additive orthogonal basis vectors or eigenvectors. The main difference is that, while Fourier analysis uses a fixed set of basis functions, the PCA basis vectors are learnt from the data set via unsupervised training. PCA can be applied to the task of palmprint recognition by converting the pixels of an image into a number of eigen-palm feature vectors, which can then be compared to measure the similarity of two palm image.

The paper is organized into 5 sections. Section II presents an overview of proposed PCA technique with reduced dimensionality which involves the generation of eigenvectors from training palmprints. Section III describes the algorithm used to extract PCA features such as eigenvectors and eigenvalues of the mean-shifted images. Section IV presents classification process which involves computation of similarity of input palmprint images with the test almprint. Section V discusses the results and finally Section VI concludes the paper.

II. PROPOSED PCA TECHNIQUE WITH REDUCED DIMENSIONALITY

Here, the hand image from every user will be captured from a digital camera. The region of interest (ROI), that is, the palmprint regions of these images are extracted using the method detailed in [9] and [12]. PCA features of these images are then extracted using principal component analysis. These features are matched with their respective template features stored during the training stage. The matching score obtained through similarity, which is used to generate a class label, that is, genuine or imposter, for each of the user, as described in [9] and [12].

A. Extraction of PCA Feature

PCA has been widely used for dimensionality reduction [13] in computer vision. Results showed that PCA performs well in various recognition tasks [12]. In this context, the basis vectors, generated from a set of palmprint images (training set) are called eigenpalm, as they have the same dimension as the original images and are like palmprint in appearance, as shown in Figure 1. Recognition is performed by projecting a new image into the subspace spanned by the eigenpalms and then classifying the palm by comparing its position in palm space with the positions of known individuals. The process of generating eigen-palms are presented as follows: Let us consider a set of M palmprint images, $i_1 i_2 \dots i_M$, and size of each image be N x N dimensions, then the average palm of the set is defined as

$$\bar{\imath} = \frac{1}{M}\sum_{j=1}^{M} i_j$$

Each palmprint image differs from the average palm $\bar{\imath}$, by the vector $\emptyset_n = i_n - \bar{\imath}$. To calculate eigenvectors, we need to calculate the covariance matrix C:

$$C = AA^T$$

Where, A= $[\emptyset_1 \emptyset_2 \dots \emptyset_M]$. As, A is of $N^2 \times M$ dimensions. Hence, C covariance matrix will be of $N^2 \times N^2$dimensions. So there will be N^2 eigenvectors each of with $N^2 \times 1$ dimension. So for large value of N, to calculate N^2 eigenvector is a huge task in terms of computation time and also system may slow down or run out of memory. For this reason, dimensionality reduction concept which involves the calculation of eigenvectors from covariance matrix with reduced dimensionality, is used. This in turn helps not only to considerably reduce the amount of computations but also reduces the effect of noise on the eigenvectors. In this concept, the covariance matrix is calculated by the formula given below:

$C = A^T A$ where, A= $[\emptyset_1 \emptyset_2 \ldots \emptyset_M]$

So, clearly the dimension of covariance matrix is reduced to M$\times M$ and hence, there are M eigenvectors each with $M \times 1$ dimension. So we can verify that M<<N^2. Hence, it is evident that it is easier to find K eigenvectors in lower dimensionality compared to higher dimensionality. The selected K eigenvector must be in the original dimensionality of the palm vector. Hence, after finding out lower dimensional subspace (i.e. M number of M x 1 eigenvectors), we need to map back to the original higher dimensional space (N^2 number of $N^2\ X\ 1$ eigenvectors). This is done by the formula:

$$u_i = Av_i$$

where, u_i is the i^{th} eigenvector of original higher dimensional space and v_i is the i^{th} eigenvectors of lower dimensional subspace.

From these eigenpalms, K(<M) eigenpalms are selected 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:

$$\omega_{nk} = b_k(i_k - \bar{\iota})$$

Where, n=1,2,….M and k=1,2,…, K

The weights obtained form a vector $\tau_n = [\omega_{n1}, \omega_{n2,\ldots,}\omega_{nK}]$ that describes the contribution of each eigenpalm in representing the input palm image, treating eigenpalms as a basis set for palm images.

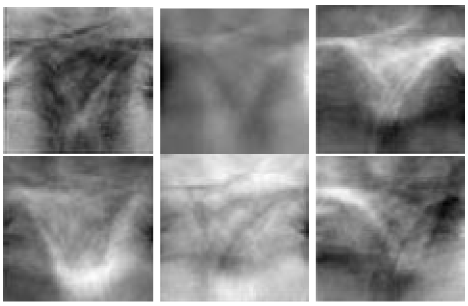

Figure1: Basis vectors generated by PCA

III. PCA ALGORITHM

The followings are the steps used to extract PCA features:

1. Calculate the mean of the input palm images
2. Subtract the mean from the input images to obtain the mean-shifted images.
3. Calculate the eigenvectors and eigenvalues from covariance matrix with proposed reduced dimensionality concept.
4. Order the eigenvectors by their corresponding eigenvalues, in decreasing order.
5. Retain only the eigenvectors with the largest eigenvalues (i.e. the principal components).
6. Project the mean-shifted images into the eigenspace using the retained eigenvectors.

IV. CLASSIFICATION

Once the palm images have been projected into the eigenspace, the similarity between any pair of palm print images can be calculated by finding the $\|y_1 - y_2\|$, the Euclidean distance between their corresponding feature vectors y_1 and y_2; the smaller the distance between the feature vectors, the more similar the palms. We can define a simple similarity score s(y_1, y_2) based on the inverse Euclidean distance:

$$s(y_1, y_2) = \frac{1}{1+|y_1 - y_2)\,|} \epsilon[0,1].$$

To perform palm recognition, the similarity score is calculated between an input palm image and each of the training images. The matched palm image is the one with the highest similarity, and the magnitude of the similarity score indicates the confidence of the match (with a unit value indicating an exact match).

V. EXPERIMENTATION & RESULT

The proposed method is implemented by collecting 100 palmprints (i.e. 5 palmprints each from 20 persons) from Poly U palmprint Database. Firstly, the ROI of all palm print images are extracted. The PCA features (eigen-palms) are extracted from the training set (60 palmprints of the Poly U database, 3 of each person) and stored in database. The remaining 40 palmprints (2 of each person) are used as test set to demonstrate the performance of the authentication system.

A. Sensitivity, specificity and accuracy of Proposed System

Based on the outcome of test results, the sensitivity, specificity and accuracy defined as follows are computed.

Sensitivity= $\frac{TP}{TP+FN}$ Specificity= $\frac{TN}{TN+FP}$

Accuracy=$\frac{\text{TP+TN}}{\text{TP+FP+FN+TN}}$

Where, TP, TN, FP and FN are the number of true positives, true negatives, false positives and false negatives respectively [12]. The results of the proposed method are presented in the table [1].

Table1: Performance of palmprint recognition system using PCA technique.

Performance parameter	***Palm Print Recognition using PCA Technique***	***Palmprint Recognition using PCA with Reduced Dimensionality***
sensitivity	90.54	98.69
specificity	81.72	90.76
accuracy	86.36	97.53

B. Verification Rate of Proposed System

Further analysis of the result was performed by calculating the standard error rates (false acceptance rate (FAR) and false rejection rate (FRR)). FAR and FRR are defined, respectively, as

$$FAR=\frac{Number\ of\ Accepted\ Imposter\ claims}{Total\ number\ of\ Imposter\ accesses}\times 100\%$$

$$FRR=\frac{Total\ Number\ of\ Rejaected\ Genuine\ claims}{Total\ number\ of\ Genuine\ accesses}\times 100\%$$

Both rates must be as low as possible for the biometric system to work efficiently. Another performance measurement is obtained from FAR and FRR which is called Total Success Rate (TSR). It represents the verification rate of the system and is defined as follow:

$$TSR=(1-\frac{FAR+FRR}{Total\ number\ of\ accesses})\times 100\%$$

Table 2 shows the verification rates of PCA, using best distance measures, Euclidean Distance for PCA.

Table2: Verification rate of Proposed system

Method	***FAR***	***FRR***	***TSR***
PCA	3.061	3.03	96.907
PCA with Reduced Dimensionality	1.27	1.19	98.84

VI. CONCLUSION

This paper suggested a new method of palmprint authentication using PCA technique with dimension reduction technique. The TSR achieved in proposed PCA with reduced dimensionality technique is (98.84) is better than the simple PCA method (TSR=96.907), prominent wavelet based, intramodal and few other approaches. Extraction of features in PCA method makes this approach computationally simple and it requires less memory due to dimension reduction while calculating principal components from training palm images.

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