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# Incorporating PCA feature extraction and evaluating feature matching methods in Palm Print Based Biometric Verification System

Medha Misar*, Damayanti Gharpure**
**(Department of Electronic Science, Baburaoji Gholap College, Pune 411027, India*
*** (Department of Electronics & Instrumentation Science, Savitribai Phule Pune University, Pune 411007, India*

**ABSTRACT**
Palm prints have many biometric features and these features can be used for the purpose of biometric identification. This paper presents use of Principal Component Analysis for feature extraction of palm print images for biometry. A prefixed number of Eigen values have been retained and corresponding Eigen vectors have been used to generate a weight matrix for every palm print image. The weight matrix has been used as a feature vector. Feature matching has been done with Neural Network, Weighted Euclidean distance as well as Pattern classifiers Networks and the performance has been analyzed in this paper.
***Keywords –*** Biometric, Principal Component Analysis, weighted Euclidean distance, neural network, and Pattern classifier

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## I. INTRODUCTION

There are increasing applications which require biometric methods for verifying the identity of a person. Palm prints are rich in features, can be easily acquired and hence different Palmprint features are used for the purpose of biometric identification. There are many different approaches to extract palm print features- line based, texture based coding based and appearance based.

In line based methods, the line patterns like principle lines, wrinkles, ridges, and creases are extracted for recognition. Edge detection methods using Sobel, Prewitt, Roberts, Canny and Laplacian are employed to extract palm lines [1]. The morphological operator and modified radon transform methods can also be used to extract palm lines [2]. Techniques like filiformity have been used to extract the line like features [3]. However, these principal lines are not sufficient to represent the uniqueness of each individual's Palmprint. It is sometimes difficult to extract lines and creases form palm print images with low resolution [4].

In texture based methods, the three approaches generally used are statistical, structural and spectral. Statistical measures such mean, variances etc. are used as features. Structural techniques deal with the arrangement of image primitives. Spectral techniques are based on the properties of the Fourier spectrum and Discrete Cosine transform have been used to transform the image into frequency domain [3, 5]. The advantage of texture analysis is that the information can be extracted from low resolution palm print images. The problem with texture method is that the abundant textural details of a palm are ignored and the extracted features are greatly affected by the lighting conditions [4].

In coding based methods, the palm print features are represented by binary codes. The filtered coefficients of Gabor filters, PalmCode, Fusion code, Competitive code, orientation code and ordinal code are the codes generated for palm prints [3].Coding approaches use one matching function to search the entire databases. Generally the matching speed of the coding algorithms is slow [4].

In appearance methods, generally analyses such as Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) are used [3,6]. Principal component analysis (PCA) is a mathematical procedure that uses a transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. It has been found that principal components offer good characteristics for palmprint recognition [4].

The basics of principal components, Eigen values and Eigen vector is explained in Section II of this paper. The methodology and processing carried out in this work is explained in Section III. The experimental work is described in Section IV. Finally, the results and discussion is given in Section V.

## II. BASIC INFORMATION

The palmprint features are selected from a region of interest ROI that is a sub image which is extracted. This ROI can be circular or square in shape. Circle based ROIs require higher amount of computation. Hence square based ROIs are commonly used [7]. The general method of selecting the ROI is to extract the boundary, then convert the image to binary image and identify key points of the image. These key points are used to construct the coordinate axes and then a fixed size square is determined and clipped [7]. The ROIs are subjected to efficient preprocessing algorithms to remove noise and illumination effects [8,9].

As part of feature extraction, subspace based approaches are also called appearance based approaches. The subspace coefficients are regarded as features [10,11]. Principal Component Analysis is an appearance based methods which extracts features in the subspace from the training images. With PCA, the data set having much variation is retained. Thus it reduces the dimensionality of the data set [12,13]. PCA has been widely used in pattern recognition. When the images are encoded into this subspace, and then returned to the original space, error between the reconstructed and the original images is minimized [14].

Usually a palmprint image is described as a two-dimensional array (N x N). In the Eigen space method, this can be defined as a vector of length $N^2$, called a “palm vector”. Since palmprints have similar structures (usually three main lines and creases), all “palm vectors” are located in a narrow image space, thus they can be described by a relatively low dimensional space. As the most optimal orthonormal expansion for image compression, the K–L transform can represent the principle components of the distribution of the palmprints or the eigenvectors of the covariance matrix of the set of Palmprint images. Those eigenvectors define the subspace of the palmprints, which are called “Eigen palms”. Then, each palmprint image in the training set can be exactly represented in terms of a linear combination of the “Eigen palms” [4].

## III. METHODOLOGY

The work presented in this paper has an objective of implementing palm print biometric recognition in a touch-less acquisition setup. In order to achieve better recognition accuracy, the palm images are appropriately aligned and then the ROI are extracted with the procedure in [15].

To make the extracted features independent of the illumination, illumination adjustment is required. This is done by using the conventional way of subtracting a certain percentage of the average intensity level from the entire palm image [16].

Principal Component Analysis has been done by finding the covariance matrix. The Eigen values and Eigen vectors have been calculated. Only the principal components have been retained. Then the mean-shifted images have been projected into the Eigen space using the retained eigenvectors. A weight matrix has been generated for each image. The weights obtained by this method have been used as feature vector.

For feature matching, Neural Networks, Weighted Euclidean distance and pattern classifiers have been used.

A neural network has also been implemented for feature matching for comparative study. Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements called neurons working in parallel to solve a specific problem. Neural networks learn by example. Neural networks have been used to solve a wide variety of tasks that are hard to solve using ordinary rule-based programming. Most ANNs contain some form of 'learning rule' which modifies the weights of the connections according to the input patterns that it is presented with. Thus ANNs learn by example. The most common class of ANNs is the Back Propagation Neural Networks (BPNNs). Back propagation is an abbreviation for the backwards propagation of error [15].

The weighted Euclidean distance is given by

$$dk = \sum_{i=1}^{N}\left(\left(\frac{(f(i)-f_k(i))^2}{(s_k)^2}\right)\right)$$

Where f is the feature vector of the unknown palmprint, $f_k$ and $s_k$denote the $k^{th}$ feature vector and its standard deviation, and N is the feature length [4]. The person with minimum value of the distance measure is considered as the recognized person [17].

Classification is a type of supervised machine learning in which an algorithm "learns" to classify new observations from examples of labelled data. Classifier learner app available in MATLAB has been used to perform automated training for searching best possible classification model type. This data is used to train a classification model which is further used to generate predictions for new data.

## IV. EXPERIMENTAL WORK

### 4.1: Using Neural Network for feature Matching

IIT Delhi has created a database of palm print images using a touch less imaging setup. The database contains images of left hand and right hand of 235 users. The resolution of the images is 800x600 pixels. Fig. 1 shows some sample images from the database.

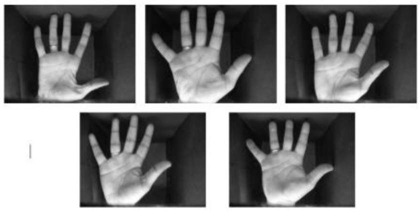

Figure 1: Palm Images from IITD database

In addition 150x150 automatically cropped images are also available. Fig. 2 shows few ROI images.

Figure 2: ROI Images from IITD database.

Images from this database are used for the study in this work. The Image processing Toolbox and Neural Network Toolbox of MATLAB R2016 has been used for the experimentation.

The feature vector is extracted using Principal Component Analysis as described in Section II. The performance of identification with this vector is analyzed with different feature matching methods.

Initially, a 3-layer feed forward back propagation neural network has been used for feature matching for evaluating authentication of 100 persons. Four images of each person have been used for training and one each for testing.

Experiments have been done to examine the results for FAR (False Acceptance Rate), GAR (Genuine Acceptance Rate) and GRR (Genuine Rejection Rate). To evaluate this, two types of case studies have been done. One with using test images of same persons used for training to examine genuine users and second with testing test images of persons other than those used for training to examine imposters. Table 1 shows the results when threshold is set at 50.

Table 1: Result with Neural Network

| Type of tests | FAR | FRR | GAR |
|---|---|---|---|
| Testing images of genuine users | 4.6% | 0.4% | 95% |
| Testing images of imposters | 89.6% | 10.3% | 0% |

It is observed that though acceptance rate of genuine users is high, there is high rate of accepting imposters also which is not desirable. When threshold value is increased more imposters are accepted, and when threshold value is decreased genuine users are rejected. Hence this feature matching method is resulting in more errors.

**4.2: Using Weighted Euclidean distance for Feature Matching**

Feature vector has been generated using PCA and feature matching has been implemented with weighted Euclidean distance. This study is undertaken from images of IITD and CASIA databases. Few sample palm images from CASIA database are shown in Fig. 3.

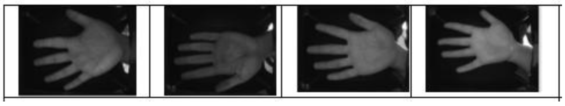

Figure 3: Palm Images from CASIA database

Experiments have been carried out to evaluate the Genuine Acceptance Rate with respect to different parameters such as number of images for training, number of principal components and the threshold to be optimised for design of a final system. Table 2 shows performance of identification with respect to varying number of training images.

Table 2. Effect of number of training images on accuracy

| Database | GAR | Number of images of each person for training | | | | | |
|---|---|---|---|---|---|---|---|
| | | 2 | 3 | 4 | 5 | 6 | 7 |
| IITD | GAR (%) | 82.5 | 92.8 | 95.2 | - | - | - |
| CASIA Palmprint | GAR (%) | 88.4 | 91.5 | 92.5 | 94.5 | 99.0 | 99.5 |

It is observed that with 40 principal components and with increase in the number of training images, the Genuine Acceptance Rate also increases. This effect is obtained as expected.

Similarly, four training samples are used and the number of principal components is varied and corresponding accuracy computed. Table 3 shows GAR with varying number of principal components.

Table 3. Effect of number of principal components on GAR

| Database | Number of principal components | | | | | | |
|---|---|---|---|---|---|---|---|
| | 20 | 30 | 40 | 50 | 60 | 70 | 80 |
| IITD | 94.7 | 94.9 | 95.6 | 95.4 | 94.9 | 94.9 | 95.1 |
| CASIA Palmprint | 98.7 | 98.6 | 98.9 | 98.6 | 98.3 | 98.0 | 97.3 |

With study on IITD and CASIA images, it is observed that GAR is maximum for 40 principal components irrespective of number of users and hence the size of feature vector can be 40.

Considering 40 components, the threshold value has been varied to find the optimum value for decision making. The performance parameters FAR (False Acceptance rate) and FRR (False Rejection Rate) have been found for different threshold values The results are shown in Fig. 4. The point where the curves intersect is the point of EER (Equal Error rate).

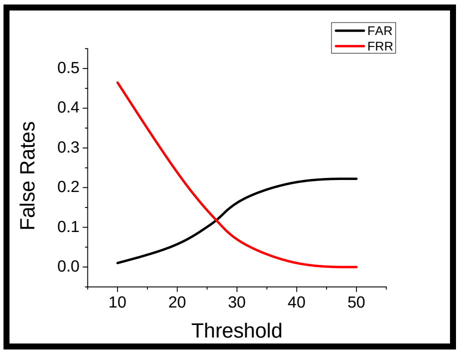


Figure 4 a: FAR,FRR vs Threshold for IITD

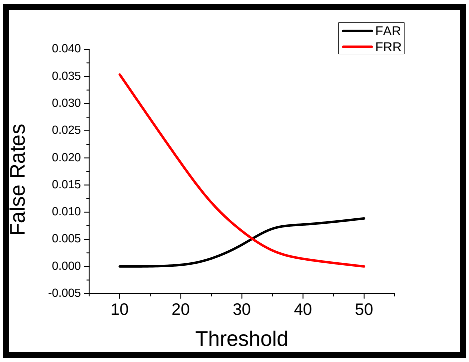


Figure 4 b: FAR,FRR vs Threshold for CASIA

The value of threshold at EER ie 27 and 32 has been chosen as the optimum value for IITD and CASIA respectively. It is observed that as the threshold value increases, false acceptance increases but false rejection decreases. Thus for low thresholds, an unauthorized person is not accepted but a genuine person is rejected. Similarly at high thresholds, genuine person is not rejected, but unauthorized persons are accepted.

The ROC graphs of GAR vs FAR are plotted as shown in figure 5.

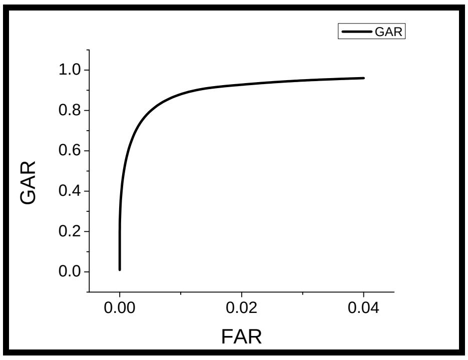


Figure 5 a: ROC curve (IITD)

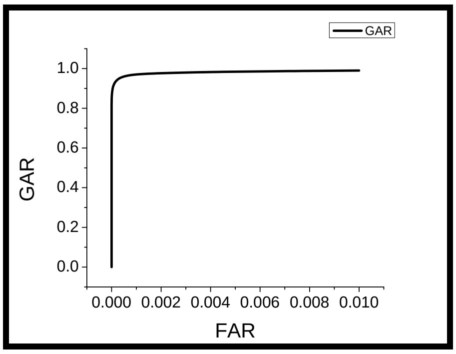


Figure 5 b: ROC (CASIA Palmprint)

The nature of the curves for IITD ROIs as well as CASIA Palmprint ROIs are close to the desired standard nature of the same. Moreover, the nature of curve with CASIA ROIs is sharper as compared to that of IITD curve, indicating better performance. Also FAR of CASIA images is very low as compared to the FAR of IITD ROIs.

**4.3: Using Pattern Classifier for Feature Matching**

Classifier learner app available in MATLAB has been used to perform automated training for searching best possible classification model type. The main objective of using this app is to classify data. Using this app, one can explore supervised machine learning using various classifiers. Considering 40 normalized PCA components, the accuracy obtained is as follows.

Palm images with White light from CASIA Multispectral database have been used as palmprint images for ROI extraction and feature extraction. Feature vectors comprising of normalized PCA weights are used as data sets for training a model. The feature vectors of test images are applied to the trained model as new data for generating predicted responses. The prediction results obtained with this method with palmprint images is given in table 4.

Table 4. Predictions with classifiers for palmprint images

| Classifier | Normalised PCA feature vector | | |
|---|---|---|---|
| | FAR | FRR | GAR |
| Fine KNN | 3.2% | 0% | 96.8% |
| LDA | 5.1% | 0% | 94.9% |
| Ensemble KNN | 93.8% | 0% | 6.2% |
| Ensemble Discriminant | 50.3% | 0% | 49.7% |

Predictions with k nearest neighbour (KNN) and Linear Discriminant Analysis (LDA) is found to be more accurate.

## V. RESULTS AND DISCUSSION

Neural network implemented has low accuracy. Here the inputs for training have to be carefully selected. Also the number of training inputs and the network parameters need to be modified to improve its performance. The work can be further extended for more number of persons and to find the optimum number of principal components essential. The training parameters of neural network need to be explored and properly selected in order to improve its accuracy rate and thereby derive benefits of the advantages of neural networks.

Use of weighted Euclidean distance for feature matching produces high recognition accuracy. It is indicated that PCA can be used for Palmprint recognition. It is essential to optimize the number of principal components required.

Although, the predictions with k nearest neighbour (KNN) and Linear Discriminant Analysis (LDA) is found to be more accurate. As all the test images were assigned one or the other class no image was rejected by the algorithm, which lead to increase in FAR.

Thus feature matching has been evaluated for performance of biometric system using palmprints by using Neural network, weighted

Euclidean distance and various classifiers. Matching with the help of Weighted Euclidean distance was found to be the simplest and effective method for purpose of identification.

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