A Comparative Analysis of Eigen Palm, Fisher Palm and Combined Eigen Palm with Fisher Palm Based Palm Print Authentication

[1]Vinodkumar, [2] R. Srikantaswamy
[1] M.Tech Student, [2] Professor
Dept of ECE, Siddaganga Institute of Technology
[1]vinodd99@gmail.com, [2] rsswamy@rediffmail.com

Abstract— — **Personal recognition utilizing palm print, has become a most promising approach recommended by several researchers. Palm print, recognition algorithms are very essentially worthwhile in a wide variety of applications like crime investigation, security control, passport verification etc. This paper describes comparative analysis of palm print, recognition algorithms such as PCA, LDA and combined PCA with LDA. In PCA, the unique images of palm print, are mapped to a minor set of the feature space, which is termed as Eigen palms; they are training set's eigenvectors and they signify the palm print's' principal components pretty best. Formerly, the Eigen palm features will be acquired thru projecting a novel image of palm print, to the subspace which is being spanned by the Eigen palms. In LDA, Every single palm print, image is treated like a coordinate point in higher dimension space of image, which is called palm print, space. Fisher's linear discriminate is utilized to map palm print, image linearly from this palm print, space into a considerably lesser dimensional space of feature (Fisher palm space), in this space the palm print's image from the different palm will be discriminated considerably much more proficiently. In combined PCA with LDA: initially we map the palm print, image from image space to Eigen palm space via PCA, furthermore we make use of LDA to attain a classifier which is of linear. The elementary objective of combined LDA and is PCA to advance LDA's generalization capability. The obtained recognition result from combined PCA with LDA outperforms similar work in the literature including Eigen palms and Fisher palms matching algorithms individually.**

Index Terms— **PCA; LDA; Eigen palms; Fisher palms**

I. INTRODUCTION

Biometrics alludes to automatic identification of people in view of their behavioral and physiological biometric traits such as iris, face, fingerprint, hand geometry, signature, palm print,, speech etc. Among the aforementioned systems palm print, recognition has various favorable advantages: palm print's contain more data than fingerprints and subsequently expected to produce more reliable results, palm print, catch gadgets are less expensive than iris examining and retinal checking gadgets and thus picture securing procedures are less demanding, they can be joined with other related like hand geometry and fingerprint recognition techniques to improve recognition accuracies, both shape and surface recognition techniques can be applied to model palm print, lines and curves.

There are numerous methodologies for palm print, recognition in different written works, the greater part of which depend on essential structural attributes, statistical attributes or the mixture of such two varieties of attributes. Conversely, structural attributes for instance feature points, minutiae, principal lines, delta points, wrinkles and interesting points are challenging to extract, signify and match though the statistical features' discriminability for example texture energy is not robust for palm print, recognition. To conquer such issues, alternative sort of attributes, called algebraic attributes is taken out from palm print, images for person identification in this paper. Algebraic attributes, which signify inborn image attributions, can be acquired in light of different algebraic transforms or matrix decompositions. Here, 1) Principal component analyses (PCA), 2) linear discriminant analysis (LDA) and 3) Combined PCA with LDA are efficient approaches to get the algebraic features as they have strong discriminability.

PCA features incorporate the separating capacities of these different features; thus, feature extraction using PCA is a favorable decision for the sake of recognition of palm print,. PCA is a technique which involves transforming various correlated variables to a reduced number of uncorrelated variables. PCA is employed to the job of recognition of palm print, thru converting over the image pixels into various eigen-palm feature vectors, which is then be contrasted with measure the closeness of two palm print, image. Another powerful approach for algebraic features extraction is linear Discriminant analysis (LDA), which clearly efforts to model the variation among the data classes. LDA is very much powerful and dominant palm print, recognition method that overwhelms the drawback of PCA method by employing the LDA. This benchmark attempts to boost the proportion of the between (among the classes) class scatter matrix's determinant of the mapped samples to the within (inside) class scatter matrix's determinant of the mapped image samples. The label variable may perhaps possess two or furthermore categories.

The images are anticipated from spaces of two dimensional into space of c dimension; here c is the numeral of classes of the sample of images. So, in order to recognize the test images, anticipated test image is matched to every anticipated training image, and the test sample of image will be recognized as a nearby training image. Another most prevailing approach for algebraic features extraction is combined PCA with LDA. The main intension of uniting PCA & LDA is to increase generalization proficiency of LDA. We establish significant enhancement when the principal components instead of original palm print, are served to LDA classifier. The paper is prepared into 8 sections such that: section 2 describes palm print, preprocessing, section 3 describes eigenpalm based palm print, recognition, section 4 describes Fisher palm based palm print, recognition and section 5 describes combined eigenpalm with Fisher palm based method palm print, recognition respectively. Section 6 describes the support vector machine; Section 7 offers the investigational results. Finally section 8 presents conclusion.

II. PALM PRINT, PREPROCESSING

Preprocessing is utilized to adjust distinctive palm print, images as well as to section the center ROI of palm print, for the sake of feature extraction. The majority of palm print, algorithms of preprocessing utilize the key indicates in between the fingers to build the coordinate system. The five most important strides in processing the image are:

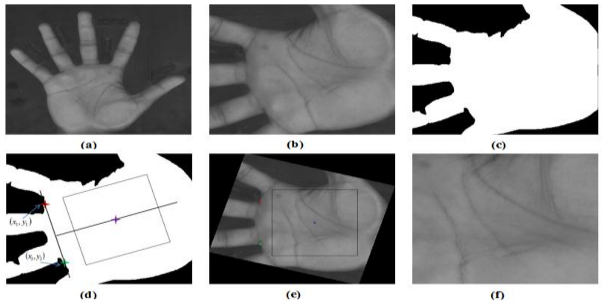


Figure 1: the main preprocessing steps. (a) original image, (b) cropped and rotated 90 degree left, (c) binary image, (d) boundary tracking, (e) coordinate system set up, and (e) preprocessed result.

Step 1: low pass GAUSSIAN smoothing filter, l(u, v) is applied to the novel (original) image, o(x, y). Then threshold, TP, is utilized to perform thresholding of convolved image in order to transform it into a binary image b(x, y), as seen in fig. 1c.

Step 2: the borders of the gaps between the fingers are acquired, $(f_i x_j,\ f_i y_j)(i=1,2)$, via a boundary tracking algorithm (see fig. 3d). The boundary gap between the middle and ring fingers is not taking out because that is not appropriate for the subsequent preprocessing.

Step 3: find the two gap's tangent. Let us consider (x_1, y_1) and (x_2, y_2) are some points on coordinates (f_1x_j, f_1y_j) and (f_2x_j, f_2y_j), correspondingly. The line y=mx+c passing through these two points will fulfill the inequity, $f_iy_j \le mf_ix_j$, for all that i and j (see fig. 1d), formerly the line y=mx+c is preferred as two gap's tangent.

Step 4: line up or join two points (x_1, y_1) and (x_2, y_2) in order to acquire the palm print, coordinate system's y-axis, and utilize a line transitory through the center of these 2 points, that is at right angles to the y-axis, to delineate coordinate system's origin (see fig. 1d).

Step 5: excerpt a sub image of stable size centered about coordinate system and the sub-image will situated be at a definite palm print,'s area for feature extraction purpose (see figs. 1e and 1f).

III. EIGEN PALM BASED PALM PRINT, RECOGNITION

The Eigen space concept is extensively utilized in facial recognition. That accomplishment illustrates that the acquired ''Eigen faces'' will efficiently signify the faces' principal components. In this section, we realize that it likewise offers very worthy attributes for identification of palm print,. The original palm print, images that are acquired for training are transmuted to a minor characteristic set image features, called ‘‘Eigen palms’’, they are nothing but the training set’s eigenvectors. Then, extraction of feature is accomplished by anticipating a fresh palm print, into the subspace which in turn spanned thru the ‘‘Eigen palms’’. The flow for palm print, recognition using Eigen palms approach is as shown in Fig 2.

Eigen palms: feature extraction

Let $\Gamma_1, \Gamma_{2,......,}\Gamma_M$ are palm print, images of training set. The median palm of the set is illustrated as

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$$

Every palm diverges from the median thru the vector $\Phi_i = \Gamma_i - \Psi$. This very large vector set is then given to PCA, which finds M vectors whish are orthonormal to each other and they are called set of orthonormal vectors, u_n, which can well defines the discrimination of data and K_{th} the vector, u_k, is defined such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}\left(u_k{}^T\Phi_n\right)^2$$

is a extreme, essence to

$$u_l{}^T u_k = \delta_k = \begin{cases} 1, & if \;\; l = k \\ 0, & if \;\; otherwise \end{cases}$$

Where vectors u_k are eigenvectors and λ_k are scalars values and are nothing but Eigen values, correspondingly, of covariance matrix

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n{}^T = AA^T$$

Here, the matrix $A = [\Phi_1, \Phi_2, ..., \Phi_M]$ and the matrix $C = AA^T$, though, are N^2 by N^2, and determining the N^2 eigen values and eigenvectors in a stubborn task for usual images’ sizes. So, we consider $C = A^TA$, which is M by M computationally reasonable to determine these eigenvectors.

Mark the eigenvector v_1 of A^TA such that

$$A^TAv_1 = \mu_i v_1$$

Pre-Multiplying On Both The Sides Thru A, We Will Obtain

$$AA^TAv_i = \mu_i Av_i$$

From the above equation we can observe that Av_i remain the eigenvectors of $C = AA^T$. Therefore, A^TA and AA^T will have the identical eigenvalues as well as their eigenvectors are interrelated as follows: $u_i = Av_i$. The M eigenvalues of A^TA resemble to the M principal eigenvalues of AA^T. A fresh palm print, image (Γ) is transmuted into its eigenpalm components (mapped into “palm space”) by an elementary operation,

$$w_k = u_k^T(\Gamma - \Psi), \quad k = 1,2,...,M$$

Where the weight of the projection w_k denote to the normal feature vector of each person. The weight forms a vector:

$$\Omega_i^T = [w_1^i, w_2^i, ..., w_M^i]$$

That designates the influence of every Eigen palms in signifying the input palm print,, considering Eigen palm as a palm images’ basis set.

Classification Using Support Vector Machine

Support vector machine is utilized for recognition. The more detail of SVM is explained in section 6.

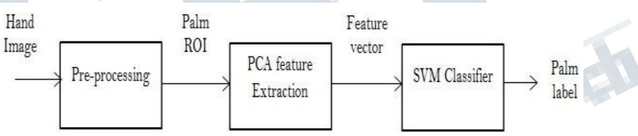


Figure 2: Flow for palm print, recognition using Eigen palms approach.

IV. FISHER PALM BASED PALM PRINT, RECOGNITION

In this section, a unique approach of recognition of palm print,, called Fisher palms, is employed. Fisher’s linear discriminate analysis is utilized to map palm prints images linearly from this higher dimensional unique space of palm print, to a considerably lesser dimensional space of feature (Fisher palm space), in this Fisher palm space the palm print’s images from the dissimilar palms will be discriminated considerably further proficiently. The flow for palm print, recognition using Fisher palms is as shown in Fig 3.

Fisher palms: feature extraction

The LDA features are obtained by combining the eigenpalm images to a matrix of data of size m $\times$n where m is the numeral of palm samples which are in the training set and n is the product of rows and columns of a single image.

$$I = I_1, I_2, ..., I_M$$

The data comes from K classes, denoted by $c_1, c_2, .., c_k$. The scatter matrix of within class computes the quantity of disseminate among objects inside the equivalent class and is defined as,

$$S_w = \sum_{i=1}^{k} \sum_{I_j \in C_i} (I_j - \mu_i)(I_j - \mu_i)^T$$

The between class scatter matrix is computed via the sum of all the covariance matrices of altogether the classes, weighted thru the number of palm print's in per class.

$$S_B = \sum_{i=1}^{k} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

where $\mu_i = \frac{1}{N} \sum_{I_j \in C_i} I_j$ the mean of the images IN C_I IS,

$\mu = \frac{1}{M} \sum_{i=1}^{k} \sum_{I_j \in C_i} I_j$ is the global mean and N_i is nothing but number of images in each class. Here the eigen vectors (w_{opt}) is the ideal discernment projection and will be gotten by resolving the generalized eigen value problem. Generalized eigen value (λ) and eigen vectors of the within (inside) and among class scatter matrices are calculated as shown in below equation.

$$S_B W_{opt} = \lambda S_W W_{opt}$$

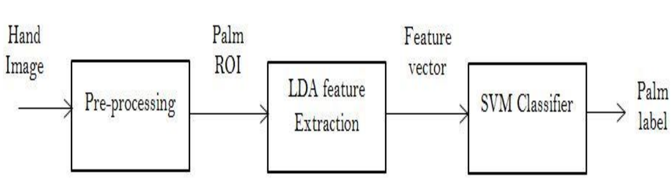
If s_w is non-singular, the optimum projection w_{opt} is preferred as that which will maximize the ratio of determinant of among-class scatter matrix of the mapped palm print, images to the determinant of the within-class scatter matrix of the mapped palm print, image samples, i.e.,

$$W_{opt} = \arg\max_{W} \frac{|W^T S_B W|}{|W^T S_W W|} = [w_1, w_2, ..., w_m]$$

An upper limitation m is k-1 where k is the classes' number. The eigenvectors whose Eigen values remain unequal to zero are selected and are arranged in the descending order. The feature vector is obtained by projecting the original data matrix on to the fisher space.

Classification using Support Vector Machine

Support vector machine is utilized for recognition. The more detail of SVM is explained in section 6.



Combined Eigen palm with Fisher palm based Palm print, Recognition

In this section, PCA is combined with LDA and used to map the points from two-dimensional down to one-dimensional. The elementary intension of joining PCA with LDA is to upturn the LDA's generalization capability. PCA essentially libels the classes together with the intention that they will no longer be linearly distinguishable in the mapped space. It has been understood that even though PCA accomplishes greater overall scatter, LDA accomplishes even superior in the middle of class scatter, and subsequently classification will come to be much easier, the flow for palm print, recognition using combined Eigen palm and fisher palm based approach is as shown in fig 4.

Feature extraction using combined Eigen palms and fisher palms

Conjoining LDA and PCA, we attain linear mapping which draws the input matrix x first to the Eigen palm space y, and formerly into the fisher palm space z.

$$Y = W_{PCA}^T X$$

$$Z = W_{LDA}^T Y$$

$$Z = W_C^T X$$

Where W_{PCA} Is termed as PCA transform matrix, w_{LDA} is the best linearly discriminating transform on PCA feature space; combined linear mapping from the original (indigenous) image space to the cataloguing space is performed using W_c. After this compound linear mapping, identification is achieved in the cataloguing space which is based on certain distance compute benchmark.

Classification using support vector machine

Support vector machine is utilized for recognition. The more detail of SVM is explained in section 6.

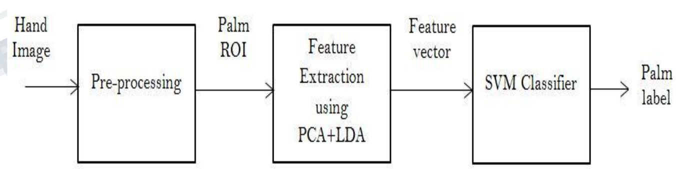


Figure 4: flow for palm print, recognition using combined Eigen palm and Fisher palm approach.

V. SUPPORT VECTOR MACHINE

In this paper, support vector machine (SVM) is utilized for recognition, which accomplishes a non-linear mapping through a kernel from the input space to the higher-dimensional space, which is an imperative component of SVM learning. A recognition task using SVM generally comprises sorting out data into training sets and testing sets. The aim of SVM will yield a model (using training data) that foresees the label values of test data inputted merely the test sample attributes.

In SVM approach, the main aim of an SVM classifier is attaining *f(x)* a function, which will determine the decision boundary or hyper plane. This hyper-plane will optimally separate input data points of two classes. SVM does mapping which is non-linear through a kernel from the input space into a higher-dimensional space, which is an essential component of SVM learning. A classification job typically includes separating data into the training and testing sets. Every sample in the training set holds one label value and more than a few attributes. The objective of SVM is to yield model which forecasts the target values of the test data specified merely the test information characteristics.

Known a set of training instance label duos (X_i, Y_i), i=1,2,…,*l*. where, $(X_i \in R^n)$ and $Y_i \in [-1,+1]^l$, the SVM need the resolution of the succeeding optimization problem:

$$\min_{W,b,\xi} \frac{1}{2} W^T W + C \sum_{i=1}^{l} \xi_i$$

Essence to, $Y_i(W^T X_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$

Here, X_i training vectors are drawn to space of high dimensional using the function. The SVM discovers a linearly sorting out hyper plane along with the utmost fringe in this space of high dimension. C>0 is the penalty factor of the fault term. Also, $K(X_i, Y_i)=(X_i)^T(X_i)$ is entitled as kernel function.

VI. EXPERIMENTAL RESULTS

The database consists of hand images acquired from 50 subjects (15 samples/subject, total 750 samples) using normal HP Scanjet-3010 document scanner. Hand image acquisition system is attached with finger alignment six black colored rubbers, which will provide guidance of placing hand on the scanner in ideal position. From the database (13 samples/subject), total 650 samples used in training and (2 samples/subject), total 100 samples used in testing to demonstrate the recognition performance (recognition percentage) of the biometric system. The recognition performance is computed by means of False Acceptance Rate (FAR), False Rejection Rate (FRR), and Recognition rate. The FAR is the percent error of a system that accepts imposters as genuine users while FRR is the percent error of a system that rejects genuine users as imposters. The recognition rate is computed as given by the beneath equation

$$RR = 100 - \left(\frac{FAR + FRR}{2} \right)$$

Where, RR is the recognition rate.

TABLE I COMPARISION OF ALL THREE ALGORITHMS

Algorithm	FAR (%)	FRR (%)	Recognition Rate (%)
Eigen palm	20	27	76.5
Fisher palm	16	22	81.0
Eigen palm + Fisher palm	14	19	83.5

It is found that palm print, recognition using PCA alone gives recognition rate of 75.3%, palm print, recognition using LDA alone gives recognition rate of 81.2% and combined PCA with LDA gives 83.5% recognition rate. So, PCA combined with LDA outperforms PCA alone and LDA alone in terms of recognition rate.

VII. CONCLUSION

A unimodal palm print, based biometric recognition system has been proposed in this paper using Eigen palm, Fisher palm and combined Eigen palm with Fisher palm features and SVM for classification. It is evident from the experimental results that the combined Eigen palm with Fisher palm performs well in case of pattern-based palm print, classification methods.

REFERENCES

[1] D. Zhang, W. Kong, J. You and M. Wong, "Online palm print, identification," IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 25, pp. 1041-1050, September 2003.

[2] Guangming Lu, David Zhang and Kuanquan Wang, "Palm print, recognition using Eigen palms features," Pattern Recognition Letters, vol. 24, pp. 1463–1467, October 2003.

[3] Ashutosh Kumar and Ranjan Parekh, "Palm print, Recognition in Eigen-space," International Journal on Computer Science and Engineering (IJCSE), vol. 4, pp. 788-794, May 2012.

[4] Mithuna Behera and V.K. Govindan, "Palm print Authentication Using PCA Technique," International Journal of Computer Science and Information Technologies (IJCSIT), vol. 5, pp. 3638-3640, 2014.

[5] Xiangqian Wu, David Zhang and Kuanquan Wang, "Fisher palms based palm print, recognition," Pattern

Recognition Letters, vol. 24, pp. 2829–2838, June 2003.

[6] Shuang Xu and Jifeng Ding, “Palm print, Image Processing and Linear Discriminant Analysis Method,” Journal of Multimedia, vol. 7, pp. 269-276, June 2012.

[7] Wenyi Zhao, Arvindh Krishnaswamy, Rama Chellappa, Daniel L.Swets and John Weng, “Discrmininant Analysis of Principal Components for Face Recognition,” IEEE International Conference on Automatic Face and Gesture Recognition, pp. 336-341, April 1998.