New Fusion Techniques to Extract Image Features and Recognition of Palm Vascular Pattern

Savitha A. P, Ramegowda

Abstract**: *A strong and efficient Feature extraction algorithm is highly recommended for individual recognition in human authentication systems. This paper presents the work carried on palm vein image to extract features of the person vein for recognition and classification using improved canny edge detector. This paper describes a novel method to extract valuable features of the people's vein pattern and achieving high recognition rate. The experiments carried using two algorithms 1) PCACE (principal component analysis with canny edge) algorithm and 2) LDACE (linear discriminant analysis with canny edge) algorithm. These two methods are analyzed on palm vein image and found LDACE algorithm is a best extractor compare to PCACE method. An Equal Error Rate (EER) is applied to evaluate two algorithms. Hidden Markova Model (HMM) is utilized for image feature classification and matching using contactless Palm Under Test (PUT) palm vein database. The percentage of recognition is measured by False Acceptance Ratio (FAR) and False Rejection Ratio (FRR). This method shows robust response with respect to human palm vein identification process computation time and improved recognition rate.***

Keywords: Contactless, EER, FAR, FRR, PUT, Recognition.

I. INTRODUCTION

Today's technology of the world is growing at a very fast pace. Ever-changing technology is leading to globalization of business. Most of the systems are automated by adopting new techniques. Therefore, advancement in automation is demanding not only new techniques but also a more reliable system to secure valuable data in daily life. Due to these reasons, the technology demands a secure system, which results in safe transaction of data. The recent trend of authentication for data is done by using biometric system [1-8]. Biometric authentication is a method to identify an individual based on physiological or behavioral characteristics. The characteristic, which identifies each individual, is called as features. Hence, identification and authentication of features in real-time plays a vital role.

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The review of literature on palm vein features shows that optimized feature extraction methods are the key for effective authentication [10],[11],[12],[13]. The objective of the proposed work is to identify and analyze the algorithms that are best suited for Palm Vein Feature Extraction and authentication. Palm vein pattern is a complex, but its unique vein pattern makes biometric authentication high secure and reliable [14]. The present paper focuses on improving the palm vein authentication by choosing efficient feature extraction algorithm. Palm vein pattern can effectively utilize the natural representation of palm vein minutiae, which is an unordered set [9]. Therefore, the proposed work intends to analyze palm vein features by novel algorithms and look into its discriminative energy as a biometric feature.

II. PALM VEIN PATTERN RECOGNITION SYSTEM

Vein Pattern Recognition System (VPRS), is one of the biometric method, which comes under contactless system [8], [16]. Using near-infrared light, images of blood vessels of the palm are captured. Captured image is used for personal recognition. Since image is captured through contactless sensor, it is hygienic. It is also secure method due its uniqueness of vein pattern. The review of feature extraction algorithms convey there is continual development of new algorithms and checking their capabilities, compact abilities for the current topic, practice of feature extraction algorithms and continual improvements to the palm vein pattern recognition techniques. Literature survey reveals that the principal component analysis (PCA) and linear discriminant analysis (LDA) techniques itself act as feature selector and extractor. Since PCA is an unsupervised feature extraction algorithm and LDA is a supervised feature extraction algorithm, the author is analyzing the present work in both the methods to find an efficient algorithm for feature extraction. The literature review shows feature selection and feature extraction algorithms itself act as an automatic dimension reduction techniques [23-24], [26]. The present work aims to detect and characterize the superficial structures of the palm. Contactless palm vein biometric is used to investigate the uniqueness of various quantifiable features across a population of individuals. Therefore, the contactless palm vein biometric method is more reliable and statistically a robust method compared to other modalities. The use of the palm vein uniqueness in biometric is promising as a contactless palm vein based system.

The core challenge in this system is the development of an efficient and fast feature extractor to recognize the individual.

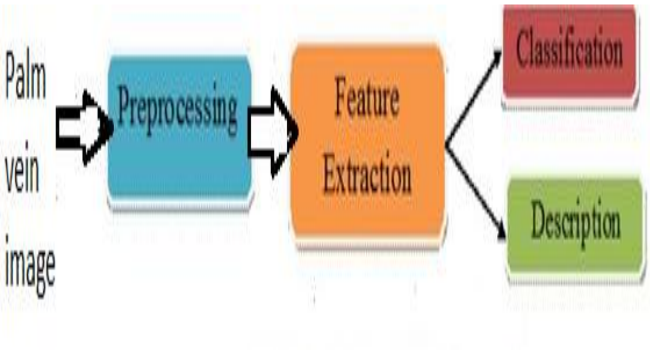


Fig. 1. Palm vein feature extraction and verification model

The images undergo several preprocessing, enhancement steps, gained with different algorithms. Because the lack of contrast is evident to poor quality image, it is not possible to apply noisy images directly to detection steps. The present work goal is to observe and represent the possibility of vein mapping as a statistically robust technique for comparison and classification.

The vein images are enhanced by preprocessing using normalization and segmentation algorithms to improve identification of features. Fig.1. illustrates different stages/steps carried out in the present work. The palm vein image is first preprocessed by applying suitable techniques for image normalization, image segmentation and image enhancement. In feature extraction stage, PCACE and LDACE techniques are employed to extract and analyze palm vein image features. The goal is to investigate an efficient algorithm for the recognition purpose. The next stage is classification and verification of the extracted image. Description will give the information about the validity of the image for authentication.

The database for the experiment is taken from Institute of Control and Information Engineering (ICIE) and named as Palm Under Test (PUT) Vein Database [17]. These data are then preprocessed followed by segmentation, dimension reduction, normalization, filtration and orientation estimation. The preprocessed data is then analyzed with feature extraction algorithms using PCA with edge-detector and LDA with edge-detector. Hidden Markova Model is used for classification. This method shows robust response and accuracy with respect to computation time and recognition rate. The obtained result is verified with the evaluation metrics namely False Accept Ratio (FAR), False Rejection Ratio (FRR), Equal Error Rate (EER).

III. PROPOSED TECHNIQUES

PCA and LDA are two data preprocessing linear transformation techniques used to select relevant features. The process of selecting only relevant features is called dimensionality reduction. We focus here on PCACE and LDACE, which are used to optimize the palm vein features and classification.

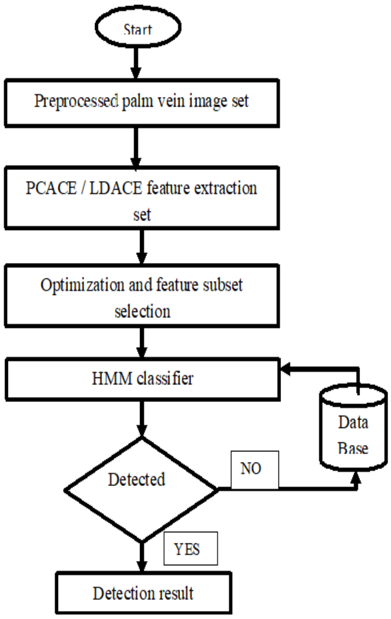


Fig. 2. Proposed Pattern based palm vein recognition system flow

Fig. 2. shows the implementation steps adopted in proposed approach.

IV. ALGORITHM IMPLEMENTATION

The implementation of PCA with Canny Edge-Detection for palm vein feature extraction is obtained from implementation of canny edge detection algorithm to extract all possible features on palm and then applying PCA and LDA to optimize the features.

A. Canny edge-detection algorithm implementation:

The following steps are applied on to palm vein image to extract all possible edge-detection.

1. First, the Gaussian filter is applied to smooth the image in order to remove the noise. The equation for a Gaussian filter kernel of size $(2k+1)\times(2k+1)$ is given by (1),

$$Hij = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{(i-(k+1)^2+(j-(k+1)^2}{2\sigma^2}\right); 1 \le i,j \le (2k+1) \quad (1)$$

2. Then intensity gradients of the image is calculated using (2).

$$\text{Edge gradient } G = \sqrt{G_{x^2} + G_{y^2}} \quad (2)$$

And direction can be determined by using (3)

$$\theta = atan2(G_y, G_x) \quad (3)$$

3. Non-maximum suppression is applied to remove false edge detection
4. To determine probable edges double threshold is applied.
5. Hysteresis is applied to track edges and finalize the edges.

All the above steps will select the possible true edges of the image. Now for this resultant image we applied PCA to get the finite and vital features.

B. Principal component analysis

PCA works on eigen vectors and eigen values of the covariance matrix, which is the equivalent of fitting those straight principal component lines to the variance of the data. The PCA implementation steps followed are as explained below.

1. Represent image pixels by a vector Γ of dimension *N*.
2. Find the average values of palm *M* images and is defined by (4)

$$\boldsymbol{\Psi} = \frac{\mathbf{1}}{\boldsymbol{M}} \sum_{i=1}^{M} \boldsymbol{\Gamma}_i \tag{4}$$

where $\{\Gamma_i | i = 1, \ldots, M\}$ training samples

3. Every vein in vector Γ_i differs from the average vein Ψ by Φ_i and is given by (5)

$$\boldsymbol{\Phi}_i = \boldsymbol{\Gamma}_i - \boldsymbol{\Psi}; i = 1, \ldots, M. \tag{5}$$

4. Covariance matrix of the training images constructed by (6)

$$C = AA^T \tag{6}$$

Where, $A = [\phi_1 \ldots \ldots, \phi_M]$.

5.Finding the eigenvectors, $v_l\,(l = 1, \ldots, M)$, of the *M* by *M* matrix *L* expressed by (7)

$$L = A^T A \tag{7}$$

6.The eigenvectors, $u_l\,(l = 1, \ldots, M)$, of the covariance matrix C are expressed by (8), a linear combination of the difference palm images, $\Phi_i\,(i = 1, \ldots, M)$, weighted by $v_l\,(l = 1, \ldots, M)$

$$U = [u_1, \ldots, u_M] = [\Phi_1, \ldots, \Phi_M][v_1, \ldots, v_M] = AV \tag{8}$$

Practically, a smaller set of M^I ($M^I < M$) eigen value is sufficient for palm identification. Hence, only M^I considerable eigenvectors of *L*, corresponding to the largest M^I eigen values are selected for the palm eigen value calculation, resulting in data compression. Therefore M^I is determined by a threshold, θ_λ of the ratio of the eigen value summation.

$$M^I = \min_r \{ r \mid \frac{\sum_{i=1}^{r} \lambda^I}{\sum_{i=1}^{M} \lambda^I} > \theta_\lambda \} \tag{9}$$

Equation (9) results in dimension reduction by minimized features.

C. Linear discriminant analysis

LDA is a subspace projection and supervised method. It is also one of the methods used to reduce the feature dimension in linear passion.

Let there are set of n, d-dimensional palm features $x_1, x_2, , , x_n$, the separating function is $y = w^t x$, where we like to find vector w (direction of line) such that the projected data set must separate. The 'c' class problem, the LDA algorithms generate c[1] discriminant functions to separate 'c' classes. Hence, the projection is from d dimension space to c[1] dimension space. Within-class scatter matrix S_w and between-class scatter matrix S_B is used to obtain the criterion function given by Generalized Ralyleigh Quotient (10).

$$J(\mathbf{w}) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} = \frac{|\mathbf{w}^t(\mathbf{m}_1 - \mathbf{m}_2)|^2}{\mathbf{w}^t\mathbf{S}_1\mathbf{w} + \mathbf{w}^t\mathbf{S}_2\mathbf{w}} = \frac{\mathbf{w}^t\mathbf{S}_B\mathbf{w}}{\mathbf{w}^t\mathbf{S}_W\mathbf{w}} \tag{10}$$

the general scatter matrix is represented in (11)

$$\mathbf{S}_i = \sum_{\mathbf{x} \in D_i} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^t \tag{11}$$

Where the sample means and projected sample means are calculating using (12) and (13) respectively

$$\mathbf{m}_i = \frac{1}{n_i} \sum_{\mathbf{x} \in D_i} \mathbf{x} \qquad \tilde{m}_i = \frac{1}{n_i} \sum_{y \in Y_i} y = \frac{1}{n_i} \sum_{\mathbf{x} \in D_i} \mathbf{w}^t\mathbf{x} = \mathbf{w}^t\mathbf{m}_i \tag{12}$$

Projected scatter matrix is

$$\tilde{s}_i^2 = \sum_{y \in Y_i} (y - \tilde{m}_i)^2 = \sum_{\mathbf{x} \in D_i} (\mathbf{w}^t\mathbf{x} - \mathbf{w}^t\mathbf{m}_i)^2 = \sum_{\mathbf{x} \in D_i} \mathbf{w}^t(\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^t\mathbf{w} = \mathbf{w}^t\mathbf{S}_i\mathbf{w} \tag{13}$$

Then, the between scatter matrix is computing by using (14)

$$\mathbf{S}_B = (\mathbf{m}_1 - \mathbf{m}_2)(\mathbf{m}_1 - \mathbf{m}_2)^t \tag{14}$$

within scatter matrix is computing by using (15)

$$\mathbf{S}_W = \mathbf{S}_1 + \mathbf{S}_2 = \sum_{i=1}^{2} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^t \tag{15}$$

And the 'w' vectors, we need to find the 'w' which maximizes $J(w)$. Then, 'w' becomes

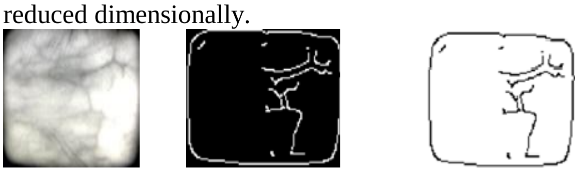
$$\mathbf{w} = \mathbf{S}_W^{-1}(\mathbf{m}_1 - \mathbf{m}_2) \tag{16}$$

equation (16) is the final compressed image features of the palm. LDA algorithm is used for dimensionality reduction for pattern classification and better class-separability in order to avoid over fitting and to reduce computational costs. Now, these features are the vital features to represent an image. Now based on these optimized features, the classification process is initiated.

V. PCACE AND LDACE REALIZATION

A. Realization of PCACE Algorithm

This process start with applying edge detection algorithm to extract branch like patterns followed by dimension reduction. The edge features detected by canny edge-detector must be reduced dimensionally.



(a)Vein image (b) Optimized Features (c) Pattern extracted

Fig. 3. PCACE pattern extraction

Features will undergo dimension reduction process to speed up our process for feature extraction and classification. Fig. 3 illustrates results of combined features and pattern extraction using PCA and Canny edge-detector.

B. Realization of LDACE Algorithm

Another approach proposed on pattern extraction is combined LDA and Canny edge-detector. Since PCA extracts the features on principal component direction, many vital features which are outside the principal region may not be able to extract. This is one of the constrains we observed in PCA. Therefore, we used LDA to overcome the constraints in PCA. The LDA project features in all the directions and features are extracted in all the directions. LDA with Canny edge-detector algorithm was employed for accuracy and robustness of vein image data.

(a) Vein image (b) Optimized Features (c) pattern extracted

Fig. 4. LDACE pattern extraction

The experimental result shows the feasibility of our proposal method. Fig. 4. shows the results of LDACE method. By comparing the simulation result of Fig. 3 and Fig. 4, we highlight more features extracted from the palm vein using LDACE combination rather than PCACE.

VI. RESULT AND DISCUSSION

A. Combined Extracted Feature Performance Analysis

The algorithm's consistency was analyzed by using evaluation metrics FAR and FRR. The EER will measure the algorithm's accuracy to identify and verify the genuine person. The proposed work shows EER=0.62 for combined Canny edge and PCA algorithm as shown in Fig.5 and EER=0.52 for combined Canny edge and LDA approach as shown in Fig. 6. The EER values conclude that LDACE is most versatile algorithm compared to PCACE for pattern identification and recognition. In addition, the verification result shows that the HMM as a classifier does the classification verification is less than a second. Results are tabulated in Table-I. Fig.5 depict the recognition rate and matching time achieved from the proposed work.

Table-I PCACE and LDACE Result

FAR and FRR are computed by (17) and (18) respectively.

$$FAR = \frac{\text{number of false acceptance images}}{\text{total number of sample images}} \quad (17)$$

$$FRR = \frac{\text{number of false rejected images}}{\text{total number of sample images}} \quad (18)$$

Table-II depicts the result obtained for proposed algorithms PCACE and LDACE in terms of FRR and FAR respectively. Equal Error Rate (EER) is the location of the curve at the point where the FAR and FRR are equal. This condition is known as equilibrium condition described by (19)

$$EER=(FAR=FRR) \quad (19)$$

Fig. 6 and Fig. 7 visualize the EER-accuracy of the proposed algorithms. Fig. 8 shows the EER results of the pattern-based methods. We observed that the results obtained are best suited for pattern recognition and verification process compare to the already existing system [16].

Proposed methods	Recognition rate (%)	Feature vector size	Matching time (sec)
PCA+CANNY FE WITH HMM CLASSIFIER	99.12	255*255	1.68
LDA+CANNY FE WITH HMM CLASSIFIER	99.5	255*255	1.52

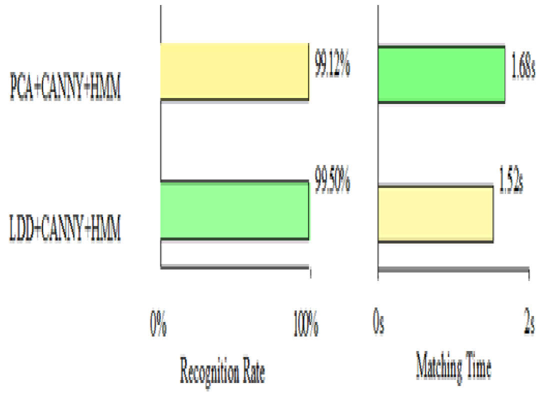


Fig. 5. Recognition rate and matching achieved

Table-II Proposed work FRR and FAR results

PCACE		LDACE	
FRR	***FAR***	***FRR***	***FAR***
0.12	**0.93**	**0.2**	**0.97**
0.22	**0.91**	**0.25**	**0.92**
0.29	**0.79**	**0.31**	**0.82**
0.36	**0.76**	**0.42**	**0.76**
0.45	**0.62**	**0.55**	**0.67**
0.56	**0.59**	**0.66**	**0.58**
0.66	**0.54**	**0.76**	**0.54**
0.71	**0.42**	**0.81**	**0.45**
0.77	**0.33**	**0.87**	**0.39**
0.89	**0.25**	**0.92**	**0.3**

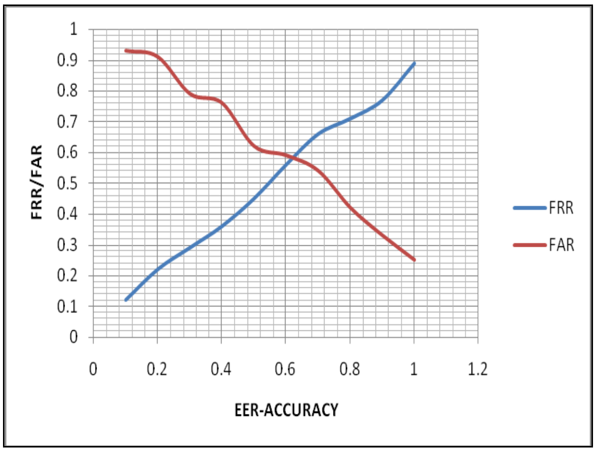


Fig. 6. EER- Accuracy 0.62 for PCACE

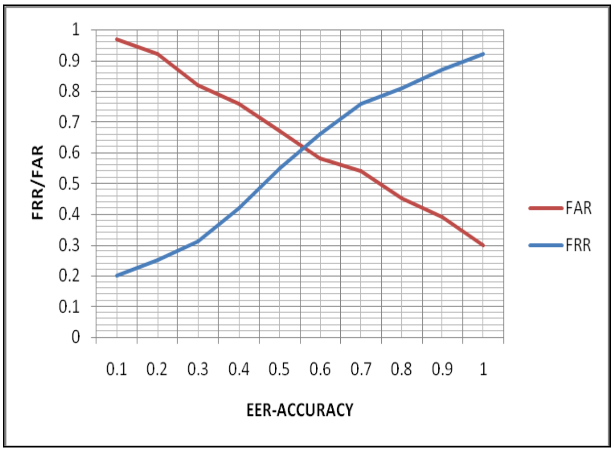


Fig. 7. EER- Accuracy 0.52 for LDACE

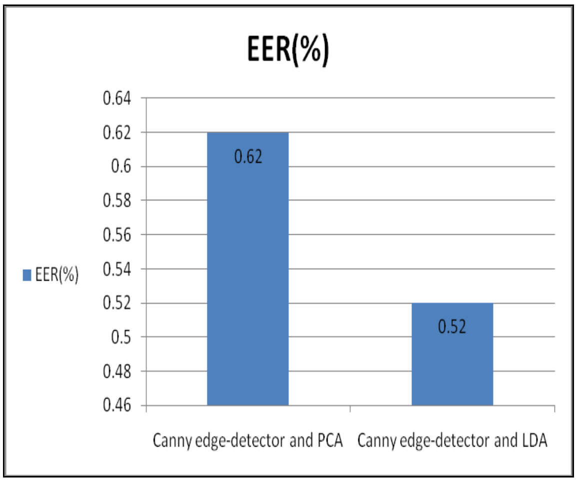


Fig. 8. EER Summary for Pattern-based methods

VII. CONCLUSION

The presented work demonstrated two combined approaches based on canny edge-detector with PCA/LDA and HMM classifier. The machine-learning algorithm PCA and LDA methods were applied for dimension reduction, which helped in robust palm vein feature classification and feature matching. A novel LDA with canny edge-detector searched the features within the pattern and retained the pattern features more discriminant from the unwanted features. This enabled the novel LDACE algorithm to increase the recognition rate of 99.5% significantly than the PCACE fusion approach with HMM classifier. We finally conclude that a novel proposed algorithm LDACE outperform PCACE in terms of computation time and recognition rate. Our future work is developing deep learning algorithms for image feature extraction process.

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