COMPREHENSIVE EVALUATION OF APPEARANCE-BASED TECHNIQUES FOR PALMPRINT FEATURES EXTRACTION USING PROBABILISTIC NEURAL NETWORK, COSINE MEASURES AND EUCLIDEAN DISTANCE CLASSIFIERS

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Abstract: *Most biometric systems work by comparing features extracted from a query biometric trait with those extracted from a stored biometric trait. Therefore, to a great extent, the accuracy of any biometric system is dependent on the effectiveness of its features extraction stage. With an intention to establish a suitable appearance based features extraction technique, an independent comparative study of Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) algorithms for palmprint features extraction is reported in this article. Euclidean distance, Probabilistic Neural Network (PNN) and cosine measures were used as classifiers. Results obtained revealed that cosine metrics is preferable for ICA features extraction while PNN is preferable for LDA features extraction. Both PNN and Euclidean distance yielded a better recognition rate for PCA. However, ICA yielded the best recognition rate in terms of FAR and FRR followed by LDA then PCA.*

1. INTRODUCTION

Physiological biometric traits in the hand region that could be used for human authentication, verification and identification are majorly fingerprint and palmprint. Of these, fingerprints are the most widely used [1], however, they contain few information or features that could be extracted and used as biometric traits. On the contrary, palmprint provides a large surface from which more features can be extracted when compared to fingerprint [2]. Besides this large surface, non-intrusiveness, low cost, low resolution and stable features have given palmprint an edge over fingerprint [3, 4]. Also, instances where fingerprint recognition system have refused fingerprints of labourers' and elderly people have been reported which have further revealed the limitations of fingerprint systems [5].

Prominent features that could be used for palmprint recognition purposes include principal lines [6, 7], palm geometry [8, 9], wrinkles [10, ridges and valley features, datum points and miniature features [11]. This could be extracted from offline palmprint images using inked images as well as online images using low and high resolution imaging. High resolution palmprint images ranges from 400 dpi or more while low resolution imaging ranges from 150 dpi or less [12]. Most offline applications employ high resolution images while online applications make use of low resolution images [13].

Biometric trait of interest is not enough to guarantee a reliable recognition system, the feature extraction approach employed has a great determinant effect. The most widely used features extraction approach include appearance based approaches, hybrid approaches, texture based approaches, statistical based approaches and local feature based approaches [11, 14]. However, features extracted from palmprint images are of high dimensions which decreases recognition accuracy and results in high computation complication [15]. Therefore, in addition to extracting features from palmprint images, reducing the dimensions of these features are necessary to achieve a high recognition accuracy. Appearance-based approaches also called subspace projection methods could effectively be used to reduce dimensions of computed feature space in addition to features extraction. Principal Component Analysis (PCA) and its variants, Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) are the most employed techniques among other appearance-based approaches [16, 17]. Due to high dimensions of palm print feature vector after being converted to one dimensional vector; PCA, LDA and ICA attempt to map computed features vector from a high dimension to a low dimension so as to achieve high accuracy and speed [14]. However, different distance measures and classifiers are used by each technique.

PCA extracts global interrelated features, reduces its dimensions and identifies new underlying variables that may be used to represent the original image. It further uses mathematical procedure to transform computed correlated variables into a smaller number of uncorrelated variables called principal components [18]. However, instead of reducing within class variations among extracted features, PCA increases it thereby resulting in its low performance [19]. Also, attempt to linearly translate the multi-dimensional feature vector into one-dimensional feature vector produces a loss of spatial information [20].

In contrast, LDA also called Fisher Discriminant Analysis (FDA) leverages on the class information of the extracted features to obtain a set of vector that maximizes the between-class scatter matrix while minimizing the within-class scatter matrix of the extracted features [21, 22, 23]. Unlike PCA, LDA attempts to lower down the high dimension of the computed feature vector so as to achieve maximum discrimination [24]. ICA uses both second-order-statistics and higher-order-statistics to compute statistically independent features from high dimensional data [25]. To achieve this, ICA computes the correlation among the data and further de-correlates the data by reducing or enhancing its contrast information. While PCA computes and removes correlation among features extracted, it does not compute nor remove higher order dependence between the extracted features. In contrast, ICA does not only compute and remove correlations among extracted features, it further computes and removes higher order dependence between them [26]. While these approaches are not without limitations; they are still the most widely used appearance-based features extraction techniques. This paper independently employs each technique for palmprint features extraction with a view to determine how each fare. A comparative analysis of their performance was carried out using their recognition accuracy and Acceptance/rejection rates.

2. RELATED WORKS

Several approaches have been employed to extract unique features from palmprint images. Such include the PCA feature extraction technique implemented in [27]. The PCA technique was used to compute eigen values and vectors used for palm vein identification. Afterwards, template matching algorithm was used for the features matching. The recognition system was finally implemented on a Dual core ADSP Blackfin BF561 processor. An image reconstruction technique was proposed in [28]. Unlike the traditional PCA which removes higher-order features, image reconstruction using whitening PCA utilizes the extracted principal features as well as the higher-order features. Recognition accuracy of the technique was better when compared to the traditional PCA. Furthermore, a hybrid ICA-PCA technique called Enhanced Principal Component Analysis (EPCA) was proposed for palmprint features extraction by [19]. To complement the limitation of PCA features extraction technique, principal components extracted from the palmprint images were used as inputs to the ICA algorithm. The recognition rate and computational time observed revealed that the approach yielded a better output than when PCA alone was used. Similarly, two different ICA frameworks for palmprint features extraction called FastICA were proposed in [29] and also implemented in [30]. Both frameworks process the palmprint images as random variables, however, pixels were treated as the outcomes in the first framework while images were used as outcome the second framework. The second framework yielded the best performance after evaluation. Furthermore, the robustness of PCA feature vector to noise was studied in [31]. The palmprint images were degraded by several blurs and noises such as Salt and pepper noise, Blur with disk filter, motion blur, Gaussian noise. The performance of the blurs and noises were evaluated with palmprint images acquired from two different public palmprint databases. Results obtained revealed that the PCA features extraction is less sensitive to blur and noise effects as the recognition accuracy was not affected by both the blurs and noises introduced.

Moreover, local Gabor filters was used with PCA for palmprint features extraction in [18]. Gabor filter was used for the texture features extraction while PCA was used for global features extraction. Sum rule was used to combine feature scores obtained from both techniques and a high recognition accuracy was achieved. A two dimensional discrete wavelet transform for palmprint feature extraction was introduced in [32]. In order to reduce the dimension of the feature space computed, PCA was employed. Results obtained revealed the prowess of PCA as a powerful and efficient dimensionality reduction technique. Similarly, a three dimensional palmprint recognition technique was proposed by [33]. Histogram of blocked surface type map was used as the palmprint feature, however, the large dimension of the feature space obtained and its computational complexity necessitated the need to use PCA for the dimension reduction. Comparative analysis carried out with other variants of PCA like kernel PCA, bidirectional PCA, two-dimensional PCA and ICA revealed that the approach was efficient with a recognition rate of 99.25%. Closely related is the fusion of blockwise bi-directional two-dimensional PCA (2D2PCA) and grouping sparse representation feature extraction technique proposed in [20]. The palmprint image was initially divided into equal blocks after which the 2D2PCA was employed to extract feature matrix from two directions of both rows and columns of each blocks. The dimensions of the extracted features were further reduced by the 2D2PCA on a block by block basis. Afterwards, sparse group representation technique was employed to restore the lost spatial information as a result of the 2D2PCA technique. A better recognition result was recorded when the proposed technique was evaluated. Furthermore, the similarity measures computed between the feature vector of a query image and the stored image could influence the eventual recognition accuracy of the biometric system. Therefore, [34] studied the effects of normalized Euclidean distance and backpropagation neural network on the recognition accuracy of a palmprint recognition system. With 50 and 100 principal components, 86.7% and 93.3% recognition accuracies were achieved respectively with backpropagation neural network while 95% recognition accuracy was obtained with normalized Euclidean distance for 50 and 100 principal components respectively.

LDA was employed to extract global algebraic features from 3D palmprint images in [15]. The effects of different resolutions (16 x 16, 32 x 32, 64 x 64 and 128 x 128) on the recognition accuracy was studied. The best recognition accuracy was obtained with 16 x 16 and 32 x 32 resolutions. Furthermore, Gabor wavelets and two-dimensional linear discriminant (2DLDA) approach was proposed in [23]. The proposed approach avoids whitening process which was believed to be redundant and increases computational complexity. Gabor wavelets was used to compute orientation, spatial localization, phase relationship and spatial frequency from the palmprint images. Afterwards, the 2DLDA technique was used to project the high-dimensional feature space output of the Gabor wavelets to a low-dimensional feature space. Similarly, an online palmprint recognition system using kernel FDA was proposed in [35]. Gabor wavelets was initially used for palmprint features extraction after which kernel FDA was used to extract higher order relations among the Gabor wavelets features. Furthermore, a local FDA was employed to extract low projection vectors in [22]. The approach placed emphasis on the local structure of the palmprint images so that its multidimensional features can be easily embedded for a better recognition task. Though the approach yielded a higher recognition rate and extracts the best classification information when compared to PCA; PCA was adjudged to extract the best feature vectors. Palmprint recognition using LDA technique with L1norm was proposed in [36]. L1 norm was proposed with a view to eradicate the sensitivity of L2 norm to outliers. An iterative method was employed to obtain series of projection vectors which maximizes inter class scatter matrix while minimizing within class scatter matrix. Results obtained showed that the approach was robust to outliers. Furthermore, an Image-Based LDA was proposed in [15]. Their approach entails dividing the four bands of a coloured palmprint image into two groups, after which low-dimensional features were extracted from each group at feature level. The proposed approach fully maximized the information embedded in the colour bands of multispectral palmprint images. To further improve the performance of LDA feature extraction technique, a two dimensional discrete wavelet transform (2D-DWT) was proposed in [37]. The 2D-DWT was used to decompose the palmprint images high and low frequency components, however, the high frequency sub bands were ignored due to the presence of noise while the low frequency sub-bands of the palmprint images were then used as an input into the LDA algorithm. The approach yielded a high recognition rate.

Palmprint recognition system using ICA was implemented in [38]. ICA was used to decompose the computed multivariate vector into independent Non-Gaussian vectors; this entails iteratively multiplying the multivariate vector with a random vector until independence is achieved. Similarly, Gaussian Mixture Model (GMM) and two variants of ICA were used for palmprint features extraction in [14, 39]. Multiple covariance matrices were computed using GMM; these were used as an input to the two ICA variants. The first ICA variant-ICA I separates the feature matrices with emphasis on higher order statistics while the second ICA variant- ICA II focuses on second order statistics. Results obtained revealed that the second ICA variant performed better. Moreover, features extraction technique which merges sequentially the outputs of incremental PCA and ICA was introduced in [40]. The technique computes the principal components of a sequence of image vectors incrementally without estimating the covariance matrix (so covariance-free) and at the same time the principal components were transformed to independent components that maximize the non-Gaussianity of the source. The incremental PCA-ICA yielded a better recognition performance when compared to traditional PCA-ICA technique.

3. RESEARCH METHODOLOGY

This section explains the palmprint features extraction process using PCA, LDA and ICA techniques.

3.1 Palmprint Image Acquisition

Palmprint images used in this work were acquired from India Instutiute of Technology (IIT) palmprint database. The database comprises of 1645 left and right contactless palmprint images acquired from 235 staff and students of IIT. Of these, 400 palm images which consists of 200 right hand images and 200 left hand images of 150 x 150 pixels were used as testing and training data.

3.2 Image Pre-processing and Region of Interest Extraction

Some environmental and external factors such as temperature, humidity and brightness do affect the quality of acquired images, therefore, preprocessing is needed to enhance the quality of the images and make them suitable for features extraction. Image enhancement techniques such as brightness stretching, gray scale conversion, histogram equalization, normalization and image de-noising were applied to the acquired palmprint images.

Afterwards, the palmprint Region of Interest (ROI) was determined. This region contains features such as principle lines, wrinkles and ridges needed for features extraction. ROI can either be circular, half elliptical or square region, however, the square region is the easiest and widely used [31]. The following ROI extraction stages as proposed in [41] was adopted:

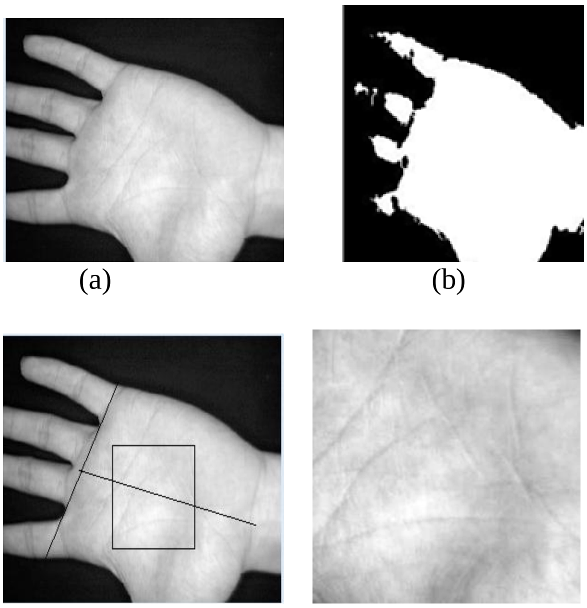
a) Gaussian low pass filter, $F(x,y)$ was applied to the original image $O(m,n)$ as shown in Figure 1a. Afterwards, a threshold, T_p was used to translate the convolved image to a binary image $B(m,n.)$ as shown in Figure 1b.

b) Using gaps between the fingers as reference points, boundary tracking algorithm was used to trace out the boundaries $L_i x_j, L_i y_j$ of the gaps; where i = 1,2 as shown in Figure 1c. However, boundary of the gap between the ring and middle fingers were exempted since they were not needed.

c) The tangents of the two gaps were computed such that (x_1, y_1) and (x_2, y_2) are points on $L_i x_j$ and $L_i y_j$.The line ($y = mx + c$) passing through the two points must satisfy the condition $L_i y_j \leq m\, L_i x_j + c$ for all i and j.

d) To obtain the Y-axis of the palmprint coordinate, points (x_1, y_1) and (x_2, y_2) are connected together as shown in Figure 1c. The line passing through the midpoint of points (x_1, y_1) and (x_2, y_2) , which is perpendicular to the Y-axis indicates the origin of the coordinate system.

e) A sub-image (ROI) of 350 x 250 dimension located at the center of the palmprint image was cropped out as shown in Figure 1d based on the coordinate system.



(a) (b)
(c) (d)

Fig. 1: (a) Original Palmprint Images (b) the Binary Image (c) Calculating the Central Part of the image (d) the Extracted ROI

3.2 FEATURES EXTRACTION

Three appearance based features extraction techniques were independently employed for the palmprint features extraction. They are:

3.2.1 PCA FEATURES EXTRACTION TECHNIQUES

PCA features extraction entails computing the Eigen value, criterion function, algorithmic mean of palmprint features, data covariance matrix as well as finding the difference of the dimension vector. PCA features extraction steps employed in this research work are enumerated below:

1) A palmprint dataset x with k-dimensions such that $x_i \in R_k$ where i=1,2,…n was supplied
2) A mean vector m such that $m = \frac{1}{n}\sum_{i=1}^{n} x_i$ was generated
3) Scatter matrix S such that $S = \sum_{i=1}^{n}(x_i - mxi{-}mT$ was generated
4) Eigen vectors $(e_1, e_2, \ldots e_k)$ and the corresponding Eigen values $(\gamma_1, \gamma_2, \ldots \gamma_k)$ from the scatter matrix m was computed.
5) The Eigenvectors and Eigenvalues were re-arranged in decreasing order and the corresponding eigenvectors with small eigenvalues were discarded.
6) A $k \times i$ dimensional matrix w with the topmost i-eigenvectors was computed
7) Dimensional matrix w was used to transform the dataset into a principal subspace y such that $y = WT \times X$.

3.2.2 LDA Features Extraction Technique

LDA attempts to find the optimal subspace for palmprint feature extraction in the sense that it maximizes the distance between different subspaces while minimizing the compactness of the subspace. LDA features extraction steps proposed by Elnasir & Shamsuddin [37] were implemented in this work. The detailed steps include:

1) Given a set of palmprint images $P = \{p_1, p_2, \ldots, p_3\} \in R^{m \times n}$, a projection matrix M

that maximizes fisher criteria $F^{LDA} = argmax_F \frac{M^T S_B M}{M^T S_w M}$ is computed.

2) The palmprint images P were divided into classes such that $P = \{C_1, C_2, \ldots, C_N\}$, $a_j \in C_i; i = 1,2, \ldots, N \; and \; j = 1,2, \ldots, n$

3) The class mean m_i was computed such that $m_i = \frac{1}{n_i} \sum_{j=1}^{n_i} a_j$

4) The global mean m was computed such that $m = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n_i} a_j$. Where $n_i$is the number of elements in class

5) The between class scatter matrix S_B was computed such that: $S_{B=} \sum_{i=1}^{N} n_i \, (m_i - m)(m_i - m)^T$

6) The within class scatter matrix S_W was also computed such that:

$S_{w=} \sum_{i=1}^{N} \sum_{i=1}^{n_i} \frac{n_i}{n} (a_j - m)(a_j - m)^T$

7) The expected projection matrix M is derived by solving the Eigen value problem:

$$S_B M = S_W \, M\gamma, \gamma \neq 0$$

Where γ is the diagonal matrix of the Eigen values.

However, if S_W is non-singular, then the projection matrix M will be computed as:

$$S_W^{-1} S_B \, M \; = M\gamma, \gamma \neq 0$$

8) Finally, the LDA features are computed such that: $f_i = M^T (a_i - m)$ where $f_i \in R^r$ is the r dimensional feature vector.

3.2.3 ICA Features Extraction Technique

ICA attempts to extract independent data from a collection of data that are linearly dependent on each other. To achieve this, ICA finds the correlation among these data and de-correlates the data by maximizing or minimizing its contrast information. ICA feature extraction technique as proposed by Yoshinori, Seiichi & Ozawa [42], was employed. The detailed steps include:

Assuming the input data $x(k)$ contains statistically independent components $s(k)$ with an unknown mixing matrix A. The relationship between these components can be established using:

$$x(k) = A \, s(k) \quad (1)$$

ICA attempts to de-correlate mixing matrix A such that the component of $s(k)$ becomes independent of each other. Prior to this, $x(k)$ is whitened such that

$$v(k) = D^{-1/2} U^T x(k) \quad (2)$$

Where $v(k)$ is the mutually uncorrelated and normalized whitened vector,

$D = diag[\gamma_1, \ldots, \gamma_M]$ and $U = [u_1, \ldots, u_M]$. Also, u_i is the ith eigenvector and γ_i is the largest eigenvalue of the covariance matrix $E\,\{x(k)\; x\;(k)^T\}$ and u_i.

Subsequently, from the whitened vector $v(k)$, the independent components $\check{s}(k)$ can be computed such that

$$\check{s}(k) = W \, v(k) \quad (3)$$

Where W is the separation matrix.

Equations 2 and 3 will be combined to obtain the independent components $\check{s}(k)$such that:

$$\check{s}(k) = WD^{-1/2} U^T x(k) = Bx(k) \quad (4)$$

Where B is the ICA-base vector.

4. RESULTS AND DISCUSSION

The performance of the appearance based features extraction techniques were evaluated using recognition rate as well as their acceptance and rejection rates. Three different classifiers viz: Euclidean distance, Probabilistic Neural Network (PNN) and cosine measure were also employed.

4.1 RECOGNITION RATE

This measures the degree of correctly identified individual among the total individuals in the palmprint database. The palmprint images were grouped into four batches of 50, 100, 150 and 200 images, though the recogntiion rate recorded increases with minute difference with an increase in palmprint images.

Results obtained as shown in Table 1 revealed that the recognition rate observed were acceptably high for all the techniques across the distance metrics adopted. However, for the ICA features extraction technique, it is observed that the best distance metrics is the cosine metrics which was closely followed by PNN. This is consistent with the observation in [30]. The basis vectors of ICA is known to be non-orthogonal and the distance and angles between its images are different, this could be responsible for the higher recognition accuracy recorded with cosine metrics among others.

PNN can easily relate with data it has not seen before and this could be responsible for the high recognition rate recorded. Recogntion rate recorded with Euclidean Distance metrics was poor when compared with other distance metrics. So, it is advisable not to use it for ICA. As regards LDA features extraction technique, PNN yielded the best recogntiion rate among other metrics while cosine measure distance metric could also be used. A low recognition accuracy was recorded when euclidean distance measure was used.

Table 1: Recognition Accuracy of PCA, LDA and ICA Features Extraction Techniques

Distance Metrics	Euclidean Distance			Probabilistic Neural Network			Cosine Measure		
Number of Palmprint Images	Recognition Accuracy (%)			Recognition Accuracy (%)			Recognition Accuracy (%)		
	PCA	LDA	ICA	PCA	LDA	ICA	PCA	LDA	ICA
50	96.2548	92.2333	94.2319	95.7523	96.4604	95.4311	94.1256	94.3142	96.7627
100	96.2554	92.2364	94.3856	95.7686	96.4622	95.7524	94.2315	94.3487	96.6514
150	96.4585	92.2410	94.4375	95.8219	96.5321	96.2130	94.3423	94.3654	97.7546
200	96.5392	92.5641	94.5420	95.8324	96.6718	96.5826	94.3645	94.3679	97.8420

PCA performed averagely well across all the distance metrics though it was observed that both PNN and Euclidean Distance yielded a better recogniton rate than cosine measure. Comparing the performance of PCA, LDA and ICA across all the distance metrics, it can be conjectured that ICA performs best with cosine measure while LDA performs best with PNN and PCA is best used with Euclidean

4.2 Acceptance/Rejection Rates

Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR) and False Rejection Rate (FAR) will be used to determine the degree of accetance or rejection of an individual.

GAR is determined by comparing the extracted palmprint features of an individual with other palmprint images of the same individual. The GAR is expected to be high which connotes that a high number of genuine individual were recognized. It could be computed using GAR=100-FRR.

FAR measures the number of imposters that were accepted or rejected. This could be determined by comparing the extracted palmprint features of an individual with the palmprint features of other individuals. An imposter is said to be accepted if the match scores obtained is greater than the set threshold. FAR is a function of Genuine Rejection (GR) and False Acceptance (FA). GR measures the number of imposters that were correctly identified and rejected while FA measures the number of false individual that were wronlgy accepted instead of being rejected. FAR is expected to be low which connotes that imposters are expected to be prevented from being authenticated. FAR could be computed using equation (11):

$$\mathrm{FAR} = \frac{\mathrm{FA}}{\mathrm{FA+GR}} \tag{11}$$

FRR measures the number of genuine individual that were wrongly rejected. This could be determied by estimating the False Rejection (FR) and Genuine Acceptance (GA). FR measures the number of genuine individual that were wrongly rejected while GA is the number of genuine individual that were rightly accepted. This could be computed using equation (12):

$$\mathrm{FRR} = \frac{\mathrm{FR}}{\mathrm{FR+GA}} \tag{12}$$

The Receiver Operating Characteristics (ROC) curve which shows the relationship between GAR and FAR as well as FRR and FAR are shown in Figure 2 and 3 respectively.

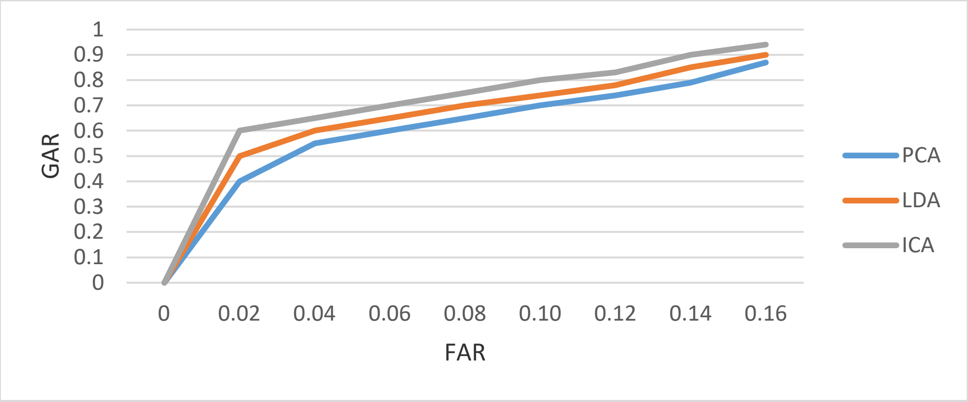


Fig. 2: ROC Curve for GAR and FAR

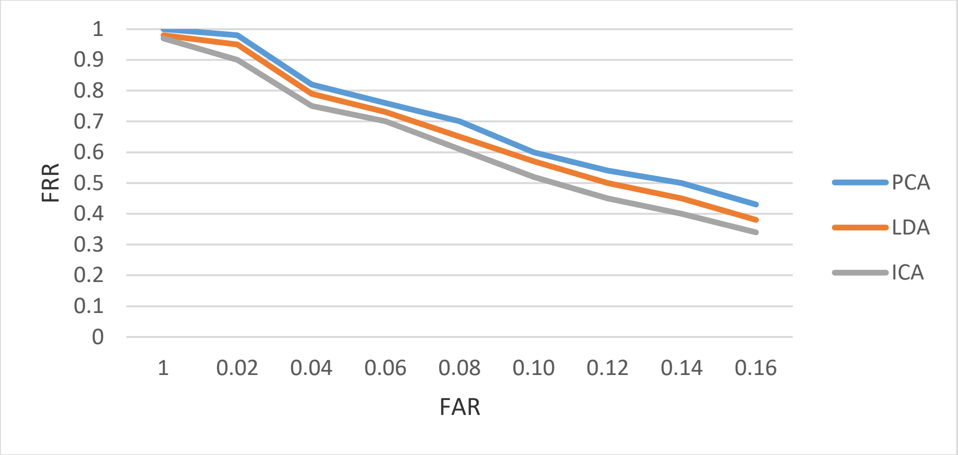


Fig. 3: ROC Curve for FAR and FRR

Both ROC curve provided a general overview of the three algorithms. It revealed that there is a minimal difference among the recognition ability of the three algorithms, however, no mmatter insignifican the difference seems to be, ICA performed better than LDA follwed by PCA.

5. CONCLUSION

An independent evaluation of the performances of three prominent appearance based features extraction techniques have been carried out in this article. Three classifiers have been employed viz: Euclidean distance, Probabilistic Neural Network (PNN) and cosine measure. Results obtained revealed that cosine metrics is best used for ICA features extraction closely followed by PNN. PNN yielded the best recognition rate for LDA features extraction technique followed by cosine measure distance metrics. As for PCA, both PNN and Euclidean Distance yielded a better recognition rate. A general overview of the appearance based features extraction techniques revealed that ICA yielded the best recognition rate in terms of FAR and FRR followed by LDA then PCA. This could be due to the fact that ICA decorrelate the input data using higher-order statistics while LDA and PCA uses second-order statistics. The results showed the sensitivity of ICA to important details available at the higher-order statistics.

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