LDA-PAFF: Linear Discriminate Analysis Based Personal Authentication using Finger Vein and Face Images

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Abstract— **Biometric based identifications are widely used for individuals personnel identification in recognition system. The unimodal recognition systems currently suffer from noisy data, spoofing attacks, biometric sensor data quality and many more. Robust personnel recognition can be achieved considering multimodal biometric traits. In this paper the LDA(Linear Discriminate analysis) based Personnel Authentication using Finger vein and Face Images (LDA-PAFF) is introduced considering the Finger Vein and Face biometric traits. The Magnitude and Phase features obtained from Gabor Kernels is considered to define the biometric traits of personnel. The biometric feature space is reduced using Fischer Score and Linear Discriminate Analysis. Personnel recognition is achieved using the weighted K-nearest neighbor classifier. The experimental study presented in the paper considers the (Group of Machine Learning and Applications, Shandong University-Homologous Multimodal Traits) SDUMLA-HMT multimodal biometric dataset. The performance of the LDA-PAFF is compared with the existing recognition systems and the performance improvement is proved through the results obtained.**

Keywords-SDUMLA_HMT; LDA-PAFF; Phase; Magnitude; fisher Score

I. INTRODUCTION

The use of biometrics to identify personnel is widely adopted in our day-to-day scenario. A biometric recognition system identifies an each personnel using one or more specific physiological characteristics possessed by the individuals [1]. If one physiological characteristics is considered for recognition then they are termed as unimodal recognition systems. When multiple or a combination of personnel biometrics are considered then they are termed as multimodal biometric recognition systems. Enrollment and verification of authorized personnel are the important functions of the recognition systems. The recognition systems enroll authorized personnel based on the data provided from the biometric sensors and store the data for future verification or matching. During verification the recognition systems validates with the existing whether the biometric data presented is valid or invalid. Predominantly unimodal systems are adopted for personnel identification [2].

Key challenges in unimodal biometic systems:

The unimodal biometric recognition systems currently used in day-to-day activities suffers from large number of drawbacks [2][3][4]. Biometric recognition systems solely rely on the data provided in the biometric sensors. The data input provided to the recognition systems from the sensors are generally noisy in nature which can affect the verification results and also cause faulty enrollment techniques. The illumination variation for face recognition systems is one such example. Interpersonal biometric similarities is another drawback of unimodal biometric systems [4]. Unimodal biometric recognition system presented in the research work using the finger print [5] it clearly illustrates the biometric similarity problem. Spoofing attacks are the common causes in unimodal recognition systems. Spoofing attacks are commonly noticed when biometrics like signature, voice, face and finger prints are considered [2] in the recognition system.

Motivation:

Multimodal biometric recognition systems is used to overcome the drawbacks of the unimodal recognition systems and have proved to be

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successful [6][7]. The LDA-PAFF is a multimodal recognition system. Limited work has been carried out by researchers considering a comprehensive set of biometric traits of personnel. The research work carried out by other researchers considers either the magnitude features [8][9][10][11] or the phase features[12][13][14][15].

Contribution:

Considering the research findings, a LDA based Personnel Authentication using Finger vein and Face Images (LDA-PAFF) are introduced in this paper. The state of art work presented by Shekar et al., [7] considers the Iris, Finger print and Face biometrics for recognition. In LDA-PAFF the finger vein and face biometric is considered for recognition. In LDA-PAFF, the personnel are identified on the basis of the Gabor kernel features extracted. To enable efficient feature extraction and recognition the biometric data obtained from the sensors are pre processed to obtain the region of interest(ROI) for the considered biometric traits. On obtaining the ROI, data feature extraction is performed using Gabor kernels. The novelty of LDA-PAFF is that both the phase features and magnitude feature are considered.

Organization:

The manuscript is organized as follows. Section 2 discusses the related work. The background is discussed in Section 3. The LDA-PAFF proposed is presented in Section 4. The penultimate section of the manuscript discusses the experimental work and results obtained. The conclusions are drawn in the last section.

2. Related Work

Many number of researches have been done till these days for human traits based biometric identification system where some are emphasized for multi model consideration while taking into account of performance and classification accuracy as prime objectives. Some of them are as follows:

Monwar M et al., [13] develop a multimodal biometric system using Fisher Extraction Scheme on the basis of PCA and Fisher's linear discriminant (FLD) approach which do employs face, ear and signature for identification. They employed rank-level fusion process and used Borda count paradigm (combination of ranks for individual model) and logistic regression technique. This system exhibited that the fusion of varied models could lead to performance enhancement.

Dinakardas C et al., [14] in their system developed a multimodal face recognition system using fusion of results from PCA, fisherface as well as minutia extraction with LBP feature extraction for varied biometric traction. The authors emphasized system optimization for accuracy of recognition.

Jihyeon Jang et al., [15] developed a multiple biometric system taking into consideration of non-linear classifiers and derived varied score vectors which was classified using SVM, Kernel Fisher Discriminant (KFD) and further by Bayesian Classifier. They exhibited their system functional efficiently with multi-model architecture.

Jian Yang et al., [16] emphasized their research for projection using unsupervised discriminant projection (UDP) scheme for reducing dimensionality of high-dimensional data in certain defined small sample size cases. The uniqueness of this system was that it (UDP) characterizes the local scatter factor as well as the available nonlocal scatter, requiring estimation of certain data projection which could optimize the nonlocal scatter simultaneously. They employed this system with face and palm based biometric identification. The authors advocated their system to be used for real time biometrics utilities.

3. Background Work

This is the fact that a number of researcher have made effort to enhance the system performance and among them Jiwen Lu et al., [22] have employed cost sensitive analysis paradigm for face recognition. In general the traditional subspace oriented face identification approaches need lower dimensional feature subspaces for accomplishing higher accuracy of classification[24][25][26][27]. In fact such kind of assumptions could not possess effectiveness in varied circumstances. In [22], the developed system employs a cost matrix factor which specifies varied cost factors in relation with

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different types of misclassification, and for this the author have taken discriminative subspace analysis approach into consideration, of which was further devised into the cost-sensitive linear discriminant analysis (CSLDA). Later a cost-sensitive marginal fisher analysis (CSMFA) approach was employed for accomplishing the value of minimum identification loss by exhibiting identification with learned low-dimensional subspaces.

In order to enhance the system by exploiting complementary details from multiple extracted features they proposed a multi-view cost sensitive subspace analysis scheme that needs a common feature subspace for fusing multiple features. In fact this work was an enhanced form of [23] which has already employed certain cost-sensitive PCA and LPP (CSLPP) approach for face identification. On the other hand generic PCA and LPP approaches are unsupervised and author enhanced it with supervised, which resulted into better results. In their work they have enriched the system with two discriminative subspace analysis approach called (LDA and marginal Fisher analysis (MFA). Some other works such as [14][15][21] have also emphasized their system for multimodal biometric application and have tried to function on reduced dimensionality with linear subspaces.

This is the matter of fact that the existing approaches have performed better, but taking into consideration of varied critical human traits and associated real time circumstances such as lighting, contrast and orientation, major systems gets limited to exhibit better. On the contrary the implementation of traditional LDA doesn't ensure optimal results. Therefore these requirements become a motivation for this present research and we have proposed a highly robust and efficient system employing phase congruency with Gabor extraction, fisher matrix enriched with LDA paradigm and the system has been further optimized with K-nearest neighbor classification system which makes the system optimal in terms of accuracy, efficiency and overall performance.

4. Proposed Model

The proposed architecture for LDA based personal authentication using finger vein and face images is LDA-PAFF as shown in Fig.1.

Let us consider a multimodal biometric dataset of $\mathcal{P}$ personnel. There exists a classification problem of $\mathcal{P}$ personnel to be identified based on their $\mathbb{B}$ biometric feature set. The biometric feature set consisting of Finger Vein and Face can be defined as

$$\mathbb{B} = \{\mathbb{V}^g \cup \mathbb{F}^g\} \quad (1)$$

Where $\mathbb{V}^g$ is the phase features for the finger vein and $\mathbb{F}^g$ represents the feature set of the face biometric.

The LDA-PAFF proposed in this paper considers primarily Two biometric features of $\mathcal{P}$ personnel namely the finger vein $(\mathcal{V})$ and frontal face $(\mathcal{F})$. Pre-processing is adopted on all the raw biometric images to obtain the regions of interest $(\mathcal{ROI})$. The $\mathcal{ROI}$ identification procedures adopted is discussed in the future section of the paper. The $\mathcal{ROI}$ identified for finger vein and face are represented as $\mathcal{V}, \mathcal{F}$ in the remaining manuscript. The use of Gabor kernels is considered for phase congruency feature extraction i.e. $\mathbb{V}^g, \mathbb{F}^g$

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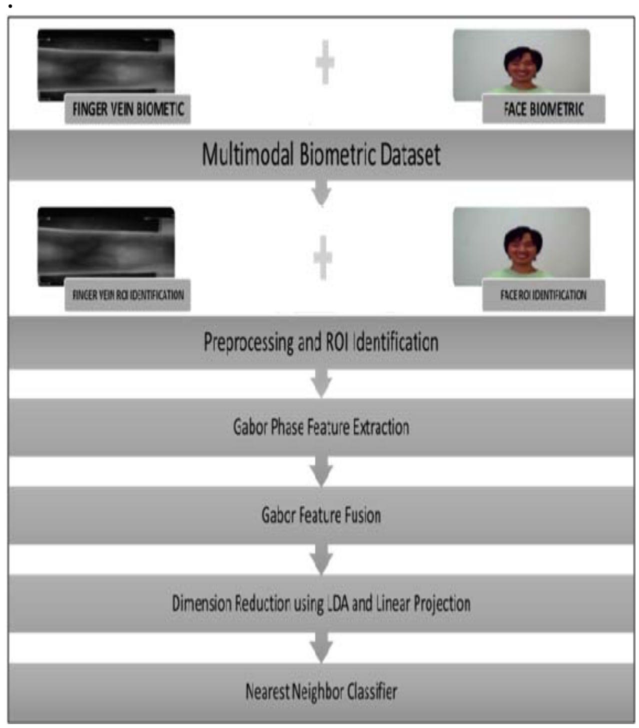

Fig. 1. System Architecture

4.1. Finger Vein Biometric F-ROI Identification

The finger vein biometric image set v can be represented as

$v = \{v_1, v_2, v_3 \ldots v_P\}$	**(2)**

For precise ROI extraction of finger veins, in LDA-PAFF grey scaling, edge detection, ROI area normalization and greyscale normalization techniques are adopted. The grey scaling $_{LDA-PAFF}^{G\_Scale}PP(v_n)$ operation[16] for an image $v_n \in v$ can be defined as

$_{LDA-PAFF}^{G\_Scale}PP(v_n) = \sum^{i=a}\sum^{j=b}([0.2989 \times R(v_n(i,j))] + A + B)$	**(3)**

A=$[0.5870 \times G(v_n(i,j))]$, B=$[0.11400 \times B(v_n(i,j))]$

Where $R(v_n(i,j))$, $G(v_n(i,j))$ and $B(v_n(i,j))$ represent the red, green and blue channel values on the pixel at the location (i,j). The dimensions of the image v_x are represented as $a \times b$ .We have employed the Sobel operator for edge detection on the $_{LDA-PAFF}^{G\_Scale}PP(v_n)$ image with a masking scale of 3×3. The $_{LDA-PAFF}^{Sobel\_Mask}PP$ mask utilized is

$_{LDA-PAFF}^{Sobel\_Mask}PP = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$	**(4)**

The Edge detected images vary in size. To normalize the size of the image to 128×128, bilinear interpolation is adopted [17].

4.2. Face Biometric F-ROI Identification

In LDA-PAFF, the ROI of the face is identified by localization, image segmentation, face region classification and non-face region classifications techniques. The face image dataset f of P number of personnel can be defined as

$f = \{f_1, f_2, f_3 \ldots, f_P\}$	**(5)**

Consider an image $f_n \in f$ represented as a vector $b = \{b_1, b_2, \ldots, b_p\}$, where b_i is the color of i^{th} pixel and p is the total number of pixels. To obtain the face ROI image the vector $A = \{a_1, a_2, \ldots, a_p\}$ needs to be computed, where a_i represents the level to which the particular pixel i^{th} is assigned to. The variable a_i accepts values from the level set $X = \{x_1, x_2, \ldots, x_n\}$. The level set X comprises only two possible levels, either Face or Non-face. The subsequent probability for a for the given b is represented as $L(a|b)$ and is computed using

$L(a\|b) = \dfrac{L(b\|a) + L(a)}{L(b)} \infty L(b\|a)l(a)$	**(6)**

Using the probability $L(a|b)$ the energy facto (EF) for a face or non-face level is

$EF(a) = (-\log L(a\|b) + K) = (\emptyset(a,b) + \psi(a) + K)$	**(7)**

Where $\emptyset(a,b) = -\log L(a|b)$, $\psi(a) = \log L(a)$ and K represents a constant.

The greyscale face ROI dataset constructed is defined as

$F = \{F_1, F_2, F_3 \ldots, F_P\}$	**(8)**

4.3. Multimodal Biometric Feature Extraction Using Gabor Filters and Fusion Set Creation

The use of Gabor kernels for feature extraction have proved to be robust and efficient in personnel biometrics identification systems [18]. In LDA-PAFF the use of Gabor kernels for feature extraction from the multimodal ROI image datasets of Finger Vein and Face is adopted. The magnitude features and the phase features have been considered to define the ROI images. The Gabor kernels are complex band limited filters that enable fine grained localization in the frequency and spatial domain [19]. For a confined frequency band the Gabor kernels enable robust feature extractions in terms of spatially local features, orientation features and multi resolutional features. The Gabor features extracted efficiently negate the varied environmental conditions changes occurring due to

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illumination, intensity, position and orientations. The Gabor kernels relate to the simple cells of the mammalian visual cortex and are thus are relevant from the biological point of few as well [20].
Let us consider an ROI image represented as $I^{ROI}(a,b)$ where $I^{ROI} \in \mathbb{V} \parallel \mathbb{F}$. If the orientation is θ_o, center frequency is f_s then the Gabor kernel is represented by $\mathcal{K}_{s,o}(a,b)$. The feature extraction process in LDA-PAFF is achieved by performing the filtering operation on $I^{ROI}(a,b)$, utilizing the kernel function of size s and orientation o represented as $\mathcal{K}_{s,o}(a,b)$. The feature extraction function $_{LDA-PAFF}^{\mathcal{G}}FE(\mathbb{D}_n) | \mathbb{D}_n \in \mathbb{V} \parallel \mathbb{F}$ can be defined as

$_{LDA-PAFF}^{\mathcal{G}}FE(\mathbb{D}_n) = \mathcal{G}_{s,o}(a,b) = I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)$	**(9)**

The features obtained $\mathcal{G}_{s,o}(a,b)$ are complex in nature and consist of the real and imaginary components defined as

$\mathcal{G}^{re}_{s,o}(a,b) = Re[\mathcal{G}_{s,o}(a,b)] = Re[I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)]$	**(10)**

$\mathcal{G}^{i}_{s,o}(a,b) = Im[\mathcal{G}_{s,o}(a,b)] = Im[I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)]$	**(11)**

It can be observed that the feature vectors obtained for the finger vein and face biometric possess same dimensions and a simple union method is adopted in the LDA-PAFF to create the feature fusion set. The feature fusion set $\mathbb{B}$ can be defined as

$\mathbb{B} = \sum_{n=1}^{\mathcal{P}} (\mathbb{V}_n^{\mathcal{G}} \cup \mathbb{F}_n^{\mathcal{G}})$	**(12)**

4.4. Feature Sub Space Dimensional Reduction

The fusion datasets $\mathbb{B}$ consists of a large number of h data points. The large dimensions of the set $\mathbb{B}$ induce huge computational and space requirements for personnel classification in the LDA-PAFF. The data available in the set $\mathbb{B}$ is considered to encompass g points in c clusters. Each cluster represents a personnel $\wp \in \mathcal{P}$ and is a subspace in the space $\mathbb{B}^h$. Each data point can be represented as

$\{(g_k, c_k)\} \forall k \in h$	**(13)**

Where g_k is the Gabor feature and $g_k \in \mathbb{B}^h$. The class assignment variable is represented as $c_k \in \mathcal{P}$. The Gabor Feature matrix $\mathcal{G} \in \mathbb{B}^{h \times g}$ can be represented as

$\mathcal{G} = \{g_1, g_1, g_2, \dots g_h\}$	**(14)**

To reduce the dimensions of the subspace projection the use of Fisher Scores and Linear Discriminate Analysis is considered in the LDA-PAFF. The Fischer scores [21] enable dimensional reduction. In addition the Fischer Scores optimize the subspace projections by increasing the inter cluster distances and reducing the intra cluster distances. The Linear Discriminate Analysis assists in feature combinations and enables accurate projections of the subspaces [22].

4.5. Classification Using K-Nearest Neighbor

Let the set $\mathcal{T} = \{t_1, \dots, t_{\mathcal{P}}\} \subseteq \mathbb{B}^{\mathcal{P} \times r}$ represent the training set. The training vector $t_z = \{(g_z, p_z)\} \forall z \in \mathcal{P}$ where g_z is the Gabor feature set representing the $p \in \mathcal{P}$ class. The training set $\mathcal{T}$ is considered as the dataset of the registered $\mathcal{P}$ personnel enrolled in the LDA-PAFF. Let $\mathcal{U} = \{u_1, \dots, u_y\} \subseteq \mathbb{B}^{\mathcal{P} \times r}$ represent the unknown or testing dataset and $\mathcal{U} \not\subset \mathcal{T}$. Similar to the training set the testing set vector can be represented as $u_v = \{(g_v, p_v)\} \forall v \in y$ with the class variable p_v is treated as an unknown. The Gabor feature set of the training or testing sets is represented as $g_x = \{g_{1x}, g_{2x}, g_{3x}, \dots g_{rx}\}$.
To identify the unknown class in the test data $\mathcal{U}$ the use of Weighted K Nearest Neighbor Classifier is adopted in the LDA-PAFF . To classify the vectors $u_v \in \mathcal{U}$ the Weighted K Nearest Neighbor ranks the Gabor features of the test vector amongst the Gabor features of the training vectors. Using the rank and the known $\mathcal{P}$ classes of the train data the classifier predicts the unknown personnel class of the test vector using the personnel classes of the

similar neighbors. The similarity amongst the test and train vectors u_p, t_p is computed using

$$ {}^{Classify}_{LDA-PAFF}Sm(u_p, t_p, w_p) = \left(\sum_{f=1}^{r}\{w_{pf} \times t_{pf} \times u_{pf}\}\right) \times \left(\left(\sqrt{\sum_{f=1}^{r}(u_{pf})^2}\right)\left(\sqrt{\sum_{f=1}^{r}(t_{pf})^2}\right)\right)^{-1} \quad (15) $$

Where w is the weight vector, r represents the total number of Gabor Kernel features of the biometric feature under consideration.

A weighing or scoring operation is performed to identify the nearest neighbors of the test vector using the similarity matrix.

$$ {}^{Classify}_{LDA-PAFF}Sc(u_p, \mathcal{P}_p, w_p) = \sum_{t_p \in {}^{Classify}_{LDA-PAFF}nn(u_p)} {}^{Classify}_{LDA-PAFF}Sm(u_p, t_p, w_p)\, {}^{Classify}_{LDA-PAFF}CI(t_p, \mathcal{P}_p) \quad (16) $$

Where ${}^{Classify}_{LDA-PAFF}nn(u_p)$ is the nearest neighbors of the unknown test vector u_p, ${}^{Classify}_{LDA-PAFF}CI(t_p, \mathcal{P}_p)$ is the classification index of the train vector t_p with respect to the personnel class $\mathcal{P}_p$.

5. EXPERIMENTAL STUDY

To evaluate the performance of the LDA-PAFF use of the SDUMLA-HMT multimodal biometric dataset [23] is considered. The SDUMLA-HMT data set consists of five biometric traits namely finger vein, iris, face, fingerprint and gait. The SDUMLA-HMT encompasses biometric traits of 106 personnel. A total of 45 female and 61 males aged between 17 and 31 are the personnel considered in the dataset. To evaluate the performance the use of Finger Vein and Face biometric data from the SDUMLA-HMT dataset is considered. The finger vein data provides data about the ring finger, index finger and middle finger collected over six sessions.

A total of 84 face images per personnel are provided. Personnel accessories, phase and expression variations are considered in the face data. Environmental illumination variations considered data is also provided in the face dataset.

The dataset available is split into training and testing data i.e. T, V. Equal number of train and test images are considered in the finger vein and face data. The dataset used and the construction of the test and train data is summarized in Table 1.

Table 1: SDUMLA-HMT DATA SET PARAMETERS CONSIDERD

Biometric Feature	No of Personnel	Biometric Data Per Personnel	Total Number of Images	Training Data Size	Testing Data Size
Finger Vein	106	36	3816	1908	1908
Face	106	84	8904	4452	4452

The ROI images extracted from the raw train and test data are converted to greyscale images and down sampled to 128×128. The Gabor kernel considered in the LDA-PAFF is constructed using 8 orientations i.e. $o = \{0,1,2,\dots,6,7\}$ and 5 scales i.e. $s = \{0,1,\dots,4\}$ resulting in 40 complex filters. The feature fused data is obtained is dimensionally reduced using the ${}_{LDA-PAFF}^{DR}F\_Feat$ function. A dimensional reduction of about 77% is achieved. The performance evaluation is carried out using Mat lab 2013b on an Intel i5 system.

The Cumulative Match Characteristic(CMC) are computed for the Proposed System and Existing System. The results obtained considering 106 p personnel or ranks is shown in Fig 2 . From Fig 2 it is observed that the Proposed System exhibits a better recognition rate. The CMC analysis is also used to compute the multimodal biometric system recognition rate. The CMC analysis results are summarized in Table 2. The cumulative system

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recognition rates for the Proposed system and Existing systems is shown in Fig 3.

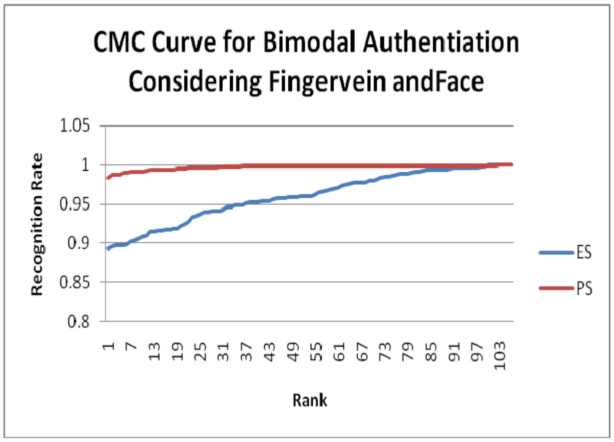

Fig. 2. Performance comparison considering CMC analysis for Bimodal biometric verification

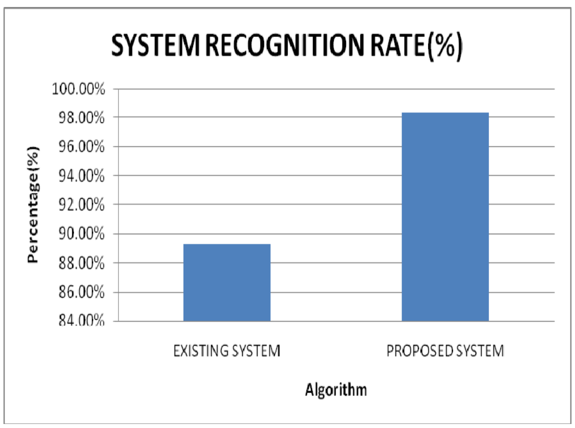

Fig.3. CMC Analysis – Cumulative System Recognition Rate Comparison

Table 2. CMC Analysis Results

ALGORITHM	NO OF PERSONNEL/RANKS	SYSTEM RECOGNITION RATE
Existing System	106	89.31%
Proposed System	106	98.43%

To evaluate the performance of the Proposed system and Existing System receiver operating characteristics (ROC) were computed. The ROC curves obtained is shown in Fig 4 of this paper. From the figure the performance improvement considering the proposed Bimodal is evident considering the vein and face dataset. The average recognition rate of Proposed system is around 92.89 and of the Existing is around 90.83 as shown in Fig 5. The ROC computation results are summarized in Table 3 of this paper.

The classification error statistics computed is graphically displayed in Fig 6. The receiver operating characteristics analysis can also be used to compute the verification rate normalized between 0-1 and the False Acceptance Rate. The false acceptance rate results are shown Fig 7. The performance improvement considering the Proposed System is clear from the results shown.

Table 3. ROC computation results of Proposed System and *Existing system*

ALGORITHM	ROC CLASSIFICATION ERROR (%)	ROC AVERAGE RECOGNITION RATE(%)	ROC FALSE ACCEPTANCE RATE (FAR %)
Existing System	5.13	90.83	5.12
Proposed System	0.74	92.89	0.74

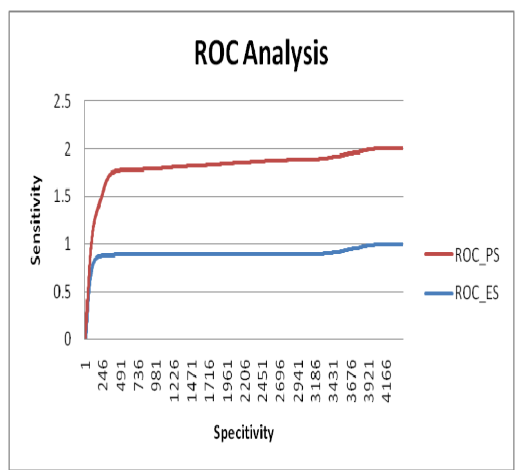

Fig .4. ROC Analysis Comparison Considering SDUMLA-HMT Dataset

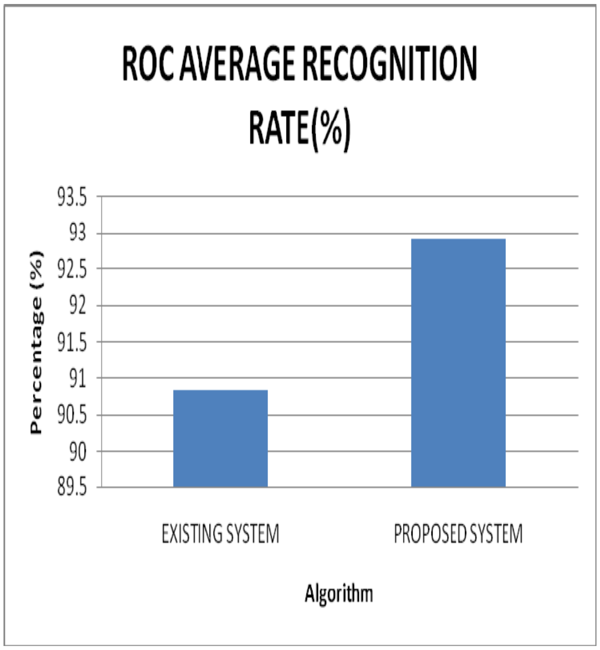

Fig.5.ROC Analysis – Average Recognition Rate Comparison

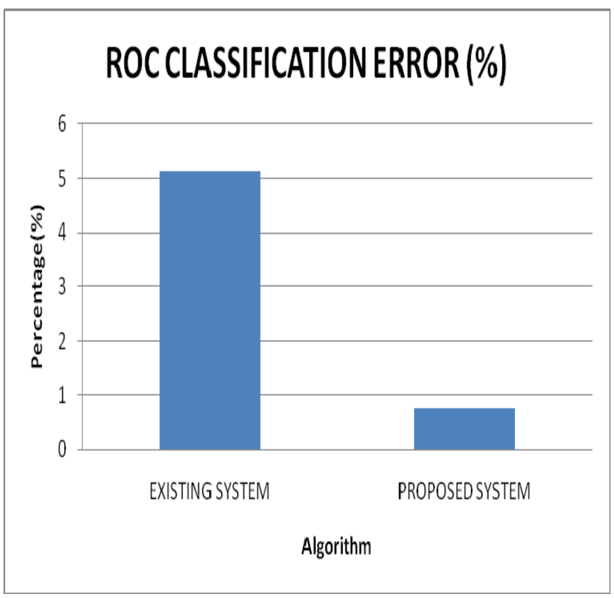

Fig.6.ROC Analysis – Classification Error Comparison

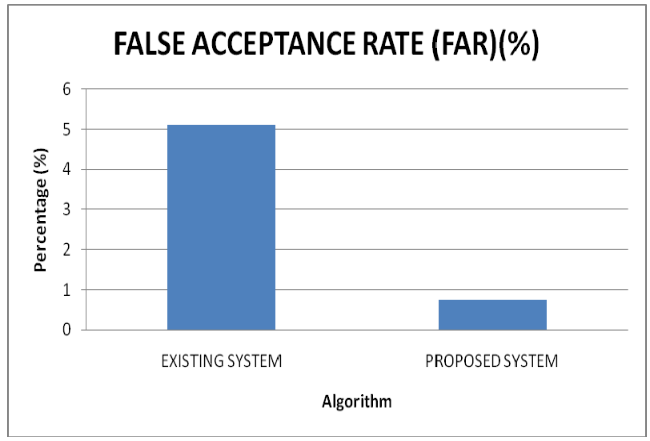

Fig.7.ROC Analysis – False Acceptance Comparison

The EPC analysis is used to compute the unbiased estimates of verification performance of the Existing System and Proposed System . The results obtained is shown in Fig. 8. The average Half total error rate considering the proposed system is 0.004% compared to the half total error rate of 0.051% observed considering the existing system. Based on the analysis carried out and the results presented it can be concluded that the proposed is robust and exhibits better user verification when compared to the existing mechanism.

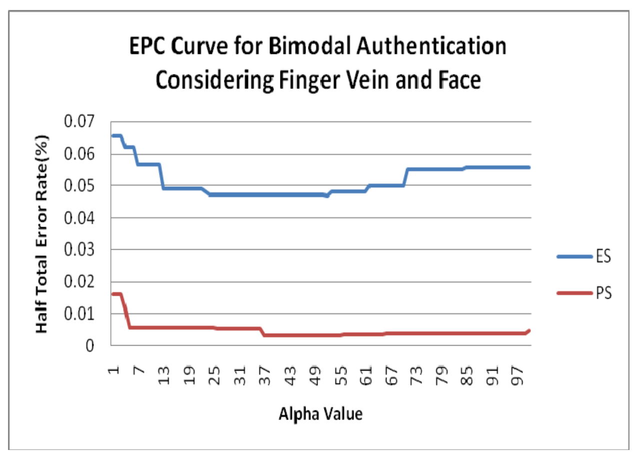

Fig. 8. Performance comparison considering EPC analysis for Bimodal Authentication

6. Conclusions

The use of biometrics for personnel identification is very common. The unimodal biometric recognition systems suffer from a number of drawbacks discussed in this paper. To over-come these drawbacks the LDA-PAFF is introduced in this paper. The LDA-PAFF considers the finger vein and face biometric traits for enrolment and recognitions of personnel into the system. The raw data obtained from the biometric sensors are preprocessed to obtain the relevant ROI'S. The use of Gabor Kernels is considered for feature extraction. The magnitude and phase features are considered. Limited work is carried out considering both these features for extraction in multimodal biometric systems. Fischer score and linear discriminate Analysis is considered for dimensional reduction. Feature dimension reduction of 77% is achieved using this methodology. For personnel verification the weighted k-nearest neighbor classifier is used. SDUMLA-HMT multimodal biometric dataset is used for performance evaluation.

The future of the work presented in this paper is consideration of additional biometric traits and additional biometric trait combinations for building robust and reliable recognition systems for personnel identification.

REFERENCES

[1]. Monwar M and Gavrilova, M.L., "Multimodal Biometric System Using Rank-Level Fusion Approach," IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 39, no. 4, pp. 867-878, Aug 2009.

[2] A. Ross and A. K. Jain, "Multimodal biometrics: an overview," Proc.European Signal Processing Conference, pp. 1221-1224, Vienna, Austria, Sept 2004.

[3] A. Ross, K. Nandakumar, and A. K. Jain, Handbook of Multibiometrics, Springer, 2006.

[4] Golfarelli, M. Maio, D. Malton, D., "On the error-reject trade-off in biometric verification systems," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 786-796, July 1997.

[5] P. Krishnasamy, S. Belongie, and D. Kriegman, "Wet fingerprint recognition:Challenges and opportunities," International Joint Conference on Biometrics, Washington DC, USA, pp. 1-7, Oct 2011.

[6] L. Hong, A. K. Jain, and S. Pankanti, "Can multibiometrics improve performance," in Proceedings AutoID'99, (Summit(NJ), USA), pp. 59-64, Oct 1999.

[7] Shekhar S. Patel V.M. Nasrabadi N.M. Chellappa R., "Joint Sparse Representation for Robust Multimodal Biometrics Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 1, pp. 113-126, Jan 2014.

[8] Chengjun Liu, Wechsler H, "Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition," IEEE Transactions on Image Processing, vol. 11, no. 4, pp. 467-476, Apr 2002.

[9] Struc, V, Vesnicer B,Pavesic, N, "The Phase-based Gabor Fisher Classifier and its application to face recognition under varying illumination conditions," 2nd International Conference on Signal Processing and Communication Systems, ICSPCS 2008., pp. 1,6, 15-17 Dec 2008.

[10] S. Gundimada, V. K. Asari, and N. Gudur, "Face recognition in multi-sensor images based on a novel modular feature selection technique," Information Fusion, vol. 11, no. 2, pp.124-132, 2010.

[11] Laiyun Qing, Shiguang Shan,Xilin Chen, Wen Gao, "Face Recognition under Varying Lighting Based on the Probabilistic Model of Gabor Phase," 18th International Conference on Pattern Recognition, ICPR 2006, vol.3, pp.1139-1142, 2006.

[12] SÌŒ. Vitomir P. Nikola et al, "The complete gabor-fisher classifier for robust face recognition," EURASIP Journal on Advances in Signal Processing, 2010.

[13] Zhenhua Chai, Zhenan Sun, Mendez-Vazquez, H, Ran He, Tieniu Tan, "Gabor Ordinal Measures for Face Recognition," IEEE Transactions on Information Forensics and Security, vol. 9, no. 1, pp.14-26, Jan. 2014.

https://sites.google.com/site/ijcsis/
ISSN 1947-5500

[14] Nicolo, F, Schmid, N.A, "Long Range Cross-Spectral Face Recognition: Matching SWIR Against Visible Light Images," IEEE Transactions on Information Forensics and Security, vol. 7, no. 6, pp.1717-1726, Dec. 2012.

[15] Faten bellakhdhar, Mossaad ben ayed, Kais loukil,Faouzi bouchhima and Mohamed abid."Multimodal biometric identification system based on face and fingerprint", Proceedings Engineering & Technology, vol. 3, pp. 219-222, 2013.

[16] Ruksar Fatima, Mohammed Zafar Ali Khan, A. Govardhan and Kashyap D Dhruve. *"Computer Aided Multi-Parameter Extraction System to Aid Early Detection of Skin Cancer Melanoma"*, International Journal of computer Science & Network Security, vol. 12 ,no. 10, pp. 74-86, Oct2012.

[17] De Oliveira, J.J., Jr.; Veloso, L.R.; de Carvalho, J.M., *"Interpolation/decimation scheme applied to size normalization of character images,"* 15th International Conference on Pattern Recognition, vol. 2, pp.577-580,2000.

[18] Weitao Li, Kezhi Mao, Hong Zhang, Tianyou Chai, *"Selection of Gabor filters for improved texture feature extraction,"* 17th IEEE International Conference on Image Processing (ICIP), pp.361-364, 26-29 Sept. 2010.

[19] Chengjun Liu, Wechsler H, *"Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition,"* IEEE Transactions on Image Processing, vol.11, no.4, pp.467-476, Apr 2002.

[20] J. G . Daugman, *"Uncertainty relation for resolution in space, spatial frequency, and orientation optimized by two-dimensional visual cortical filters"*, JOSA A, 2(7):1160–1169, July 1985.{R11}

[21] Fukunaga K," *Introduction to statistical pattern recognition (2nd ed.)",*. Academic Press Professional, Inc., San Diego, CA, USA (1990).

[22] R. O. Duda P E H, Stork D G, Pattern Classification. Wiley-Interscience Publication-2001.

[23] Yilong Yin, Lili Liu and Xiwei Sun ,"SDUMLA-HMT: A Multimodal Biometric Database", LNCS 7098, pp. 260–268, 2011.

[24] Manjunathswamy B E, Thriveni J, K. R. Venugopal, L. M. Patnaik, "Efficient Iris Retrieval Using Neural Networks", IEEE NUICONE 2012, at Nirma University Ahemedabad, India, December 06-08, 2012.

[25] Manjunathswamy B E, Appaji M Abhishek, Thriveni J, K. R. Venugopal, L. M. Patnaik, "Multimodel Biometrics Using ECG and Fingerprint", International Conference on Advances in Communication Network and Computing-CNC, at Chennai, India, February 21-22, 2014.

[26] Manjunathswamy B E, Thriveni J, K. R. Venugopal, L. M. Patnaik, "MultiModel Personal Authentication Using Finger Vein and Iris Images(MPAFII)", Fifth International Conference on Advances in Computer Engineering-ACE, at Kochi, India, December 26-27, 2014.

[27] Manjunathswamy B E, Thriveni J, K. R. Venugopal, L. M. Patnaik, "MultiModel Personal Authentication Using Finger Vein and Face Images(MPAFFI)", Third International Conference on Parallel, Distributed and Grid Computing-PDGC, at Waknaghat, Solan, Himachal Pradesh, India, December 11-13, 2014.

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