MULTIMODEL PERSONAL AUTHENTICATION USING FINGER VEIN AND IRIS IMAGES (MPAFII)

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ABSTRACT: Biometric based identifications are widely used for personnel identification in the world. The unimodal recognition systems has many more disadvantages such as noisy data, spoofing attacks, biometric sensor data quality etc., Robust personnel recognition can be achieved using multimodal biometric traits. This paper introduces the Multimodal Personnel Authentication using Finger vein and Iris Images ($MPAFII$) considering the Finger Vein and Iris biometric traits. The use of 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 $MPAFII$ is compared with the existing recognition systems and the performance improvement is proved through the results obtained in this work.

KEYWORDS: SDUMLA_HMT, Finger Vein, Iris, Gabor filter, LDA, MPAFFI.

INTRODUCTION

The use of biometrics identification system is widely used in recent days to identify individual feature traits. A biometric recognition system identifies varied personnel using one or more specific physiological characteristics possessed by the individual [1]. If one physiological characteristics is considered for recognition then that system is termed as unimodal recognition system. When multiple or a combination of each individual biometrics are considered then that systems are termed as multimodal biometric recognition system. Enrollment and verification of authorized personnel are the important functions of the recognition systems.

The recognition systems identifies each individuals based on the data provided from the biometric sensor and the data are been stored for future verification, matching and identification. During verification the recognition systems check if the individuals data presented in the database are valid or invalid. Predominantly unimodal identification systems are used for individuals identification [2].

KEY CHALLENGES IN UNIMODAL BIOMETIC SYSTEMS

The unimodal biometric recognition systems currently suffer from a large number of drawbacks [2][3][4]. Biometric recognition systems widely depend on the data acquired from biometric sensors. The data sets presented to the recognition systems from the sensors are generally noisy in nature which can affect the verification results and also cause faulty enrollment techniques. Interpersonal biometric similarities is another disadvantage of unimodal biometric systems [4][5]. Considering the finger print the research work presented in [5] clearly demonstrates the biometric similarity problem. Spoofing attacks can also cause errors in unimodal recognition systems. Spoofing attacks or noisy data commonly notices when biometrics like signature, voice and finger prints are considered [2].

MOTIVATION

The use of multimodal biometric recognition systems to overcome the drawbacks of the unimodal recognition systems have proved to be successful [6][7]. Considering the research findings, this paper introduces a Multimodal Personnel Authentication using Finger Vein and Iris Images($MPAFII$). The state of art work presented by Shekar et al., [7] considers the Iris, Finger print and Face biometrics for recognition. In $MPAFII$ the finger vein and iris biometric is considered for recognition.

CONTRIBUTION

The $MPAFII$ is a multimodal recognition system. Limited work has been carried out by researchers considering such a comprehensive set of biometric features of personnel[8] [9] [10] [11]. The novelty of $MPAFII$ is that both the phase features and magnitude feature are considered. The research work carried out by other researchers considers either the magnitude features [8] [9] or the phase features [10] [11]. Limited work is carried out considering a combination of the phase and magnitude features for multimodal biometric recognition systems [12][13][14].

For dimensional reduction the use of Fisher Score and Linear Discriminate Analysis is considered[22]. Fischer score enables efficient dimensional reduction, Linear Discriminate Analysis enables feature combinations and effective sub space projections of the personnel clusters[15]. The multimodal biometric i.e finger Vein and Iris are fused using a linear fusion scheme in $MPAFII$. The use of the weighted K Nearest Neighbor classifier is considered for verification or classification.

ORGANIZATION

The manuscript is organized as follows. Section 2 discusses the related work. The background is discussed in Section 3. The $MPAFII$ 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.

Related Work

A number of researches have been done till 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:

Muhammad Imran et al., [9] developed a multimodal biometric system comprising face and finger veins detection approach for enhancing biometric identification system. In their system they proposed a multilevel score fusion paradigm for face and finger veins for facilitating higher accuracy and ultimately, they exhibited better results in terms of reduction in the false rejection rate. **Faten et al., [10]** developed a bimodal biometric identification system with face and fingerprint identification. In their work, they explored the advantages of the ability of individual biometrics score and efficiency. The authors advocated a scheme for evaluating a binary classification schemes with SVM to exhibit score fusion. The positive result of this system was its accuracy.

SumitShekhar et al., [11] developed a multimodal sparse depiction approach that illustrates the test data using a sparse linear combination of training data. In their research they taken into consideration of the correlations as well as the coupling of varied information in different models under use. In order to achieve non-linearity they employed Kernels and further they enhanced their system using an alternative directional approach.

Zhenhua Chai et al., [12] employed Gabor ordinal measures (GOM) scheme for face feature extraction and they enhanced the system using Gabor features with the effectiveness of ordinal estimations as a potential solution that could ensure both inter-person resemblance and intra-person deviations for face image data. In their system they employed varied categories of ordinal estimations derived from its intensity, phase, magnitude and real and imaginary components of Gabor filter. Ultimately, they employed a two phase cascade learning scheme and a greedy block selection approach that could be employed for training certain classifier for face data. In their research they emphasized on face recognition accuracy.

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.

BACKGROUND WORK

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[22]. 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 made it enhanced 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.

On the contrary the implementation of traditional LDA doesn't ensure optimal results. Therefore these all 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 neighbour classification system which makes the system optimal in terms of accuracy, efficiency and overall performance.

PROPOSED SYSTEM

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 Iris can be defined as

$$\mathbb{B} = \{\mathbb{V}^{\mathcal{G}} \cup \mathbb{I}^{\mathcal{G}}\} \quad (1)$$

Where $\mathbb{V}^{\mathcal{G}}$ is the phase features for the finger vein, $\mathbb{I}^{\mathcal{G}}$ is the phase feature set for the iris biometric

The $MPAFII$ proposed in this paper considers primarily two biometric features of $\mathcal{P}$ personnel namely the finger vein$(\mathbb{v})$ and iris$(\mathbb{i})$. Preprocessing is adopted on all the raw biometric images to obtain the regions of interest(ROI). The ROI identification procedures adopted is discussed in the future section of the paper. The ROI identified for finger vein and iris are represented as $\mathbb{V}, \mathbb{I}$, in the remaining manuscript. The use of Gabor kernels is considered for phase congruency feature extraction i.e. $\mathrm{V}^{\mathrm{G}}, \mathrm{I}^{\mathrm{G}}$.

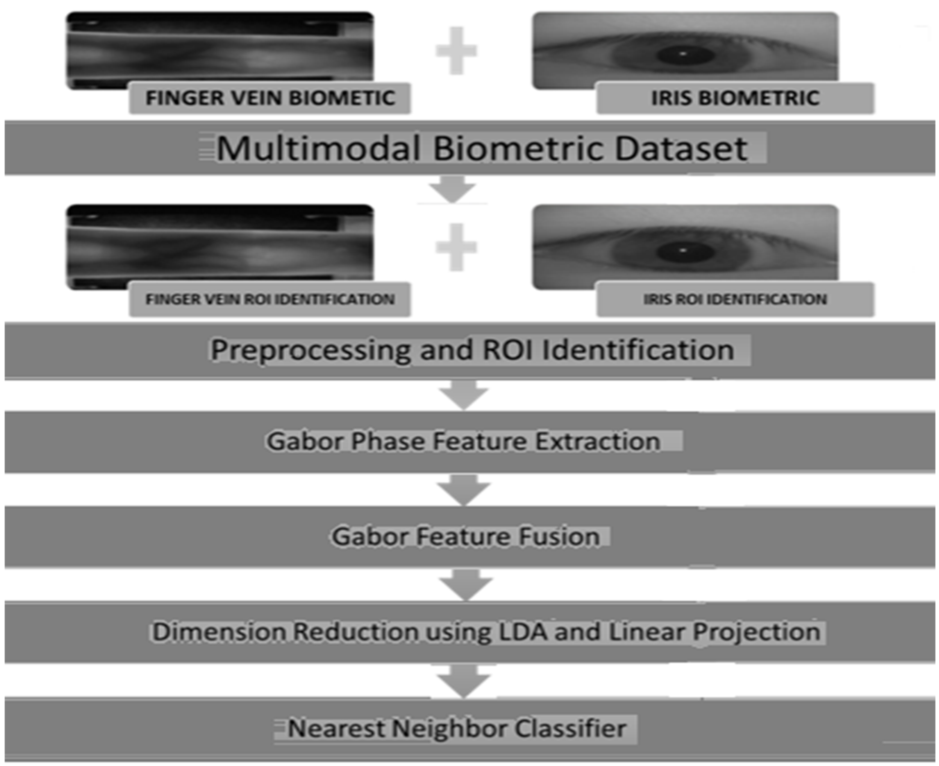

Fig. 1. System Architecture

Fig 1 shows the Proposed System Architecture consists of many steps followed by multimodal dataset, preprocessing and ROI identification ,Gabor Phase feature extraction, Gabor feature fusion, dimension reduction using LDA and linear projection, Nearest neighbor classifier.

Finger Vein Biometric $\mathbb{F} - \boldsymbol{ROI}$ Identification

The finger vein biometric image set $\mathbb{v}$ can be represented as

$$\mathbb{v} = \{\mathbb{v}_1, \mathbb{v}_2, \mathbb{v}_3 \ldots\ldots \mathbb{v}_{\mathcal{P}}\} \quad (1)$$

For precise ROI extraction of finger veins, in $MPAFII$ grey scaling, edge detection, ROI area normalization and greyscale normalization techniques are adopted.

The grey scaling ${}^{G\_Scale}_{MPAFII}PP(\mathbb{v}_n)$ operation[16] for an image $\mathbb{v}_n \in \mathbb{v}$ can be defined as

$$ {}^{G\_Scale}_{MPAFII}PP(\mathbb{v}_n) = \sum^{i=a}\sum^{j=b}\Big(\big[0.2989 \times R\big(\mathbb{v}_n(i,j)\big)\big] + \big[0.5870 \times G\big(\mathbb{v}_n(i,j)\big)\big] + \big[0.11400 \times B\big(\mathbb{v}_n(i,j)\big)\big]\Big) \quad (2)$$

Where $R\big(\mathbb{v}_n(i,j)\big)$, $G\big(\mathbb{v}_n(i,j)\big)$ and $B\big(\mathbb{v}_n(i,j)\big)$ represent the red, green and blue channel values on the pixel at the location(i,j) . The dimensions of the image $\mathbb{v}_n$ are represented as $a \times b$.

We have employed the Sobel operator for edge detection on the ${}^{G\_Scale}_{MPAFII}PP(\mathbb{v}_n)$ image with a masking scale of 3×3. The ${}^{Sobel\_Mask}_{MPAFII}PP$ mask utilized is

$$ {}^{Sobel\_Mask}_{MPAFII}PP = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (3)$$

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

Post image normalization gray scale normalization $\left({}^{Gray\_Norm}_{MPAFII}PP\right)$ is adopted. If $N_{Norm}(i,j)$ represents the grey value at pixel(i,j), G_{min} is the minimum grey value of $\mathbb{v}_n$ and the maximum gray value of $\mathbb{v}_n$ is given by G_{max} then the function ${}^{Gray\_Norm}_{MPAFII}PP$ can be defined as.

$$ {}^{Gray\_Norm}_{MPAFII}PP(\mathbb{v}_n) = \sum^{i=a}\sum^{j=b}\left(\frac{N_{Norm}(i,j) - G_{min}}{G_{max} - G_{min}}\right) \quad (4)$$

The resultant image $\mathbb{V}_n$ is the ROI to be considered for feature extraction from $\mathbb{v}_n$. i.e. $\mathbb{V}_n = {}^{Gray\_Norm}_{MPAFII}PP(\mathbb{v}_n)$. The finger vein ROI dataset obtained $\forall\, n \in \mathcal{P}$ is defined as follows.

$$\mathbb{V} = \{\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3 \ldots\ldots \mathbb{V}_{\mathcal{P}}\} \quad (5)$$

Iris Biometric $\mathbb{I} - \boldsymbol{ROI}$ Identification

To obtain the iris ROI for the n^{th} personnel i.e. $\mathbb{I}_n : \forall\, n \in \mathcal{P}$ from $\mathbb{i}_n$ using segmentation, normalization, illumination compensation and image enhancement. The iris dataset $\mathbb{i}_n$ is defined as follows

$$\mathbb{i} = \{\mathbb{i}_1, \mathbb{i}_2, \mathbb{i}_3 \ldots\ldots \mathbb{i}_{\mathcal{P}}\} \quad (6)$$

To identify the circular iris and the circular pupil regions edge detection techniques [18] and Hough transforms [19] are adopted. The pupil region of $\mathbb{i}_n$ is darker when compared to the other regions. The iris image i.e. $\mathbb{i}_n$ is projected in the horizontal and vertical direction to obtain the center of the pupil. The minima of the projections in the horizontal and vertical direction provide the center coordinates of the pupil regions and the function ${}^{Iris\_pupilCoord}_{MPAFII}PP(\mathbb{i}_n)$ is defined as

$${}^{Iris\_pupilCoord}_{MPAFII}PP(\mathbb{i}_n) = \left[\left(\arg\min_i\left(\sum_j \mathbb{i}_n(i,j)\right)\right), \left(\arg\min_j\left(\sum_i \mathbb{i}_n(i,j)\right)\right)\right] \quad (7)$$

The pupil coordinates identified and the circular iris region segmented from $\mathbb{i}$ exhibit position, illumination, orientation and dimension variations. The normalization technique [20] adopted is basically projecting the i^{th} and j^{th} Cartesian coordinates of the iris region to the non-centric $(\mathscr{r}, \theta)$ polar coordinate system. Let $\left(i_{pupil}(\theta), j_{pupil}(\theta)\right), \left(i_{iris}(\theta), j_{iris}(\theta)\right)$ represent the outer boundary point sets of pupil and iris then the projection for normalization can be defined as

$${}^{Iris\_norm}_{MPAFII}PP(\mathbb{i}_n) = \mathbb{i}_n\left(i(\mathscr{r},\theta), j(\mathscr{r},\theta)\right) \Longrightarrow \mathbb{i}_n(\mathscr{r},\theta) \quad (8)$$

Where $i(\mathscr{r},\theta), j(\mathscr{r},\theta)$ represent the linear combinations of the sets $\left(i_{pupil}(\theta), j_{pupil}(\theta)\right), \left(i_{iris}(\theta), j_{iris}(\theta)\right)$ and is defined as

$$\begin{aligned} i(\mathscr{r},\theta) &= \left(\left(\mathscr{r} \times i_{iris}(\theta)\right) + \left((1-\mathscr{r}) \times i_{pupil}(\theta)\right)\right) \\ j(\mathscr{r},\theta) &= \left(\left(\mathscr{r} \times j_{iris}(\theta)\right) + \left((1-\mathscr{r}) \times j_{pupil}(\theta)\right)\right) \end{aligned} \quad (9)$$

The normalized image ${}^{Iris\_norm}_{MPAFII}PP(\mathbb{i}_n)$ has a low contrast and the illumination effects are not neutralized. To enhance the image quality and account for the illumination variations the equalization technique [21] is adopted. The pixel intensities of the normalized image is constrained by the set $\{0,1,2,\cdots(P^{Intsty\_Max}-1)\}$. $P^{Intsty\_Max} = 256$ is the maximum pixel intensity of the normalized image. The discrete function to represent the normalized histogram of the ${}^{Iris\_norm}_{MPAFII}PP(v)$ is defined as

$${}^{NormInt\_Hst}_{MPAFII}PP(v) = Pxl_v \quad (10)$$

Where Pxl_v is the total number of pixels having the intensity value v and $v \in \{0,1,2,\cdots(P^{Intsty\_Max}-1)\}$

The normalization applied to the image with respect to the pixels is defined as

$${}^{NormPxl\_Hst}_{MPAFII}PP(v) = \frac{Pxl_v}{i \times j}$$	(11)

The enhanced and the illumination compensated image or iris ROI image pixel value (i, j) can be computed using

$${}^{IrisEnhcd}_{MPAFII}PP(\mathbb{I}_n(i,j)) = Round\left((P^{Intsty\_Max} - 1) \times \left(\sum_{v=0}^{\mathbb{I}_n(i,j)} {}^{NormPxl\_Hst}_{MPAFII}PP(v) \right) \right)$$	(12)

The iris ROI data set $\mathbb{I}$ is constructed post the enhancement and illumination compensation process and is defined as

$$\mathbb{I} = \{\mathbb{I}_1, \mathbb{I}_2, \mathbb{I}_3 \ldots \ldots \mathbb{I}_{\mathcal{P}}\}$$	(13)

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 $MPAFII$ the use of Gabor kernels for feature extraction from the multimodal ROI image datasets of Finger Vein, Iris 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 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 $MPAFII$ 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 ${}^{\mathcal{G}}_{MPAFII}FE(\mathbb{D}_n): \mathbb{D}_n \in \mathbb{V} \parallel \mathbb{F}$ can be defined as

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

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

$$\mathcal{G}^{r}_{s,o}(a,b) = Re[\mathcal{G}_{s,o}(a,b)] = Re[I^{ROI}(a,b) * \mathcal{K}_{s,o}(a,b)]$$	(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 $MPAFII$ to create the feature fusion set. The feature fusion set $\mathbb{B}$ can be defined as

$$\mathbb{B} = \sum_{P=1}^{\mathcal{P}} \left(\mathbb{V}_P^{\mathcal{G}} \cup \mathbb{F}_P^{\mathcal{G}}\right) \tag{12}$$

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 $MPAFII$ The data available in the set $\mathbb{B}$ is considered to encompass $\mathcal{g}$ points in c clusters. Each cluster represents a personnel $\mathcal{p} \in \mathcal{P}$ and is a subspace in the space $\mathbb{B}^h$. Each data point can be represented as

$$\{(\mathcal{g}_k, c_k)\} \forall\ k \in h \tag{13}$$

Where $\mathcal{g}_k$ is the Gabor feature and $\mathcal{g}_k \in \mathbb{B}^h$. The class assignment variable is represented as $c_k \in \mathcal{P}$.

The Gabor Feature matrix $\mathcal{G} \in \mathbb{B}^{h \times p}$ can be represented as

$$\mathcal{G} = \{\mathcal{g}_1, \mathcal{g}_1, \mathcal{g}_3, \ldots\ \mathcal{g}_h\} \tag{14}$$

To reduce the dimensions of the subspace projection the use of Fisher Scores and Linear Discriminant Analysis is considered in the $MPAFII$. 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 Discriminant Analysis assists in feature combinations and enables accurate projections of the subspaces [22].

Classification Using K-Nearest Neighbor

Let the set $T = \{t_1, \cdots, t_{\mathcal{P}}\} \subset \mathbb{B}^{p \times r}$ represent the training set. The training vector $t_z = \{(\mathcal{g}_z, p_z)\} \forall\ z \in \mathcal{P}$ where $\mathcal{g}_z$ is the Gabor feature set representing the $p \in \mathcal{P}$ class. The training set T is considered as the dataset of the registered $\mathcal{P}$ personnel enrolled in the $MPAFII$. Let $U = \{u_1, \ldots, u_y\} \subset \mathbb{B}^{p \times r}$ represent the unknown or testing dataset and $U \not\subset T$. Similar to the training set the testing set vector can be represented as $u_v = \{(\mathcal{g}_v, p_v)\} \forall\ v \in y$ with the class variable p_v is treated as an unknown. The Gabor feature set of the training or testing sets is represented as $\mathcal{g}_x = \{\mathcal{g}_{1x}, \mathcal{g}_{2x}, \mathcal{g}_{3x}, \ldots\ \mathcal{g}_{rx}\}$.

To identify the unknown class in the test data U the use of Weighted K Nearest Neighbor Classifier is adopted in the $MPAFII$. To classify the vectors $u_v \in U$ 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

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

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.

$$\underset{MPAFII}{\overset{Classify}{}}Sc(u_p, \mathcal{P}_p, w_p) = \sum_{t_p \in \underset{MPAFII}{\overset{Classify}{}}nn(u_p)} \underset{MPAFII}{\overset{Classify}{}}Sm(u_p, t_p, w_p) \underset{MPAFII}{\overset{Classify}{}}CI(t_p, \mathcal{P}_p) \quad (16)$$

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

EXPERIMENTAL STUDY

To evaluate the performance of the $MPAFII$ the 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, Iris 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.

The iris data in the SDUMLA-HMT dataset is captured in near infrared illumination environments. Five iris samples per eye per personnel is provided in the dataset. The dataset available is split into training and testing data i.e. T, U. Equal number of train and test images are considered in the finger vein and iris data. Six images per personnel (i.e. three left eye and three right eye) are considered for the iris training dataset. 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
Iris	106	10	1060	636	424

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 $MPAFII$ 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

${}_{MPAFII}^{DR}F\_Feat$ function. A dimensional reduction of about 77% is achieved. The performance evaluation is carried out using Matlab 2013b on an Intel i5 system.

Table 2: Recognition Rate

Recognition Rate	
Existing System	Proposed System
81.3	93.02

Table 2 shows the Recognition Rate between existing and proposed system. The proposed method is computationally efficient when compared to the existing approach and also shown the same Graphically in Fig 2.

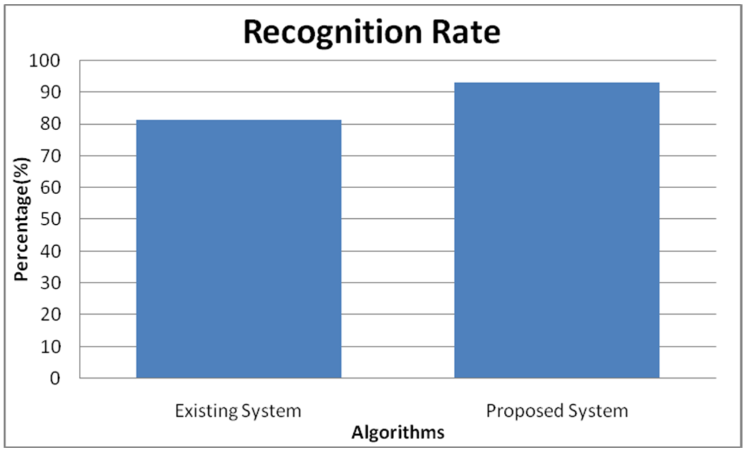

Fig.2. Comparison between Existing and proposed Systems

Table 3 shows the performance evaluation metrics of proposed and existing systems. It consists of error in classification and false acceptance rate for Evaluation data (ED) and also consists of error in classification and false acceptance rate for Training data (TD).

Table 3: Performance Evaluation Metrics

Performance Evaluation Metrics		
	Existing System(%)	Proposed System(%)
Error in Classification(ED)	0	46.75
False Acceptance Rate(ED)	0.94	0.2
Error in Classification(TD)	0	46.75
False Acceptance Rate(TD)	0.94	0.2

CONCLUSIONS

The use of biometric recognition in individual identification is very common. The unimodal biometric recognition systems suffer from a number of disadvantages discussed in this paper. To over-come these disadvantages the $MPAFII$ is introduced in this paper. The $MPAFII$ considers the finger vein and iris 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 and recognition.

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.

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