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Enhancing the Accuracy of Bimodal Feature Recognition using Deep Learning Techniques

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Abstract

Human recognition through multimodal biometrics has become an emerging trend. Multimodal biometric advancements achieves high authentication and hence are being attracted by the researchers to ameliorate the performance and accuracy of human recognition. Human face can well exhibit the emotions, behavior, age, expressions and more precisely, it replicates the human brain. Iris biometrics has a high stability rate and cannot be compromised easily. In this paper, a new approach is proposed to enhance the accuracy of human recognition based on the match score fusion of iris and face biometric traits through deep learning feature extractor, Autoencoder and Extreme Learning Machine (ELM) matcher. ELM is executed on the extracted features of face and iris traits to generate the individual match scores. The scores are then fused to amplify the recognition accuracy. The experiments are conducted on CASIA and FEI datasets. The results demonstrated a high level of accuracy and effectiveness of the proposed system.

Keywords: Autolncoders; Extreme learning machine; Gabor Filter; Match score fusion;

I. INTRODUCTION

Human recognition deals with metrics of both physical and behavioral traits of an individual to assure high authentication after seeking their assistance. Face, iris, fingerprint and retina are physiological traits of the human body, while signature, voice and gait are the dynamic behavioral traits of the human body. Face is considered as a replica of the human brain and it is captured from a certain distance without any great manual effort. Iris is the high recognition accuracy trait, which helps in unique identification of an individual and has a unique structure which is amenable to remote examination with the help of vision systems.

As the innovation world emerges, difficulties to execute secure individual identification conventions with biometric innovation are expanding and the requirement for accurate human recognition is also increasing in various businesses over the world. In biometric systems, individual's physiological or behavioral features are used for the identification and verification of an authorized person. These features are classified into single modal biometric systems and multimodal biometric systems. Traditional authorization systems like passwords, ID cards and tokens recognize the user based on proof of knowledge. These tokens and ID systems are easily stolen by a different techniques, algorithms and equipment's. Unlike traditional systems, biometric system possess various qualities like universality, uniqueness, permanence, measurability, performance, acceptability and circumvention which aids to achieve the higher accuracy and performance in human identification system. Biometric features cannot be stolen, forgotten or easily forged. Parallel advancement of the biometric identification team has recognized that utilization of a solitary equipment methodology for identification purposes may never again be the wisest decision for some businesses. Theoretically unimodal or single modal biometric system is very useful but in reality it faces many limitations like.

A. Environment

This is the major parameter in acquiring the biometric data. If there is no proper environment this may have an effect on the system performance to identify an individual.

For example: The accuracy of fingerprint and face recognition system are affected by noise, illumination, saturation and different facial expressions.

B. Noise in sensed data

This makes a high impact on the biometric data which leads to increase in false rejection rate. It could be from improperly functioning or defective sensors.

For example: Dirt on the finger print or on the sensors may lead to noise in the acquired biometric data.

C. Intra class variation

Due to misplacement of biometric data causes mismatch between the enrolled data and authenticated data.

For example: Facial data acquired from an individual during authentication may vary from the enrolled data which helps in template generation due to different facial expressions. Similarly, due to misplacement of the finger on the acquiring device, it may affect the matching process between the enrolled data and authenticated data.

D. Non-Universality

A few people can't physically give an independent biometric accreditation because of sickness or inabilities or due to accidents.

E. Spoofing

An impostor may endeavor to spoof the biometric characteristic of a legitimate user with a specific end goal that leads to many disasters.

Some of the above problems of unimodal or single modal biometrics are addressed by the multimodal biometric systems. These are anticipated to more reliable due to the fusion of two or more independent traits as an individual system. Input data to these systems is acquired by single or multiple sensors for measuring the two or more different modality characteristics. For example a system which combines a face and iris biometric traits are acquired from a single or multiple scanning devices. By fusing the two or more biometric traits help to increase the recognition rate, which is more suitable for various applications. The various types of multi modal biometric systems are

A. Multi algorithm biometric system

It uses single biometric data acquired from a single sensor then after process with two or more distinct algorithms.

B. Multi instance biometric system

It uses one or more sensors to capture the two or more samples of the same biometric trait.

For example: Acquiring the multiple fingers.

C. Multi sensorial biometric system

It uses different sensors to capture the single trait and processes them with single or different algorithms.

Hence, using the above systems yield to form more than one decision as outcomes. Such decisions are combined to form a single system known as biometric fusion. This fusion helps to minimize the weakness of individual traits and ameliorate the strength of the system. It also addresses the various challenges faced in biometric implementation like accuracy, robustness, efficiency and universality. The various biometric traits are fused in various levels like sensor level fusion, feature level fusion, match score level fusion and decision level fusion in order to maximize the robustness of the multimodal biometric system. This also provides various additional advantages in the individual identification system [17]-[19]-[21].

The exactness of recognizing an individual increases fundamentally when multi-modular biometrics are utilized. It's exceedingly sudden that, multiple types of biometrics will be influenced by the noisy conditions in which it has been caught [22]-[23].

Multi-modal biometric systems make the intruder more troublesome to spoof the multi modal biometric data at once through various anti-spoofing measures.

This system can effectively address the non-universality problem by acquiring multiple traits of an individual can ensure sufficient population coverage.

Fusion in multimodal biometrics can be done on distinct different traits of an individual like Face, Fingerprint, Palm, Hand, Iris, Retinal scan , DNA etc. This paper presents match score fusion of face and iris. Face recognition system measures the overall structure of the face and also distance between the nose, eyes, lips, etc. These are considered as holistic features of an individual identification. The major advantage of considering this trait is non-intrusive, it can be operated in low cost environment and easily captured with normal cameras. Maintaining the quality is the major factor for this recognition system.

The iris recognition system helps to identify the individual by considering the features like rings, furrows, freckles which surrounds the pupil. This is one of the most accurate recognition systems. An article at silicon.com stated that the experiment conducted by the government on fingerprint, iris and face recognition systems, it explored that iris recognition system was best for verification of individual identity among the remaining traits.

Iris is one of the most accurate traits which is obtained by the normal video camera. In the iris acquisition getting a clear image is mandatory. So, the device must be in a way that when a user places his head in front of the device, it must reflect the iris in the device, this indicates the clear image formulation. It ensures the extraction of the unique features, i.e. The system is not fooled by some other fake input. The main advantage of this recognition system is, cannot be easily forged by the intruder. Iris biometric data is stable irrespective of the age of an individual and left and right eye are identical. Considering these two traits in match score level fusion provides lesser complexity than the other fusion methods.

Many experiments have been conducted over several years based on face and iris traits. Raghavendra, R. et al. [18] employed the applicability of the light field camera on iris and face biometrics. Darabkh, K. A.et al. [4] proposed novel methods for iris recognition patterns. Adams Kong, A. W. K. [16] utilized the chi-square for statistical analysis and demonstrated the bit probabilities of iris images. John Daugman et al. [5] explored the sequence of iris codes and dealt with the real iris and white noise images through random and correlated pixel values. Over years, researchers (Xie, J.et al. (2012); Boureau, Y. L., & Cun, Y. L. (2008); Glorot, X.et.al(2011); and Ding, C., & Tao, D. (2015)) Boureau, Y. L., & Cun, Y. L. (2008); Glorot, X.et.al(2011); and Ding, C., & Tao, D. (2015)) [26]-[1]-[10]-[9] proposed various machine learning techniques such as deep neural networks[27], deep belief networks, multimodal sentiment analysis and conserving face space through a deep learner. Recently, many experiments are conducted on multimodal emotion recognition and sentiment analysis.

Siddiqua, U. A.et al. [20] experimented on microblog for sentiment analysis by combing a rule classifier with ensemble feature sets and machine learning techniques. Asif Hassan et al. [12] Performed sentiment analysis on the Bangla and Romanized Bangla datasets by employing deep recurrent models. Zhou, Y.et al [3] Operated Convolution Neural Networks (CNN) for mapping the sentences into sequential feature space and then latent topics in text are modeled by diversified Restrict Boltzmann Machine. Erik et al. [4] Demonstrated extreme learning machine (ELM) as an emerging learning technique and generated unique solutions. Deepa, S. N., & Arunadevi, B. [6] Explored the use of extreme learning machine (ELM) [13] on 3D Magnetic Resonance Imaging (MRI) image for pattern classification and to identify the tissue abnormalities in the brain. Huang, Z. et al. [14] Demonstrated competent usage of extreme learning machine (ELM) on Traffic sign recognition. Thomas, S. et al. [24] applied the autoencoder to Mass Spectrometry Imaging (MSI) data for the reduction of dimensionality. Caliskan, A.et al. [2] investigated the effect of autoencoders over reducing dimensionality of a medical dataset. Gondara, L.et.al. [11] Used convolution denoising autoencoders for efficient denoising of medical images. Input dimensionality and intra class variations have been reduced through these techniques and also helps to reconstruct the feature vector for accurate feature recognition.

Unimodal traits like iris and face are being impacted by different factors like illuminations, expressions and noisy data, and thus cause the face recognition performance to vitiate. Further, in case of non-cooperative situations, iris performance also gets tarnished [7]-[8]-[15].

To overcome these factors, a multimodal biometric system is proposed in this paper to strengthen the performance of the recognition system developed by [25]. The key motivation behind this paper is to exhibit high level accuracy and performance in recognition of an individual. The proposed method employs iris and face to reconstruct a feature map with the help of an autoencoder to generate biometric template. Extreme Learning Machine (ELM) is employed to classify and fuse the generated matching scores of individual traits in match score level fusion to maximize the recognition accuracy of this multimodal system. Employing the unsupervised deep learner and appropriate Extreme Learning Machine technique reduces error rates, increases the accuracy and performance of the recognition system [28].

The rest of the paper is organized as follows. Section 2 demonstrates the proposed methodology. Section 3 illustrates the set of experiments carried out on datasets of iris and face. Finally, Section 4 concludes the paper.

II. METHODOLOGY

Multi modal biometrics chains different traits to authenticate an individual. The proposed system illustrated in “Fig.1” demonstrates the match score fusion of iris and face biometric traits to enhance the accuracy of individual recognition. Gabor filter is used to eliminate different variations in face and iris because of illuminations and noises. An auto encoder is used to extract the features of face and iris traits individually. ELM is employed on the individual feature maps of iris and face biometric to enhance the performance and accuracy of individual authentication. In match score fusion, scores obtained from the ELM classifier of iris and face modalities are integrated to generate high accurate recognition rate.

A. ***Image Acquisition***

The iris and face images are acquired from CASIA and FEI datasets. These images are transformed into grayscale for preprocessing.

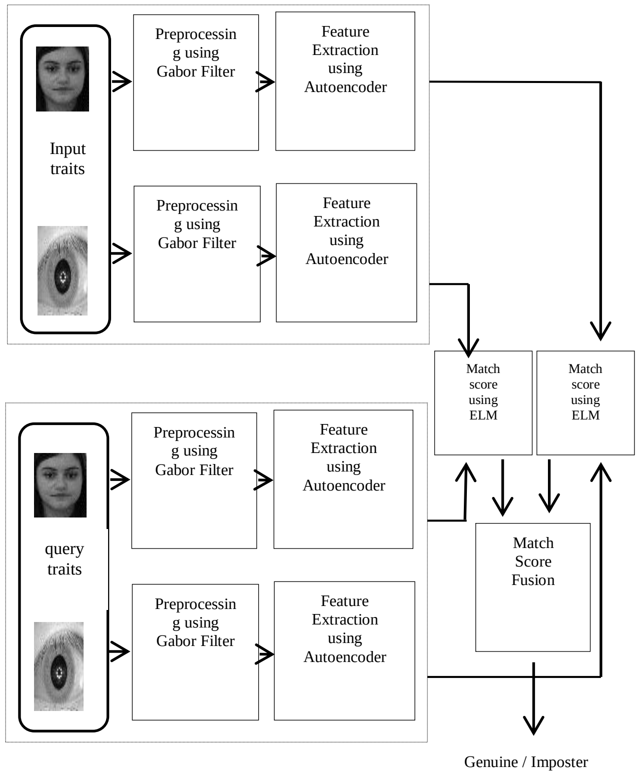

Fig. 1 Architecture of Proposed System

B. ***Preprocessing***

Preprocessing aims at eliminating the image distortion and various illuminations of two traits. Gabor filter is employed on both face and iris traits to filter the noisy data and to maximize edge strength. It localizes the iris by eliminating the unwanted data like eye lids, eyelashes and pupil area, nullifying the image distortion of face by preserving the unique properties of iris and face modalities.

C. ***Feature extraction using Autoencoder***

An autoencoder is employed on both iris and face modalities individually to obtain deeper representation of the global features of face and iris. It also aids in obtaining the compressed data and to achieve the dimensionality reduction. Autoencoder trains the large input data in an unsupervised manner to generate smaller representations at the output and reconstructs the original data as in “Fig. 2”. Let input $I^{\rightarrow}$ is sent to the feed forward neural network and after training output $o^{\rightarrow}$is generated. The ($b^{m\rightarrow}$,w^{m}) represents the weight-bias matrices of N layered neural network. ‘m’ notifies the layer to which (b, w) belongs to. $f^{\vec{m}}$ is the activation of each layer. It depends on its preceding layer activation function which is formulated by "(1)".

$$f^{m'+1}(b^{m'}, w^m, f^{m'}) = tanh(b^{m'} + w^m f^{m'}) \quad (1)$$

"Equestion (2)" Represents the reconstructed output from the input, where $f^{\vec{m}+1}$ represent the output activation layer. Nonlinear neural network is generated by tan (h) function. A minimum error is calculated between the actual($\vec{u}$) and desired output ($\vec{v}$) by "(3)".

$$f_n^{\vec{m}+1}(b_n^{\vec{m}}, w_n^m, f^{\vec{m}}) = tanh(b_n^{\vec{m}} + w_n^m f^{\vec{m}}) \quad (2)$$

$$Min_\theta E(\vec{u}, \vec{v}, \theta) \quad (3)$$

Where:

$$E(\vec{u}, \vec{v}, \theta) = \frac{1}{2} \| f(\vec{v}, \theta) - \vec{u} \|^2$$

$$\theta = \{w^{0....Z-1} b^{\vec{0}....Z-1}\}$$

Feature extraction of iris is done through autoencoder aiming at deeper representations and to reconstruct the original data by eliminating the noisy data like eye lids, eyelashes and pupil area. It also helps in minimization of error rates. Extraction of iris features is processed similar to face feature extraction. Features extracted through autoencoder helps to reconstruct and ameliorate the quality of image data.

Autoencoder is employed on a sample face image to encode the input into smaller dimensions at the hidden layers and finally decodes it into reconstructed output as illustrated in Table 1.

D. Process:

Let I_i is the input to the autoencoder where i={1,2,3,4}, H_j is the hidden layer j={1,2}, and O_K is the output features of the image k={1,2,3,4}.

Table 1. Reconstructed output of a trained face image

No of Units	Input Layer	Hidden Layer	Output Layer
1	2		1.21
2	4	4.3	2.75
3	1	2.7	4.07
4	3		3.74

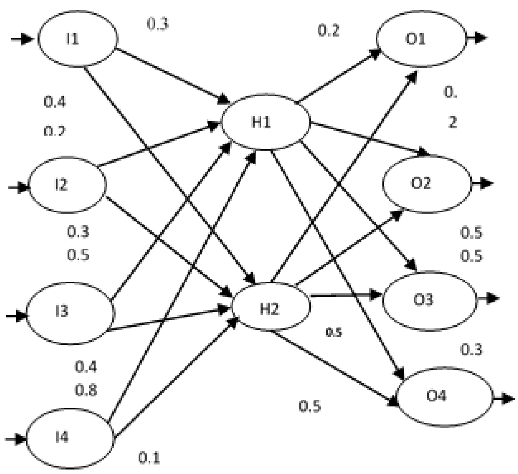

Fig. 2 Feature Extraction through Autoencoder by considering random weights

Ex: Input Layer

Consider input I_i = {2,4,1,3}

Input layer weights= [0.3 0.4; 0.2 0.3; 0.5 0.4; 0.8 0.1]

Hidden Layer

H1=2*0.3+4*0.2+1*0.5+3*0.8= 4.3

H2=2*0.4+4*0.3+1*0.4+3*0.1= 2.7

Hidden layer weights =[0.2 0.2 0.5 0.3; 0.1 0.5 0.4 0.5]

Output Layer

O1=4.3*0.2+2.7*0.1 =1.13

O2= 4.3*0.2+2.7*0.5=2.21

O3=4.3*0.5+2.7*0.4= 3.2

O4=4.3*0.3+2.7*0.5=2.6

E. Match Score Generation through ELM

Extreme Learning Machine is applied on the individual extracted features of iris and face traits for multi-class classification and to obtain the unified learning platform with face and iris feature maps. Unlike traditional learners the hidden features are consider in arbitrarily through ELM learner before considering the training data. These hidden features are independent of training data and also to each other, i.e. unique for each individual.

Suppose 'I' is an input vector i.e. extracted features of iris and face are given to the ELM. It learns M different samples from the input data at hidden layers and gives the match score from the input as output vector 'O' which is depicted in Fig. 3. M different samples are learned through the f(x) activation function illustrated in "(4)". In ELM, the hidden weights and biases are generated randomly and the nonlinear system can be changed into a linear system. f_{ii} Is the output of i th hidden feature with respect to y_i .The w_i is the weight vector interlinked to the i th hidden feature and input features. β_iIs the weight vector interlinked to output features and input features. X is the desired output matrix calculated by "(4)" and individual matching is performed between the desired and actual output of individual traits.

$$X=\sum_{i=1}^{M}\beta_i f(w_i * y_i + b_i) \quad (4)$$

F. *Match Score Fusion*

ELM is employed on the individual feature maps of iris and face biometric to boost the performance and accuracy. Decision is made by combining individual matching scores. Fusion is done by operating a simple weighted sum-rule method as calculated by "(5)" & "(6)" for high level authentication. Let H_k be

$$H_k=\alpha_1 H_{IRIS}+\alpha_2 H_{FACE} \quad (5)$$

$$\begin{cases} \alpha_1 = \frac{EER_{IRIS}}{EER_{IRIS}+EER_{FACE}} \\ \alpha_2 = \frac{EER_{FACE}}{EER_{IRIS}+EER_{FACE}} \end{cases} \quad (6)$$

Where: $\alpha_1, \alpha_2 \in [0\ 1]$

Let H_{IRIS} and H_{FACE} are two individual matching scores extracted from ELM which are multiplied with weights α_1, α_2. Weight are determined depending on Equal Error Rate (EER) value of a single system. The weight of each modality is measured by dividing the single EER with the sum of EER_{IRIS} and EER_{FACE}.

The main aim of this weighing scheme is that the system which gained highest EER value is multiplied with smallest weight and vice versa.

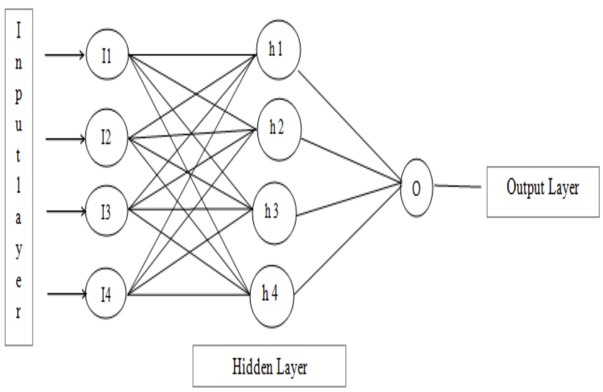

Fig. 3 Match score generation with Extreme Learning Machine

III. EXPERIMENTS AND RESULTS

The proposed recognition system's accuracy and performance is analyzed using Fundacao Educacional Inaciana (FEI Portuguese dataset) and Chinese Academy of Sciences Institute of Automation (CASIA) datasets with 200 sample images of both iris and face traits. Every individual iris image in CASIA dataset is of size 320*280 and is in JPEG format. The face images in FEI dataset are of size of 250*300 in JPEG format. The performance of the proposed recognition system is expressed in terms of accuracy formulated in math statements "(7)" and "(8)".

$$Accuracy = 100 - EER \quad (7)$$

$$EER = (FAR + FRR)/2 \quad (8)$$

Where EER is explained as Equal Error Rate. It is computed on average of False Acceptance Rate (FAR) and False Rejection Rate (FRR).

Fig. 4 & 5 shows the enrolled and query images of an individual's face and iris. "Fig.6" & "Fig.7" depicts the preprocessing of iris and face with Gabor filter respectively. Iris and face traits of an individual are processed without any noise and then holistic features of iris and face modalities are extracted using the unsupervised deep learner autoencoder as shown in Fig. 8 & 9. Individual matching scores of query image and enrolled image are generated by using Extreme Machine Learning (ELM) technique and are depicted in "Fig. 10". ELM is executed on the sample image to generate matching scores based on "(4)" as follows:

Let Input Image = [1 0 1 1];

Input Layer Weight = [0.5 0.1 0.2 0.1;

0.7 0.9 0.3 0.2;

0.4 0.5 0.1 0.3;

0.5 0.6 0.3 0.4]

Input Layer bias (b_i) = [0.2 0.3 0.4 0.5]

h1 = (1*0.5+0.2) + (0*0.7+0.2) +

(0.4*1+0.2) + (1*0.5+0.2) = f (h1)

H1 = 0.9

h2 = (1*0.1+0.3) + (0*0.9+0.3) +

(0.5*1+0.3) + (1*0.6+0.3) = f (h2)

H2 = 0.91

h3 = (1*0.2+0.4) + (0*0.3+0.4) +

(0.1*1+0.4) + (1*0.3+0.4)= f (h3)

H3 = 0.90

h4 = (1*0.1+0.5) + (0*0.2+0.5) +

(0.3*1+0.5) + (1*0.4+0.5)= f (h4)

H4 = 0.94.

Output Weight (β_i) = [0.1 0.5 0.3 0.2];

X = 0.1*0.9+0.5*0.91+0.3*0.90+0.2*0.94=1

Weighted sum rule is used to fuse the match scores of these individual matching scores.

Fig. 4 Query face and iris images of User

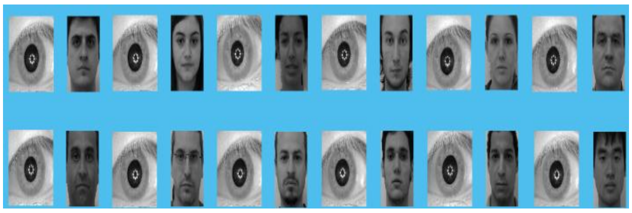

Fig. 5 Enrolled face and iris images of User

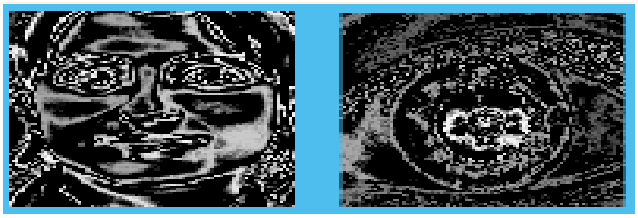

Fig. 6 Gabor Preprocessed query images of face and iris

Fig. 7 Gabor Preprocessed enrolled images of face and iris

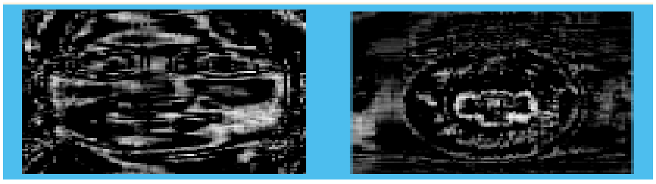

Fig. 8 Feature Extraction of face and iris for Query users using Autoencoder

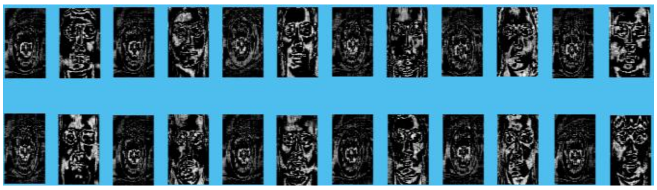

Fig. 9 Feature Extraction of face and iris for enrolled users using Autoencoder

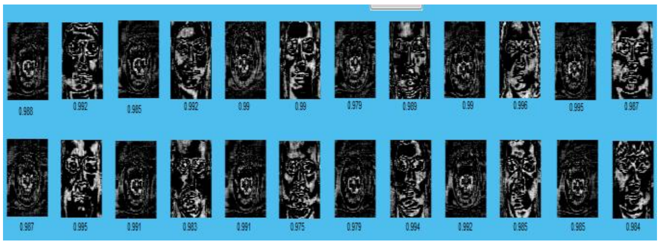

Fig. 10 Individual Match Sscore Generation of both iris and face images using ELM (Gabor method operated in preprocessing)

The improvement of the present methods is observed and compared by sobel method used for preprocessing. Finally, autoencoder is applied on sobel preprocessed image and ELM is performed to generate the individual match scores of iris and face traits. This comparison results show that gabor accuracy rates are higher than the sobel method as indicated in Table 2.

“Fig.11” & “Fig.12” shows the individual accuracy curves of iris and face traits when the Sobel method is operated for preprocessing. “Fig.13” depict the high accuracy fused curve over the individual curves of both iris and face traits.

“Fig.14” & “Fig.15” shows the individual accuracy curves of iris and face traits when the Gabor method is employed for preprocessing. “Fig.16” illustrates the match score fusion strength of the proposed multimodal system accuracy over individual traits. The performance of the proposed system is measured through multiple samples up to 100 images (of both iris and face). “Fig.17” proves that overall system recognition accuracy is high for the proposed system when compared to the Sobel method.

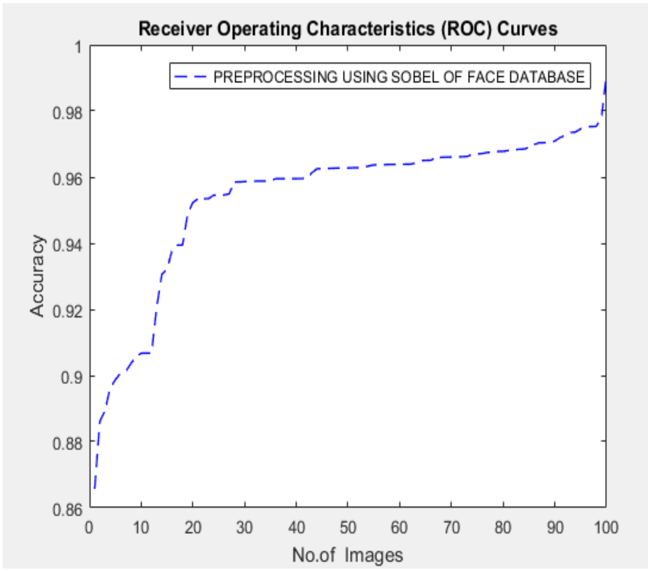

Fig. 11 ROC curve depicting the performance of IRIS database using ELM (SOBEL PREPROCESSING)

Table 2. Comparison of matching scores of preprocessing for Gabor and Sobel filters

	Matching Score	
Image Number	**Gabor Filter**	**Sobel Operator**
1	0.9830	0.96
2	0.9725	0.97
3	0.9532	0.96
4	0.9830	0.99
5	0.9627	0.99
6	0.945	0.94
7	0.967	0.94
8	0.954	0.94
9	0.935	0.97
10	0.956	0.98
11	0.992	0.93
12	0.980	0.93
13	0.984	0.95
14	0.986	0.96
15	0.986	0.97
16	0.9675	0.92
17	0.9667	0.92
18	0.9765	0.99
19	0.9726	0.95
20	0.9669	0.95
21	0.970	0.89
22	0.967	0.89
23	0.987	0.96
24	0990	0.93
25	0.989	0.94

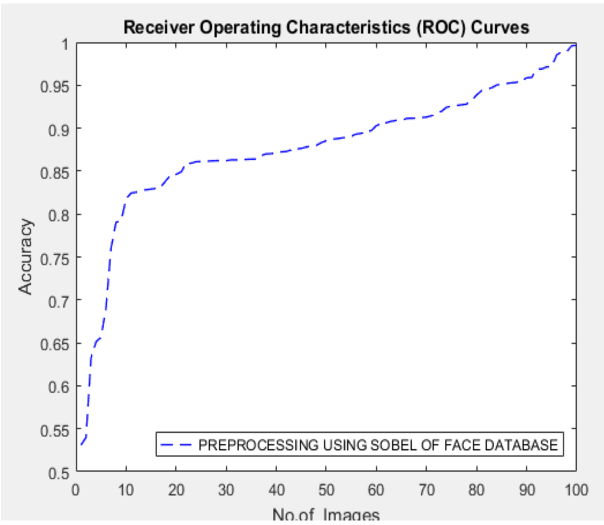

Fig. 12 ROC curve depicting the performance of FACE database using ELM (SOBEL PREPROCESSING)

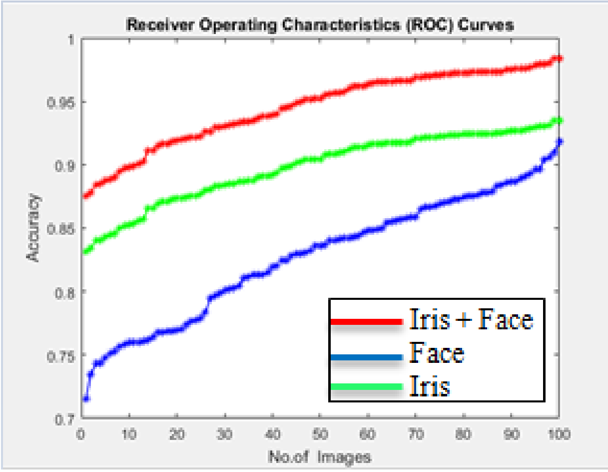

Fig. 13 ROC curve depicting the high performance through fusion of IRIS and FACE database (SOBEL PREPROCESSING)

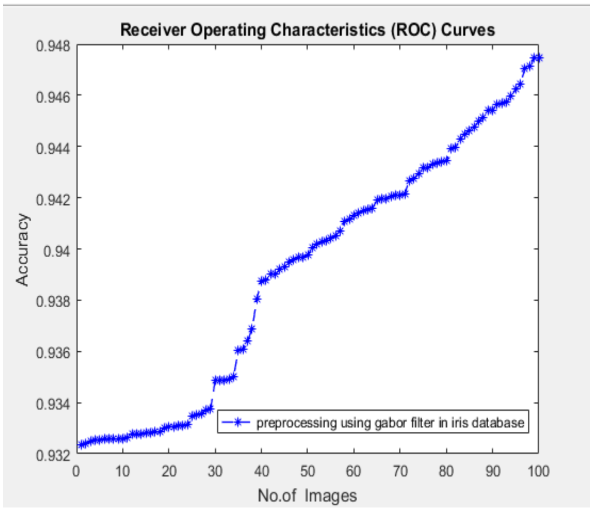

Fig. 14 ROC curve depicting the performance of IRIS database using ELM(GABOR PREPROCESSING)

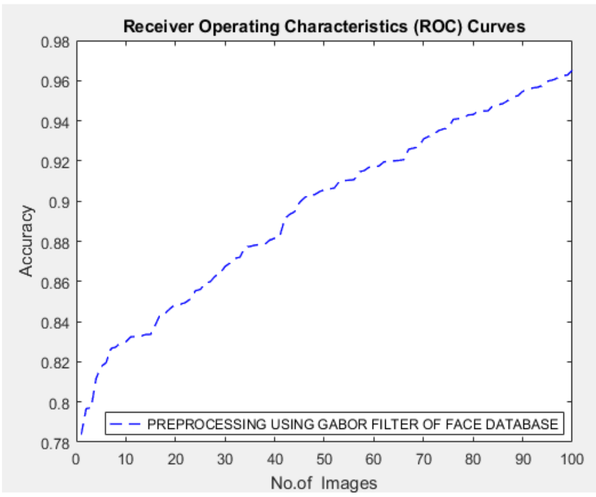

Fig. 15 ROC curve depicting the performance of FACE database using ELM (GABOR PREPROCESSING)

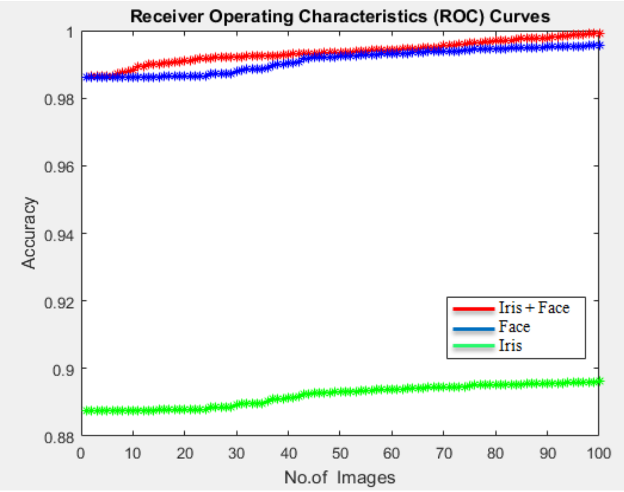

Fig. 16 ROC curve depicting the high performance through fusion of IRIS and FACE database (GABOR PREPROCESSING)

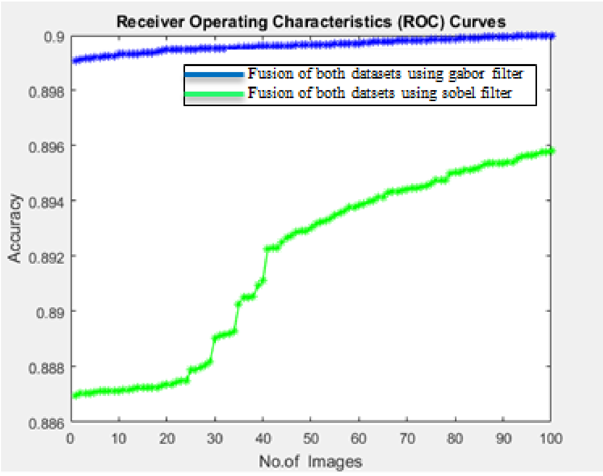

Fig. 17 ROC curve depicting the high performance of proposed system when compared with sobel pre-processing

IV. CONCLUSION

Fused multimodal biometrics has got high stability over unimodal biometric traits. The proposed system demonstrates the match score fusion of iris and face biometrics to enhance the accuracy of human recognition. The face and iris holistic features are extracted through autoencoder to reconstruct feature vectors, which gives deeper representation of a biometric template generation. ELM is employed on the individual extracted feature traits and query traits to generate the match scores. High level accuracy and performance is achieved by fusing match scores with simple weighted sum rule. The proposed system acknowledges the non-universality and spoofing attacks through diminishing the equal error rate. Restricted Boltzmann machine can be integrated in a proposed multimodal system for effective representation and reconstruction of feature vector. The experimental results demonstrate the superiority of the proposed face and iris recognition system over the Sobel operated system.

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