International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 5, No.6 (Nov-2016)

http://dx.doi.org/10.12785/ijcds/050602

Personal Verification Using Two Level Fusion Schemes Based on Ear and Iris Biometrics

Farida Khursheed[1] and Ajaz Hussain Mir[1]

[1]*Electronics and Communication Engineering Department, National Institute of Technology, Srinagar (J & K)-INDIA*

Received 22 Jan. 2016, Revised 31 Mar. 2016, Accepted 7 Jul. 2016, Published 1 Nov. 2016

Abstract: Increased threats to conventional personnel verification methods, have given rise to verification methods based on biometrics. This paper presents a novel approach for personal verification based on fusion of two biometric modalities: Ear and Iris. Fusion has been done in two levels. In level one right iris and left iris features have been fused using texture based Grey Level Concurrence Matrix (GLCM) and in level two these features have been fused with AR coefficients taken from ear substructure. It has been found that this two level fusion of features improves the recognition rate of a person to the extent of 100%. The biometric modalities of ear and iris have been chosen on the basis of their desirable properties like uniqueness, universality, permanency and acceptability.

Keywords: Fusion, Texture, Grey level co occurrence matrix, AR model, Personnel verification.

1. INTRODUCTION

The increased activities of adversaries have resulted in more attention being given to highly secure and reliable authentication technologies. Daily transactions between individuals and various organizations are conducted through highly interconnected electronic devices [1]. Thus establishing the identity of a person is becoming more and more critical in our vastly interconnected society. Traditional methods of establishing a person's identity include knowledge-based and token based mechanisms. But these traditional ways of identification do not last long as these can be broken, lost or stolen. Biometrics, described as the science of recognizing an individual based on her physiological or behavioral traits, is beginning to gain acceptance as a legitimate method for determining an individual's identity [2]. For establishing identity of individual, biometric systems have been deployed in various commercial, civilian and forensic applications. These systems rely on the evidence using human biometric either to validate or to determine an identity [2]. Most biometric systems that are used in practical applications use a single biometric for identification or verification are known as unimodal biometric systems. Some of the unimodal biometric are: Iris [3], Fingerprint [4], Face [5], Hand Geometry [6], Gait [7], Signature [8], and Ear Shape [9]. A survey of unimodal biometric technologies is given in [10][11]. However, unimodal biometric verification systems have certain limitations [12] such as noisy sensor data, inter-class variations, and inter-class similarities, lack of universality, spoof attacks and inacceptable error rates. Due to these practical limitations, the error rates associated with unimodal biometric systems are quite high which makes them inacceptable for deployment in critical security applications. Some of these limitations of the unimodel biometric systems can be alleviated by using a multimodal biometric system [13]. A biometric system that combines more than one source of biometrics for establishing human verification is called a multimodal biometric system. Such systems, are expected to be more reliable due to the presence of multiple, independent pieces of evidence [14]. Fusing the evidence obtained from different modalities using an effective fusion scheme can significantly improve the overall accuracy of the biometric system [15]. The fusion in multimodal system can be performed at four potential levels: sensor, feature, matching and decision. The sensor and feature levels are referred to as a pre-mapping fusion and fusion on the basis of matching score and decision levels are referred to as a post-mapping fusion [16].In pre-mapping fusion, the biometric data are combined before classification, while in post-mapping fusion, each biometric data are modeled separately and then all the biometric traits are combined after mapping into matching score or decision space. Fusion at sensor level stage is expected to improve the recognition accuracy as it would potentially represent the richest source of information as compared with other levels of fusion but

E-mail address: fklone@nitsri.net, ahmir@nitsri.net

raw data may be corrupted by noise and may emphasize the intra-class variations [17-18]. It is also not applicable with incompatible data gathered from different modalities. Fusion at feature level can be applied to the extraction of different features from the same modality or different multimodalities to construct a joint feature vector. Since the feature level is certainly much richer and exploits more useful information about the raw data, fusion at feature level is expected to perform better in contrast with fusion at score and decision levels [19]. Feature level fusion may be helpful for closely-related modalities or for integrated features of the same modality with multiple sensors. However, such fusion type is not always feasible because in many approaches the given features might not be compatible due to differences in the nature of modalities [20]. In addition, concatenating two feature sets may lead to the dimensionality problem. Furthermore, the majority of the practical commercial biometric systems do not provide access to the feature sets such as the raw fingerprint impressions of a fingerprint based commercial-of-the–self authentication systems. In Decision level fusion approach, also denoted as abstract level, separate decision taken from each biometric trait are combined at a very late stage. This seriously limits any effort in enhancing the accuracy of the system through the fusion process. Thus, fusion at such a level is the least powerful [21]. Rank level fusion is possible only in identification systems where each classifier outputs a list of possible classes with rankings for each subject. The ranks of individual matchers are combined using techniques such as the highest rank, borda count and logistic regression approaches [22]. At matching score level also referred to as decision, confidence, expert or opinion level, it is possible to combine scores obtained from the same biometric trait or different ones using one or more classifiers [23]. This fusion level can be divided into two categories namely as combination and classification. In the former approach, the separate matching scores are gathered to produce one score, which is used to make the final decision. In the latter approach, the input matching scores are considered as input features for a two-class pattern recognition problem, to check if subject is classified as legitimate or an Imposter. The classifier presents a distance measure or a similarity measure between the input feature vector and the template previously stored in the database. It may be pointed out that prior to matching score fusion; normalization of data must be carried out. In this paper, matching score fusion is attempted. Here match score outputs by different biometric matchers are consolidated in order to arrive at a final recognition decision.

2. RELATED WORK AT MATCHING SCORE LEVEL

The work related to biometric fusion for recognition is tabulated in Table I.

Table I. Comparison of work related to Biometric Fusion

Paper	*Fusing Modalities*	*Feature extraction Technique*	*Classifier*	*Recognition Rate in %*
Karim et al(2008) [24]	Ear and Palm	Gaussian and Gabor filter	K-NN and SVM	100
Souheil et al. (1999)[25]	Face and Speech	Gabor filter and HMM modal	SVM and Bayesian	FA, FR, EER 1.07,.25,1.2 1.16,0.0,1.0
Shrikant et. al.(2012)[26]	Face and soft biometrics		PCA,ICA, LDA,LBP , SURF	89.23
Fan Yang et.al. (2007) [27]	Fingerprint, palmprint and hand geometry	Wavelet transform and width and length of hand	Euclidean distance	> 90
Khalid et al.(2010) [28]	Face and Iris	Wavelet transform	City bank distance	99.50
Mahesh et.al.(2010) [29]	Speech and Palmprint	MFCC ceptrals+ Wavelet based kernal PCA	Weighted Euclidean distance	98.63
Alipur et. Al.(2010) [30]	Face, Ear and Gait	Gabor filter and PCA	Euclidean distance	97.5
Ali et.al.(2013) [31]	Fingerprint and Finger-vein	Mono LBP descriptor	Distance between two feature histograms using Chi-square formula	93
V.Arulala et.al.(2014) [32]	Iris and Inner Knuckle	Haar Wavelet and Gabor filter	Hamming distance	Only quantitative improvement mentioned

A complete survey of all techniques is given in [33-35].Literature survey reveals that various methods have been adopted by researchers for performing fusion at matching score level. On the basis of Literature survey it is concluded that despite the intensive research in multimodal biometrics at matching score level, no attempt has been made to fuse Auto Regressive (AR) modal parameters obtained from ear shape and texture parameters using Grey Level Co occurrence Matrix (GLCM) obtained from Iris. The reason for choosing ear and iris for fusion is that ear shape and iris texture patterns are considered stable that do not change with age, emotions and cosmetic change [36-40] and acceptable in addition to being unique.

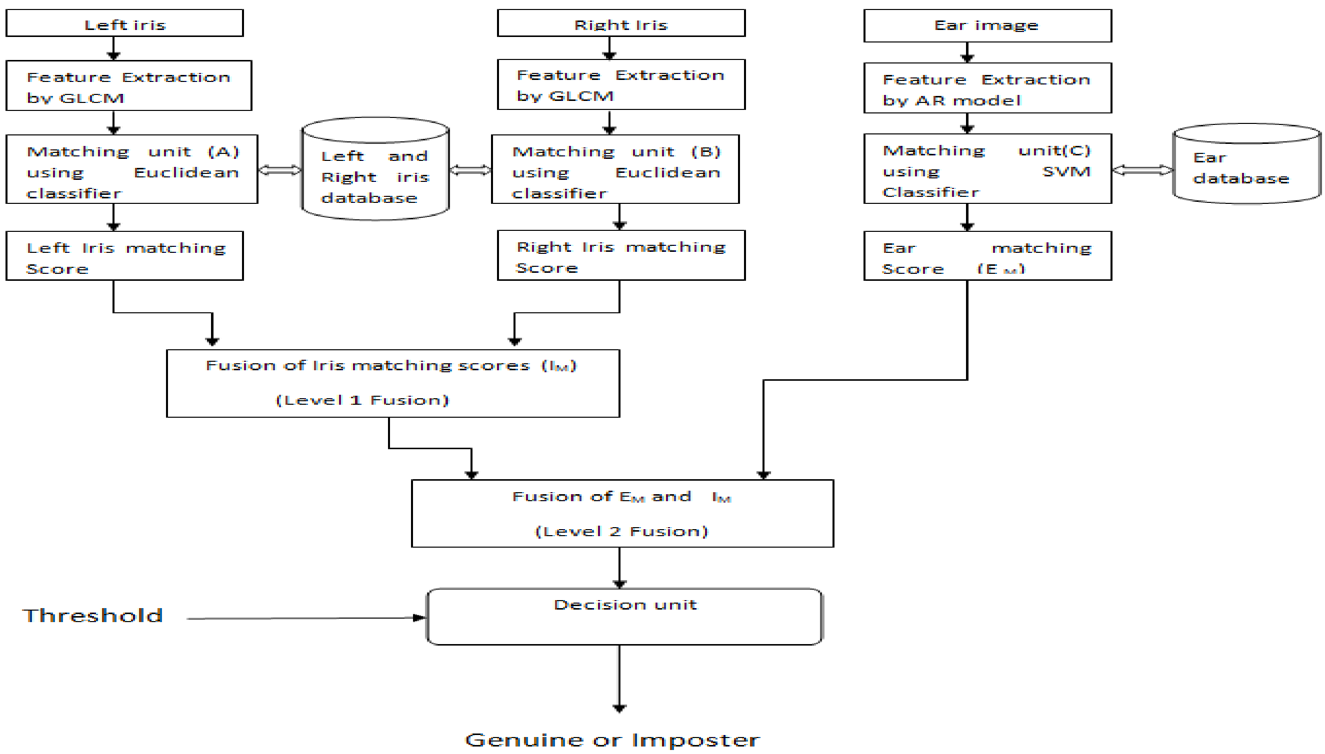

Figure. 1: Block diagram of proposed methodology

3. OUR APPROACH

"Fig.1"is the overall framework of the proposed method. We propose fusion of ear image and iris image at matching score level. We have divided our fusion scheme into two phases:

- Level - 1 fusion
- Level - 2 fusion

A. Level -1 fusion scheme

In this scheme left and right iris texture features are extracted using GLCM texture technique. The feature vectors obtained from both left and right irises are fed to the matching units A and B independently as shown in "fig 1". The matching units A and B outputs matching scores based on Euclidean distance between test image comprising of left and right irises and corresponding images in the database. The matching scores (I_M) obtained from both matching units are fused using SUM method of fusion.

B. Level -2 fusion scheme

Here features from ear shape are extracted using time series based AR modal. Feature vectors thus obtained are fed to the matching unit for comparison against the template stored in the ear database. The matching unit C on account of taking SVM as a classifier outputs a matching score (E_M) corresponding to each template in the ear database.

At the final stage we are again fusing matching score namely E_M and I_M of both modalities. The fused matching score thus obtained is fed to the decision unit for verification. The decision unit on the basis of threshold classifies the subject as Genuine or an Imposter.

C. Threshold Determination

In order to check the efficacy of proposed biometric system we compute following three performance parameters:

False Acceptance Rate (FAR); False Rejection Rate (FRR); Recognition rate (RR) FAR is the expected proportion of attempts when attempt is erroneously accepted by the system when it should have been rejected. Similarly FRR is the proportion of attempts when attempt is erroneously rejected by the system when it should have been accepted.

Normally it is desirable to reduce both FAR and FRR but there is always a trade-off between the two parameters. The values of FAR and FRR depends on selection of threshold.

FAR increases with the increase in threshold and FRR decrease as we increase the threshold. So judicious selection of threshold plays a very significant role in any biometric system. Therefore, threshold should be such that the value of both FAR and FRR is minimum.

From the security aspect of any biometric system reducing FAR is more important than FRR since giving access to an unauthorized person can be more fatal than rejecting an authorized person.

4. TIME SERIES BASED AR MODELING

Time series is defined as a record of stochastic process ordered chronologically with respect to some index variable. A contour may be considered as a series of large number of straight line segments, say . In case is large the desired accuracy of the approximation can be improved. Therefore, the sequence of boundary points (x), $i = \{1, 2, \dots \dots N -$ on bounding curve of any substructure constitutes a time series. In present application parameters of AR model can be obtained from the contour points.

Originally AR model was developed as useful tool to describe and analyze 1-D discrete time signals in [41,42]. 2-D applications of the AR model were first proposed by Kashyap and Chellpa [43] who used the model for shape storage, transmission and reconstruction. Dubois and Glanz [44] investigated the usefulness of this model for representing shapes of different pattern sets. Mir et al. [45] used AR model for shape description of human organs in medical images. In this paper we investigate the usefulness of time series AR for verification of humans on the basis of ear biometrics. The time series for this purpose is obtained from structural information contained in ear contour.

A. Autoregressive Model

In this approach, the time series is extracted from ordered sets of lengths of n boundary points measured from the centroid of ear contour substructure .

Let be the length of a vector between the boundary points and centroid. The real AR model is formed from the sequence of 's as:

$$= \sum_{k=1}^{m} a_k \; y_{j-k} + \qquad (1)$$

The model is thus based on parameters where k = 1….. m, m is the order of the model and w_j is the error term

The AR coefficients can be estimated in many ways such as Ordinary least square procedure, Markove chain Monte-Carlo method and methods based on moments. We are computing AR coefficients by moments using Yule Walker equations.

Thus multiplying (1) by y_{j-1}, and so on and taking the Expectation, the following Yule-Walker equations are obtained:

$$= \sum_{k=1}^{m} a_k \, r \qquad (2)$$

Where = 0........, m yielding m+1 equations. Hence is the autocovariance function of ,

Using the evenness of the auto covariance

$$r_l = r_{-l} = E\{y_j \; y_{j-1}\}$$

Rewriting equation (2)

$$r_1 = a_1 r_0 + a_2 r_1 + a_3 r_2 + \cdots + a_{m-1} r_{m-2} + a_m r_{m-1}$$

$$r_2 = a_1 r_1 + a_2 r_0 + a_3 r_1 + \cdots + a_{m-1} r_{m-3} + a_m r_{m-2}$$

$$\vdots$$

$$\vdots$$

$$r_{m-1} = a_1 r_{m-2} + a_2 r_{m-3} + a_3 r_{m-4} + \cdots + a_{m-1} r_0 + a_m r_1$$

$$r_m = a_1 r_{m-1} + a_2 r_{m-2} + a_3 r_{m-3} + \cdots + a_{m-1} r_1 + a_m r_0$$

This can be also written as

$$\begin{bmatrix} r_1 \\ r_2 \\ \cdot \\ \cdot \\ \cdot \\ r_{m-1} \\ r_m \end{bmatrix} = \begin{bmatrix} r_0 & r_1 & r_2 & \cdots & r_{m-2} & r_{m-1} \\ r_1 & r_0 & r_1 & \cdots & r_{m-3} & r_{m-2} \\ & & & & & \\ r_{m-2} & r_{m-3} & r_{m-4} & \cdots & r_0 & r_1 \\ r_{m-1} & r_{m-2} & r_{m-3} & \cdots & r_1 & r_0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \cdot \\ \cdot \\ \cdot \\ a_{m-1} \\ a_m \end{bmatrix} \qquad \ldots\ldots (3)$$

For $r_0 = 1$;

$$\begin{bmatrix} r_1 \\ r_2 \\ . \\ . \\ r_{m-1} \\ r_m \end{bmatrix} = r \;\; ; \;\; \begin{bmatrix} 1 & r_1 & r_2 & \cdots & r_{m-2} & r_{m-1} \\ r_1 & 1 & r_1 & \cdots & r_{m-3} & r_{m-2} \\ & & & & & \\ r_{m-2} & r_{m-3} & r_{m-4} & \cdots & 1 & r_1 \\ r_{m-1} & r_{m-2} & r_{m-3} & \cdots & r_1 & 1 \end{bmatrix} = R$$

$$\begin{bmatrix} a_1 \\ a_2 \\ . \\ . \\ a_{m-1} \\ a_m \end{bmatrix} = a$$

We may write it as:

$$r = R\,a \qquad (4)$$

Where is full-rank and symmetric so that invertability is guaranteed. or

$$a = R_{AR}^{-1}(\mu)\, r \qquad (5)$$

The coefficients { } which form the feature vector are obtained from equation (5).

5. IRIS VERIFICATION USING TEXTURE

Texture can be defined as an entity consisting of mutually related pixels and group of pixels. This group of pixels is called as texture primitives or texture elements (texels) [46]. An image texture can be also described by the number and type of its primitives and the spatial organization or layout of its primitives. The spatial organization may be random, may have a pairwise dependence of one primitive on a neighboring primitive, or may have a dependence of n primitives at a time. The dependence may be structural, probabilistic, or functional [47].

Computer based methods of texture analysis were originally developed for use in satellite application, geological surveys, remote sensing and other related applications [48-51]. A wide range of techniques are in existence. These techniques are broadly categorized into: structural, statistical, transform based and model based. A survey of all these techniques in these categories is given in [52, 53].

Mir et al used texture for obtaining information beyond visual perception from CT images [54]. In our approach we have attempted to make use of texture for personal verification. Texture has been chosen because the spatial relation of the pixels does not change with intensity, illumination [55, 56]. Thus if an image undergoes any manipulation like changing contrast, brightness, texture features does not change.

Structural approaches represent texture by well defined primitives and a hierarchy of spatial arrangements of those primitives. The advantage of the structural method based feature extraction is that it provides a good symbolic description of the image; however, this feature is more useful for image synthesis than analysis tasks [57, 58]. Model based texture analysis describes an image as a probability model or as a linear combination of a set of basic functions. This approach is useful for modeling certain natural textures those have a statistical quality of roughness at different scales and self similarity, and for texture analysis and discrimination [57, 58]. Statistical methods characterize the texture indirectly according to the non- deterministic properties that manage the relationships between the gray levels of an image. This approach is used to analyze the spatial distribution of gray values by computing local features at each point in the image and deriving a set of statistics from the distributions of the local features [57, 58]. Transform based methods depend on transformation and inverse transformation and are therefore time consuming.

The statistical methods can be classified into first order (one pixel), second order (pair of pixels) and a higher order (three or more pixels) statistics [57]. The first order statistics estimate properties like average and variance of individual pixel values by waiving the spatial interaction between image pixels. The second order and higher order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. The different types of second order statistical methods are, spatial grey level dependence method (SGLDM), the grey level run length method(GLRLM), grey level difference method(GLDM) and grey level co-occurrence method(GLCM).

A. GLCM (Grey Level Co-occurrence Matrix)

GLCM is a statistical method which consists in constructing co-occurrence matrices to reflect the spatial distribution of grey levels in the region of interest. This concept was first used by Julesz [59] in texture discrimination experiments.

This method is based on the estimation of the second order conditional probability density function $(i, j \mid d$ where $t\, 0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0$ and 315^0.

Each $p(i, j \mid d$ is the probability of going from grey level to grey level , given that inter- sample spacing is and the direction is given by the angle . The estimated value for this probability density function can thus be written in matrix form:

$$\emptyset = (d, \theta) = [\, p(i, j \mid d, \tag{6}$$

For computing these probability distribution functions, scanning of the image in four directions viz., $t\, 0^0$, 45^0, 90^0 and 135^0 is sufficient, since the probability density matrix for the rest of directions can be computed from these four basic directions.

Let $\emptyset'(d$ denote the transpose of the matrix $\emptyset(d$ for the inter-sample spacing, and direction, .

$$\emptyset(d, \quad = \quad \emptyset'(d, 18$$

$$\emptyset(d, 4 \quad = \quad \emptyset'(d, 22$$

$$\emptyset(d, 9 \quad = \quad \emptyset'(d, 27$$

$$\emptyset(d, 13 \quad = \quad \emptyset'(d, 315 \tag{7}$$

Thus knowledge of $\emptyset(d, 18$ $\emptyset(d, 22$, $\emptyset(d, 27$, $\emptyset(d, 315$ add nothing to the characterization of texture.

Features

Using this method, approximately two dozen co-occurrence features can be obtained [60]. Consideration of the number of distance angle relations also will lead to a potentially large number of dependant features.

Out of eight GLCM texture features given by Haralick, we hypothesized that following three features as likely candidates to have discriminatory power required for personal verification.

These are

$$Correlation = \sum_{i,j} \frac{(i \times j) \times p(i,j) - (\mu_x \times \mu_y)}{\sigma_x \times \sigma_y} \tag{8}$$

$$Entropy = -\sum_{i,j} p(i,j)\, \mathrm{lo} \tag{9}$$

$$Local\ Homogeneity = \sum_{i,j} \frac{1}{1-(i-j)^2}\, p(\tag{10}$$

6. Implementation and Results

To check the potential of proposed methodology two databases have been used.

A. Test Data:

Ear database

To check the usefulness of proposed models, test images for formulation of data set used have been taken from IIT Delhi, India ear database. The data base contains 363 2D ear images taken from 121 subjects in three different random postures. The resolution of image database is 272 × 204 pixels and all these images are available in JPEG format.

Iris database:

Chinese Academy of science- Institute of Automation (CASIA) eye image database version 1.0 has been used for experimentation. The experiments were carried on 40 subjects with each subject having 3 images. The eye images in this database are mainly from persons of Asian descent. These images have been captured specially for iris recognition research using specialized digital optics. The iris images are grayscale bit map with a resolution of 320 X 280. The images have been downloaded on to a work station and processed using MATLAB-7.9.

B. Ear Shape Feature Extraction:

In this proposed system for computation of AR coefficients a sample of ear image shown in "Fig.2a" selected from the database for preprocessing. The preprocessing involves i) cropping of ear to get the ear substructure as in "Fig.2b" ii) Application of Canny edge detector [61] to cropped ear substructure as shown in "Fig.2c" iii) the image is binarized to facilitate easy contour tracing. This is shown in "Fig.2d" iv). The outer boundary of the ear image is thus traced as shown in "Fig.2e". The coordinates of the boundary are stored for further processing to obtain AR coefficients. AR coefficients thus obtained can be used for formulation of feature vector. In the present formulation, corresponding to three postures of a person, AR coefficients of ear contour are obtained at rotations: 0^0, 45^0, 90^0, 135^0 and 180^0 with respect to reference as shown in "Fig. 2(e, f,g,h,i)". This amounts to computation of 15 features in terms of AR coefficients corresponding to three ear images of a person. In order to check the invariance of AR coefficients at three different postures and at five different rotations, the feature vector consists of these 15 AR coefficients are computed at a particular order. In this paper, we compute feature vector at orders ranging from 5 to 100 with an interval of 5 for each subject.

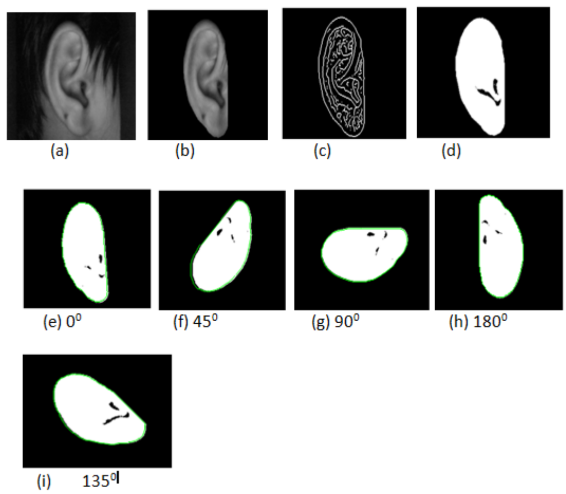

Figure 2. Processing stages of Ear

C. Iris texture feature extraction:

The sample iris color image is firstly converted into grayscale image as shown in Figure (3). To compute the textural features from this image we isolated iris substructure from the sample image. After extracting the iris three features are computed from GLCM matrix of left and right iris images.

Figure 3. Iris Images

GLCM features are computed based on two parameters namely distance between the pixel pair 'd' and their angular rotation 'θ' . Smaller values of ‘d’ have been taken in our experimental work because iris has a soft texture i.e., the grey level tone relationship between the pixel changes over small values of inter pixel distance 'd'. The features are calculated at angles 0^0,45^0, 90^0, 180^0. The distance‘d’ between pixel pairs is selected as 2. Experimentation was done at angles 0^0,45^0, 90^0, 180^0. However, it was found that the performance in terms of discrimination is far more superior when angle 45^0 is used than at other angles. This is depicted in scatter plots shown in “Fig. 4”.

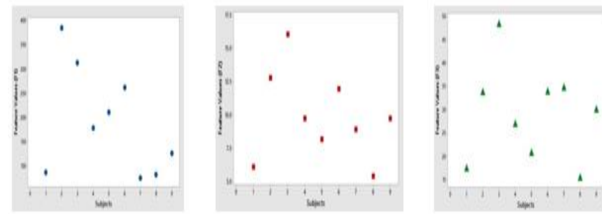

Figure 4. Feature Vector versus Subjects

D. Assignment of iris and ear samples:

The 40 iris samples of right and left eye are assigned to 40 ear samples of the ear database. Therefore, one image of ear and one image each of right and left eye belong to the same individual. Out of 40 subjects in the database, features of 30 subjects are kept for training and features of 10 subjects are kept for testing.

E. Training and Testing:

For verification of subjects, we have divided our training and testing into two phases:

i) First Level Training and Testing phase.

ii) Second Level Training and Testing phase.

In first training phase, feature vectors from both right and left irises of 30 subjects are selected for training. In testing phase, feature vectors of test images say I_i Where = (1, 2, 3…10) Selected for testing. These features vectors of a test image corresponding to both right and left iris are fed to the matching units (A and B) independently for determination of matching scores. The matching scores of the test image I_i obtained are fused using SUM method of fusion.

In the second training phase feature vectors from ear shape of 30 subjects are selected for training. In testing phase, features of same test image I_i are selected for testing. The extracted features are fed to the matching unit(C) for determination of matching scores. The matching unit outputs matching scores.

Finally matching scores of test image I_i obtained in first and second training and testing phases are again fused using SUM method of fusion. These fused matching scores are fed to the decision unit which on the basis of threshold classifies the test image as Genuine or an imposter.

F. Results

We have obtained fused matching scores corresponding to right and left iris images, matching scores of ear and fused matching score obtained from ear and iris images. Genuine and Imposter score distribution have been plotted for these matching scores. We have categorized our results into three cases.

Case 1 We have plotted Genuine and Imposter score distribution of the fused matching score of right and left iris images shown "Fig.5". Plot shows the overlapped portion of Genuine /Imposter score distribution.

Overlap indicates a region where some queries are falsely accepted and some are falsely rejected by any recognition system. Minimization of this percentage of overlap between Genuine and Imposter score distribution is the main objective of any biometric recognition system. The least the overlap, more efficient and accurate the recognition system.

Case 2 Genuine and Imposter score distribution of the matching score of ear image is plotted in. "Fig.6".Plot shows the overlapped portion of Genuine /Imposter score.

Case3 Genuine and Imposter score distribution of the fused matching score of iris and ear images is plotted in "Fig.7". It is evident from the plots; that overlap has reduced further indicating improvement in recognition.

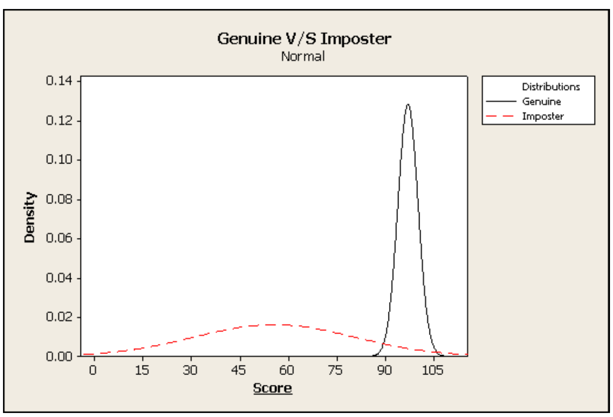

Figure 5. Genuine versus Imposter Score of fused left and right Irises

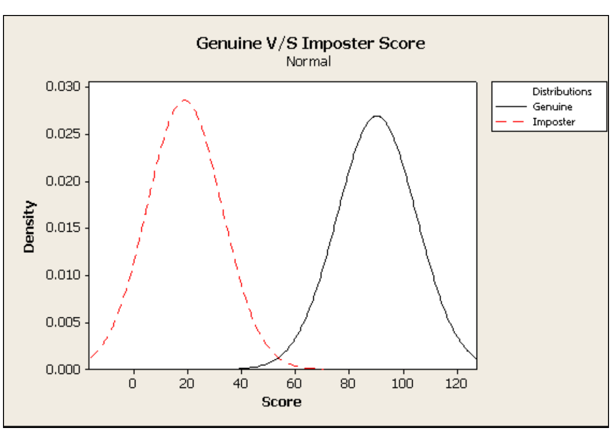

Figure 6. Genuine versus imposter Score of Ear

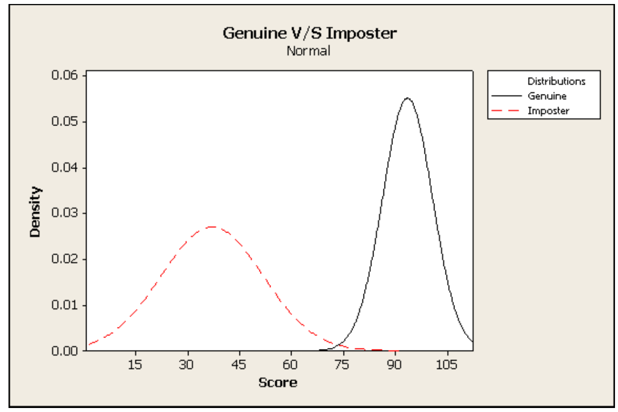

Figure 7. Genuine versus Imposter Score of (Ear and fused left and right Irises)

7. RECOGNITION RATES FOR CASE 1, CASE 2 AND CASE 3

Table II. Shows FAR, RR . The results obtained have confirmed the fact that when multimodal biometrics is used, the performance parameters are improved.

$$F = \frac{Number\ of\ falsely\ accepted\ samp}{Total\ number\ of\ samples\ compa}$$

$$FRR = \frac{Number\ of\ falsely\ rejected\ samples}{Total\ number\ of\ samples\ compared}$$

$$RR = \frac{Genuinely\ accepted\ samples + Genuinely\ rejected\ samples}{Total\ number\ of\ samples}$$

Table II. Comparison of FAR, FRR and RR before and after fusion

Modality	Threshold	FAR	FRR	RR %
Fused left and right iris	30	.17	1.66	98.17
Ear	65	0	.076	98.29
Fusion of ear and fused left and right iris	65	0	0	100

Comparison of results using two level fusion reveals that recognition rate of proposed technique is 100% with FAR and FRR equal to zero. In state of art techniques given in table I, although recognition rate goes up to 100% but important performance parameters FAR and FRR have not been calculated. In addition, it may be realized that AR coefficients are obtained from the contour and are invariant to illumination apart from being invariant with respect to posture and rotation.

Accordingly the iris data can be taken easily over a set up and processed on line. Therefore, the proposed technique is suitable to be used for on line verification as well.

8. DISCUSSION

In this paper attempt has been made to fuse biometric modalities for maximizing recognition rate for personal verification. The modalities used are ear shape and right and left iris. Here two level fusions have been attempted. In level 1 fusion of left and right using three texture based GLCM parameters, recognition rate of 98.17% could be achieved. In this case, however FAR and FRR is finite. Accordingly, when AR model is used the recognition rate of 98.29% is achieved again with finite FAR and FRR. In contrast, when the two modalities are fused the recognition rate increases to 100% and FAR, FRR reduced to zero. Comparison of recognition rate of present technique with the state of art techniques reveals that in [24] a recognition rate of 100% has been achieved. It may be pointed out that, important performance parameters FAR and FRR have not been given consideration and has not been calculated. But considering the importance of recognition rate, the superiority of fusion of proposed modalities has shown promising results.

9. CONCLUSION

The present study has shown benefit of using multimodal biometrics in comparison to unimodal biometrics for personal verification. Two biometrics namely ear and iris have been used for establishing the advantage of biometric fusion. Feature vectors have been obtained from both modalities using AR modal and GLCM texture technique. Matching score have been computed from feature vectors of both modalities. In our studies fusion at matching score level have been used to check the efficiency of the method. It has been seen that when matching scores obtained from AR coefficients and texture features are used separately give a recognition rate of 98.29 % and 98.17% respectively. However, when matching scores are fused recognition rate increases to 100%.

REFERENCES

[1] Lin Hong, Anil Jain, Integrating faces and fingerprints for personal Identification, IEEE Transactions on Pattern Analysis and Machine, vol. 20, no. 12, Dec. 1999.

[2] Arun Ross, Anil K. jain, Multimodal Biometrics : An overview, In proceeding of 12th European Signal Processing Conference (EUSIPCO),pp. 1221-1224, Sep 2004.

[3] K. W. Bower, H. Worth and P. J. Flynn. Image understanding for iris biometrics: A survey, In Computer Vision and Image Understanding, vol. 1105, pages 12, 2008.

[4] V. Sravya, P. K. Murthy, R. B. Kallam and B. Srujana. A Surey on Fingerprint Biometric System, In International Journal of Advanced Research in Computer Science and Software Engineering, vol. 2, no. 4, April 2012.

[5] S. Goel, A. Kaushik and K. Geol. A Review paper on Biometrics: Facial Recognition, In International Journal of Scientific Research Engineering & Technology (IJSRET), vol. 1no. 017,August 2012.

[6] Duta. A survey of Biometric technology based on hand shape, In Pattern Recognition, Elsevier,2009.

[7] Z. Zhang, M. Hu and Y. Wang, "A survey of advances in biometric gait recognition", CCBR'11 Proc. of the 6th Chinese Conference on Biometric recognition, Springer- Verlag Berlin, Heidelberg, (2011), pp. 150-158.

[8] Patel Bhuminha A, Shashwat Kumar, A survey on handwritten signature verification Techniques,Insrumentation journal of Advance Research in computer Science and Management Studies, Vol. 3, Issue 1, Jan. 2015.

[9] Devesh Narayan, Sipi Dubey, A survey paper on human identification using ear biometric, International Journal of Innovation Science and Modern Engineering(IJISME), Vol.2, Issue 10 ,Sept. 2014.

[10] Anil K. jain, Arun Ross and Salil Prabhakar, An introduction to biometric Recognition, IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, No. 1, Jan. 2004.

[11] Kresimir Delac, Mislav Grgic, A survey of biometric Recognition Methods,46th International Symposium Electronics in Marine, ELMAR-2004, 16-18, June 2004.

[12] A.K.Jain,A.Ross, Multibiometrics Systems, Communications of the ACM, special Issue on Multimodal Interfaces, 47(1), pp. 34-40, January 2004.

[13] A.Ross, A.K.Jain,"Information fusion in biometrics," Pattern Recognition Letters, vol. 24, pp. 2115-2125, Sep 2003.

[14] L.I.Kuncheva, C.J.Whitaker, C. A. Shipp, R.P.W.Duin, "Is independent good for combining classifiers?," in proc. of International Conf. on Pattern Recognition(ICPR), vol 2, (Barcelona,Spain), pp. 168-171, 2000.

[15] L.Hong, A.K.Jain,S.Pankanti, Can Multibiometrics Improve Performance, In proceedings of IEEE workshop on Automatic Identification Advanced Technologies, pp. 59-64, New Jursey, October,1999.

[16] C.Sanderson, K.K.Paliwal, Information Fusion and person verification using speech and face information, IDIAP-RR, pp. 2-33, 2003.

[17] Hybrid Fusion for Biometrics: Combining Score-level and Decision-level Fusion Qian Tao Raymond Veldhuis 2008 IEEE.

[18] Dakshina Kisku, Ajita Rattani, Phalguni Gupta, Massimo Tistarelli and Jamuna Kanta Sing (2010). Biometrics Sensor Fusion, Sensor Fusion and its Applications, Ciza Thomas (Ed.), ISBN: 978-953-307-101-5, In Tech, Available from:http://www.intechopen.com/books/sensor-fusion-and-its-applications/biometrics-sensor-fusion.

[19] M.Faundez-Zanut, Data Fusion in Biometrics, IEEE Aerospace and Electronic Systems Magazine, Vol. 20, pp.34-38,2005.

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

[21] A.Ross, A. Jain, Multimodal biometrics: An overview, Proceedings of the 12th European Signal Processing Conference(EUSIPCO), (Vienna, Austria), pp. 1221-1224, 2004.

[22] K. Nandakumar, Fusion in Multibiometrics Identification systems, WWW.cse.msu.edu

[23] A. Ross, A.Jain, Information fusion in biometrics, Pattern Recognition Letters, Special Issue on Multimodal Biometrics, Vol. 24, pp. 2115-2125, 2003.

[24] Karim Faez, Sara Motamed, Mahboubeh Yaqubi, Personal Verification using Ear and Palm-print Biometrics,IEEE International Conference on Systems, Men and Cybernetics(SMC 2008).

[25] Souheil Ben- Yacoub, Yousri Abdelijaoued, Eddy Mayoraz, Fusion of face and speech data for person identity verification, IEEE transactions on neural networks, vol. 10no. 5 September, 1999.

[26] Shrikant Twari,Aruni Singh, Sanjay Kumar Singh, Integrating faces and soft biometrics for newborn recognition, International journal of Advanced Computer Engg. and Architecture, Vol 2, No.2(June-July 2012).

[27] Fan Yang, Baofeng Ma. A new mixed mode biometrics Information fusion based on fingerprint, hand geometry and palm-print,Fourth International Conference on Image and Graphics, 2007 IEEE.

[28] Khalid Fakhar, Mohmmad EI Aroussi, Rachid Saadane, Mohmmad Wahbi, Fusion of face and iris features extraction based on steerable pyramid representation for multimodal biometrics, 2010 IEEE.

[29] Mahesh P.K., M.N. Shanmukha Swammy, A Biometric Identification System based on the fusion of palmprint and speech signal, 2010 IEEE .

[30] Alipure yazdanPanah,Karim Faez ,RasoulAmir Fattahi,Multimodal biometric system using face ear and Gait Biometrics,tenth internetional conference on INFORMATION science ,Signal processing and their application (ISSPA 2010 IEE).

[31] Alimadamakmasmoudi,RandaBoukhristrabelisi,Dorasellemimas moudi,A New Biometric Identification based on fusion fingerprints and finger veins using monoLBP descriptor,International scholerly and Scientific research anfd innovation,World Acadamy of Science,Engineering and Technology Vol.7 2013.

[32] V.Arulalan,N.Getha,V.Premanand,Multimodal Biometric system using Iris and inner-Knuckle print,International general of computer applications(0975-887) Vol.106,No.6 Nov.2014.

[33] Cherif Taouche,Mohd. Berkane, Multimodal Biometric Systems,2014 IEEE.

[34] S.R. Soruba, Dr. N. Radha, A Survey on fusion techniques for Multimodal biometric Identification, International Journal of Innovative Research in computer and Communication Engineering, vol. 2, issue 12,Dec. 2014.

[35] P.S. Sanjayekar, J.B.Patil, An overview of multimdal biometrics, Signal and Image processing: An International Journal (SIPIJ) vol. 4, no..1 Feb. 2013.

[36] Stanz. Li, Anil K. Jain, Encyclopedia of biometrics: (I-Z), Vol.1, 2009.

[37] J.Daugman, How iris recognition works, IEEE Transactions on circuits and Systems for video Technology, Vol. 14(1), PP. 21-30, 2004.

[38] A.K.Jain, A.Ross and S.Prabhkar, An Introduction to Biometric Recognition,IEEE Transactions on circuits and Systems for video Technology, Special issue on image and video based biometrics, Vol14(1), pp. 4-20, 2004.

[39] A.K.Jain, A.Ross, S.Pankanti, Biometrics: A tool for information security, IEEE transaction on information Forensics ans security, Vol.1(2),pp. 125-143, 2006.

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

[41] M. Poulos, M. Rangoussi, V. Chrissicopoulos and A. E. Gelou. Person Identification Based on Parametric Processing on the EEG, In Proceedings of the 6th International Conference on Electronics Ciruits and Systems, vol. 1, pages. 281-286, 1999.

[42] R. B. Paranjape. Electroencephalogram as a Biometric, In Proceedings of the Canadian Conference on Electrical and Computer Engineering, vol. 2, (2001), pages 1363-1366, 2001.

[43] R. L. Kashyap and R. Chellapa. Stochastic Models for Closed Boundary Analysis: Representation and reconstruction, In IEEE Trans. Inform. Theory, vol. IT-27, pages 627-635, 1981.

[44] S. R. Dubois and F. H. Glanz. An autoregressive model approach to two dimensional shape classification, In IEEE Transactions Pattern Anal. Machine Intelligence PAMI-8, pages 55-66, January 1986.

[45] A. H. Mir, M. Handmandlu and S. N. Tandon. Description of shapes in CT Images the Usefulness of Time-Series Modeling Techniques for Identifying Organs, In IEEE Eng. Med, Biol. Mag, vol. 18, pages 79–84 1999.

[46] Statistical Texture Analysis G. N. Srinivasan, and Shobha G., proceedings of world academy of science, Engineering and Technology , vol. 36 Dec.2008, ISSN 2070-3740.

[47] Statistical and Structural Approaches to Texture ROBERT M. Haralick, Proceedings of IEEE ,vol. 67, No. 5, MAY 1979.

[48] E. M. Darling, and R. D. Joseph: Pattern recognition from satellite altitudes. IEEE Trans on Syst., Man, and Cyber. SMC-4: 38-47, March 1968.

[49] R. M. Harlick, and K. Shanmugam: Computer classification of Reservoir sand stones. IEEE Trans on Geoscience Electronics, GE-11: 171-177, Oct. 1973.

[50] R. M. Harlik: A texture-context feature extraction algorithm for remotely sensed imagery. Proc of the 1971 IEEE Decision and Control Conf., Calfornia: 1971.

[51] R. M. Harlick, and K. Shanmugam: Combined Spectral and spatial processing of ERTS imagery Data. /. of Remote Sensing of Environment, 3: 3-13, 1974.

[52] L. Van Gool, P. Dewaele, and A. Oosterlink: Texture analysis Anno 1983. Computer Vision, Graphics, and Image Processing, 29: 337-357, 1985.

[53] Todd R. Reed, and J. M. Hans Du Bui: A review of recent texture segmentation and feature extraction techniques. Computer Vision, Graphics, and Image Processing, 57: 359-372, May 1993.

[54] A.H.Mir, M.Hanmandlu,S.N.Tandon1 Texture Analysis of CT Images, IEEE Engineering In Medicine and Biology November, 1995.

[55] G. Healey and L. Wang, "Illumination-invariant recognition of texture in color images," Journal of Optical Society of America, vol. 12, pp. 1877–1883, 1995.

[56] Texture Classification across Illumination Color Variations Rahat Khan, Damien Muselet, and Alain Trémeau International Journal of Computer Theory and Engineering, Vol. 5, February 2013.

[57] shodhganga.inflibnet.ac.in/bitstream/10603/24460/9/09_chapter 4.pdf by T Sree Sharmila - 2014.

[58] A. Materka, M. Strzelecki, Texture Analysis Methods – A Review, Technical University of Lodz, Institute of Electronics, COST B11 report, Brussels 1998.

[59] Julesz, Bela, Visual Pattern Discrimination, IRE Trans. On Information theory, vol. 8,No. 2, February 1962, pp.84-92.

[60] R.M.Haralick, Statistical and structural approaches to texture. In proc. 4th International Joint Conference Pattern Recognition, 45-69, 1978.

[61] J. Canny .A Computational Approach to Edge Detection. In IEEE Trans. Pattern Analysis Machine I Intelligence, PAMI-8, November 1986.

Farida Khursheed, has done her B.E in Electronics & Communication Engineering (ECE) and M.Tech in Communication and Information Technology in the year 2007 both from National Institute of Technology (NIT), Srinagar, Jammu and Kashmir. India. Presently she is working as Associate Professor in the Department of ECE at NIT Srinagar, India. She has guided a number of M.Tech thesis and B.Tech projects. She has a number of publications in her credit. Currently she is perusing her Ph.D in the area of Biometrics. Her areas of interest are Biometrics, Image processing and Security.

Ajaz Hussain Mir, has done his B.E in Electrical Engineering with specialization in Electronics & Communication Engineering (ECE) .He did his M.Tech in Computer Technology and Ph.D both from IIT Delhi in the year 1989 and 1996 respectively. He is Chief Investigator of Ministry of Communication and Information Technology, Govt. of India project: Information Security Education and Awareness (ISEA). He has been guiding Ph.D and M.Tech thesis related to the area of Security and other related areas and has a number of International publications to his credit Presently he is working as Professor in the Department of Electronics & Communication Engineering at NIT Srinagar, India. His areas of interest are Biometrics, Image processing, Security, Wireless Communication and Networks.