Multimodal Biometrics using Face, Ear and Iris Modalities

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ABSTRACT
Automatic person identification is an important task in computer vision and related applications. Multimodal biometrics involves more than two modalities. The proposed work is an implementation of person identification fusing face, ear and iris biometric modalities used PCA based neural network classifier for feature extraction from the face and ear images and hamming distance for calculating iris templates. These features fused and used for identification. Better result was obtained if the modalities were combined. Identification was made using Eigen faces, Eigen ears, Template of iris and their features tested over the self created image database.

General Terms
Principal component analysis (PCA), Segmentation, Normalization, Hough transform.

Keywords
Multimodal biometrics, PCA, Eigen faces, Eigen ears, Euclidian distance, Hamming distance.

1. INTRODUCTION
Now, most of the new applications of technology employ some kind of biometrics for authentication purposes. Biometrics deals with identification of a person based on biometric traits such as face, ear, fingerprint, iris etc. As a result, recognition based on a single biometric trait may not be sufficiently robust and it has a limited ability to overcome spoofing. The biometric technologies can be combined to provide enhanced security over a single modal biometrics, which is called as multimodal biometric system [1]. A multimodal bio-metric system integrates multiple source of information obtained from different biometric sources. Multimodal biometrics system involves various levels of fusion, namely, sensor level, feature level, matching score level, decision level and rank level [2-4]. Identity management system is challenging task in providing authorized user with secure and easy access to information and services across a wide verity of networked system. Biometrics refers to the use of physiological or biological characteristics to measure the identity of an individual [5]. These features are unique to each individual and remain unaltered during lifetime. Many problems arise because of the variation in several parameters such as scale, lighting, poor illumination and other environmental parameters [6, 7]. Biometric systems are designed to make binary decisions-accepting the authorized personnel and rejecting the impostors. Two types of errors are encountered in biometric systems namely false acceptance (FA) errors allowing the impostor in and false rejection (FR) errors which keep the authorized personnel out.

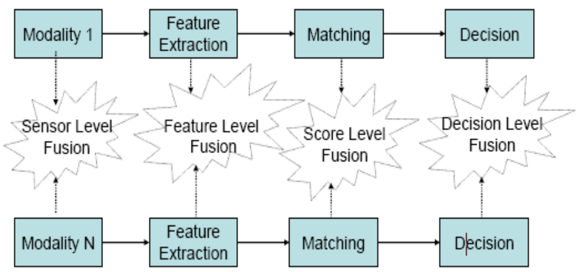

Fig 1: Multimodal biometric system.

Figure 1 shows a multimodal biometric system. In the proposed work, PCA classifier is used to obtain the features by the input face and ear images and Hamming distance for iris images. segmentation, normalization and feature encoding are the subsystem . Decision is made by matching the test image with the images registered in the database using Euclidean distance and Hamming Distance approach. The system error of a multimodal biometric system is a combination of the FAR and the FRR from different biometric technologies. Unlike unimodal biometrics, the combination of several measurements makes it harder to analyze the accuracy of a multimodal biometric system.

The remainder of this paper is organized as follows: Section 2 describes related research in this field. Section 3 gives brief description of PCA, segmentation, normalization, feature encoding and Hamming distance as a pre processing technique. Section 4 discusses the preprocessing steps involved to recognize face, ear and iris images. Section 5 presents a method of combining the face matching score, the ear matching score and iris matching score. The proposed method has been tested on self created database. Experimental results have been analyzed and conclusion and future work has been discussed.

2. RELATED RESEARCH
Single biometric multiple representation fusion involves using multiple representations on a single biometric indicator. Several research papers were studied on multimodal biometrics. Ho et al. (2004) suggested a technique relevant to the identification problem in which a large number of classes (identities) are present. The fusion in this approach takes place at the matching stage and the classifiers report a similarity score for each class [8]. Cappelli et al. (2000) suggested fingerprint classification system that combines a structural classifier by integrating the scores generated by the two classifiers [9]. Jain et al (2003) used K nearest neighbor classifier and a set of 10 neural network classifiers to classify fingerprints. All the approaches presented (the highest rank method, the Borda count method and logistic regression)

attempt to reduce a given set of classes[10]. Prabhakar and Jain (1999) shows that selecting classifiers based on some ‘‘goodness’’ statistic may be necessary to avoid performance degradation when using classifier combination techniques [11]. Kisku et al. (2009) proposed a sensor level fusion scheme for face and palm print biometrics where face and palm print are decomposed using Haar wavelet and then average of wavelet coefficients is fused as image of face and palm print. Finally, inverse wavelet transform is carried out to form a fused image of face and palm print. Feature level fusion involves consolidating the evidence presented by two biometric feature sets of the same individual. The majority of the work reported on feature level fusion is related to multimodal biometric system [5]. Zhao et al. (2000) implemented a multimodal biometric system using face and palm print at feature level. Gabor features of face and palm prints are obtained individually. Extracted Gabor features are then analyzed using linear projection scheme such as PCA to obtain the dominant principal components of face and palm print separately [6]. Jing et al. (2007) employed Gabor transform for feature extraction and then Gabor features are concatenated to form fused feature vector. Then, to reduce the dimensionality of fused feature vector, non linear transformation techniques such as Kernel discriminate Common Vectors are employed [7]. R.Govindarajan et al. (2003) proposed a multimodal biometric system using Face and hand geometry at feature level. Face is represented using PCA and LDA while 32 distinct features of hand geometry is extracted and then concatenated to form a fused feature [12]. The majority of the works reported on multimodal biometric are confined to score level fusion.

Score level fusion techniques can be divided into three different categories: transformation based methods, classifier based methods and density based score fusion. In transformation based method, scores obtained from different modalities are normalized so that, they will lie in the same range weights are calculated depending on the individual performance of the modalities. In classifier based score fusion, a pattern classifier is used to indirectly learn the relationship between the vectors of match scores. Heo et al. (2004) used classical K-means clustering, fuzzy clustering and median Radial Basis Function (RBF) for fusion at match score level [13]. Sinha et al. (2010) implemented modified PCA based Noise reduction of CFA images [14]. Hong et al. (1998) used the logistic function to map the matching scores obtained from two different fingerprint-matching algorithms into a single score. This type of fusion also takes place at the matching stage of a biometric system [15]. Vatsa et al. (2008) proposed a weighted image fusion using 2V-SVM where weights are assigned by finding the activity level of visible and thermal face image [16]. Gyaourova et al. (2004) employed Genetic Algorithm for feature selection and fusion where group of wavelet features from visible and thermal face images are selected and fused to form a single image. But there is no scope for weighting [17]. Sinha, et al. (2010) suggested that biometric security technologies need to be developed that should be robust [18].

3. METHEDOLOGY

3.1 Principal Component Analysis

The most popular person recognition algorithms is Principal Component Analysis (PCA). The main idea is to de-correlate data in order to highlight differences and similarities by finding the principal directions (i.e. the eigenvectors) of the covariance matrix of a multidimensional data. For testing the biometric system, face or ear images were used from the training set of face and ear images. Before going to next step first train the PCA using the training set of images, to generate eigenvectors. The mean image is computed of the training data as:

$$\psi_{Train} = \frac{1}{M}\sum_{n-1}^{M}\Gamma_n \qquad (1)$$

Each training image is subtracted by mean image as:

$$\phi_i = \Gamma_i - \psi_{Train} \quad i = 1,2,\ldots\ldots M \qquad (2)$$

It is large vectors set subjected to PCA which seeks a set of M ortho-normal vectors, U_n. The k^{th} vector, U_k, is chosen such that:

$$\lambda_K = \frac{1}{M}\sum_{n-1}^{M}(U_k^T \ \Phi_n)^2 \qquad (3)$$

The vectors U_k and scalars λ_k are the eigenvectors and Eigen values respectively of the following covariance matrix (CM):

$$C = \frac{1}{M}\sum_{n-1}^{M}\left(\Phi_n \Phi_n{}^T\right) = AA^T \qquad (4)$$

The mean image Ψ of the gallery set is computed. This is projected onto the “face space” or “ear space” by the M eigen vectors derived from the training set. This gives:

$$\omega_K = U_K^T \Phi_i \quad K = 1 \ldots M \qquad (5)$$

Euclidian distance is calculated for face or ear class as follows:

$$d_K = \| \Omega - \Omega_k \| \qquad (6)$$

Where k^{th} face or ear class is describing by d_k vector. Each image in the training set is transformed into the image space and its components are stored in memory. The image space has to be populated with these known images. Euclidian distance to be calculating by this stored images. Figure 2 shows a general view of identification process.

3.2 Segmentation

In iris recognition automatically segment the iris region from the eye image in to a digital eye image. The iris region, shown in Figure3, can be approximated by two circles, one indicate

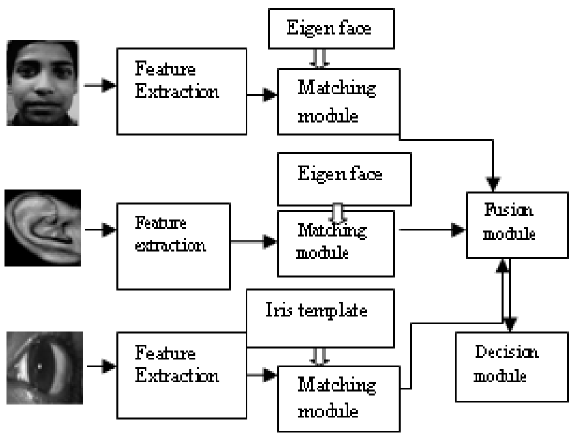

Fig. 2: An identification process

the iris boundary and second, pupil boundary. The eyelids and eyelashes are upper and lower parts of the iris region. Kong and Zhang [19] presented a method for eyelash detection, where eyelashes are treated as belonging to two types, separable eyelashes, which are isolated in the image, and multiple eyelashes, which are bunched together and overlap in the eye image. Separable eyelashes are detected using 1D Gabor filters, since the convolution of a separable eyelash with the Secular reflections along the eye image are detected using thresholding since the intensity values at these regions will be higher than at any other regions in the image.

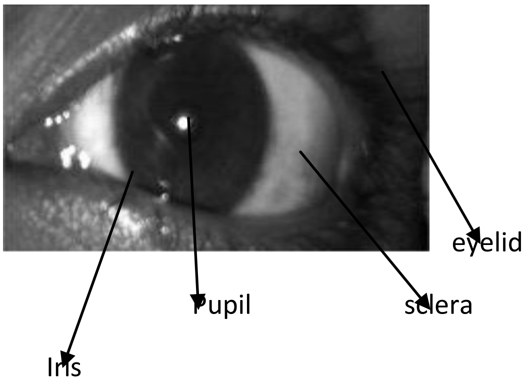

Fig 3: Human eye

The most popular computer vision algorithm is Hough transform which is used for geometric shapes like lines and circles in an object. the circular Hough transform can be used to deduce iris regions radius and centre coordinates. J. Asmuth et al. develop A system for automated iris recognition [20], Kong and Zhang et al. prepare Accurate iris segmentation based on novel reflection and eyelash detection model. [19], Tisse et al. [26], and Ma et al. [25] find out person identification technique using human iris recognition. From the edge map, votes are cast in Hough space for the parameters of circles passing through each edge point. These parameters are the centre coordinates x_{c} and y_c, and the radius r. A maximum point in the Hough space will correspond to the radius and centre coordinates of the circle best defined by the edge points. The eyelid is detecting by the horizontal direction and the outer circular boundary of the iris is detecting by vertical direction derivatives shows in Figure 4.

Fig 4: Segmented iris image

3.3 Normalization and Feature Encoding

After successful iris region segmentation, the region is transformed so that it has fixed dimensions in order to allow comparisons. The dimensional inconsistencies between eye images are mainly due to the stretching of the iris caused by pupil dilation from varying levels of illumination. The normalization process will produce iris regions having same constant dimensions. The homogenous rubber sheet model devised by Daugman [23] remaps each point within the iris region to a pair of polar coordinates (r,θ) where r is on the interval [0, 1] and θ is angle [0,2π]. In the Daugman system, rotation is accounted for during matching by shifting the iris templates in the direction until two iris templates are aligned.

Feature encoding was implemented by convolving the normalized iris pattern with 1D Log-Gabor wavelets. The 2D normalized pattern is broken up into a number of 1D signal, and then these 1D signals are convolved with 1D Gabor wavelets. The rows of the 2D normalized pattern are taken as the 1D signal; each row corresponds to a circular ring on the iris region. The intensity values at known noise areas in the normalized pattern are set to the average intensity of surrounding pixels to prevent influence of noise in the output of the filtering. The output of filtering is then phase quantized to four levels using the Duggan method [23], with each filter producing two bits of data for each phase. A disadvantage of the Gabor filter is that the even symmetric filter will have a DC component whenever the bandwidth is larger than one octave [24].

3.4 Matching Using Hamming Distance

For matching, the Hamming distance was chosen as a metric for recognition, since bit-wise comparisons were necessary. The Hamming distance algorithm employed also incorporates noise masking, Hamming distance are calculated between two iris template by using only important bits. Now when taking the Hamming distance, only those bits in the iris pattern that corresponds to '0' bits in noise masks of both iris patterns will be used in the calculation. The Hamming distance will be calculated using only the bits generated from the accurate iris region, and this modified by each template. Although, in theory, hamming distance is 0 when the result calculated on same iris templates but in put into practice this will not occur.

4. EXPERIMENTAL RESULTS

A face image and ear image of size p × q pixels is represented by a vector in p.q dimensional space. In iris recognition Iris image region completed in sub parts. The input to the system will be an eye image and the output will be an iris template, which provides a mathematical representation of the iris region. PCA implementation consists in classifying faces of 100 people including girls and boys to recognize. The information extracted from each face is represented by the distances corresponding to the 100 people. For each person, we can handle a large input vector, facial image, only by taking its small weight vector in the face space. The first step is to train the PCA using the training set and then each face in the training set is transformed into the face space and its components are stored in memory. Figure 5 shows the training set of face images. Two dimensional images are considered as a vector, by concatenating each row or column of the image. Each classifier has its own representation of basis vectors of a high dimensional face vector space. Figure 6 shows a normalized training set of face images with normalized face images. Figure 7 shows mean image which is computed by addition of all training images and dividing the image by number of images.

Fig. 5: Training set of face images.

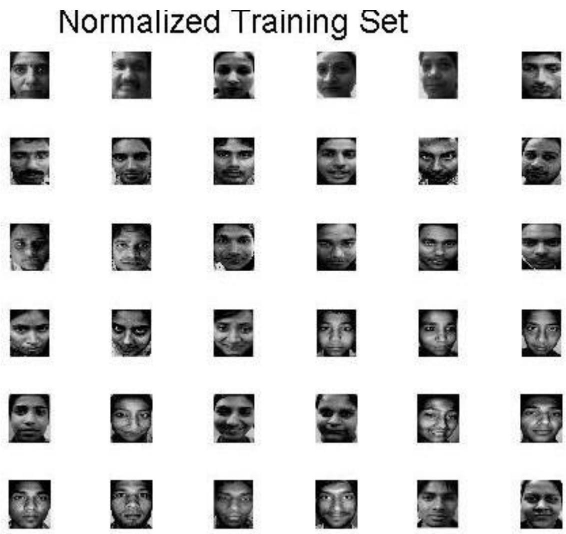

Fig. 6: Normalized images.

Fig. 7: Face Mean image.

Figure 8 shows Eigen faces that represented as feature set.

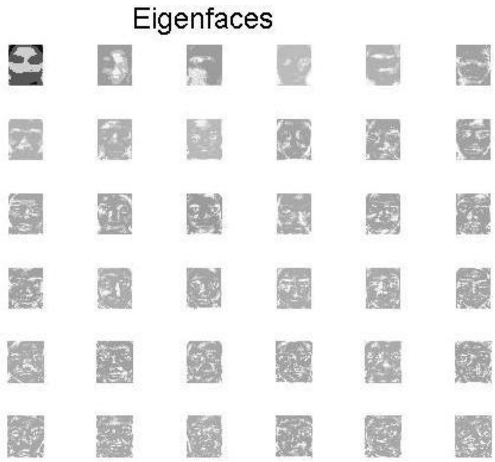

Fig. 8 : Eigen faces.

Figure 9 shows the input image and reconstructed image and Figure 10 shows weight of input face and the distance of input image. Their weights are stored. An acceptance or rejection is determined by applying a Euclidian distance comparison producing a distance, as mentioned in Table 1.

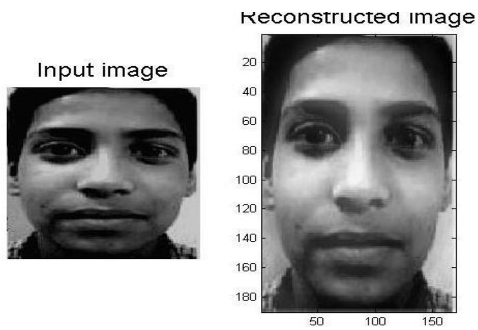

Fig. 9: Input image and reconstructed image.

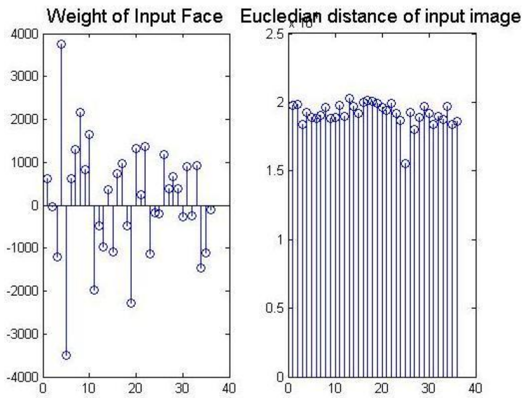

Fig. 10: Weight of input face and Euclidian distance.

Figure 11 to Figure 15 present results for ear images.

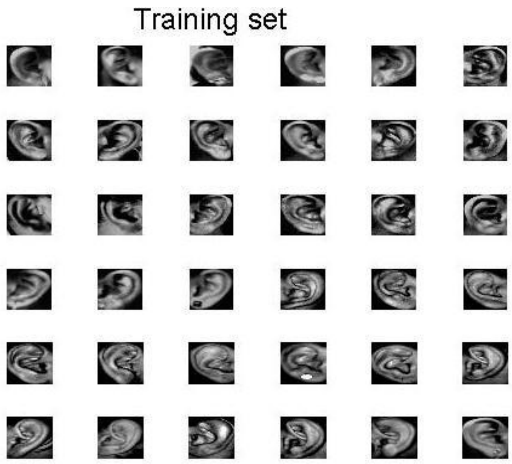

Fig 11: Training set of ear images.

Fig 12: Normalized training set of ears.

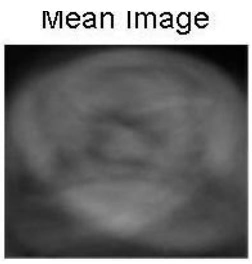

Fig 13: Ear Mean image.

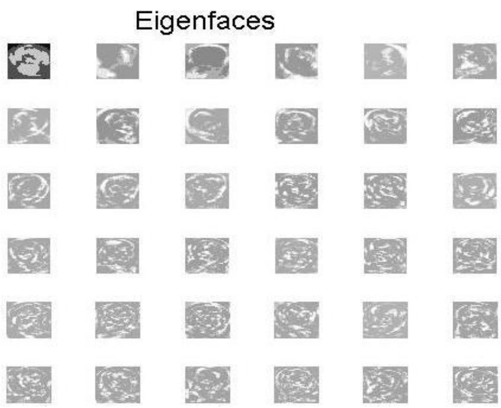

Fig 14:   Eigen image set of ears.

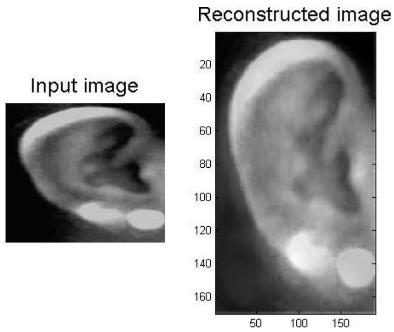

Fig 15: Input image and reconstructed ear image.

Iris database collect segmented images of iris that gives only 75% accurate result due to poor imaging conditions. Next step the encoding process 1D Log-Gabor filter to provide accurate recognition. For data set, ideal recognition was possible when false accept and false reject rates is minimum. recognition rate was achieved with the our data set These results confirm that iris recognition is a reliable and accurate biometric technology.

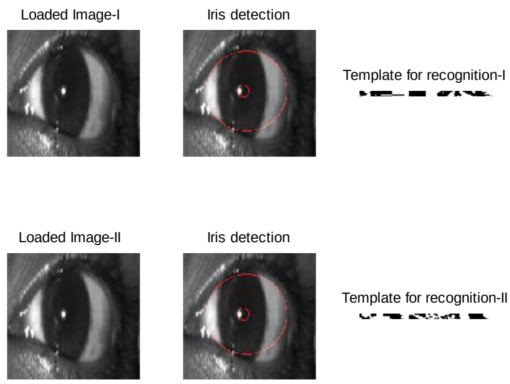

Fig 16: (a) Input image and database, (b) Segmented Iris Image using Hough Transform and (c)The binary iris Biometrics template extracted

A database of faces, ears and iris are created that consists of 100 person’s images for face ,ear and iris using high quality camera and sufficient light. Figure 17 shows cropped and resize data sample for faces ,ears and iris.

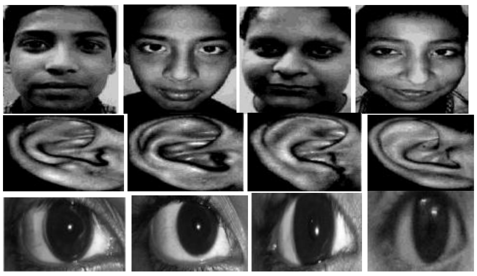

Fig. 17: Cropped and resized data sample.

Before performing recognition based on fusion of face, ear and iris input images should be pre-processed and normalized. First only face images, ear images and iris images in the profile face images are cropped. Both face and ear face images are filtered and transformed into the size of 170×190 pixels and iris images are filtered and transformed into the size of 256×256 pixels. Training set for face, ear or iris images per person are used as the gallery and test data images are used as the probe. The dimension of the training samples space of face or ear is reduced applying PCA. The minimum-distance classifier is used for classification. Euclidian distance for faces or ears and hamming distance for iris has been shown in Table 1.

Table 1 : Euclidian distance for faces or ears and hamming distance for iris

Faces	Minimum Euclidian distance for faces	Ears	Minimum Euclidian distance for ears	Iris	Hamming distance for iris
Pf1	1.5488E+04	PE1	1.5343E+04	pI1	0.3167
Pf2	1.5485E+04	PE2	1.5307E+04	pI2	0.3167
Pf3	1.5483E+04	PE3	1.5274E+04	pI3	0.3167
Pf4	1.5504E+04	PE4	1.5265E+04	pI4	0.3167
Pf5	1.5488E+04	PE5	1.5257E+04	pI5	0.3167
Pf6	1.5495E+04	PE6	1.5252E+04	pI6	0.3167
Pf7	1.5492E+04	PE7	1.5244E+04	pI7	0.3167
Pf8	1.5515E+04	PE8	1.5247E+04	pI8	0.3167
Pf9	1.5496E+04	PE9	1.5247E+04	pI9	0.3167
Pf10	1.5502E+04	PE10	1.5254E+04	pI10	0.3167
Pf11	1.5511E+04	PE11	1.5241E+04	pI11	0.3167
Pf12	1.5514E+04	PE12	1.5260E+04	pI12	0.3167
Pf13	1.5516E+04	PE13	1.5249E+04	pI13	0.3167
Pf14	1.5512E+04	PE14	1.5224E+04	pI14	0.3167
Pf15	1.5517E+04	PE15	1.5229E+04	pI15	0.3167
Pf16	1.5519E+04	PE16	1.5254E+04	pI16	0.3167
Pf17	1.5507E+04	PE17	1.5241E+04	pI17	0.3167
Pf18	1.5516E+04	PE18	1.5253E+04	pI18	0.3167
Pf19	1.5486E+04	PE19	1.5256E+04	pI19	0.3167

Face and ear iris algorithms are tested individually and individual weight for face is found to be 92%, for ear 96% and iris 30% as shown in Table 2. The overall performance of the system has increased showing weight for face, ear of 98.24% with FAR(False Accept Rate) of 1.06 and FRR (False Reject Rate) of 0.93 respectively. The overall performance of the system has increased showing weight for face, ear and iris of 99.24% with FAR of 1.07 and FRR of 0.94 respectively

Table 2: Individual and Combined Accuracy

Traits	Weight %	FAR	FRR
Faces	92	1.08	0.98
Ears	96	1.17	0.99
Iris	30	1.09	0.95
Combined (Face + Ear)	98	1.06	0.93
Combined (Face + Ear + Iris)	99	1.07	0.94

5. CONCLUSIONS

Recently, several contributions have been made in the field of biometrics and investigations have been carried out in the domain of multi-modal biometrics. When multiple biometric traits combine using different fusion methods to achieved optimal result .Paper shows, PCA, Hamming Distance based multimodal biometrics has been presented using faces ears and iris modalities for self created databases. Multimodal biometrics has resulted improved performance in terms of recognition accuracy, FAR and FRR.

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