A Robust Multi-Biometric System with Compact Code for Iris and Face

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Abstract: Multimodal biometric can overcome the limitations of the single biometric trait and gives better classification accuracy. This paper proposes a face-iris multimodal biometric system based on fusion at the matching score level. The iris recognition system is composed of segmentation, normalization, feature encoding and matching. The wavelet transform is used in feature extraction to generate a compact feature vector length of 128 bits; this reduces the computational time and storage of the iris code. The face recognition system is composed of enhancement, feature encoding and matching. The new method called 'Phase-based Gabor Fisher Classifier (PBGFC)' is used in feature extraction; PBGFC employs only 16 Gabor filters, i.e., filters with 2 scales and eight orientations. This fact makes the resulting feature vector for the PBGFC method very compact. The scores from iris and face are then combined using several score normalization and fusion techniques. To validate our approach, experiments are conducted on the iris and face images obtained from the CASIA and ORL datasets respectively. The results show that our multimodal biometric system achieves higher accuracy than both single biometric approaches and the other existing multi-biometric systems based on fusion of iris and face.

Keywords: Multi-biometrics, Iris recognition, face recognition, Hamming distance.

1. Introduction

The science of measuring personal features such as iris, face, fingerprints, retina, hand geometry, voice or signatures for the purpose of security is called biometrics, and is becoming the technology of the future in the field of security. For this reason, many research works are turning to this horizon. However, systems that use unimodal biometrics suffer from various problems [1], [2], [3]. For example in face recognition, variations in terms of illumination, pose and expression lead to degradation of performance [4], while in iris recognition, no cooperative situation may degrade iris recognition accuracy [5]. In fact, multimodal biometrics fusion technology extracts information from multiple biometric traits to improve the recognition performance and overcome the limitations of unimodal biometric systems [6], [7], [8].

Multi-biometric systems can offer some advantages over single biometric systems, such as:
(1) Significantly improving the accuracy of the biometric authentication (identification or verification) process.
(2) Providing a high degree of flexibility, since unusable or non-preferred biometric traits in particular individuals can be compensated by information of other biometric modalities.
(3) Providing an additional difficulty to avoid spoofing attacks [9].

Fusion of information can be done at four different levels:

Sensor level combination of the raw data from the biometric sensor, feature level concatenation of different feature vectors [10] [11], matching score level combination of matching scores obtained by different biometric systems [12] [13] [14] [15] [16], and decision level combination of decisions already taken by individual systems [17] [18]. The most popular choice is fusion at the matching score level due to the ease in accessing and combining the scores generated by different matchers [14]. For the matching score level fusion, it can be further divided into three major categories: transformation-based score fusion (e.g., sum-rule based fusion preceded by

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min–max normalization) [13] [14] [19], density-based score fusion (e.g., likelihood ratio test with Gaussian Mixture Model) [20], and classifier-based score level fusion (e.g., SVM- based fusion) [21].

Multimodal biometric systems use the face and iris features for constructing a high reliable biometric system because the face recognition is friendly and non-invasive whereas iris recognition is the most accurate.

In this paper, we propose a biometric verification system based on the fusion of two modalities face and iris to improve the accuracy of unimodal biometric systems. Experimental results show that a recognition rate of 99.2 % at FAR= 0.01% is obtained in this work. This shows a very good improvement in the recognition rate compared to single modalities. An increase of 6.7% for the IRIS and 15% for the face has been obtained which is better than the other existing systems. The rest of the paper is organized as follows. The related work is presented in Section 2. The iris and face systems are described in sections 3 and 4, respectively. An overview of the fusion level and the algorithm structure for fusing face+iris biometrics is derived in Section 5. Results of experiments are reported in Section 6. Finally, the related conclusions are given in Section 7.

2. Related Works

The most common method of multi-biometric fusion is the score-level fusion. Chen *et al* [22] used an unweighted average of the outputs of matchers based on neural networks, Wang *et al* [23] combined the matching scores of face and iris recognition as a two dimensional feature vector. Linear discriminate analysis (LDA) and the neural network based on the radial basis function (NNRBF) are employed as classifiers.

Wang *et al* [21] employed SVM which incorporated radial basis function as the kernel for the face-iris biometric system. Their result showed that the SVM-based score level fusion method outperforms LDA and the weighted sum-rule.

Heng Fui Liau *et al* [4] proposed a feature selection method to select an optimal subset of features while matching scores are integrated to become a 2D feature vector and SVM is employed as classifier.

In [26], the features from face and iris are extracted using local and global feature extraction methods such as PCA, subspace LDA, spPCA, mPCA and LBP. A transformation based score fusion and a classifier-based score fusion are then involved in the process to obtain, concatenate and classify the matching scores.

Another common approach to biometric fusion is the feature-level fusion through concatenation. Rattani *et al* [11] computed SIFT features for chimeric face and iris images and concatenated the resulting feature vectors. The number of matching SIFT features between two vectors (measured by Euclidean distance) is used as a match score for that comparison.

Son *et al* [28] extracted features for face and iris images based on a Daubechies wavelet transform. Concatenation is used to form a joint feature vector while the Euclidean distance between feature vectors is used to generate the matching scores.

Zhifang Wang *et al* [29] adopted an efficient feature-level fusion scheme for iris and face. The algorithm normalizes the original features of both iris and face using the z-score model to eliminate the unbalance in the order of magnitude and the distribution between two different kinds of feature vectors, and then connects the normalized feature vectors in serial rule. In the first phase, the features of iris and face are extracted respectively. They then normalized the features before fusion. Finally, they fused the normalized features in series and used the Euclidean distance to classify.

Kapale *et al* [30] used PCA, Haar wavelet and a morphological method for the fusion at decision level which is less studied in literature.

3. Iris Recognition System

Firstly, we locate the iris by a segmentation process and then we normalize the iris image to get a (512x64) rectangular iris image. Secondly, we extract features with the Haar wavelet transform. At different levels, the vertical coefficients are encoded into the iris template to give a compact feature vector length of 128 bits. Finally, the Hamming distance similarity measure is employed for recognition.

A. Iris Extraction

The first step of the iris recognition is to isolate the region of the iris in a digital image. The localized iris is shown in fig.1.

To isolate the area of the iris in a digital image, we used the Hough transform. The technique is based on the study of Masek [31] where the image is first converted to an 8-bit grey scale and reduced to (225 x 300) pixels for faster execution and consistency.

The segmentation process is based on the circular Hough transform which defines a circle, according to equation (1).

$$x_c^2 + y_c^2 - r = 0 \tag{1}$$

Where a maximum point in the Hough space will correspond to the radius r and center coordinates x_c and y_c of the circle best defined by the edge points.

The Hough transform is a standard computer vision algorithm that can be used to determine the parameters of simple geometric objects such as lines and circles, present in an image [32].

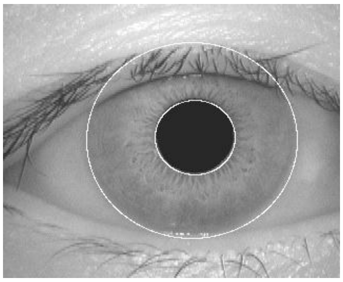

Figure 1. Iris localized image

B. Normalization and Enhancement

The Daugman's normalization method transforms a localized iris texture from Cartesian to polar coordinates, a pair of dimensionless real co-ordinates (r, θ), where 'r' lies in the unit interval [0,1] and 'θ' is the usual angular quantity that is cyclic over [0,2π]. The remapping of the iris image I(x,y) from raw co-ordinates (x,y) to the doubly dimensionless non concentric polar co-ordinate system (r,θ) is explained in [33].

The normalized image was generated and an enhancement method was used to get the proper intensity, the (512 x 64) image is shown in figure. 2.

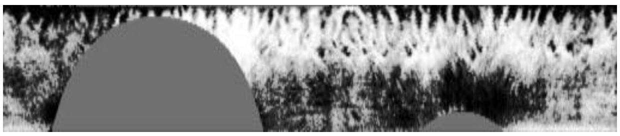

Figure 2. Normalized Iris after enhancement.

C. Features Extraction

In this study, the wavelet transform was used to extract the discriminating information in an iris pattern. Wavelets namely Haar [34] are experimented. The wavelet coefficients can be used to describe the characteristics and reflect the nature of the image information, Decomposition at level 4 with only vertical coefficients was adopted and gives a compact feature vector length of 128 bits.

D. Hamming Distance

The last module for the iris recognition system is the template matching. Once the features are extracted using the Haar wavelet, the coefficients are converted to binary using sign quantization.

The following algorithm is used for conversion:

If Coeff(i)>= 0 then Coeff(i) = 1;
If Coeff(i)<0 then Coeff(i) = 0;

We employed the Hamming distance (HD) technique to measure the similarities given by the formula:

$$HD = \frac{1}{B}\sum_{1}^{B} X_i \otimes Y_i \tag{2}$$

Where X_i and Y_i represent the i-th bit in sequences X and Y respectively, and B is the total number of bits in each sequence. The symbol $\otimes$ is the "XOR" operator. The XOR is the known Boolean operator that gives a binary 1 if the bits at position i in X and Y are different and 0 if they are similar.

4. Face Recognition System

The system is composed of a number of subsystems. Firstly and prior to extract the feature, a histogram equalization and photometric normalization procedure that normalized face images from the database to zero mean and unit variance was used. Secondly, the method called 'Phase-based Gabor Fisher Classifier (PBGFC)' by Struc [35] was used to extract of features, while the linear discriminant analysis (LDA) was employed in the second step to project the augmented feature vectors into a low dimensional space. Finally, the cosine Mahalanobis distance similarity measure was employed for recognition.

A. Features Extraction

For feature extraction, we adopted the method proposed by Struc [35] called 'Phase-based Gabor Fisher Classifier (PBGFC)' which has given the best results with 2 scales and eight orientations. This method is really robust in varying illumination conditions and it significantly reduces the computational burden required for extraction of the facial features. It is however different from the other Gabor wavelet based methods since it exploits Gabor-phase information rather than Gabor magnitude information. It first constructs an augmented feature vector that contains Gabor-phase information derived from a novel representation of face images - the oriented Gabor phase congruency image (OGPCI) - and then applies LDA [36] to reduce the size of the feature vectors for an efficient implementation of the matching procedure.

The presented OGPCIs form the foundation for the PBGFC method which computes an augmented (phase based) feature vector from a given face image by taking the following steps [3]:
(I) For the given face image, the *OGPCIs* it computes for all v orientations *and* for a number of filter scales *equal to 2.*
(II) It downsamples the resulting OGPCIs with the help of a rectangular sampling grid with 16 horizontal and 16 vertical grid lines.
(III) Forms the final feature vector x by concatenating the rows (or columns) of the vectors D_v^T constructed from the downsampled OGPCIs, i.e.

$$x = \left(D_1^T \; D_2^T \; \cdots \; D_{r-1}^T \right)^T \tag{3}$$

Where *T* denotes the transform operator and D_v stands for the vector derived from the OGPCI at the v-th orientation ($v = 0, 1, \ldots, r - 1$).

The oriented Gabor phase congruency image (OGPCI) is given by:

$$OPGCI_{\mu}(y,x)=\frac{\sum_{\mu}^{p-1}A_{\mu,\nu}(y,x)\Delta\Phi_{\mu,\nu}(y,x)}{\sum_{\mu}^{p-1}\left(A_{\mu,\nu}(y,x)+\varepsilon\right)} \tag{4}$$

Where ε denotes a small constant which prevents division by zero and $\Delta\Phi_{\mu,\nu}(y,x)$ Stands for the following phase deviation measure:

$$\Delta\Phi_{\mu,\nu}(Z)=\cos\left(\phi_{\mu,\nu}(z)-\bar{\phi}_{\nu}(z)\right)-\left|\sin(\phi_{\mu,\nu}(z)-\bar{\phi}_{\nu}(z))\right| \tag{5}$$

Here $\phi_{\mu,\nu}(z)$ denotes the phase angle of the Gabor filter (with a frequency f_{μ} and orientation θ_{ν}) at the spatial location $z=(y, x)$, while $\bar{\phi}_{\nu}(z)$ represents the mean phase angle at the vth orientation. . Several examples of the OGPCIs for a sample image are shown in Figure 3.

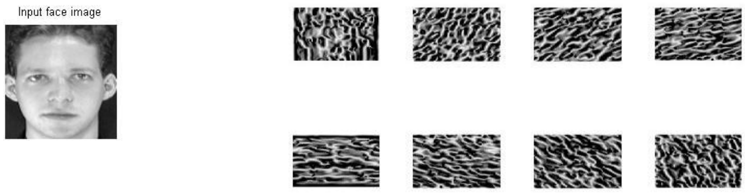

Figure. 3 Phase congruency features for all 8 filter orientations and 2 scales.

B. Matching and Decision

Matching is a process where the extracted features are compared against the stored templates to generate match scores. We employed The MahCosine Distance to measure the similarities. The MahCosine measure is the cosine of the angle between the images after they have been transformed to the Mahalanobis space and normalized by the variance estimates. Formally, the MahCosine measure
between images i and j with projections a and b in the Mahalanobis space is computed as:

$$MahCos\text{in\_}Distance(i,j)=\cos\left(\theta_{i,j}\right)=\frac{|a|*|b|*\cos\left(\theta_{i,j}\right)}{|a|*|b|} \tag{6}$$

5. Score Level Fusion

Development of the multimodal system has been done using fusion techniques at the matching score level. Fusion at this level is the most commonly discussed approach in the biometric literature due to primarily the ease of accessing and processing match scores (compared to the raw biometric data or the feature set extracted from the data).

There are two approaches for fusion at score level fusion. The first one is to formulate it as a classification problem. The second one is to treat it as a combination problem. The individual matching scores output by multiple biometric matchers are combined to generate a new match score (a scalar) which is then compared to a threshold to make the final decision.

To ensure a meaningful combination of scores, the scores must be transformed to a common domain. Normalization methods and combination approaches have been proposed in the literature [14].

A. Normalization Techniques

a. Min max Normalization:

Min max normalization is best suited for the case where the bounds (maximum and minimum values) of the scores produced by the matcher are known. This method is not robust; therefore, it is highly sensitive to outliers.

Minmax normalization technique is calculated as:

$$s'_k = \frac{s_k - \min}{\max - \min} \tag{7}$$

b. Decimal Scaling Normalization:

Decimal scaling can be applied when the scores of different matchers are on a logarithmic scale (lack of robustness and assumption that the scores of different matchers vary by a logarithmic factor).

$$s'_k = \frac{s_k}{10^n} \tag{8}$$

c. Z-score Normalization:

The Z-score normalization is calculated using the arithmetic mean and standard deviation of the given data. It is sensitive to outliers and does not guarantee a common numerical range for the normalized scores from different matchers.

$$s'_k = \frac{s_k - \mu}{\sigma} \tag{9}$$

d. Median and Median Absolute Deviation (MAD) Normalization:

The median and median absolute deviation (MAD) method is insensitive to outliers and the points in the extreme tails of the distribution, but has low efficiency compared with Z-scores.

$$s'_k = \frac{s_k - median}{MAD} \tag{10}$$

e. TanH Normalization:

TanH estimators are robust and highly efficient. The normalization is given by.

$$s'_k = \frac{1}{2}\left\{\tanh\left(0.01\left(\frac{s_k - \mu_{GH}}{\sigma_{GH}}\right)\right) + 1\right\} \tag{11}$$

Where μ_{GH} and σ_{GH} are the mean and standard deviation estimates, respectively, of the genuine score distribution as given by Hampel estimators.

B. Fusion Techniques

A list of fusion techniques that can be used to combine multiple normalized scores into a single score are provided in this section.

If s_i is the matching score from an ith modality, s represents the resulting fused score.

a. The Simple Product Rule

It combines the scores by multiplying all of the individual scores.

$$s = s_1 \times s_2 \times \ldots \times s_n \tag{12}$$

b. The Simple Sum Rule

Combines the scores as a linear transformation. a_i and b_i represents the weights and biases, respectively, which can be entered by the user.

$$s = (s_1 \times a_1 - b_1) + \ldots + (s_n \times a_n - b_n) \tag{13}$$

c. The Simple Max Rule

The maximum score from the different modalities

$$s = \max\left(s_1 s_2 ... s_n\right) \tag{14}$$

d. The Simple Min Rule

The minimum score from the different modalities.

$$s = \min\left(s_1 s_2 ... s_n\right) \tag{15}$$

C. Summary of Algorithm

Figure 4 summarizes the structure of the algorithm face+iris biometric Fusion. The proposed algorithm of our face-iris multimodal biometric system is as:

1. Face/Iris image preprocessing (Histogram Equalization (HE) + Mean-Variance Normalization (MVN)).
2. Extraction of iris features using wavelet transform.
3. Face feature extraction using the Phase-based Gabor Fisher Classifier (PBGFC) method.
4. Obtaining iris matching scores using Hamming distance measurement.
5. Obtaining face matching scores using Mahanalobis distance measurement.
6. Face/Iris scores normalization using different normalization methods.
7. Face/Iris scores fusion using different Rules.
8. Comparing the fused scores to a threshold to make the final decision.

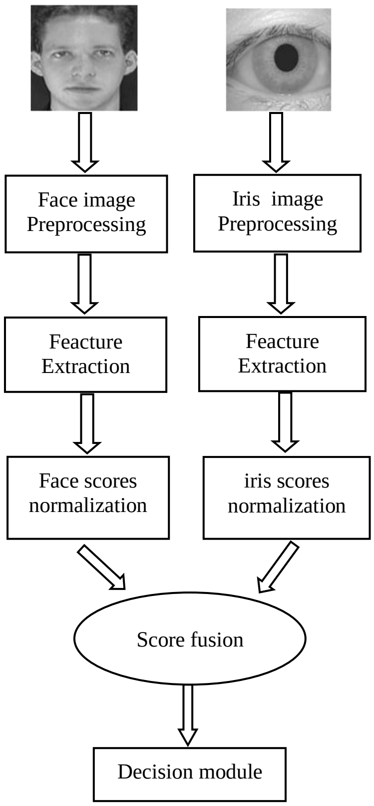

Figure 4. Algorithm structure for fusing face+iris biometrics

6. Experiments Results and Discussion

A. Database

As far as our knowledge, the main problems most researchers are facing are the lack of real-user databases [37]. There are no free available multimodal databases which combine face and iris modalities of the same person (real-user). However, in most of the recent fusion studies [10, 22, 23, 27] on face and iris biometrics, experiments are carried out on independent face and iris databases which result in the creation of chimeric users (the virtual subjects created with biometric traits of different users) [38]. To validate the performance of algorithms and fusion methods in our multimodal biometric system, a multimodal biometric database using the ORL face database [39] and the CASIA iris database [40] is constructed. In the ORL face data, the face images are sampled from 40 subjects, each subject having 10 images with varying lighting, facial expressions (open / closed eyes, smiling / non smiling), facial details (glasses / no glasses) and head pose (tilting and rotation up to 20 degrees).

For each subject, in our multimodal system, all 40 subjects are considered. Among the first seven images, we assigned randomly four images as train samples and the remaining tree images as test samples. The CASIA iris database contains 756 iris images acquired from 108 subjects (7 images per subject). 40 subjects are randomly selected from the CASIA iris database and for each subject; four images are randomly sampled as train samples and the remaining three images as test samples. Each subject in CASIA is randomly paired with each subject in the ORL face database.

Similarity matrix was generated contains genuine scores: 480 = 4x3x40 and impostor scores: 18720=40x39x4x3.

B. Results

Comparisons of multiple biometric images of different persons generate inter user values and comparison of samples of the same person gives intra user values. The performance measures used in our analysis are Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR), False Rejection Rate (FAR) and Equal Error Rate (EER). The rate of accepting a genuine user is called GAR and the rate of accepting an imposter is called FAR. The rate of rejecting genuine user as an imposter is called FRR.

Face and iris matching scores are obtained using the wavelet transform and PBGFC based methods respectively.

We use the different normalizations mentioned in section V to normalize the matching scores output from face/iris verification, while for fusion, we use different fusion techniques mentioned in section V to combine the normalized scores.

Table 1 shows the genuine acceptance rate (GAR) when the false acceptance rate (FAR) is at 0.01% for our unimodal system for face and iris.

Table 2 shows the results obtained with different normalization techniques and fusion rules.

Figure 5 shows the ROC curves for the obtained score level fusion with different normalization techniques of face and iris. Min-max normalization with sum rule and tanh normalization with product rule have given the best result with a 99.2 GAR and a 0.01%FAR, which means a very good GAR increase of 6.7% for Iris modality and 15% for Face modality.

Figure 6 shows the ROC curves of FAR and FRR of unimodal methods as well as the proposed multimodal method. The unimodal (face and iris) methods achieve a performance of 1.68 % EER. The proposed multimodal face and iris method (min-max normalization and sum rule) achieves a performance of 0.032 % EER. The improvement of the proposed method over the unimodal methods is clearly shown on ROC curve in Figure 6.

Table 1. Unimodal system for iris and face

Modalité	GAR 0.01 %
Face	84.2
Iris	92.5

Table 2. Results obtained with different normalization and fusion rules

Fusion ruls	Normalization methods.				
	Min-max	Z scor	decimal	TanH	median
Sum rule	99.2	98.5	90	98.2	97.6
Product rule	99.1	96.7	16	99.2	96.7
Max rule	92.5	93.3	92.5	84.2	94.1
Min rule	98.3	95.8	84.2	92.5	94

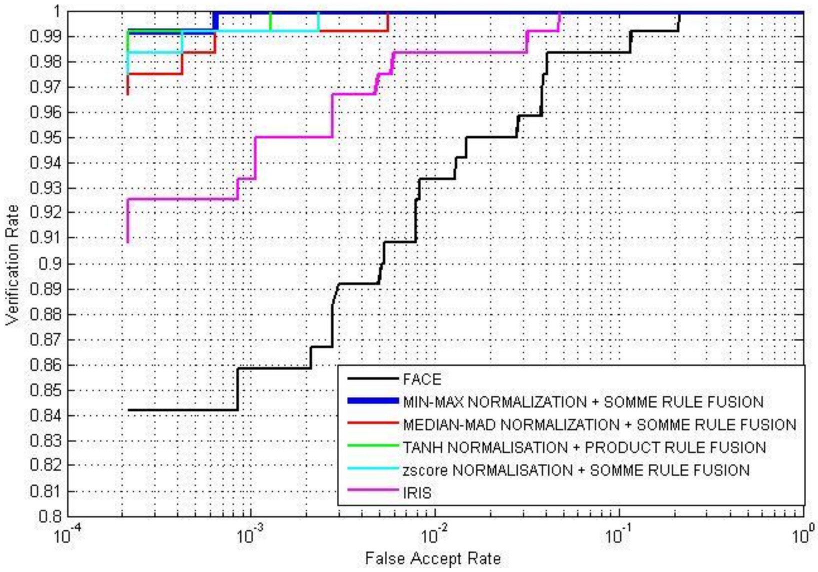

Figure 5. ROC Curves for the best ‘normalization +fusion rule’ combination

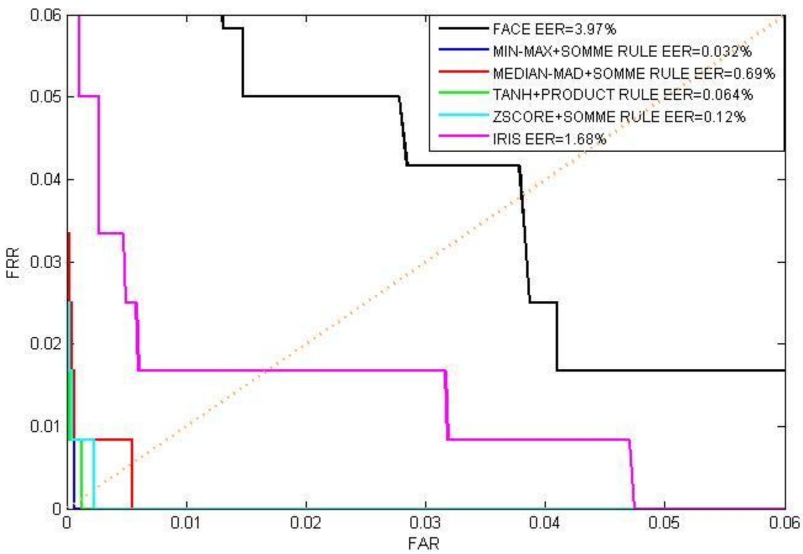

Figure 6. ROC curves of FAR and FRR of unimodal methods
and the proposed multimodal method

C. Comparison with The Existing Multimodal Systems Used for Face and Iris Modality

Table 3 shows a comparison of the proposed method with some of the existing methods in the literature. The results reported in recent articles are used.

Table 3. Comparison of the proposed method with some of the existing methods in the literature

Date	Author of the existing method	Fusion levels	Database	Number of subjets	Best result
2003	Wang et al [23]	Score level	ORL-MIT-YAL- NLPR	90	EER =0.24%
2005	Chen et chu [22]	Feature level	CASIA-ORL	40	EER=0.33%
2007	Zhang et al [27]	Score level	intern	112	GAR=99.38 at FAR= 0.0001
2009	Rattani et Tistarelli [11]	Feature level	Equinox/CASIA	57	EER=0.050%
2009	F. WANG* and J. HAN [21]	Score level	ORL _UBIRIS	40	EER=0.35%
2010	Rui Wang et al [24]	Score level	intern	112	GAR ;98.9 % EER=0.39%
2011	Kapale et al [30]	Decision level		10	FAR 0% et FRR 4% et GAR 94%
2011	Zhifang Wang, Erfu Wang [29]	Feature level	CASIA-ORL	40	EER= 1.67%
2011	Heng Fui Liau ⇑, Dino Isa [4]	Score level	CASIA-ORL	40	TER= 4.4%
2012	Yeong Gon Kim et al. [25]	Score level	intern	30	EER=0.131%
2013	MARYAM ESKAN-DARI et al[26]	Score level	ORL and BANCA CASIA and UBIRIS	80	GAR= 98.25% EER=1.02%
2015	**Our approach**	Score level	CASIA-ORL	40	GAR=99.2 at FAR=0.0001 et EER=0.032%

7. Conclusion

The paper proposes a multimodal biometric system based on fusion of Face and Iris. First, in the extraction phase, for the iris, the wavelet transform is used to generate a compact code of 128 bits, then for the face, the PBGFC based method is used using only 16 Gabor filters, i.e., filters with 2 scales and eight orientations against the traditional GFC method which requires 40 Gabor filters, i.e., filters with five scales and eight orientations. This fact makes the resulting feature vector for PBGFC very compact. The individual scores of the two traits, iris and face are combined at the matching score level using several score normalization and fusion techniques to develop a multimodal biometric system. The results show that the proposed multibiometric fusion achieves some improved recognition accuracy compared to unimodal methods to reach a 99.2 GAR and a 0.01% FAR, which means a very good GAR increase of 6.7% for the iris modality and 15% for the face modality. The results show also that the recognition accuracy is better than the other existing multi-biometric systems based on fusion of iris and face at different levels of fusion such as feature level fusion, decision level fusion and commonly used matching score level fusion techniques.

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