A Feature level Fusion of Multimodal Biometric Authentication System

Asst. Prof. Mazen M. Selim, Dr. Rasha O. Mahmoud, Omar A. Muhi
mazen_selim@yahoo.com
omar4321adel@yahoo.com
rasha.abdelkreem@fci.bu.edu.eg

Abstract

Biometric authentication plays an extremely important role all over the world over the last few decades. Biometrics literally means all technological techniques utilized to authenticate or identify persons relying on their physical and/ or behavioral characteristics. However, single biometric trait, such as face, iris, and fingerprint, usually fails to meet the security requirements of many applications with large population data. Therefore, multimodal biometrics, which employs two or more biometric modalities, has gained an increasing attention to overcome the problems associated with unimodal biometric system. This paper aims to propose a multimodal biometric authentication method based on the face and iris recognition First, the face and iris features are extracted separately using 2D wavelet transform and 2D Gabor filters, respectively. Second, the paper applies a feature-level fusion using a novel fusion method which employs both the canonical correlation process and the proposed serial concatenation. Finally, a deep belief network is used for the recognition process. The proposed system has been validated and its performance has been evaluated through a set of experiments on SDUMLA-HMT database. The proposed method has been compared with another method. The results of this paper have shown that the propped system has succeeded to achieve recognition accuracy up to 99%. It has shown a lower equal error rate (EER) and fusion time in comparison with other systems.

Keywords: *Multimodal Biometrics, Face Recognition, Iris Recognition, Feature Fusion, Deep Belief Network*

1. Introduction

As the security issue increases in modern societies, human recognition using biometrics has gained an increasing attention over the last years. Biometrics literally means to all technological techniques utilized to authenticate or identify persons relying on their physical and/ or behavioral characteristics. Multi-biometric system is a biometric recognition system which collects the biometric information through multiple biometric resources to determine a person's identity. The process of combing the collected information is known as information fusion process. Any evidence that can be independently utilized to identify a person is called a source of biometric information [1].

Generally, multi-biometric systems have attracted much attention from researchers because of the limitations of unibiometric system where the biometric source may become unreliable because of a set of reasons which includes sensor or software malfunction, noisy data, non-universality... etc. Moreover, many applications have stringent accuracy requirements, such as US-VISIT software, which cannot be met using unibiometric systems [2]. Multi-biometric systems depend on representing each client by multiple sources of biometric information. Based on the adopted way (i.e., used biometric sources) in representing each client, multi-biometric systems can be classified into six classes including multimodal, multi-algorithm, multi-instance, multi-sample, multi-sensor, and hybrid systems [3].

Multimodal system is a common method used to build a multi-biometric system in which two or more biometric traits are used such as face, iris, finger, and palm. More powerful and effective biometric system can be built by fusing the information obtained from multiple biometric traits through exploiting the strengths of each trait for achieving better authentication accuracy. In multimodal biometric systems, the fusion process can be operated through different approaches including feature fusing, match scores, and decision fusing. Applying the fusion at each level has its advantages and disadvantages [1] [3]. However, feature level fusion can take advantage of the most discriminative information and remove any redundancy and/or adverse information from the raw biometric data; therefore, feature level fusion is expected to achieve better performance when compared to other fusion levels [4].

Face and iris are widely accepted biometric traits that have achieved high identification and verification accuracy. Iris recognition can be considered one of the most accurate biometric modalities, where many systems, which are based on iris features, have succeeded to achieve verification rates close to 98% [5]. On the other side, face is one of the most widely adopted biometric traits due to its ease of capture. However, they still suffer from the problems related to any unibiometric system such as noise in sensed data, non-universality, inter-class similarities, and spoofing attacks. In this paper, a multi-modal system is proposed to verify the identity of a person based on his face and iris features.

The rest of paper is organized as follows: Section 2 presents some of the relevant works which are based on face and iris features to determine human identity. Section 3 describes in detail the proposed multimodal biometric system. Section 4 highlights the used dataset in addition to the conducted experiments. The last section consists of the conclusion and the future work.

2. Related Works

Developing multimodal biometric systems based on face and iris biometric modalities is a popular methodology that has been widely adopted over the last years. This is due to their advantages and the natural connection between them [5]. The fusion of face and iris biometric traits has achieved a significant performance compared to fusion of other biometric modalities, likely due to the common features of face and iris. Vast number of studies on face and iris fusion strategies has been developed through the past few years alone [6].

Throughout these studies, Cheng Rd et al [7] have presented a face-iris multimodal biometric system. The proposed system proceeds with extracting face and iris features separately. Then, the extracted information has been used as input data to a classifier based on a Wavelet Probabilistic Neural Network (WPNN) to make its decision. A multimodal biometric database has been built using ORL (Olivetti Research Laboratory) and CASIA (Chinese Academy of Sciences, Institute of Automation) databases to validate as well as evaluating the performance of their approach. The obtained experimental results revealed that the verification results obtained from multimodal biometrics is more reliable and accurate than unibiometric approaches with an average ERR of 0.33%.

Gan and Liang [8] proposed a method using face-iris fusion feature combined with the characteristics of 2-Dimensional Fisher Linear Discriminant Analysis (2DFLD). The proposed approach has been validated, and its performance has been evaluated using ORL face database and CASIA iris database. In this paper, feature fusion and extraction are discussed according to the characteristics of 2DFLD. Correct recognition rate based on the two random databases is proved to be 98% respectively.

Zhang et al [9] developed a system that requires face and iris fusion from the same near infrared (NIR) image. This image is acquired by employing a high resolution NIR camera. They argued that their system starts with segmenting the face and iris from a NIR image; then, it extracts the discriminating features from the segmented parts. After that, face and iris features are matched and a matching score fusion is done by adopting various rules. The proposed system achieved genuine acceptance rate (GAR) up to 97.81 % while FAR is 0.001%.

Liau and Isa [10] proposed feature selection method for improving the performance through choosing a minimal optimal set of features. They, also, suggested a method for accelerating the computation of SVM. The obtained results showed that the employed feature selection method has obviously reduced the total error rate of the classification process. Moreover, they demonstrated that the proposed SVM-based fusion method has given very good results. The proposed system has an EER of 0.142%.

Zhifang et al [11] provided a new multimodal biometric system using face-iris feature fusion. First, they extracted face and iris features separately; then they normalized them using z-score model. Afterwards, they performed an efficient feature level fusion. They mentioned that the normalization process is used to remove any unbalance in the magnitudes' order and distribution between face feature vector and iris feature vector. Finally, they fused the features in serial rule. The proposed approach has been validated and its performance has been evaluated on CASIA iris database and two face databases (ORL database and Yale database). The proposed system has an EER of 1.67%. The experimental results have proved the effectiveness of their approach.

Maryam and Toygar [6] introduced a face-iris multimodal biometric system in which Local Binary Patterns (LBP) has been adopted for extracting the local features and subspace Linear Discriminant

Analysis (LDA) for extracting the global features from face and iris images separately. Then, face and iris feature vectors are matched and the tanh normalization method is applied on the matching scores before the fusion. The fusion of the matching scores is done using the Weighted Sum Rule. The proposed system has been evaluated using different subset of iris and face images including CASIA, UBIRIS, ORL, and FERET. The results demonstrated that the proposed system has better recognition accuracy up to 97%, in comparison with unimodal and multimodal systems which use other feature extractors with face and iris features [6].

Maryam et al [12] created a new approach based on score matching level fusion to get a powerful verification system by combining face and iris scores of several standard classifiers. A set of global and local feature extraction method has been adopted including LBP, Principal Component Analysis (PCA), subspace PCA (spPCA) and subspace LDA. Then, score fusion process based on transformation and classification is done for obtaining, concatenating, and classifying the match scores. Different fusion methods at different fusion levels are compared to the proposed fusion method to show its effectiveness and superiority. A multimodal biometric database has been built using CASIA, UBIRIS, ORL and BANCA databases. The obtained results have asserted the superiority of their approach compared to other biometric based recognition approaches. The EER of the proposed approach is 1.02%.

Fei et al [13] proposed a new fusion method for a multimodal biometric system that uses face, iris, and fingerprint biometric traits. Throughout their study, they used particle swarm optimization (PSO) for training a group of adaptive Gabor filters to obtain the appropriate Gabor basic functions for the different biometric traits. Two local Gabor features for each biometric trait are obtained using the corresponding Gabor coefficients to analyze texture information. The experimental results have demonstrated the effectiveness of their fusion methodology as well as proving the superiority of their system over other unimodal and multimodal biometric systems with EER of 0.4617%.

Kirti et al [5] presented a multimodal biometric algorithm which employs face and iris features to verify the people identities. The proposed approach applies score level fusion. Moreover, the proposed approach uses Gabor filters and LBP for extracting face feature and Gabor filters only for extracting iris features. Therefore, the proposed system can be considered a multi-modal (combining iris and face), multi-algorithmic (Gabor filters and LBP) biometric system. The obtained results have demonstrated that the proposed approach has achieved more than 85% improvements in the verification accuracy in terms of EER compared to the unibiometrics based systems.

Valentine et al [14] designed a multi-modal system based on iris and face features along with a newly proposed hybrid fusion strategy. The proposed fusion approach performed the fusion process at different fusion levels through three classifiers which depended on feature and score level fusion using a decision level fusion rule. The proposed fusion approach has been compared to other fusion approach in the literature using ORL face and CASIA iris databases. The experimental results demonstrated that their approach has a recognition accuracy of 98.75% [14].

Guang et al [15] introduced feature level fusion based recognition method which uses face and iris features. They made a number of procedures. First, the extraction of face and iris local texture features is performed using a special two-dimensional-Gabor filter bank. Then, the histogram statics is used to transform the extracted features into an energy-orientation variance histogram feature. The newly obtained feature has lower dimensionality and higher discrimination capability. Finally, feature level fusion and a number of identification processes are performed using fusion-recognition strategy (FRSPS) which use SVM. Their method provided higher recognition accuracy with an EER of 0.0167.

Maryam and Sharifi [16] suggested a new hybrid optimum face-iris fusion approach, which performs the multi-level fusion including feature, score, and decision levels. Before adopting the proposed fusion approach, many fusion schemes are implemented separately at each level and their effectiveness have been evaluated. The experimental results referred to that the proposed fusion approach is better than other unimodal and multimodal fusion schemes with GAR up to 96.37 % while FAR is 0.001% [16].

Leila and Adjoudj [17] devised a new multi-biometric technique that employs the face modality with the left and right irises to authenticate people. Both face and iris features are obtained by adopting the wavelets, while SVM is employed for obtaining the fusion scores. After that, the Min-Max operator is adopted for normalizing the matching scores. Afterwards, combination and classification methods are used to perform a score level fusion. Also, the two researchers used the Chikhaoui and Mokhtari (SVM based classification) for the classification. The SDUMLA-HMT database has been used for validating and assessing the performance of the proposed approach. The experimental results proved that the multi-biometric systems can achieve batter recognition rates than the unimodal systems. The achieved EER of the proposed system was 0.1080% in their best case.

3. Proposed Approach

This section describes a proposed multimodal biometric system that based on face and iris biometric traits. The proposed system can identify the individuals with high accuracy despite the challenges associated with face images such as different poses, different illuminations, different face expressions, and occlusion. The proposed system obtains its decision after a series of steps as depicted in Figure 1.

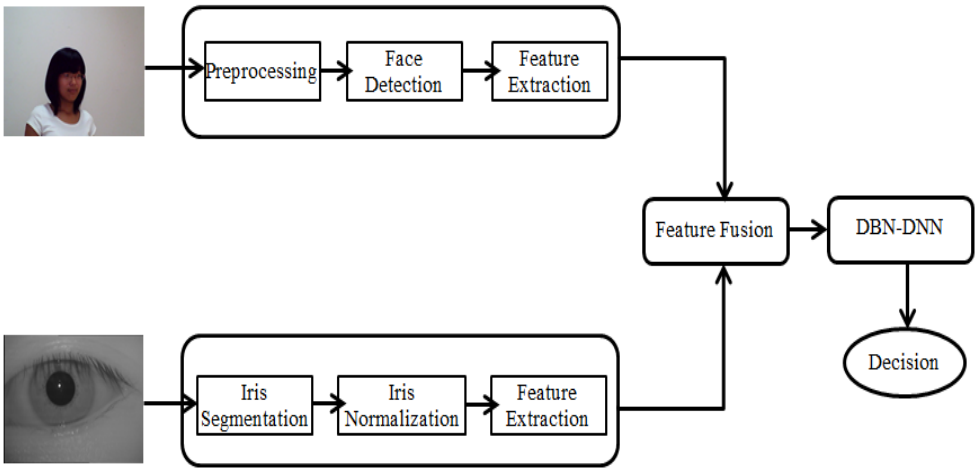

Figure 1. The block diagram of the proposed biometric system

The acquisition of biometric traits and its processing are two significant steps in the multimodal biometric systems. To do these steps, one of two modes can be used: serial mode or parallel mode. However, the latter mode is the most frequently used because in this mode all of the available biometric information is used; hence, high recognition accuracy can be achieved by adopting the fusion approach. Regarding the acquisition step, a standard database called SDUMLA-HMT is used in the proposed system for assessing the performance of the proposed approach. The detailed description of SDUMLA-HMT will be given below.

3.1. Face Images Processing and Feature Extraction

The proposed system suggests a set of steps to be done on face images for obtaining the discriminating features including preprocessing, face detection, and feature extraction. In the preprocessing step, the face image is cropped and resized to be 135*135 as shown in Figure 2.

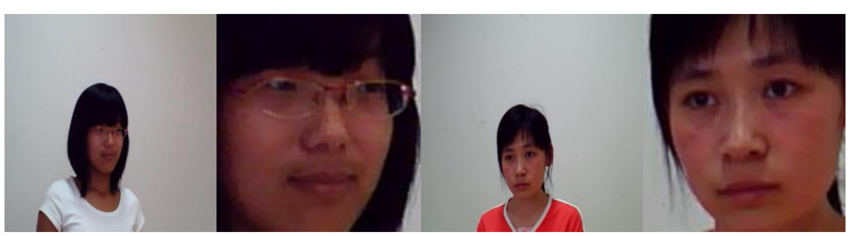

Figure 2. face images before and after preprocessing

After that, the face detection step is applied using the well-known face detection mechanism, Viola–Jones detection approach. The popularity of the Viola-Jones detection comes from its capability to work well in real-time and its capability to achieve high accuracy. For locating people's faces in a certain image, Viola-Jones face detector uses detection windows of different sizes for scanning the input image. It makes a decision whether each window has a face or not. In each window, the existence of a face candidate is decided by applying a classifier to simple local features derived using Haar-like filters. In Haar-like filters, the feature values are obtained by computing the difference between the sums of the pixel intensities in the light [2].

Finally, the discriminating face features are obtained using wavelet transform. The advantage of wavelet transform above Fourier transforms is temporal resolution. Wavelet transform apprehends both time and frequency i.e. information location. The Discrete Wavelet Transform (DWT) has been used in many fields including science, computer science, engineering and mathematics [18]. DWT for a 2-D image can be derived from 1-D DWT. Scaling and wavelet functions in two dimensions can be obtained easily through multiplying two 1-D functions. The scaling functions for 2-D DWT can be obtained by multiplying two1-D scaling functions [18] [19].

$$\psi^{H}(x,y) = \psi(x)\varphi(y) \tag{1}$$
$$\psi^{v}(x,y) = \varphi(x)\psi(y) \tag{2}$$
$$\psi^{D}(x,y) = \psi(x)\psi(y) \tag{3}$$

where ψ^{H}, ψ^{v}, and ψ^{D} denotes the variation along columns, rows, and diagonals, respectively.

$$W_{\psi}^{i}(j,m,n) = \frac{1}{\sqrt{MN}}\sum_{i=H,V,D}\sum_{m}\sum_{n} W_{\psi}^{i}(j,m,n)\,\psi_{j,m,n}^{i}(x,y) \tag{4}$$

Where $W_{\psi}^{i}(j,m,n)$ coefficients add horizontal, vertical, and diagonal details for scales $j \geq j_0$, $m = n = 0, 1, 2, \ldots, 2^{j} - 1$, $N = M = 2^{j}$ and $j = 0, 1, 2, \ldots, J - 1$.

Throughout the proposed work, the 2-D DWT is adopted for extracting the face features where each face is represented using a feature vector that consists of 441 values.

3.2 Iris Images Processing and Feature Extraction

On the other hand, in the proposed system, a set of steps has been done on iris images in order to get the discriminating features including localization, normalization, segmentation, and feature extraction. Segmentation refers to the process of dividing an image into a set of pixels [20]. Iris is segmented by two circles for locating the inner and outer boundaries. The output of this process is iris signature. In the propose system, the localization and segmentation process starts with specifying the region which contains the iris inside the iris image (i.e., specifying the Region of Interest (ROI)). After that, the canny edge detection approach is applied to determine the outer and inner circles/boundaries of the iris as shown in Figure 3.

(a) (b) (c)

Figure 3. Iris localization and segmentation process (a) the original iris image (b) the region of interest (c) the segmented iris image

To achieve its goals, canny edge detection algorithm involves a set of steps. It starts with a smoothing step to remove noise in image. The next step is known as finding gradients. It is applied to mark the possible edges in the image by detecting the large magnitude of gradient of image. Then, a threshold is used for determining the candidate edge. Finally, the final edges are specified by looking for the edges connected to strong edges and other edge that are not connected to strong edges are suppressed [21].

The size of valid iris pixels is variable due the dilation and contraction of pupil area according to the current amount of light entering the eye. If a large amount of light entering the eye, the pupil area contracts and the iris area increases. On other hand, if a small amount of light entering the aye, the pupil area dilates and the iris area decreases. Also, other factors can affect the number of iris pixels that can be extracted from the eye's image including the resolution of the used sensor and the distance from which the image is acquired. To address the variety in size, the segmented iris is subjected to the process of normalization process in which the segmented iris is represented as a rectangular image [2]. In the normalization process, the segmented iris image is represented using polar form (r, θ) instead of coordinate form (x, y). In the proposed approach, the normalization process is performed using Daugman's Rubber sheet model as shown in Figure 4 [2]. In the proposed system, after applying the normalization process, the circular iris texture is transformed into an equivalent rectangular shape of size 480x20 pixels.

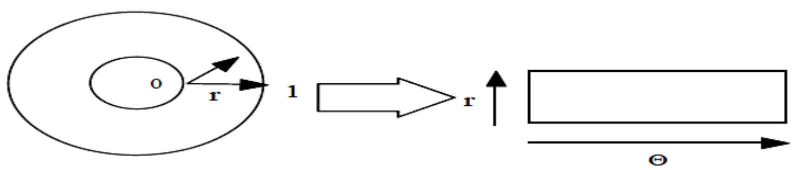

Figure 4. Daugman's Rubber sheet model

Finally, a set of a numerical features are obtained from the normalized iris image. This process is known as iris encoding. In the proposed system, the 2D Gabor wavelet is used to perform this process. To perform the encoding process for the normalized iris image, a 2D Gabor wavelet is usually convolved with the unwrapped iris image. However, as the normalization process is previously done in the polar coordinates, the wavelet in polar coordinates can be represented as shown in Equation 5:

$$H(r, \theta) = e^{-i\omega(\theta - \theta_0)} e^{-(r - r_0)^2/\alpha^2} e^{-i(\theta - \theta_0)^2/\beta^2} \tag{5}$$

where (r_0, θ_0) refers the center frequency of the wavelet and (α, β) refer to the effective width and length. This operation resulted in a binary output named iris code. In the proposed system, the iris code length is 9600.

3.3. Feature Fusion

Canonical correlation analysis (CCA) is a statistical technique employed to examine relationships among two or more variable sets. Each set should have at least two variables [22]. On the other side, the serial concatenation is adopted by many multimodal systems to perform feature level fusion. It an effective approach that can be easily extended to combine two or more biometric traits. Additionally, in case of the absence of one or more modalities of query samples, the multimodal feature template dataset can be easily adjusted to perform the authentication process using the available biometric traits [23]. In the proposed system, we have proposed a feature fusion mechanism based on CCA and serial concatenation. The proposed mechanism consists of the following set of steps:

1- Computing the canonical correlation coefficients between the face features and the iris features.
2- Multiplying canonical correlation coefficients using the original feature vectors.
3- Concatenating the results of the multiplication process to obtain the fused feature vector.

This fusion mechanism has been designed to achieve some objectives. First, it reduces the feature vectors dimension before the concatenation process. Second, it turns the values of the iris features from the binary into the real domain.

3.4. Deep Belief Network (DBN)

The emergence of deep learning has revolutionized Pattern Recognition and Machine Learning. Deep learning leaves its impact on many fields including healthcare, transportation, manufacturing, etc. Companies are directed towards deep learning in an attempt for solving complicated problems, like speech recognition, object recognition, and machine translation. Deep learning is defined as a sub-field of machine learning which contains a set of approaches that employs representation learning methods. Deep learning approaches have a set of advantages. Above all, it has a unique ability to handle very complex input-output mapping problem effectively. Moreover, deep learning approaches can handle large scale problems of the large or extremely large dataset. Deep belief network (DBN) is one of deep learning approaches that proved its effectiveness in many applications such as generating and recognizing images, video sequences, and motion-capture data. Also, DBN is defined as a generative graphical model, or a category of deep neural networks that consists of a number of layers of latent variables ("hidden units"), where the layers itself are connected not the nodes inside these layers [24]. DBNs are able to learn to probabilistically reconstruct its inputs, given a group of example during an unsupervised training phase. The layers contained in a DBN, then, works as feature detection modules. After performing this learning step, a DBN can be further trained in a supervised mode to accomplish the classification task [25]. DBNs can be constructed using a group of simple, unsupervised networks such as restricted Boltzmann machines (RBMs) [24].

In the proposed system, we have designed a DBN based on RBMs to recognize the identity of persons. The proposed deep neural network (DNN) is called DBN-DNN. The idea of this network is given in [27]. The architecture of the proposed deep network DBN-BNN is given in Figure 5.

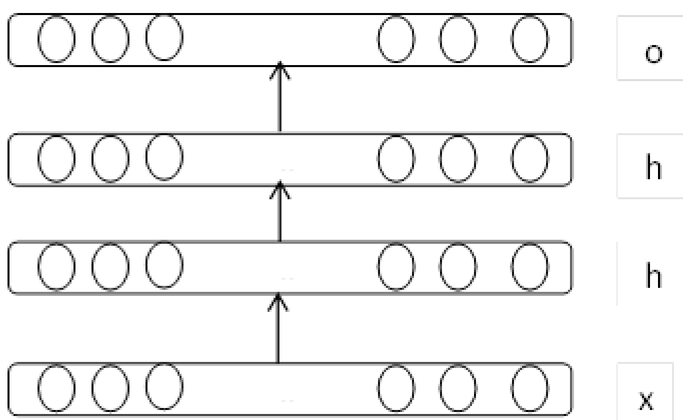

Figure 5. the Architecture of the proposed DBN-BNN

Figure 5 shows that the proposed DBN-DNN consists of four layers: an input layer, two hidden layers, and an output layer. The size of input layer is equal to the size of input vector or the fused feature vectors, while each hidden layer contains 8000 node. The size of output layer is equal to the number of subjects that need to be identified. In the training phase, the back propagation algorithm has been used with cross entropy activation function that is defined by Eq. 6, where batch size is 100, number of iteration is 1000, and learning rate is 0.1.

$$E = -\sum_i y'_i \log(y_i) \qquad (6)$$

where y_i is the predicted probability distribution of the class i and y'_i is the true probability for that class.

4. Experiments and Results

This section starts with describing the used dataset. It also contains the set of experiments that have been performed to evaluate the proposed system in terms of the set criteria.

4.1 Dataset Description

A publicly available database called SDUMLA-HMT has been used to evaluate the proposed system. SDUMLA-HMT database has been collected in 2010 by Shandong University, Jinan, China. It consists of five sub-databases, namely, face, iris, finger vein, finger print, and gait databases for 106 subjects (61 males and 45 females) with ages range between 17 and 31. In work, we have used the face and iris databases only [28].

Face database has been built using seven digital cameras. Each camera has been used to capture the face image of every subject with different poses (3 images), different expressions (4 images), different accessories (1 image with a hat and 1 image with glasses), and under different illumination conditions (3 images). Face database consists of 106*7*(3+4+2+3) = 8,904 images. All face images are of 640 × 480 pixels and "BMP" format. Some face images of subject number 69 under different condition are shown in Figure 6.

Figure 6. some face images of subject number 69 under different conditions

On the other hand, iris database contains the iris images for the 106 subject with 5 images for each iris with a total number of 1060 image. All iris images are of size 768 × 576 pixels and "BMP" format. The iris images of subject number 69 are shown in Figure 7.

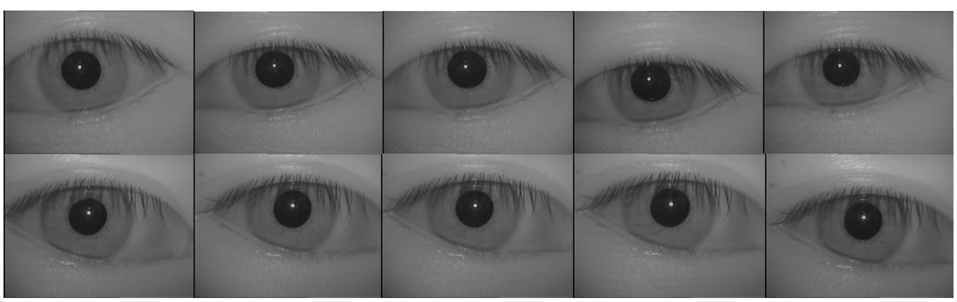

Figure 7. The iris images of subject number 69 (row1 – right iris) (row2 – left iris)

4.2 Experiments and Results Analysis

In this section, many experiments are performed to evaluate the performance of the proposed multimodal biometric system in terms of a set of criteria including Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR), accuracy, and error.

Two preliminary experiments have been performed. In the first experiment, face images and left iris images have been used while in the second experiment face images and right iris images have been used. In the first experiment, the size of input layer of the DBN-DNN is 452 while the size of input layer in the second experiment is 438. The size of the output layer the DBN-DNN is 106. The DBN-DNN has been implemented using the code written by Masayuki Tanaka which is publicly available at [29].

In each case, five face images are chosen randomly from the face images of each subject covered with the corresponding iris images and all cases are covered once without dividing the sub-databases. Each subject has 5 × 5 = 25 feature vectors. The total number of feature vectors 25 × 106 = 2650.

On the other side, the proposed work gives a comparable performance when compared to the work proposed in [17] which use face, left iris, and right iris to recognize people. In [17], they divided the SDUMLA-HMT database into 12 sub-databases in which face images are captured under the same conditions. Unlike [17], the proposed approach has chosen five face images randomly for each subject without dividing the database.

A simple comparison between the proposed work in the present study and that provided by Leila and Adjoudj [17] shows that the two works have used the same tools of measurements, and systems with the same following qualifications: (Intel (R), Core (TM) i7, 4510U CPU @ 2.00GHz 2.60GHz & 4 GB of memory). However, there are major differences in the results of the two works as shown in Table 2.

Table 2. The differences between the proposed work and the work of Leila and Adjoudj [17]

Criteria	Proposed Work	Leila and Adjoudj [17]
Database Division	No Works on the whole database	Yes Works on sub-databases
Face Images Selection	Random	Homogenous
Fusion Level	Feature level Fusion	Score Level Fusion
Classification Method	Deep learning (DBN)	Chikhaoui and Mokhtari (SVM based classification) Chikhaoui and Mokhtari [26]
EER	0.1071	0.1080
Fusion Time	54s – 56s	70s – 150s

In the light of Table 2, the proposed system has achieved better results than the system proposed by Leila and Adjoudj [17] in terms of EER, fusion time and size database.

5. Conclusion

This paper has presented a multimodal biometric technique based on face and iris characteristics. Also, a novel feature fusion mechanism based on CCA and serial concatenation is proposed and adopted. DBN with RBMs has been used as a classifier in the proposed approach. In addition, the present study uses SDUMLA-HMT database to validate the performance of the proposed multimodal biometric system. Also, the performance of the system using the face and left iris has been evaluated against the face and right iris in terms of a set of performance measures including FRR, FAR, EER, Accuracy, and Error. The experimental results in both cases have shown that the proposed system has a robust and efficient performance despite the random selection of face images of each subject. Moreover, the proposed work has been compared to another recent work that uses the same database. The comparison has resulted in emphasizing the superiority of the proposed system over the other work system in terms of EER, fusion time and size database.

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