Multimodal Biometric Using a Hierarchical Fusion of a Person's Face, Voice, and Online Signature

Youssef Elmir*,**, Zakaria Elberrichi**, and Réda Adjoudj**

Abstract—Biometric performance improvement is a challenging task. In this paper, a hierarchical strategy fusion based on multimodal biometric system is presented. This strategy relies on a combination of several biometric traits using a multi-level biometric fusion hierarchy. The multi-level biometric fusion includes a pre-classification fusion with optimal feature selection and a post-classification fusion that is based on the similarity of the maximum of matching scores. The proposed solution enhances biometric recognition performances based on suitable feature selection and reduction, such as principal component analysis (PCA) and linear discriminant analysis (LDA), as much as not all of the feature vectors components support the performance improvement degree.

Keywords—Hierarchical Fusion, LDA, Multimodal Biometric Fusion, PCA

1. INTRODUCTION

With the increasing need for security in our life, biometrics has rapidly become a hot research topic because of its potential application values in personal identification. From among these applications, face recognition, which is user-friendly and requires less user cooperation. However, although many methods (e.g., eigenface, manifold, Gabor, sparse representation) [1] have been proposed, it is still difficult to achieve high accuracy due to there being numerous appearance variations. However, in some situations where the voice is the only collectable data (e.g., phone communications) voice recognition is thought to be one of the most useful biometrics, but its performance dramatically decreases in non-cooperative situations. Furthermore, online signature recognition is very accurate, but its performance depends on the quality of the collected dynamic data. Recently, the use of multimodal biometrics [2] fusion techniques has significantly improved the performance of biometric systems. Therefore, the fusion of a person's face, voice, and online signature could be a promising strategy in practical applications where accuracy is imperative. Inspired by this idea, a face, voice and online signature fusion based biometric system has been developed for personal identification and authentication tasks.

Some fusion strategies [3-6] have been proposed in the past few years. These methods show high performances on good quality images and samples captured in controlled conditions. Recently, Poh and Kittler [7] proposed a novel fusion classier that incorporates both the quality and device information simultaneously based on the Bayesian network, but it is difficult to perform on practical applications due to its computational complexity.

In this paper, a hierarchical face, voice, and online signature fusion framework is proposed, as illustrated in Fig. 1. In the training stage, features are extracted from the face using Gabor filters [8,9], from voice using Mel-frequency cepstral coefficients, and a set of samples are extracted from online signatures. Each sample corresponds to the point coordinates on the digitizing tablet along with the corresponding pressure X_t, Y_t and P_t where t corresponds to time. In the testing stage, the probe face, voice, and online signature are used to obtain a subset of reference samples in the face, voice, and online signature databases. Finally, the fusion at score level of the face, voice, and online signature is performed on the candidate subset for personal identification.

Any Mutlimodal biometric system is expected to achieve a reduced equal error rate (EER). To release this requirement, the hierarchical strategy is used for biometric traits fusion. The main contributions of this paper are summarized as follows: first, the proposed method reduces the fusion template size by fusing the features of two biometric traits, instead of three, at the same time, and then by using principal component analysis (PCA) or linear discriminant analysis (LDA) for data reduction to improve system speed. The hierarchical fusion strategy is the combination of the fusion of features and the fusion of scores. The reduced signature size thus improves the system speed without paying any significant cost in terms of accuracy. Second, the fusion strategy used in the proposed method has reduced the equal error rate significantly. Finally, this work compares the obtained results with a few of the existing methods.

These kinds of multimodal biometric systems are often required in various areas, such as banking biometric systems and secured mobile phone operating systems.

The remainder of this paper is structured as follows: Section 2 presents the system architecture with the hierarchical strategy of fusion. Section 3 introduces the extraction of face, voice, and online signature features. Section 4 describes feature representations for face, voice, and online signature and the fusion strategy. Section 5 shows the classification method that we used. Section 6 presents the experimental results and discussions and our conclusions are presented in Section 7.

2. THE SYSTEM ARCHITECTURE WITH THE HIERARCHICAL STRATEGY

The proposed multimodal biometric system architecture is shown in Fig. 1. This architecture is based on a hierarchical approach for biometric data fusion and classification. The system includes two main identification components, which are listed below.

1) The face and voice identification sub-system: this component relies on a feature-level biometric fusion scheme;
2) The online signature identification subsystem;
3) The post-classification fusion scheme, which combines the two previous components scores;
4) The decision module, which provides the final decision based on the global score.

The proposed multimodal approach is featured by multi-level integration, as shown in Fig. 1.

3. FEATURE EXTRACTION

3.1 Gabor Filters

A Gabor filter bank is used to construct the face vector code. The default parameters correspond to the most common parameters that are used in conjunction with localized face images that are 128 × 128 pixels in size. Optionally, the function returns a filter bank structure that contains the spatial and frequency representations of the constructed Gabor filter bank and some meta-data.
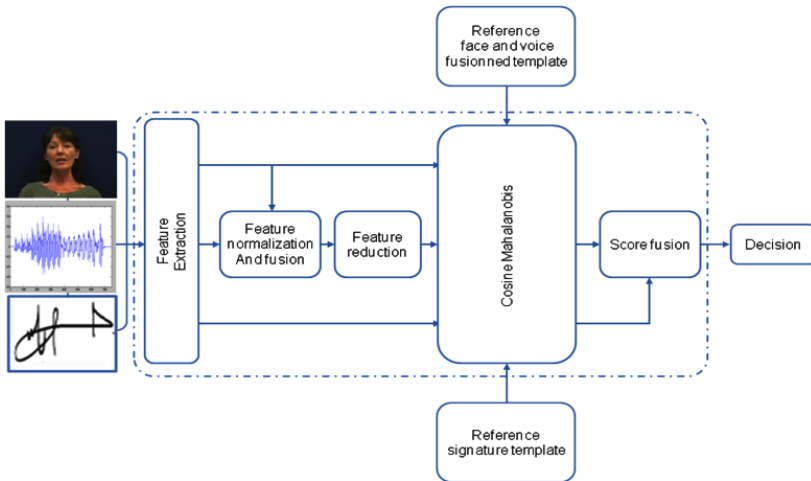

Fig. 1. The multimodal biometric system architecture with a hierarchical approach.

(1) Original image	(2) Localized face	(3) Magnitudes responses

Fig. 2. Magnitude responses of the filtering operation with the Gabor filter bank (no down-sampling) using the 1st subject image in VidTIMIT database.

A facial image of the localized face is filtered with a bank of Gabor filters that are constructed using the construct Gabor filters, which uses the PhD toolbox [8,9]. All filters are applied to the input image and the magnitude responses are then computed. Each of the computed magnitude responses is down-sampled. And finally, the down-sampled magnitude responses are

concatenated into a single feature vector. Note that these feature vectors are produced, such as those produced in [8,10,11].

In Fig. 2, a Gabor filter bank of 40 filters (8 orientations × 5 scales) has been constructed; a sample of the face image of the first subjects of VidTIMIT database is used for filtering operation.

3.2 Mel-Frequency Cepstrum Coefficients

The signal of a voice is first processed by software that converts the speech waveform to some type of parametric feature and score fusion representation (at a considerably lower information rate) for further analysis and processing. The speech signal is a slowly timed varying signal, which is called quasi-stationary signal. When examined over a sufficiently short period of time (between 5 and 100 ms), its characteristics are fairly stationary. However, over long periods of time (on the order of 1/5 seconds or more) the signal characteristic changes to reflect the different speech sounds being spoken. Therefore, short-time spectral analysis is the most common way to characterize the speech signal. A wide range of possibilities exist for parametrically representing the speech signal for the speaker recognition task, such as linear prediction coding (LPC), Gaussian mixture models (GMM) [12], Mel-frequency cepstrum coefficients (MFCCs), etc.

MFCCs are based on the known variation of the human ear's critical bandwidths with frequency. Filters that are spaced linearly at low frequencies and logarithmically at high frequencies have been used to capture the phonetically important characteristics of speech. This is expressed in the Mel-frequency scale, which is a linear frequency spacing that is below 1,000 Hz and that has a logarithmic spacing above 1,000 Hz. The process of computing MFCCs is described in more detail in [13,14].

3.3 Online Signature Features

Two kinds of modalities are considered when dealing with the verification of signatures. There is offline modality, in which scanned copies of the signatures are available for comparison, and the online modality, in which the signatures are acquired using digital tablets. The online modality provides more information about the signatures (trajectory, speed, pressure, etc.) and, consequently, achieves better verification performance than the offline modality. This is why the online modality is used in this paper.

Signature verification is performed by comparing a questioned/unknown signature with a reference signature. This comparison is performed at the feature level after extracting the characterizing features from both signatures.

Online signatures contain a set of samples. Each sample corresponds to the point coordinates on the digitizing tablet along with the corresponding pressure X_t, Y_t and P_t where t corresponds to time. From those three features (or signals) several other features are extracted:

- Distances: the Euclidian distance is computed between each successive X and Y coordinates of the signature as: $d_t = \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2}$;
- Angles: the angle between the X axis and the line formed with the first signature point and the current point is: $\alpha_t = atan \frac{y_t - y_0}{x_t - x_0}$;

- Speeds: the difference between successive distances is: $S_t = d_t - d_{t-1}$;
- Angular speeds: the difference between successive angles is: $AS_t = \alpha_t - \alpha_{t-1}$.

4. DATA FUSION AND REDUCTION

4.1 The Fusion at Feature Level

The second proposed system is based on a fusion at the feature level method. The used features are obtained from the same monomodal systems that are used in the first proposed system (see Fig. 1).

4.2 Features Normalization

After feature extraction, the obtained feature vectors may exhibit significant variations in both their range and distribution. In our experiments, the min-max strategy of normalization is used to fuse the face and voice feature vectors. The goal of feature normalization is to modify the location (mean) and scale (variance) of the feature values in order to ensure that the contribution of each component to the final match score is comparable to the scores of the other modalities [15]. Adopting an appropriate normalization scheme also helps address the problem of outliers in feature values. The simple min-max techniques were tested in this work. Let x and x' denote a feature value before and after normalization, respectively. The min-max technique computes x' as:

$$x' = \frac{x - \min(F_x)}{\max(F_x) - \min(F_x)}, \tag{1}$$

Where F_x is the function that generates x. The min-max technique is effective when the minimum and the maximum values of the component feature values are known beforehand. In cases where such information is not available, an estimate of these parameters has to be obtained from the available sample training data. The estimate may be affected by the presence of outliers in the training data and this makes min-max normalization sensitive to outliers [16].

4.3 Feature Selection and Reduction

4.3.1 Principal component analysis

PCA can be used to approximate the original data with lower dimensional feature vectors. The basic approach is to compute the eigenvectors of the covariance matrix of the original data, and to approximate it by making a linear combination of the leading eigenvectors [17]. By using the PCA procedure, the test vector can be identified by first, projecting the image onto the eigenvector space to obtain the corresponding set of weights, and then by comparing it with the set of weights for the vectors in the training set [18,19]. The problem of low-dimensional feature representation can be stated as follows: Let $X = (x_1, x_2, \ldots, x_i, \ldots, x_n)$ represents the n × N data matrix, where each x_i is a vector of dimension n, concatenated from a face and online signature feature vectors. Here, n represents the total number of elements in the face and online signature feature vectors and N is the number of subjects' references in the training set. The PCA can be considered as a linear transformation (2) from the original vector to a projection feature vector.

For example:

$$Y = W^T X \qquad (2)$$

Where Y is the m × N feature vector matrix, m is the dimension of the feature vector and transformation matrix W is an n × m transformation matrix whose columns are the eigenvectors corresponding to the m largest eigenvalues that have been computed according to Eq. (3):

$$\lambda e_i = S e_i \qquad (3)$$

Where e_i, λ are eigenvectors and the eigenvalues matrix, respectively. Here, the total scatter matrix S and the mean image of all samples are defined as:

$$S = \sum_{i=1}^{N}(x_i - \mu)(x_i - \mu)^T, \quad \mu = \frac{1}{N} + \sum_{i=1}^{N} x_i \qquad (4)$$

After applying the linear transformation W^T, the scatter of the transformed feature vectors {y_1, y_2... y_N} is W^TSW. In PCA, the projection W_{opt} is chosen to maximize the determinant of the total scatter matrix of the projected samples. For example:

$$W_{opt} = \arg \max_w |W^TSW| = [w_1 w_2 \dots w_m] \qquad (5)$$

Where {$w_i | i = 1, 2,\dots, m$} is the set of n-dimensional eigenvectors of S corresponding to the m largest eigenvalues. In other words, the input vector in an n-dimensional space is reduced to a feature vector in an m-dimensional subspace.

4.3.2 Linear discriminant analysis

LDA is a dimensionality reduction technique, which is used for classification problems. LDA is also known as Fisher discriminant analysis and it searches for those vectors in the underlying space that best discriminate among classes (rather than those that best describe data as in PCA) [20-22].

LDA creates a linear combination of independent features, which yields the largest mean differences between the desired classes. The basic idea of LDA is to find a linear transformation where the feature clusters are most separable after their linear transformation, which can be achieved through a scatter matrix analysis [22]. The goal of LDA is to maximize the between-class scatter matrix measure while minimizing the within-class scatter matrix measure [21].

The basic steps in LDA are as follows:

• Calculate the within-class scatter matrix, S_w :

$$S_w = \sum_{j=1}^{C} \sum_{i=1}^{N_j}(x_i^j - \mu_j)(x_i^j - \mu_j)^T \qquad (6)$$

Where x_i^j is the ith sample of class j, μ_j is the mean of class j, C is the number of classes, N_j is the number of samples in class j.

• Calculate the between-class scatter matrix, S_b

$$S_b = \sum_{j=1}^{C} (\mu_{j-}\mu)(\mu_{j-}\mu)^T \tag{7}$$

Where μ represents the mean of all classes.

• Calculate the eigenvectors of the projection matrix:

$$W = \text{eig} (S_w^{-1}S_b) \tag{8}$$

• Compare the test image's projection matrix with the projection matrix of each training image by using a similarity measure. The result is the training image, which is the closest to the test image.

4.4 The Fusion at Score Level

A system based on the fusion at the score level is proposed. The used scores are obtained from the monomodal systems (see Fig. 1).

The first and the second monomodal systems are based respectively on face and voice; the features of these two biometric traits are fused into one single feature code at the feature level. The third monomodal system is based on online signature. The classification is released using the cosine Mahalanobis distance due to it's efficiency; and max-of-scores strategy is used to fuse the scores obtained from the first block (face and voice) with the second block, based on online signature scores.

5. CLASSIFICATION

This section describes the method for computing the various parameters that are used to compute the threshold and our image denoising algorithm. The wavelet transform approach is used for the recovery of the corrupted image with optimal filter.

To compute the similarity measure, a bank of face, voice, and online signature vector codes is adopted by the proposed framework. As in the references bank a gallery of vector codes of face and voice images and online signature signals is available. Four eigenspaces are created at the stage of feature selection and reduction. The similarity measure between the test vector codes and the codes in the gallery is defined as the cosine Mahalanobis distance [23] between the projection of the test vector code and the projections of the gallery vector codes.

Let $\Gamma_1, \Gamma_2, \Gamma_3... \Gamma_N$ be the vector picked from the gallery. Let $\Theta = \frac{1}{N} + \sum_{i=1}^{N} \Gamma i$ be the average vector code. Let $\Phi_i = \Gamma_i - \Theta$ be the mean subtracted vector codes. Let the data matrix A be defined as $A = [\Phi_1 \Phi_2 ..... \Phi_N]$. The eigenvectors of A^TA can be computed as $A^T Av_i = \mu_i v_i$. Pre-multiply both sides by A, $AA^TAv_i = \mu_i Av_i$. Thus, Av_i are the eigenvectors of AA^T. If w_i is the projection of the mean subtracted vector code on the ith eigenvector, then the projection coefficients of the vector code are $u = [w_1, w_2, ... w_N]$. The cosine Mahalanobis distance is used to measure the similarity between projection coefficients. The use of the cosine

Mahalanobis distance is motivated by the results in [23].

The eigenvectors span the vector space. The eigenvalues correspond to the variance along each eigenvector. It is important to understand the transformation between the vector space and the Mahalanobis space before computing the cosine Mahalanobis distance. The Mahalanobis space has unit variance along each dimension. Let u and v be two vectors in the eigenspace. Let $\mu_i = \sigma_i^2$ be the variance along the ith dimension. Let m and n be the corresponding vectors in the Mahalanobis space. The relationship between the vectors is defined as:

$$m_i = \frac{u_i}{\sigma_i} \ , \ n_i = \frac{v_i}{\sigma_i} \tag{9}$$

The Mahalanobis cosine is the cosine of the angle between the projections of the vectors on the Mahalanobis space. So, the cosine Mahalanobis distance between u and v is computed in terms of m and n.

$$D_{MahCosine(u,v)} = \cos \theta_{(mn)} = \frac{mn}{|m||n|} \tag{10}$$

6. RESULTS AND ANALYSIS

6.1 Data Sets

We used the VidTIMIT bimodal database to evaluate our proposed fusion method. It is comprised of video and corresponding audio recordings of 43 volunteers (19 female and 24 male), reciting short sentences [24]. In order to apply a hierarchical fusion strategy, it is necessary to use at least three biometric traits, VidTIMIT is a bimodal database (face and voice), a second database for the third biometric traits is proposed; It is QU-PRIP database of online signature [25]. This database is available from the Department of Computer Science and Engineering in Qatar University. It contains 138 subjects with 3 reference signatures each, and some of the subjects have as many as 6 references.

Considering the number of subjects in the VidTIMIT database, 43 subjects were selected from the QU-PRIP signature verification datasets. By taking advantage of the independence of the face and voice traits from the online signature trait, 43 virtual subjects were created from both subsets.

The training and testing processes for monomodal systems were established and are described below.

For training purposes: each face was modeled using four samples, and each voice and online signature was modeled using the same number of samples and one sample of each trait was modeled for validation purposes.

For validation and testing: for each client one more sample of each trait (face, voice, and online signature) was also selected for validation and one more sample was selected for testing. The same 43 clients were used as impostors, except that each client claimed an identity different from his own. Each client was considered and one sample was selected from each impostor.

Consequently, the sub-corpus for the experiments consisted of 43 clients, and $42 \times 43 \times 2 =$

3,612 multimodal impostor attempts.

6.2 Results

The experiments demonstrate that the hierarchical fusion-based method improves the efficiency of the multimodal authentication as compared to both the score and feature based fusion methods. Table 1 demonstrates that, for identification purposes, the best recognition rate (RR) is obtained using hierarchical and score fusion strategies (RR=100%). Furthermore, without making errors based on LDA, the results obtained by features fusion strategy are not so far. Additionally, for verification purposes, the lowest equal error rate (EER) is obtained by using the hierarchical fusion strategy (EER=0%). Additionally, the feature and score fusion strategy demonstrate low EERs in comparison with the monomodal systems. The same observation is noted for the minimal half total error rate (MHTER) and for the verification rate (VR) when the false accept rate (FAR) is equal to 1% or 0.1% and on the contrary, when it equals 0.01% the VR is the same for all the studied systems.

Table 1. Performance metrics

	PCA						LDA					
	RR at rank one (%)	EER (%)	MHTER (%)	VR at 1% FAR (%)	VR at 0.1% FAR (%)	VR at 0.01% FAR (%)	RR at rank one (%)	EER (%)	MHTER (%)	VR at 1% FAR (%)	VR at 0.1% FAR (%)	VR at 0.01% FAR (%)
Face	88.37	2.41	1.99	95.35	95.35	2.33	95.35	2.19	1.02	97.67	95.35	2.33
Voice	16.28	25.58	23.03	20.93	4.65	2.33	30.23	23.26	22.37	25.58	9.30	2.33
Online signature	83.72	1.77	0.61	97.67	88.37	2.33	95.35	0.3	0.3	100	86.05	2.33
Feature fusion level	88.37	2.19	1.05	95.35	93.02	2.33	95.35	0.39	0.39	100	95.35	2.33
Score fusion level	97.67	0.00	0.00	100	100	2.33	100	0.00	0.00	100	100	2.33
Hierarchical fusion	97.67	0.00	0.00	100	100	2.33	100	0.00	0.00	100	100	2.33

It is clear that the results obtained by fusion strategies are much better than those obtained by monomodal biometric systems, and the results obtained using LDA are much better than those obtained using PCA.

Furthermore, as shown in Fig. 3, the cumulative match characteristic (CMC) curve is used to evaluate the identification performance as a comparison. Fig. 3 shows the experimental results.

Hierarchical and score fusion strategies generate the better results (100%).

Using LDA, hierarchical and score fusions have identical curves, but using PCA, it is clear that the best curve is the one obtained by hierarchical fusion.

To evaluate the performance of verification, the Receiver Operating Characteristic (ROC) curve and detection error trade-off (DET) curve are used, and the results are shown in Fig. 3. The ROC and the DET curves of the face, voice, online signature, feature fusion, score fusion and hierarchical fusion based verification as comparisons are given in Fig. 3.
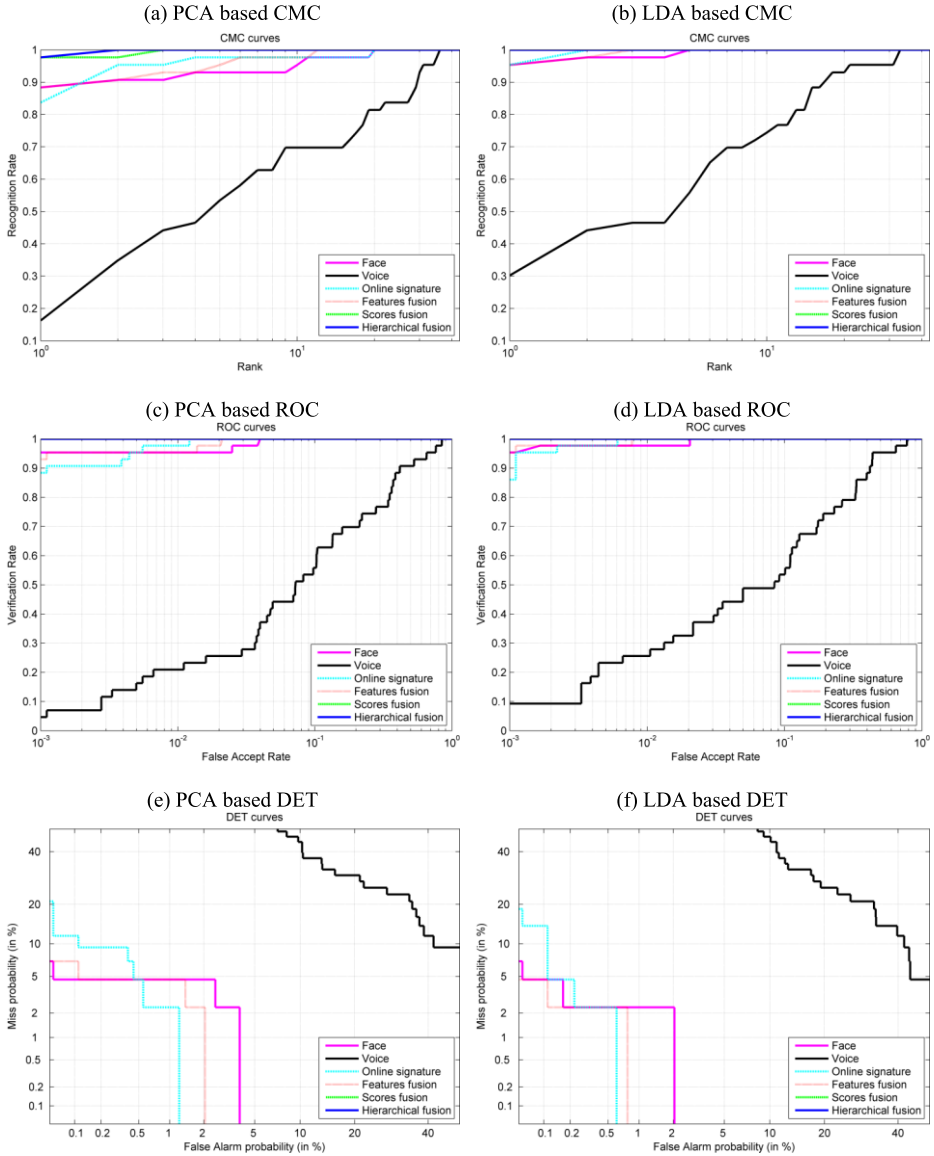
(a) PCA based CMC

(b) LDA based CMC

(c) PCA based ROC

(d) LDA based ROC

(e) PCA based DET

(f) LDA based DET

Fig. 3. Cumulative match characteristic curves, receiver operating characteristic (ROC) curves, and detection error trade-off (DET) curves.

It is noted that the ROC curves of the hierarchical and score fusion strategies are identical. This is because they generate the highest recognition rate using both PCA and LDA.

On the contrary, for ROC and DET curves, where hierarchical and score fusion strategies obtained the same verification performance, the hierarchical fusion strategy produces fewer errors than the score fusion strategy in the task of identification. As such, it is clear that the hierarchical fusion based multimodal systems could benefit from the advantages of the other fusion strategies to improve the method's overall efficiency.

From these figures, the hierarchical fusion of face, voice, and online signature improves the performance of the biometric recognition and authentication, which indicates how highly effective multimodal biometrics are. This strategy significantly improves the performances of both feature and score fusion strategies.

Table 2 gives a comparison of existing methods and the proposed method. It is evident from this table that the results obtained by the proposed method are comparatively much better than the existing methods. The lowest EER obtained was 0%. For verification purposes, the score fusion based method gives the same results as the hierarchical fusion method, but in terms of identification purposes, as shown in Fig. 3, the best performance is the one obtained by the hierarchical fusion strategy. Thus, it is evident that the results are comparatively outperforming other methods.

Table 2. Comparison with existing methods.

Method			EER (%)	Database	Population
MinMax + GMM (face, voice, and signature) [26]			2.39,1.54, 2.3	PDA	60
Fused feature with PCA (face, voice, and signature) [27]			1	Their own	20
The proposed	Feature fusion	PCA	2.19	VidTIMIT + QU-PRIP	43
		LDA	0.39		
	Score fusion	PCA	0		
		LDA	0		
	Hierarchical fusion	PCA	0		
		LDA	0		

7. CONCLUSION

In this paper a new vision has been introduced for a highly accurate biometric system, which combines face, voice, and online signature authentication systems in order to optimize the accuracy and performance of the biometric recognition and authentication. The proposed approach is based on the hierarchical multilevel biometric fusion integration of feature-level fusion strategy and matching score-level fusion strategy. The hierarchical biometric fusion strategy provides most of the overall performance improvement for the entire multimodal biometric system.

Finally, further research should be performed, especially on feature-level biometric fusion, and its impact on biometric recognition accuracy.

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