NEW MULTIPLE CLASSIFIER SYSTEMS FOR FACE AUTHENTIFICATION

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ABSTRACT

In this paper a multiple classifier systems for face verification is proposed based on the study of scores fusion for four face authentication systems. Extraction features is realized by the Gabor wavelets phases, Principal Component Analysis (PCA) with the Enhanced Fisher linear discriminant Model (EFM) are used as a method of reducing data space. For the study of fusion of scores we used two approaches, the first based on the classification of scores using Fisher statistical method, Support Vector Machine (SVM) and artificial neural networks (MLP) and the second is based on combinations of scores by the weighted sum and fuzzy logic.

KEYWORDS: Multiple Classifier Systems (MCS) ; Fusion ; Gabor Wavelets; Enhanced Fisher linear discriminant Model ; Classification.

1 INTRODUCTION

Over the last ten years the Multiple Classifier Systems (MCS) have become unestablished approach to design classification systems. A large number of works both theoretical and experimental are published and confirm that the MCS can perform a single classifier in many real applications in terms of classification accuracy [1]. In particular, several authors have shown that MCS can improve biometric authentication of faces [2]. However, it is not clear how the classifiers are fused. The mechanism of fusion can be done at different levels of classification [3,4] : in the data at the level of extracted features, in terms of scores and level of decisions. The work presented in this article focuses on the fusion of the scores because it is the most commonly type used in fusion. It can be applied to all types of systems (as opposed to the merger in the data and the level of extracted features). The fusion of scores is performed in a limited space of dimension represented by a scores vector whose dimension is equal to the number of subsystems, with relatively simple methods and effective but dealing more information that the merger decision.

As part of our work we focus first, on the use of faces authentication system using Gabor wavelets as a method of feature extraction followed by the reduction of space (PCA + EFM). The best verification systems selected are finally used to study the methods of scores normalization and fusion. The fusion of scores is therefore classified a vector of real numbers by Yes or No for the final decision. There are two approaches to fusion the scores obtained by different classifiers, classification and combination. Several classifiers were used to classify scores to arrive at decision level. One can for example include, the work realized by Wang and al [5], who consider the scores from modules facial recognition and iris recognition as a feature vector in two dimensions. A Fisher linear discriminant analysis (LDA) classifier and a neural network combined with a radial basis function (RBF) are then used for classification. Verlinde and Chollet [6] combine the scores from two face recognition modules and a module for speech recognition with the help of three classifiers: one classifier using the method of K-Nearest neighbor algorithm (KNN) with a vector quantization, a second classifier based on a decision tree classifier and a final based on a logistic regression model. Chatzis and al. [7] use a method of clustering called fuzzy k-means and a fuzzy vector quantization, coupled with a classifier neural network RBF center to fusion the scores obtained from biometric systems based on visual characteristics (face) and acoustic (voice). Sanderson and al. [8] use a classifier based on Support Vector Machine (SVM) to combine the scores from a facial recognition module and a module for speech recognition. They show that the performance of such a classifier deteriorates in the presence of input noise conditions. To overcome this problem, they implement classifiers resistant structural noise as defined by a piece-wise linear classification and a Bayesian classification changed. Ross and Jain [9] use a decision tree and linear discriminant classifiers to combine the scores of the terms of face, fingerprint and hand geometry. Combination of scores approach treats the subject as a problem of combining scores for mathematical methods of combination. For example, Kittler and al [10] have developed a theoretical framework to combine the credentials obtained from multiple classifiers using simple methods such as, sum rule, product rule, the max rule, the min rule and median rule. In order to use these patterns, the matching scores must be converted into posterior probabilities. They consider the problem of classifying an input pattern X in one of m possible classes (in a verification system, m = 2) based on the identification information provided by R classifiers or different matchers. Rasheed and al [11] using the fuzzy Sugeno integral for the combination of scores for a multiple classifier systems for the decomposition of an electro myographic signal(EMG). Chia and al [12] use a hybrid method for calculating the minimum or sum of scores for the combination of two authentication systems of faces and voices. Yong Li and al [13] use the weighted sum for the fusion by combining the scores. Shukla and al [14] propose an adaptive computing and hybrid scores using the combination of fuzzy logic based on the integral of Sugeno and Choquet. Recently Morizet and Allano tried to use the two previous approaches and arrive at very interesting success rates. Allano [3] used two approaches based on SVM approach to classification scores and the combination of simple methods mentioned above and the statistical approach by combining scores. Morizet [15] worked only with the approach based on the combination of scores using the same methods as Allano and a new fusion technique called Wavelet Denoising Statistical Score Fusion (WSDSF).

In this article, inspired from the work of Morizet [15] and Allano [3] we use the two approaches mentioned above for the study of fusion strategies by adding more methods with the aim of reducing the cost and time of use of multimodal systems and improve the performance of the biometric system. Then we make a comparative study of these methods. We propose to make the normalization of scores in the case of the fusion by classification. While in previous work the authors were limited to the normalization of scores in the case of the fusion by combining the scores.

In the first approach (fusion classification scores), in addition to the method of support vector machines SVM used by Allano [3] and [16], we use the Fisher statistics [17] and artificial neural networks (MLP) [18] by adding more normalization phase to the previous works in this what makes the originality of our work.

In the case of the second approach (fusion by combining the scores) we use simple methods such as the weighted sum [13] and combination scores of fuzzy logic based on the integral of Sugeno and Choquet [14]. Another important question that we give answer is the normalization of scores as presented by [19] which is a necessary stage before the combination.

The rest of paper is organized as follows. In Section 2, we first choose the best authentication system faces in the sense of performance. In Section 3, we try to study at this point two methods of normalization of scores. We associate with fusion methods in the case of classification approaches and combined scores. Finally, we conclude our work by the results obtained, conclusion and perspectives.

2 FACE AUTHENTICATION

2.1 The Gabor wavelets

The Gabor wavelets are known as the means of space-frequency analysis that minimizes the Heisenberg uncertainty. The general equation of a 2D Gabor wavelet [20] is:

$$W(x,y,\theta,\lambda,\varphi,\sigma,\gamma) = e^{-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}} e^{i\left(\frac{x'}{\lambda}+\varphi\right)} \quad (1)$$

Or : $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$.

So there are five parameters that control the wavelet analysis. This data set therefore, allows a comprehensive analysis of the texture of a region of the image. By [19, 20] we set φ, σ, γ, and we used eight directions (θ ={0, π /8, π /4,3 π /8, π /2, 5π /8, 3π /4, 7π /8}) and 5 wavelength (λ={4,4$\sqrt{2}$,8,8$\sqrt{2}$,16}).

2.2 Enhanced Fisher linear discriminant Model (EFM)

First, the Principal Component Analysis (PCA) [22] is used to project images in a data space inferior. Let the training set contain *L* classes and each class *Xi* contains n_l samples. The intra-class matrix (**S_w**) and inter-class matrix (**S_b**) are defined as:

$$S_w = \sum_{i=1}^{L} \sum_{\bar{x}_k \in X_i} (\bar{x}_k - \bar{m}_i)(\bar{x}_k - \bar{m}_i)^T \quad (2)$$

$$S_b = \sum_{i=1}^{L} n_i(\bar{m}_i - \bar{m})(\bar{m}_i - \bar{m})^T \quad (3)$$

Whiten first **S_w** :

$$\Theta^{-1/2} \phi^T S_w \phi \Theta^{-1/2} = I, \quad (4)$$

Where, $\Theta \in R^{m\times m}$ is the matrix of eigenvectors and the

diagonal matrix of eigenvalues of S_W respectively. Second ***EFM*** proceeds to calculate the dispersion matrix inter-class **K_b** as follows:

$$K_b = \Theta^{-1/2} \phi^T S_b \phi \Theta^{-1/2} \quad (5)$$

We diagonalize now the new dispersion matrix inter-class K_b :

$$K_b \Psi = \Psi \Lambda \quad (6)$$

Where $\boldsymbol{\Psi}$, $\Lambda \in R^{m \times m}$ is the matrix of eigenvectors and the diagonal matrix of eigenvalues of K_b respectively. The transformation matrix of the global ***EFM*** is defined as follows [21]:

$$W = \phi \Theta^{-1/2} \Psi \quad (7)$$

2.3 Comparaisons

We used the normalized correlation distance [23] to compare two feature reduced vectors A and B which is defined by:

$$S(A,B) = \frac{A^T B}{\|A\|\|B\|} \quad (8)$$

2.4 Experimental evaluation

2.4.1 Data base

Our experiments were performed on frontal face images of the XM2VTS database. It is a multimodal database developed within the ACTS European project, it is used for verification of identity, it contains 8 images per face of 295 people. For the verification task, a standard protocol for estimating performance was developed called «*Lausanne protocol splits randomly*», there are two different configurations, the configuration I and configuration II. We used the configuration I because it is the most complex and it separates people into two classes, client and impostor. The client group contains 200 subjects, while the impostor group is divided into 25 impostors for evaluation impostors and 70 for testing. Eight images of the four sessions are used [24].

2.4.2 Results

Each image consists of several information : color, background, hair, shirt collars, ears....For this, the first necessary step is to cut the image with a rectangular window with size 132x120 centered around the most stable characteristics related to the eyes, eyebrows, nose and mouth (Fig. 1.b). A decimation factor 1 by 4 is used to reduce the size of the cut image (Fig. 1.c) and then we used the HSV (Hue, Saturation, Value) color space. It is the most commonly used in the literature (Fig. 1.d) [20]. We consider the component S "Saturation" according to [21, 22, 26, 27] as characteristic of the image (Fig. 1.e).

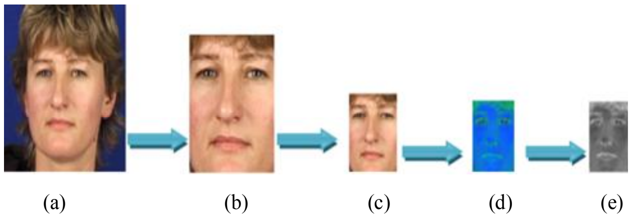

***Figure 1:** (a) Original image, (b) Image cut, (c) Image decimate, (d) Image system HSV, (e) the S composant (e). PCA+EFM is used as a method of reducing data space. The best result achieves a EER=2.66±0.13% overall assessment and RR =94.33±1.49% in the test set with a number of characteristics 80. EER: Equal Error Rate and RR: the recognition rate (RR=100-FRR - FAR). FRR: the False Reject Rate and FAR: the False Accept Rate. Our result is found by 95% parametric confidence interval see [21].*

The Gabor wavelets

Gabor representation of a face image is obtained by convolution of the image with the family Gabor filters defined by $IG(r,o)= I * G(r,o)$, where $IG(r, o)$ is the result of the convolution of the image with Gabor filter at a certain resolution r and an orientation o. As can be seen in Equation 1, the Gabor filters have a complex shape, it is important to use the information given by the real and the imaginary part of Gabor coefficients. Trivial two choices: the Gabor amplitude and phase study.

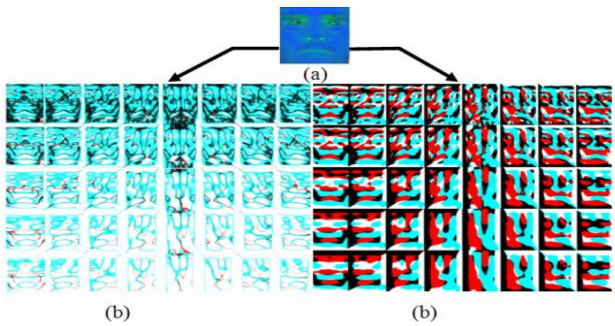

***Figure 2:** Results of the convolution of a face image with a family of 40 Gabor filters (8 orientations (horizontal) and 5 resolutions (vertical)).(a) Image in HSV color space, the set (b) represents the amplitudes and (c) phases of the convolution.*

The influence of characteristics Gabor filters on the performance recognition

We begin by studying the influence of characteristics Gabor filters on the recognition performance to derive the optimal choice. The image representation in question is the amplitude responses Gabor filters of the image Fig.2. (e). The algorithm recognition used EFM and the similarity was measured by the correlation. Table 1 presents the results in terms of recognition EER for different levels filters resolution and orientation.

Table 1: EER for different levels filters resolution and orientation.

Resolution ($\sigma = \lambda$)	Orientations of the filters (θ)							
	0	$\pi/8$	$\pi/4$	$3\pi/8$	$\pi/2$	$5\pi/8$	$3\pi/4$	$7\pi/8$
4	9.28	10.1	8.13	8.02	8.01	8.04	8.63	7.3
$4\sqrt{2}$	8.33	9.01	7.54	9.61	5.35	7.95	7.2	8.5
8	9.31	7.34	8.7	5.7	7.85	5.13	8.02	8.17
$8\sqrt{2}$	9.54	8.64	7.31	9.36	10.19	8.3	7.07	7.54
16	9.17	8.48	8.65	9.18	9.18	8.64	7.84	7.62

In this table we find that the best result obtained with a EER = 5.13%, which is not a good result.

Problem using Gabor phase for faces

When we see the face image, parts of the face has no texture information that could be analyzed by the low resolution Gabor filters. For these regions, the analysis by Gabor filtering gives *Real (IGs,o)*$\cong$ 0 and *Im (IGs,o)*$\cong$ 0. Although these values are very close to *0*, the amplitude of the convolution is not affected by this problem, while the phase becomes an indeterminate form for these regions. To avoid indeterminate forms, we select informative regions by thresholding the amplitude at each point of analysis.

$$P(IG_{s,o}(x,y)) = \begin{cases} \arctan\left(\dfrac{Im(IG_{s,o}(x,y))}{Real(IG_{s,o}(x,y))}\right) & if M(IG_{s,o})(x,y) > TH \\ 0 & if M(IG_{s,o})(x,y) < TH \end{cases} \quad (9)$$

Where *(x, y)* are the coordinates of the analyzed pixel and TH is the threshold for phase selection.

Optimization of the threshold for the selection phase

To study the influence of the thresholding phase based on performance, Fig.3 shows the evolution of equal error rate (TEE) based on the threshold TH by a Gabor filter with $\sigma=\lambda$ resolution$\sigma = \lambda$=4 and direction $\theta = \pi/2$.

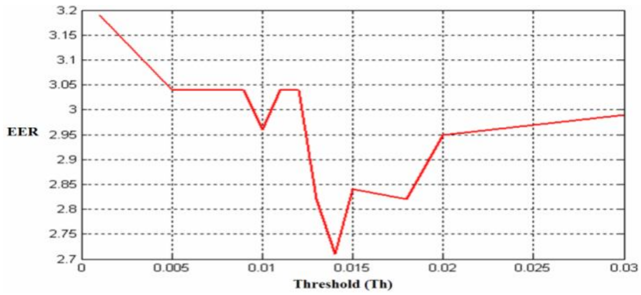

Figure 3: EER based on the threshold Th.

The curve in Fig.3 shows that the variation of EER using the Gabor phase is related to filtering levels. Our choice is then focused on choosing filtering threshold TH =0.014. In the second step, we choose the optimal phase Gabor filters in Table 2.

Table 2: EER for different levels filters resolution and orientation.

λ	Filters Orientations (θ)							
	0	$\pi/8$	$\pi/4$	$3\pi/8$	$\pi/2$	$5\pi/8$	$3\pi/4$	$7\pi/8$
4	4.79	5.14	4.12	4.96	2.69	3.3	3.79	4.64
$4\sqrt{2}$	4.8	5.29	6	5.28	4.15	4.88	4.87	5.3
8	6.03	6.53	7.16	6.79	6.04	6.85	6.29	7.04
$8\sqrt{2}$	6.64	7.47	7.29	8.21	8.52	8.14	7.66	7.8
16	6.5	7.01	8.16	8.45	9.01	8.61	7.99	7.84

We note that the first resolution and orientations $\boldsymbol{\theta} = \pi/2$, $5\pi/8$, $3\pi/4$ give the best EER. The results obtained by Gabor phases are satisfactory and encouraging. We will use in what follows and for the design of our multiple classifier systems all three phases of Gabor filters. The best face authentication systems are presented in Table 3.

Table 3: Face authentication system results for the top four systems included in all evaluation and test set (parametric confidence interval 95%).

methods	Over all Evaluation	Test set		
	EER %	FRR%	FAR %	RR %
system 1	2.66 ± 0.72	2 ± 1.37	3.66 ± 0.11	94.33 ± 1.48
system 2	2.69 ± 0.72	0.5 ± 0.69	4.07 ± 0.12	95.43 ± 0.81
system 3	3.3 ± 0.8	2 ± 1.37	4.41 ± 0.12	93.59 ± 1.49
system 4	3.79 ± 0.85	0.5 ± 0.69	4.47 ± 0.12	95.03 ± 0.82

System 1: Uses the stage of Figure 2 and PCA+EFM reduction step of space and a comparison with the correlation metric.

System 2: using the filtered phase of the convolution of the image in Figure 2 (e) by the Gabor filter of the first resolution ($\sigma = \lambda$= 4) and orientation (θ= π /2) and PCA + EFM as a step reduction of space and finally the correlation for comparison.

System 3: is identical with the system 2 ($\sigma = \lambda = 4$) and orientation ($\theta = 5\pi/8$).

System 4: is also identical to the systems 2 and 3 ($\sigma = \lambda = 4$) and orientation ($\theta = 3\pi/4$).

3 SCORES FUSION

A fusion of scores consists of two modules, a fusion module and decision module (Fig. 4). The problem becomes a classification problem with two classes (Yes or No Client or Impostor).

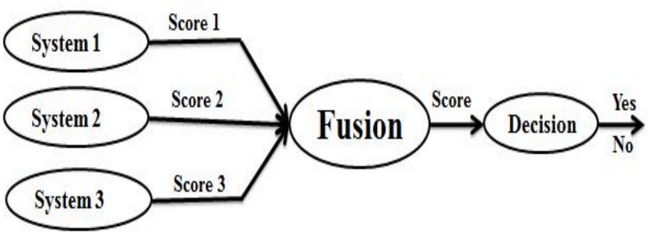

Figure 4: Diagram of the merger of scores.

There are two approaches for combining the scores of different systems. The first approach is to treat the subject as a classification problem, while the other approach is to see it as a problem of combination.

3.1 Fusion methods for classification scores

3.1.1 Statistical method of Fisher

The statistical method introduced here is based on the work of Fischer [25, 28] and uses a linear decision boundary to separate two populations. Consider now the decision rule developed by Fisher. It is based on the likelihood ratio given below:

$$\frac{T(z|c)}{T(z|i)} > k \qquad (10)$$

Where k is an acceptance threshold, the problem that concerns us, T (z | c) and T (z | i) are unknown and must be estimated from the training data. A common assumption is to approximate actual distributions by normal distributions with p variables Np (μA, Σ), where A = {c, i} is the class of individuals, μA is the vector of mean scores and the covariance matrix Σ among experts. At first, we assume the matrix Σ independent of the class of individuals. Under these assumptions, the probability density functions are written as:

$$f_A(z) = (2\pi)^{-p/2}|\Sigma|^{-1/2} exp\left\{-\frac{1}{2}(z-\mu_A)'\Sigma^{-1}(z-\mu_A)\right\} \qquad (11)$$

The parameters μ_c, μ_i and Σ are unknown, but may be estimated from the training data, x is the n_c data access to clients and the data access or impostors (simulated). We have:

$$\hat{\mu}_c = \sum_{q=1}^{n_x} \frac{x_q}{n_c}, \qquad \hat{\mu}_i = \sum_{q=1}^{n_y} \frac{y_q}{n_i} \qquad (12)$$

$$\hat{\Sigma}_c = \sum_{q=1}^{n_x} (x_q - \hat{\mu}_c)(x_q - \hat{\mu}_c)' / (n_c - 1) \qquad (13)$$

$$\hat{\Sigma}_i = \sum_{q=1}^{n_y} (y_q - \hat{\mu}_i)(y_q - \hat{\mu}_i)' / (n_i - 1) \qquad (14)$$

$$\hat{\Sigma} = [(n_c - 1)\hat{\Sigma}_c + (n_i - 1)\hat{\Sigma}_i]/(n_c + n_i - 2) \qquad (15)$$

Note that we consider here, through Σ, dependence that may exist between experts. Combining equations (10) to (15) can be rewritten :

$\frac{\hat{f}_c(z)}{\hat{f}_i(z)} \geq k$ in the form of $D_L(z) \geq \ln(k) = k^*$ where :

$$D_L(z) = \left(z - \tfrac{1}{2}(\hat{\mu}_c + \hat{\mu}_i)\right)' \hat{\Sigma}^{-1}(\hat{\mu}_c - \hat{\mu}_i) \qquad (16)$$

Fisher was the first to use this feature for classification. As $D_L(z)$ is linear in z, it was commonly known as Linear Discriminant Function (LDF) [17].

3.1.2 Support Vector Machine (SVM)

The Support Vector Machine, also known as separators wide margin, aim to define a Hyperplan separating the two classes, Hyperplan that minimizes the misclassification on training set. This supervised learning method can learn a separating more or less complex depending on the choice of kernel. The kernel is the simplest linear kernel which is looking for a linear separation in the n-dimensional space scores. The purpose of the core functions is to transform the initial space (N-dimensional scores) in a space of higher dimension in which the data could be linearly separable. Separation is always linear in the space transformed by the kernel function, but is no longer in the space of scores. The goal of SVM is to find a separator that minimizes the classification error on the training set but which will also be performing generalization on data not used in learning. For this, the concept used is the fusion (hence the name separators wide margin). The fusion is the mean square distance between separator and learning elements it called support vectors (Fig. 5), it is only on those elements of the training set that is optimized separation.

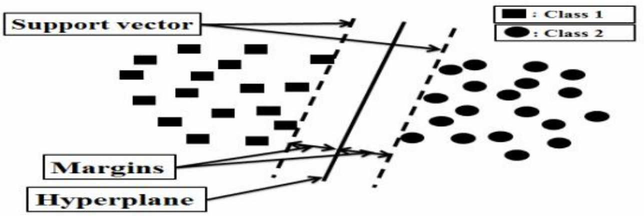

Figure 5: Separation in a linear two-dimensional space.

Any classifier designed to classify an item $\boldsymbol{x}$, by $x = (s_1, \ldots s_N)$ is a vector of scores of dimension N, in one of the possible classes. In our problem there are two classes, client or impostor, whose label is denoted with y = -1, 1, -1 corresponding to the class of an impostor and 1 the class of customers. The classifier has to determine $\boldsymbol{f}$ such that:

$$Y = f(x) \tag{17}$$

The SVM aims to find the best linear separation (in terms of maximum margin, is the best generalization) in the space transformed by the kernel function $\boldsymbol{K}$, is to determine the vector $\boldsymbol{w}$ and the constant b such that separation is the equation:

$$w \ k(x) + b = 0 \tag{18}$$

The distance between a point in space x_i and the hyperplan equation $w .K(x) + b = 0$ is equal to:

$$\boldsymbol{h}(x_i) = \frac{w.K(x_i) + b}{\|w\|} \tag{19}$$

To maximize the fusion, it is necessary to minimize $\|w\|$ and maximize $w\ K(x_i) + b$ for x_i defined as support vectors. These materials are the vectors x_i for i = 1: m from the base of learning such as $w\ K(xi) + b = \pm 1$. Solving this optimization problem is done by using Lagrange multipliers, where the Lagrangian is given by:

$$L(w, b, a) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{m}[a_i(y_i(w.k(x_i) + b - 1))] \tag{20}$$

With the coefficients $\boldsymbol{\alpha_i}$ called Lagrange multipliers. To resolve this optimization problem, we must minimize the Lagrangian with respect to $\boldsymbol{w}$ and $\boldsymbol{b}$ and maximized with respect to $\boldsymbol{\alpha}$. In practice, it is often impossible to find a linear separator (the space transformed by the kernel function) because there are always errors in classification. It has been introduced by Vapnik, the technique of soft margin. This principle of flexible margin tolerates poor rankings by the introduction of variables ζ_i springs that allow to relax the constraints on the elements of learning should be at a distance greater than or equal to1margin (equal corresponding to support vector), but at a distance greater than or equal to 1-ζ_i, is:

$$y_i(w.k(x_i) + b \geq 1 - \zeta_i \tag{21}$$

With $\zeta_i \geq 0$ for i = 1 : M, M being the number of elements in the training set. The optimization problem is modified and the Lagrangian becomes:

$$L(w, b, a) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{M}\zeta_i - \sum_{i=1}^{M}[a_i(y_i(w.k(x_i) + b - 1)]) \tag{22}$$

Where C is a positive constant that adjusts the balance between the number of classification errors and the width of the margin. This constant is usually determined empirically by cross-validation on the training set [29, 30].

3.1.3 The artificial neural networks

The general principle of Artificial Neural Networks was originally inspired by some basic functions of natural neurons of the brain. An artificial neural network is usually organized in several layers, one input layer, an output layer and intermediate layers called hidden layers. The presence of hidden layers is to discriminate classes of objects non-linearly separable. In general, a neural network is basically classifier, it does a job classification during the learning phase, and classification in the recognition. But it can be used to perform data fusion to separate two given populations, including clients and impostors in our case [18].

3.2 Fusion methods by scores combinations

3.2.1 Scores combination by simple operators

The methods are simple scores combinations with very simple methods whose purpose is to obtain a final scores from N scores available if for i = 1 to N from N systems. The methods most used are the average of the product, min, max, median and weighted sum. But in our work we used only the weighted sum is the best because according Allano [3].

$$s = \sum_{i=1}^{N} w_i s_i \tag{23}$$

3.2.2 Scores combination by fuzzy logic

The theory of fuzzy logic (fuzzy subsets) was introduced by Zadeh in 1965 [31] as an extension of binary logic on the one hand and improved multivalued logic on the other. The following algorithm shows how it's done by combining the two integrals of Sugeno and Choquet [32]:

3.2.2.1 Calculating the fuzzy density function g^i

$$\begin{cases} g^i = \beta p_i, & i = 1 \\ g^i = (1-\beta) p_i, & i = 2,3,4 \end{cases} \quad (24)$$

With : p is the classification rate in the interval [0, 1] for

each system. $B \in [0, 1]$ is a factor that establishes a balance

between the results of the classification and I : the index of each system.

3.2.2.2 Calculation of λ

$$\lambda+1=\prod_{(i=1)}^{n}(1+\lambda g^i) \quad (25)$$

Where: $\lambda \in (-1, +\infty)$, $\lambda \neq 0$.

3.2.2.3 Calculation of g(Ai) on the extent fuzzy subsets by

$$g(A_1)=g(y_1)=g^1 \quad (26)$$

$$g(A_i) = g^i + g(A_{i-1}) + \lambda g^i g(A_{i-1}) \quad (27)$$

3.2.2.4 Calculation of Sugeno fuzzy integral by

$h(y_i)$ are the scores and are ranked in descending order, n=4.

$$\int_Y h(y) \circ g(\cdot) = \max_{i=1:n}\left[\min\left(h(y_i), g(A_i)\right)\right] \quad (28)$$

Or calculate the fuzzy **Choquet** integral by:

$$\int_Y h(y) d\, g(\cdot) = \sum_{i=1}^{n}\left[h(y_i) - h(y_{i+1})\right] g(A_i) h(y_{n+1}) = 0 \quad (29)$$

3.3 Normalization scores methods

Methods for normalization scores are designed to transform individual scores from each of the systems to make them homogeneous before combining. Indeed, the scores from each system can be of different nature. In addition, each system can have ranges of different scores. There are several ways to normalize scores as: Min-Max, Z-Score, hyperbolic tangent, median and median absolute deviation, normalization by a quadratic-linear-quadratic (QLQ) and the double sigmoid function. We will limit ourselves to the study of the following two methods of standardization.

3.3.1 Normalization method Z-Score

The technical standards used to score. The most is definitely the Z-Score who uses the arithmetic mean (μ) and standard deviation (σ) of the data [15].

$$s'_{ik} = \frac{s_{ik} - \mu}{\sigma} \quad (30)$$

3.3.2 Standardization by a double sigmoid function

Cappelli and al [31] used a double sigmoid function for the normalization scores in a multimodal biometric system that combines fingerprint systems. The normalized score is given by:

$$s'_{ik} = \begin{cases} \dfrac{1}{1+exp\left(-2\left(\frac{s_{ik}-t}{r_1}\right)\right)} & si\, s_{ik} < t, \\ \dfrac{1}{1+exp\left(-2\left(\frac{s_{ik}-t}{r_2}\right)\right)} & sinon \end{cases} \quad (31)$$

Where t is the operating point of reference and r_1 and r_2 are respectively the left and right edges of the region in which the function is linear ,that is to say that the double sigmoid function shows linear features in the interval ($t - r_1$, $t - r_2$).

3.4 Experimental evaluation

3.4.1 Scores distributions and standardization

The distribution's scores for the four authentication systems faces is shown in Fig.6. We note that the four systems give different distributions Client and Impostor. Distributions are different in terms of range variation, making necessary step to standardize scores. They are also different in their shapes and overlap between the two classes. All the distributions have a single mode (but not necessarily symmetric).

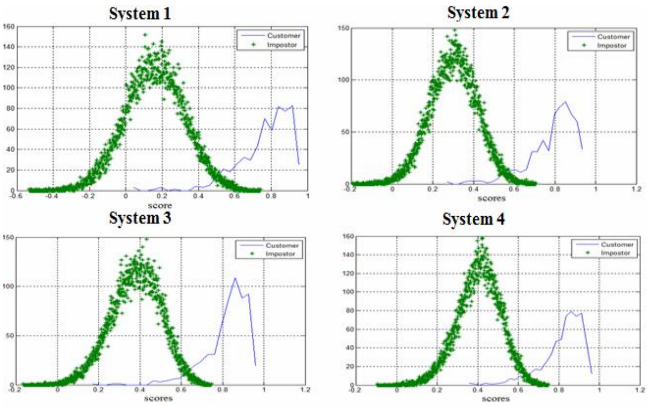

Figure 6: Scores distributions of the four authentification faces systems.

In Fig.7, the transformation scores of the first system are presented for the two normalizations.

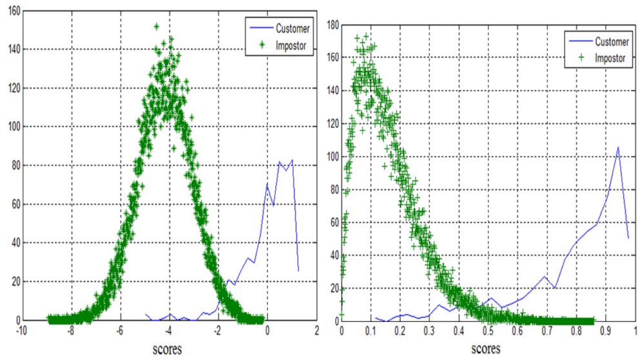

Figure 7: Scores normalization

We note that the normalization method Z-norm, do not change the shape of the distributions, their difference lies in how each distribution will be distributed in the interval and thus in how systems combine juxtaposed in the range (Z-norm with the average distribution of customers in each system will be 0). In addition, the normalization method double sigmoid function changes the shape of distributions.

3.4.2 Comparison of normalization methods associated with the classification methods

The different rates of error and success in all evaluation and testing using the fusion classification scores with and without standardization methods are in Table 4. We use a support vector machine (SVM) with **RBF** kernel (Radial Basis Function). The SVM was implemented using freely available libsvm library site (http://www.csie.ntu.edu.tw/cjlin/libsvm/). The RBF kernel used is in the form:

$$K_{RBF}(u,v) = e^{-\gamma\|u-v\|^2} \tag{32}$$

Where γ is a parameter that sets the margin width. The parameters selected by our experience to the classification by MLP are: 1) Two inputs are the scores for each system, 2) A hidden layer with ten neurons and sigmoid activation function, 3) Two neurons in the output layer and hyperbolic tangent activation function.

Table 4: Method performance standards associated with classification methods (parametric confidence interval 95%).

Standardization methods	Perform. Rate	Classification Rules		
		LDF	SVM	MLP
Without standardization	EER	2.14 ± 0.64	2±0.62	1.83±0.6
	FRR	0.5 ± 0.69	0.5±0.69	1±0.97
	FAR	3.18 ± 0.1	2.93±0.1	2.75±0.1
	RR	96.32 ± 0.79	96.53±0.79	96.25±1.07
Z-Score	EER	1.98 ± 0.62	1.5±0.54	1.69±0.57
	FRR	0.5 ± 0.69	0.5±0.69	1.5±1.19
	FAR	2.84 ± 0.1	2.06±0.08	1.81±0.08
	RR	96.66 ± 0.79	97.44±0.77	96.69±1.27
Double Sigmoid Function	EER	2.17 ± 0.65	1.66±0.0.62	1.33±0.51
	FRR	0.5 ± 0.69	0.5±0.69	0.5±0.69
	FAR	3.15 ± 0.1	2.39±0.9	2.01±0.08
	RR	96.35 ± 0.79	97.11±0.78	97.49±0.77

We can say that the proposed method uses the normalization scores before the classification scores improves overall performance of authentication of faces. The two methods of classification scores of SVM (EER= 1.5±0.54% and RR=97.44±0.77%) and MLP (EER=1.33±0.51% and RR=97.49±0.77%) give almost the same result.

3.4.3 Comparison of normalization methods associated with combinations of methods

The different rates of error and success in all evaluation and testing using combinations of fusion scores are in Table 5. We can say that the score normalization methods that modify the shape of the distributions (double sigmoid function) gives the best result for the Sugeno fuzzy integral with **EER= 1.14±0.47%** and **RR =98.36± 0.75%**.

The method used is the combination of scores fusion by Sugeno fuzzy integral which gives the best multiple classifier authentification of faces with very small computation time **t =0.94 seconds** (programming language used is MATLAB R2009b and computer: Intel Pentium Dual CPU2..2 GHz, 1.49 GHz RAM).

Table5: Method performance standards associated with combinations of methods (parametric confidence interval 95%).

Standardization methods	Perform. Rate	Classification Rules		
		Weighted sum	Sugeno fuzzy integral	Choquet fuzzy integral
Z-Score	EER	1.95±0.62	2.08 ± 0.64	2.16 ±0.65
	FRR	0.5±0.69	0.5 ± 0.69	0.5 ± 0.69
	FAR	2.77±0.1	3.22 ± 0.11	3.19 ± 0.1
	RR	96.73±0.79	96.28 ± 0.8	96.31 ±0.79
Double Sigmoid Function	EER	2.17±0.65	1.14 ± 0.47	2.4 ± 0.68
	FRR	0.5±0. 69	0.5 ± 0.69	0.5 ± 0.69
	FAR	3.14±0.1	1.14 ± 0.06	3.82 ± 0.11
	RR	96.36±0.79	98.36 ± 0.75	95.68 ± 0.81

4 CONCLUSION

Spatial-frequency representation of the face has been widely used and studied in the literature. In most of these studies, only the amplitude of the response of Gabor filters was used as the phase is omitted. We explained the reasons for the restriction of the use of this phase and we have provided a simple solution to overcome this limitation by thresholding the phase that gives the best results compared to the amplitudes.

In this paper, we showed how the use of a multi-classifiers can significantly improve the performance of a system of identity verification of monomodal face and we affirm that the methods of normalizing scores improve performance in general faces authentication for all methods of classification scores used. The best result was obtained with a **EER= 1.14±0.47%** and **RR =98.36± 0.75%** by the method of normalizing scores double sigmoid function, and the combination method of Sugeno fuzzy integral.

In future work we propose to seek further verification systems face monomodal by improving the extraction phases of the features of face and space reduction algorithms and we propose the fusion in terms of features in a space of larger size by wavelets, an SVM classifier type or multi-dimensional modeling.

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