Sensors & Transducers Journal, Vol. 145, Issue 10, October 2012, pp. 106-118

Sensors & Transducers

ISSN 1726-5479

http://www.sensorsportal.com

The Classification of Scores from Multi-classifiers for Face Verification

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Received: 14 June 2012 /Accepted: 22 October 2012 /Published: 31 October 2012

Abstract: We have proposed a multiple classifier systems for face verification by the study of classification of scores of the four face authentication systems built by facial feature extraction phase is filtered using Gabor wavelets and Principal Component Analysis (PCA) plus the Enhanced Fisher linear discriminant Model (EFM) as a method of reducing data space. For the study of classification of scores we used three methods: statistical method of Fisher, the Support Vector Machine (SVM) and artificial neural networks (MLP). Another important issue addressed in this work is the normalization of scores is proposed by the classification scores, why we try to study at this stage three methods of normalization of scores: Z-Score, quadratic-linear-quadratic (QLQ) and double sigmoid function. *Copyright © 2012 IFSA.*

Keywords: Multiple classifier systems, Gabor wavelets, Enhanced Fisher linear discriminant Model (EFM), classification of scores.

1. Introduction

A large number of works both theoretical and experimental shows that multi-classifier systems (MCS) can outperform 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].

The work presented in this article focuses on the fusion of the scores because it is the type most commonly used fusion. It can be applied to all types of systems (as opposed to the merger in the data and the level of extracted features). As part of our work we focus first choice of authentication system faces by Gabor wavelets as a method of feature extraction methods followed by the reduction of space (PCA + EFM). The best verification systems selected faces are finally used to study the methods of classification of scores.

The classification of scores is to see this as a problem of classification scores. Several classifiers were used to classify the scores to arrive at a decision. These include:

- Wang and al. [3] who see the scores from facial recognition modules and iris recognition as a feature vector in two dimensions. A Fisher linear discriminant analysis (FLD) classifier and a neural network combined with a radial basis function (RBF) are then used for classification;
- Verlinde and Chollet [4] combine scores from two modules facial recognition module and speech recognition with the help of three classifiers: one classifier using the method of “knearest neighbor algorithm”, “k-NN” with vector quantization, a second classifier is based on a decision tree classifier and a final based on a logistic regression model;
- Chatzis and al. [5] use a method of fuzzy k-means and a fuzzy vector quantization, coupled with a classifier neural network RBF center to merge the scores obtained from systems biometric-based visual features (face) and acoustic (voice);
- Ross and Jain [6] use a decision tree and linear discriminant classifiers to combine the scores of the terms of the face, fingerprint and hand geometry.

We used third methods to merge score: the statistical method of Fisher, the Support Vector Machine (SVM) and artificial neural networks (MLP). But before the merger of scores a score normalization step is proposed to convert individual scores from each of the systems to make them homogeneous.

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 is [7, 8]:

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

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.

So we chose the following set of variables:

1) θ specifies the orientation of the filter. Was used in this case eight directions:
   $\theta = \{0, \pi / 8, \pi / 4, 3\pi / 8, \pi / 2, 5\pi / 8, 3\pi / 4, 7\pi / 8\}$
2) λ specifies the wavelength and thus the frequency of the sine wave: $\lambda = \{4, 4\sqrt{2}, 8, 8\sqrt{2}, 16\}$.
3) φ specifies the phase of the sinusoid. It is 0 or $\pi / 2$ depending on whether you want the real part or imaginary.

4) σ specifies the variance of the Gaussian (size). It is proportional to the wavelength of the sinusoid. In our case $\sigma = \lambda$.
5) γ specifies the appearance of the Gaussian. Here are circular Gaussian: $\gamma = 1$.

The Fig. 1 masks presented 40 different Gabor wavelets with five frequencies and eight orientations.

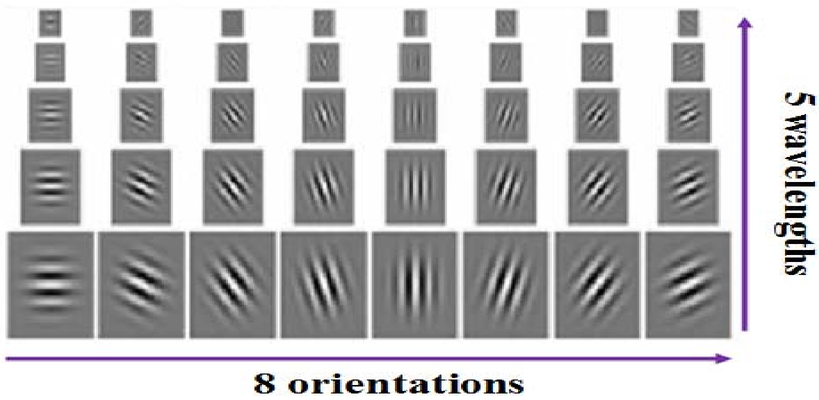


Fig. 1. The 40 Gabor wavelet masks.

2.2. Reduction of Data Space

First, the Principal Component Analysis (PCA) is used to project images in a data space inferior. Second Enhanced Fisher linear discriminant Model (EFM) proceeds to project data in an inferior data space and discriminant [9].

2.3. Comparisons

We used the normalized correlation distance [8] to compare two vectors A and B feature reduces which is defined by:

$$S(A,B) = \frac{A^T B}{\|A\|\|B\|} \tag{2}$$

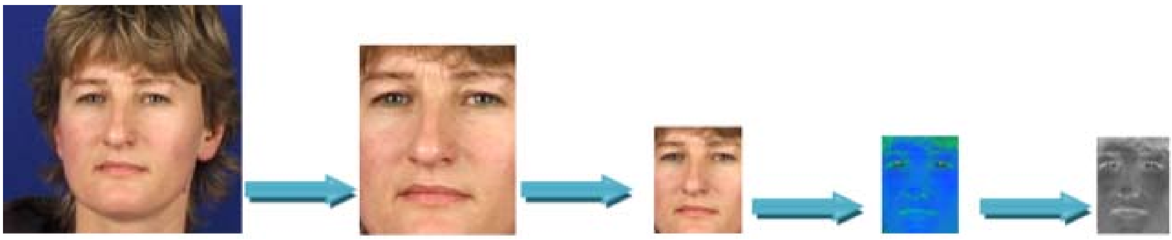
2.4. Experimental Evaluation

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 will use the configuration I because it is the most complex and it is to separate 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 [10].

2.4.2. Results

Each image consists of several information such as: color, background, hair, shirt collars, ears etc. For this, the first necessary step is to cut the image with a rectangular window of size 132×120 centered around the most stable characteristics related to the eyes, eyebrows, nose and mouth (Fig. 2 b). A decimation factor of 2 by 4 to reduce the size of the cut image (Fig. 2 c) and then we used the HSV color space (Hue, Saturation, Value) because the most commonly used in the literature (Fig. 2 d) [7]. We consider the component S "Saturation" according to [11] as characteristic of the image (Fig. 2 e).



(a) (b) (c) (d) (e)

Fig. 2. (a) Original image, (b) Image cut, (c) Image decimate, (d) Image system HSV, (e) the S compose (e).

PCA + EFM is used as a method of reducing data space. In our article [9] the best result is given 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 [8].

2.4.2.1. The Gabor Wavelets

Gabor representation of a face image is obtained by convolution of the image with the family of 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 the Gabor filter at a certain resolution *r* and an orientation *o*. 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 before us: the study of the amplitude and phase of the study of Gabor (Fig. 3).

2.4.2.2. Influence of the Family of Gabor Filters on the Performance of Recognition

We begin by studying the influence of family characteristics Gabor filters on the recognition performance to derive the optimal choice. The representation of the image in question is the amplitude of the responses of Gabor filters of the image in Fig. 2 e. The recognition algorithm is used EFM and the similarity measure used is the correlation. Table 1 presents the results in terms of EER for different levels of resolution and orientations of the filters. EER for different levels of resolution and orientations of the filters. In this table we find that the best result obtained with a EER = 5.13 %, which is not a good result.

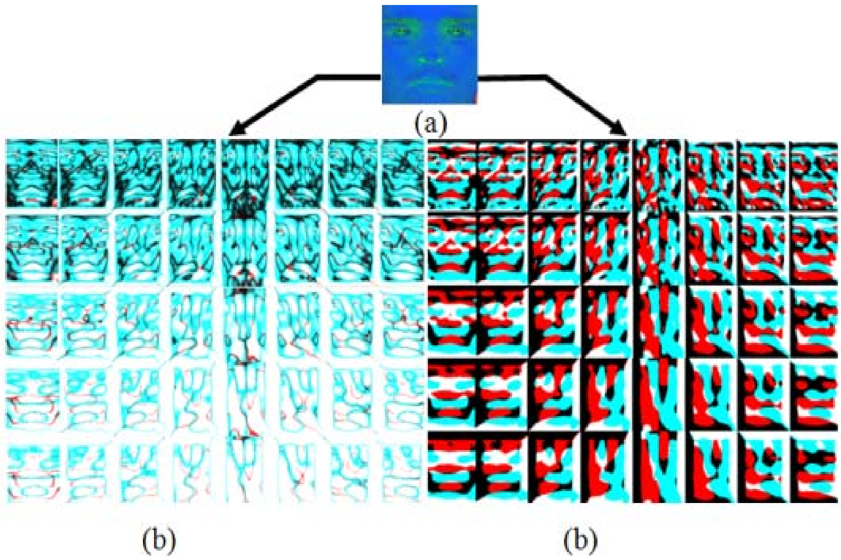


Fig. 3. Results of the convolution of a face image with a family of 40 Gabor filters (8 orientations (horizontal) and 5 resolutions (vertical)): (a) Image in HSV color space, (b) represents the amplitudes, and (c) phases of the convolution.

Table 1. EER for different levels of resolution and orientations of the filters.

λ	**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

2.4.2.3. Problem of Using the Gabor Phase for Faces

When we see an image of the face, parts of the face has no texture information that could be analyzed by the low resolution of the Gabor filters. For these regions, the analysis by Gabor filtering gives *Real(IGs,o)* ≅ 0 and *Im(IGs,o)* ≅ 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.

$$P(IG_{s,o}(x,y)) = \begin{cases} \arctan\left(\frac{Im(IG_{s,o}(x,y))}{Real(IG_{s,o}(x,y))}\right) & \text{if } M(IG_{s,o})(x,y) > TH \\ 0 & \text{if } M(IG_{s,o})(x,y) < TH \end{cases}, \tag{3}$$

where (*x, y*) are the coordinates of the analyzed and *Th* is the threshold for phase selection.

To study the influence of the thresholding phase based on performance. Fig. 4. shows the TEE based on the threshold *Th* by a Gabor filter with σ = λ =4 resolution and orientations θ = $\pi/2$.

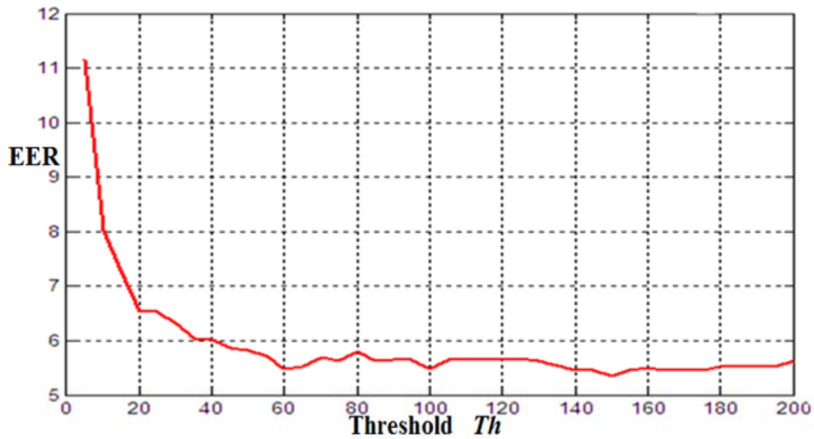


Fig. 4. EER based on the threshold *Th*

The curve in Fig. 4 shows that the variation of TEE using the Gabor phase is related to levels of filtering. So our choice is focused on the threshold of filtering Th = 0014.

In this second phase, we choose the optimal Gabor filters for phase in Table 2.

Table 2. EER for different levels of resolution level and orientation of the filters.

λ	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	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: $\theta = \pi/2$, $5\pi/8$, $3\pi/4$, 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 multi-classifier all three phases of Gabor filters. The best face authentication systems are presented in Table 111.

Table 3. Results of face authentication system for the top four systems included in all evaluation and test (parametric confidence interval 95).

Methods	Overall 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 (σ = λ= 4) and orientation ($\theta = \pi/2$) and PCA + EFM as a step reduction of space and finally the correlation for comparison.

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

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

3. Classification of Scores

A fusion of scores consists of two modules, a merge module and decision module (Fig. 5.). The problem becomes a classification problem with two classes (Yes or No Client or Impostor).

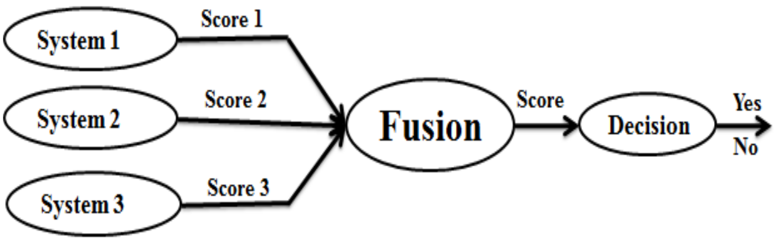


Fig. 5. Diagram of the merger of scores.

There are two approaches for combining the scores of different systems. The first approach is to treat the subject as a problem of classification, while the other approach is to see this as a combination problem. In our article [12] we have studied the second approach.

3.1. Statistical Method of Fisher

The statistical method introduced here is based on the work of Fischer [13] and uses a linear decision boundary to separate two given populations, including clients and impostors in our case. Consider now the decision rule developed by Fisher. It is based on the likelihood ratio given below:

$$\frac{T(z|c)}{T(z|i)} > k \quad , \tag{4}$$

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

$$f_A(z) = (2\pi)^{-p/2}|\Sigma|^{-1/2} exp\left\{-\frac{1}{2}(z-\mu_A)'\Sigma^{-1}(z-\mu_A)\right\} \tag{5}$$

Microcontroller parameters $\boldsymbol{\mu_c}$, $\boldsymbol{\mu_i}$ and $\boldsymbol{\Sigma}$ are unknown, but may be estimated from training data, $\boldsymbol{x}$ is the $\boldsymbol{n_c}$ data access to customers and $\boldsymbol{y}$ the $\boldsymbol{n_i}$ data access or impostors (simulated). We have:

$$\hat{\mu}_c = \sum_{q=1}^{n_x} x_q / n_c \ , \ \hat{\mu}_t = \sum_{q=1}^{n_y} y_q / n_t \tag{6}$$

$$\hat{\Sigma}_c = \sum_{q=1}^{n_x} (x_q - \hat{\mu}_c)(x_q - \hat{\mu}_c)' / (n_c - 1) \tag{7}$$

$$\hat{\Sigma}_t = \sum_{q=1}^{n_y} (y_q - \hat{\mu}_t)(y_q - \hat{\mu}_t)' / (n_t - 1) \tag{8}$$

$$\hat{\Sigma} = [(n_c - 1)\hat{\Sigma}_c + (n_t - 1)\hat{\Sigma}_t] / (n_c + n_t - 2) \tag{9}$$

Note that we consider here, via Σ, dependence that may exist between experts. Combining equations (5) to (9) can be rewritten $\hat{f}_c(z) / \hat{f}_t(z) \geq k$ in the form of $D_L(z) \geq \ln(k) = k^*$ where

$$D_L(z) = \left(z - \frac{1}{2}(\hat{\mu}_c + \hat{\mu}_t)\right)' \hat{\Sigma}^{-1}(\hat{\mu}_c - \hat{\mu}_t) \tag{10}$$

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). Thus, the procedure for verifying the identity, $\boldsymbol{\mu_c}$, $\boldsymbol{\mu_i}$ and **Σ** is to calculate from the data drive (which is done once and for all) and $\mathbf{D_L(z)}$ and compare it to the threshold $\boldsymbol{k}^*$given. If $D_L(z) \geq \boldsymbol{k}^*$, the candidate is accepted as a client. In the case of distributions of clients and impostors scores do not meet the assumption of covariance Σ single decision rule can be rewritten in the form $D_Q(z) \geq 2\,k^*$ where

$$D_Q(z) = (z - \hat{\mu}_t)'\hat{\Sigma}_t^{-1}(z - \hat{\mu}_t) - (z - \hat{\mu}_c)'\hat{\Sigma}_c^{-1}(z - \hat{\mu}_c) + \ln\left(|\hat{\Sigma}_t| / |\hat{\Sigma}_c|\right) \tag{11}$$

$\mathbf{D_Q(z)}$ is called Quadratic Discriminant Function (**QDF**) [14].

3.2. Support Vector Machine (SVM)

The goal of SVM is to find a separator that minimizes the classification error on the training set but will also be performing generalization on data not used in learning [15].

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 to the class of customers. The classifier has to determine $\boldsymbol{f}$ such that:

$$y = f(x) \tag{12}$$

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:

$$w\,.k\,(x) + b = 0 \tag{13}$$

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

$$h(x_i) = \frac{w.K(x_i)+b}{\|w\|} \tag{14}$$

To maximize the margin, 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 Lagrangien is given by:

$$L(w,b,a) = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{m} a_i(y_i(w.k(x_i) + b - 1)) \tag{15}$$

With the coefficients $\boldsymbol{\alpha_i}$ called Lagrange multipliers. To resolve this optimization problem, we must minimize the Lagrangien with respect to $\boldsymbol{w}$ and $\boldsymbol{b}$ and maximized with respect to $\boldsymbol{\alpha}$.

3.3. 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 to discriminate classes of objects non-linearly separable. In general, a neural network is basically a 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 [16].

3.4. Normalization Method of Scoring

Methods for normalization of scores are intended to transform individual scores from each of the systems to make them consistent before combining. Indeed, the scores from each system can be of different nature. In addition, each system can have ranges of different scores, for example for a system scores range between 0 and 1 and another scores range between 0 and 1000. We understand the need to normalize the scores before combining [17]. There are several methods of normalization of scores such as Min-Max, Z-Score, hyperbolic tangent, the median and median absolute deviation, normalization by a quadratic-linear-quadratic (QLQ) and the double sigmoid function. Our best results on the database XM2VTS are obtained for the following normalizations: Z-Score method, the quadratic-linear-quadratic (QLQ), the double sigmoid function. For this we restrict ourselves to the study of three methods of normalization following.

3.4.1. Normalization by Z-Score

The normalization technique used to score the most is certainly the Z-Score, which uses the arithmetic mean and standard deviation data [17].

$$s'_{ik} = \frac{s_{ik} - \mu}{\sigma} \tag{16}$$

where: s_{ik} is the score; μ is the arithmetic mean and σ is the standard deviation of the data.

3.4.2. Normalization by a Quadratic-linear-Quadratic

Snelick et al [18] use a quadratic-linear-quadratic (QLQ) to normalize the scores previously processed in the interval [0, 1] (S_{MM}) using a MinMax normalization.

$$s'_{ik} = \frac{s_{ik} - \min(\{s_{i0}\})}{\max(\{s_{i0}\}) - \min(\{s_{i0}\})}. \tag{17}$$

This normalization QLQ takes as parameters the center c and width w of the overlap of the distributions of scores impostors and client (Fig. 6.).

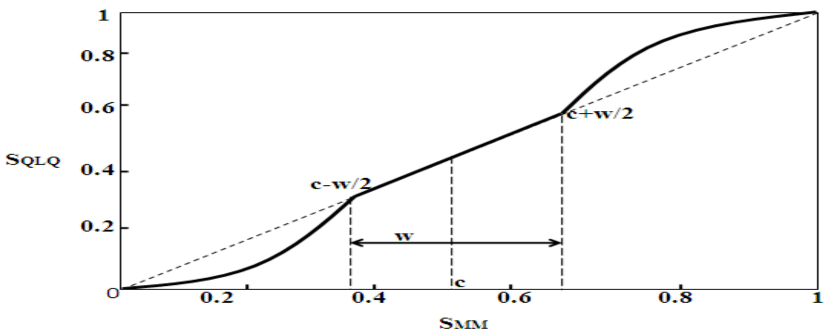


Fig. 6. Normalization QLQ.

The overlap zone remains unchanged while other regions are processed using two quadratic functions per segment. The normalized score is given by:

$$s_{QLQ} \begin{cases} \frac{1}{c-\frac{\omega}{2}} s_{MM}^2, & \text{if } s_{MM} \leq \left(c - \frac{\omega}{2}\right) \\ s_{MM}, & \text{if } \left(c - \frac{\omega}{2}\right) < s_{MM} \leq \left(c + \frac{\omega}{2}\right) \\ \left(c + \frac{\omega}{2}\right) + \sqrt{\left(1 - c - \frac{\omega}{2}\right)\left(s_{MM} - c - \frac{\omega}{2}\right)}, & \text{if not} \end{cases} \tag{18}$$

3.4.3. Normalization by a Double Sigmoid Function

Cappelli et al. [19] used a double sigmoid function for the normalization of scores in multimodal biometric system that combines different fingerprint systems. The normalized score is given by:

$$s'_{ik} = \begin{cases} \frac{1}{1+\exp\left(-2\left(\frac{s_{ik}-t}{r_1}\right)\right)} & \text{if } s_k < t, \\ \frac{1}{1+\exp\left(-2\left(\frac{s_{ik}-t}{r_2}\right)\right)} & \text{if not} \end{cases} \tag{19}$$

where t is the operating point of reference and $\boldsymbol{r_1}$ and $\boldsymbol{r_2}$ 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 range $(t - r_1, t - r_2)$.

3.5. Experimental Evaluation

The distributions of scores for the four faces of authentication systems are shown in Fig. 7. We note that the four systems give different distributions Client and Impostor. Distributions are different in terms of range of variation, making necessary step to standardize scores.

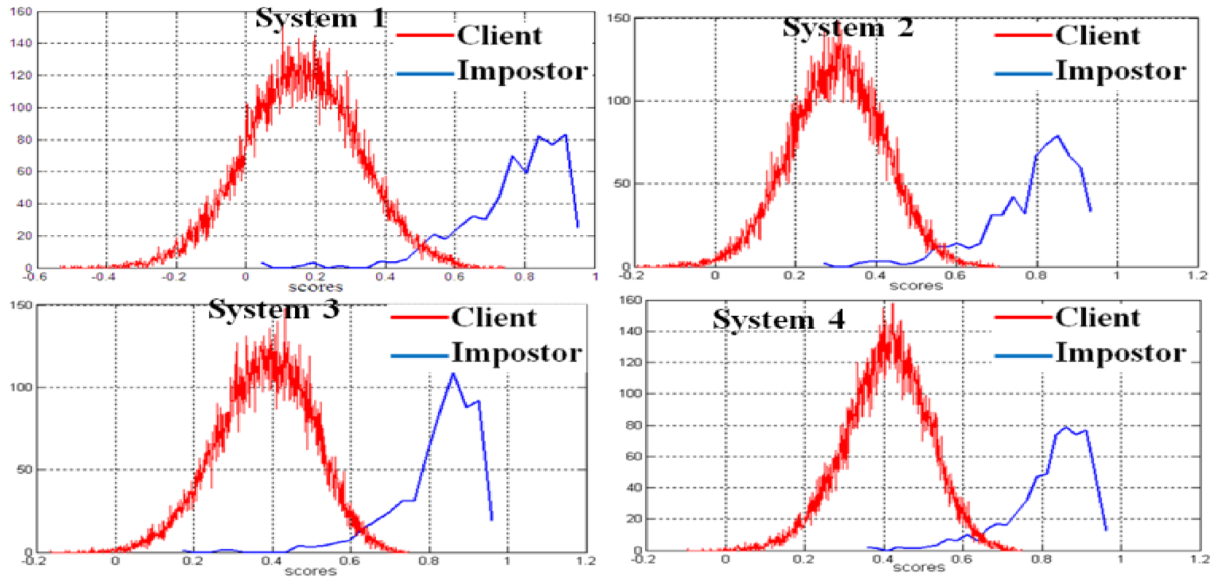


Fig. 7. The distributions of scores of the four faces of authentication systems.

In Fig. 8. the transformation of the scores of the first system is presented for the three normalizations.

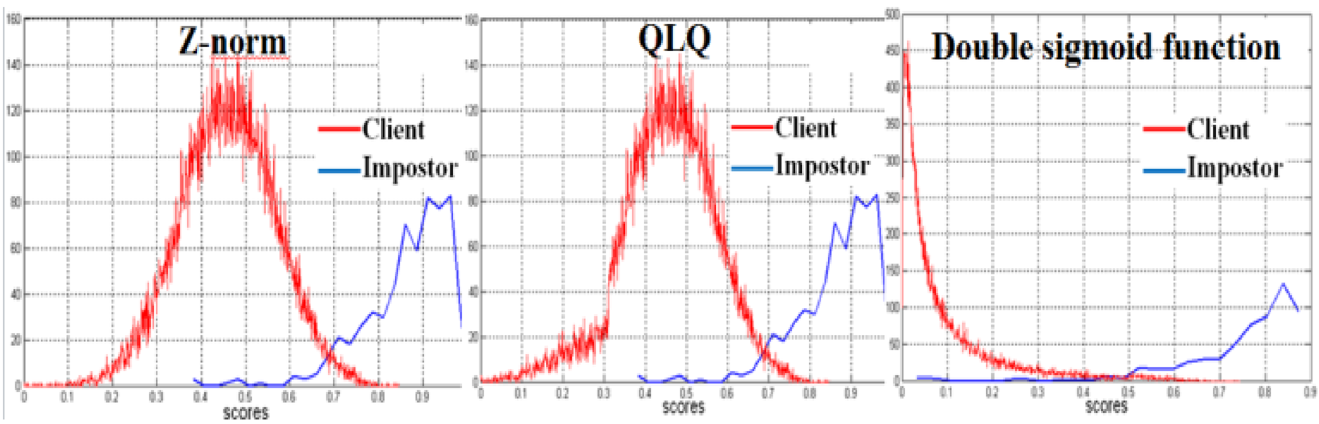


Fig.8. Normalization of scores.

We note that the Z-norm normalization method, do not change the shape of the distributions. While standard methods for quadratic-linear-quadratic (QLQ) and double sigmoid function changes the shape of distributions.

We use a support vector machine (SVM) with RBF kernel (Radial Basis Function). Finally we try to apply the fusion classification scores with simple neural networks like Multi Layer Perceptron (MLP).

The different rates of error and success in all evaluation and testing using the merger of the three classification methods with and without the normalization methods are presented in Table 4.

Table 4 shows that the proposed method that uses the normalization of scores before the classification scores improves overall performance of authentication of faces. In most cases the standard methods that modify the shape of the distributions perform better than methods that do not change the shape of the distributions. The two methods of classification of scores 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.

Table 4. Performance of the classification scores (parametric confidence interval 95).

Standardization methods	**Error rate**	**Fusion Rules**			
		LDF	**QDF**	**SVM**	**MLP**
Without normalization	EER	2.14 ± 0.64	2.15 ± 0.65	2±0.62	1.83±0.6
	TFR	0.5 ± 0.69	0.5 ± 0.69	0.5±0.69	1±0.97
	TFA	3.18 ± 0.1	3.12 ± 0.1	2.93±0.1	2.75±0.1
	RR	96.32 ± 0.79	96.38 ± 0.79	96.53±0.79	96.25±1.07
Z-norm	EER	1.98 ± 0.62	**2 ± 0.62**	**1.5±0.54**	1.69±0.57
	TFR	0.5 ± 0.69	**0.5 ± 0.69**	**0.5±0.69**	1.5±1.19
	TFA	2.84 ± 0.1	**2.89 ± 0.1**	**2.06±0.08**	1.81±0.08
	RR	96.66 ± 0.79	**96.61 ± 0.79**	**97.44±0.77**	96.69±1.27
Quadratic-linear-quadratic (QLQ)	EER	**1.97 ± 0.62**	2.2 ± 0.68	1.96±0.62	1.66±0.57
	TFR	**0.5 ± 0.69**	0.5 ± 0.69	0.5±0.69	**0.5±0.69**
	TFA	**2.68 ± 0.1**	3.06 ± 0.1	2.14±0.09	**1.93±0.08**
	RR	**96.82 ± 0.79**	96.44 ± 0.79	97.36±0.78	**97.84±0.77**
Double sigmoid function	EER	2.17 ± 0.65	2.18 ± 0.65	1.66±0.0.62	**1.33±0.51**
	TFR	0.5 ± 0.69	0.5 ± 0.69	0.5±0.69	0.5±0.69
	TFA	3.15 ± 0.1	3.19 ± 0.1	2.39±0.9	2.01±0.08
	RR	96.35 ± 0.79	96.31 ± 0.79	97.11±0.78	97.49±0.77

4. Conclusion

In this paper, we explained the reasons for the restriction of the use of the phase of Gabor filters and have provided a simple solution to overcome this limitation by thresholding phase. We also showed that the phases of the convolution filtered images of faces by Gabor filters have given the best results compared to the amplitudes.

In this paper, we showed how the use of multi-classifiers can significantly improve the performance of a system of unimodal identity verification of 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 is obtained with a RR = 97.84 ± 0.77 % by the method of normalization of scores Quadratic-linear-quadratic (QLQ) and the method of classification MLP.

In future work we propose to look for other unimodal face verification systems and we propose the merger in terms of features in a space of higher dimension. 3D and 4D. Multimodal fusion could be good candidate.

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