Enhancing Multimodal Biometric Frameworks Using Fuzzy Fusion at Matching Score Level

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***Abstract*—Multimodal biometric systems aim to achieve the best performance in persons recognition, by combining more than one biometric modality so that the combination is done using the fusion principle. In fact, although different levels of fusion are available, score-level fusion is the most commonly used. Indeed, in this process and before combining, the heterogeneous scores provided by the different biometric subsystems must be normalized. In this paper and in order to cancel the scores normalization step, a fuzzy fusion strategy has been proposed. Our experimental results, using a PolyU finger-knuckle-print database, show that the proposed fusion scheme improves the results compared to the Z-score normalization method followed by the min and max classical combining arithmetic rules.**

***Index Terms*—Biometrics, Multimodal biometrics, Data fusion, fusion at score level, Fuzzy logic.**

I. Introduction

BIOMETRICS is the process of automated individuals identification based on their physical characteristics (fingerprint, iris, palm, ear, etc.) and/or their behavioral characteristics (gait, signature, voice, keystroke, etc.). Indeed, these characteristics must meet certain conditions to be valid for being used as distinctive biometric traits [1]: *i)* Universality which means everyone has the concerned characteristics, *ii)* Uniqueness which indicates that these characteristics can't be the same for two or more persons, *iii)* Permanence is another factor, which means that the characteristics must be invariant over time, and finally, *iv)* Measurability, which means that these characteristics can be collected and analyzed.

Unfortunately, despite the advantages of unimodal biometric systems over traditional systems (password, ID cards, etc.), it can suffer from several limitations which can considerably degrade their performance. For example, some person lack some modalities due to a disability [2], and the facial traits of real twins are very similar [3]. In addition to the aforementioned, sensor errors caused by different sources (*e.g.* noise, sensor physic characteristic changes, digitization errors) can significantly affect the unimodal biometric system. In order to overcome these limitations, information from several biometric modalities can be combined and consolidated (synthesis) for better system performance [4, 5]. However, there are five possible scenarios for the sources of information that can be considered in a multimodal biometric system: multiple sensors for the same biometric, multiple instances (multiple prints of different fingers), multiples snapshots, multiple feature extraction/matching, and finally different biometric traits (*e.g.* fingerprint and Iris). The multimodal biometric system is the result of the fusion of several unimodal biometric systems, which requires the processing of multiple information. As shown in Fig. 1, the processing process can be performed simultaneously (parallel mode, Fig. 1.*(a)*) or successively (serial mode, Fig. 1.*(b)*).

In a multimodal biometric system, the fusion can be performed in four different levels [6, 7, 8]: at the sensor level, at the feature extraction level, at the score level or at the decision level. Thus, sensor-level fusion directly combines information from sensors (raw data). The use of this level is relatively low because it requires homogeneity between the data to be combined. Feature-level fusion combines different biometric feature vectors obtained from various processing and analysis phases [9]. This level has the advantage that most of the computations can be done on a single fused feature. Fusing at the matching score level refers to the combination of different scores provided by different classifiers (subsystems). Combination at this level is preferred due to the ease of combining the matching scores and the low computational complexity [10]. Finally, decision-level fusion is the combination of decisions obtained from each subsystem [11]. This level of fusion is often used for its simplicity. This is because each unimodal biometric subsystem provides a binary decision in the form of *yes* or *no*, and the system must make a final decision based on this series of *yes* and *no*.

In the biometrics literature, fusing at matching score seems to be the effective fusion level because of its simplicity as well as the promising results obtained, which allows it to become the most useful level in multimodal biometrics [10]. In this technique, each biometric system operates independently and then their results are combined to obtain a scalar score that is later used for decision making. Many techniques are used to combine scores obtained from biometric subsystems, but the most effective method is known as the rule-based [10], in which simple rules are used (such as sum, minimum, maximum). Indeed, the scores provided by the different biometric systems are generally heterogeneous, of different nature and scales depending on the classifier used (for example if an SVM classifier is used, more the distance is important from margin lines more the score is important, unlike in a KNN classifier, more the distance is important more the score is small). In addition, the scores belonging to different ranges

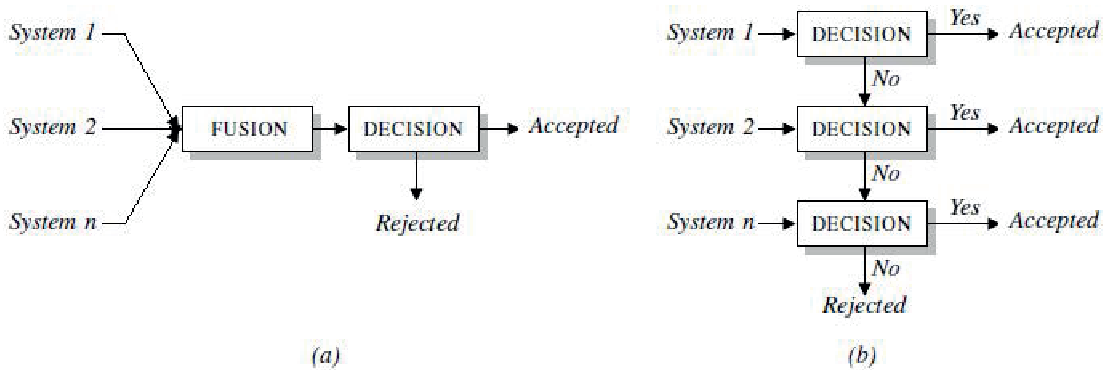


Fig. 1. Processing of multiple information. *(a)* Parallel architecture, and *(b)* Serial Architecture

of values, leads to a statistically different distribution of the scores [10]. The score fusion step must therefore be preceded by a normalization step, which consists in transforming the heterogeneous scores into a common domain before any combining process. In addition to the fact that the normalization step increases processing time, it may not effectively improve system performance. Thus, in order to efficiently combine the scores, we have proposed in this paper an efficient method based on fuzzy logic to directly fuse the matching scores of subsystems without normalization process.

The rest of this paper is organized as follows: Section 2 briefly describes the relevant work. In section 3, we present and discuss in detail the proposed method. This section includes a brief overview of the two hand-crafted feature extraction methods, namely Four Patch Local Binary Patterns (FP-LBP) and Gabor Filtering. Section 4 deals with the experimental results in which a popular Finger-Knuckle-Print (FKP) database is used. Finally, the conclusion and future work are presented in section 5.

II. Related works

Biometric technologies have proven their effectiveness in various security systems, leading many sectors to include this technology in many applications that require a high-security level, but despite this, their use still poses many security and privacy challenges, and therefore the researchers made a great effort to improve the level of security thanks to the multimodality principle. Thus, by consulting the biometric literature, several approaches and attempts have been presented with the aim of improving score level fusion techniques. *A. Ben khalifa et al.* [10] have proposed an adaptive score normalization coupling of face, palmprint and fingerprint modalities before score fusion. In fact, they conclude that the system performance is strongly dependent on the normalization technique. In addition, an adaptive multimodal biometric system using various modalities has also been proposed by *A. Kumar et al.* [12], in which Particle Swarm Optimization (PSO) method was used to optimize the matching score fusion. *S. Aratbez et al.* introduced a new multibiometric fusion scheme based on optimized and weighted functions [13]. Also, *A.P. Yazdanpanah et al.* [14] have proposed a multimodal system based on face, ear and gait with fusion at matching score level using classical arithmetic rules, such as the weighted sum and weighted product approaches.

Artificial Intelligence (AI) is used to describe the many technologies and applications that reproduce human intelligence. Currently, available AI systems are in their infancy, but technology promises to change almost every aspect of our life over the next few decades. As one of the main categories of AI, fuzzy logic has proven to be impressive, so it has been used effectively in many multimodal biometric schemes, but it is still too early to judge its effectiveness. *V. Aarohi et al.* [15] used fuzzy rules in score level fusion to enhance cloud access security, by combining face and fingerprint modalities. In this study, the authors show the simplicity and effectiveness of fuzzy rules in score level fusion. In [16], *H. Benaliouche and al.* fuse the iris and the fingerprint at the matching score level using fuzzy logic schemes. In these two previous works, authors conclude that fuzzy logic is a soft and simple way and gives enhanced results.

III. Proposed method

The proposed architecture in this paper (see Fig. 2) improves the security level in the biometric systems schemes. Our method uses a multi-algorithm scenario, *i.e.* the same biometric modality is analyzed in two different ways to extract the discriminating biometric features. Each biometric subsystem (unimodal biometric system) uses one of the extracted feature vectors to identify the person, and then the two obtained scores are combined to obtain a single score (multimodal biometric system) which is used to make the final decision to reject or accept the concerned person.

A. Feature extraction

The efficient extraction of the salient features of an image is an essential task in any pattern recognition system. Therefore, the extracted features must adequately represent the overall information contained in the image, because the good results are directly related to the uniqueness and the variability of these features, which make it possible to distinguish different patterns [17]. In the image, various features can be extracted and then used as a distinctive vector, but texture-based feature extraction methods have proven to be effective due to the high degree of discrimination of the resulting feature vectors. In our work, we used two efficient and well-known hand-crafted feature extraction methods in the field of texture analysis, namely Local Binary Pattern (LBP) and Gabor Filtering (GF). We give hereafter a brief overview of these two methods.

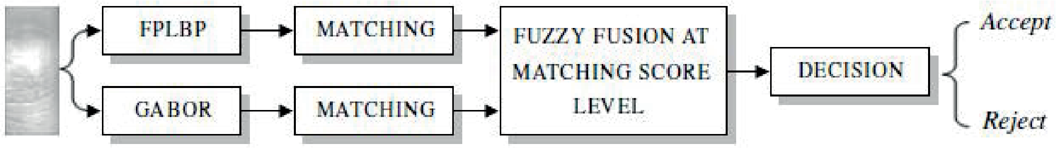


Fig. 2. Proposed multi-algorithmic based multimodal biometric system

1) Four Patch Local Binary Patterns : Given the growing interest in the use of images in machine vision applications, several methods were used to analyze and therefore understand the content of images. One of the most effective methods is the LBP operator that was first proposed by *Ojala et al.* [18] for the texture classification. The basic idea of this method is to define the structure of an image by subdividing it into sliding windows, in which for a given window all the central neighbors are calculated by subtracting the central value from all the pixel values, after whereby the resulting negative-values are coded as 0, while zero and positive-values are coded as 1, formally, the LBP operator can be defined as follows [19]:

$$\text{LBP}_{P,R}(p) = \sum_{p=0}^{P-1} \mathcal{S}(q_p - q_c)2^p \tag{1}$$

Where q_c is the central pixel, P and R denote respectively the number of neighboring pixels and the Radius. The function $\mathcal{S}(x)$ is equal to 0 if x is negative, and to 1 otherwise. the binary code is obtained by concatenating all the codes clockwise, and converting them to a decimal value, finally the center of the window is updated to this decimal value. In Fig. 3.*(a)* we give an example to illustrate the process of calculating the LBP operator for a given pixel. It is clear that the LBP value of each pixel is between 0 and 255, which is similar to the pixel intensity in a gray-scale image. Finally after having calculated all the LBP operators for all the pixels, a feature vector is generated in the form of a histogram.

Due to the efficiency of the LBP technique in image analysis, many researchers have tried to improve it, which has led to the emergence of many variants, in which FP-LBP (introduced by Wolf et al in 2008) is one of the effective extensions of LBP. The new variant changes the scale of LBP to provide other categories of local information [20]. In this approach, two rings are examined for a considered pixel at the origin. Patches of size $n \times n$ spread out consistently over each ring, as shown in Fig. 3.*(b)*. The number of bits in the binary code will be half of the patches in each ring. The FP-LBP is generated by relating two center symmetric patches in the outer ring with two center symmetric patches in the inner ring. The binary code is determined based on which of the two pairs of patches in each ring is closest.

Mathematically, the FP-LBP variant is defined for a center pixel P with coordinate C, a set S of patches of size $w \times w$ distributed uniformly out evenly on each ring of radius r_1 and r_2, respectively, as follows:

$$\text{FP-LBP}_{r_1,r_2,S,w,\alpha}(p) = \sum_{i}^{S/2} f[d(C_{1,i}, C_{2,i+\alpha \mod S}) - d(C_{1,i+S/2}, C_{2,i+S/2+\alpha \mod S})] \times 2^i \tag{2}$$

where $d(\bullet, \bullet)$ the distance between two patches and f is defined as $f(x) = 1$ if $x > \tau$, otherwise 0. The value of τ is set slightly greater than zero. Finally, the resulting response is divided into non-overlapping regions and a histogram is calculated for each region. The histograms are normalized to the unit-rank and concatenated into a single vector to represent the entire image feature.

2) Gabor filtering: The Gabor filter was proposed as a feature extraction method in the field of image analysis and computer vision [21] by the British physicist *Gabor* (the one-dimensional (1D) Gabor function) in 1946. Shortly afterwards and because of the promising results of this method, *Daugmann* [22] proposed the 2D Gabor function in 1980. Gabor filters are characterized by a good time-domain and frequency-domain transform presentation so that it can capture local structure information corresponding to spatial frequency (scale), spatial location and direction selectivity.

The Gabor filter is a combination of a Gaussian kernel, with standard deviations (σ_x, σ_y), and an illumination function which is a sinusoid, at a center frequency (μ_0, ν_0). This filter is sensitive to contours, therefore to differences in illumination (contrast) and not to the absolute value of luminance. In dimension 2, in the spatial domain, the impulse response of this filter is defined as a sine wave modulated by a Gaussian kernel (see Fig. 4).

$$\mathcal{G}(x, y) = e^{2j\pi(\mu_0 x + \nu_0 y)} \times e^{-(\frac{(x-x_0)^2}{\sigma_x^2} + \frac{(y-y_0)^2}{\sigma_y^2})} \tag{3}$$

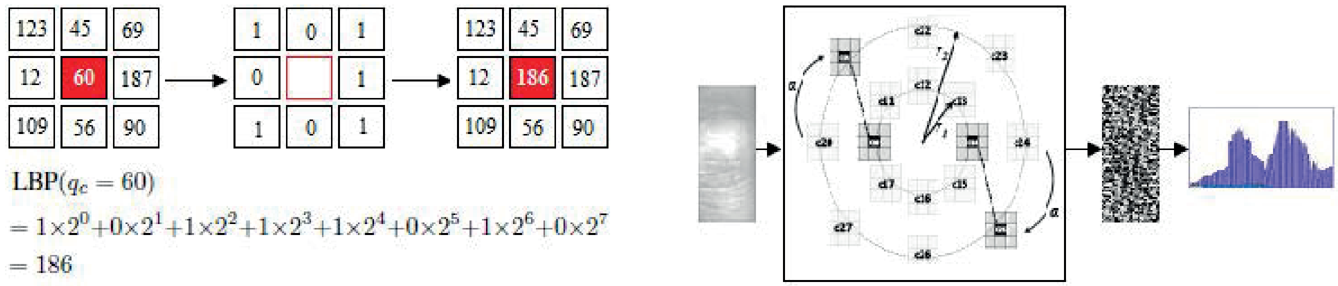
The Gabor function has a real and imaginary component that represents orthogonal directions. To obtain the feature vector $(\mathcal{V})$, the input image $(\mathcal{I})$ must be filtered with the Gabor filter $\mathcal{G}$, as follows:

$$\mathcal{V} = \mathcal{F}(\hat{\mathcal{I}}) = \mathcal{F}(\mathcal{G} * \mathcal{I}) \tag{4}$$

where the $*$ symbol denotes 2D convolution process and $\hat{\mathcal{I}}$ is the output filtered image. The function $\mathcal{F}$ denotes the method used to extract the feature vector from the filtered image, such as the histograming or the binary conversion.

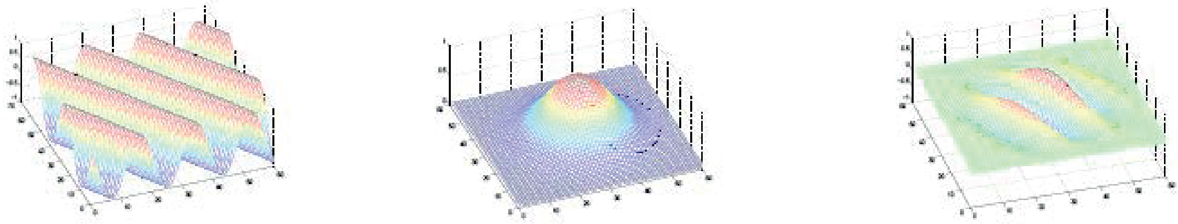
B. Fuzzy Logic based score level fusion

In the fusion process, the individual scores are combined to form a single score which is then used to make the final decision. In order to ensure that the combination of scores from different modalities is consistent, the scores must first be transformed into a common domain called the normalization of scores. Indeed, the normalization step consists of transforming heterogeneous scores into a common domain, in this paper the *Min-Max* and *Z-scores* methods are used, these are the most commonly used score normalization techniques [23].



(a) *(b)*

Fig. 3. Texture analysis using LBP. *(a)* LBP operator calculation, and *(b)* FP-LBP based image feature extraction



(a) *(b)* *(c)*

Fig. 4. 2D Gabor filter composition. *(a)* 2D sinusoid oriented with respect to the horizontal axis, *(b)* Gaussian kernel, and *(c)* corresponding Gabor filter

The *Min-Max* technique is known as the simplest normalization technique. In fact, for a given vector $S = (s_1, s_2, \cdots s_k, \cdots, s_n)$, the normalized scores are given as follows:

$$S_k^N = \frac{s_k - \rho_{\min}}{\rho_{\max} - \rho_{\min}} \tag{5}$$

Where $\rho_{\max}$ and $\rho_{\min}$ are respectively the maximum and minimum values of the raw scores (S). The *Min-Max* technique has the spectacular advantage of confining all the normalized scores in a common interval [0, 1], on the other hand this method is very sensitive to the presence of outliers, therefore this method is not very robust.

The *Z-score* is calculated using the arithmetic mean and standard deviation of the raw data. In this case, the normalized scores are given by:

$$S_k^N = \frac{s_k - \mu(S)}{\sigma(S)} \tag{6}$$

Where μ and σ are respectively the mean and the standard deviation of the set of scores (S). The *Z-score* technique generates positive client scores and negative impostor scores [10], on the other hand, it is not very sensitive to outliers because it is based on mean and standard deviation values.

The score combination approaches are very simple methods and aim to obtain a final score S_f from the N available scores (if N biometric subsystems are combined). Indeed, the most used methods are the minimum, the maximum, the sum, the weighted sum and the product. In this paper, we only use the first two methods to combine the *Z-scores* normalized results.

The Fuzzy Logic based score level fusion is based on decision switching between geniune and imposters based on strict breakpoints, which can affect system performance. On the other hand, Fuzzy Logic (FL) aims to design a low cost and robust solution [24, 12], for "partial truth" or "degrees of truth" problems. It exploits the tolerance for imprecision and uncertainty, considering truth values between 0 and 1. In addition, fuzzy rules show a large margin of simplicity and elasticity, which allows the fuzzy designer to easily obtain the best and adequate solution for his problem. In this work, FL is used to fuse the scores provided by the FP-LBP and Gabor filters based biometric unimodal system using FKP modality.

1- The fuzzy variables for the two systems (FP-LBP scores and Gabor filtering scores) are defined using trapezoidal membership functions (see Fig. 5.*(a)*).

2- The output fuzzy variable is defined as "Score Fusion" also using trapezoidal member functions.

3- For both input and output, 3 fuzzy sets are used to present the 3 regions: Bad, Average and Good.

The trapezoidal membership function is represented by:

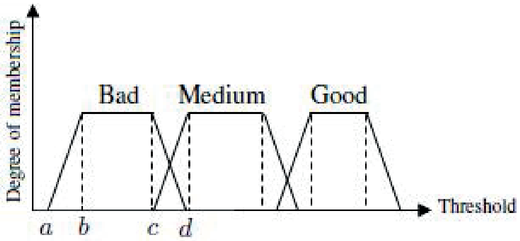
$$\mu(x) \begin{cases} 0 & (x \leq a) \\ \frac{x-a}{b-a} & (a \leq x \leq b) \\ 1 & (b \leq x \leq c) \\ \frac{d-x}{d-c} & (c \leq x \leq d) \end{cases} \tag{7}$$

Fuzzy *if-then* rules are defined in Fig. 5.*(b)*.

IV. Experiment Result

In this work, the proposed method will be evaluated using FKP images provided by Hong Kong Polytechnic University (PolyU) [25]. This database contains 7920 images collected from 165 persons. Each person provides 48 images of four different fingers, with an average of 12 images each of the Left Index Finger (LIF), Left Middle Finger (LMF), Right Index Finger (RIF), and Right Middle Finger (RMF).

In order to limit the set of tests, only multimodal/unimodal biometric systems based on the LIF modality were evaluated.



(a)

		Gabor filter		
		Bad	**Med**	**Good**
FP-LBP	**Bad**	Bad	Med	Good
	Med	Med	Med	Good
	Good	Med	Good	Good

(b)

Fig. 5. Fuzzy rules. *(a)* Trapezoidal membership functions, and *(b)* Fuzzy *if-then* rules

In addition, the systems to be examined use one of two feature extraction methods (FP-LBP and Gabor filtering). In our experimental tests, five samples will be randomly selected for enrolment, and the remaining samples (seven samples) for identification tests. Thus, a total of 95865 match scores can be obtained, in which 1155 matching scores are genuine experiments and 94710 matching scores are impostor experiments. Thus, in our study, the experimental results will be divided into two parts. In the first part, the performance of FP-LBP/Gabor based unimodal biometric identification systems are tested and evaluated. In the second part, we will focus on multimodal biometric identification systems, in which various fusion techniques (classical and Fuzzy fusion techniques) will be examined and compared.

A. Unimodal biometric system performance

To perform a fair assessment, all methods were implemented using the same methodology. This part is also divided into two sub-parts so that the first deals with FP-LBP-based biometric identification systems, while the second deals with Gabor-based biometric identification systems.

1) FP-LBP based unimodal biometric system: The FP-LBP-based feature extraction method is based on various parameters, including patches size, a set of patches (S), two rings of radii r_1 and r_2, and an α patch along the circle. Several tests can be performed to select these parameters, but in our work we have limited our tests only to selecting the best patch size. In our series of tests, we attempted to determine the value of the patch size among three predefined values (3×3, 5×5 or 7×7) while the remaining parameters of the FP-LBP based feature extraction method were taken from the predefined values (r_1 = 2, r_2 = 8, S = 8, α = 1). In general, as a first remark on all the obtained results, we can note that FP-LBP allows to obtain better unimodal biometric identification performance, which generally exceeds 99.50%, but the best value was 98.99% using a patch size 5×5.

Fig. 6.*(a)* clearly shows the system performance in terms of Equal Error Rate (EER). In fact, an excellent error equal to 1.10% can be obtained at a security threshold (T_o) equal to 0.289. In crisps logic framework scores less than threshold will be considered as impostors, whereas if the score is high than threshold the system accept the user as genuine. This functional period, around the threshold, represents the area of uncertainty that will be fuzzified. This experimental result is very satisfactory because it will also be combined with the second feature extraction method and thus increase the security level of the biometric identification system in order to achieve the best case (EER $\rightsquigarrow$ 0.00%).

2) Gabor filtering based unimodal biometric system: This method also depends on several parameters, mainly the standard deviations and the center frequency (orientation). Therefore, in order to assess the effectiveness of the identification system, it is first necessary to choose these parameters. Note that, as in the previous experiments, we examined only one parameter, which is the orientation, and selected the best value from a set of predetermined values ($[0^o, 30^o, 45^o, 60^o, 90^o]$). Indeed, this sub-part consists in studying the effect of orientation on the performance of the identification system, so the EER of system at all orientations was measured.

In our tests, all the obtained results show that with the exception of the Gabor orientation of 90^o, which gives a poor performance, the remaining Gabor orientations work best, in which excellent EER not exceeded 1.50% can be obtained. Thus, the obtained results demonstrate that the orientation of 0^o gives the best biometric system performance with an EER equal to 1.25% at the threshold of 0.284, as shown in Fig. 6.*(b)*, for this, this area will be fuzzified.

B. Multimodal biometric system performance

Although the developed unimodal biometric systems give very acceptable identification results, this does not exclude the possibility of accepting unauthorized persons or rejecting authorized persons. For this and in order to improve the performance of the proposed unimodal systems, we can fuse the two feature vectors (extracted by FP-LBP and Gabor) to obtain a multimodal biometric system.

To evaluate the performance of the proposed fusion method, we compared the results obtained from the fuzzy fusion method with those based on two classical methods using simple rules, namely the maximum scores and the minimum scores. Of course, before the score fusion step, a score normalization step will be applied (*Z-scores* and *Min-Max* normalization methods). Thus, Table 1 summarizes the EER of multimodal biometric systems obtained by the different fusion methods (*Z-scores*/min, *Z-scores*/max, *Min-Max*/min, *Min-Max*/max and *fuzzy* fusion method). To clarify, in Fig. 7.*(a)* we have plotted the Receiver Operating Characteristic (ROC) curves of all cases in order to compare the system performance under all the fusion methods studied.

From Table 1 and Fig. 7.*(a)*, we can clearly see the superiority of the classical method, in particular *Min-Max*/Min and *Min-Max*/Max over the fuzzy fusion method. In general,

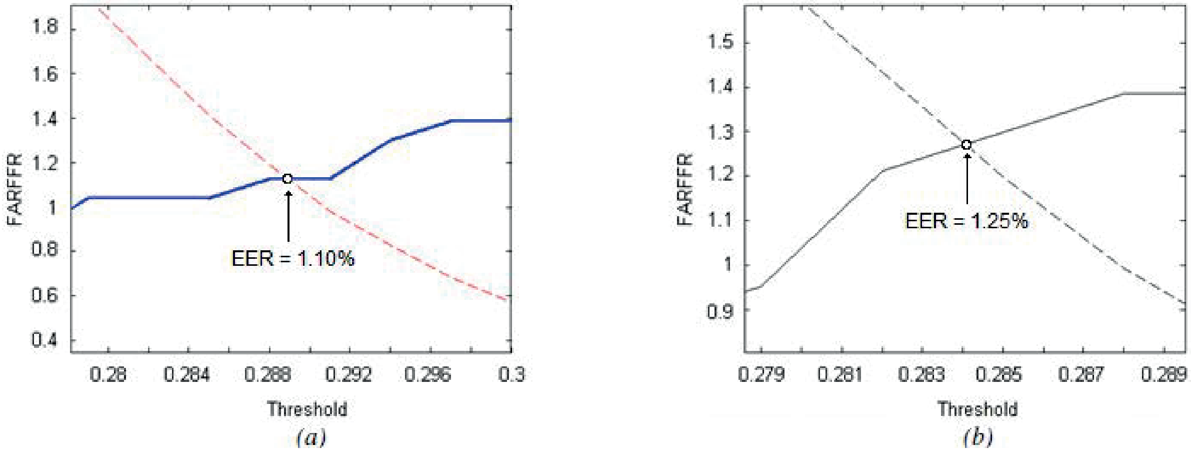


Fig. 6. Unimodal biometric system performance. *(a)* FP-LBP based unimodal biometric system, and *(b)* Gabor filtering based unimodal biometric system

Table 1: Equal Error Rate (EER)

Normalization/Fusion	EER [%]
Z-score/Min-Score	0.90
Z-score/Max-Score	0.75
Min-Max/Min-Score	0.33
Min-Max/Max-Score	0.17
Fuzzy Fusion	0.43

Table 2: Genuine Acceptance Rate (GAR) at FAR=1%

Normalization Techniques	Fusion Techniques		
	Min-Score	Max-Score	Fuzzy Fusion
Z-score	99 ,22%	99 ,57%	/
Min-Max	99.14%	100.00%	/
/			99.65%

the fusion process improves the unimodal system performance in all cases. Thus, an improvement of about 18%, 31%, 70%, 84.5% and 60.9% was obtained compared to the FP-LBP-based unimodal biometric identification system for *Z-score*/Min, *Z-score*/Max, *Min-Max*/Min, *Min-Max*/Max, and Fuzzy Fusion method, respectively. Similarly, an improvement of about 28%, 40%, 73.6%, 86.4% and 65.6% was obtained compared to the FP-LBP-based unimodal biometric system for *Z-score*/Min, *Z-score*/Max, *Min-Max*/Min, *Min-Max*/Max, and Fuzzy Fusion method, respectively.

As earlier mentioned, the *Min-Max* normalization method is very sensitive to outliers, therefore, different techniques will be evaluated after adding random outliers to the score matrices. Thus, after adding the outliers, the biometric system performance was re-evaluated and the results obtained are shown in Fig. 7.*(b)*. From this figure, the sudden degradation in system performance can be observed in the case of Min-Max. Also, unlike the *Z-scores* which show a slight degradation, the fuzzy fusion shows a slight improvement.

V. Conclusion and further work

Multimodal systems are strongly dependent on the chosen normalization and fusion techniques; the effectiveness of the system is determined by the overlap between the two distributions genuine and impostor. To separate these two classes, Boolean logic-based methods switch values observing strict breakpoints, which cannot deal clearly with confusion zone. Fuzzy logic is a very robust and simple implementation tool for managing the systems behavior in the uncertainty area. Thus, in this paper, we exploit fuzzy logic to improve the performance of multimodal systems based on fusion at the score level. Fortunately, the proposed method does not require any scores normalization process, and therefore, it avoids a lot of errors, difficulties and extra-calculation. The experimental results show that the fuzzy fusion method provides better results in the presence of outliers compared to the classical normalization (*Z-score* and *Min-Max* normalization techniques) followed by min and max fusion rules. The flexibility offered by fuzzy logic makes it efficient and easy to study and describe biometric systems especially in the area of uncertainty. In future work, we plan to use this technique with other classifiers such as Random Forest Tree (RFT) and Radial Basis Function (RBF). We are also trying to extend the proposed approach to other fusion levels, such as the sensor, feature and decision levels.

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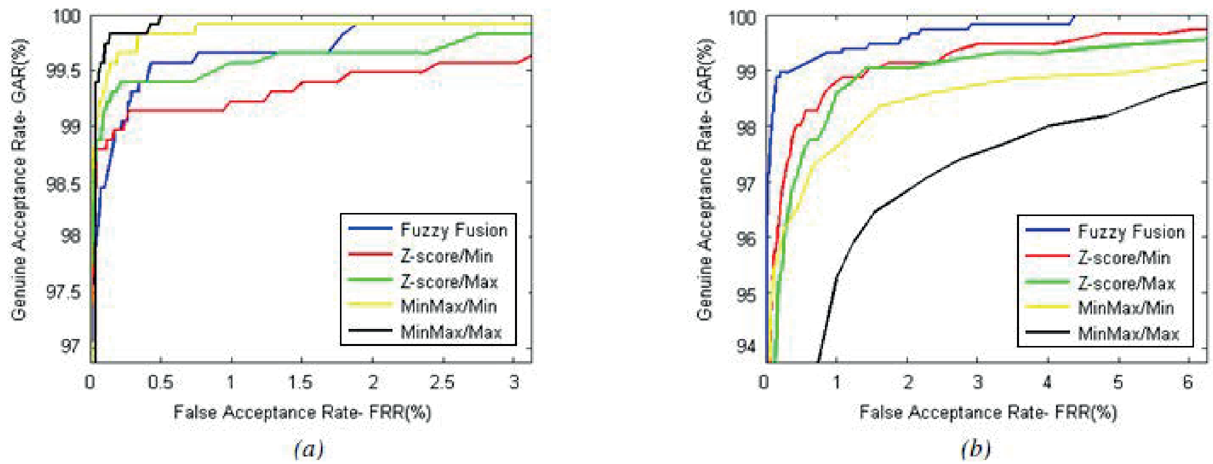

Fig. 7. Multimodal biometric system performance. *(a)* Multimodal system performance under different fusion methods, and *(b)* Multimodal system performance under different fusion methods in case of outliers

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