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Advanced Multimodal Fusion for Biometric Recognition System based on Performance Comparison of SVM and ANN Techniques

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Abstract: In a multimodal biometric system, an efficient fusion method is necessary for combining information from various single modality systems. The score level fusion is used to combine several biometric features derived from different biometric modalities. Three biometric characteristics are considered in this study: Face, fingerprint and Voice. Classification methods represent also the basis of important recognition accuracy improvements. The artificial neural networks (ANN) and support vector machines (SVM) are considered as an excellent technique for classification. This paper presents a comparison of multimodal biometric recognition performances based on some methods that have been successfully applied using the fusion of scores. After exploring each modality (face, fingerprint and voice), we recovered three similarity scores. These scores are then introduced into two different classifiers: ANN and SVM. Experimental results demonstrate that a multimodal biometric system provides better performances than those using just one modalities system. Comparison of support vector machine and ANN based on score-level fusion methods is obtained and demonstrates that an average recognition rate(ARR=57.69%) is obtained using ANN. While fusion based on SVM gives an ARR= 63.31%.

Keywords:Multimodal biometric system, Voice, Fingerprint, Face, Recognition, Score-level, Fusion, ANN, SVM.

I. INTRODUCTION

Nowadays, there is a strong request for automatic and secure identity verification systems. The individual's identification becomes an essential task to ensure the safety of systems and organizations. Multimodal Biometric identification is a new technology to solve this problem. Many biometrics modalities, including fingerprint, face and speech have been proposed for verification and identification purposes. Several works on multimodal biometric systems has already been done in the literature. Dieckmann et al. [1] proposed a summary level fusion scheme: "2-of-3 approach" that integrates the movement of the lips, face, and voice based on the principle that man uses, parallel, several indices identify a person. Brunelli Falavian [2] proposed a system level measurement to combine the outputs of the sub-graders, Kitter et al. [3] and demonstrated the effectiveness of an integration strategy that merges multiple snapshots of a biometric property initials using a Bayesian framework. Bibun et al. [4] proposed a Bayesian integration scheme of combining different evidence. Maes et al. [5] proposed to combine biometric data (e.g. fingerprint) with not biometric data (e.g. passwords). Hong and Jain [6], developed a multimodal identification system that incorporates two different biometrics (fingerprints and face).

However, despite significant research, biometric matching accuracy remains low. This accuracy problem has recently been addressed through multi-modal biometric fusion, which combines the matching scores obtained through individual biometric classifiers.

In fact, in this paper, we provide a multimodal biometric system respecting several constraints comfort [10] and reliabilities (Increase rate recognition calculation inexpensive, robustness). The fusion phase allows address the lack of information resulting from the use of a single modality. We propose also, an adaptive system of recognition of individuals by the merger of three biometric modalities: fingerprints, face and voice. Fusion was made using a hand machines support vector (SVM), and artificial neural networks (ANN) on the other hand. These classification methods have greatly enriched the biometric recognition methods.

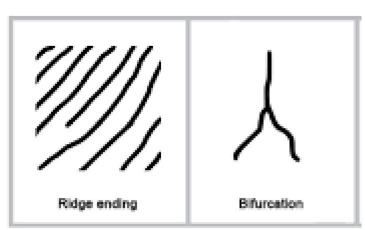
This article is organized as follows: SectionII describes the unimodal biometric systems. SectionIII presents the proposed multimodal system using respectively ANN and SVM. Section IV discusses the experimental results of these approaches. The performance of the proposed multimodal approach using ANN is analyzed and compared with respect to that of the proposed multimodal approach using SVM. The final section presents the conclusion and discusses our work perspectives.

II. UNIMODAL RECOGNITION

To test our multi-modal fusion technique, we use one classifier for each of the following biometric modalities: Fingerprint, face and voice.

A. *Fingerprint Recognition*

This method relies on the principle of extracting the minutiae; settings relevant characteristic footprint such as Ridge ending: the point where the ridge is stopped (Figure 1-a) and Bifurcation: the point where the ridge is divided into two (Figure 1-b).



-a- -b-
Figure 1: Fingerprint minutiae

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The preprocessing phase is essential in a system for recognizing forms. To improve the quality of the information extracted from the images, one can specify regions of interest or enhance the contrast of images[5]. To avoid the extraction of false minutiae, several pretreatment steps have been performed like: Binarization, Skeletonization, (Thinning), Region of Interest, Minutiae extraction.

The overall architecture of a fingerprint recognition system is described on figure 2.

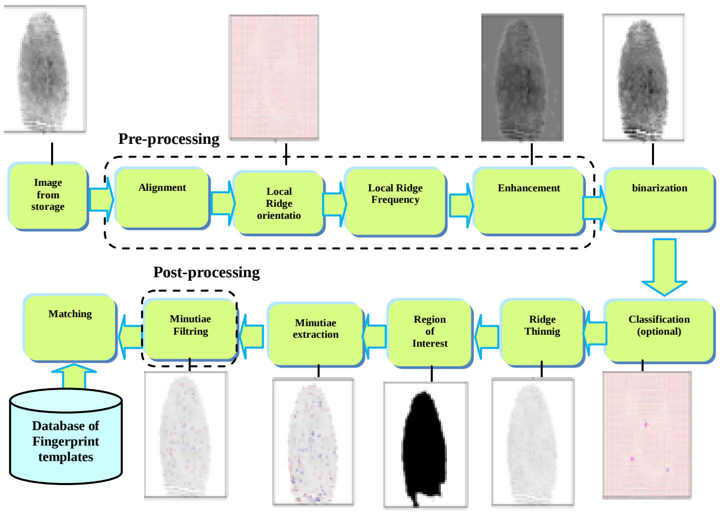

Figure 2: Principle of a fingerprint recognition system

Fingerprint matching is known to be a relatively accurate biometric even with only partial fingerprint data. [32], [33]

B. *Face recognition*

Facial recognition is a task that humans naturally and effortlessly perform in their daily lives.It is one of the basic biometric technologies, took a share of more and more important in the field of research, this being due to rapid advances in technologies such as digital cameras, Internet and mobile devices, all associated with security needs constantly increasing.

Facial recognition has several advantages over other biometric technologies. It is an inexpensive used technique, very well accepted by the public and requires no action by the user (Non-intrusive and no contact).The basic principle of operation of a facial recognition system is illustrated by (Figure 3). It can be summarized in four stages: detection [3] and standardization [4] of the face and the last two blocks represent the recognition phase made by a subsequent extraction of features which will be compared with others features stored in data base.

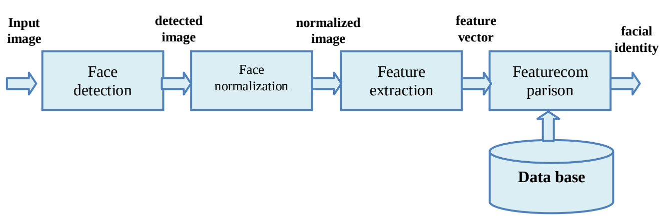

Figure 3: Principle of a facial recognition system

C. *Voice recognition*

This is a transformation of a speech signal into a sequence of symbols representative of the signal content. The most commonly used extracting algorithms are the Mel frequency cepstral coefficients (MFCC) that showed on the following figure 4.

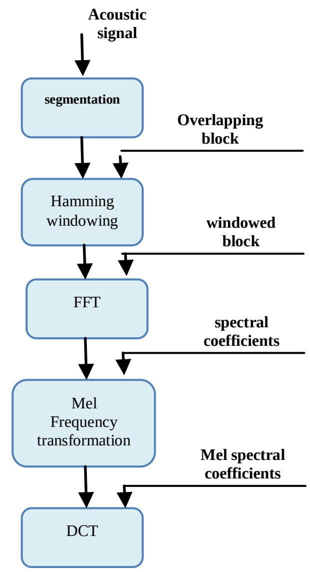

Figure 4: Principle of the extraction of MFCC coefficients

III. THE PROPOSED MULTIMODAL ARCHITECTURE

Using the unimodal biometric systems based on just a unique biometric signature cannot currently guarantee an excellent recognition rate. Thus, the error rate associated with unimodal biometric systems are relatively high, which makes them unacceptable for deployment of safety critical applications. To overcome these drawbacks, we proposed a novel multimodal architecture based on fusion between the presented biometric modalities. This multimodal system needs an effective fusion scheme to combine biometric characteristics derived from one or more modalities. In fact, we used the fusion method at the score level which has a high potential for efficient consolidation of multiple unimodal biometric matcher outputs.

This proposed approach is to merge the output score of three different unimodal recognition systems using two types of classifiers: ANN and SVM. We chose to compare the performance of the ANN merger with those of SVM merger.

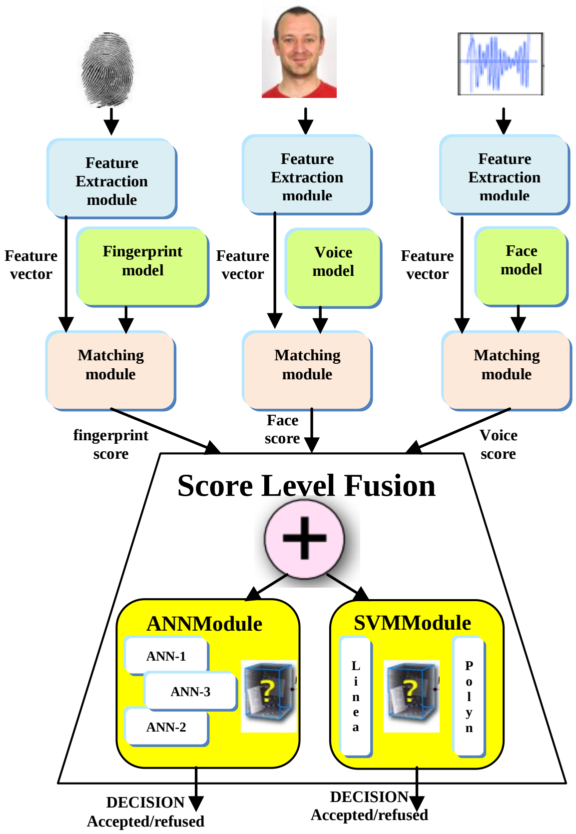

Figure 5: Fusion Score level for the multimodal biometric system

A. *Fusion with ANN*

The work done to try to understand the behavior of the human brain has led to represent it by a set of structural components called neurons, massively interconnected. The human brain contains hundreds of billions, and each of them would be, on average, connected to ten thousand. The brain is able to organize these neurons in a complex assembly, non-linear and highly parallel, so as to accomplish sophisticated tasks. For example, anyone is able to recognize faces, while this task is almost impossible for a classical computer. It is the attempt to give the computer the perceptual qualities of the human brain which leads to electrical modeling thereof. It is this model that is trying to achieve artificial neural networks. Haykin in the following definition:

"A neural network is a distributed process of massively parallel manner, which has a natural propensity for storing experimentally knowledge and make it available for use. It resembles the brain in two points:

- Knowledge is acquired through a learning process.
- The weights of the connections between neurons are used for storing the knowledge ".

The development of artificial neural networks, is based on this definition rests.

Neural networks are widely used for classification, process control, modeling of static data, modeling of dynamic processes, etc.

The interconnection of neurons forms a network. Neurons are arranged in layers, namely: an input layer, an output layer and one or more hidden layers between the input layer and the output layer. This kind of network is called Network Multilayer (Figure 10).

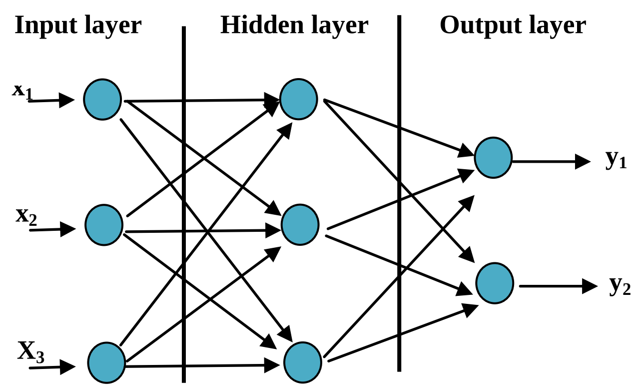

Figure 6: multilayer neural network

To achieve performance close to those observed in humans, the classifier based on artificial neural networks (ANN)have been used, associated with the fusion of the three modalities biometric data collected and processed by the individual classifiers. Indeed, using ANN for three separated biometrics, we will obtain two different scores which are recovered using a third ANN network in order to find the final decision. Figure7 shows the global structure of the proposed system.

In this proposed approach, we chose to combine the fingerprint with the face and the voice with the face.

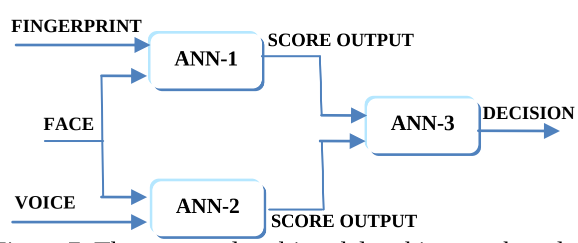

Figure 7: The proposed multimodal architecture based on ANN

B. *Fusion with SVM*

The main idea of the classification approach is to construct a feature vector using the matching score outputs by the separate matchers. This feature vector is classified into one of two classes: "Accept" (genuine user) or "Reject" (impostor). In general, the classifier utilized for this aim is able of acquiring knowledge of the decision frontier without regard for how the feature vector is constructed.

Overview of Support Vector Machine (SVM)

In 1992, Boser, Guyon, and Vapnik introduced Support Vector Machine (SVM) which became rather popular since SVM are a set of related supervised learning methods used for classification

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and regression [21]. They appertain to a family of generalized linear classifiers.

Vapnik have developed the foundations of Support Vector Machines (SVM) [19] which have been gained popularity due to many promising features such as better empirical performance. The formulation utilizes the Structural Risk Minimization (SRM) principle, which has been shown to be upper, to traditional Empirical Risk Minimization (ERM) principle, utilized by conventional neural networks. SRM minimizes a superior bound on the expected risk, where as ERM keep down the error on the training data.

In biometrics, Support Vector Machine has been utilized for different learning based operations such as face recognition and multimodal fusion.

SVM is therefore a classifier that executes classification by building hyper planes in a multidimensional space and separating the data points into different classes.

Linearly separable data

Let {xi, yi} be a set of N data vectors with xi ∈ Rn, yi ∈ {+1, −1}, and i = 1, . . .,N. xi is the ith data vector that belongs to a binary class yi.

A binary classifier should find a function f that maps the points from their data space to their label space
f :Rn→ {+1,-1}
xi→yi

For the benefit of simplicity, we suppose that the data space is R2 and that a hyperplane separates the data. There are in fact an infinite number of hyperplanes that could divide the data into two classes. In accordance with the SRM principle, SVM utilizes an iterative training algorithm which maximizes the margin between two classes to construct just one optimal hyperplane.

Assuming that we have a hyper plane separating the positive data and negative data, xi belongs to the hyper plane which satisfies the relationship:

w .xi+b= 0 (1)

In this equation w is the normal to the hyper plane and it is also a vector, b is the parameter of the hyper plane.
For mathematical calculations we have,

w × xi + b = +1,yi= +1 (2)

w × xi + b = - 1, yi= - 1 (3)

These equations can be combined in the following inequality:

yi (w × xi + b) ³ 1 (4)

The following figure shows the linearly separable case we have treated above:

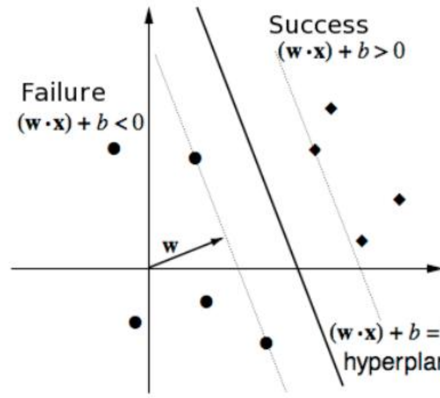

Figure8: Linear separation hyper plane for linearly separable data.

The points satisfying equality (2) belong to a hyper plane H1:

w × x + b = +1 (5)

Similarly, the checking point equal (3), belong to the hyper plane H2:

w × x + b = -1 (6)

The distance d (w, b; x) of a point x from the hyperplane (w, b) is,

$$d(w,b;x) = \frac{|(wXxi+b)|}{||w||} \quad (7)$$

Optimal hyper plane was constructed which the distance to the nearest points (margin) is Max. Maximize margin amounts to minimizing 2 / ||w||. For this, the problem is reformulated as Lagrangian. There are two reasons for this; the first is that the constraint (4) will be replaced by a constraint on the Lagrangian multipliers which will be easier to treat. In addition, in this reformulation of the problem, only data learning appear as a dot product.Thus, it introduces positive multipliers αi " i = 1... l in (4).Constraints in equation (4) are multiplied by αi and the equation becomes:

$L\,(w,b,\alpha) = \frac{1}{2} \parallel w \parallel 2 - \sum_{i=1}^{l} \gamma i \; [yi\,(w \times xi + b) - 1]$,$\alpha_i$ >= 0 (8)

L is called the Lagrangian primal.
It must minimize the Lagrangian with respect to w and simultaneously require its derivatives with compared to all of the Lagrangian multipliers αi disappears. By imposing that gradients of L with respect to w and b disappear and it obtained:

$$L' = \sum_{i=1}^{1} \alpha i - \frac{1}{2}\sum_{j=1}^{1} yiyj\sigma i\sigma jxixj \quad (9)$$

L' is called Lagrangian dual.

The points, which αi are strictly greater than 0, are called support vectors and they belong to one of the hyperplanes H1 or H2. These points are closest to the border decision and they form the separator plan.

No linearly separable data

If no hyperplane can be found to separate the data, a nonlinear mapping function is then needed. To overcome the disadvantages of non-linearly separable case, the idea of SVM is to change the data space. The data will be mapped nonlinearly in a high-dimensional space and the optimal hyper plane is computed in the high-dimensional space. The nonlinear transformation of data can allow linear separation examples in a new space. So we will have a change in dimension. This new dimension is called "re-description of space." Indeed, intuitively, the more the size of the redescription space, the greater the probability to find a separating hyper plane between examples is high. This is illustrated by the following scheme:

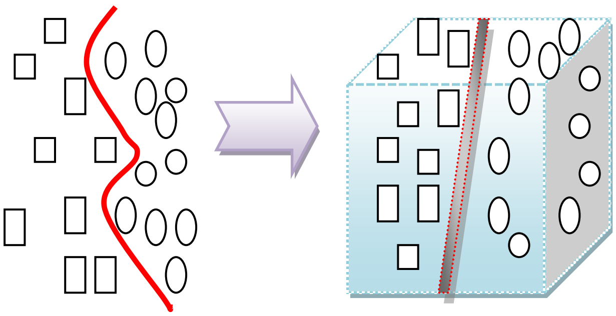

Figure9: Non linearly separable data.

Where examples are not linearly separable, the constraints (2) and (3) are released by introducing slack variables xi ≠0 " i = 1... l which become:

w × xi + b = +1 - xi, yi= +1 (10)

w × xi + b = - 1 + xi, yi= - 1 (11)

Therefore there is a transformation of a nonlinear problem of separation in the space of representation to a linear separation problem in an area of re-description of largest dimension. This non-linear transformation is performed using a specific kernel function.

Upon receiving the three match scores from the participating individual biometric modules, the fusion phase creates an attribute vector out of these individual scores, and applies the learned SVM that best corresponds to the incoming data.

IV. EXPERIMENTAL RESULTS

The experimental results that we present are divided into two parts. We will summarize first the results obtained for each unimodal recognition system (fingerprint, face, and voice) based on artificial neural networks (ANN). Secondly, we will present the results of the proposed biometric multimodal fusion system used with three ANN classifiers.

First, to evaluate the performance of a biometric system, four main criteria must be clearly defined:

- The recognition rate which is calculated as follows:

$$\text{Recognition rate} = \frac{\text{Number of recognized persons}}{\text{Number of people in the test base}} \qquad (12)$$

This metric is rather used to evaluate biometric identification systems. The system is tested by different images from those used for learning.

- The "False Reject Rate" (or FRR): This rate represents the percentage of people expected to be recognized but which are rejected by the system.

$$FRR = \frac{\text{Number of false rejection}}{\text{Total number of authentic}} \qquad (13)$$

- The "False Accept Rate" (or FAR): This rate represents the percentage of people not expected to be recognized but they are still accepted by the system,

$$FAR = \frac{\text{Number of false acceptances}}{\text{Total number of impostors}} \qquad (14)$$

- The "Equal Error Rate" (or EER): This rate is calculated from the first two criteria and is a point of current measurement performance. This is where FAR is equal to FRR, that is to say, the best compromise between false rejection and false acceptance.

$$EER = \frac{\text{Number of false rejection} + \text{Number of false acceptances}}{\text{Total acces}} \qquad (15)$$

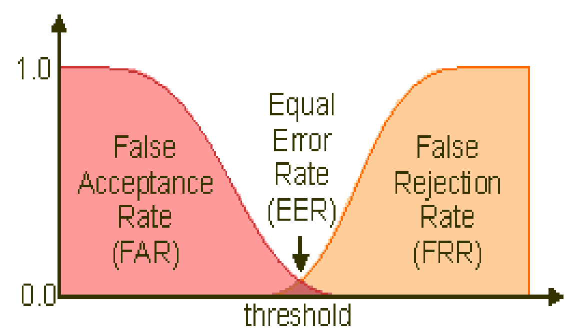

Figure10: A graphical representation of the FRR, FAR errors, the optimal threshold and the EER. [34]

Figure8 shows an example of such representation. The threshold variation along the x-axis gives different values of FAR and FRR. It may be noted that in areas where the threshold is low the False Acceptance Rate is high and that the False Rejection Rate is low and conversely in areas where the threshold value is large.

A large FAR means that an impostor has a great tendency to be accepted as a client. While a large FRR means that a client has a great tendency to be rejected. Each threshold value is a particular value of FAR and FRR. In fact, the error rate FAR and FRR vary in an inverse manner with respect to the threshold.

Both FAR and FRR rates are a function of the threshold T. A curve can be traced to present variations of the FRR according to the FAR. Figure 8 shows an example of this curve called ROC curve 'Receiver Operation Characteristic'. It is impossible to minimize both FAR and FRR rates simultaneously. The best system is one that has the lowest EER. Indeed, if the value of the EER is low, then the FAR and FRR values are also and the therefore system commits few mistakes.

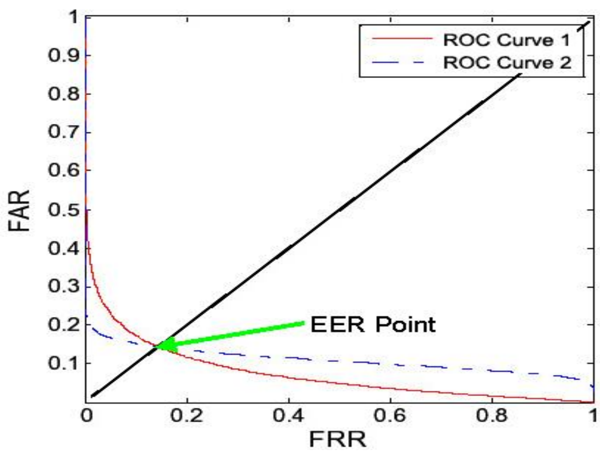

Figure 11: ROC curves. [35]

To evaluate the performance of our proposed multimodal authentication system, a database containing face, voice and fingerprint samples is required. In this work, we construct a multimodal biometric database for our experiments by using ORL (Olivetti Research Lab) face database which consists of 400 frontal faces from 40 subjects (10 images of each subject), a restriction of TIMIT (Texas Instruments & Massachusetts Institute of Technology) database for the voice to 40 classes only, and four different fingerprint databases (DB1, DB2, DB3 and DB4) which were collected by using the following sensors/technologies:

- DB1: optical sensor "TouchView II" by Identix
- DB2: optical sensor "FX2000" by Biometrika
- DB3: capacitive sensor "100 SC" by Precise Biometrics
- DB4: synthetic fingerprint generation.

A. Experiments results for the proposed architecture with ANN

Table 1 summarizes the performance of the ANN fusion of the used biometric modalities.

Table 1: Performance of the modalities fusion with ANN
In identification mode

		Number of epochs		
Fusion of modalities	HN	1000	5000	10000
Voice/Face	5	18.39 %	20.11 %	22.14 %
	10	21.55 %	28.7 %	31.55 %
	50	34.60 %	40.37 %	43.75 %
	100	44.9 %	48.03 %	56.40 %
Fingerprint/Face	5	15.03 %	21.69 %	27.15 %
	10	23.90 %	28.00%	34.29 %
	50	35.85 %	37.12 %	43.65 %
	100	42.01 %	45.2 %	54 %
Fingerprint/Face / Voice	5	11.00 %	18.50 %	27.87 %
	10	22.30 %	28.32%	35.61 %
	50	35.85 %	41.64 %	48.30 %
	100	43.97 %	48.2 %	57.69 %

An efficient and robust identification system is a priority task. From the Table 2, we notice that the Fingerprint/Face/Voice system provides better performance. As our system also allows authentication the recognition rate is not enough to evaluate its performance. Thus, the following table summarizes the values of the three other performance criteria mentioned above.

Table 2: Performance evaluation of fusion system using three ANN in Authentication mode

	FRR	FAR	EER
Fusion based on ANN	1,54 %	4,59 %	4,15%

With: FRR is False Rejection Rate; FAR is Acceptance Refuse Rate and EER is Equal Error Rate.

B. Experiments results for the proposed architecture with SVM

Table 3: Performance of the modalities fusion with SVM
in Identification mode

	Recognition Rate
Fusion using linear kernel	58,72 %
Fusion using polynomial kernel	63,31 %

Table 4: Performance evaluation of fusion system based on SVM in Authentication mode

	FRR	FAR	EER
Fusion using linear kernel	1,63 %	4,71 %	2,82%
Fusion using polynomial kernel	1,48 %	4,52 %	2,35%

A comparison of support vector machine and ANN based on score-level fusion methods can be concluded.

The experimental results showed a significant improvement of SVMs compared to ANNs. This is due to what they can suffer multiple local minima. The solution to an SVM is global and unique. Two other advantages of SVMs are that it has a simple geometric interpretation and give a sparse solution.
From experiment results we obtain the following conclusions:

- The verification accuracy is more improved than single biometrics by using fusion of three differents biometrics.
- By comparing the results of SVM using a linear kernel with those using a non-linear kernel, we note an advantage of non-linear kernels. This is due that convexity is an interesting and important property of nonlinear SVM classifiers
- A better fusion effect can be achieved by the SVM –based fusion rule comparing with SVM score level fusion.
- This method has the superiority over the previous methods due to the application of the new recognition algorithms and the SVM-based fusion rule.
- Unlike SVMs computational complexity, ANNs is proportional to the dimensionality of the input space. ANNs empirical use of risk minimization, while SVMs using structural risk minimization. Why SVMs outperform ANNs often in practice is that they deal with the biggest problem with ANNs, SVMs are less prone to overfitting.

V. Conclusion

In this paper, we introduced the concepts of recognition unimodal and multimodal biometrics. The principle is to design unimodal recognition systems and combine their scores from different biometric modalities to increase the power of identification.
This work provides new contribution to the field of biometrics multimodal. In fact, it shows the authentication of individuals by multimodal fusion based on ANN or SVM using the fingerprint, face and speech recognition. Among the various levels of existing fusion, we have chosen to work for the score level. It offers the best compromise between the wealth of information and the ease of implementation.
The errors come from the imperfection of one biometric have been remedied by the fusion process by ensuring better recognition rate.
In addition, we detailed the concept of classification by neural network and support vector machines for multimodal fusion.
In score-level fusion, SVM provides better performance as compare to the ANN.
Future work will investigate on better alternative recognition technique suitable for fusion of fingerprint, speech and face.
We think that the performance of multi-biometric systems can be improved if a suitable fusion strategy is used in particular for the system running in an uncontrolled environment. Therefore, it would be interesting to apply other approach of fusion and to compare its results with those obtained by the ANN and SVM to maximize the performance of multi-biometric system.

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