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Theme

Conception of Biometric System Based on Optimization of a Fuzzy System

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Dedication

First of all I have to thank my god to help complete this thesis, all praise to Allah. And I'd like to dedicate this modest work to the big heart and my right hand my mother, and my father, I pray to my god to grant them his mercy and reward them well. To my family, to wife who's always encouraging me, to my children whose give me the confident. To all our professors who paved my way of knowledge. And also warmly thank all people who helped me.

Benaoun Mohamed

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ملخص

في الآونة الأخيرة ، يعد تعريف المستخدم أساسًا أساسيًا لحماية المعلومات في العديد من التطبيقات. للتغلب على وسائل الأمن الكلاسيكية ، يتم تقديم حل طبيعي وموثوق لهذه المشكلة عن طريق تقنيات القياس الحيوي. لذلك من بين العديد من الطرائق البيومترية، هذه المستخرجة من اليد، على سبيل المثال تم استخدام للبصمات بشكل منهجي لتحديد الهوية في السنوات الأخيرة. في هذا العمل، اقترحنا خوارزمية استخراج ميزة جديدة لغرض تحديد الهوية البيولوجية. المتجه المميز هو مجموعة من معلمات قاعدة بيانات نضام ضبابي تم الحصول عليها من خلال تحسين وظيفة الهدف من الخطأ. لذلك يتم استخدام طريقة نيوتن رافسون لتأسيس الخوارزمية المقترحة. وبالتالي، مساهمتنا هي مقدمة وتطوير نظام ضبابي على التكيف كمصمم صورة بيومترية. ثم من أجل تقييم هذه الطريقة، قدمنا قاعدة بيانات للبصمات متعددة الأطياف وقمنا بتوضيح الطريقة المقترحة في كلتا الحالتين قبل وبعد دمج البيانات. أظهرت النتائج أن طريقتنا سريعة و ذات قدرة تحديد عالية ويمكن استخدامها في تطبيق آمن للغاية.

الكلمات المفتاحية: نظام البيومترية. نموذج ضبابي. طريقة نيوتن رافسون. بصمات متعددة الأطياف. دمج البيانات.

Abstract

Recently, user identification is an essential foundation for protecting information in several applications. To overcome the classical security means, a natural and reliable solution to this problem is offered by biometric technologies. So among several biometric modalities, these extracted from the hand, e.g. palmprint have been systematically used to make identification for the last years. In this work we proposed a new feature extraction algorithm for biometric identification purpose. The characteristic vector is a collection of fuzzy data base rule parameters obtained through optimization of error target function. For that Newton Raphson method is used to establish the proposed algorithm. Thus, our contribution is the introduction and the development of adaptive fuzzy system as biometric image modeler. Then for the evaluation of this method we presented Poly U multispectral palmprint database and we exanimated the proposed method in both cases before and after the data fusion. The results showed that our method is fast with high identification accuracy and can be used in high secure application.

Keywords: biometric system. Fuzzy model. Newton Raphson method. Multispectral palmprint. Data fusion.

Résumé

Récemment, l'identification de l'utilisateur est une base essentielle pour la protection des informations dans plusieurs applications. Pour surmonter les moyens de sécurité classiques, les technologies biométriques offrent une solution naturelle et fiable à ce problème. Ainsi, parmi plusieurs modalités biométriques, celles-ci sont extraites de la main, par ex. l'empreinte palmaire a été systématiquement utilisée pour l'identification dans les dernières années. Dans ce travail, nous avons proposé un nouvel algorithme d'extraction de caractéristiques pour d’identification biométrique. Le vecteur caractéristique est une collection de paramètres de règle de base de données floue obtenus par optimisation de fonction d'erreur. Pour cela, la méthode Newton Raphson est utilisée pour établir l'algorithme proposé. Ainsi, notre contribution est l’introduction et le développement du système flou adaptatif en tant que outils de modélisation d’image biométrique. Ensuite, pour l’évaluation de cette méthode, nous avons présenté la base de données multi spectrales de l'empreinte palmaire Poly U et avons examiné la méthode proposée dans les deux cas, avant et après la fusion des données. Les résultats ont montré que notre méthode est rapide avec une grande précision d'identification et peut être utilisée dans des applications hautement sécurisées.

Mots clés : système biométrique. Modèle flou. Méthode de Newton Raphson. Empreinte palmaire multi spectrale. La fusion des données.

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List of Abbreviations

CCD	Charge Coupled Device
CMC	Cumulative Match Characteristics
DNA	Deoxyribo Nucleic Acid
EER	Equal Error Rate
FAR	False Acceptance Rate
FRR	False Reject Rate
RGB	Red, Green, Blue
RGBN	Red, Green, Blue, NIR
ROC	Receiver Operating Characteristic
ROI	Region of interest
ROR	Rank-One recognition
RPR	Rate perfect Rank
TS	Takagi-Sugeno

General Introduction

General introduction

Today, we are talking more and more about insecurity in various sectors. The verification and identification of individuals is one of the means to ensure this security. In particular, designing a reliable, efficient and robust identification system is a priority task, with this growing demand, several biometric recognition methods have been proposed, palmprint recognition, facial recognition, fingerprint recognition …etc.

In this work, we will focus on the biometric recognition system uses the palm print as a biometric modality for extracting the biometric identification characteristics of individuals.

Fuzzy logic is a technique widely used in the field of system control and the identification of industrial processes [1]. In this work, we will use this technic to propose a new feature extraction algorithm for biometric identification purpose, the feature vector in the collection of fuzzy model parameters obtained through optimization of error target function. For that we will use the Newton Raphson method as fuzzy model adaptation law. Thus our contribution, is the introduction and development of adptive fuzzy system as biometric image modeler with convergent feature extraction algorithm.

In the first chapter, we will introduce some definitions of biometrics and the different biometric modalities

In the second chapter, we will have discuss the basic and theoretical notions of fuzzy logic, fuzzy models and Newton Raphson optimization method.

In the third chapter a Poly U multispectral palmprint database will be used for the evaluation of the proposed unimodal and multimodal biometric sysstem then we endup with general conclusion.

Chapter I

Introduction to biometric systems

I.1 Introduction

In several applications, user identification is an essential foundation for protecting information. However, the need for enhancing this identification has expanded the research to focus on the biometric traits of the users. Thus, the biometrics offers a natural and reliable solution to the problem of identity determination by recognizing personals based on their physical and behavioral characteristic.

This chapter gives basic notions and definitions related to biometrics. We will also introduce the operating principle of a biometric system and its performance as well as the different modalities used.

I.2 What is biometrics?

The term Biometrics is split into two words − Bio means life which is a (Greek word for Life) and Metrics means the (Measurements).

Biometrics is a computer technology used for the identification of an individual from his biological, behavioral or morphological attributes these characteristics should be reliable, universal, measurable, permanent, not easy falsifiable, and recordable [2].

I.3 Biometric modalities

A biometric modality is a measurable physical or behavioral characteristic of an individual that can be distinguished. Also are called biometric trait, It determines how an individual is going to be recognized. For a biometric system the choice of one modality with known technology is dependent on the targeted application and the desired performance [3]. These modalities are generally classified into three categories: biological, behavioral and morphological biometrics.

I.4 Main types of biometric techniques

There are several biometric techniques used for identification in several applications and sectors. We can distinguish three main categories, see Fig I.1.

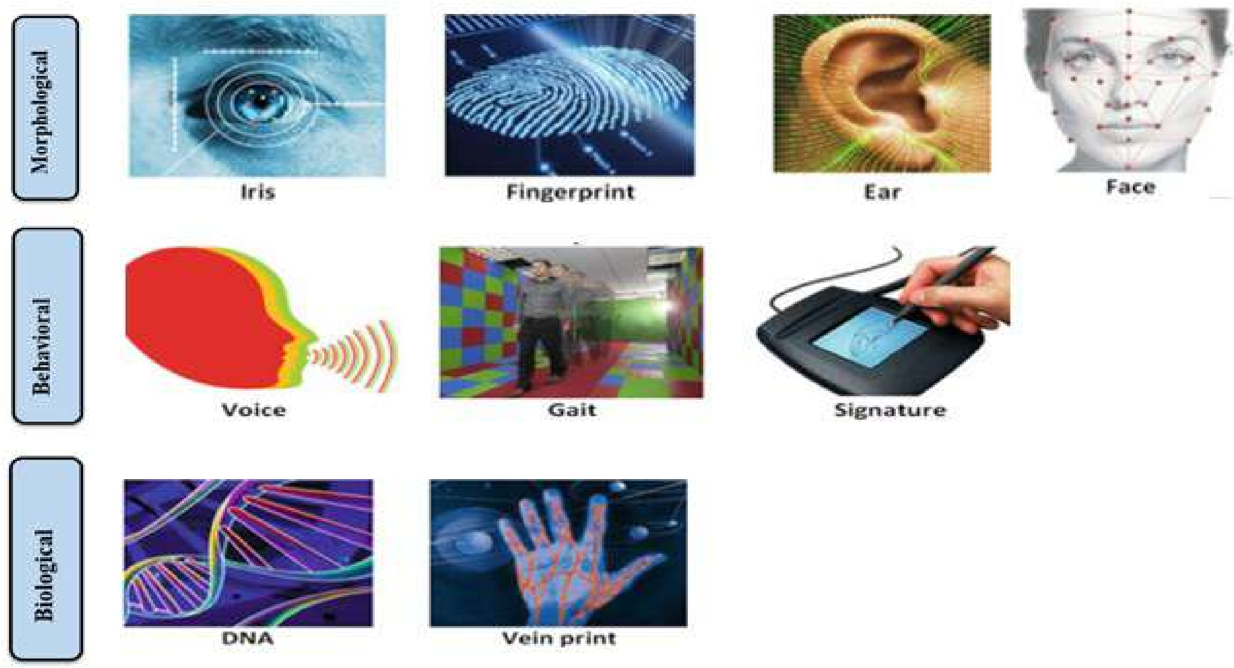

Fig I.1: Biometric modalities

I.4.1 Morphologic modalities

These modalities are unique and permanent. Their principle is based on the identification of particular physical traits of the person, for example, the shape of the hand, also the shape of the face, the fingerprints, the iris, retina, etc.

1 Facial recognition

Facial recognition (face) allows adapting the biometric verification to all situations. It is a very efficient technology used in many security-related applications. It is for example, a very reliable tool to help police forces identify criminals [4], see Fig I.2.

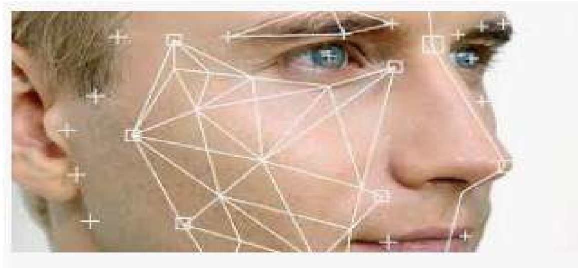

Fig I.2: Face recognition.

2 Fingerprint

In biometrics science, a fingerprint is the texture pattern formed by the interleaved ridges and valleys on the fingertips Figure I.3. Fingerprint recognition is one of the most popular and successful methods used for person identification, which takes advantage of the fact that the fingerprint has some unique characteristics called minutiae witch are the points where the lines of the ridges begin, end, branch off and merge.

Fingerprint is the most dominant modality in the market; it constitutes a trade-off in terms of accuracy, security and cost among other modalities.

Fig.I.3 Fingerprint recognition

3 Iris recognition

Iris recognition is another biometric of recent interest and is one of the morphologic biometric traits which is regarded as highly reliable in biometric identification systems. The iris is a well-protected part of the eye, although it is externally visible whose unique self-generated pattern remains stable throughout adult life. These key factors make the iris suitable as a biometric for identifying individuals, see Fig I.4.

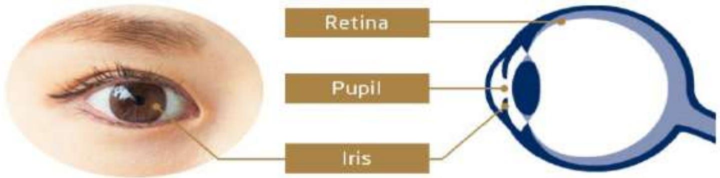

Fig I.4 Iris recognition

4 Palmprint recognition

A palmprint refers to an image acquired from the palm region of the hand, it consists of principal lines and secondary lines (wrinkles). Palmprints contain more information than fingerprints, so they are more discriminating. See Fig I.5.

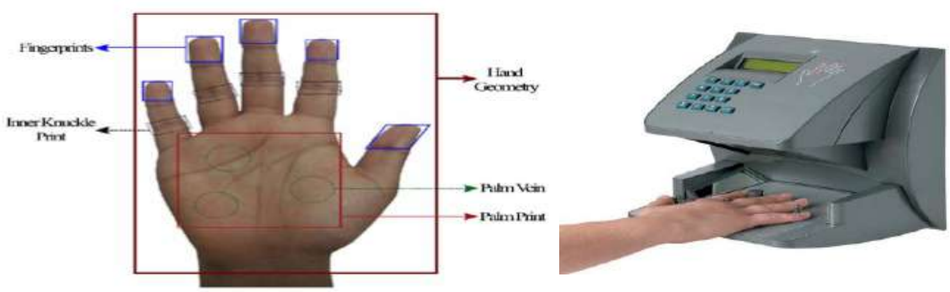

Fig I.5 Palmprint recognition

I.4.2 Behavioral modalities

These modalities are based on the analysis of certain behaviors of a person such as the tracing of his signature, voice recognition, his gait and his way of typing on a keyboard.

1 Gait recognition

People often feel that they can identify a familiar person from a far simply by recognizing the way the person walks. This common experience, combined with recent interest biometrics, has lead to the development of gait recognition as a form of biometric identification Figure I.6.

The biometric gait is not supposed to be very distinctive, but discriminatory enough to allow identification in some low security applications.

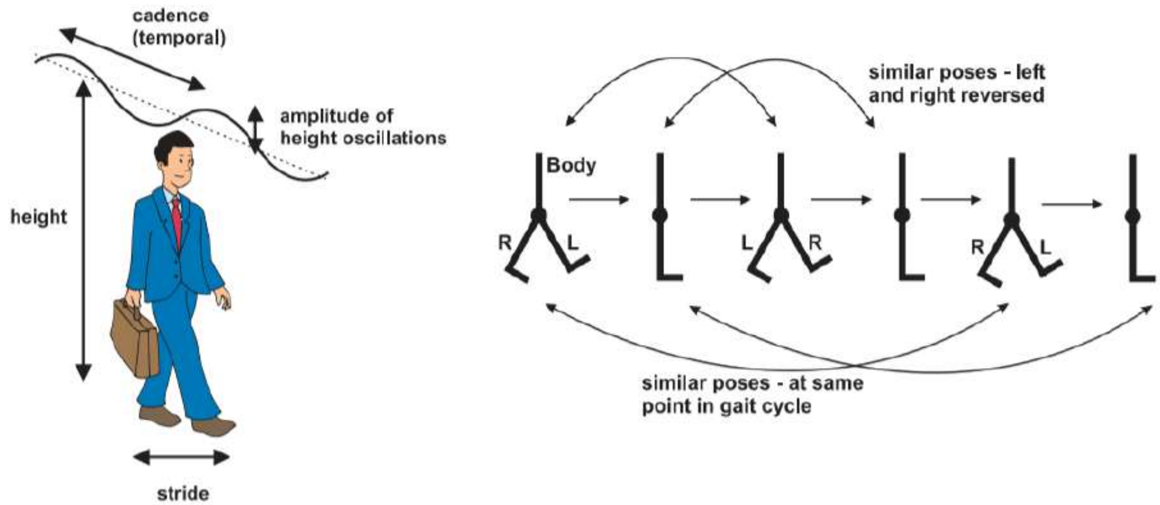

Fig I.6 Gait recognition

2 Voice recognition

Voice recognition is an extremely desirable feature in systems related to remotely applications where the person authenticates by phone for example. However, it is a very delicate characteristic to use because it is extremely subject to external conditions (illness, stress of the person, etc.). See Fig.7. It is sometimes chosen in combination with another characteristic; for example voice and writing [5].

Fig I.7 Voice recognition

I.4.3 Biological modalities

This analysis is based on the biological characteristics of individuals (DNA, saliva, Odor). This type of biometric technology is very complex to implement in a conventional recognition system and is used only in cases of extreme necessity (eg: Criminal investigation, paternity testing ... etc.).

DNA recognition

DNA is present in the cells of the body. DNA is specific to the individual and allows to identify it with certainty from a trace of blood or a drop of saliva see figure I.8. Currently, the time required for analysis and the cost associated with it, restrict its use to areas such as juridical identification. However, this biometric process is the subject of intensive research since it represents the identification technology par excellence with a margin of error well below other biometric technics, see Fig I.8.

Fig I.8 DNA recognition

I.5 Biometric system

A biometric system is essentially a pattern recognition system that uses the biometric data of an individual, a set of characteristics extracted from this data and compared to a set of data stored in advance in a database to end up with a decision from the result of this comparison.

Depending on the context of the application, a biometric system will operate in two main phases; Enrollment and recognition [6].

I.5.1 The enrollment phase

It is the first phase of any biometric system, in which the biometric characteristics of individuals are captured by a biometric sensor, represented in digital form then finally stored in database. The phase is illustrated in Fig I.9.

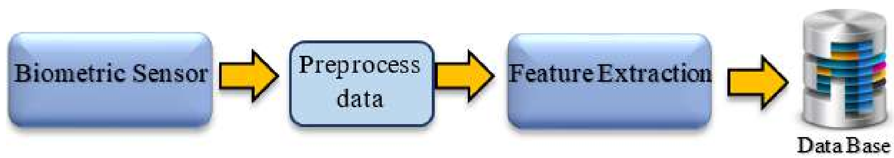

Fig I.9 The enrollment phase

I.5.2 The recognition phase

The task of the recognition phase is to verify or identify the identity of the person who intends to access the system. During the recognition phase, the biometric characteristic is measured and extracted as during the enrollment phase. The next steps of the recognition will be different according to the operating mode of the system verification or identification.

1 Verification mode

Verification, also called authentication, it is a "1 to 1" comparison, in which the system validates the identity of a person by comparing the captured biometric data with the biometric template of that person which was already stored in the system database (see fig I.10).

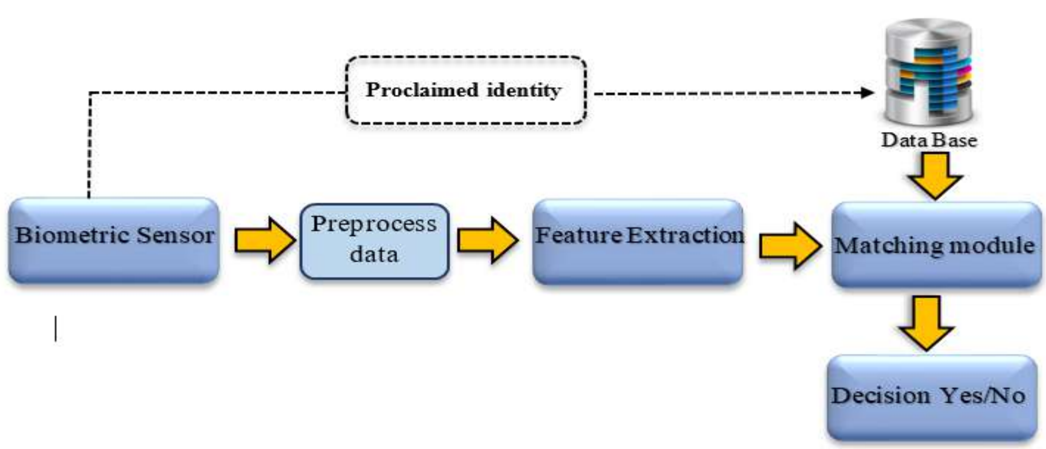

Fig. I.10 The verification mode

2 Identification mode

It is a comparison "1 to N", in which the system recognizes an individual by matching it with one of the models of the database, (See fig I.11).

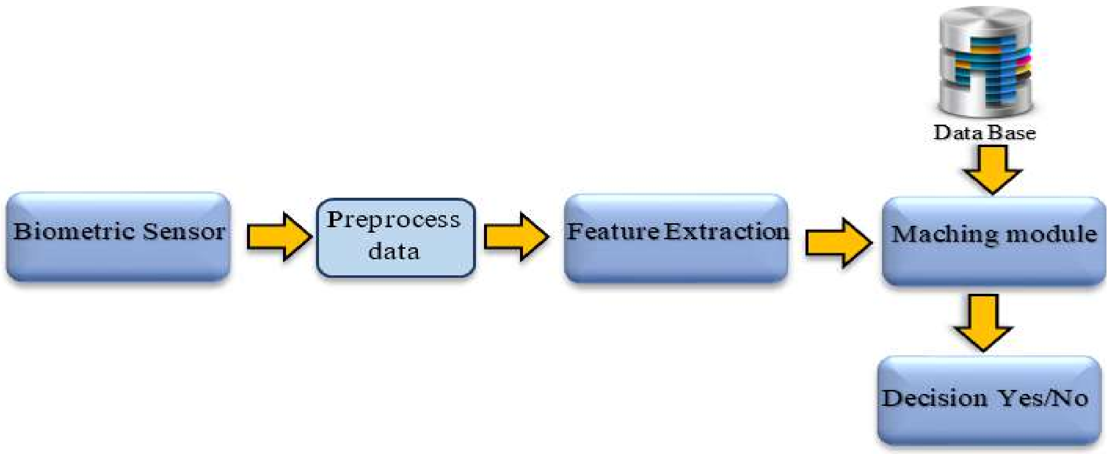

Fig I.11 The identification mode

I.6 Structure of a biometric system

A typical biometric system is composed of five principal modules.

I.6.1 Capture module

Is responsible for capturing the raw data from the biometric subject to extract the numerical representation.

I.6.2 Feature extraction module

Where the acquired data is processed to extract feature vectors.

I.6.3 Storage module

In which the biometric templates of the enrolled users are stored.

I.6.4 Matching module

Where feature vectors are compared against those in the template

I.6.5 Decision module

In which the user's identity is established or a claimed identity is accepted or rejected.

I.7. Multi-Modal Biometric System

A multimodal biometric system combines two or more features extracted from a person. Multimodality can considerably improve the system recognition and is expected to be more reliable due to the presence of multiple, independent pieces of evidence (See fig I.12).

I.7.1 Multi biometric system categories

According to the nature of information sources, a multi-modal biometric system can be classified into one of the following five categories (see figure I.12).

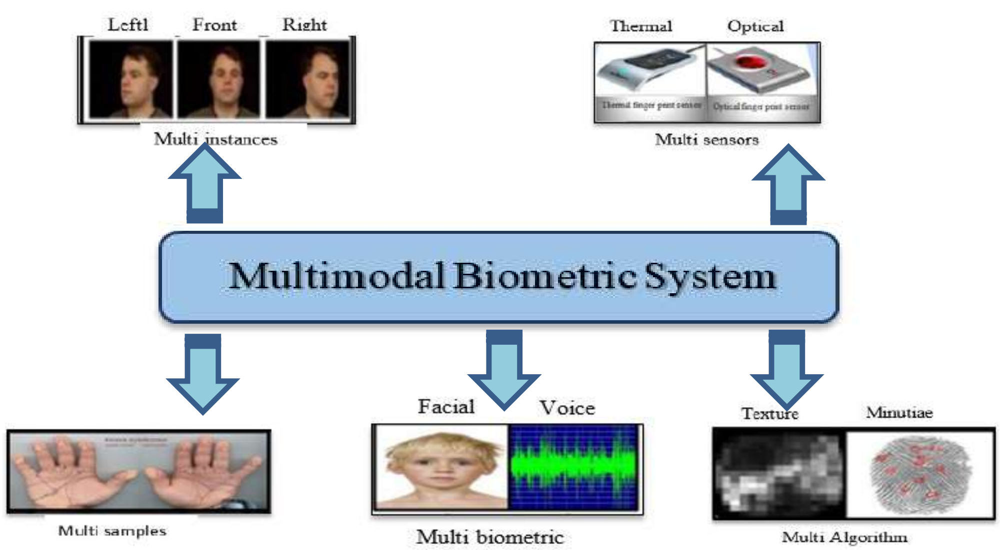

Fig I.12 Different types of multi-biometric system

1 Multi-sensor systems

These systems aim to capture the same biometric characteristics (modality) using several different sensors, in order to acquire as much information as possible, for example use of a thermal fingerprint reader and an optical fingerprint reader.

2 Multi-modal systems

More than one biometric trait is used for user identification. For example, the information obtained using face and voice characteristics [7]. This can be more costly however; the improvement in performance is significant.

3 Multi-instance systems

When several captured instances of the same biometry are combined for recognition, for example the acquisition of several face images with changes of pose, expression or illumination

4 Multi-sample systems

Several different samples of the same modality are captured, for example two palmprints of different hands. In this case, the different data are processed by the same algorithm.

5 Multi-algorithm systems

A single biometric input is processed with different feature extraction algorithms in order to create a template with different information content.

1.7.2 Fusion Levels in Multi-Modal Biometric Systems

In a multi-modal biometric system, the combination of biometric information obtained from multiple sources can take place at four different levels.

1 Fusion at the sensor level

The raw data captured from the sensors is merged at the sensor level (Fig. I.13). The fusion at the sensor level can be done only if the various captures are instances of the same biometric trait obtained from several sensors compatible between them or several instances of the same biometric trait obtained from a single sensor.

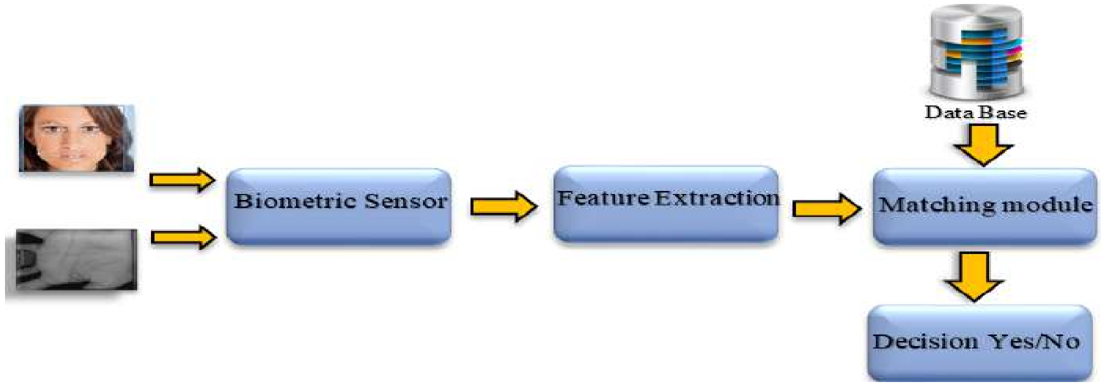

Fig I.13 Fusion at the sensor

2 Fusion at feature extraction level

Feature level fusion refers to combining different feature vectors that are obtained from one of the following sources; multiple sensors for the same biometric trait, multiple instances of the same biometric trait, multiple samples of the same biometric trait or multiple biometric traits [8] (Fig. I.14).

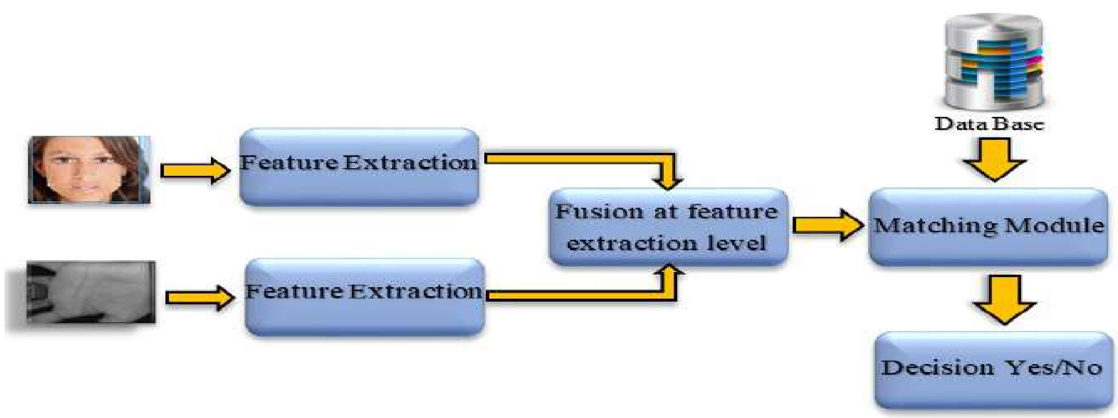

Fig I.14 Fusion at feature extraction level

3 Fusion at the score level

The matching scores generated by the comparison modules contain the richest information about the input pattern. Also, it is relatively easy to access and combine the scores generated by the different comparison modules [3] (see Fig I.15). Consequently, the fusion at the score level is the most common approach in multimodal biometric systems.

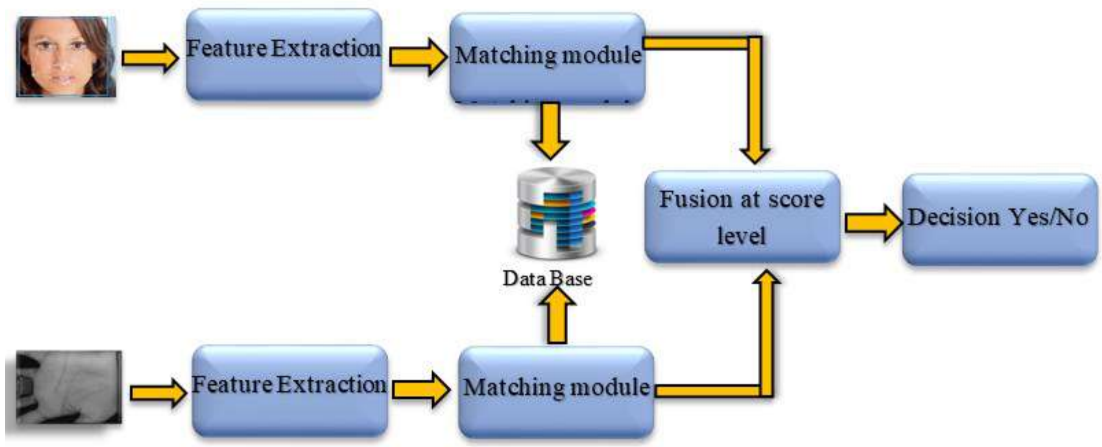

Fig I.15 Fusion at score level

4 Fusion at decision level

The different results of decision modules associated with the different modalities are combined to produce a single final decision [5].

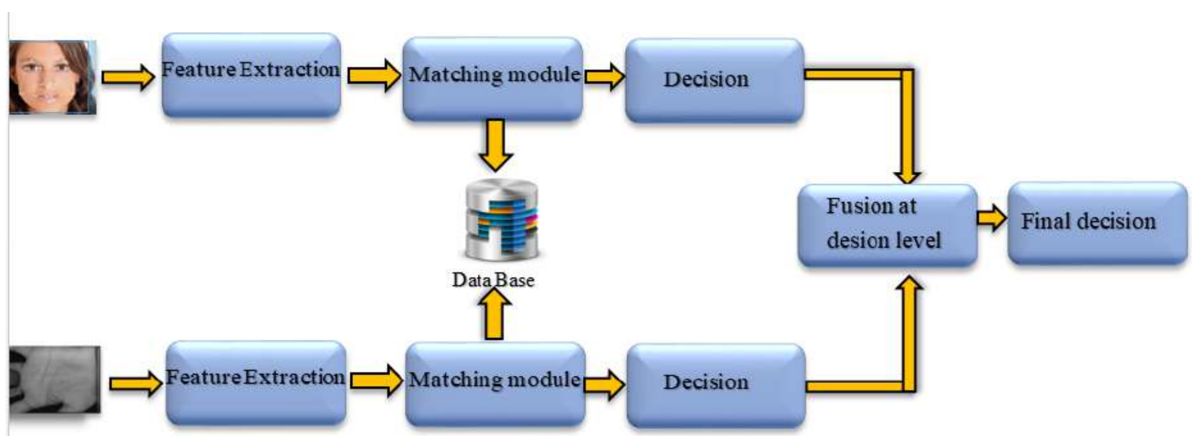

Fig I.16 Fusion at decision level

I.8 Performance measurement of a biometric system

First, in order to understand how to determine the performance of a biometric system, we need to define three main criteria:

I.8.1 False Acceptance Rate (FAR)

This rate represents the percentage of persons who are expected to be unrecognized but they are still accepted by the system:

$$\boldsymbol{FAR}(\%) = \frac{number\ of\ accepted\ imposter}{total\ number\ of\ impster\ access} \quad \textbf{(I.1)}$$

I.8.2 False reject rate (FRR)

This rate represents the percentage of persons who are supposed to be recognized but they are rejected by the system.

$$\boldsymbol{FRR}(\%) = \frac{Number\ of\ False\ rejection}{total\ number\ of\ genuine\ access} \quad \textbf{(I.2)}$$

I.8.3 Equal Error Rate (EER)

This rate is calculated from the first two criteria and is a common performance measurement point. This point corresponds to the place where $FRR = FAR$, that is the best compromise between false rejections and false acceptances, see Fig. I.17

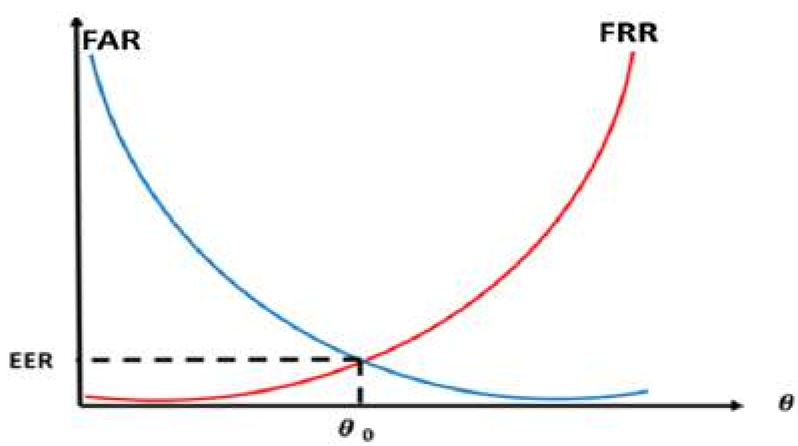

Fig I.17 Equal Error Rate (EER).

The Fig.I.18 shows the distribution of impostors and clients scores according to the decision threshold. The main objective of any biometric system operating at the score level is to be able to separate as much as possible the score distributions of impostors and authentic ones, By minimizing the overlap between these two distributions, the overall performance of the system will be improved by increasing the recognition rate.

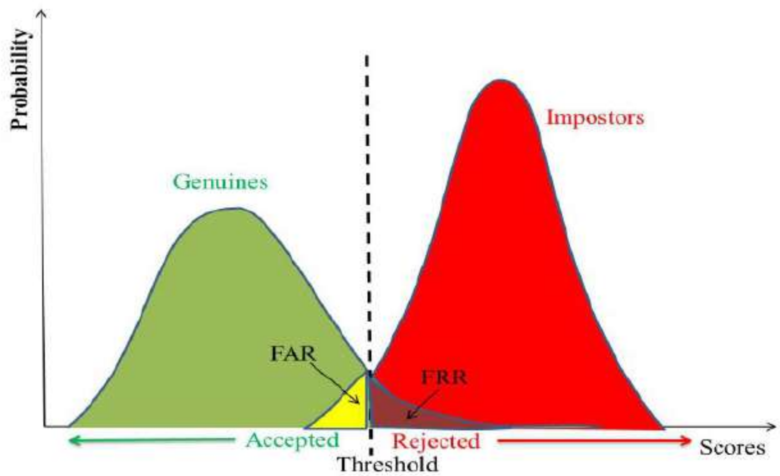

Fig I.18 Distribution of curves impostors and clients.

Depending on the operation mode of biometric system (verification or identification), there are two ways to measure the performance of the system:

a. Receiver operating characteristic (ROC)

When the system operates in verification mode, we use what we call (ROC) curve "Receiver Operating Characteristic", the ROC Curve is a graphical illustration of the evolution of the FRR against FAR for all possible operating thresholds. It permits to describe the recognition system performance independently of the threshold θ Figure (I.19) shows an example of a ROC curve. According to this figure, we can distinguish three security zones [9].

1. High-security zone: It is defined by high values of FRR (corresponding to low values of FAR) so that the system considers the majority of users as being imposters. This is suitable for critical applications needing high-security level such as bank accounts.

2. Low-security zone: It is defined by high values of FAR (corresponding to low values of FRR) so the system grants authorization to the majority of users. This is suitable for low secure access control systems such as universities or restaurants where security is desired but it is not a critical issue.

3. Medium security zone: determined by values of FAR and FRR closer to each other. This zone defines a trade-off in terms of security where a medium level is required such as in regular civilian biometric applications.

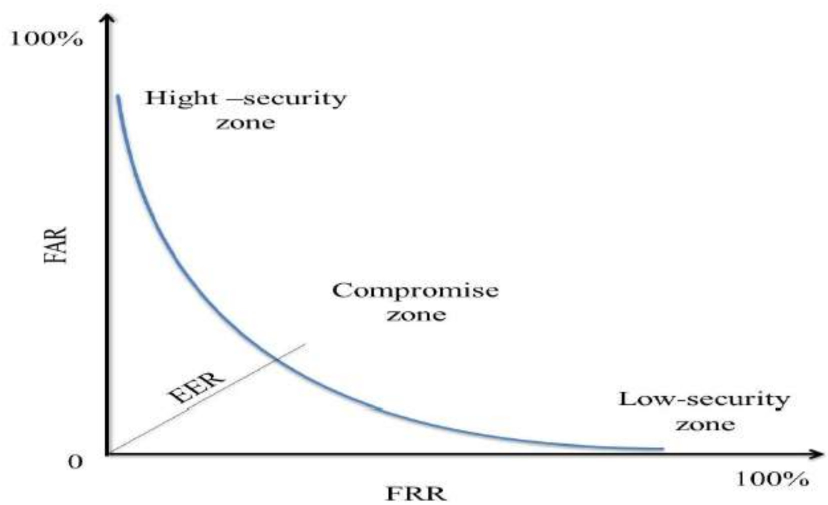

Fig I.19 Demonstrate ROC curve.

b. Cumulative Match Characteristics (CMC):

When the system operates in identification mode, it may be useful to know if the right choice is among the N first responses of the system. This is realized through CMC curve, Fig (I.20).

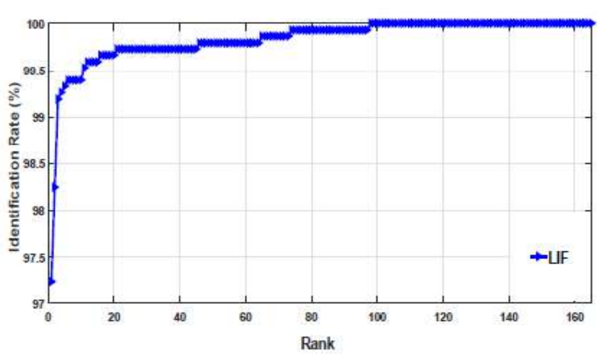

Fig I.20 Demonstrate CMC curve.

I.9 Conclusion

In this first chapter, we presented the conceptual framework of this memory. We started with some basic notions and definitions related to biometrics followed with illustration of the different categories and the structure of a biometric system. All of these allow us to go through the multimodal biometric system principles and the presentation of the different types and levels of fusion. In addition, we gave an overview on some techniques of performance measurement for a biometric system.

Chapter II

Optimization of Sugeno fuzzy model for biometric feature extraction

II.1 introduction

Fuzzy logic is an extension of Boolean logic by Lotfi_ Zadeh in 1965 based on the mathematical theory of fuzzy sets, which is a generalization of the classical set theory [10]. Fuzzy logic allow the representation and processing of imprecise knowledge it does so with information that can be uncertain in a sense of being vague or fuzzy, thus, fuzzy systems are useful in the formulation and quantification of human observations.

The primary benefit of fuzzy system is to approximate system behavior where analytic functions or numerical relations do not exist. Hence, fuzzy systems have high potential to understand the systems that are devoid of analytic formulations [1].

Fuzzy logic techniques have attracted significant interest and have become an important part of modern engineering technics. The use of linguistic knowledge in the form of IF-THEN rules gives a fuzzy system the ability to work as a universal approximation to model the nonlinear functions. This allowed the application of fuzzy systems in parametric and non-parametric identification but, unfortunately, this research does not provide a systematic methodology for determining parameters. In this chapter we will propose a biometric feature extraction solution based on fuzzy system identification.

In the next section, we will develop the main notions of fuzzy systems as well as its use for modeling. Then, the definition of an optimization problem, and its quadratic criterion formulation, will allow us to exploit an algorithm for the optimization based on numerical Newton method for the determination of the Feature vector.

II.2 Fuzzy systems

The fuzzy rule-based system is most useful in modeling some complex systems that can be observed by humans, because they make use of linguistic variables to formulate their antecedents and consequents; as described in this chapter these linguistic variables can be naturally represented by fuzzy sets and logical connectives of these sets.

II.2.1 Fuzzy sets

Fuzzy logic extended the notion of binary membership to accommodate **various degrees of membership** on the real continuous interval [0, 1], where the endpoints of 0 and 1 conform to no membership and full membership, respectively and the values in between represent the various degrees of membership [10].

To elaborate, suppose we have an exhaustive collection of individual elements x, which make up a universe of information (discourse) U

A fuzzy set A of U is characterized by a membership function which associates with each element x of U a real number in the interval [0,1] which represents the degree of membership of this element to A, thus the fuzzy set A of U is defined by:

$$A = \{(x, \mu_A(x)), x \in U\} \, with \, \mu_A \in [0,1], \forall \; x \in U \qquad \text{(II.1)}$$

Example

Let, as above, U be the set of temperature values between 14 and 26. Fig II.1 shows two examples of temperature representation, one in classical logic, and the other in fuzzy logic.

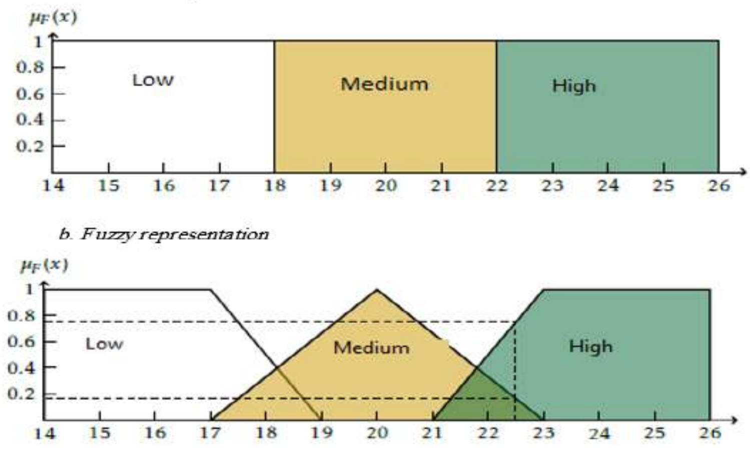

Fig II.1 Comparison of temperature membership in classical vs fuzzy logic

According to Figure II.1, in classical logic, a temperature of 22.5 is considered high.

In fuzzy logic a temperature of 22.5 belongs to the Medium group with a membership of 0.167, and belongs to the high group with a degree of membership of 0.75.

II.2.2 Membership functions

The forms of the most common used membership functions are Singleton, triangular, trapezoidal, Gaussian [17], see Fig II.2.

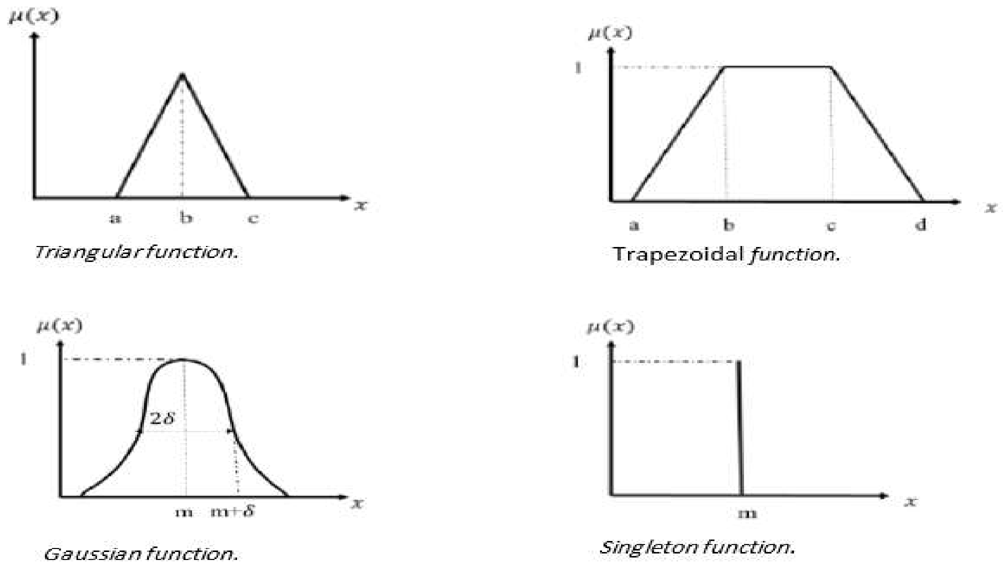

Fig II.2 Typical membership functions

II.2.3 Fuzzy set operations

Define three fuzzy sets *A, B,* and *C* on the universe *U* for a given element x of the universe, the fuzzy operations of union, intersection, and complement are defined for *A, B*, and *C* on *U* as follow:

Union $\mu_{A\cup B}(x) = \mu_A(x) \vee \mu_B(x)$

Intersection $\mu_{A\cap B}(x) = \mu_A(x) \wedge \mu_B(x)$

Complement $\mu_{\bar{A}}(x) = 1 - \mu_A(x)$

II.2.4 Operations on fuzzy relations

Fuzzy relations also map elements of one universe, say X, to those of another universe, say Y, through the Cartesian product of the two universes.

The fuzzy relation R is a mapping from the Cartesian space X × Y to the interval [0,1], where the strength of the mapping is expressed by the membership function of the relation from the two universes, or $\mu_R(x, y)$.

Let R and S be fuzzy relations on the Cartesian space X × Y. Then the following operations apply for the membership values for various set operations:

Union $\mu_{R\cup S}(x, y) = \max(\mu_R(x, y), \mu_S(x, y))$.

Intersection $\mu_{R\cap S}(x, y) = \min(\mu_R(x, y), \mu_S(x, y))$.

Complement $\mu_R(x, y) = 1 - \mu_R(x, y)$.

Containment $R \subset S \Rightarrow \mu_R(x, y) \leq \mu_S(x, y)$

II.2.5 Fuzzy Implication

As before in binary logic, the Fuzzy implication connective can be modeled in rule-based form; **IF x is A THEN y is B** and it is equivalent to the fuzzy relation;

$R = (A \times B) \cup (\overline{A} \times Y)$, where A and B are fuzzy sets on universe X and Y respectively

Just as it is in classical logic, the membership function of R is expressed by the following formula.

$$\mu_R(x, y) = max[\mu_A(x) \wedge \mu_B(y), (1 - \mu_A(x))]$$

II.2.6 Fuzzy system structure

A typical fuzzy system consists of four main modules a fuzzification, Knowledge-base, fuzzy inference engine, defuzzification (see Figure II.3).

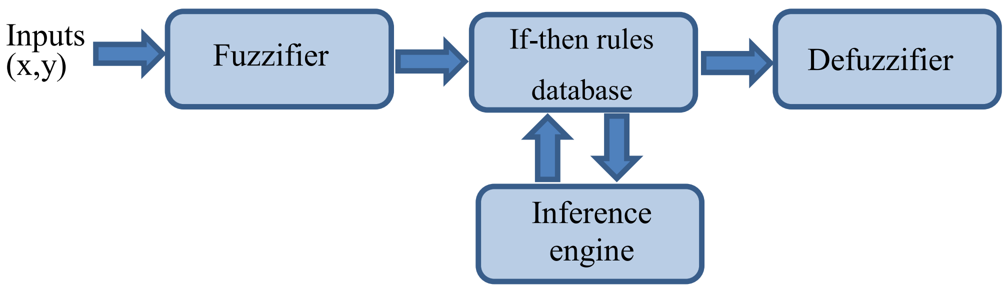

Fig II.3 Fuzzy system structure

1 Fuzzification module

Fuzzification is the process of making a crisp quantity fuzzy. We do this by simply recognizing that many of the quantities that we consider to be crisp and deterministic are actually not deterministic at all; they carry considerable uncertainty. Because of imprecision, ambiguity or vagueness, then the variable is probably fuzzy and can be represented by a membership function [5].

For utility in fuzzy systems, the inputs generally originate from a piece of hardware and the inputs derive from sensor measurements should first be fuzzified, that is, translated into a membership function, and can then be used to form the input structure necessary for a fuzzy system.

2 Knowledge-base module

Fuzzy relations rules can also be assembled from linguistic knowledge, expressed as **if–then rules.** Such knowledge may come from experts, from polls, or from consensus building.

By using the basic properties and operations defined for fuzzy sets, any compound rule structure may be decomposed and reduced to a number of simple canonical rules as given in Table II.1

3 Inference engine module

Fuzzy inference provides the methodologies for building intelligent decision support systems through fuzzy logic based processes. The fuzzy inference process is made up of membership functions, fuzzy logical operations and fuzzy If-Then Rules to obtain the linguistic or fuzzy output of the rules-based system.

This operation is carried out by one of the following methods based on fuzzy implication operators:

a- The max-min inference method

b- Max-prod inference method

c- Sum-prod inference method

Table II.1 The canonical form for a fuzzy rule- system

Rule 1:	IF condition C^1, THEN restriction R^1
Rule 2:	IF condition C^2, THEN restriction R^2
⋮	
Rule r:	IF condition C^r, THEN restriction R^r

4 Defuzzification

A process that converts the fuzzy resulting membership function to conventional expressions quantified by real-valued functions.

II.2.7 Type of fuzzy inference system

There are two main types of fuzzy inference system (FIS),

a. Mamdani fuzzy model

This model is more popularly used, because it provides reasonably good results with a relatively simple structure. The consequent membership functions are also fuzzy in nature and the **If - Then** fuzzy rules are written in the following form [11]:

$$R_i: \quad \boldsymbol{If}\ x\ is\ A_{1i}\ \boldsymbol{and}\ y\ is\ A_{2i}\ \boldsymbol{Then}\ \hat{I}\ is\ B_i \qquad i = 1..n_R$$

A_{ij} are linguistic values, n_R is the number of rules

This model is well suited to the description of systems in the form of linguistic decision rules.

b. Takagi-Sugeno fuzzy model

In this fuzzy reasoning model, **If - Then** rules are written in the form:

$$R_i: \quad \boldsymbol{If}\ x\ is\ A_{i1}\ \boldsymbol{and}\ y\ is\ A_{i2}\ \boldsymbol{Then}\ \hat{I} = f_i\ (x, y)$$

very often, the functions of the consequences are chosen with a polynomial expression, the output of the fuzzy system will be given by:

$$\hat{I}(x, y) = \frac{\sum_{i=1}^{n_R} \mu_{A_{1i}}(x)\mu_{A_{2i}}(y) f_i\ (x,y)}{\sum_{i=1}^{n_R} \mu_{A_{1i}}(x)\mu_{A_{2i}}(y)} \qquad \text{(II.2)}$$

With $\boldsymbol{f_i}\ (\boldsymbol{x}, \boldsymbol{y})$ a scalar function often chosen with a polynomial form in the case of first order system.

In the case of zero order polynomials, we have $f_i\ (x, y) = a_{i0}\ or\ a_{i0}$ are real constant parameters then the output expression will become:

$$\hat{I}(x, y) = \xi^T(x, y).\theta \qquad \text{(II.3)}$$

$\xi = \left[\xi_1 \dots \xi_{n_R}\right]^T$ called activation vector [12], and is given by:

$$\xi_i(x, y) = \frac{\mu_{A_{1i}}(x)\mu_{A_{2i}}(y)}{\sum_{i=1}^{n_R}\mu_{A_{1i}}(x)\mu_{A_{2i}}(y)} \qquad i = 1 \dots n_R \qquad \text{(II.4)}$$

The vector of the parameters $\theta = \left[a_{10} \dots a_{n_R0}\right]^T$ groups the different gains of the polynomial functions.

The output of the fuzzy system is the product of the two vectors ξ and θ and, the first vector is chosen by the system designer, thus, the choice of membership functions completely defines this vector if the inputs (x and y) are available. During the determination of a fuzzy system, the major problem lies in the identification of the parameter vector θ.

II.2.8 Fuzzy system as universal approximation

According to the expression of the fuzzy system output, the fuzzy model can be considered as a function having several variables and a single output. Fuzzy rules are supposed to define the characteristics of function $\hat{I}(x, y)$ since they represent the knowledge on which the fuzzy model is based.

In 1992 Kosko proved that fuzzy systems are universal approximations. These systems are able to approximate any sufficiently smooth function with a bounded error [1]. This implies that

$$\forall\ x, y\ \in (X, Y)\left|I(x, y) - \hat{I}(x, y)\right| \leq \varepsilon_{max} \qquad \text{(II.5)}$$

Where $I(x, y)$ is the function to be approximated and ε_{max} "can be chosen to be arbitrarily small. The error ε_{max} can be reduced considerably with a good choice of the parameters of the fuzzy system (eg: increase in the number and distribution of the membership functions).

When we regard the fuzzy system as a discretization of the function $I(x, y)$, and know that between these discretizations, interpolation is performed by means of fuzzy inference, it is clear that increasing the number of rules can provide a better approximation. This is similar to the approximation of a continuous function by a number of points: the higher the number of points is the better the approximation of the continuous function can be [1].

In addition to the fact that the function can be nonlinear because of the fuzzy rules, the mapping can also be nonlinear because of the choice of operators, membership functions, and so on.

The universal approximation property gives us an important tool to characterize non-linear functions. Our objective in the next section is to determine a fuzzy model to approximate the function associated to a biometric image.

II.3 Biometric image

The image is a representation of a person or object through painting, drawing, photography, film, etc. [5]. It is also a structured set of information that, after being displayed on the screen, has a meaning for the human eye.

II.3.1 Digital image

An image may be defined as a two-dimensional function I(x, y), where x and y are spatial coordinates of a point in the image. The amplitude of *I(x, y)* at any pair of coordinates *(x, y)* is called intensity or gray level of image at that point. When x, y, and the amplitude values of *I(x, y)* are all finite, discrete quantities, the image is called a digital image. The processing of digital images by means of digital computer is called digital image processing. Note that, a digital image is composed of finite number of elements, each of which has a particular location and value. These elements are referred to as image elements, picture elements or pixels. Pixel is the term used most widely to denote the elements of a digital image.

The image in its digital form is usually stored as a two-dimensional array. If ***M* = *{1,2,...,x,...,m}*** and ***N* = *{{1,2,...,y,...,n}*** are the spatial domain, then ***D* = *M*** × ***N*** is the set of resolution cells.

$$I(x,y) = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2n} & \dots & x_{2N} \\ x_{31} & x_{32} & \dots & x_{3n} & \dots & x_{3N} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{M1} & x_{M2} & \dots & x_{Mn} & \dots & x_{MN} \end{bmatrix}$$

Fig II.4 Grayscale Image

The gray level is the value of the luminous intensity at a point. The color of the pixel can take values ranging from black to white through a finite number of intermediate levels. So to represent grayscale images, for example figure. II.4, we can assign to each pixel of the image a value corresponding to the quantity of luminous returned

II.3.2 Image modeling with a fuzzy model

1. **Formulation of the optimization problem**

We consider a nonlinear function associated to a biometric image given by $I(x, y)$, this function is bounded and a relatively with smooth variation.

With the collection of all the approaches understand and seen previously, the fuzzy approximation model can be expressed by $\hat{I}(x, y) = \xi^T(x, y).\theta$. We propose the determination of the vector θ through the minimization of the following criterion:

$$E^2 = \frac{1}{N_p}\sum_{x,y}\left(I_{mage}(x, y) - \hat{I}(x, y)\right)^2 \tag{II.6}$$

Where N_p is the number of pixels contained in the image. This criterion E^2 is the average of the squares of the approximation errors on the whole image also called Mean squared error (MSE), then the previous equation would be:

$$E^2 = \frac{1}{N_p}\sum_{x,y}\left(I_{mage}(x, y) - \xi^T(x, y).\theta\right)^2 \tag{II.7}$$

After development of this expression, we obtain:

$$E^2 = \frac{1}{N_p}\sum_{x,y}\theta^T\xi(x,y)\xi^T(x,y).\theta - \frac{1}{N_p}\sum_{x,y}2I_{mage}(x,y)\xi^T(x,y).\theta + \frac{1}{N_p}\sum_{x,y}(I_{mage}(x,y))^2 \quad \text{(II.8)}$$

In matrix form the MSE expression becomes

$$E^2 = \frac{1}{2}\boldsymbol{\theta^T A\,\theta} + \boldsymbol{b^T\,\theta} + C \quad \text{(II.9)}$$

Where the matrix A, the vector b and the scalar c are given by:

$$A = 2\sum_{x,y}\frac{\xi(x,y)\xi^T(x,y)}{N_p} \quad \text{(II.10)}$$

$$b^T = -\sum_{x,y}\frac{2I_{mage}(x,y)\xi^T(x,y)}{N_p} \quad \text{(II.10)}$$

$$C = \sum_{x,y}\frac{(I_{mage}(x,y))^2}{N_p} \quad \text{(II.11)}$$

It is clear now that the criterion E^2 is reformulated as a quadratic function. To find an optimal vector $(\boldsymbol{\theta})$**,** the literature offers us several optimization algorithms,. Many of them are deterministic (or exact) methods for solving certain types of optimization problems and for obtaining the optimal solution of the problem in a reasonable time. These methods require that the criterion to be minimized; presents a certain number of characteristics such as convexity, continuity or differentiability.

2. Newton-Raphson method

Newton's method sometimes called Newton-Raphson method, allows to build an algorithm to resolve the quadratic function for the criterion E^2given by (II.7) or (II.9), we will develop the Newton method, which is one of well-known optimization algorithm

The basic Newton method proposes an iterative algorithm to resolve nonlinear optimization problem. In this method, an arbitrary fixed step θ_0 is used to compute a new solution vector see (Fig II.5).

Let us consider the optimization problem of the criterion:

$$E^2 = \frac{1}{2}\boldsymbol{\theta^T A\,\theta} + \boldsymbol{b^T\,\theta} + C \leq \varepsilon_{max} \quad \text{(II.12)}$$

We show that the matrix A is symmetric, positive definite and ε_{max} chosen to be arbitrarily small.

The basic algorithm is given by [13]:

$$\theta_{k+1} = \theta_k - \left[{\nabla_{\theta_k}}^2 E^2(\theta_k)\right]^{-1} . \nabla_{\theta_k} E^2(\theta_k) \qquad \text{(II.13)}$$

Where the integer k and the operator ∇_{θ_k}denotes iteration index and gradient function vector respectively. In the particular case of quadratic criterion and after development we find:

$$\theta_{k+1} = \theta_k - A^{-1}.A.\theta_k - A^{-1}b \qquad \text{(II.14)}$$

$$\theta_{k+1} = -A^{-1}b = \theta^* \qquad \text{(II.15)}$$

$$\theta_1 = -A^{-1}b = \theta^* \qquad \text{(II.16)}$$

Newton's method reaches the point θ^* such that $\nabla E^2(\theta^*) = 0$ in just one step for proposed quadratic criterion $E^2 \leq \varepsilon_{max}$, we find the algorithm Newton was the best choice for minimizing a given objective function. It's giving the optimum solution and in the first iteration *K=1* starting from any initial point θ_0.

Therefore, for the nonlinear optimization problem formulated in quadratic function associated with a symmetric positive definite matrix; we highly recommend the use of Newton method as it require just one iteration to convergence to the desired solution form any initial point. Newton's method uses first and second derivatives and indeed performs better. The proposed algorithm is illustrated in the following figure.

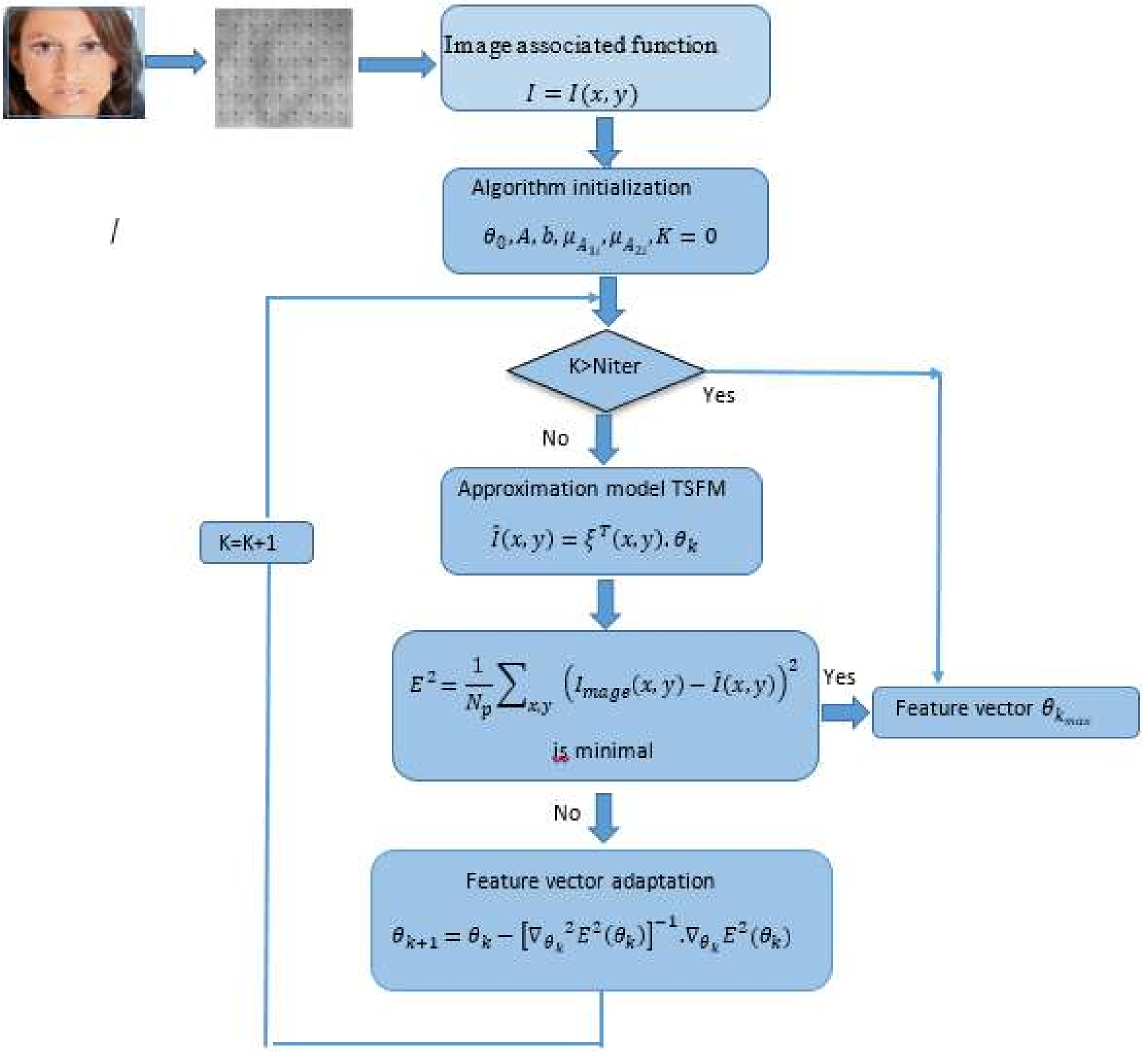

Fig II.5 The proposed feature extraction algorithm

II.4 Conclusion

In this chapter, we presented the main tools needed for image modeling by a TS fuzzy system. The particular formula of TS fuzzy model output, allow us to formulate a quadratic criterion to minimize.

The Newton algorithm, as presented, offers a recursive procedure to determine the optimum feature vector of the fuzzy model from the first iteration. Thus, Newton is the best optimization method as long as the associated matrix (A) remain symmetric positive definite and invertible.

In the next chapter, we will apply this algorithm as part of a biometric system.

Chapter III

Experimental results and discussion

III.1 introduction

As we introduced in the first chapter, there are various biometric modalities applied in the field of identification and authentication among of these modalities, the one that is extracted from the hand, e.g. Palmprint, have been effectively used to make person identification for the last years.

In this chapter we will use the Newton algorithm to find an appropriate feature vector as developed in the previous chapter. The biometric identification is based on palmprint database.

Thus, we will first introduce palmprint recognition then the PolyU multispectral palmprint database that will be used in the evaluation of proposed biometric system.

III.2 Palmprint recognition

The palmprint is the inside part of the hand from the wrist to the roots of the fingers, with his large surface and the abundance of the biometric traits, it is expected that the palm prints are very robust to noise and unique to each individual. The palm surface consists of many unique features such as principal lines, ridges, wrinkles [13] as shown in figure III.1.

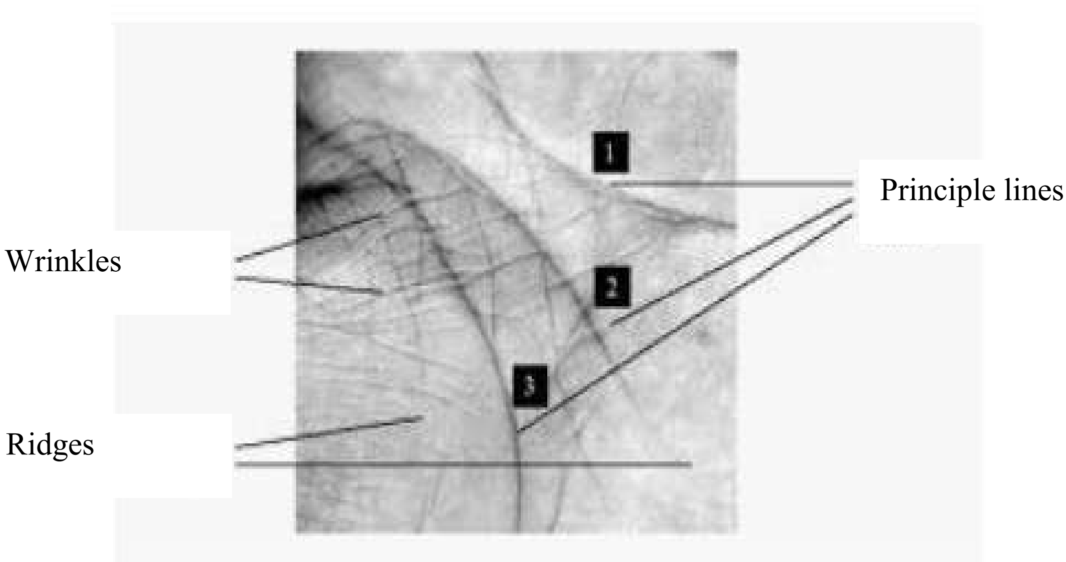

Fig III.1 Principle characteristic of palmprint

Compared to other physical characteristics, palmprint recognition has several advantages [14].

1. Palm prints contain more information than fingerprints.
2. They are more discriminating.
3. Palmprints capture are much less expensive than those for iris capture
4. Palmprints contain additional distinctive features such as principle lines and wrinkles.
5. The line features are stable.
6. High acceptance rate by users

III.3 Proposed biometric recognition system

We propose a multimodal biometric system (Multi-samples) based on modality of palmprint and with fusion at score level (see Fig. III.2).

The proposed system is desired to determine the identity of the relevant person. To achieve this, it is necessary to have reference images (database of palmprint of all persons known by the system). Each image is associated with a features vector. The recognition then consists of comparing the feature vector of the palmprint to be recognized with each feature vector (palmprint) in the database. This allows finding the person with the most similar palmprint.

The goal of the fusion process is to investigate the systems performance when the information from some color bands of a person is fused. In fact, in such case the system works as a kind of multi-modal system with a single biometric trait but with multiple units. Therefore, the information presented by different bands (Blue, Green, Red and Nir) is fused to make the system efficient.

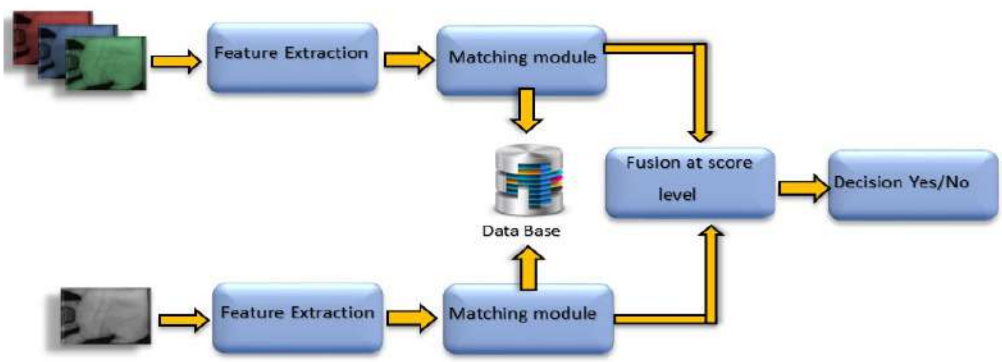

Fig III.2 Proposed multimodal system with fusion at score level

III.3.1 Online palmprint capture device

To accomplish an effective identification by palmprints in real time, it’s required to make in place a particular device that must be fast enough in the acquisition of palmprints [15].

Fig III.3 Online palmprint capture device

III.3.2
Features extraction

The feature extraction step allows constructing vectors containing the discriminant characteristics of an image of a biometric modality (palmprint) obtained with a biometric sensor and recorded in a database as mathematical values

In the previous chapter, we have shown that the fuzzy system is a universal approximator, based on this advantage we will use the Newton Raphson algorithm to find fuzzy model corresponding to the considered image. A vector of these parameters will be considered as biometric feature vector. The figure III.4 explains the feature extraction steps with the optimized fuzzy system.

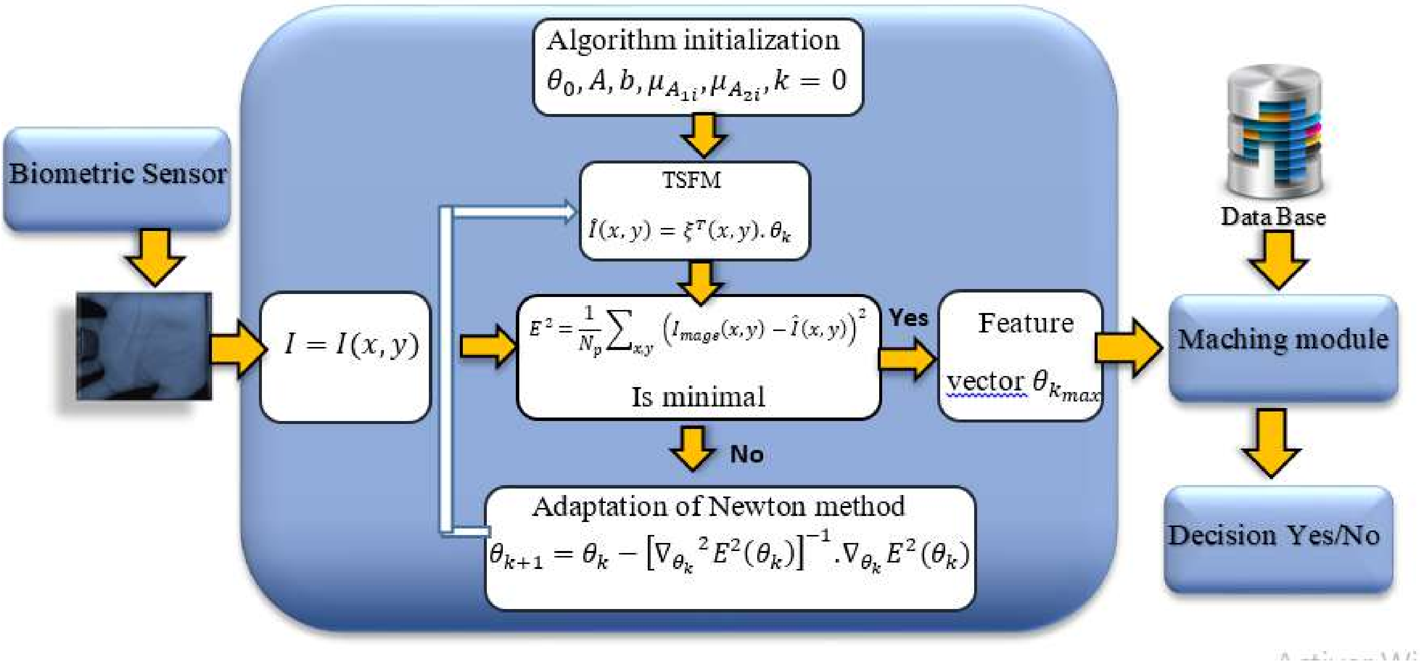

Fig III.4 Feature extraction in the proposed biometric system

There are several works that use the method of "Euclidean Distance". In our proposed biometric system we proceeded to the comparison at the maching module level with this method between the image approximated by the fuzzy model and the models already stored in the database.

Euclidean Distance is calculated as follow:

$$d(\theta, \theta p_j) = \left[\sum_{i=1}^{m} (\theta_{ipj} - \theta_i)^2\right]^{\frac{1}{2}}$$

Where $\theta = [\theta_1 \ \theta_2 \ \theta_3 \ldots \theta_m]^T$ is feature vector of palmprint recognition

And $\theta_{pj} = \left[\theta_{1pj} \ \theta_{2pj} \ \theta_{3pj} \ldots \theta_{mpn}\right]$ is the feature vector of the model stored in the database. This distance will then be normalized between 0 and 1.

III.4 Multi-spectral palmprint database

The Biometric Research Center of Hong Kong Polytechnic University has developed a real-time multi-spectral palmprint capture device that can capture Palmprint images under blue, green, red and infrared illuminations, and used it to build a large-scale palmprint multi-spectral database [12].

This database is constructed to advance research and provide researchers working in the field of multi-spectral recognition with a platform to compare the effectiveness of different multispectral algorithms palmprint recognition

The database has 6000 images obtained from 500 persons. The images were taken in two different sessions separated by a time interval of about two months. During each periode, each individual had to take at least 6 pictures of his palmprint. Moreover in the second period, the light source and the (CCD) camera lens are adjusted so that the images of the first and second session gave the impression of having been taken by different light condition to test the robustness of the biometric system. However, the extracted ROI sub-image size is equal to 128 x 128 with a resolution of 75 dpi, finally we note that the acquisition system collect 4 images from 4 hand (Red, Green, Blue and NIR) [17].

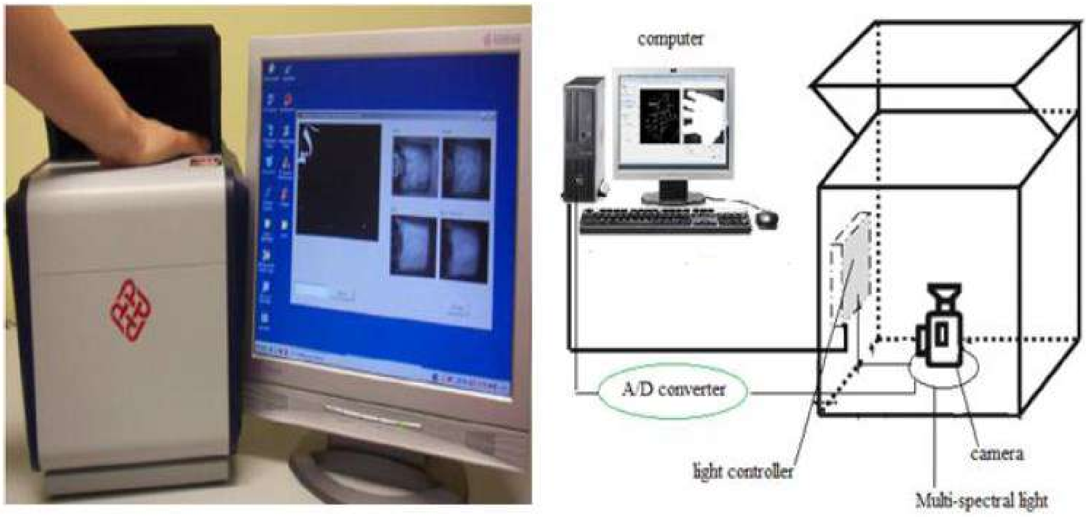

Fig III.5 Multi-spectral palmprint recognition.

To develop a palmprint identification system, it is necessary to take 2 database:

One database to perform learning and other one to test and determine the system performance. There are no rule that fixes the manner to share one available database into two parts. In our series of test, we have divided the multi spectral palmprint database as follows:

Learning Image: the first, fifth and ninth image of each person (for each spectral band) to serve learning phase.

Test Image: the remaining 9 images for each individual have helped us achieving different test.

III.5 Experimental result and discussion

After that we will first discuss the influence of fuzzy parameters design in the proposed optimization method and we will chose the best parameters to achieve the desirable system performance. Then we will examine the impact of the proposed algorithm in case of use unimodal biometric system followed by the case of multi-modalities.

III.5.1 Adaptation of parameters

The objective of the parameters adaptation is the estimation of the parameters that ensures the best and the desirable performance.

The proposed algorithm contains two important design parameters: the number of iteration N_{max}, as algorithm stop condition and the number of membership function K_{max}, for this we have studied our experience in 3 steps

First step:

Shows the Influences of the membership function on the performance of the biometric system. Table III.1 illustrate the ROR and ERR against the number of membership functions with iteration N_{max}=20. In this table we note that the biometric system gives ROR values greater than 97% for number of function K_{max} equal 10, 15, 20, 25 but the best is obtained with K_{max} equal 10, it gives 97.77% from the ROR. This value suggested that 10 membership function is the best choice.

Table III.1 EER and ROR against the membership function number

k_{max} (Membership function number)	Open mode	Close mode
	EER	**ROR**
5	94.4	0.977
10	97.77	0.35
15	97.488	0.4
20	97.33	0.5
25	97	0.58
30	96.84	0.64
35	96.64	0.66
40	96.64	0.7

Second step

In the second step, we hold the number of membership function K_{max}=10 and we recorded the influence of iteration number N_{max} relative to the optimization method

The following Table III.2 represents the results of EER and ROR for this variation.

Table III.2 EER, ROR in function of iteration number

Iteration N_{max}	Open set	Close set
	EER	**ROR**
5	97.77	0.35
10	97.77	0.35
15	97.77	0.35
20	97.77	0.35
25	97.77	0.35
30	97.77	0.35
35	97.77	0.35
40	97.77	0.35

From table III.2 we note that we got the best value of ROR =97.77 with all different iteration number N_{max} thus the increase of iteration number will just increase the computing time without recording enhancement.

Third step:

At the end and after the comparison of the previous result we conclude that best parameters of the proposed method are obtained with **number of iterations** equal to **5** and the **number of membership functions** equal to **10.**

III.5.2 Unimodal application

To evaluate the identification system performance, we will use the information from each spectral band of palmprint modality.

Table III.3 compares the performance of unimodal system using fuzzy feature extraction for different spectral bands (Red, Green, Blue, Nir).

Table III.3 EER. ROR and RPR for different unimodal bands

Modality	Open set		Close set	
	EER	Threshold	ROR	RPR
Blue	0.022	0.1308	99.75	282
Nir	0.06	0.1611	99.6	320
Red	0.35	0.1413	97.77	235
Green	6.23	0.1376	82.51	482

From the experimental results resumed in Table III.3. We can conclude that the blue perform better than the Nir, Red and Green in EER. It gives an EER =0.022% with threshold θ_0=0.1308, and the rest of bands give relatively good results, EER is less than 0.4% except for the green recorded low results EER=6.23 and ROR=82.51.

Graphical interpretation:

Figure III.6 shows the Receiver Operating Characteristic (ROC) curves of the system, in the open set mode for the four palmprint bands (Red, Green, Blue, Nir). This figure represents the distribution of the EER values that are mentioned in the previous table III.3. EER values are the result of intersection between the first bisector and the ROC curves of the different spectral bands

This figure classified the spectral bands on EER basis. We clearly notice that the best band is the blue with EER=0.022%.

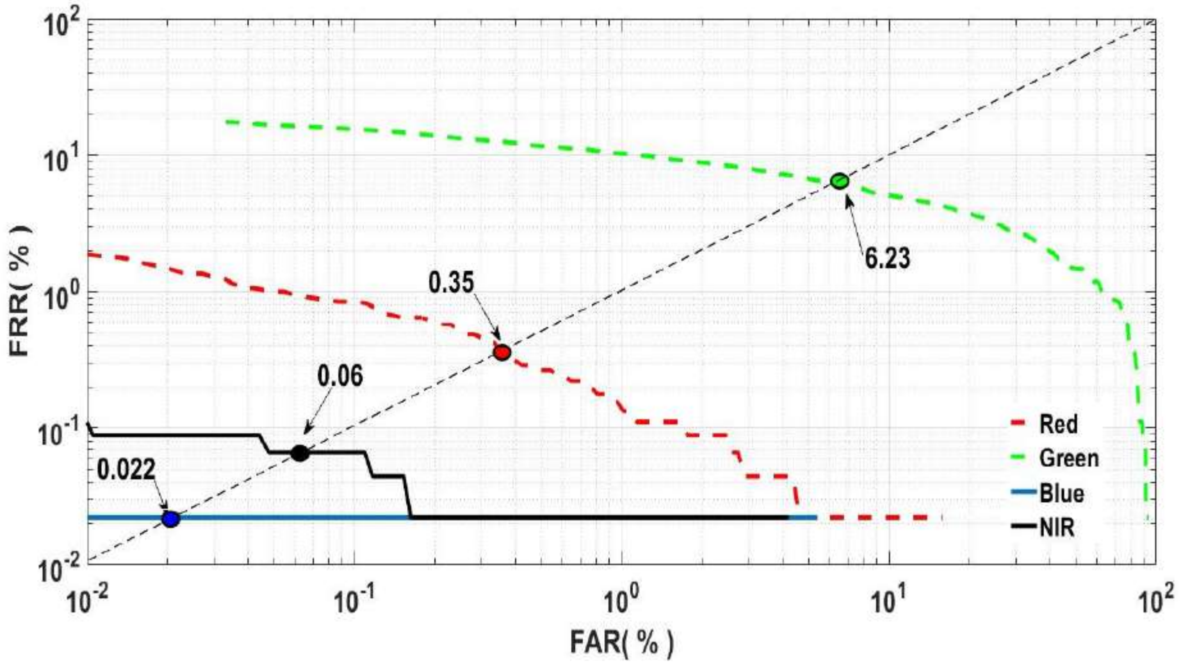

Fig III.6 Unimodal system performance (ROC).

Then we tested the biometric system in the case of closed set identification system. Figure III.7 shows the cumulative match characteristic (CMC) curves witch represent the identification rate against all ranks. In this figure all bands show a good result superior to 97% in ROR, except the green band. The perfect result is obtained with Blue with 99.75% of ROR.

However, for the RPR, we notice that the Red band gives a better RPR with a value of 235.

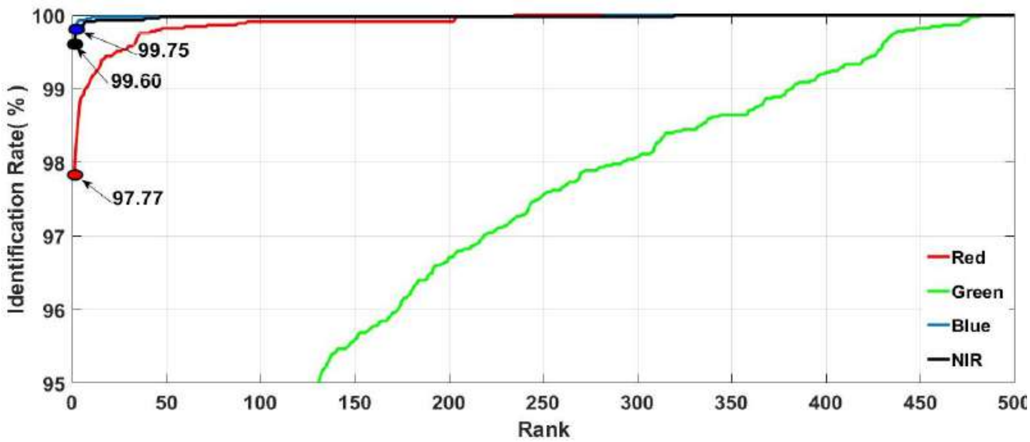

Fig III.7 Unimodal system performance (CMC).

III.5.3 Multimodal application

As we have seen earlier in the chapter 1, multi modalities is one of the good solution to increase the biometric system performance. The objective of this section is to investigate the combination of all color bands features in order to achieve higher performances that may not be possible with unimodal biometric.

In order to see the performance of the system, we have evaluated different fusions of color bands, and Table III.4 summarizes the equal error rates for these experiments. From Table III.4, we can observe the advantages of using the RGBN (Red, Green, Blue, and Nir) fusion modalities. For example, a fusion of RGB gives an EER equal to 0.066 % at θ = 0.1429 by using Sum rule fusion. This system can achieve a minimum EER of 0.044 % for θ = 0.1850 in the case of RGBN fusion with same fusion rule

Table III.4 EER, ROR and RPR for different multimodal

Rules	Red+Green+Blue				Red+Green+Blue+Nir			
	Open set		Close set		Open set		Close set	
	EER	Threshold θ	ROR	RPR	EER	Threshold θ	ROR	RPR
Sum	0.066	0.1429	99.6	7	0.044	0.1850	100	1
Mul	0.0888	$2.03\text{x } 10^{-3}$	87	3	0.0536	$2.9\text{x}10^{-4}$	87	4
Min	0.111	0.02768	87	3	0.066	0.01870	87	4
Max	0.1772	0.2060	99	223	0.0888	0.2463	99.8	4
W Sum	0.0440	0.1604	100	1	0.044	0.1826	100	1

Graphical interpretation:

In order to show the effectiveness of the RGB and RGBN bands, we have plotted ROC curves in the below figure III.8 which also illustrate he projection of EER values mentioned in Table III.4 and allows us to classify the different fusion at the score level for the proposed biometric system

For fusion based on RGB, the best performance achieved by the weighted rule with a minimum EER of 0.044% and a threshold θ= 0.1604.For RGBN fusion, fusion based on weighted sum rule is also achieved a minimum EER of 0.044 % and a threshold θ= 0.1826.

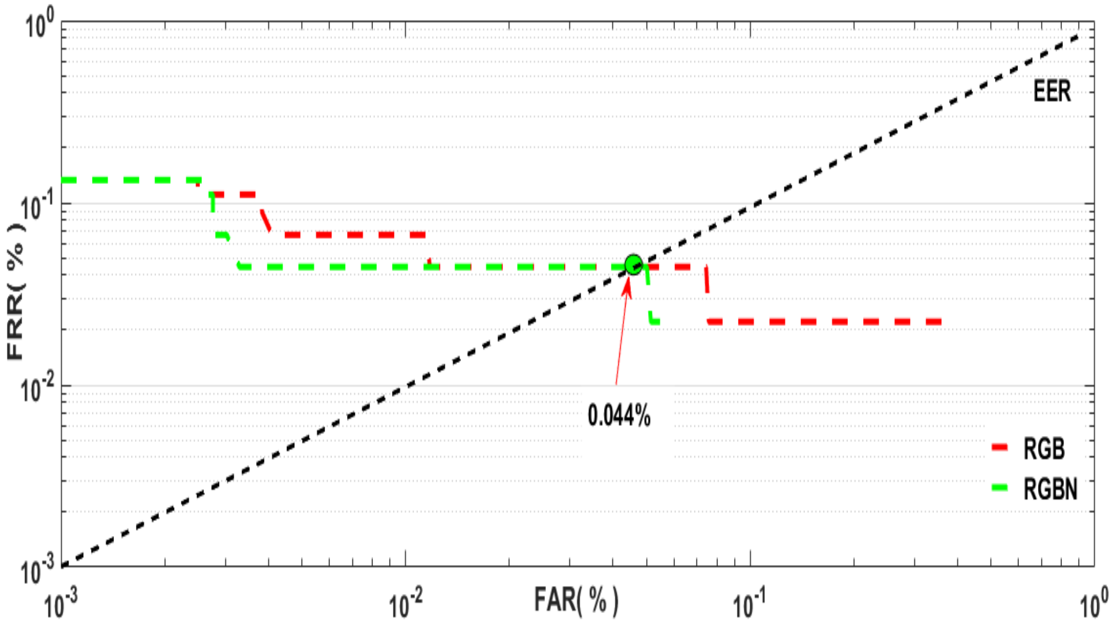

Fig III.8 Multimodal system performance (ROC).

From the Cumulative Match Curve (CMC) in the below figure III.9 we conclude the performance of the biometric system with the different combination of modalities and fusion rules.

The experimental results show that fusion of all color bands (RGBN) with weighted sum rule fusion is much higher than the individual color bands. In addition is clearly that the weighted sum fusion rule delivers the best results in RPR and ROR. With this combination, the system achieves a 100% ROR and 1 RPR for both multi spectral RGB and RGBN fusion

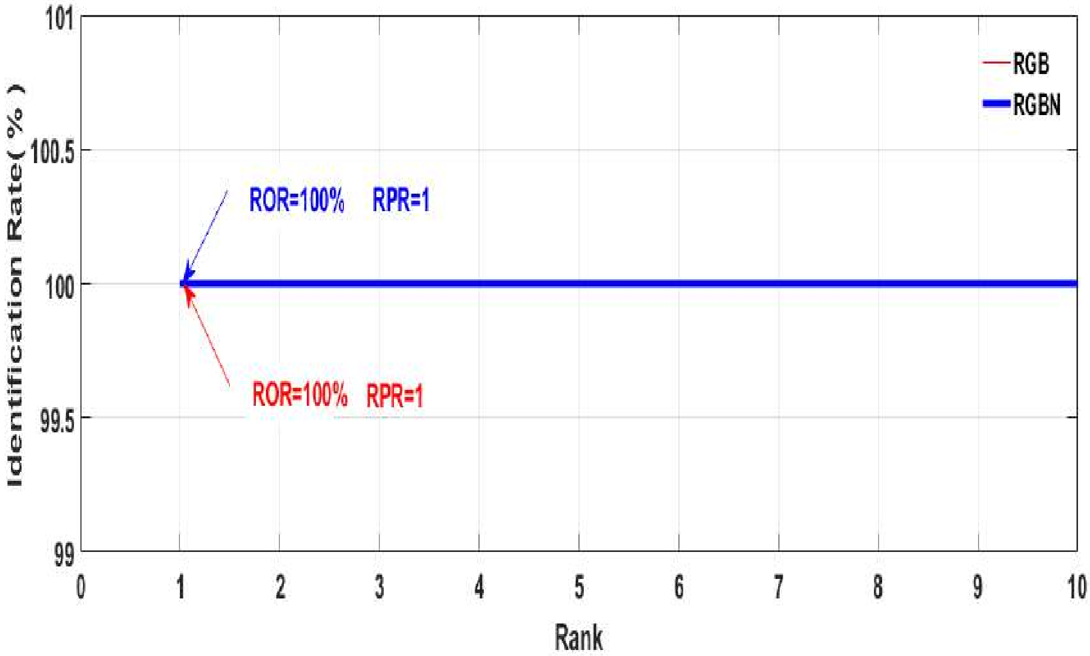

Fig III.9 Multimodal system performance (CMC).

III.6 Conclusion

PolyU multispectral palmprint database is used in the evaluation of the proposed unimodal and multimodal biometric system. The obtained results in unimodal case show relatively high performance. These results are enhanced by the adaption of multimodal biometric system where more biometric trait were combined by fusion at score level.

As well as we took advantage of the fuzzy system characteristics as a universal approximator optimized with Newton method to achieve the desirable performance of the biometric system.

General Conclusion

General Conclusion

In this work, we have presented an overview on biometrics basics, the architecture and modules of a biometric system. In addition, we gave an insight into fusion levels and principle technics to evaluate biometric system performance measurements

Our objective is to develop a robust algorithm to recognize an individual by his palmprint, for this purpose we proposed a new approach to extract the discriminant features within a biometric image in order to be used in the proposed biometric identification system. Thus, qualified as universal approximator. Takagi-Sgeno fuzzy system is adopted to model the biometric image through optimization of error target function, in which Newton Raphson method is used to establish the proposed algorithm.

In order to evaluate our model, the Poly U multispectral palmprint database is used. The obtained results show that the biometric system error are extremely reduced especially when the blue spectral band id used. The obtained results in unimodal case show relatively high performance. These results enhanced by the adaption of multimodal biometric system. In this modest work we achieved a reliable system with ROR of 100% and RPR enhanced to 1 When more biometric trait combined by fusion at score level. These results illustrate the important role of fusion in biometric field.

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