CONTRIBUTIONS TO NON-CONVENTIONAL BIOMETRIC SYSTEMS: IMPROVEMENTS ON THE FINGERPRINT, FACIAL AND HANDWRITING RECOGNITION APPROACH

CAUÊ ZAGHETTO

DOCTORAL THESIS ON MECHATRONIC SYSTEMS

DEPARTMENT OF MECHANICAL ENGINEERING

FACULTY OF TECHNOLOGY

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DOCTORAL THESIS SUBMITTED TO THE DEPARTMENT OF MECHANICAL ENGINEERING OF THE FACULTY OF TECHNOLOGY OF THE UNIVERSITY OF BRASILIA AS PART OF THE REQUIREMENTS TO OBTAIN THE DEGREE OF DOCTOR IN MECHATRONIC SYSTEMS.

APROVED BY:

Prof. Dr. Flavio de Barros Vidal, PPMEC/CIC/UnB
(Advisor)

Prof. Dr. Flavio Elias Gomes de Deus, ENE/UnB
External Member

Prof. Dr. David Menotti Gomes, DInf/UFPR
External Member

Prof. Dr. Dibio Leandro Borges, PPMEC/CIC/UnB
Internal Member

Prof. Dr. Carlos Humberto Llanos Quintero PPMEC/ENM/UnB
Internal Member

BRASILIA, FEBRUARY 21 , 2021.

CATALOGUING

ZAGHETTO, CAUÊ
CONTRIBUTIONS TO NON-CONVENTIONALBIOMETRIC SYSTEMS: IMPROVEMENTS ON THE FINGERPRINT, FACIAL AND HANDWRITING RECOGNITION APPROACH [Federal District] 2021.
xiv,75p., 210 x 297 mm (ENM/FT/UnB, Doctor, Mechatronic Systems, 2021).
Doctoral Thesis – University of Brasilia, Faculty of Technology.
Department of Mechanical Engineering

1. Biometrics	2. Fingerprints
3. Handwriting Recognition	4. Facial Recognition
I. ENM/FT/UnB	II. Title (série)

BIBLIOGRAPHIC REFERENCE

ZAGHETTO, C. (2021). CONTRIBUTIONS TO NON-CONVENTIONALBIOMETRIC SYSTEMS: IMPROVEMENTS ON THE FINGERPRINT, FACIAL AND HANDWRITING RECOGNITION APPROACH, Doctoral Thesis on Mechatronic Systems, Publication ENM.XX-96/16, Department of Mechanical Engineering, University of Brasilia, Brasilia, DF, 75p.

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Cauê Zaghetto
Department of Mechanical Engineering (ENM) - FT
University of Brasilia (UnB)
Campus Darcy Ribeiro
CEP 70919-970 - Brasilia - DF - Brasil

To my sons Kiara and Icaro. Light and wings of my life.

ACKNOWLEDGMENTS

First of all, I would like to thank all the teachers who during my academic career contributed to my formation. Teachers are the artisans of social transformation. They guide paths, shape futures, transform lives, change the world. While out of blindness or neglect, or even worse, as long as men deliberately do not recognize this compelling reality, the world will not take a single step towards a virtuous destiny.

Undoubtedly, I need to thank my parents Elvira and Sidney Zaghetto. They were my biggest and best teachers. But more than that, they were my friends in life. I was taught that it is possible to love unconditionally. They made me a good man. With affection, I thank you for every joule you spent with me and every tender gesture you made. Although most of the events in my life were the result of dedication and merit, I was lucky: I was able to be born into a family that loved me and taught me to love.

I want to especially thank my brothers Alexandre and Leticia Zaghetto. Living with you was an opportunity for my spirit. Between encounters and mismatches, affections and differences, there is something that has always remained: love. Thanks for the patience you had with the youngest. Without you, I wouldn't be. Especially my sister Leticia, I make it clear here that I have "defects". Many. But she taught me that the biggest defect in life is hurting someone we love. After that teaching, I was never the same again. I'm better because of that.

To the good old friends Andreu Wilson Pereira Leandro (B. Beauty), Rodrigo Carvalhal de Carvalho, Luiz Fernando Silva Barreto, Leonardo Valim Craveira, Marcio Goncalves Nunes and Diego Rocha Granado, the result of the elective affinities, the chosen paths, the built loves, thank you for sharing your life with me. I carry a little of each one of you with me.

To the good and new friends, Andre Luiz, Alessandro e Daniela Viana, Renata Grehs and Antonio Frederico Melo de Oliveira, I thank the affection that we were able to build in an already more mature phase of life. I still want to live with you a lot.

To the brothers of "free thought" and tireless search for the best questions, a special thanks. Tiago Carvalho, Julio Biddah, Luciano Coutinho, Eryc Leão and Daniel Jatobá, that we may still have many moments of insignificance together. If we are just a grain of sand in the infinite and material universe, I am happy to at least be on the same shore with you.

With great affection, I need to highlight the friendship of Luiz Henrique Morais Aguiar. From student to brother, we build paths together. Without him, I wouldn't have gotten here.

My special thanks to my professor Flavio de Barros Vidal. In the shared walk, there were many moments of doubt and discouragement. In some of them, I wanted to stop. But the generous look, the enduring patience and the friendly guidance kept me on track. Thank you for all the time you spent on me. To you, my teacher, I always wish all the peace and joy that the world can give.

I also feel indebted to the Brazilian people. I did my high school at a state public college funded by the people, I graduated from a federal university funded by the people, I did a master's degree at another federal university funded by the people and now I am in the process of potential completion of my doctorate also funded by the people. To be funded several times - and I repeat the word funded on purpose, because the linguistic error is less relevant than the semantic importance - by the Brazilian people makes me almost ashamed. My counterpart is to be the best professional I can be, to be tireless in the search for new knowledge and to always return part of everything I can build for my people, my nation.

At last and kindly, I would like to thank my wife Daniele Zaghetto. My love, my soulmate. We ran away together. A black bag, an uncertain future: my best decision.

ABSTRACT

CONTRIBUTIONS TO NON-CONVENTIONAL BIOMETRIC SYSTEMS: IMPROVEMENTS ON THE FINGERPRINT, FACIAL AND HANDWRITING RECOGNITION APPROACH

Author: Cauê Zaghetto

Supervisor: Prof. Dr. Flavio de Barros Vidal, PPMEC/CIC/UnB

Postgraduate Program in Mechatronics Systems

Biometric systems are widely used by society. Most applications are associated with civil identification and criminal investigation. However, over time, traditional methods of performing biometrics have been reaching their limits. In this context, emerging or nonconventional biometric systems (NCBS) are gaining ground. Although promising, new systems, as well as any new technology, bring not only potentialities but also weaknesses. This work presents contributions to three important non-conventional biometric systems: fingerprint, facial, and handwriting recognition. With regard to fingerprints, this work presents a novel method for detecting life on Touchless Multi-view Fingerprint Devices, using Texture Descriptors and Artificial Neural Networks. With regard to face recognition, a facial recognition method is presented, based on Scale Invariant Feature Algorithms (SIFT and SURF), that operates without the need of previous training of a classifier and can be used to track individuals in an unconstrained environment. Finally, a low-cost on-line handwriting signature recognition method that uses accelerometer and gyroscope signals obtained from a sensor coupled to conventional pens to identify individuals in real time is presented. Results show that the proposed methods are promising and that together may contribute to the improvement of the NCBS.

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SIMBOLS

CBS	Conventional Biometric Systems
$NCBS$	Non-conventional biometric system
TMF	Touchless Multi-view Fingerprint
$FRSS$	Facial Recognition based on SIFT and SURF
$HRAS$	Handwrite Recognition based on Accelerometer Signals
$AFIS$	Automatic Fingerprint Identification System
$SIFT$	Scale Invariant Feature Transform
$SURF$	Speeded Up Robust Features
$\vec{a}(t)$	Instantaneous acceleration vector
$\vec{a_x}(t)$	Acceleration component on axes x
$\vec{a_y}(t)$	Acceleration component on axes y
$\vec{a_z}(t)$	Acceleration component on axes z
EGG	Electroencephalogram
LBP	Local Binary Pattern
$GLCM$	Gray-level Co-occurrence Matrix
G	Number of gray levels in the image
$p(n,m)$	is the normalized GLCM matrix
μ_x	mean for $p_x(i)$
μ_y	mean for $p_y(j)$
σ_x	standard deviations for $p_x(i)$
σ_y	standard deviations for $p_y(j)$
$p_y(j)$	Marginal-probability vectors obtained by summing the rows and the columns of $p(i,j)$
v_c	Feature vector
PCA	Principal Component Analysis
$\hat{i}$,	Unit vectors of axis x
$\hat{j}$,	Unit vectors of axis y
$\hat{k}$	Unit vectors of axis z
g	Acceleration of gravity on earth
t	Time
DTW	Dynamic time warping
Ag_1	Face detector agent
Ag_2	Face tracker agent
Ag_3	Manager agent

1 INTRODUCTION

Since the beginning of their existence, the human beings have created ways to recognize or identify each other. People recognize themselves by face, by voice, by grimaces, or even by their personalities [6]. The work of [7] shows that this ability to recognize people through their characteristics has given man the ability to establish groups and live socially. If not for this peculiar human characteristic, perhaps our species, the *Sapiens*, would have already been extinct [7].

In addition to the need for direct and mutual recognition among human beings, as more complex societies were being established, the need for individuals to authenticate themselves asynchronously arose. The work of [8] presents the idea that the necessity of asynchronous authentication of the individual was mainly because together with the concept of ownership, there is the concept of exchange, often performed between individuals who do not know each other and therefore do not recognize each other. To resolve this problem, authentication methods of individuals were created [8]. These methods were usually overridden by an authority (e.g. doctor or notary) or by an institution (e.g. cabinet or registry), as described in [8].

More precisely, the first authentication systems emerged in the 19th century by the French with the anthropometric system [9] of Alphonse Bertillon and with the collective efforts of John Evangelista Purkinje, William James Herschel, Henry Faulds, and especially Sir Francis Galton [10], which contributed greatly to what has now become known as Fingerprint-Based Biometrics. Although initially these processes of authentication were carried out all manually by a person, with the advance of the technologies (second half of XX century), automated biometric systems were created and biometric identification became an automatic process [8].

Biometric authentication, or simply biometrics, may be defined as the automatic verification or identity recognition of an individual, based on physiological and behavioral characteristics [11]. Fingerprint [8], hand geometry [12], voice [13], iris [14], face (2D and 3D [15]), handwriting [16], and keystroke [17] are examples of such characteristics. Different biometric systems require specific technologies, depending on the physiological/behavioral characteristic being used [18, 19].

The search for biometric systems that are increasingly safe and efficient is what moves researchers in the field of biometrics. Although there are traditional biometric systems with high performance (e.g. fingerprints), these systems are not perfect and open up space for new ones to emerge, as presented in [1], [2], [5], [20], and [21]. Caution is needed, however, because although there are many modern systems applying to receive the title of biometric system, it should be noted that a high matching rate is not sufficient for them to be characterized as such. In fact, factors such as universality, permanence, acceptability, and others also need to be taken into account [22].

Observing the technological or methodological limits of some Conventional Biometric Systems (CBS), this work saw opportunities to present contributions. In particular, we will consider three widely used biometrics: fingerprints, facial and handwriting recognitions. Although considering the state-of-the-art, they all have many frailties and limitations [23]. Through the limitations of CBS, emerging systems, here called non-conventional biometric system (NCBS), are being proposed. It is at this moment that the main idea of this work is formed: contribute to non-conventional biometric system (NCBS) modalities based fingerprint, facial and handwriting recognitions.

In this work, the following systems will be called unconventional or non-conventional: Facial Recognition based on SIFT and SURF (FRSS), Touchless Multi-view Fingerprint (TMF) and on-line Handwritten Recognition based on Accelerometer/Gyroscope Signals (HRAS). In the next Sections (Sec. 1.1, Sec. 1.2, and Sec. 1.3) an overview of each of these systems and the problems that will be addressed by this work is presented.

1.1 FINGERPRINTS

Fingerprint-based biometric is nowadays the most used and acknowledge system [24]. If compared to other biometric features, fingerprints are considered to be most popular and largely used all over the world. A great part of applications is associated with civil identification and criminal investigation. Practically, all law enforcement departments [25] have an Automatic Fingerprint Identification System (AFIS) [26]. Despite its maturity and wide dissemination, it is believed that fingerprint acquisition, image processing and matching algorithms are not at their full and definitive potential [27]. Therefore, a more careful analysis shows that there is plenty of room for improvement in directions that do not only enhances the state-of-the-art, but also show new and better ways of performing biometry.We briefly describe a new **non-conventional** touchless multiview fingerprinting technology, illustrated in Fig. 1.1. It solves many problems of touch-based scanners, but is susceptible to new ones.

1.1.1 Problem Definition and Motivations - Liveness Detection on TMF Devices Using Texture Descriptors and Artificial Neural Networks

The evolution of biometric systems can be achieved through improvements in algorithms designed to extract discriminant features, or in acquisition hardware. Regarding biometric fingerprint-based technologies one may mention two principal categories [2]: (a) the traditional touchbased technology; and (b) the photographic touchless technology that do not require the user to place his fingers on an acquisition surface. Regardless the technology

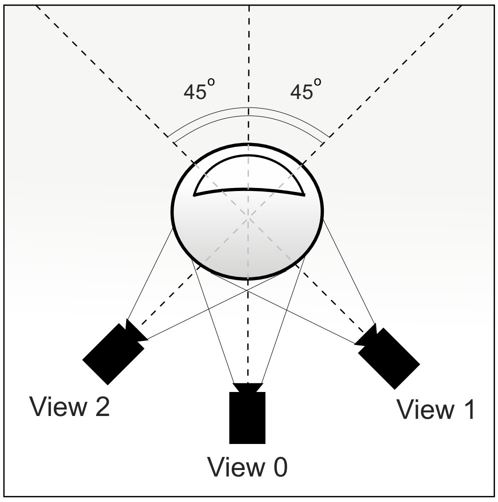


Fig. 1.1 – Schematic illustration of a touchless multi-view fingerprint device. There are three cameras that capture the central part and the two sides of the finger [1].

in use, the problem with biometric systems in general is that they do not perform perfect matches and, therefore, are subject to be attacked by fraudulent agents whose objective is to be identified as a valid user. Attacks on touchbased systems have been largely investigated. Regarding touchless technology, there is not much being done. Hence, in order to provide an understanding about malicious interactions with touchless devices, this work presents a method based on texture descriptors and artificial neural networks (ANN) that distinguishes whether a user is interacting with the scanner using a real finger or not (liveness detection).

1.2 FACIAL RECOGNITION

Facial recognition is the medium most commonly used by humans in the process of mutual identification. An individual is able to recognize a familiar face in an uncontrolled environment in about 100 a $200ms$ (milliseconds) [28]. Biometric systems based on the recognition of the human face generally explore characteristics related to the location and shape of facial attributes such as eyes, eyebrows, noses, lips and others. Challenges arise when the system is subjected to adverse conditions, e.g., movement of the identifiable persons, unpredictable behavior of the background of the image, multiple facial angles, variation of illumination. Even considering the state-of-the-art with regard to detection [4] and recognizing [29, 30, 31], this type of biometric system is still far from its definitive form and is a open field for improvements [32]. Although many techniques can be applied to improve face recognition, a good part of them make use of techniques based on artificial intelligence [33].

Artificial Intelligence (AI) research has evolved from different paradigms since its birth at the Dartmouth Conference in 1956 [34]. From the classical to the modern approach, where computational intelligence is the study of the design of intelligent agents [35], AI is concerned with intelligent behavior in artifacts [36]. Thus, modern AI deals with the design of intelligent systems with rational agents that can perceive and act upon the environment [37]. From this modern paradigm, new perspectives of AI study has emerged where traditional concepts such as pattern recognition, data mining, and numerical optimization are types of algorithms grounded to an environment as a systems approach using the sensor–algorithm–effecter view [38].

For the next-generation AI, known as the AI 2.0, the advanced intelligent systems have to be empowered with intelligent perceptual capabilities. Perception is cited as the interaction interface between intelligent systems and the real world. Perception is thus the most significant capability to empower intelligent systems. The state-of-the-art across different areas of perception in the AI 2.0 era includes visual perception [39, 40, 41].

Considering the research and development trends in visual perception of AI 2.0, this work investigates how a robust agent-based framework with face detection and identification can be used to manage individual tracking in real time on unconstrained environments. Our hypothesis is that without a flexible visual perception feature it is impossible to create advanced intelligent systems. Perception in an intelligent system begins with sensor data in various forms that is processed along with prior knowledge and models to extract relevant information to the task of agents in the AI system. Therefore, data from perception forms situational awareness that provides agents with a comprehensive knowledge about the state of the world necessary to understand, plan and execute tasks effectively and safely. In this sense, the idea is to used techniques that combine artificial intelligence, computer vision and multi-agent systems to enhance NCBS in order to perform individual tracking in unconstrained environments based on facial recognition.

1.2.1 Problem Definition and Motivations - Agent-based framework to individual tracking in unconstrained environments using FRSS

As a transformative perception technology, this work focuses on the non conventional automatic verification or recognition of an individual, based on physiological and behavioral characteristics through biometric systems [42, 43]. The current state-of-the-art face biometric algorithms performance is encouraging, as far as identification in controlled conditions is concerned [44, 45]. Thus, face recognition in constrained environments, especially considering the advances in deep learning, has achieved great success. Nevertheless, in more realistic scenarios, such as in unconstrained environments, it needs more research to effectively exhibit intelligent perception.

With the aim to contribute to NCBS based on face recognition that perform on unconstrained environments, this work presents a novel framework that combine various techniques to extract relevant information and proceed towards the task of detecting/identifying faces and perform individual tracking in unconstrained environments. Is is noteworthy that many real-world applications such as federal agencies, commercial organizations and banks can benefit from this kind of approach to increase their security systems, since they are public spaces and therefore cannot guarantee ideal operating conditions for conventional facial recognition systems to function properly.

The proposed framework performs face detection and identification using the Viola-Jones [4] and the Scale Invariant Feature Transform/Speeded Up Robust Features (SIFT /SURF) algorithms [46, 47], respectively. In addition, it makes use of a multi-agent system to carry out the individual tracking in unconstrained environment.

As the main contributions of this work we may cite:

- the development of a NCBS based on facial recognition that adequately recognizes and tracks individuals in unconstrained environments, indicating the path each individual has taken and how much time he spent in the field of view of the surveillance cameras;
- propose a NCBS that can be distributed in heterogeneous computational infrastructures equipped with a large variety of hardware and software.

1.3 HANDWRITING RECOGNITION

The way in which an individual writes is recognized as a characteristic of the individual [48, 49]. Handwriting, which is a behavioral characteristic (non-physiological) [50], is used as a legal mechanism of authenticity in notaries, bank transactions, and others. It is emphasized that because it is a behavioral characteristic, it changes over time and that sometimes the same individual produces substantially different signatures capable of inducing the system to mismatch [51, 50]. In this sense, it is important to search for improved methods that can perform better handwriting recognition biometrics despite these limitations. It is also noteworthy the fact that it is possible, with relative simplicity and depending on the signature/handwriting, that counterfeiters reproduce forged copies [52] capable of deceiving this biometric system (circumvention problem).

Although recent works have contributed to greatly improve the performance of handwriting recognition [53, 54, 55, 56], there is still a lot of room for refinements, especially with regard to circumventing the fraud problem. In this sense, on-line recognition emerges as a solution [57, 53].

1.3.1 Problem Definition and Motivations - On-line Handwriting Signature Recognition using Accelerometer and Gyroscope Signals

As previously mentioned, on-line handwritten signature recognition systems emerges because of the conventional system (off-line) frailties, especially with regard to circumvention. Although other works use methods based on on-line handwriting signature recognition [58, 59, 60, 61], to the best of our knowledge, none of them use of accelerometer signals obtained from a device embedded in a conventional low-cost pen. It is here that our method distinguishes itself. The idea is to propose an on-line handwriting signature recognition method using accelerometer signals. The signals are obtained from an accelerometer embedded in a traditional pen. The main hypothesis is that it is possible to identify an individual based on the analysis of their behavior while writing. This behavior will be expressed, in real time, in terms of a vector $\vec{a}(t)$, presenting the components $\vec{a_x}(t)$, $\vec{a_y}(t)$, and $\vec{a_z}(t)$, in axes x, y, and z.

Here, the principal motivation of the proposed solution is presented: build a low-cost device that can be embedded into a conventional pen that transmits accelerometer and gyroscope signals to a computer; build a database containing handwritten signals acquired from different subjects using the constructed device; develop a classifier to perform on-line handwriting signature recognition using accelerometer and gyroscope signals.

1.4 GENERAL HYPOTHESIS

Considering the limitations of traditional biometric systems, the general hypothesis is that it is possible to present unconventional solutions that use integrative techniques in a creative way in order to contribute to the advancement of biometrics since these solutions could operate better in certain situations in which conventional biometric systems are unable to operate or show limitations. Since this work seeks to contribute to the improvement of three biometric systems (fingerprint, facial and handwriting) in a particular way, the general hypothesis will be divided into three concrete sub-hypotheses.

1.4.1 First Concrete Hypothesis - Fingerprint

1.4.1.1 Context

The liveness detection is a step of fundamental importance to guarantee the integrity and reliability of biometric systems based on fingerprints. Although there are already known methods and techniques for performing life detection in touch-based fingerprint systems, there is still no consolidated method for detecting life in TMF-type systems.

1.4.1.2 Hypothesis

It is possible to detect life in photographic images of fingerprints obtained from TMF devices using texture descriptors and multilayer perceptron (MLP) classifiers differentiating real fingers from false fingers made of beeswax, corn flour play dough, latex, silicone, or wood glue.

1.4.2 Second Concrete Hypothesis - Facial

1.4.2.1 Context

Tracking individuals in uncontrolled environments has the potential for several applications. Here, applications related to security and commerce are highlighted. The problem is that limitations in network and hardware configurations, in addition to the limitations linked to traditional face recognition algorithms that require prior classifier training, add obstacles to the implementation of tracking systems/models that are interoperable and flexible and that can operate in a vast and uncontrolled environment such as a mall or even a smart city.

1.4.2.2 Hypothesis

It is possible to create an interaction and communication model that is capable of operating regardless of any network, operating system and hardware configurations using intelligent agents to track individuals in unconstrained environments using and flexible facial recognition techniques that do not require prior training.

1.4.3 Third Concrete Hypothesis - Handwriting

1.4.3.1 Context

The individual's hand moves uniquely when handling pens during the writing process. In this sense, it would be possible to use accelerometer signals acquired from sensors embedded into pens for biometric purposes to perform online signature recognition.

1.4.3.2 Hypothesis

Simple characteristics extracted from accelerometer and gyroscope signals acquired by a sensor embedded into a pen that captures these signals while users sign their names are sufficient to identify individuals with a reasonable level of precision when submitted to an MLP classifier.

1.5 OBJECTIVES

1.5.1 General Objective

Contribute to the improvement of non-conventional biometric systems based on fingerprint, facial and handwriting recognitions presenting methods that can operate better in certain situations where conventional systems cannot operate or show limitations.

1.5.2 Specific Objectives

To contribute to the improvement of non-conventional biometric systems based on fingerprint, facial and handwriting recognitions, the following specific objectives are presented:

- Present a novel method for detecting life on TMF Devices using Texture Descriptors and Artificial Neural Networks;
- Create a novel method of tracking people using multi-agent systems and cloud communication based on unconventional facial recognition to perform the tracking;
- To propose an on-line low-cost handwritten signature recognition method that uses accelerometer and gyroscope signals obtained from a sensor coupled to a conventional pen, to identify individuals in real time.

1.6 A GLIMPSE OF THE RESULTS

With regard to the detection of life in TMF-type devices, the proposed method was able to distinguish between real fingers and fake fingers 100% of the time. In an attempt to not only detect fake fingers, but also to correctly classify them in one of the six classes (real, beeswax, corn flour play dough, latex, silicone and wood glue), the accuracy was not absolute only when using silicone fingers. In this case, 7.14% of the times, silicone fingers were confused by being classified as beeswax or corn flour play dough. Although the method for detecting life has achieved its objective since it always correctly detects life, silicone has proved to be the most challenging material to be correctly classified.

Regarding the model for tracking individuals in an uncontrolled environment, the results were also promising. The tests were performed in real time simulating real operating conditions and were conducted using different hardware and software configurations and the individuals were correctly tracked. There was no occurrence of false negatives and the records made by the system were consistent with the records noted by the human operator.

Finally, with regard to on-line handwriting signature recognition using accelerometer and gyroscope signals, results were also promising. The trained and tested classifier has reached an overall hit rate of 92.4%. All detailed results achieved by this work can be found in Chapter 6.

1.7 DOCUMENT STRUCTURE

This document is defined as follows: Chapter 2 presents a survey of biometric systems as well as a discussion about the relevance of this work. Chapter 3 presents the related works and base concepts of TMF, FRSS and HRAS. Chapter 4 contains the methodological aspects of the research and Chapter 5 contains the proposed solutions for the three NCBS explored in this work. Finally, Chapter 6 and Chapter 7 present the detailed results and conclusions, respectively.

2 BIOMETRIC SYSTEMS

Due to the real needs of each practical application, different biometric systems can be used proposed. Each system presents pros and cons and suited a certain degree of requirement with regard to the seven biometric factors (universality, distinctiveness, permanence, collectability, performance, acceptability, circumvention). Among the various types of existing biometrics systems, here we highlight the main ones:

1. **Fingerprints** - Fingerprints have been used as an attempt to identify individuals for decades [8, 32]. They are recognized for their high correspondence rate [62, 63] and the low cost of sensors (less than U$50.00 for most sensors) [32]. They are notoriously the most commonly used type of biometrics, whether on popular devices (e.g., laptop, smart-phone, record and point of workers and others) or for government purposes associated with civil identification or criminal investigation. Although it is the most widely used biometric system, it is possible to highlight some vulnerabilities such as the need for huge amounts of computational resources to perform the identification of individuals taking into account the millions of fingerprints stored in databases and the fact that a small fraction of the population is unfit for this type of biometry because of genetic characteristics, aging, or working conditions (e.g., manual workers performing activities that destroys their fingerprints [32]).

2. **Handwriting** - The way in which an individual writes is recognized as a characteristic of the individual [48, 49]. The Handwriting, which is a behavioral characteristic (non-physiological), is used as a legal mechanism of authenticity in notaries, bank transactions and others. It is emphasized that because it is a behavioral characteristic, it changes over time and that sometimes the same individual produces substantially different signatures capable of inducing the system to mismatch. Also noteworthy is the fact that it is possible, with relative simplicity and depending on the handwriting style of individuals, that counterfeiters reproduce forged copies [52] capable of deceiving this biometric system (circumvention problem).

3. **Face Recognition** - Facial recognition is undoubtedly the medium most commonly used by humans to identify themselves [64]. An individual is able to recognize a familiar face in an uncontrolled environment in about $100 - 200$ ms (milliseconds) [28]. Biometric systems based on the recognition of the human face generally explore characteristics related to the location and shape of facial attributes such as eyes, eyebrows, noses, lips and others. The problem with this type of system is that when subjected to adverse conditions (e.g., movement of the identifiable persons, background of the image does not present predictable behavior, different angles of the same face, different lighting conditions and others) results in a low correspondence rate. Even

considering the state of the art in terms of detection [1] (*Viola-Jones*) [4] and face recognition [29, 30, 31], this type of biometric system is still far from its definitive form and is open field for enhancements [32].

4. **Voice Recognition** - Voice-based biometrics is a combination of physiological and behavioral characteristics [65]. In terms of physiological characteristics it is possible to highlight the shape of the mouths, vocal cords, nose and others. In terms of behavioral characteristics it is possible to highlight the emotional state, aging, how environmental characteristics (humidity and temperature) influence the voice and others. Due to the above mentioned facts and also due to the noise generated by generic environments, speech recognition is not used in a large scale, being generally restricted to uses of less complexity [32].

5. **Hand Geometry** - The general shape of the hands, finger sizes, finger thickness, palm area, and other measures can be used as discriminant characteristics among individuals [66]. One of the major problems in this type of biometry is permanence factor, since the geometry of the hand undergoes very relevant changes with the aging of the individual, especially when young. Although it is not susceptible to problems related to the environment (e.g., dryness, humidity and others), hand geometry is not recognized as being a biometry that has traits of singularities that are very discriminative and also presents problems related to accessibility once that individuals may have skill problems, jewelry on the fingers and difficulties in properly positioning the hand in the correct position for acquisition [32].

6. **Palm-print** - In much the same way as fingerprints, the impressions of the palms of the hand are composed of ridges and valleys from which it is possible to extract singular discriminating minutiae [66]. The major limitation of this type of system is that because the area of the palms is larger than the area of fingerprints, they require larger and more expensive sensors [32]. However, with the advancement of high-definition quality photo capturing devices, it is possible to glimpse a promising future for this type of system [67].

7. **Iris** - Iris recognition can be defined as the process of recognizing a person by analyzing the iris pattern of that individual's iris. Its texture has permanent minutiae and discriminative enough to guarantee the uniqueness of this type of biometrics [68]. In spite of having high matching rates, it is a relatively invasive method, since the subject must position his eye (fragile and prone to being protected by the human) in a scanner for the acquisition of iris sample [69].

8. **Keystroke** - Biometrics based on the way an individual types on a computer keyboard is called keystroke. Although it is not a sufficiently discriminatory biometric system

[1] Detection means only that there is a face in a given scenario, it should not be confused with recognition or identification that carries the meaning of correspondence.

to obtain the trait of uniqueness among all individuals, it is discriminative enough to allow, to some extent, the identification of persons [70]. It should be noted that this biometric system is based on behavioral and non-physiological aspects [32].

9. **Gait Recognition** - This biometric system is based on extracting traces of uniqueness from the way people walk (march). It is a biometric system that combines behavioral and physiological traits. It distinguishes itself from other biometric systems because it is capable of recognizing individuals at a distance, for example in environments with security cameras. In general this type of biometry takes into account the shape of the individual's silhouette [71] (e.g., optical flow) pattern and patterns of movement [72].

10. **Brain-prints** - A type of biometry that allows individuals to be identified from electroencephalogram (EEG) patterns [73]. In this biometric system, people are presented with situations in which there is a pattern of brain response associated with certain external stimuli (e.g., presentation of written words before the eyes). The stimuli cause distinct reactions in the brain of each individual, and these reactions can be imprinted and stored in EEGs that are presented in a discriminant enough way so that individuals can be recognized [74]. It is noteworthy that this biometric system is both behavioral and physiological [74, 73, 75].

Note that all types of biometric systems previously described can be classified as physiological, behavioral or physiological-behavioral. The Figure 2.1 illustrates the classification of biometric systems taking into account these aspects.

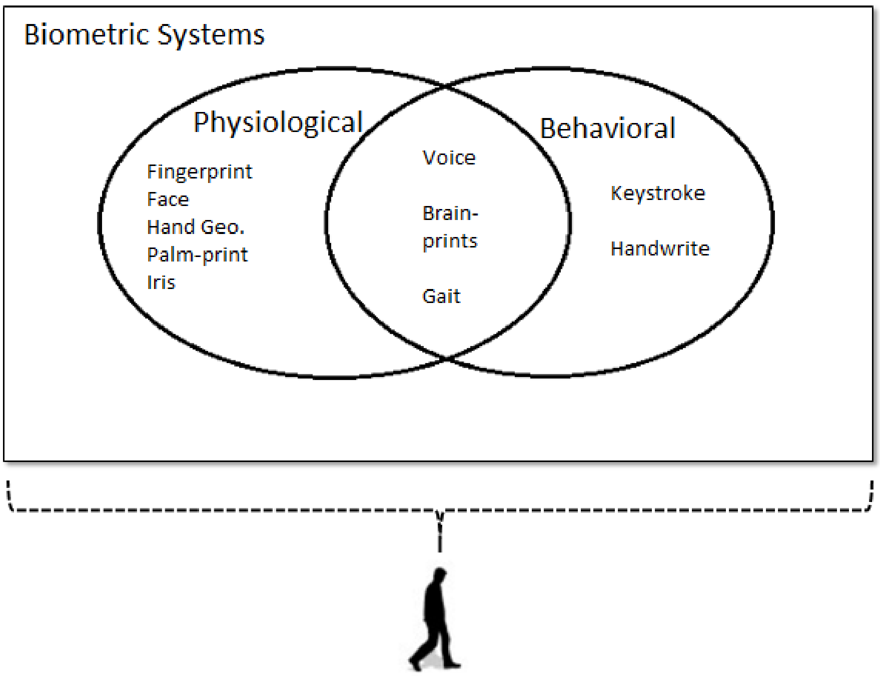


Fig. 2.1 – Illustration of Biometric types.

2.1 NON-COVENTIONAL BIOMETRIC SYSTEMS APPROACH

Various studies on user's acceptance and satisfaction of biometric systems have being carried out [76, 77, 78, 79, 80]. It is noteworthy that fingerprint, facial and handwriting recognitions figure among the most relevant and used biometric systems. Considering this three biometric modalities, they all present limitations. In this sense, emergents NCBS modalities for each one of them are being proposed.

Here we highlight three NCBS:

- Touchless Multiview Fingerprint Systems [81, 1, 2, 82];
- Unconstrained Facial Recognition based on SIFT/SURF transforms applied to individual tracking [5, 20, 83, 84, 85].
- On-line handwriting Recognition [86, 57, 87].

In Chapter 3, a detailed discussion of these systems is presented. In addition, the main concepts to understanding the proposed solutions are also presented in Chapter 3. In the next Section, a short quantitative survey of related works is presented.

2.2 QUANTITATIVE SURVEY OF RELATED WORKS

With the purpose of attesting the relevance of this research, a quantitative survey of published papers related to this work was carried out. The idea is to compare the progression of the number of papers published on CBS and NCBS over the year (from 2010 to 2018). Figures 2.2, 2.3, and 2.4 present side by side two graphics. The ones on the left refer to traditional systems and the ones on the right refer to non-conventional systems. Scales are normalized.

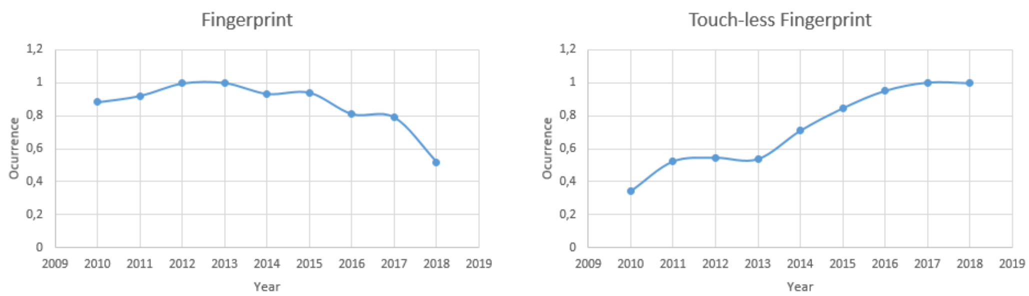


Fig. 2.2 – Comparison between fingerprint CBS and NCBS with respect to progression of number of papers published over the years.

Undoubtedly, non-conventional biometric systems are gaining notoriety. It is clear that the number of papers related to NCBS based on fingerprint and facial is increasing, on the

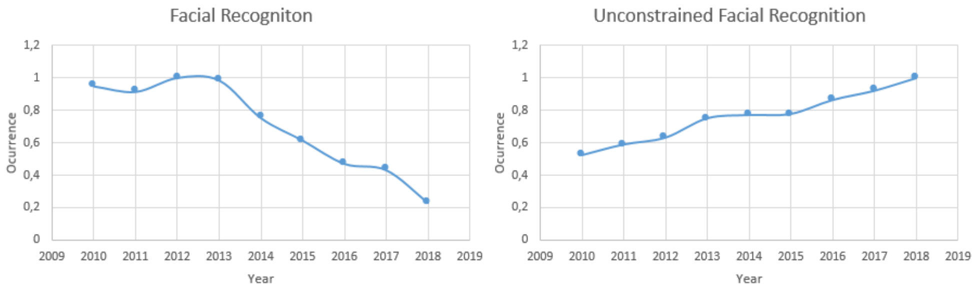


Fig. 2.3 – Comparison between facial CBS and NCBS with respect to progression of number of papers published over the years.

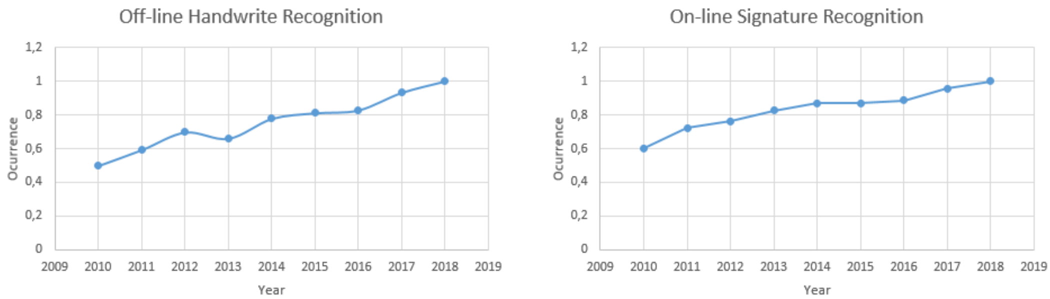


Fig. 2.4 – Comparison between handwriting CBS and NCBS with respect to progression of number of papers published over the years.

other hand, with respect to CBS, the number is decreasing. For handwriting biometric systems, one should note that for both (CBS and NCBS) the number of papers are increasing. Finally, it should be remarked that this quantitative survey was made using Google Scholar as search engine. A more complete and qualitative survey related to state of art on TMF, FRSS and HRAS can be found in Sections 3.1, 3.2 and 3.3, respectively.

3 RELATED WORKS

This Chapter is divided into three sections containing related works of: i) fingerprints systems; ii) face recognition; iii) handwriting recognition. Although these sections address different issues, they all have the same structure. The idea is to present general concepts and related works about each type of NCBS.

3.1 FINGERPRINT SYSTEMS

The input of fingerprint authentication systems are digital images representing the ridge-valley structure of real fingers [32]. In general, fingerprint technologies deal with touchbased acquisitions. That means, they require users to press their fingers against an acquisition surface. However, solutions that do not demand contact (touchless) have increasingly being proposed [88, 89, 90, 91, 92] in order to overcome the intrinsic problems related to touchbased technologies. Next, these two paradigms are briefly discussed.

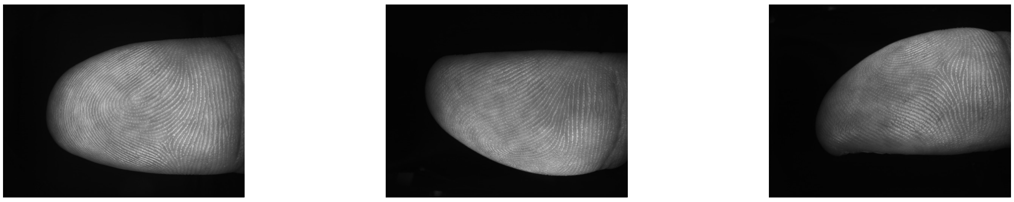
3.1.1 Touchbased acquisitions

The quality of acquired fingerprints clearly affects the overall performance of a fingerprint recognition system. Most of today's fingerprinting technology is touchbased. Major problems with this kind of technology are the uncontrollable distortions and inconsistencies that may be introduced due to skin elasticity. Fingerprint quality may also be seriously influenced by non-ideal contact caused by dirt, sweat, moisture, excessive dryness, air humidity, temperature and latent fingerprints [32]. In some scenarios, the above-mentioned drawbacks impose the need of several acquisition attempts per finger, in order to ensure a high quality template and the enrollment process may become very time-consuming if the number of users to be registered is large. Although over the past few years many algorithms have been proposed to compensate the limitations of touchbased technology, this sensing paradigm may represent a bottleneck for further improvement of fingerprint image quality. Instead of generating a representation of the finger that tries to mimic ink-based samples, one can use a more faithful high definition photographic image [93, 94].

3.1.2 Touchless acquisitions

Touchless devices do not compel users to press their fingers on a platen and rely on photographic acquisitions. Among the proposed touchless solutions, TBS'[1] devices [92] use

[1] http://www.tbs-biometrics.com/de/



(a) (b) (c)

Fig. 3.1 – Set of images captured by a three-camera touchless fingerprint sensor: (a), (b), and (c) exemplify capture by the main camera and cameras spaced 45 degrees counterclockwise and clockwise, respectively [2].

an interesting approach. It combines reflection-based touchless finger imaging with a three-camera multiview system. One camera is positioned to capture the portion of the finger where normally the core and deltas are located; and taking this central camera as a reference, the other two are displaced by 45 degrees clockwise and counter-clockwise. An example of acquisition is depicted in Figure 3.1.

3.1.3 Attacks on Biometric Systems

The attempt to circumvent a biometric system is called attack. It can be performed in many different ways and is classified into indirect attack (consists of an action inside the system) or direct attack (the attacker interacts with the biometric system directly through the acquisition sensor) [95]. In Figure 3.2, (a) illustrates a direct attack, while (b) to (e) show indirect attacks. Although in (b) the attack is performed on the sensor level, it requires some knowledge about the internal architecture of the system, thus is considered as an indirect attack. This work is concerned only with direct synthesis attacks (fingerprints are synthesized and presented to the sensor).

Traditionally, a direct attack can be further classified into 3 subcategories: (a) obfuscation (the attacker changes his biometric traits so that the system is not able to recognize him); (b) zero-effort attack (the attacker presents himself as a valid user and simply provides his biometric traits unchanged); and (c) spoofing (the attacker mimics the biometric traits of a valid user) [95]. It is important to mention that direct attacks do not require an intruder to have any specific technological skills, representing a great risk regarding identification systems [95].

Spoofing requires the use of some kind of artificial material in order to reproduce an authentic fingerprint captured from latent samples, which, for instance, are very likely to be found on mobile phone touch-screens. Therefore, before allowing the system to perform feature extraction and posterior matching, one may insert a liveness detection module right after or in parallel to the acquisition step [2].

Liveness detection algorithms design must consider three dimensions: (a) static or dy-

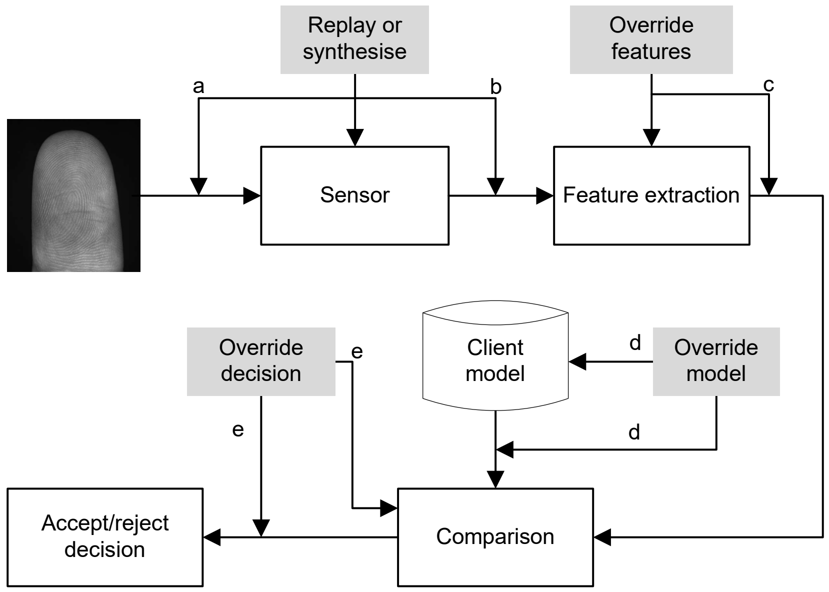


Fig. 3.2 – Points of vulnerability of a biometric system: (a) attack on the acquisition module, replayed or a synthesized finger is presented to the sensor; (b) attack on the acquisition module, insertion of a replayed or synthesized fingerprint image into system, after the sensor; (c) attack on features detection module; (d) attack on the client model (template database); (e) attack on the accept/reject module [2, 3].

namic (operates on one or multiple frames); (b) dependent of user training (requires the user to perform a specific previously trained procedure); and (c) binary or user specific (indistinctly classifies all presented samples as live or spoof; or is included as part of the user's biometric template) [96].

Liveness detection for traditional touchbased scanners has already been addressed [97, 98, 99, 100]. For touchless scanners, however, the topic still remains to be explored. Considering the previous definitions, the main objective in this work is to present a method based on artificial neural networks, texture descriptors and principal component analysis that implements a static, user independent, binary liveness detection for touchless biometric fingerprinting devices. It is assumed that also in this kind of scanners an efficient liveness detection module will decisively contribute to minimize successful spoofing attacks [2].

Next we describe the texture descriptors used as inputs to our classifier.

3.1.4 Texture Descriptors

Texture descriptors are techniques that extract features from an image and use them to provide information that differentiates it from other images. Three texture descriptors will be described, as follows: Local Binary Pattern [101], Improved Local Binary Pattern [102] and Gray Level Co-occurrence Matrix [103].

3.1.5 Improved Local Binary Pattern

The Local Binary Pattern (LBP) [104] is a simple computational technique that consists of analyzing the neighborhood around each pixel in grayscale images in order to generate codes that describe them.

The neighborhood of a pixel p can be defined in many different ways. The neighborhood of special interest in this work is the one composed by the 8-connected closest pixels $N_8(p)$ that surround p in the vertical, horizontal and diagonal directions.

Since an 8-connected neighborhood is used, the LBP algorithm generates an 8-bit code for all pixels p in the image. The bits are set to 0 or 1 depending on the difference between p and each of its 8 neighbors $N_8^i(p)|_{i=0..7}$. If the difference is greater than or equal to 0, then a bit 1 is assigned to that specific neighbor. Otherwise, the bit is set to zero. Finally, in order to guarantee rotational invariance, 7 circular shifts are applied to the 8-bit binary code. The minimum integer value observed is chosen as the final descriptor.

The Improved Local Binary Pattern (ILBP)[105] includes the main properties of LBP, but presents some extra features which enable the detection of patterns that classic LBP is not able to detect. The first difference between them is that instead of using p to compute de binary codes, it uses the average (here denoted avg) of N_8 including p. In other words, considering $P_9(p) = \{N_8^i(p)|_{i=0..7} \cup p\}$, if $avg(P_9(p)) - P_9^i(p)|_{i=0..8} \geqslant 0$, then a bit 1 is assigned to the $i\text{-}th$ pixel of $P_9(p)$. Otherwise, the bit is set to zero. It is important to notice that, since the central pixel is now included, i varies from 0 to 8 and the binary code has 9 bits. Here rotational invariance is also achieved by successive shifts until the code with minimum value is found.

3.1.6 Gray-level Co-occurrence Matrix

The Gray-level Co-occurrence Matrix (GLCM) [106] is another technique used for image texture description. Its simplest configuration consist of a $L \times L$ matrix where the elements at coordinate (i, j) represent the number of times two adjacent pixels have the values i and j in the original image. However, this method is not limited to just one specific direction, a single neighboring pixel or two dimensions. More complex uses may be employed.

Among the 14 measurements that can be derived from the GLCM, 4 are most commonly used [106, 107], namely, contrast (f_1), correlation (f_2), energy (f_3) and homogeneity (f_4). These measurements, used to compose the texture descriptor, are defined according to Equations 3.1 to 3.4,

$$f_1 = \sum_{k=0}^{G-1} n^2 \left\{ \sum_{n=1}^{G} \sum_{n=1}^{G} p(n,m) \Big|_{|n-m|=k} \right\} \quad (3.1)$$

$$f_2 = \sum_{n=0}^{G-1} \sum_{m=0}^{G-1} \frac{(nm)p(n,m) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (3.2)$$

$$f_3 = \sum_{n=0}^{G-1} \sum_{m=0}^{G-1} p(n,m)^2 \quad (3.3)$$

$$f_4 = \sum_{n=0}^{G-1} \sum_{m=0}^{G-1} \frac{p(n,m)}{1 + (n-m)^2} \quad (3.4)$$

where G is the number of gray levels in the image, $p(n, m)$ is the normalized GLCM matrix, and μ_x, μ_y, σ_x and σ_y are the mean and standard deviations for $p_x(i)$ and $p_y(j)$, marginal-probability vectors obtained by summing the rows and the columns of $p(i, j)$, respectively.

In Section 5.1 the proposed method is detailed and in Section 6.1 results are presented.

3.2 FACE RECOGNITION

In this Section, an overview of concepts related to intelligent agents and MAS, face detection and face identification will be presented. The idea is to present related works and some concepts that are essential to completely understand the proposed solution presented in Section 5.2.

3.2.1 Intelligent Agents and MAS

According to [108] and [109], MAS are systems composed of multiple interacting computing elements called agents. An agent is a computational entity situated in some environment being able to perceive its states and act upon it. As intelligent entities, agents have autonomous capabilities to act with flexibility, according to a variety of environmental circumstances. Agents can use diverse processes, such as searching mechanisms, constraint satisfaction, planning and learning skills. Thus, intelligent agents are to some extent able to act autonomously in order to achieve their design objectives and interact with other agents, not simply exchanging data but actively engaging in cooperative and/or competitive scenarios. In summary, intelligent agents are capable of social interactions, analogous to humans daily activities, involving communication (e.g., semantically rich languages) and making decisions based on norms, negotiation, argumentation, voting, auctioning, and coalition formation.

In [108] there is a formal definition of the abstract concept of an agent. We can assume that each agent has a finite set of actions Ac to transform the states of the environment $Ac = \{\alpha_0, \alpha_1, \alpha_2, ...\}$. The environment E is formed by a discrete set of states $E = \{\epsilon_0, \epsilon_1, \epsilon_2, ...\}$.

The run r of an agent in an environment is a sequence of states and actions $r : \epsilon_0 \overset{\alpha_0}{\rightarrow} \epsilon_1 \overset{\alpha_1}{\rightarrow} ... \overset{\alpha_{n-1}}{\rightarrow} \epsilon_n$, while R is the set of all possible finite sequences over E and Ac. R^{Ac} and R^E are subsets of R that end with an action or an environment state, respectively. The effect that an agent's actions have on the environment is represented by the state transformer function $\Gamma : R^{Ac} \rightarrow \wp(E)$. This function maps a run that ends with an action to a set of possible environmental states. In addition, the environment is assumed to be history-dependent, which means that earlier actions also play a part in determining the current state in the environment. Since agents are autonomous, there is uncertainty about the result of performing an action in some state (non-determinism). If $\Gamma(r) = \emptyset$ and r ends with an action, the system has ended its run. Thus, an environment can be represented by a triple $Env =< E, \epsilon_0, \Gamma >$. Based on the presented definitions, we say that two agents Ag_a and Ag_b are behaviorally equivalent with respect to Env, if $R(Ag_a, Env) = R(Ag_b, Env)$.

In order to exchange and understand messages, agents in MAS must use an ACL. In literature, there are many proposed agent languages, e.g., speech acts [110], knowledge query and manipulation language (KQML)/knowledge interchange format (KIF), and the ACL standard of FIPA [111]. In general, an ACL can be seen to have two main components: a performative verb (request, inform, inquire) and a propositional content (propose, accept, reject, retract, disagree, counter-propose a course of action). In FIPA-ACL there are many performatives with a basic structure including information of sender, receiver, content, language, and ontology (i.e., specific concepts and relationships of a domain). The performatives are used to pass or request information, negotiate, perform actions, or error handling (failure, not-understood). The communication protocol of MAS can be specified at several levels: lowest – specifies the method of interconnection; middle – specifies the format (syntax) of information being transferred; and top – specifies the meaning (semantics) of the information.

Another well-known important requirement of MAS is the interaction protocol [108, 37, 109]. Agent interaction protocols enable agents to have conversations with a structured exchange of a series of messages where agents have conflicting (self-interested) or similar goals (cooperative). In literature, there are some well-known interaction protocols for expertise exchange (blackboard systems) or negotiation (contract net, unified negotiation protocol, market mechanisms). The widely-applied task-sharing protocol for task allocation is the contract net. The contract net has two agents with different roles: the manager - announce a task, receive/evaluate bids, award a contract, receive results; and the contactor - receive task announcement, evaluate/respond/decline/perform the task, report results.

To perform the communication process among MAS, it is possible to use cloud storage services hosted by a third party outside of the organization and accessed through the public Internet. According to [112], many applications require communication and synchronization between processes. Normally, commercial cloud platforms provide ready access to scalable compute and storage services, implementing communication and synchronization. The use of cloud resources releases the dependence on communication processes that is important to many applications that rely on distributed and parallel processing, involving the exchange of data, information and knowledge in unconstrained environments.

3.2.2 Face Detection

The Viola-Jones object detection framework is cited in literature as a real-time algorithm for human face detection that can use images directly acquired from devices [4]. The algorithm is constructed over four main concepts: Haar-like features, integral image, AdaBoost and cascade classifier. A Haar-like feature can be defined as a two-dimensional Haar function used to represent local aspects of objects [113], as exemplified in Figure 3.3.

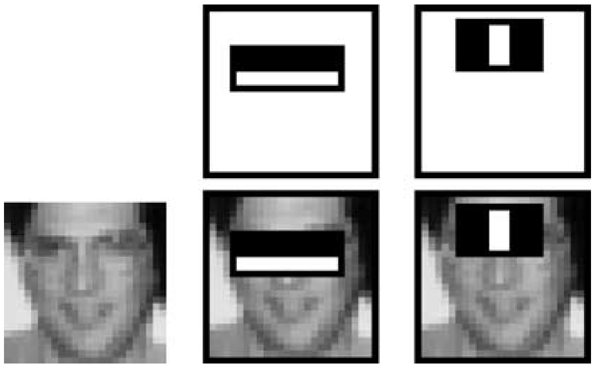


Fig. 3.3 – Examples of Haar-like features used by the Viola-Jones algorithm [4].

The sum of the pixels within the white area is subtracted from the sum of the pixels in the black area. Since the set of rectangular features may be very large, an integral image $I(x, y)$ is used as an alternative representation for the original image $O(x, y)$. In this representation, the values of $I(x, y)$ are equal to the sum of all values above and to the left of $O(x, y)$. Once an integral image is available, the features can be more efficiently calculated, since the vertices of rectangular areas now represent previously computed summations and, consequently, are sufficient to compute the summation of the pixels within these areas. The extracted features are then used to train a classifier. [4] introduced in their framework a variant of AdaBoost [114]. In fact, a cascade of classifiers is applied. The idea is to construct a single, fast and strong classifier combining many weak classifiers.

The visual perception process starts with the object detection stage, but following that the next step is to perform identification. In this work we have used the *Speeded-up Robust Features* (SURF) algorithm [46, 115] which will be detailed in Section 3.2.3 focusing on face identification.

3.2.3 Face Identification and Tracking

Since our framework is meant to track individuals using facial identification, it is necessary to determine which algorithm should be used. Three of the most predominant approaches are Principal Components Analysis (PCA), commonly called Eigenfaces [29], Linear Discriminant Analysis (LDA) [30], and Elastic Bunch Graph Matching (EBGM) [31]. Although the SURF detector [115] has not been originally proposed as a biometric tool, it has been applied as such as described in [116]. In this research work, we used SURF in the identification module because of complexity matters, since the framework is meant to be flexible. Nevertheless, any facial identification algorithm may substitute SURF without compromising the proposed framework as a whole.

The SURF is a technique based on the *Scale-Invariant Feature Transform* (SIFT) algorithm [47] and is intended to recognize objects by extracting points of interest [115]. According to [47], the SIFT technique evaluates four major stages to achieve a scale-invariant feature descriptor: scale-space extrema detection, keypoint localization, orientation assignment and keypoint descriptor. Both techniques, SIFT and SURF, evaluate these four major stages [115, 47]. Given these four stages, the main differences between both techniques is that scale-space is implemented in SIFT using *Difference of Gaussians* (DoG) convolved by images with different sizes (spatial resolution); in SURF, this stage is implemented using different sizes of the box filter convolved with the integral image, as described in [4]. In the keypoint descriptor stage, both use non-maximum suppression and determine the potential keypoints using the Hessian matrix. Compared with SIFT, the SURF technique is more robust and uses less computation time to extract the keypoint descriptors.

The SURF technique may be adapted to perform face identification if applied after the face detection (Section 3.2.2). When a face is detected in an image, a region of interest that contains the detected face is used to extract an array with a set of keypoints descriptors returned by SURF. This array is used as a face template at the user enrolment and identification processes. To achieve a true positive identification, at least three keypoint matches between the enrolled template and any acquired image is required.

Although there is a considerable number of work related in some sense to the agent-based framework proposed, none present a solution to the agents' visual perception that encompasses all aspects of this research work, as will be explained.

Face recognition systems are among the most reliable biometric systems. They are totally unobtrusive and a natural mode of identification among humans. In well-behaved environments, the performance can be compared to fingerprints. However, in unconstrained environments, the accuracy is reduced due to a number of factors, such as illumination and pose, and the challenge is to improve robustness under adverse settings [117]. For instance, [118] present a fully automatic face recognition system robust to most common face variations in unconstrained environments. The system is capable of recognizing faces from non-frontal views and under different illumination conditions using only a single gallery sample for each subject. Another approach is proposed by [119], which addresses the problem of unconstrained environments using a multiscale directional framework called Shearlet Network (SN), to extract facial features, and a refinement of the Multi-Task Sparse Learning (MTSL) framework. As one last example, [120] apply multiscale morphological techniques to compensate the illumination effects that appeared while extracting both the small-scale features and the texture information.

In [119], [118], and [120] the main goal is to improve the robustness of face recognition systems in general. There is no concern with a specific application, but in [121] an application is presented. It aims to enable the participants of a conference to easily identify each other, thus facilitating socialization and avoiding embarrassments. According to the authors, recognition is possible from an arbitrary view of a subject, although only frontal images are used as training images. It is assumed that the conference participants have uploaded a frontal photo during the registration process.

It is important to say that, although face recognition is an important feature in the proposed framework, this work is not about improving facial biometric systems methods. Hence, an off-the-shelf algorithm is used (SIFT/SURF). Nevertheless, the SIFT/SURF algorithm can be replaced by another more robust face recognition module without interfering with the framework as a whole.

Considering human tracking, environment monitoring and video surveillance topics, we note an increasing attention over them in the past years. As a first example, one may cite the work of [122], where a laser-based system that can simultaneously perform tracking, semantic scene learning, and abnormality detection in a fully online and unsupervised way is proposed. These tasks are done cooperatively, improving their respective performances. The main operation scenario is a large, crowded public area that demands public security. Another example of human tracking is the online human interaction detection and recognition presented by [123]. The authors address this problem using a network of multiple cameras from which interactions are modeled. A survey is presented by [124] on this topic. Finally, regarding human tracking, the paper presented by [125] is worth mentioning. Their solution addresses a multiagent path-planning problem where several robots track humans to obtain detailed information on human behaviors and characteristics. The distinctive factor here is that a multiagent approach is applied.

In summary, [119], [118], and [120] address only the problem of face recognition robustness. The method presented by [121] involves face recognition but is meant to be applied in a specific scenario and depends on registration, human interaction and training. Furthermore, it does not use a multiagent/camera approach and cloud storage. Human tracking presented by [122] is a laser-based system and does not rely on video cameras. In [123] a multicamera approach for human tracking is presented, but as in [122] and [125] no face recognition is performed. In [125] a multiagent approach for human tracking is used, although it is not done by means of face recognition.

MAS applied to face identification has already been presented by previous work from [126]. In this example, the multiagent approach improves facial identification, but does not use a multicamera and is not meant to be applied in an unconstrained environment. A surveillance system based on multicamera face detection, identification and tracking has also been presented by previous work from [127]. However, it does not use agents and cloud storage. Some very recent works uses convolutional neural networks to perform face identification. [128], for instance, propose a comprehensive framework based on Convolutional Neural Networks (CNN) to overcome challenges in video-based face recognition. Another example is [129], which propose a multi-scale parallel convolutional neural network architecture to extract deep robust facial features with high discriminative ability. In summary, there is much work related to face recognition, individual tracking, and MAS, but none present a framework that unifies such characteristics. Table 3.1 summarizes the comparison between the related work and the proposed method in this paper. Thus, to the best of our knowledge, the framework presented in this work is the only one that combines agents, cloud storage services and face recognition techniques to track individuals in unconstrained environments useful to real applications (e.g. surveillance).

Tab. 3.1 – Comparison between methods using the characteristics: Agent Oriented, Cloud Storage Services, Face Recognition, Unconstrained Environment, Real Application, and Tracking.

Method	**Characteristics**					
	Ag. Oriented	Cloud	Face Recog.	Unc. Env.	Real Aplic.	Tracking
[118]			X	X		
[119]			X	X		
[120]			X	X		
[121]			X	X	X	
[122]				X	X	X
[123]			X	X	X	X
[125]	X			X	X	X
[3]	X		X			
[127]			X	X	X	X
Proposed Method	**X**	**X**	**X**	**X**	**X**	**X**

3.3 HANDWRITING RECOGNITION

In this Section, an overview of concepts and works related to handwriting biometric systems are presented. The idea is to make clear the relevance of the research and provide all the information necessary to ensure fully understanding of the proposed solution presented in Section 5.3.

Signature verification is not a trivial process, even for human specialists. Since it is classified as a form of behavioral biometry, handwritten signature is the result of a complex process depending on the physical and psychological circumstances of the signer, as well as the circumstances of the signing process [130, 131, 132].

Therefore, signature verification has attracted many researchers who are interested in the development of applications that automatically recognize signatures, in view of the important role of signatures for biometric recognition of individuals [131].

The signature acquisition methods are divided into on-line (dynamic) and off-line (static). Static systems use off-line acquisition devices that capture signature data after it has been written. Dynamic systems use on-line acquisition devices that generate electronic signals that represent the signature during the writing process [133, 134].

A large number of papers deal with off-line handwriting identification [86]. Regardless of the specificities of the used method, handwritten input is always an image (e.g. scanning the writing on paper) which contains letters or words [86].

With the advancement of computer systems, automatic methods to identify individuals based on handwriting traits have been gaining ground. Thus, a series of techniques, features, and classifiers are proposed in order to achieve higher accuracy in the people authentication process, based on their signatures. One of the most popular classifiers is the Support Vector Machine (SVM) [135, 136, 137, 135]. However, other classifiers such as Bayesian-based [138], Voting Features Intervals (VFI) [139], a combination of multiple distance-based classification techniques (Euclidean Distance and fractional distance classification techniques) [140], bio-inspired [141], k-nearest neighbor (KNN) [142], and pixel-to-pixel relationship [143, 144] are also proposed.

Some recent papers present very interesting methods and results. In [53], a system and method that is able to recognize a user's natural superimposed handwriting without any explicit separation between characters is presented. Another interesting approach is presented in [145], which improves signature verification exploring multi-loss functions for convolutional neural networks (CNN). Another proposal is presented in [146], where an Adaptive Neuro-Fuzzy Inference System (ANFIS) is used. First, an efficient feature extraction module based on five feature extraction techniques is performed. Second, an optimal feature selection method for feature ranking and feature reduction is proposed.

In the work of [147], a deep neural network is used to solve the problem of biometric identification. Additionally, it also applies neuroevolution techniques to enhance the classifier performance. As well as [147], [148] also use deep neural networks, but rather than use neuroevolution, it uses connectionist temporal classification to identify the user. Although all the papers cited are recent, none of them makes use of on-line handwriting signature recognition techniques. On-line methods are considered more efficient than off-line, but more challenging too [86].

Another approach of signature acquisition with a biometric objective is using electronic devices equipped with touch screens and sensors, such as tablets. Some examples of works that use this technology are [149], [150], [151], and [152]. Despite having data of movements of the pen on the screen during the signature, the on-line method has inconsistencies since the sensors of different device models generally have different levels of capture quality, making the comparison between signatures of the same individual captured in distinct devices more improbable. Another disadvantage of this approach in contrast to signatures made on paper is the general lack of ergonomics of touch screens devices, which may influence the format of the signatures [153].

Another type of on-line signature capture system is dedicated pens with specialized hardware attached to provide on-line signature data [133]. In this way, individuals normally sign on paper and the pen extracts data related to movement, tilt, pressure, and other features during the signature process. For example, [154] presents a method of performing the biometric authentication using artificial neural networks (ANN) fed with the sound of frictions between rigid-nib pen and paper.

Also using a pen equipped with sensors, [155] present a study of user authentication based on the Reduced Dynamic Time Warping (RDTW) technique. The Biometric Smart Pen BiSP, a ballpoint pen equipped with 5 sensors (pressure on the tip, x and y position, grip pressure, acceleration, and tilt), performed the acquisition of handwritten single characters of 10 different persons, PIN words, and signatures of 21 different persons. Dynamic Time Warping (DTW) is a widely used method for aligning signals and compute the Euclidean Distance between them, which is used as an important feature in the classification process. Beyond Bashir and Kempf's work, [156], [157], and [158] are examples of classification using the DTW technique.

More similar to the proposed method, [159] provide user classification from signals acquired from a six-axis motion sensor attached at the top of the pen. The motion sensor consists of a Bluetooth 4.0 module and a motion-tracking sensor MPU 6050 that comprises a 3-axis gyroscope and a 3-axis accelerometer. Connected to the motion sensor, a mobile phone records the signature movement and sends the data to a server that is responsible for preprocessing, feature extraction, and classification.

Another interesting method is using data from movement sensors attached to a glove. [137] captures in-air-handwriting signatures and uses SVM as a classifier.

[160] present a word generator method that simulates handwriting using Generative Adversarial Networks (GAN) [161]. If it is applied to the signature, this method may be able to forge handwritten signatures, which can compromise the off-line signature authentication method, since the analysis of signature images leaves great opportunities for signature forgery [162].

Table 3.2 summarizes the main characteristics of the present methods and shows that the proposed method is the only one that uses accelerometer signals, is low-cost, uses a common pen, and artificial neural networks (ANN) as classification method, thus making evident the contribution of this work for biometric systems based on on-line signatures.

Tab. 3.2 – Comparison among related works that used a dynamic (on-line) system. The presented characteristics are: Biometrics purpose, type of capture sensor, number of individuals in dataset, number of samples per individual in dataset, low-cost method, uses a common pen, ANN classifier, and number of features. The proposed method is the only one that uses accelerometer signals, is low-cost, uses a common pen, and ANN as a classification method.

Work	Bio.	Cap. Sensor	Dataset		Low-cost	Common pen	ANN	No. Feat.
			no. of persons	samples per person				
[163]		touchpad and pen	25	3				-
[164]		PDA	18	1040				21
[165]		digital notepad	300	100				181
[166]		touchscreen tablet	100	1000				4
[167]	X	touchscreen device	16	6				-
[149]	X	touchscreen tablet	100	10				23
[150]	X	touchscreen device	40	20			X	not fixed
[152]	X	digital pen and notebook	15	50				62
[154]	X	microphone	6	50	X	X	X	100
[155]	X	multi-sensors	21	10				-
[159]	X	accelerometer	63	312		X		14
Proposed method	**X**	**accelerometer**	**50**	**12**	**X**	**X**	**X**	**133**

4 METHODOLOGY

The methodology of this work is exploratory. As a primary reference source we used conference articles, journal articles, master's thesis and doctoral thesis. As secondary sources books, survey articles and participation in conferences in the area of biometrics were used. After the bibliographical survey, it was possible to verify that the area of biometrics has been gaining more and more space among the scientists and that a special attention to the Non-Conventional Biometric Systems has been given. Also as a result of the bibliographic survey, it was possible to realize that although the research in conventional biometric systems has been losing space among the researchers, for non conventional systems, because their emerging nature, there are still many gaps and problems to be solved. In particular, there were three major problems in the literature that caught our attention:

- There is no definitive method to Liveness Detection on Touchless Fingerprint Devices;
- Facial Recognition Algorithms tend to lose performance when subjected to adverse conditions, most of these algorithms require previous classifier training in order to work and tracking of individuals using face identification is still a challenge to researchers;
- There is no definitive method accepted by the community to perform on-line handwriting signature recognition.

In order to contribute to the solution of these problems we have proposed three new solutions that we believe contribute to NCBS:

- A method to perform liveness detection on touchless fingerprint devices using texture descriptors and artificial neural networks;
- An agent-based framework to individual tracking in unconstrained environments using face recognition based on SIFT/SURF;
- An on-line low-cost handwriting signature recognition method using accelerometer signals and artificial neural networks.

After the bibliographic survey, the definition of the problem and the solutions proposal, the data collection phase was started for further testing and validation of the proposed methods. To do so, we used a set of biometrics acquired from people that serve as subject to this research.

To test and validate the method of Live Detection on TMF Devices, a dataset of images was constructed and used to train, validate and test the feedforward neural network classifier.

This dataset is composed by images of real fingers and images of fake fingers synthesized using 5 different materials (beeswax, corn flour play dough, latex, silicone, and wood glue). The real fingers subset was constructed as diversified as possible, containing different skin tones, thus raising the classification challenge. To acquire these samples a TMF device described in Section 6.1 was used.

To test and validate the agent-based framework to individual tracking in unconstrained environments using face recognition based on SIFT/SURF, individuals served as subjects. In real time, they exchanged places with each other in the front of the Intelligent Agents 1 and 2 in order to simulate an uncontrolled environment and situation. Details of this experiments can be found in 5.2.1.

Finally, to test and validate the on-line handwriting signature recognition method using accelerometer and gyrosvope signals, handwritten samples from people was collected. To acquire the database, a conventional pen was used in which a MPU 6050 sensor that comprises a 3-axis gyroscope and a 3-axis accelerometer was coupled. In summary, the proposed method consists of five phases: 1) signals acquisition and database creation; 2) samples preprocessing; 3) features extraction; 4) classifier training with cross-validation; and 5) best classifier architecture definition.

Next Chapter presents the detailed proposed solutions for the three above-mentioned NCBS, as will be seen.

5 PROPOSED SOLUTIONS

In this Chapter, the proposed solutions for all three NCBs problems explored is this works are presented. First, we present a solution to liveness detection on touchless fingerprint devices using texture descriptors and artificial neural networks. Secondly, a agent-based framework to individual tracking in unconstrained environments are presented. And finally, an on-line low-cost method to handwriting signature recognition using accelerometer signals is shown.

5.1 LIVENESS DETECTION ON TOUCHLESS FINGERPRINT DEVICES USING TEXTURE DESCRIPTORS AND ARTIFICIAL NEURAL NETWORKS

The proposed method aims to evaluate images captured by a multiview touchless fingerprinting devices in order to detect liveness as means of preventing spoofing attacks. Each step, presented in Figure 5.1, will be detailed in the next sections.

5.1.1 Image Acquisition

The biometric device produces samples composed by three images captured by equidistant cameras placed along a 90 degrees arch. Although all three images may be used, only the main view, shown in Figure 3.1 (a) is considered. As described in Section 6.1, satisfactory results are achieved without using the other two views, with the advantage of reducing the complexity of the training algorithm.

5.1.2 Pre-processing

The pre-processing steps prepare the image for the ILBP and GLCM texture extraction algorithms. The result is an enhanced image with the finger's region segmented. The pre-processing steps are detailed below.

1. **Circular averaging filter**: reduces noise.
2. **Binarization**: binarizes image with a global threshold.
3. **Morphological operation**: removes remaining noise after binarization.
4. **Segmentation**: defines a region of interest.
5. **Histogram equalization**: applies histogram equalization to the region of interest.

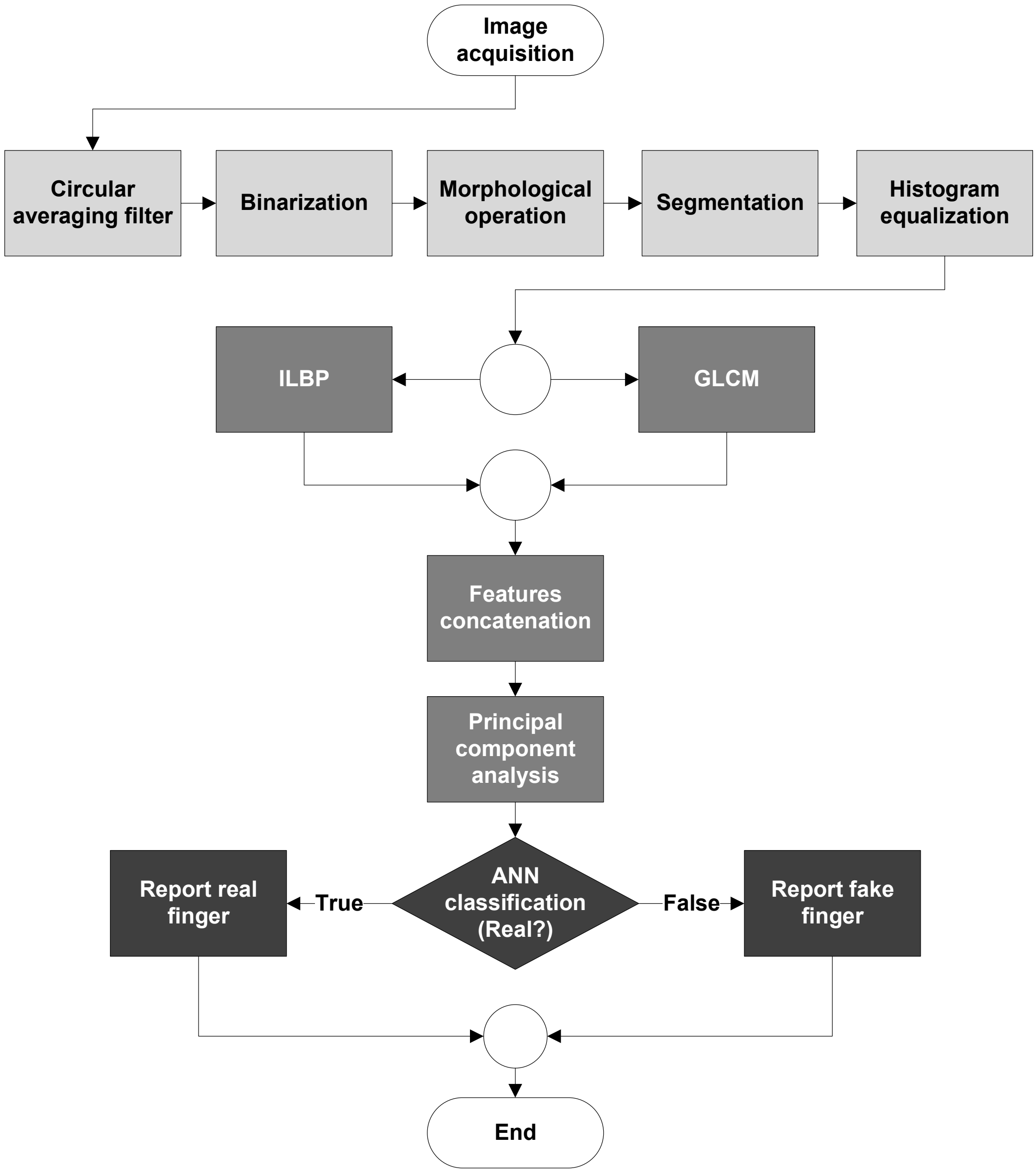


Fig. 5.1 – Fluxogram of the proposed method: (a) pre-processing (light gray); (b) feature extraction and dimensionality reduction (mid gray); (c) classification (dark gray).

5.1.3 Feature Extraction

The proposed method uses a combination of the ILBP and GLCM texture descriptor. They are evaluated only for pixels belonging to the region of interest (foreground). From the GLCM matrix, the contrast, correlation, energy and homogeneity calculations are used. The features vector, v_c, is defined by Equation 5.1. It is noteworthy that 8 GLCM matrices are calculated considering all the directions determined by the current pixel being analyzed, p, and the pixels belonging to $N_8(p)$. The final value for contrast, correlation, energy and homogeneity are defined as the average of the 8 values calculated from the 8 GLCM matrices.

$$v_c = [a_1 \ldots \; a_{512} \quad b_1 \quad b_2 \quad b_3 \quad b_4], \tag{5.1}$$

The coefficients a_1 to a_{512} and b_1 to b_4 represent the ILBP and GLCM descriptors, respectively.

5.1.4 Principal Component Analysis

The Principal Component Analysis (PCA) [168] is a technique that may be applied to problems where the reduction of complexity is critically necessary. In classification problems, for instance, it accomplishes this goal by reducing the dimensionality of feature vectors. PCA generates the so-called principal components, an orthogonal basis which are nothing more than new features that result from the linear combination of those that make up the original vector. The dimensionality reduction of the original problem occurs through the elimination of principal components that do not contribute significantly to the reconstruction of the original signal. In other words, it concentrates in a small number of components most part of the energy contained in a signal. Our input vector, v_c, is composed by a significant number of features (516) and, therefore, a principal component analysis is performed in order to eliminate potential irrelevant data, generating a new input vector, v_{PCA}.

5.1.5 Classification

Using the processed vector v_{PCA} as input, a feedforward artificial neural network (ANN) will be used to classify the acquired samples. The possible classification scenarios are:

1. real fingers $\times$ all fake fingers;
2. real fingers $\times$ fake beeswax fingers;
3. real fingers $\times$ fake corn flour play dough fingers;
4. real fingers $\times$ fake latex fingers;
5. real fingers $\times$ fake silicone fingers;
6. real fingers $\times$ fake wood glue fingers;

7. classification returns one of six possible classes (real, beeswax, corn flour play dough, latex, silicone, or wood glue).

The proposed ANN is composed by three layers: the input layer, one hidden layer and the output layer. The first layer is composed by the input vector v_{PCA}. The hidden layer is composed by a variable number of neurons defined experimentally for each scenario. Here it is assumed that the kind of neural network chosen as our classifier can approximate any function with a finite number of discontinuities arbitrarily well [169]. As for the output layer, there are two possibilities: for Scenarios 1 to 6 (see above), the output layer has only one neuron and generates a real number between -1 and $+1$. In this case, the expected target α is defined as shown in Eq.5.2; for Scenario 7, the output layer is composed by 6 neurons and generates an output vector. Here, the classifications are made comparing the output vector with the expected target vector Φ, as shown in Eq.5.3.

$$\alpha = \begin{cases} +1, & if \;\; real\, finger \\ -1, & if \;\; fake\, figer \end{cases} \tag{5.2}$$

$$\Phi = \begin{cases} [+1\ -1\ -1\ -1\ -1\ -1]^t, & if\, real \\ [-1\ +1\ -1\ -1\ -1\ -1]^t, & if\, beeswax \\ [-1\ -1\ +1\ -1\ -1\ -1]^t, & if\, dough \\ [-1\ -1\ -1\ +1\ -1\ -1]^t, & if\, latex \\ [-1\ -1\ -1\ -1\ +1\ -1]^t, & if\, silicone \\ [-1\ -1\ -1\ -1\ -1\ +1]^t, & if\, woodglue \end{cases} \tag{5.3}$$

Except for the input layer, whose neurons uses linear transfer function, all neurons, in all scenarios, have hyperbolic tangent transfer functions [64]. Section 6.1 shows the experimental results obtained by the proposed method.

5.2 AGENT-BASED FRAMEWORK TO INDIVIDUAL TRACKING IN UNCONSTRAINED ENVIRONMENTS USING FRSS

Consider a public environment under video surveillance, such as a mall with many places and individuals. With a set of cameras, the individuals are detected as soon as they enter the mall entrance by distributed surveillance agents. The agents, located in different parts of the environment, are using face detection, identification and tracking algorithms. Thus, it is possible to track the individual throughout his journey and send the information to other agents using a shared directory in the cloud. The agent-based framework can integrate heterogeneous computational infrastructures from different organizations as illustrated in Figure 5.2.

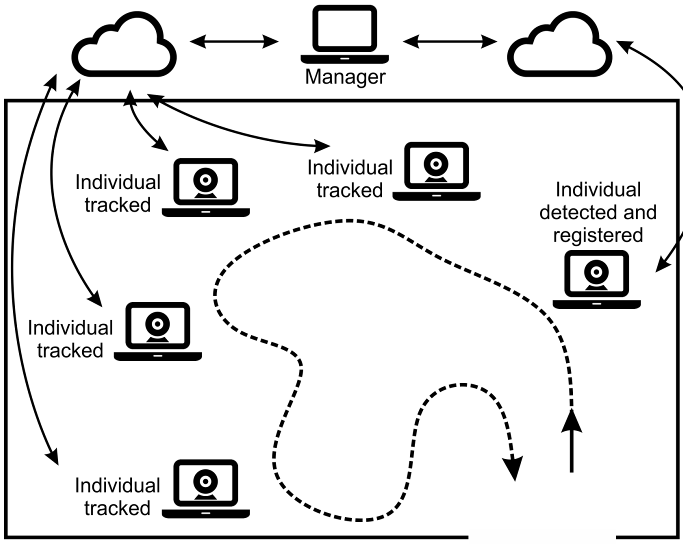


Fig. 5.2 – Agents with specific computer vision tasks such as detection, identification and tracking of individuals within a surveillance area [5].

In this way, the shop owners can customize client services in an individual-based way or security processes can be applied to specific environments or events. With this motivation in mind, the agent-based framework is detailed in the next sections.

5.2.1 Agents Design

According to the definitions presented in Section 3.2.1, in order to propose a NCBS that carry out individual tracking on unconstrained environment, a MAS is proposed. Three different types of agents were defined: Ag_1, Ag_2, and Ag_3. A finite set of actions Ac was defined for each type of agent related to the environment's discrete set of states E. The tasks for each type of agent are different since they have different design objectives: face detector (Ag_1), face tracker (Ag_2), and manager (Ag_3). Our proposal is extensible, since we can have many agents of the same type which are behaviorally equivalent. Depending on the size of the environment where the framework is running, we can define more agents of the same or different types. In addition, it does not matter where they are located (e.g., different stores, halls, food courts) since they communicate using the same protocol through cloud resources.

According to [37], to specify the agent design project four properties must be considered. These properties form the acronym PEAS – **P**erformance measure, **E**nvironment, **A**ctuators, **S**ensors. The PEAS description is also called the task environment and is considered the first step to design an agent, being as fully detailed as possible. In the PEAS description, the performance measure describes the desired qualities of the agent. The environment definition is related to where the agent is going to perceive and act. The environment can be described as fully or partially observable, deterministic or stochastic, episodic or sequential, static or dynamic, discrete or continuous, and single or multiagent. The actuators describe the possible actions taken by agents. The sensors capture the agents' perceptions in relation to the state of the environment.

Table 5.1 presents the PEAS for each type of agent in the proposed framework. The environment of the manager agent (Ag_3) is fully observable considering the shared directory in the cloud since it guarantees communication among all agents in the framework. Note that the environment in which the agents are designed is the real world, known to be the most complex to implement the agents' functions since it involves the following dimensions: partially observable, stochastic, sequential, dynamic, continuous, and multiagent.

Tab. 5.1 – PEAS description of the task environment for agent types Ag_1, Ag_2, and Ag_3.

Face Detector (Ag_1)	**Face Tracker** (Ag_2)	**Manager** (Ag_3)
Performance: 1. correctly crop face template; 2. automatically detect individuals.	**Performance**: 1. recognize faces (true positives); 2. track faces; 3. properly register tracking time.	**Performance**: 1. guarantee communication; 2. generate reliable and complete logs.
Environment: partially observable, stochastic, sequential, dynamic, continuous and multiagent.	**Environment**: partially observable, stochastic, sequential, dynamic, continuous and multiagent.	**Environment**: fully observable, stochastic, sequential, dynamic, continuous and multiagent.
Actuators: 1. Viola-Jones algorithm; 2. send messages.	**Actuators**: 1. SURF algorithm; 2. send messages.	**Actuators**: 1. define ID numbers; 2. send messages; 3. start up and shut down system.
Sensors: 1. camera; 2. receive messages.	**Sensors**: 1. camera; 2. receive messages.	**Sensors**: receive messages.

5.2.2 Framework Architecture

The defined agent-based framework is composed of the three different types of intelligent agents illustrated in Figure 5.3.

Considering the multiple interactions and different tasks executed by the three agents described in Table 5.1, we highlight the visual perception scheme where the agents' functions can be executed in a public environment, e.g., a shopping mall or bank. Briefly explaining the architecture, the manager agent Ag_3 is responsible for starting up (inform begin system message) and shutting down the system (inform end system message), sending messages to agents type Ag_1 and Ag_2 (arrows number 1 and 4). The face detector agents $Ag_{1,1}$ +

$Ag_{1,2}...Ag_{1,n}$ are responsible for detecting individuals, taking pictures, cropping faces and sending the cropped faces to a shared directory in the cloud. They also send the path and the file name of the cropped faces to the manager agent Ag_3 (inform cropped face message, arrow number 2) (see also Figure 5.4). Manager agent Ag_3 is responsible for managing the individuals tracking in the surveillance environment. It sends a *cfp* message in broadcast to the face tracker agents $Ag_{2,1} + Ag_{2,2}...Ag_{2,n}$ (Figure 5.7) (call for proposal message, arrow number 4). Face tracker agents Ag_2 send proposals to the manager agent Ag_3 (proposal message, arrow number 3). Manager agent Ag_3 accepts one of the proposals and refuses the others from the tracker agents Ag_2 (accept/reject messages, arrow number 4). The contracted tracker agent Ag_2 performs the identification and individual tracking sending messages to manager agent Ag_3 (inform statistics and new status "available", arrow number 3). Notice that the communication of the agents is performed in the cloud, allowing the interaction despite the computational specificities of the devices where each agent is installed.

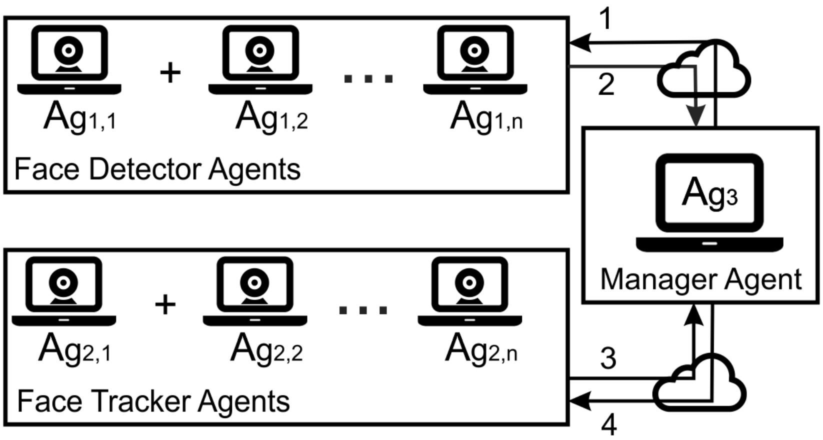


Fig. 5.3 – The agent-based framework architecture.

The tasks executed by the three defined agents are detailed as follows:

- Face detector (Ag_1): detects the presence of an individual entering the environment, stores the arrival time and takes a picture of the individual. It acts on the image captured by the entrance camera and uses the Viola-Jones algorithm to detect the individual's face in an efficient and timely manner (Section 3.2.2). After detecting the face, the region where it was found is automatically cropped and saved in the online directory shared among the other agents. After saving the face, Ag_1 sends a message to Ag_3 (Figure 5.4) informing where it was stored in the shared directory in the cloud (path and file name).

- Face tracker (Ag_2): identifies individuals that enter the areas that are under surveillance. Since there are several agents of this type, Ag_3 is responsible for deciding which one will execute the identification and face tracking task. When the Ag_2 receives the *cfp* from Ag_3 informing that a new individual has been detected by Ag_1, it reads the image specified in the content of the message sent by Ag_1 and begins the tracking procedure. As detailed in Section 3.2.3, the identification algorithm uses the individual's face (detected and sent by Ag_1) as the face template. Ag_2 also generates the statistics of each individual and sends them to Ag_3.

- Manager (Ag_3): performs the *cfp* for identification and tracking of individuals. This agent receives the image (face) path sent by Ag_1 and makes a proposal for all agents of type Ag_2. The Ag_2 agents that identify an individual send a bid to Ag_3, which in turn decides who will be in charge of facial tracking. Figure 5.7 illustrates this process. In addition, Ag_3 may be connected to an internal database and saves details of the individuals' behavior. With this information, it is possible to make inferences and predict an individual preference. If the framework is installed in a mall, for instance, the system may propose customized services for frequent customers using their mapped behavior. In addition, Ag_3 may suggest new product pricing, sales promotions, inform about details of the inventory, among other functionalities.

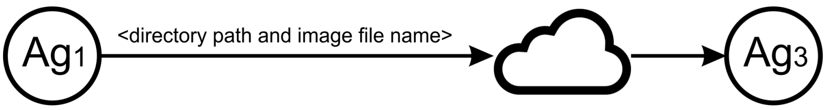


Fig. 5.4 – Communication between Ag_1 and Ag_3: the Ag_1 sends the directory path (e.g.:/user/cloud/) and the name of the file that contains face detected to Ag_3. Under these conditions, Ag_3 will be able to carry out the call for proposal.

5.2.3 Communication and Interaction Protocols

The agent-based framework uses the FIPA-ACL (see Section 3.2.1) as the communication protocol. Details of the performatives are presented in Figure 5.5. The presented eleven performatives include the four negotiation performatives provided by the FIPA communication language: *accept-proposal*, *call for proposal–cfp*, *proposal*, and *reject-proposal*. The passing information FIPA performative *inform* with six inform messages: *begin system, ID number, cropped face, status, statistics, and end system*. And the performing actions FIPA performative *request* with *request ID number*.

As shown below, the two fundamental performatives of FIPA communication language *request* and *inform* are exemplified (as presented in Figure 5.5). These performatives form the basic mechanism for communicating information. Note (see example below) that the *request ID number* performative is sent by Ag_2 (agent2) and received by Ag_3 (agent3), where the content is the "ID number"using the FIPA-ACL language and the system ontology. The *inform ID number* performative is sent by Ag_3 (agent3) and received by Ag_2 (agent2) with the content of the ID number 50.

```
(inform begin system
        :sender agent 3
        :receiver all
        :content "begin system"
        :language FIPA ACL
        :ontology system
)
```

```
(request ID number
        :sender agent 2
        :receiver agent 3
        :content  ID
        :language FIPA ACL
        :ontology system
)

(inform status
        :sender agent 2
        :receiver agent 3
        :content "available/busy"
        :language FIPA ACL
        :ontology system
)

(call for proposal
        :sender agent 3
        :receiver all agents 2
        :content  directory path
        :language FIPA ACL
        :ontology face recognition
)

(accept-proposal
        :sender agent 3
        :receiver agent 2
        :content "begin tracking"
        :language FIPA ACL
        :ontology system
)

(inform statistics
        :sender agent 2
        :receiver agent 3
        :content  Face number; time
        :language FIPA ACL
        :ontology time; log
)
```

```
(inform ID number
        :sender agent 3
        :receiver agent 2
        :content  ID number
        :language FIPA ACL
        :ontology system
)

(inform cropped face
        :sender agent 1
        :receiver agent 3
        :content directory path; and time
        :language FIPA ACL
        :ontology Viola-Jones; Face detection
)

(proposal
        :sender agent 2
        :receiver agents 3
        :content "able to track"
        :language FIPA ACL
        :ontology system; SURF algorithm
)

(reject-proposal
        :sender agent 3
        :receiver agent 2
        :content "cancel tracking"
        :language FIPA ACL
        :ontology system
)

(inform end system
        :sender agent 3
        :receiver all
        :content "end system"
        :language FIPA ACL
        :ontology system
)
```

Fig. 5.5 – Communication performatives used by agents according to the FIPA communication language.

```
(request ID number                 (inform ID number
     :sender agent2                     :sender agent3
     :receiver agent3                   :receiver agent2
     :content ID number                 :content ID number 50
     :language FIPA ACL                 :language FIPA ACL
     :ontology system                   :ontology system
)                                  )
```

In this research, the cloud communication is used by the framework agents allowing the share of information through a directory as illustrated in Figure 5.6. Since the communication between the agents is performed via cloud communication, no operating systems or devices will be regarded as incompatible or will affect the exchange of messages. Any agent running on any machine with sufficient computational power, located in any place, will be able to exchange messages and files with other agents.

Fig. 5.6 – Cloud communication among agents.

The interaction protocol used to allocate tasks is the contract net [170], as illustrated by the UML sequence diagram of Figure 5.7. Notice that agent Ag_3 sends a *cfp* broadcast to all agents Ag_2, which send back tracking bids. Agent Ag_3 then awards a contract to the closest agent Ag_2 that is next to the tracked individual, who sends back an "accept" answer. The chosen agent Ag_2 keeps tracking the individual's face until it is unable to continue and sends a failure message to agent Ag_3. The agent Ag_3 sends a new *cfp* and the cycle restarts.

5.2.4 The Framework in a Nutshell

As presented, the cloud communication is carried on by three types of cooperative agents that work together to perform recognition and tracking of individuals in unconstrained distributed environments using conventional cameras and computers. The detailed description of each agent type, the architecture and the communication and interaction protocols have already been explained (Sections 5.2.1, 5.2.2, and 5.2.3). The framework implementation was done using open source resources. In fact, the C^{++} language [171] and OpenCV library Version 2.9 [172, 173] were the resources used. The complete implementation code is available in Github at `https://github.com/BiT-Group/AgentBasedFramework`.

Figure 5.8 details the proposed framework. Note that the agents' interaction and communication are such that the system is capable of performing the detection, identification and

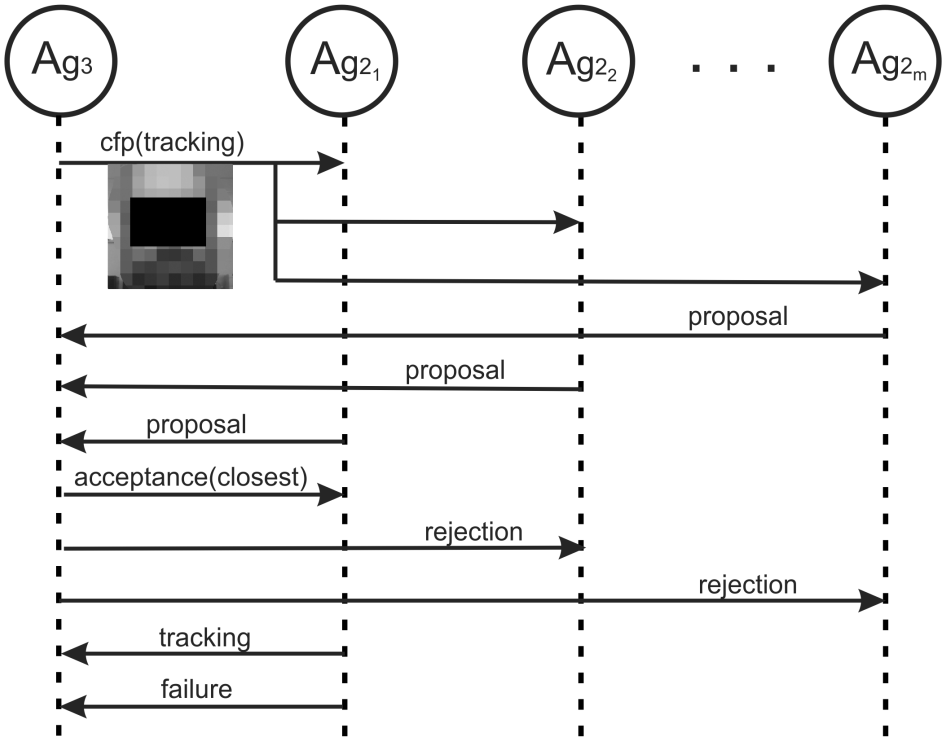


Fig. 5.7 – UML sequence diagram of the Contract Net Protocol.

tracking of individuals. Most of the multiple agents are equipped with cameras running on different computers. As detailed in Sections 5.2.1 and 5.2.2, face detector agent type Ag_1 is responsible for carrying out the detection of new individuals that step into the environment. Face tracker agent type Ag_2 is responsible for the recognition of individuals. The manager agent is Ag_3 that is responsible for managing the tracking as a global task, among other tasks.

The workflow shows that there are no limits or restrictions to the number of Ag_1 or Ag_2 that can be added to the framework, but only one Ag_3 is allowed. One thing to observe is that a new Ag_2 needs to receive an ID number (*request ID number* and *inform ID number* performatives) from Ag_3 as presented in Section 5.2.3. However, this is not necessary for a new Ag_1. This happens because, as shown in Figure 5.7, the Contract Net Protocol between Ag_3 and Ag_2 demands Ag_2 agents to have univocal identification in order to guarantee that the performatives work properly (see Figure 5.5).

To ensure a more comprehensive understanding of the agent-based framework, a step-by-step of the agents' behavior is presented:

1. The Ag_3 sends a performative (*inform begin system*) which is available to all agents of the framework indicating that the system is set up.

2. At any time, multiple Ag_1 and Ag_2 log in or out of the framework.

3. One of the Ag_1 detects an individual and sends a performative (*inform cropped face*) to the Ag_3.

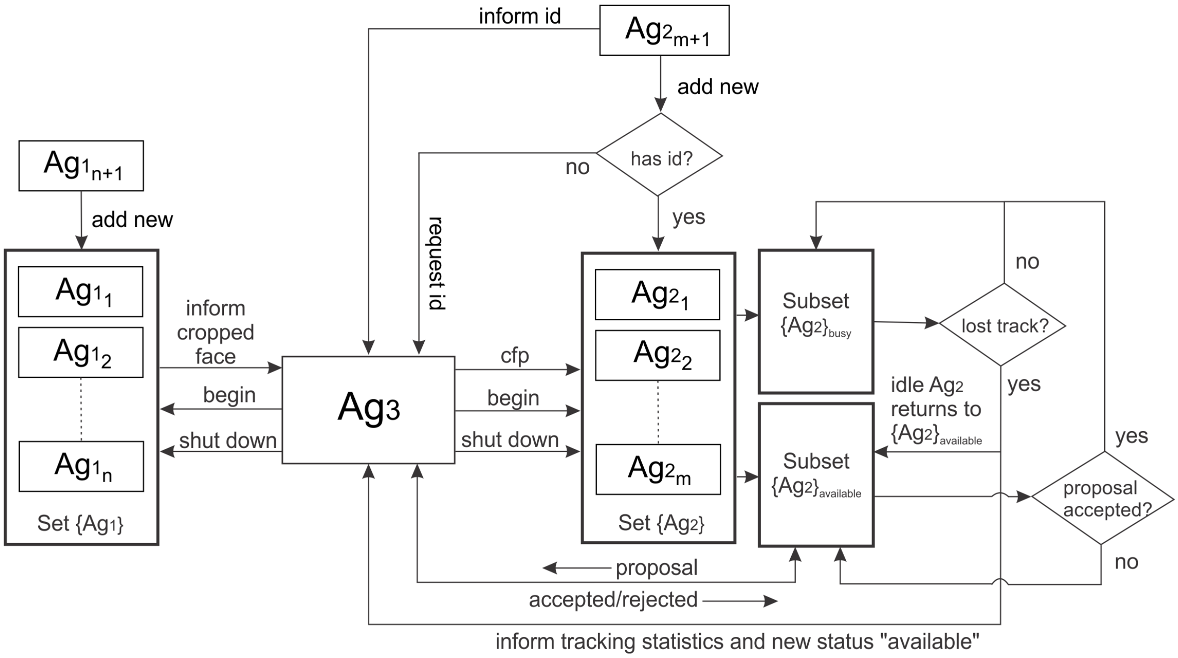


Fig. 5.8 – Workflow of the proposed framework: interaction and communication between agents.

4. Ag_3 triggers a *call for proposal* performative to all Ag_2.

5. All available Ag_2 send a *proposal* performative.

6. Ag_3 accepts one of the proposals (*accept proposal* performative) and refuses all others (*reject proposal* performative).

7. Ag_2, which is carrying out the facial tracking, is now characterized as a busy agent and stays this way until it loses track and reports *inform statistics* and a new status (*inform status* “available”) to Ag_3, showing that now it is able to identify and track a new individual.

8. At any time, Ag_3 can *inform end system* to shut down the framework.

It is important to notice that the framework agents generate a log file showing all times and positions in which each individual was identified during his permanence inside the environment where the framework is being executed. The log file is generated using the complete set of statistics sent to Ag_3 through the *inform statistics* performatives executed by Ag_2. With this statistics it is possible to track all the places where an individual has been, as well as the exact time he visited each place.

Tests were performed in order to evaluate the feasibility of the proposed framework. The tests description and the results are presented in Section 6.2.

5.3 ON-LINE HANDWRITING RECOGNITION USING ACCELEROMETER AND GYROSCOPE SIGNALS

Considering that the purpose of the present method is to identify users (biometry) based on real-time signals obtained from an accelerometer embedded in a pen and using a classifier, a database was created and a feedforward multilayer artificial neural network is considered as a classifier. In summary, the proposed method consists of five phases: 1) signals acquisition and database creation; 2) samples prepossessing; 3) features extraction; 4) classifier training with cross-validation; and 5) best classifier architecture definition. In Figure 5.9, the condensed proposed method workflow is presented. Details of the method will be presented in the subsections that follow.

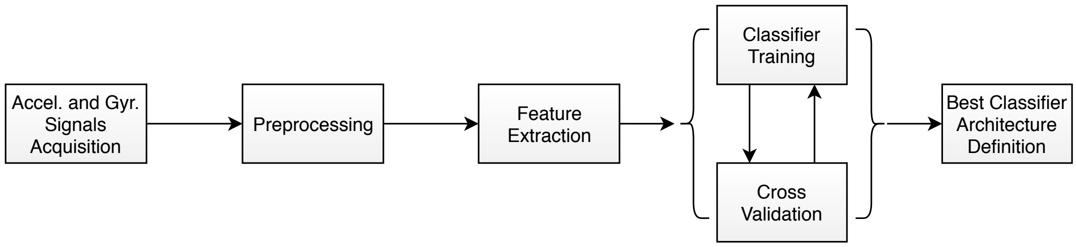


Fig. 5.9 – Condensed Proposed Method Workflow.

To acquire the database, a conventional pen was used in which a MPU 6050 sensor that comprises a 3-axis gyroscope and a 3-axis accelerometer was coupled. All forces applied to the device at a given time point were being acquired. From these forces, it is possible to extract the orientation and sense of the device's movement through its instantaneous acceleration. The value of acceleration $\vec{a}(t)$ is expressed as a vector presenting the components $\vec{a_x}(t)$, $\vec{a_y}(t)$, and $\vec{a_z}(t)$, in axes x, y, and z in gravitational units ($g = 9.780327 m/s^2$). Considering the coordinate system adopted by the sensor, in which $\hat{\imath}$, $\hat{\jmath}$, $\hat{k}$ are the unit vectors of axes x, y, and z, respectively, the acceleration is given by $\vec{a}(t) = a_x\hat{\imath} + a_y\hat{\jmath} + a_z\hat{k}$. Figure 5.10 presents an illustration of the device used to capture instantaneous acceleration signals.

Each sample is composed of all instantaneous [1] values of the Vector $\vec{a}$ acquired while the subject was assigning his name (signature). Although handwriting biometrics may be text invariant, only signatures will be used for the initial test. The hypothesis is that it is possible to extract discriminative features from these signature signals and to train a classifier using these features.

As already discussed, the sensor used during the sample acquisition process is an MPU 6050, which captures accelerometer and gyroscope signals for axes x, y, and z, making a total of 6 different input signals. Here, it should be remarked that a sample is thus defined as a set of these six signals. Figure 5.11 presents an example of an acquired sample.

[1] considering the device frequency limitation of MPU6050

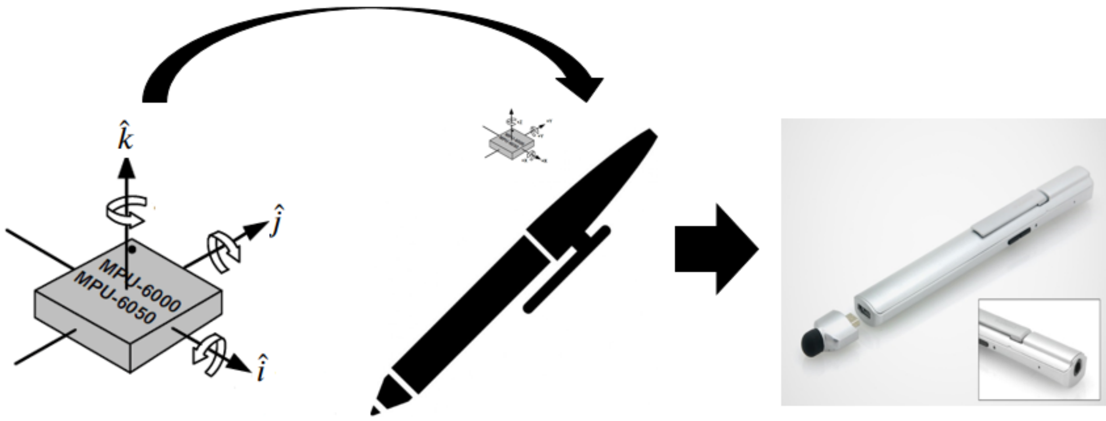


Fig. 5.10 – Illustration of the device used to capture handwritten accelerometer and gyroscope signals from users.

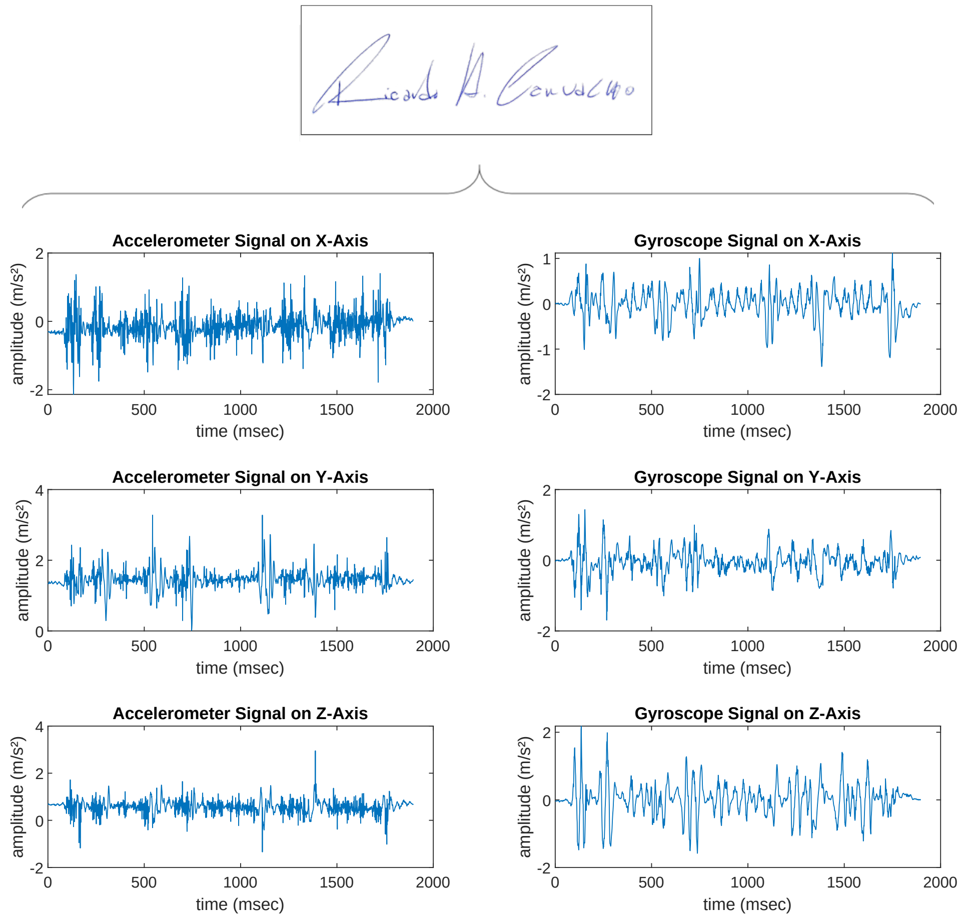


Fig. 5.11 – Example of a sample. Samples are composed of three-axis accelerometer signals and three-axis gyroscope signals.

5.3.1 Preprocessing

First of all, the samples need to undergo a preprocessing process; only then can they be used to train and test the proposed classifier. Figure 5.12 shows a workflow that resumes the principal aspects of the proposed method.

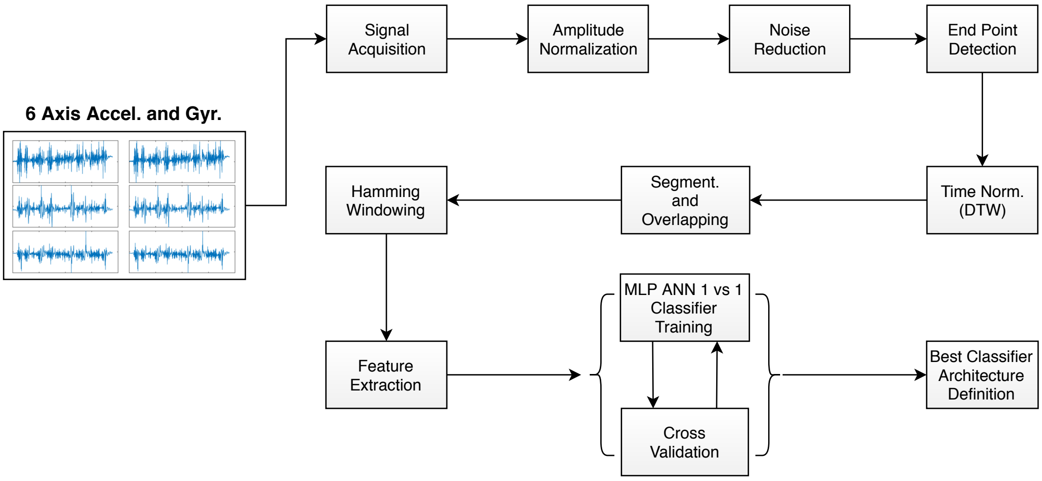


Fig. 5.12 – Proposed Method Workflow.

The first step consists of normalizing the amplitude of the signal between the $[-1, +1]$ interval. Considering that $x[n]$ is defined as the original vector in the function of n ($n = 1, 2, 3, \ \ldots \ , \ vector \ length$), the normalization was simply made following Equation 5.4 and an example of the normalization processes is presented in Figure 5.13.

$$x[n]' = a + \frac{(x - min(x))}{(b - a)/max(x) - min(x)}, \text{ where } [a, b] = [-1, +1] \text{ and } x[n]' \quad (5.4)$$

is the normalized vector in the function of n.

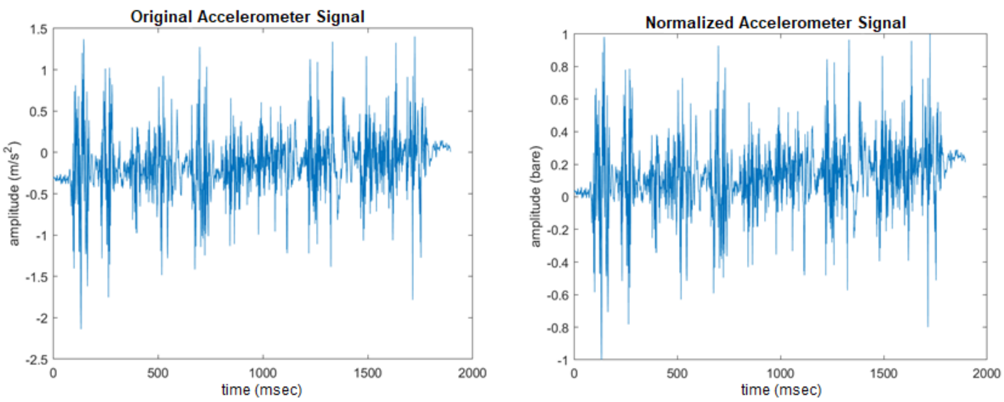


Fig. 5.13 – Example of the effect of vector normalization.

After the amplitude normalization process, the next step is to apply an one-dimensional third-order median filter in order to remove unwanted noise from the $y[k]$ vector. Here, a very traditional noise removal method that works in various different applications was applied [174]. The effect of the filter application can be seen in Figure 5.14.

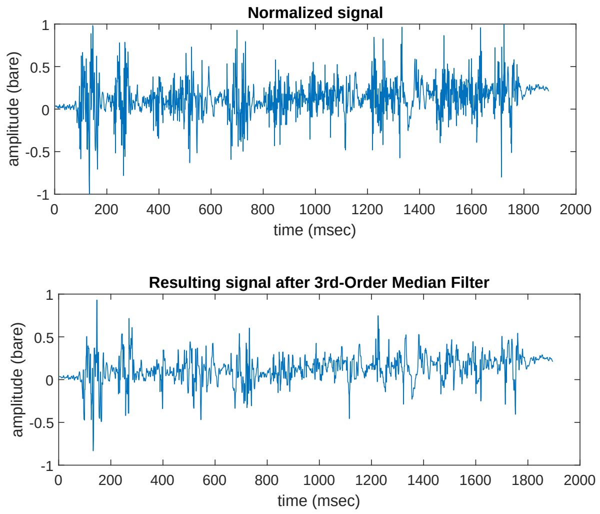


Fig. 5.14 – Effect of 3rd-order median filter applied to $x[n]$ vector. Upper signal is $x[n]$ before filter application and lower signal is the result after 3rd-order median filter application in $x[n]$.

The next step consists of detecting the exact time when the subject begins and ends signing. In this sense, an endpoint detection algorithm was implemented [175]. The idea is to remove an initial and final part of the signal that does not contain useful information, since it was not the result of the subject's signature process but from random noise. In Figure 5.15, a visual example that shows the effect of the endpoint algorithm application is presented. As the method applied was adapted from traditional energy endpoint detection methods [175], next some details and steps will be explained.

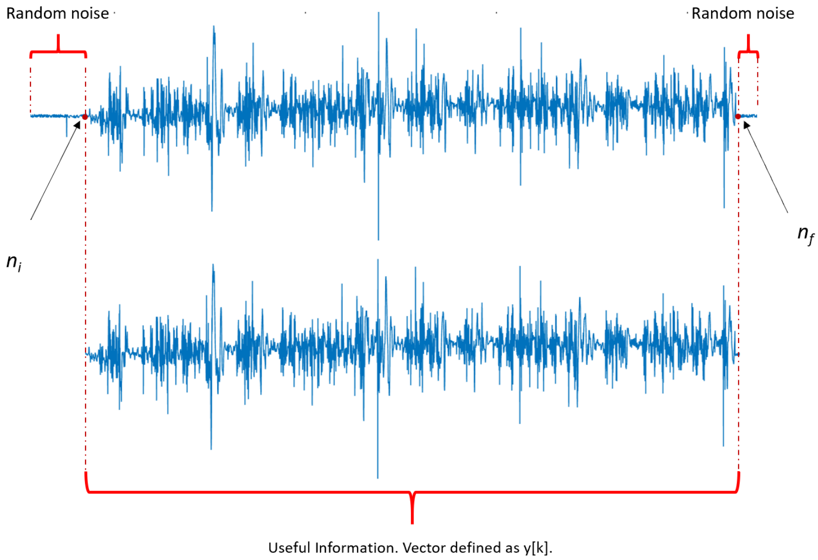


Fig. 5.15 – Endpoint detection and initial and final random noise removal.

As already defined, $x[n]$ represents the original entire vector. Here, $y[k]$ will be defined as the cropped vector after the endpoint detection algorithm application and the initial and final noise removal (see Figure 5.15). Considering that n_i and n_f are defined as initial and final points where $x[n]$ should be cropped, k is an integer number between n_i and n_f ($k = n_i, n_i + 1, n_i + 2, ..., n_f$). So, the principal objective of the endpoint algorithm is to find n_i and n_f values. n_i is defined as the first point where signal energy variation ΔE_i (Eq. 5.5) is greater than the signal mean energy μE (Eq. 5.6), where w is the window length considered to calculated the variation of energy (ΔE_i) and L is the number of windows. Similarly, n_f is the last point where ΔE_i is lower than μE.

$$\Delta E_i(i = 0, 1, 2, ..., L) = (\sum_{\alpha=(i+1)\cdot w}^{((i+2)\cdot w)-1} x[\alpha]^2) - (\sum_{\beta=i\cdot w}^{((i+1)\cdot w)-1} x[\beta]^2), and \tag{5.5}$$

$$\mu E = \frac{\sum_{j=0}^{j=vector\ length} x[j]^2}{vector\ length} \tag{5.6}$$

Visually, in Figure 5.16, a graphical representation of the effects of the algorithm is presented. It is worth mentioning that the amplitude of the input signal used in the endpoint detection algorithm is normalized in $[0, +1]$ just for simplicity purposes, and it doesn't affect the resulting signal since detected n_i and n_f are horizontal points.

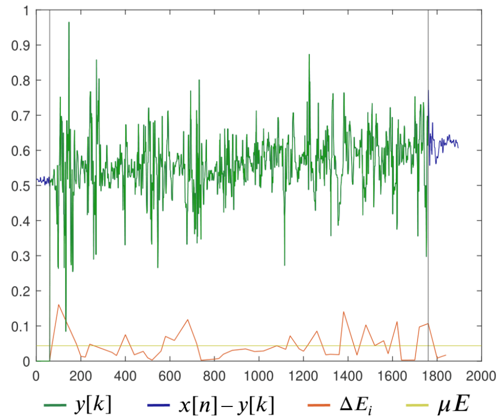


Fig. 5.16 – Endpoint detection.

Another intrinsic aspect of signature signals is that, even for the same user, each sample acquired has a different length, since the user behavior is not perfectly the same during the signing process. In this sense, in order to align and normalize all samples, the traditional Dynamic Time Warp (DTW) method was applied [176, 177]. Since DTW is always applied between two vectors, here it should be remarked that the greatest vector from the data set was fixed and all other vectors were aligned taking this vector as reference.

5.3.2 Feature Extraction

After the preprocessing phase, the next step is to extract the features that will be used to train and test the classifier. First of all, it should be remarked that each sample S was divided into 10 sub-samples (frames) defined as S_{frame_i} where $i = \{1, 2, 3, \dots, 10\}$. In this context, let A_x, A_y, and A_z be the accelerometer signals in the x-, y-, and z-axis, respectively. Analogously, let G_x, G_y, and G_z be the gyroscope signals in the x-, y-, and z-axis, respectively.

For an entire sample, S, 19 features were calculated, as shown in Eq. 5.7:

$$\begin{aligned} S_{features} = \big\{ &\bar{A_x}, \bar{A_y}, \bar{A_z}, \bar{G_x}, \bar{G_y}, \bar{G_z}, var(A_x), var(A_y), var(A_z), var(G_x), var(G_y), var(G_z), \\ &E_{A_x}, E_{A_y}, E_{A_z}, E_{G_x}, E_{G_y}, E_{G_z}, length(S) \big\}\,. \end{aligned} \tag{5.7}$$

It should be remarked that for each one of the 6 independent signals that compose a sample, mean, variance (var), and energy (E) were calculated. Furthermore, the length of the entire signal is also used as a feature. For each of the 10 frames, S_{frame_i}, the same features were considered, with the exception of length, as shown in Eq. 5.8:

$$\begin{aligned} S_{frame_i} = \big\{ &\bar{A_{x_i}}, \bar{A_{y_i}}, \bar{A_{z_i}}, \bar{G_{x_i}}, \bar{G_{y_i}}, \bar{G_{z_i}}, var(A_{x_i}), var(A_{y_i}), var(A_{z_i}), var(G_{x_i}), var(G_{y_i}), \\ &var(G_{z_i}),\, E_{A_{x_i}}, E_{A_{y_i}}, E_{A_{z_i}}, E_{G_{x_i}}, E_{G_{y_i}}, E_{G_{z_i}} \big\}\,. \end{aligned} \tag{5.8}$$

The feature vector for each sample will be defined as V, which has 199 elements, as shown in Eq. 5.9:

$$V = S_{features} \cup S_{frame_1} \cup S_{frame_2} ... \cup S_{frame_{10}} \tag{5.9}$$

In order to reduce the length of V and normalize features values, features computed for the y- and z-axis will be divided by features computed for x-axis. For example, see Eq. 5.10 which shows $S_{features}$ after the normalization process.

$$\begin{aligned} Norm\ S_{features} = \{ &\bar{A_y}/\bar{A_x},\ \ \bar{A_z}/\bar{A_x},\ \ \bar{G_y}/\bar{G_x},\ \ \bar{G_z}/\bar{G_x},\ \ var(A_y)/var(A_x), \\ &var(A_z)/var(A_x),\ \ var(G_y)/var(G_x),\ \ var(G_z)/var(G_x), \\ &E_{A_y}/E_{A_x},\ \ E_{A_z}/E_{A_x},\ \ E_{G_y}/E_{G_x},\ \ E_{G_z}/E_{G_x},\ \ length(S)\}. \end{aligned} \tag{5.10}$$

Similarly, $Norm\ S_{frame_i}$ is defined as the normalized feature vector for each one of i frames. Finally, the final input vector, V_{input}, that will be used to train and test the proposed classifier is composed of 133 features, as shown in Eq. 5.11.

$$V_{input} = Norm\ S_{features} \cup Norm\ S_{frame_1} \cup Norm\ S_{frame_2} ... \cup Norm\ S_{frame_{10}} \tag{5.11}$$

5.3.3 Classifier Architecture

After preprocessing and feature extraction phases, V_{input} is used to train and test a classifier. For the purpose of identify individuals based on their on-line signatures represented by accelerometer and gyroscope signals acquired by a MPU device embedded to a conventional pen, an Artificial Neural Network (Multilayer Perceptron [178]) classifier with Levenberg-Marquardt backpropagation algorithm [179] is proposed. Our classifier has four layers: (1) input layer; (2) two hidden layers; and (3) output layer.

In the first layer, inputs vector V_{input} is inserted into the classifier. The two hidden layers have the number of neurons determined by Algorithm 1; the output layer has 2 neurons. All neurons have hyperbolic tangent transfer functions [178]. Although it is known that neural networks with only one hidden layer can approximate any function with a finite number of arbitrary discontinuities [169], in our work, after numerous tests, it was observed that better results were achieved when two hidden layers were used. As this is a very recent work, the main idea when using an ANN classifier is to evaluate whether simple characteristics of the signature samples (accelerometer and gyroscope signals) can be discriminative enough to identify people. As will be seen in Section 6.3, the results ended up confirming this idea. Also, in order to generate more reliable results, a k-fold cross-validation method was applied. Details can be found in Section 6.3.

Algorithm 1 Procedure used to determine the number of neurons in the two hidden layers.

procedure NETARCHITECTURE
    $i \leftarrow 10$
    while $i \leq 30$ **do** ▷ Number of neurons in first hidden layer
        $j \leftarrow 10$
        while $j \leq 30$ **do** ▷ Number of neurons in second hidden layer
            Create(net, i, j)
            Configure($net, inTrain, tgtTrain$) ▷ $inTrain$: train set inputs, $tgtTrain$: train set targets
            Initialize(net)
            Train($net, inTrain, tgtTrain$)
            Test($net, inTest, outTest$) ▷ $inTest$: test set inputs, $outTest$: simulated outputs
            ConfMat($tgtTest, outTest, mat$) ▷ $tgtTest$: test set targets, mat: confusion matrix
            Save(net, i, j)
            $j \leftarrow j + 2$
        end while
        $i \leftarrow i + 2$
    end while
end procedure

6 RESULTS

Before presenting the results obtained by each of the solutions proposed in the previous section, it is necessary to highlight an important point of the work. Due to the fact that the work explores unconventional biometric systems, there is no public database that allows comparison with other methods proposed by other authors. In this sense, it is not possible to make a direct comparison between the efficiency of the proposed method with the other works produced. Here, another contribution of this work stands out, which is to provide the complete novel database created and used in our work, to allow the scientific community to have access and, therefore, to generate results in order to make fair comparisons among the proposed solutions. The next sections contain detailed results for each proposed solution presented in Chapter 5.

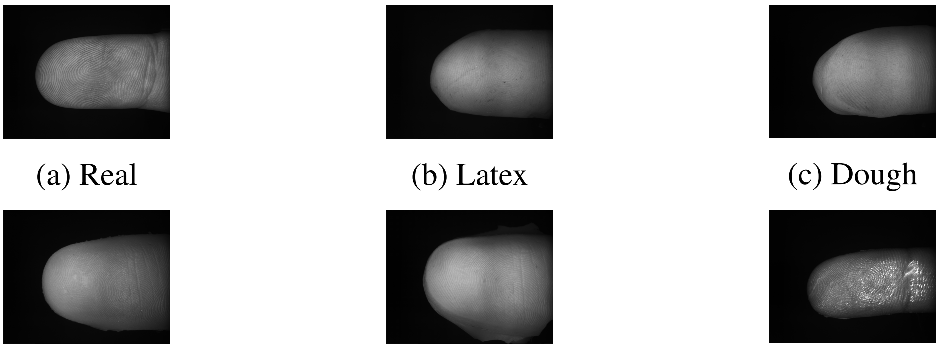
6.1 TMF LIVENESS DETECTION

As previously described, to evaluate the proposed method, 7 different scenarios are assembled. Scenario 1 is designed with the objective of testing to the efficiency of our method regarding its capacity to detect live/liveness. Scenario 2 to 6 evaluate the distinctiveness between real fingers and fake fingers synthesized using 5 different materials, individually. In Scenario 7 the general performance of the proposed classifier is evaluated. In this last scenario one of the six possible materials, including real fingers, is detected.

A dataset of 400 images was constructed and used to train, validate and test the feed-forward neural network classifier. This dataset is composed by 200 images of real fingers (20 individuals, 5 samples of thumb and 5 samples of index finger each) and 200 images of fake fingers (40 of each material). The real fingers subset was constructed as diversified as possible, containing different skin tones, thus raising the classification challenge. Figure 6.1 shows an example of an image for each one of the possible materials that compose the dataset, including a sample of a real finger.

To generate the v_{PCA} input vector, a principal component analysis is performed. In our experiments, the PCA is used to reduce the dimensionality of the input vector from 516 features to 2, 4, or 8 principal component, as will be detailed in the results. Table 6.1 summarizes the results for Scenarios 1 to 6 using 2 and 4 principal components. For 8 principal components the hit rate for all scenarios is 100%. Therefore, presenting this result in a table format is unnecessary. Note that the performance of the classifier is determined by its False Rejection Rate (FRR), False Acceptance Rate (FAR) and Hit Rate. Furthermore, the best number of neurons (#nrns) of the ANN hidden layer, for each case, is also presented. For Scenario 7, three confusion matrices are show in Tables 6.2, 6.3, and 6.4, one for each number of principal components used (2, 4, and 8). The confusion matrices contain the six possible classes, identified as follows: (R) real finger; (B) beeswax; (D) play dough; (L) latex; (S) silicone; and (W) wood glue.

One may notice that the number of principal components used to generate the input vector v_{PCA} highly influences overall results. Looking at the classifications performed in Scenarios 1 to 6 with 8 principal components, the proposed solution correctly detects liveness in 100% of times. In other words, no fake finger are mis-confused with a real one. Besides that, for Scenario 7, it can be verified that the principal diagonal of Table 6.4 shown much better results than principal diagonals from Tables 6.2 and 6.3. These principal diagonals show the hit rate in percentage when actual classes match the prediction made by the classifier. More principal components can be used. However, the classifier already presents a satisfactory performance with 8 of them. One final observation is that silicone seems to be the hardest material to be distinguished from real fingers as well as from other fake fingers.



(a) Real (b) Latex (c) Dough

(d) Beeswax (e) Silicone (f) Wood glue

Fig. 6.1 – One example of capture obtained by main camera for each one of the materials that compose our train and test sets.

Tab. 6.1 – Results: Scenarios 1 to 6.

Scn.	FAR (%)	FRR (%)	Hit Rate (%)	#nrns
2 Principal Components				
1	2.21	2.21	95.59	11
2	0.00	0.00	100.00	18
3	0.00	0.00	100.00	15
4	0.00	3.70	96.30	14
5	3.70	3.70	92.59	14
6	0.00	3.70	96.30	17
4 Principal Components				
1	0.00	1.47	98.53	15
2	0.00	0.00	100.00	16
3	0.00	0.00	100.00	10
4	0.00	0.00	100.00	13
5	0.00	0.00	100.00	16
6	0.00	0.00	100.00	16

Tab. 6.2 – Scenario 7: 2 Principal Components. 20 neurons in hidden layer.

A\P		Predicted Class					
		R	B	D	L	S	W
Actual Class	R	**92.86**	0.00	7.14	0.00	0.00	0.00
	B	0.00	**84.62**	7.69	7.69	0.00	0.00
	D	0.00	14.29	**42.86**	28.57	14.29	0.00
	L	0.00	0.00	0.00	**100.00**	0.00	0.00
	S	7.14	0.00	28.57	14.29	**50.00**	0.00
	W	0.00	0.00	0.00	0.00	0.00	**100.00**

6.2 AGENT-BASED FRAMEWORK TO INDIVIDUAL TRACKING IN UNCONSTRAINED ENVIRONMENTS

The test environment was set up with five computers spatially separated from each other, one acting as Ag_1 (face detector), one as Ag_3 (manager) and three ($Ag_{2,1}$, $Ag_{2,2}$, $Ag_{2,3}$) as Ag_2 (face trackers). Details about the computers configurations may be found in Table 6.5. Although the tests were carried out in real time with only three individuals, the images acquired from these individuals were placed in a directory containing images of 65 other individuals in order to verify the robustness of the proposed method.

Three individuals (A, B, and C) were sequentially presented to Ag_1, which detected and cropped their faces, sending the extracted information to the shared directory in the cloud. A, B and C were then presented to $Ag_{2,1}$, $Ag_{2,2}$, $Ag_{2,3}$, according to the scheme presented in Figure 6.2. In scenario one, for example, individual A was presented to $Ag_{2,1}$,

Tab. 6.3 – Scenario 7: 4 Principal Components. 20 neurons in hidden layer.

A\P		Predicted Class					
		R	B	D	L	S	W
Actual Class	R	**100.00**	0.00	0.00	0.00	0.00	0.00
	B	0.00	**84.62**	15.38	0.00	0.00	0.00
	D	0.00	14.29	**85.71**	0.00	0.00	0.00
	L	0.00	0.00	0.00	**100.00**	0.00	0.00
	S	0.00	0.00	7.14	14.29	**78.57**	0.00
	W	0.00	0.00	0.00	0.00	0.00	**100.00**

Tab. 6.4 – Scenario 7: 8 Principal Components. 11 neurons in hidden layer.

A\P		Predicted Class					
		R	B	D	L	S	W
Actual Class	R	**100.0**	0.00	0.00	0.00	0.00	0.00
	B	0.00	**100.0**	0.00	0.00	0.00	0.00
	D	0.00	0.00	**100.0**	0.00	0.00	0.00
	L	0.00	0.00	0.00	**100.00**	0.00	0.00
	S	0.00	7.14	7.14	0.00	**85.72**	0.00
	W	0.00	0.00	0.00	0.00	0.00	**100.00**

while no individual was presented to $Ag_{2,2}$ and $Ag_{2,3}$. In scenario two, individual A was presented to $Ag_{2,1}$, individual B was presented to $Ag_{2,2}$ and nobody was presented to $Ag_{2,3}$. In scenario three, individual A was presented to $Ag_{2,1}$, individual B was presented to $Ag_{2,2}$ and individual C was presented to $Ag_{2,3}$, and so on.

	Ag_{2_1}	Ag_{2_2}	Ag_{2_3}
1	A	X	X
2	A	B	X
3	A	B	C
4	A	C	B
5	B	A	C
6	B	C	A
7	C	A	B
8	C	B	A
9	C	B	X
10	C	X	X

Fig. 6.2 – Test scenarios: three individuals A, B and C permute between three agents Ag_2 ($Ag_{2,1}$, $Ag_{2,2}$ and $Ag_{2,3}$), which are spatially apart from each other. X indicates that no individual was presented to the device.

The actual start and end time that each test scenario performed were annotated by an operator. From the log generated by the framework, it was possible to observe the time the agents detected and lost the individuals. Table 6.6 compares timestamps annotated by an operator with those registered in the system log. All test scenarios were sequentially

Tab. 6.5 – Computers and its configurations used in the experiments.

Computer	Type	Ag. Type	RAM	Processor	Hard Disk	Camera	Oper. System
1	Netbook	Ag_1	1 GB	Atom N270 1.6 GHz	120 GB	720x480/30 fps	Linux Mint 17.3
2	Netbook	$Ag_{2,1}$	1 GB	Atom N270 1.6 GHz	120 GB	720x480/30 fps	Linux Mint 17.3
3	Laptop	$Ag_{2,2}$	4 GB	Core i5 i5-520M 2.4 GHz	320 GB	1280x720/30 fps	Linux Mint 17.3
4	Laptop	$Ag_{2,3}$	6 GB	Core i7 4500U 1.8 GHz	500 GB	1280x720/30 fps	Windows 10
5	Desktop	Ag_3	2 GB	Core2Quad Q6600 2.4 GHz	500 GB	no camera	Windows 7

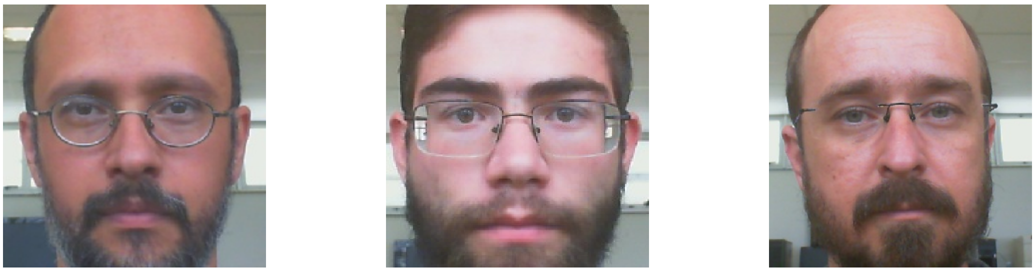
performed between 14:34 and 15:04 hours. One may notice that, in general, actual and logged timestamps are consistent with each other. Furthermore, all places have also been correctly registered for each individual. In other words, there have been no false negatives.

Tab. 6.6 – Comparison between timestamps annotated by an operator with those registered in the system log.

	Real		Ag_{2_1}		Ag_{2_2}		Ag_{2_3}	
Scenario	Start	End	Start	End	Start	End	Start	End
1	14:34	14:35	14:34:56	14:36:01	X	X	X	X
2	14:37	14:38	14:36:44	14:38:51	14:37:03	14:39:09	X	X
3	14:40	14:42	14:40:15	14:42:13	14:40:50	14:42:33	14:40:25	14:44:39
4	14:45	14:47	14:45:21	14:47:13	14:45:52	14:47:41	14:45:22	14:47:19
5	14:48	14:50	14:48:26	14:50:00	X	X	14:48:27	14:50:41
6	14:51	14:53	14:51:56	14:53:50	14:52:31	14:54:52	14:52:01	14:53:59
7	14:55	14:57	14:55:35	14:57:30	14:56:10	14:57:51	14:55:39	14:57:34
8	14:58	15:00	14:59:00	15:00:39	14:59:17	15:00:58	14:59:24	15:00:41
9	15:01	15:03	15:01:51	15:03:37	15:02:04	15:03:48	X	X
10	15:04	15:06	15:04:34	15:06:18	X	X	X	X

However, there are two anomalies that are noteworthy. First, in test scenario 3, $Ag_{2,3}$ registered the loss of individual C (end time) only two minutes after he left. The reason why this happened is that the face detection algorithm returned false positives from the time C actually left and the end time presented in the table. Second, in scenario 5, $Ag_{2,2}$ did not record the presence of individual A. In this test, $Ag_{2,2}$ was shut down on purpose. The objective was to simulate how the system would behave in face of a reduction and subsequent expansion of the number of Ag_2. As expected, $Ag_{2,2}$ did not operate during the period it was plugged out of the system and returned to operate after it was plugged in again.

Finally, Figure 6.3 shows the automatically cropped faces of the three individuals that took part in the experiments. As can be seen, the background of the images is not well behaved, showing the robustness of the Viola-Jones algorithm. Figure 6.4 shows results of the online real-time tracking being carried out by the SURF algorithm. Keypoint descriptors used as matching points between the templates and cameras acquisitions are shown and connected by colored lines.



(a) (b) (c)

Fig. 6.3 – Examples of Ag_1 face detection outputs: automatically cropped faces of the three individuals (a), (b) and (c) that took part in the experiments.

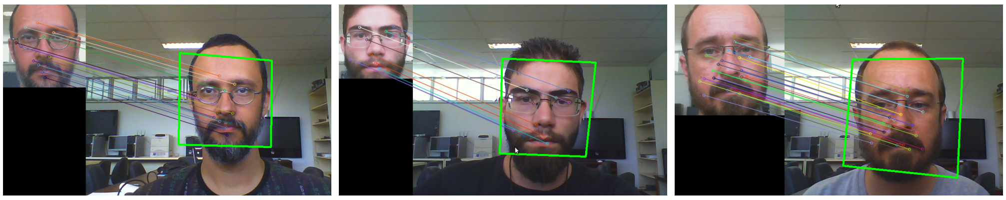


Fig. 6.4 – Examples of Ag_2 outputs: real-time face tracking being carried out by Ag_2 using SURF algorithm. Keypoint descriptors used as matching points between the templates and cameras acquisitions are shown and connected by lines.

6.3 ON-LINE HANDWRITING RECOGNITION

The database is composed by accelerometer and gyroscope signals of on-line handwritten signatures from 50 individuals. Each individual has signed 12 times, totaling 600 signatures that compose the database. Each signature is composed by 6 independent signals. It is noteworthy that a human operator was responsible for initiating and terminating the process of capturing each of the signatures of each individual.

As already discussed, the sensor used during the sample acquisition process is a MPU 6050, which captures accelerometer and gyroscope signals for axis x, y and z making a total os 6 different input signals. Here it should be remarked that a sample (signature), thus, is defined as a set of this six signals.

In our experiments, k-fold cross-validation method were applied to generated more reliable results [180]. The database were divided into three mutually exclusive subsets. One should note that, before the k-fold subset division, all data were shuffled. Figure 6.5 presents a visual representation of the database division where three models are defined.

For all models, $2/3$ of the data set were used for training the classifier while $1/3$ were use to test. Results are presented using confusion matrices, where true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) are shown for all 50 users which signatures composes our database. In Table 6.7, results for Model 1 are presented, while in Table 6.8 and Table 6.9, results for Model 2 and Model 3 are presented, respectively. In Tables 6.10, 6.11 and 6.12, overall results for each Model are also presented.

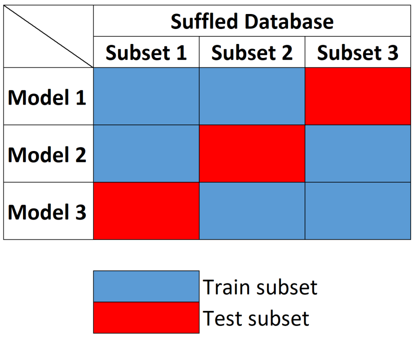


Fig. 6.5 – K-Fold cross-validation models.

Real	Predicted																		
User 1	R\P	User	Not User	User 11	R\P	User	Not User	User 21	R\P	User	Not User	User 31	R\P	User	Not User	User 41	R\P	User	Not User
	User	91.7%	8.3%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	11.2%	88.8%		Not User	2.7%	97.3%		Not User	5.1%	94.9%		Not User	11.1%	88.9%		Not User	9.4%	90.6%
User 2	R\P	User	Not User	User 12	R\P	User	Not User	User 22	R\P	User	Not User	User 32	R\P	User	Not User	User 42	R\P	User	Not User
	User	100.0%	0.0%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%		User	83.3%	16.7%
	Not User	5.6%	94.4%		Not User	9.4%	90.6%		Not User	5.8%	94.2%		Not User	12.6%	87.4%		Not User	10.7%	89.3%
User 3	R\P	User	Not User	User 13	R\P	User	Not User	User 23	R\P	User	Not User	User 33	R\P	User	Not User	User 43	R\P	User	Not User
	User	83.3%	16.7%		User	83.3%	16.7%		User	100.0%	0.0%		User	100.0%	0.0%		User	100.0%	0.0%
	Not User	9.7%	90.3%		Not User	16.2%	83.8%		Not User	2.0%	98.0%		Not User	6.1%	93.9%		Not User	4.9%	95.1%
User 4	R\P	User	Not User	User 14	R\P	User	Not User	User 24	R\P	User	Not User	User 34	R\P	User	Not User	User 44	R\P	User	Not User
	User	91.7%	8.3%		User	83.3%	16.7%		User	91.7%	8.3%		User	91.7%	8.3%		User	83.3%	16.7%
	Not User	18.4%	81.6%		Not User	7.5%	92.5%		Not User	9.5%	90.5%		Not User	5.6%	94.4%		Not User	5.8%	94.2%
User 5	R\P	User	Not User	User 15	R\P	User	Not User	User 25	R\P	User	Not User	User 35	R\P	User	Not User	User 45	R\P	User	Not User
	User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	4.6%	95.4%		Not User	14.6%	85.4%		Not User	20.2%	79.8%		Not User	11.2%	88.8%		Not User	16.8%	83.2%
User 6	R\P	User	Not User	User 16	R\P	User	Not User	User 26	R\P	User	Not User	User 36	R\P	User	Not User	User 46	R\P	User	Not User
	User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	83.3%	16.7%		User	100.0%	0.0%
	Not User	6.3%	93.7%		Not User	16.0%	84.0%		Not User	16.3%	83.7%		Not User	12.9%	87.1%		Not User	11.7%	88.3%
User 7	R\P	User	Not User	User 17	R\P	User	Not User	User 27	R\P	User	Not User	User 37	R\P	User	Not User	User 47	R\P	User	Not User
	User	91.7%	8.3%		User	100.0%	0.0%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%
	Not User	9.0%	91.0%		Not User	17.2%	82.8%		Not User	16.5%	83.5%		Not User	6.5%	93.5%		Not User	7.0%	93.0%
User 8	R\P	User	Not User	User 18	R\P	User	Not User	User 28	R\P	User	Not User	User 38	R\P	User	Not User	User 48	R\P	User	Not User
	User	83.3%	16.7%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	13.3%	86.7%		Not User	6.0%	94.0%		Not User	5.3%	94.7%		Not User	15.3%	84.7%		Not User	12.2%	87.8%
User 9	R\P	User	Not User	User 19	R\P	User	Not User	User 29	R\P	User	Not User	User 39	R\P	User	Not User	User 49	R\P	User	Not User
	User	83.3%	16.7%		User	91.7%	8.3%		User	91.7%	8.3%		User	83.3%	16.7%		User	83.3%	16.7%
	Not User	7.7%	92.3%		Not User	2.9%	97.1%		Not User	5.1%	94.9%		Not User	4.8%	95.2%		Not User	7.8%	92.2%
User 10	R\P	User	Not User	User 20	R\P	User	Not User	User 30	R\P	User	Not User	User 40	R\P	User	Not User	User 50	R\P	User	Not User
	User	100.0%	0.0%		User	91.7%	8.3%		User	100.0%	0.0%		User	100.0%	0.0%		User	100.0%	0.0%
	Not User	8.7%	91.3%		Not User	4.6%	95.4%		Not User	4.1%	95.9%		Not User	16.0%	84.0%		Not User	8.2%	91.8%

Tab. 6.7 – Model 1 results. This table shows the results for each one of 50 individuals whose signatures compose the database.

Real	Predicted																		
User 1	R\P	User	Not User	User 11	R\P	User	Not User	User 21	R\P	User	Not User	User 31	R\P	User	Not User	User 41	R\P	User	Not User
	User	83.3%	16.7%		User	100.0%	0.0%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	10.7%	89.3%		Not User	6.0%	94.0%		Not User	5.8%	94.2%		Not User	13.6%	86.4%		Not User	8.5%	91.5%
User 2	R\P	User	Not User	User 12	R\P	User	Not User	User 22	R\P	User	Not User	User 32	R\P	User	Not User	User 42	R\P	User	Not User
	User	100.0%	0.0%		User	100.0%	0.0%		User	83.3%	16.7%		User	83.3%	16.7%		User	91.7%	8.3%
	Not User	4.8%	95.2%		Not User	16.3%	83.7%		Not User	2.2%	97.8%		Not User	6.6%	93.4%		Not User	7.1%	92.9%
User 3	R\P	User	Not User	User 13	R\P	User	Not User	User 23	R\P	User	Not User	User 33	R\P	User	Not User	User 43	R\P	User	Not User
	User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%
	Not User	15.1%	84.9%		Not User	13.4%	86.6%		Not User	6.6%	93.4%		Not User	7.1%	92.9%		Not User	10.4%	89.6%
User 4	R\P	User	Not User	User 14	R\P	User	Not User	User 24	R\P	User	Not User	User 34	R\P	User	Not User	User 44	R\P	User	Not User
	User	83.3%	16.7%		User	91.7%	8.3%		User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%
	Not User	17.3%	82.7%		Not User	9.4%	90.6%		Not User	7.0%	93.0%		Not User	2.4%	97.6%		Not User	9.0%	91.0%
User 5	R\P	User	Not User	User 15	R\P	User	Not User	User 25	R\P	User	Not User	User 35	R\P	User	Not User	User 45	R\P	User	Not User
	User	83.3%	16.7%		User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%
	Not User	7.1%	92.9%		Not User	16.2%	83.8%		Not User	8.5%	91.5%		Not User	12.8%	87.2%		Not User	6.0%	94.0%
User 6	R\P	User	Not User	User 16	R\P	User	Not User	User 26	R\P	User	Not User	User 36	R\P	User	Not User	User 46	R\P	User	Not User
	User	91.7%	8.3%		User	83.3%	16.7%		User	91.7%	8.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	7.0%	93.0%		Not User	9.4%	90.6%		Not User	8.0%	92.0%		Not User	8.3%	91.7%		Not User	10.4%	89.6%
User 7	R\P	User	Not User	User 17	R\P	User	Not User	User 27	R\P	User	Not User	User 37	R\P	User	Not User	User 47	R\P	User	Not User
	User	100.0%	0.0%		User	100.0%	0.0%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%
	Not User	20.4%	79.6%		Not User	16.5%	83.5%		Not User	9.0%	91.0%		Not User	6.8%	93.2%		Not User	8.7%	91.3%
User 8	R\P	User	Not User	User 18	R\P	User	Not User	User 28	R\P	User	Not User	User 38	R\P	User	Not User	User 48	R\P	User	Not User
	User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	100.0%	0.0%
	Not User	17.5%	82.5%		Not User	8.5%	91.5%		Not User	2.6%	97.4%		Not User	18.0%	82.0%		Not User	9.9%	90.1%
User 9	R\P	User	Not User	User 19	R\P	User	Not User	User 29	R\P	User	Not User	User 39	R\P	User	Not User	User 49	R\P	User	Not User
	User	100.0%	0.0%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	7.1%	92.9%		Not User	4.1%	95.9%		Not User	10.0%	90.0%		Not User	6.8%	93.2%		Not User	6.3%	93.7%
User 10	R\P	User	Not User	User 20	R\P	User	Not User	User 30	R\P	User	Not User	User 40	R\P	User	Not User	User 50	R\P	User	Not User
	User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
	Not User	8.3%	91.7%		Not User	1.4%	98.6%		Not User	7.7%	92.3%		Not User	8.0%	92.0%		Not User	9.0%	91.0%

Tab. 6.8 – Model 2 results. This table shows the results for each one of 50 individuals whose signatures compose the database.

										Predicted										
Real	User 1	**R\P**	User	Not User	User 11	**R\P**	User	Not User	User 21	**R\P**	User	Not User	User 31	**R\P**	User	Not User	User 41	**R\P**	User	Not User
		User	83.3%	16.7%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%		User	83.3%	16.7%
		Not User	16.3%	83.7%		Not User	4.8%	95.2%		Not User	8.2%	91.8%		Not User	9.0%	91.0%		Not User	5.3%	94.7%
	User 2	**R\P**	User	Not User	User 12	**R\P**	User	Not User	User 22	**R\P**	User	Not User	User 32	**R\P**	User	Not User	User 42	**R\P**	User	Not User
		User	100.0%	0.0%		User	83.3%	16.7%		User	100.0%	0.0%		User	100.0%	0.0%		User	91.7%	8.3%
		Not User	5.1%	94.9%		Not User	7.8%	92.2%		Not User	5.6%	94.4%		Not User	13.1%	86.9%		Not User	9.7%	90.3%
	User 3	**R\P**	User	Not User	User 13	**R\P**	User	Not User	User 23	**R\P**	User	Not User	User 33	**R\P**	User	Not User	User 43	**R\P**	User	Not User
		User	83.3%	16.7%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
		Not User	8.5%	91.5%		Not User	12.4%	87.6%		Not User	7.7%	92.3%		Not User	10.2%	89.8%		Not User	6.6%	93.4%
	User 4	**R\P**	User	Not User	User 14	**R\P**	User	Not User	User 24	**R\P**	User	Not User	User 34	**R\P**	User	Not User	User 44	**R\P**	User	Not User
		User	83.3%	16.7%		User	83.3%	16.7%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
		Not User	19.4%	80.6%		Not User	9.9%	90.1%		Not User	8.7%	91.3%		Not User	8.7%	91.3%		Not User	5.1%	94.9%
	User 5	**R\P**	User	Not User	User 15	**R\P**	User	Not User	User 25	**R\P**	User	Not User	User 35	**R\P**	User	Not User	User 45	**R\P**	User	Not User
		User	83.3%	16.7%		User	100.0%	0.0%		User	83.3%	16.7%		User	91.7%	8.3%		User	100.0%	0.0%
		Not User	5.1%	94.9%		Not User	10.4%	89.6%		Not User	19.4%	80.6%		Not User	15.0%	85.0%		Not User	14.5%	85.5%
	User 6	**R\P**	User	Not User	User 16	**R\P**	User	Not User	User 26	**R\P**	User	Not User	User 36	**R\P**	User	Not User	User 46	**R\P**	User	Not User
		User	91.7%	8.3%		User	100.0%	0.0%		User	83.3%	16.7%		User	91.7%	8.3%		User	83.3%	16.7%
		Not User	5.8%	94.2%		Not User	10.5%	89.5%		Not User	11.6%	88.4%		Not User	9.2%	90.8%		Not User	7.7%	92.3%
	User 7	**R\P**	User	Not User	User 17	**R\P**	User	Not User	User 27	**R\P**	User	Not User	User 37	**R\P**	User	Not User	User 47	**R\P**	User	Not User
		User	91.7%	8.3%		User	91.7%	8.3%		User	83.3%	16.7%		User	100.0%	0.0%		User	83.3%	16.7%
		Not User	9.5%	90.5%		Not User	10.0%	90.0%		Not User	17.5%	82.5%		Not User	6.6%	93.4%		Not User	4.9%	95.1%
	User 8	**R\P**	User	Not User	User 18	**R\P**	User	Not User	User 28	**R\P**	User	Not User	User 38	**R\P**	User	Not User	User 48	**R\P**	User	Not User
		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%		User	91.7%	8.3%
		Not User	16.0%	84.0%		Not User	11.6%	88.4%		Not User	7.8%	92.2%		Not User	11.2%	88.8%		Not User	15.1%	84.9%
	User 9	**R\P**	User	Not User	User 19	**R\P**	User	Not User	User 29	**R\P**	User	Not User	User 39	**R\P**	User	Not User	User 49	**R\P**	User	Not User
		User	91.7%	8.3%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	100.0%	0.0%
		Not User	5.3%	94.7%		Not User	3.7%	96.3%		Not User	7.0%	93.0%		Not User	12.9%	87.1%		Not User	13.8%	86.2%
	User 10	**R\P**	User	Not User	User 20	**R\P**	User	Not User	User 30	**R\P**	User	Not User	User 40	**R\P**	User	Not User	User 50	**R\P**	User	Not User
		User	83.3%	16.7%		User	91.7%	8.3%		User	100.0%	0.0%		User	91.7%	8.3%		User	91.7%	8.3%
		Not User	6.6%	93.4%		Not User	5.3%	94.7%		Not User	4.8%	95.2%		Not User	11.4%	88.6%		Not User	11.6%	88.4%

Tab. 6.9 – Model 3 results. This table shows the results for each one of 50 individuals whose signatures compose the database.

Total	**R\P**	User	Not User
	User	TP	FN
	Not User	FP	TN
Hit rate	TP/(TP+FN)		

(a)

Total	**R\P**	User	Not User
	User	92.2%	7.8%
	Not User	9.6%	90.4%
Hit rate	92.17%		

(b)

Tab. 6.10 – (a) Default table used to organize all results; (b) Overall results for Model 1.

Total	**R\P**	User	Not User
	User	93.5%	6.5%
	Not User	9.2%	90.8%
Hit rate	93.51%		

Tab. 6.11 – Overall results for Model 2.

Total	**R\P**	User	Not User
	User	91.5%	8.5%
	Not User	9.7%	90.3%
Hit rate	91.50%		

Tab. 6.12 – Overall results for Model 3.

7 CONCLUSIONS

Biometric systems are constantly evolving. Regardless of the biometric modality that is being used, there is always room for improvement. In particular, when considering biometric systems based TMF, FRSS and HRAS, there are still many gaps to be filled and improvements to be proposed. This work has three main contribution, one for each one of the NCBS explored in our research, as follows:

The 1st contribution of this work is to present a liveness detection method to identify potential attempts of spoofing attacks against touchless fingerprinting devices. The method takes nothing but a photographic image of the finger as input. The main idea is to take advantage of the fact that light reflects differently according to each material, generating different texture patterns. To test our method, 200 images from real fingers of 20 different people were compared against 200 images of fake fingers made of beeswax, play-dough, latex, silicone and wood glue. Results show that using only 8 principal components, obtained from applying PCA on a 516 texture descriptors, the classifier correctly detects liveness in 100% of the time. When the method was applied to the specific scenarios where the 6 classes (materials) are presented and the classifier must indicate to which of the 6 classes the acquired sample belongs, general performance was around 97.56%. Since to the best of our knowledge there is no definitive liveness detection method for touchless fingerprint acquisition processes, the main contribution of the present work is to address this problem successfully, as show by the results. Future work may include the expansion of the dataset to have more images and more materials in an attempt to evaluate the robustness of the proposed solution. Other kinds of attacks may also be considered.

The 2nd contribution of this work, is to present an novel agent-based framework to individual tracking in unconstrained environments based on face recognition using SIFT/ SURF algorithms. In the framework, there are three types of agents: face detector, face tracker, and manager. The face detector and tracker agents perform fully automatic single-sample face recognition and track individuals using the Viola-Jones and SURF algorithms, indicating the path the individuals have taken and the time they spent in the field of view of the surveillance area. Agents communicate through a shared directory in the cloud. The framework can integrate heterogeneous computational infrastructures from different organizations, allowing to be executed in real public environments under video surveillance, such as malls, automated teller machines, movie box offices, self-paying kiosks, and notaries. The framework is open source and can be used by anyone who wants to improve security by identifying and tracking individuals in surveillance areas. A functional interaction model based on the Contract Net Protocol was defined and implemented in C^{++} language, as well as a communication protocol that uses FIPA-ACL performatives. The proposed interaction model is multi-platform which allows for communication to occur between many computers, executing many agents, no matter the operating system or the specific characteristics of the local area network where the computers are connected (Internet connection). The requirements to use the framework include the devices accessing the shared directory in the cloud through the use of the defined communication performatives and interaction protocol.

The experimental results show that the framework agents could adequately execute the tasks they were assigned to, considering the detection, identification and tracking of individuals within an environment under surveillance. Tests use one agent as a face detector, three agents as face trackers, and one manager. Three individuals were presented to the framework and spatial and temporal tracking were carried out. The framework correctly identified the individuals and determined their positions and respective times. Tracking of individuals was executed by analyzing the logs generated by each agent and extracting the spatial and temporal behavior of the individual. These logs can be used in different ways, e.g., to predict the steps of frequent costumers in order to optimize sales and improve negotiation.

The presented agent-based framework was developed for visual perception towards the creation of advanced intelligent systems. The present research has many open problems related to intelligent perceptual capabilities in the real world such as accelerated movements of individuals, camera distance, brightness and luminosity of the environment, Internet connection, and Contract Net Protocol manager (bottleneck). Nevertheless, the framework method can be applied or extended to other agent perceptions such as auditory or olfactory, by replacing the algorithms for face detection and tracking by different ones. Future works includes the development of new functionalities, an improved model removing the Ag_3 singularity, the evaluation of the proposed framework in a real public environment to evaluate scalability, and the implementation of a fuzzy inference system capable of making real-time predictions about costumers, and suggestions about prices, sales promotions, and the organization of the environment.

The 3rd considerable contribution presented in this work is a novel low-cost method to identify individuals based on accelerometer and gyroscope signals acquired from an MPU 6050 sensor embedded to a conventional pen. The signals were acquired during the signature process and a database of 600 samples from 50 different individuals was built. All samples undergo a preprocessing phase consisting of amplitude normalization, noise reduction, endpoint detection, time alignment using DTW, segmentation, and overlapping and hamming windowing.

After the preprocessing phase, an input vector of 133 extracted features was assembled for each acquired sample. These feature vectors were used to train and test a multilayer perceptron classifier. In order to verify the reliability of the achieved results and therefore the efficiency of the proposed method, a k-fold cross-validation process was used. An overall hit rate of 92.39% was achieved, which indicates that the proposed method is promising.

Although other works have already addressed the problem of on-line handwritten biometric, none of them uses accelerometer and gyroscope signals acquired from a sensor embedded to a conventional pen to perform biometrics. This work also contributes to the scientific community making available the complete, built database used to generate the results, since there is no official database for on-line signature recognition based on accelerometer and gyroscope signals. Future works may consider the use of a larger database as well as the proposal of different classification methods such as convolutional neural network and other deterministic techniques in order to seek improved results.

Considering that the main objective of this work was to contribute to the improvement of non-conventional biometric systems based on fingerprint, facial and handwriting recognitions presenting methods that can operate better in certain situations where conventional systems cannot operate or show limitations, and given the aforementioned contributions towards TMF, FRSS and HRAS, it is possible to conclude that this work has reached its goal. Traditional biometric systems will inevitably reach their limit. The technology and methods linked to these systems will also reach a limit of evolution. Therefore, new systems and methods need to be developed and explored. There is still much to be discovered, developed and explored in the field of biometrics and this work has contributed to the new possibilities and potential of this still incipient but so promising area called: biometrics.

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