



**INSTITUTO SUPERIOR DE ENGENHARIA DE LISBOA**

Área Departamental de Engenharia de Electrónica e Telecomunicações e de  
Computadores

**Mestrado em Engenharia de Electrónica e Telecomunicações**  
**(Perfil de Telecomunicações)**

## **Embedded Platform for ECG Biometric Recognition**

André Cigarro Matos  
(Licenciado em Engenharia Electrónica e Telecomunicações e de  
Computadores)

Trabalho Final de Mestrado para Obtenção do Grau de Mestre em Engenharia  
de Electrónica e Telecomunicações

Orientadores:

Mestre André Ribeiro Lourenço

Doutor José Nascimento

**18 de Outubro de 2013**



---

## Resumo Alargado

Muitas das tarefas diárias do ser humano requerem processos que validem a identidade do utilizador. Cartões de identificação, chapas de identificação militar, senhas e códigos são as estratégias mais usuais no campo da validação e identificação de utilizador. Apesar do amplo uso de tais mecanismos, os meios de autenticação baseados na entidade ou no conhecimento do sujeito levantam graves problemas de segurança no que diz respeito ao risco de fraude e roubo de identidade.

O uso de características físicas ou comportamentais dos seres vivos como forma de identificá-los unicamente, é o tópico da Biometria [bio (vida) + metria (medida)]. A principal vantagem destes sistemas é a dependência completa no indivíduo, não existindo nenhuma sujeição a objetos ou à memorização de códigos, como ocorre nas estratégias tradicionais. Isto leva a uma maior utilização de sistemas biométricos a fim de aumentar a dificuldade de falsificação de credenciais, visto este ser a principal falha dos sistemas de reconhecimento pessoal tradicionais. Por exemplo, uma foto pode fingir um rosto, a íris do olho pode ser falsificada por lentes de contacto e até mesmo a impressão digital pode ser trocada por um dedo de gel.

Este trabalho propõe um sistema de reconhecimento biométrico baseado em sinais electrocardiográficos (ECG). As diferenças de potencial podem ser obtidas pela colocação de elétrodos sobre a superfície do corpo e medindo a tensão entre eles.

O sistema de aquisição dos sinais ECG deste trabalho é constituído por dois elétrodos colocados um em cada membro superior do utilizador, preferencialmente nas mãos, para uma aquisição mais cómoda. A fim de tornar esta solução móvel e facilmente transportável para qualquer local, é proposto um sistema embebido autónomo para autenticação humana baseada no ECG de cada indivíduo. Normalmente, os sistemas baseados em ECG usam hardware capaz de adquirir o sinal e um micro-controlador para enviar os sinais para um computador onde é realizado o tratamento dos dados. Em alternativa, o objetivo deste trabalho é conceber de um prototipo capaz de adquirir e processar o sinal ECG de diferentes indivíduos e, através de um algoritmo de extração e classificação de padrões, autenticar ou identificar as pessoas em questão. Este prototipo será baseado num sistema embebidos capaz de autenticar ou identificar indivíduos em tempo real sem recurso a um computador pessoal ou a qualquer plataforma de processamento externa.

O problema do reconhecimento humano com base em biometria, é tipicamente dividido em várias fases (independentemente do tipo de biométrica) típicas de um sistema de reconhecimento de padrões:

- Aquisição do sinal biométrico por sensores;
- Pré-processamento do sinal de acordo com o sistema adotado;
- Extração das características necessárias ao reconhecimento;
- Seleção das características mais discriminativas do sujeito;
- Classificação das características escolhidas e decisão de qual a correspondência da mesma na base de dados.

Nesta abordagem o sinal ECG obtido é segmentado por batimento cardíaco, usando o pico R (complexo R, incluído no complexo QRS, nomes dados às ondas características constituintes do ECG) como ponto de pesquisa para a segmentação. Dois algoritmos de segmentação são estudados, Hamilton e Slope Sum Function (SSF), sendo o SSF a solução implementada no sistema embebido pelas suas propriedades de execução em tempo real. Outra particularidade da implementação do algoritmo SSF é que este foi desenvolvido para detetar pulsos de pressão arterial e é aqui adaptado para a deteção do complexo R, constituinte do sinal ECG.

A extração de características do sinal ECG segmentado é baseada na análise do sinal no domínio da frequência e segue um algoritmo proposto por Odínaka. Cada batimento cardíaco é analisado por troços obtidos pela segmentação do sinal em várias janelas sobrepostas. É calculada a transformada de Fourier de cada janela segmentada (em que normalmente é usada uma janela de Hamming para melhor estimativa) e estimada uma distribuição de gaussiana (caracterizada por uma média e desvio padrão) para cada intervalo de frequência que caracteriza o batimento cardíaco típico em análise. Posteriormente, para treino, é estimada a distribuição gaussiana para as janelas extraídas de cada segmento e calculada a sua média entre todos os segmentos. São estas as características guardadas na base de dados para futura comparação com novas aquisições para se efetuar o reconhecimento dos batimentos. A cada nova aquisição, é confirmada a veracidade do utilizador, e é feita uma atualização dos valores da base de dados com os novos adquiridos, através de uma média ponderada. Com este método é possível contornar o efeito temporal nos sinais ECG. É de conhecimento comum que com a evolução da idade do indivíduo, os seus sinais fisiológicos sofrem pequenas alterações e o ECG não é exceção. Para a transformada de Fourier foi aumentado a dimensão do array para aumentar a definição nas baixas frequências, onde a informação requerida para o reconhecimento pessoal é preponderante.

Neste trabalho, o sistema foi implementado para garantir uma execução em tempo real. As amostras do sinal ECG não podem ser perdidas e o processo de autenticação tem que ser realizado de forma muito eficiente de modo a permitir o funcionamento em tempo real. Para isto é necessária a escolha de hardware capaz de concretizar este objetivo. A possibilidade do uso de um microprocessador foi descartada pela sua baixa versatilidade e alto custo de desenvolvimento. Os sistemas ASIC e FPGA, também foram descartados pelos elevados custos de desenvolvimento e aquisição. Foi escolhido então, um sistema de desenvolvimento baseado num micro-controlador (MCU) com arquitetura ARM Cortex 4. O MCU escolhido, STM32F4-Discovery, conta com

uma grande versatilidade, baixo consumo de energia (100mA), grande velocidade de processamento (168MHz), integração de DSP e unidade de virgula flutuante. Memória interna não volátil também é necessária, a fim de conservar as características de treino de cada individuo.

O sistema é projetado para ser autônomo, não-intrusivo e fácil de usar em diferentes cenários. Isto é conseguido combinando a facil utilização de apenas dois elétrodos, um em cada membro superior, com um sistema embebido alimentado por bateria com processamento em tempo real e capacidade de visualização de resultados.

O sistema foi validado em duas fases. Em primeiro lugar os algoritmos foram validados usando uma base de dados já testada em estudos anteriores, e foi comprovado que o sistema tem uma percentagem de identificação de 89% e 10% de taxa de erros em autenticação. Finalmente foram realizadas novas aquisições que comprovaram a eficiência do sistema. Com 11 sujeitos na base de dados o sistema conta com uma taxa de identificação de 100% e um taxa de erros de autenticação de 9.3%.

Utilizando as propriedades dos sinais ECG, este sistema torna-se um plataforma fiável, eficaz e eficiente. Problemas cardíacos humanos, como arritmias são um problema que fazem descer o rendimento do sistema. O sistema realizado é uma prova de conceito que ilustra como os sistemas embebidos podem mudar o mundo dos sistemas de autenticação pois proporcionam segurança e uma utilização muito fácil para toda a população.



---

## Abstract

Traditional strategies for authentication are either entity-based or knowledge-based, like PIN numbers, passwords and ID cards. This raises serious security problems, concerning the risk of identity theft as these mechanisms are widely spread. They are a part of many daily tasks and they are dependent on objects or memories. This work prompts to change these mechanisms for a secure and ubiquitous biometric reckoning system based on the electrocardiographic (ECG) signal. It includes the study of all the steps required for the development of a biometric system, namely: acquisition, processing and classification. In the acquisition, the ECG signal is obtained from two electrodes placed at each limb to a electronic device that filters and amplifies the raw signal to be able to be converted to digital in the microcontroller, using the internal Analogue-to-Digital Converter; In the processing phase, the signal is digitally filtered and segmented in heartbeats. Features are selected and extracted using one algorithm created by Odinaka and herein modified to increase performance in low bandwidth ECG signals; In classification, extracted features are compared, using nearest neighbour algorithm, with data stored in the database in order to classify each heartbeat.

The work develop and implement a working prototype based on an embedded system (ARM-Based Cortex4 32 bit RISC STM32F407VGT6). Acquisition modules, processing units and algorithms are studied and developed on a prototype for identification and authentication mobile system based on the ECG. The lack of mobile real-time reckoning systems makes this thesis a challenging and self-motivated work. Unique, continuous acquisition and non-intrusive are the main characteristics of the ECG signals. These properties make ECG based reckoning system a reliable and effective platform. Preliminary evaluation showed a 100% identification rate and a 9.3% equal error rate at the authentication procedure. These results came form an acquired database of 11 subjects, with test and train sequences acquired in different procedures. Human heart problems, like arrhythmias are a challenging problem that drop the reckoning performance of the system. This kind of embedded solutions can change the world of authentication systems in order to provide security and be easy-to-use for the general population.





---

## Acknowledgments

First, I would like to thank Professor José Nascimento by its constant availability, interest and cooperation while conducting this dissertation. I also thank him for having instilled in me the importance of scientific rigour, lesson I intend to follow in the future. I am also grateful to Professor André Lourenço for the great ideas he gave me as well as for his invaluable assistance and knowledge sharing. To engineer João Costa, for providing the initial motivation and knowledge on this subject. I also would like to thank Instituto de Telecomunicações and the BIT team, Ana Priscila Alves, Carlos Carreias, Ana Fred e Hugo Silva. To all those who, in some way, support this journey and made it easier. To my friends, specially to Tiago Venturinha and to Ana Catarina Gago. To José Guerreiro, my fellow, friend, and colleague that made my academic experience a one of a kind. To my soul mate, Ana Silva, I want to thank for his patience, balance of mind and support in the hardest times. The motivation and strength she gave me, has helped me to conclude this dissertation. Finally, i want to thank my parents, António e Maria Matos, without whom it wouldn't have been possible to get here, to whom I dedicate this work.



---

## Acronyms

ABP Arterial Blood Pressure  
ADC Analogue to Digital Converter  
AEL Across Electrode Locations  
Ag Silver  
AgCl Silver Chloride  
AHB Advanced High-performance Bus  
ALU Arithmetic Logic Unit  
API Application Programming Interface  
ARM Advanced RISC Machine  
ASIC Application-Specific Integrated Circuit  
AST Across Stress Tasks  
ASWF Across Sessions with Fusion  
BPF Band Pass Filter  
CPU Central Processing Unit  
dB Decibel  
DC Direct Current  
DSP Digital Signal Processor  
DNA Deoxyribonucleic Acid  
ECG Electrocardiogram  
EER Equal Error Rate  
FAR False Acceptance Rate  
FFT Fast Fourier Transform  
FIFO First In First Out  
FIR Finite Impulse Response  
FN False Negative  
FP False Positive  
FPGA Field-Programmable Gate Array  
FPU Floating Processing Unit  
FRR False Rejection Rate

FSC Feature Selection Context  
GMC Generative Model Classifier  
GUI Graphical User Interface  
HFU High Frequency Updating  
Hz Hertz  
ID Identification  
IIR Infinite Impulse Response  
INT Interrupt  
IT Information Technology  
LDA Linear Discriminant Analysis  
LED Light Emitting Diode  
LFU Low Frequency Updating  
LLR Log-Likelihood Ratio  
MCU Microcontroller  
MFU Medium Frequency Updating  
ML Maximum Likelihood  
NN Nearest Neighbour  
PHBIA Per Heart Beat Identification Accuracy  
PIN Personal Identification Number  
RAM Random-Access Memory  
RISC Reduced Instruction Set Computing  
SNR Signal-to-Noise Ratio  
SRAM Static Random-Access Memory  
SSF Slope Sum Function  
STFT Short Term Fourier Transform  
SVM Support Vector Machine  
TN True Negative  
TP True Positive  
TV Television  
USART Universal Asynchronous Receiver/Transmitter  
WS Within Session

---

# Contents

<b>Resumo Alargado (Portuguese)</b> .....	i
<b>Abstract</b> .....	v
<b>Acknowledgments</b> .....	vii
<b>Acronyms</b> .....	ix
<b>Contents</b> .....	xii
<b>List of Figures</b> .....	xiv
<b>List of Tables</b> .....	xiv
<b>1 Introduction</b> .....	1
1.1 Biometric systems and traits .....	2
1.2 Electrocardiogram signal .....	5
1.3 Embedded Platform .....	10
1.4 Thesis goals and contributions .....	10
<b>2 Biometric Recognition System based on ECG</b> .....	13
2.1 State of the Art .....	14
2.1.1 Algorithms based on Fiducial Features .....	15
2.1.2 Algorithms based on Non-fiducial Features .....	16
2.1.3 Algorithms based on Hybrid Features .....	16
2.2 Acquisition .....	17
2.3 Preprocessing: Segmentation and Filtering .....	17
2.4 Feature Extraction .....	18
2.5 Classification .....	18

<b>3</b>	<b>Frequency-based ECG Recognition</b>	19
3.1	Filtering	20
3.2	Segmentation	22
3.2.1	Hamilton	22
3.2.2	Slope Sum Function (SSF)	23
3.2.3	Segmentation Comparison	25
3.3	Feature Extraction and Classification: Odinata's Time-frequency Method	26
3.3.1	Time-frequency Method	27
3.3.2	Proposed approach for the low resolution STFT	29
<b>4</b>	<b>Embedded System Implementation</b>	31
4.1	Embedded Devices	31
4.2	STM32F407VGT6 General Architecture	32
4.2.1	Bluetooth Module	33
4.2.2	Acquisition Module	33
4.2.3	MCU Cortex Processor, Integrated DSP and FPU	33
4.2.4	MCU Memory	34
4.2.5	MCU Analogue to Digital Converter	35
4.2.6	MCU USART	35
4.2.7	MCU TIMER	36
4.3	Software Framework	37
4.3.1	Acquisition Software Architecture	38
4.3.2	SSF Processing and Classification Software Architecture	40
4.3.3	Bluetooth Communication Layer	41
4.4	Prototype	43
<b>5</b>	<b>Experimental Evaluation</b>	47
5.1	Biometric Evaluation	47
5.2	Datasets	48
5.2.1	Himotion Database	48
5.2.2	Prototype Database	49
5.3	Experimental Results	49
5.3.1	Himotion	50
5.3.2	Embedded Platform Evaluation	53
<b>6</b>	<b>Conclusions and Future Work</b>	57
	<b>References</b>	59

---

# List of Figures

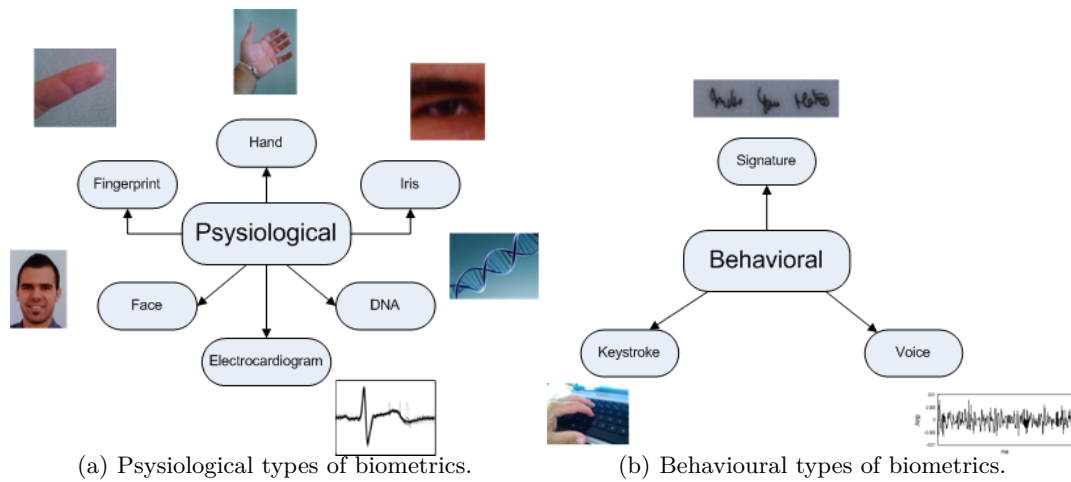
- 1.1 Various types of biometrics..... 2
- 1.2 Biometric systems usually found in our society ..... 3
- 1.3 Typical scheme of a biometric system ..... 4
- 1.4 Biometric acquisition general electrode placement. .... 7
- 1.5 The standard leads (top) and the augmented leads (bottom) reflect the limb electrodes (left arm, right arm, left leg) used to record the heart’s electrical axis in the frontal plane [1]..... 8
- 1.6 Two electrode placement, one in each hand..... 8
- 1.7 Schematic representation of normal ECG ..... 9
  
- 2.1 Generic block diagram presenting the proposed acquisition system. .... 13
- 2.2 Variability surrounding the QRS complex among heart beats of the same individual 14
- 2.3 Block diagram of an generic ECG acquire system ..... 17
- 2.4 Block diagram of an generic ECG signal preprocessing ..... 18
  
- 3.1 Same user time-frequency analysis ..... 19
- 3.2 FIR filter magnitude response. .... 21
- 3.3 Visual comparison between raw and filtered ECG samples..... 21
- 3.4 Hamilton QRS detection operations..... 22
- 3.5 Hamilton segmentation processing results. .... 23
- 3.6 SSF QRS detection operations ..... 24
- 3.7 SSF segmentation processing results..... 25
- 3.8 Spectrogram comparison between different users..... 27
- 3.9 Block diagram for Odinaka’s time-frequency method ..... 28
- 3.10 Difference between the two STFT methods of analysis of the same heartbeat ..... 30
  
- 4.1 Hardware block diagram of the system ..... 32
- 4.2 MCU generic Memory block diagram, redrawn from [2]. .... 34
- 4.3 MCU ADC block diagram, redrawn from [2]..... 35
- 4.4 MCU USART block diagram, redrawn from [2]. .... 36

4.5	MCU TIMER block diagram, redrawn from [2]. . . . .	36
4.6	System Software block diagram. . . . .	37
4.7	Timer Software block description. . . . .	39
4.8	Software block diagram of the SSF Signal preparation phase. . . . .	40
4.9	Software block diagram of the peak detector and classifier. . . . .	41
4.10	Communication data packet structure. . . . .	42
4.11	Communication data packet structure. . . . .	42
4.12	Prototype ECG acquisition sensors. . . . .	43
4.13	BITalino acquisition hardware. . . . .	44
4.14	Bluetooth module and power supply. . . . .	45
4.15	Integrated Prototype and solo evaluation board. . . . .	45
5.1	Illustration of the typical curves of error rates FAR and FRR which result in EER. . . . .	48
5.2	Block diagram for Odinaka's method without segmentation . . . . .	50
5.3	EER and recognition accuracy curves for training on 4, 8, 16, 32, 64 heartbeats and testing on 4, 8, 16, 32, and 64 heartbeats, using the Odinaka method and the proposed method without segmentation for variable analysis. . . . .	51
5.4	EER and recognition accuracy curves for training on 4, 8, 16, 32, 64 heartbeats and testing on 4, 8, 16, 32, and 64 heartbeats, using the regular algorithm and the proposed approach with segmentation and overlap for variable analysis . . . . .	52
5.5	Performance on frame size variability. . . . .	53
5.6	Performance on overlap time between frames variability. . . . .	53
5.7	Comparison of time and frequency domain representation for two different users (users: Top for individual A and bottom for individual B.). . . . .	54
5.8	FAR vs FRR curve. . . . .	55



## Introduction

Many aspects of our every day lives are becoming dependent to automatic and accurate identity validation. The wide deployment of recognition mechanisms, based on entity-based (tokens and ID cards) or knowledge-based (PIN numbers and passwords), raises securities concerns regarding the risk of identify theft. The process of recognizing a valid user identity is called identification and authentication is the process of verifying the claimed identity of a user. Security levels determine the acceptance rate of a system. If the security level is very high, like a military facility, should be no false validations of a unknown personal even if this compromises the increase of errors on the verification of accredited users. The only way to truly verify the true identity of a subject is using his biological data. The use of this data (characteristics or traits) for any identification or authentication method is called biometrics. In general, biometrics is any use of biological data in reckoning technology. Biometric systems focusing exclusively on the identification of humans have become the major kind of biometric system in today's IT world. The major benefit of these security systems is the full dependency on the individual. There are no dependencies on objects or memories as it occurs on the traditional strategies. This leads to a higher use of biometric systems in order to increase the difficulty in falsification of credentials. Biometric identifiers can be categorized as physiological (fingerprint, face recognition, DNA, palm print, hand geometry, iris recognition, retina and odour/scent) and behavioural (typing rhythm, gait and voice). Physiological characteristics are related to the shape of the body and behavioural characteristics are related to the pattern of behaviour of a person. Fig. 1.1 shows these two types and witch biometric trait is inserted in them. Some researchers have coined the term behaviometrics to describe the latter class of biometrics [3].



**Fig. 1.1.** Various types of biometrics.

Currently one of the major flaws of the majority of these systems is the ease of falsification of credentials. For instance, a photo can fake a face, the iris can be falsified by contact lenses and even the fingerprint may be exchanged for a gel finger [4]. This thesis prompts itself to study and develop a complete authentication system, based on the human ECG biometric trait, on a device capable of process the information in real time.

## 1.1 Biometric systems and traits

A biometric system is a technological procedure that uses information about a person (or other biological organism) to identify that person. Biometric systems rely on specific data about unique biological traits in order to work effectively. A biometric system will involve running data through algorithms for a particular result, usually related to a positive user identification or other individual. Fig. 1.2 refers a bunch of modern used biometric systems usually found in our society. Iris, fingerprint and palm scanners are widely used on modern systems due to its reliability and versatility. Biometric systems can be used to get more information about individuals or about a populace as a whole. Many biometric systems are developed for security applications. An airport scanning device, a "bio-password" system, or an internal data gathering protocol is an example of a biometric system that uses identifying data for a security result.



(a) Iris scanner for person identification [5].



(b) Fingerprint scanner for restricted accesses [6].



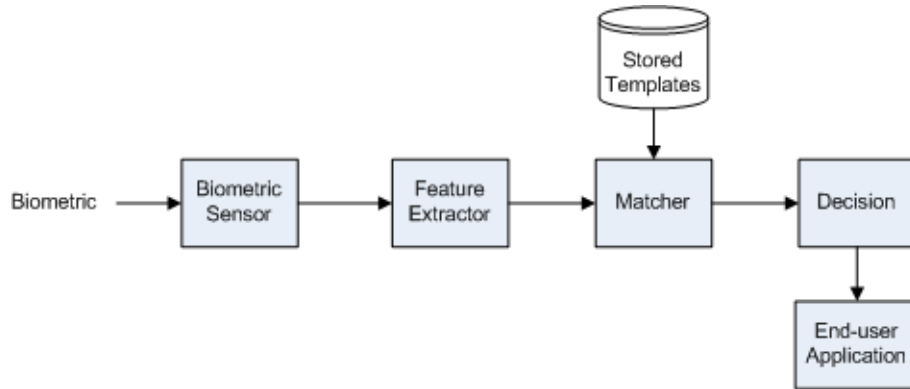
(c) Over air hand palm scanner [7].



(d) Hand palm scanner for person identification [8].

**Fig. 1.2.** Biometric systems usually found in our society

Fig. 1.3 shows the block-diagram of a typical biometric system used for any kind of biometric feature. This kind of process mainly require a biometric sensor, for acquisition, a feature extractor to choose the characteristics to match with the database. Finally, a decision is made and shown to the user. The choice of a specific biometric modality typically depends on the nature and requirements of the intended identification application. As an example, voice biometric is appropriate in authentication applications involving mobile phones since a sensor for capturing voice (microphone) is already embedded in the phone but cannot be used for high security applications since voice capture is highly susceptible to fraud and environmental noise.



**Fig. 1.3.** Typical scheme of a biometric system

Biometric systems are expected to meet various requirements to make them interesting for general or specific use. These expectations can be summarized into five categories:

- **Performance:** The recognition performance achievable from a biometric system is of utmost interest in the deployment of biometric systems. A biometric system is prone to numerous errors, mainly identification error rate and authentication equal error rate.
- **Cost:** The cost of deploying a biometric system is often estimated from its direct and indirect components. The direct component includes hardware components (sensor, processor, memory) and the software modules (GUI and matcher). Indirect costs often include system installation, training/maintenance requirements and user acceptance [9].
- **User convenience:** A biometrics system should be user friendly. Any perceived health or hygienic concerns with the continuous usage of biometric sensors can influence user acceptance [9].
- **Interoperability:** As biometrics systems are being increasingly deployed in a wide range of applications, it is necessary that the system be interoperable among different biometrics technologies (sensors/algorithms/vendors). A biometric system can no longer operate under the assumption that the same sensor, same algorithms, or same operating conditions will always be available during its lifetime [9].
- **Security:** Biometric systems are vulnerable to potential security breaches from spoof and malicious attacks. These systems should therefore offer a high degree of protection to various vulnerabilities resulting from intrinsic failures and adversary attacks [10].

Based on the above considerations, biometric systems should be easy to use, have low cost, be easy to embed and integrate in the target security application and be robust, secure, and highly accurate in their matching performance. As for traits, biometric systems rely on behavioural and physiological types of biometrics. For a reliable use, these biometrics characteristics must obey to a set of requirements, which are:

- **Universality:** each person must have the characteristic;

- **Uniqueness:** the characteristic must be different for any two persons;
- **Permanence:** the characteristic must be time invariant, with respect to the features;
- **Measurable:** quantitatively measures should be possible.

If the system is to be used as a personal recognition system there are other types of requirements, which are:

- **Performance:** which refers to the speed and performance possible to achieve by a recognition scenario and their dependence on environmental and operational factors;
- **Acceptability:** which refers to the desire of people for the daily use of the system;
- **Circumvention:** which refers to the hack proof on the use of fraudulent methods.

Table 1.1 resumes the characteristics of the main biometric trait in all of the above requirements. There is no biometric characteristic with all perfect traits and this table shows the differences among most types of biometrics. The choice of a certain characteristic depends on the particular application.

	Eye (Iris)	Finger-print	Hand Geometry	Signature	Voice	ECG	DNA	Face
Universality	High	High	High	Normal	High	High	High	High
Uniqueness	High	High	Normal	High	High	High	High	High
Permanence	High	High	Normal	Low	Normal	Normal	High	Normal
Measurable	Normal	High	High	Low	Normal	High	Low	Normal
Performance	High	Normal	Normal	Normal	Normal	High	High	Normal
Acceptability	Low	High	High	High	Normal	Normal	Low	Normal
Circumvention	High	Low	Low	Low	Normal	High	High	Low
System cost	High	Low	Normal	Normal	Normal	Low	High	Normal

**Table 1.1.** Comparison of the biometric methods.

Biometric characteristics can be either physiological or behavioural. Particularly, the ECG signal is physiological but not directly assumed as such because of the ECG compartmental characteristics that comes from human stress, motion activity or emotional thoughts. It is very like the voice, which despite being behavioural, many of its features come from the psychological state of the person.

## 1.2 Electrocardiogram signal

Recently, physiological signals are being used for a recognition purpose [11], being the electrocardiogram (ECG), the most promising [12, ?, 13]. The possibility of using ECG signals for recognition, or human identification, has been highly exploited due to their characteristics:

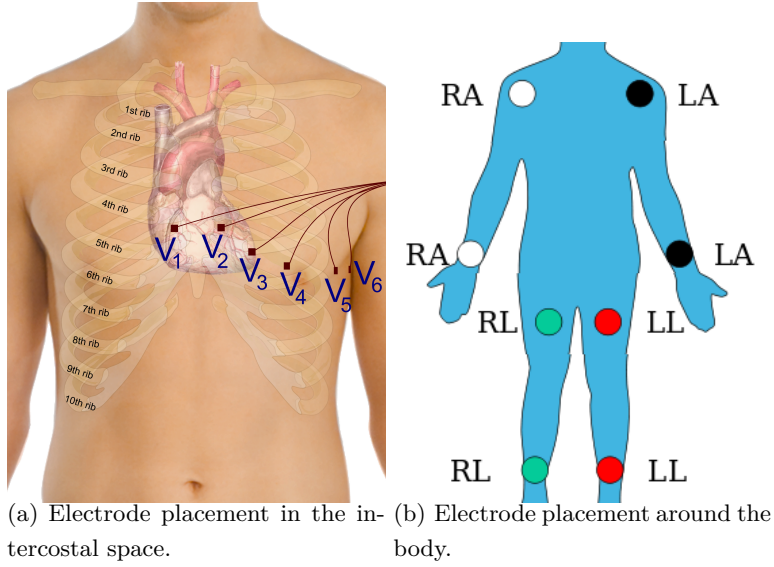
- Relatively easy to acquire: Due to recent advances in biomedical instrumentation, ECG signals acquisition can be done on the chest using a shirt with textile embedded electronics, at the neck using a necklace with a pendant, at the fingers and hand palms with a one lead sensor or using textile electrodes, and in these last one it is not necessary to be applied on the body of the person as previous approaches;
- Low computational requirements: the typical approaches leads to an algorithmic complexity that can be implemented in embedded and low-power devices (like smart-phones).

As other biometric systems, this technique has to deal with the impossibility of acquiring two exact readings from the same subject, leading to the phenomena of false rejection. A smart-phone, or any other type of embedded system, can become a device for personal recognition.

The electric potentials generated by the heart appear throughout the body and on its surface. The potential differences can be determined by placing electrodes on the surface of the body and measuring the voltage between them, being careful to draw little current (ideally there should be no current at all, because current distorts the electric field that produces the potential differences)[14]. If the two electrodes are located on different equal-potential lines of the electric field of the heart, a non-zero potential difference or voltage is measured. Different pairs of electrodes at different locations generally yield distinct voltages because of the spatial dependence of the electric field of the heart [15]. Thus it is important to have certain standard positions for clinical evaluation of the ECG, since clinic diagnostics and identification processes have different goals and therefore distinct lead placement. The limbs make fine guideposts for locating the ECG electrodes [14]. The table herein presented, Table 1.2, shows the different electrodes positions capable of acquire voltage potentials unique enough to be able to be used as biometric traits. Fig. 1.4 draws the electrode placement around the chest in intercostal acquisitions and the usual locations for limb acquisitions.

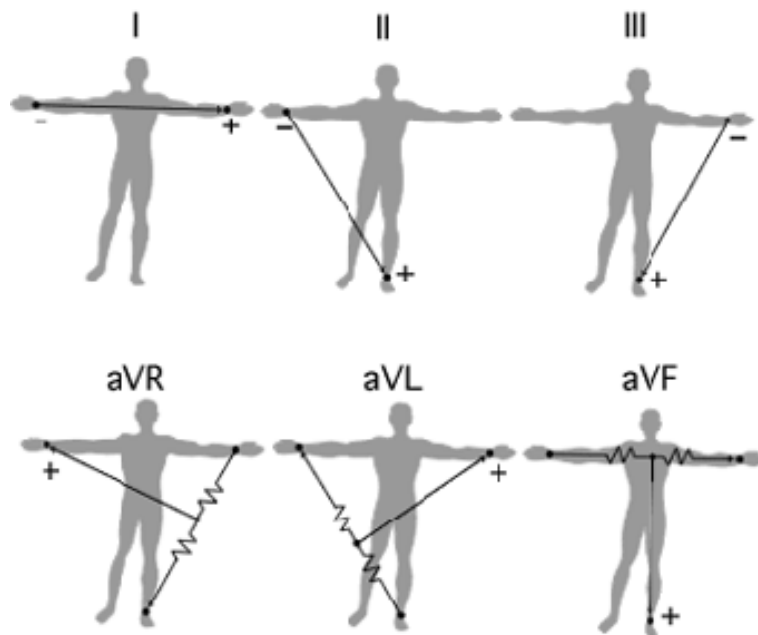
Electrode label	Electrode placement
RA	On the right arm, avoiding thick muscle.
LA	In the same location where RA was placed, but on the left arm.
RL	On the right leg, lateral calf muscle.
LL	In the same location where RL was placed, but on the left leg.
V <sub>1</sub>	In the fourth intercostal space (between ribs 4 and 5) just to the right of the sternum (breastbone).
V <sub>2</sub>	In the fourth intercostal space (between ribs 4 and 5) just to the left of the sternum.
V <sub>3</sub>	Between leads V2 and V4.
V <sub>4</sub>	In the fifth intercostal space (between ribs 5 and 6) in the mid-clavicular line.
V <sub>5</sub>	Horizontally even with V4, in the left anterior axillary line.
V <sub>6</sub>	Horizontally even with V4 and V5 in the midaxillary line.

**Table 1.2.** Different electrodes positions.



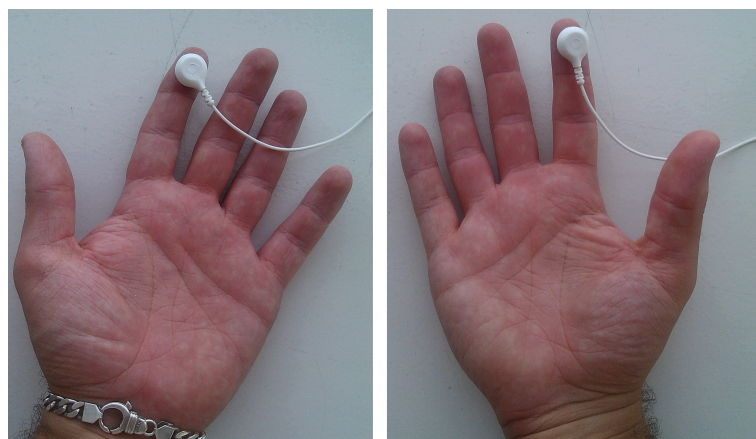
**Fig. 1.4.** Biometric acquisition general electrode placement.

There are various ways of positioning the electrodes in order to get a high signal to noise ratio (SNR) level ECG signal. As seen in Fig. 1.4, the standard positioning points are the chest and all the up and down limbs. It can be used up to 10 electrodes, six spread around the chest area and the remaining four spread in all four limbs. The stretch between two limb (arm or leg) electrodes is called a lead. Einthoven named the leads between the three limb electrodes 'standard lead I, II and III' referring to the two arm electrodes and the left leg electrode [1]. He studied the relationship between these electrodes, forming a triangle where the heart electrically constitutes the null point. The relationship between the standard leads is called Einthoven's triangle [1]. Einthoven's triangle is used when determining the electrical axis of the heart [1], Fig. 1.5 describes the leads designation and location.



**Fig. 1.5.** The standard leads (top) and the augmented leads (bottom) reflect the limb electrodes (left arm, right arm, left leg) used to record the heart's electrical axis in the frontal plane [1].

However, recent works [11] show a decrease in the electrodes number. Since the goal of this work is a way to identify an individual instead of doing clinical analyses, the identification will be done using a ECG signal acquired with a configuration of two electrodes, using lead I Einthoven standard triangle, as showed in Fig. 1.6. This approach relays on an artificially generated reference, otherwise, a third electrode would be necessary [16].



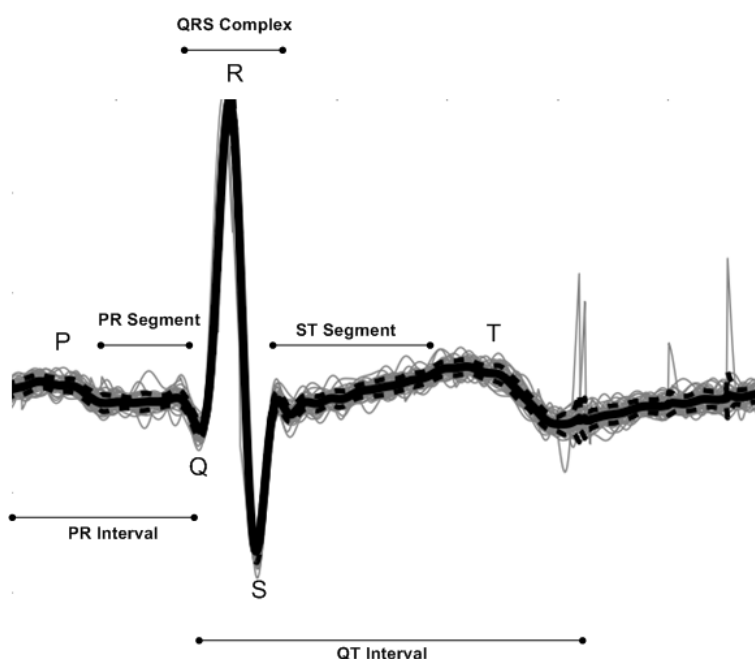
**Fig. 1.6.** Two electrode placement, one in each hand.



There are several conditions, whether physical or emotional, or even external conditions that affects the ECG signal. These constraints make the individual identification based on ECG a challenging task. Despite these, the cardiac rhythm is constant and is always available, as long as the subject is alive. This characteristic makes possible a continuous authentication testing process.

The ECG signal is created by electrical impulses coming from our brain to the heart. Each of these pulses has a purpose, arousing various parts of the heart in order to make a complete beat. Being the physiognomy of every human being different from others, it is likely that each individual creates a different ECG signal. These differences are reflected in the ECG signal and its characteristics.

The ECG consists of three main components: P wave, QRS complex, and T wave. The P wave occurs due to atrial depolarization, the QRS complex, due to ventricular de-polarization, and the T wave, due to ventricular repolarization, as seen in Fig. 1.7. Also in the figure, in grey, various ECG segmented waves, in black, the mean wave and dotted is a envelope defined by the standard deviation. Here is also noticeable the stationarity of the signal and the existence of some noise and outliers (spikes on the right).



**Fig. 1.7.** Schematic representation of normal ECG

The aim of this work is the study and development of several algorithms, both for segmentation, preprocessing and classification, to be implemented on a specific hardware device for ECG based identification.

### 1.3 Embedded Platform

In order to make the ECG recognition system an all purpose reckoning system, in this thesis it is proposed an autonomous embedded system for human authentication based on ECG. An embedded platform is a computer system with a dedicated function within a larger electrical system, often with real-time computing constraints. By contrast, a general-purpose computer is designed to be flexible and to meet a wide range of end-user needs. Usually, ECG based systems use hardware capable of acquiring the signal and a micro controller to send the data to a computer. The data analysis task is then processed in the computer to retrieve an authentication score [17]. The proposed embedded system samples the ECG with internal Analog to Digital Converters (ADC's), processes the signal and uses Odinaka's approach [18] to authenticate the user. Moreover it allows real time processing.

Embedded Systems are everywhere. Every time you look at your watch, answer the phone, take a picture, or turn on the TV you are interacting with an embedded system, cars, airplanes, and robots are also replete of controlling embedded systems. They far outnumber traditional computers (which also contain embedded processors) and it is estimated that there will be thousands of embedded devices per person by 2015 [19]. Designing and programming embedded systems is a critical skill, necessary for many industry and scientific jobs.

In this thesis the real-time constrain must be fulfilled. Samples cannot be lost and the authentication procedure must be as close as real time as it can be. Memory is also a need, in order to store the characteristics of the subjects as for a good resolution ADC for a good quality acquisition. The proposed system is a mix of a regular MCU and a DSP processor. The development MCU board, STM32F4-Discovery, was chosen due to its versatility, low power consumption, high speeds and DSP integration. Section 4 describes the state of the art in terms of technology and the chosen platform characteristics.

### 1.4 Thesis goals and contributions

The main challenge that has motivated the work presented in this thesis is the creation of an ubiquitous embedded system for ECG acquisition and on-the-fly authentication. The goals of this work are the creation and development of this system using a novel feature extraction method based on the frequency domain based on the work of Odinaka [18]. The contributions of the present work can be summarized as follows:

- Creation and implementation of an ECG Biometric Embedded system capable of acquiring the biometric signal and process the authentication algorithm on-the-fly. The system creates its own database, by acquisition, and the algorithms are developed based on characteristics of the these signals.
- Study of Odinaka's algorithm and its custom implementation aiming at the proposed problem. Since it is aimed for real-time, these implementations must fulfil a certain code performance and be adapted to the hardware in use.

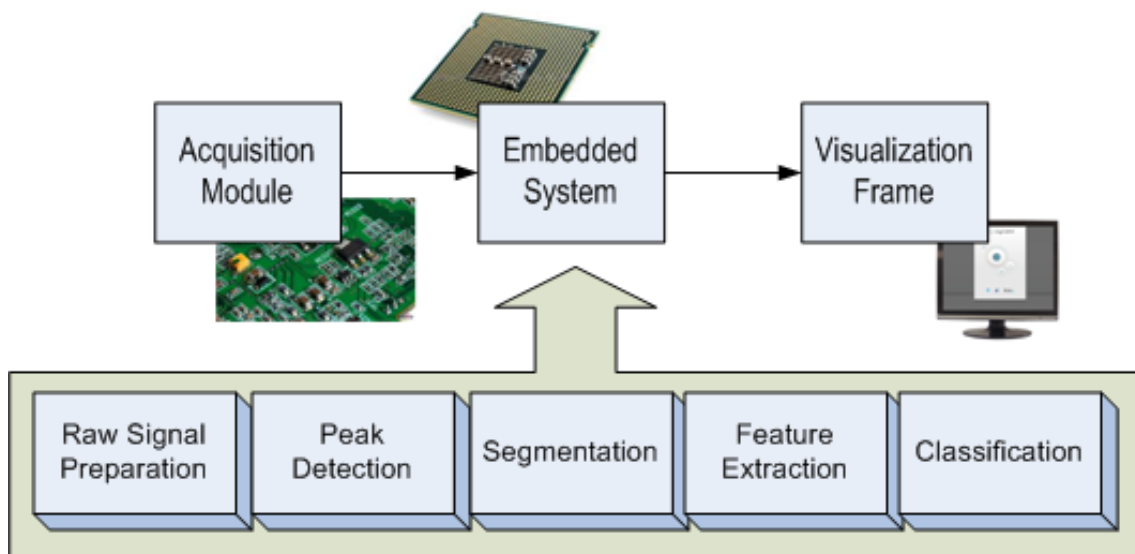
- Study of ECG acquiring system based on a two lead corporal placement. One lead in each upper limb makes the system simpler and easy to implement in any scenario.
- Finally the system performance is studied, the identification rate and authentication error rate are measured in order to evaluate the method and its real-time implementation.

Along with the study, the methods were implemented on the ARM-Based Cortex4 32 bit RISC STM32F407VGT6. The main contributions of this work were published on the 5th IEEE International Conference on e-Health Networking and CARDIOTECHNIX 2013 [20] and International Congress on Cardiovascular Technologies [21], and we have an accepted work [22] to be published on CETC 2013, Conference on Electronics, Telecommunications and Computers.



## Biometric Recognition System based on ECG

As mentioned in the previous chapter, this work proposes a biometric recognition system based on ECG. In Fig. 2.1 it is presented a block diagram of the proposed solution. The system starts with the acquisition module, composed by the electrodes and the signal conditioning hardware with appropriate noise reducers. The embedded system is the core of this work, it processes the acquisitions implementing a work flow of several methods (signal processing, peak detection, segmentation, feature extraction and classification), and in the final delivering an authentication result. The result is represented by coloured LED's (red for deny, green for approve and yellow for repeat) presented in the embedded system.



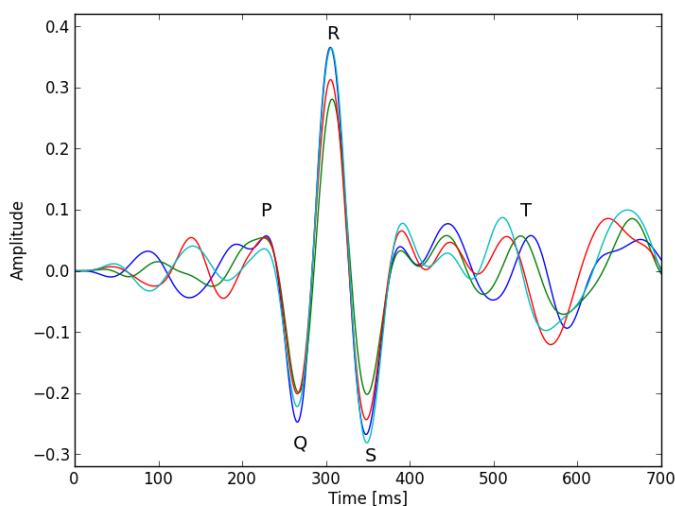
**Fig. 2.1.** Generic block diagram presenting the proposed acquisition system.

The visualization frame works bidirectionally and can be used as on-line signal checker, showing the authentication result or to set-up the reckoning system, enabling enrolment of new users.

## 2.1 State of the Art

Prior works in the ECG biometric recognition field can be categorized as either fiducial points dependent or independent. Fiducials are specific points of interest on an ECG heart beat such as the ones shown in Fig. 1.7. Therefore, fiducial based approaches rely on local features of the heart beats for biometric template design, such as the temporal or amplitude difference between consecutive fiducial points. On the other hand, fiducial points independent approaches treat the ECG signal or isolated heart beats holistically and extract features statistically based on the overall morphology of the waveform.

Both approaches have advantages and disadvantages. While fiducial oriented features risk to miss identifying information hidden behind the overall morphology of the biometric, holistic approaches deal with a large amount of redundant information that needs to be eliminated. The challenge in the later case, is to remove this information in a way that the intra-subject variability is minimized and the inter-subject is maximized. For the ECG case, detecting fiducial points is a challenging process due to the high variability of the signal.



**Fig. 2.2.** Variability surrounding the QRS complex among heart beats of the same individual

Fig. 2.2, shows an example of such a variability, superimposing different single heartbeats of the same user. Each heart beat was aligned using the QRS complex, and is evident that there is significant variability surrounding the P and the T wave. The localization of these waves onsets is a challenging task [12].

Current literature gives plenty techniques that can be used for authentication and identification. The table 2.1 shows some of the works in this area such as their different approaches. Fiducial [?, 23, 24], non-fiducial [25, 26, 27, 28, 29, 18, 30, 31] and hybrid approaches [32, 33]. To our best knowledge, authentication and identification methods used in real time are not yet

available nor published in the open literature, thus this theses will compare the results only in authentication/identification performance, not failing to mention the aspects of a embedded system (speed, price, consume, etc).

**Table 2.1.** Comparative table of ECG authentication/identification techniques.

Study	Sample Size	Fiducial Type	Session Type	Authentication Performance(%)	Identification Performance(%)
Biel <i>et.al.</i> [?]	20	Fiducial	Multiple Days	-	100
Shen <i>et.al.</i> [32]	20	Hybrid	Single Day	-	100
Israel <i>et.al.</i> [23]	29	Fiducial	Multiple States	-	97(AST), 100(AEL)
Zhang and Wei[24]	520	Fiducial	Single Day	-	97.4
Molina <i>et.al.</i> [25]	10	Non-Fiducial	Multiple Days	2(EER)	-
Silva <i>et.al.</i> [33]	168	Hybrid	Multiple States	-	99.63, 99.97(FSC)
Agrafioti and Hatzinakos[26]	14	Non-fiducial	Single Day	-	100(12 leads)
Agrafioti <i>et.al.</i> [27]	10	Non-fiducial	Multiple States	3.4(EER, HFU), 6.3(EER, MFU), 14.7(EER, LFU)	-
Yao and Wan[28]	20	Non-fiducial	Mixed	-	91.5
Coutinho <i>et.al.</i> [29]	26	Non-fiducial	Multiple States	-	85.2
Odinaka <i>et.al.</i> [18]	269	Non-fiducial	Multiple Days	0.37(EER, WS), 5.58(EER, ASWF)	99(WS), 76.9(ASWF)
Ye <i>et.al.</i> [30]	18, 18, 47, 65	Non-fiducial	Single Day	-	99.6(2 channels, PHBIA, n=47)
Lourenço <i>et.al.</i> [31]	16	Non-fiducial	Single Day	13(EER)	94.3

\*AEL = Across Electrode Locations, AST = Across Stress Tasks, ASWF = Across Sessions With Fusion, FSC = Feature Selection Context, HFU = High Frequency Updating, LFU = Low Frequency Updating, MFU = Medium Frequency Updating, PHBIA = Per Heart Beat Identification Accuracy, WS = Within Session.

### 2.1.1 Algorithms based on Fiducial Features

Algorithms based on fiducial features use the characteristic points—wave onset, peak (minima or maxima), and offset, extracted from an ECG trace to generate the feature set. It is defined as characteristic points the actual points located on an ECG trace and fiducial features to be the

features that are derived from these characteristic points. For example, the peak of the R wave is a characteristic point, while the time difference between the peaks of the R and T waves, the RT interval, is a fiducial feature. There are four types of fiducial features that have been used for ECG based recognition: temporal, amplitude, angle, and dynamic (R-R intervals) [11]. Some techniques used, based on fiducial features, are:

- Principal component analysis and generative model classifier [?];
- Wilk’s lambda feature selection and linear discriminant analysis classifier [23];
- Principal component analysis and Bayes classifier [24].

### 2.1.2 Algorithms based on Non-fiducial Features

Algorithms based on non-fiducial features do not use the characteristic points for generating the feature set. Instead, some of the algorithms use one or more of the characteristic points for heartbeat segmentation, while others do not use the characteristic points at all, but segment the ECG recording into overlapping or non overlapping segments. Most of the methods based on non-fiducial features require the detection of the R peaks for heartbeat segmentation and alignment [11]. There are a few methods that not only require the detection of the R peaks, but also some other characteristic points such as the onset and peak of the P wave, the onset and end of the QRS complex, the peak and end of the T wave [11]. Some methods require the detection of all or a subset of the three major components of each heartbeat (P wave, QRS complex, and T wave) for feature extraction [11]. However, there are other methodologies that do not extract any characteristic points, but rather segment the entire ECG trace into non overlapping or overlapping windows, and extract features from those windows [11]. Example techniques used, based on non-fiducial features, are:

- Morphological synthesis of R-R segments and euclidean distance [25];
- Autocorrelation/linear discriminant analysis and nearest neighbour classifier [26];
- Template updating [27];
- Discrete wavelet transform of mean R-R segments and principal component analysis [28];
- Quantization of heartbeat, Ziv-Merhav cross parsing and minimum description length [29];
- Log-normal spectrogram [18];
- Discrete wavelet transform, independent component analysis and support vector machine radial basis kernel [30];
- Mean of amplitude-normalized re-sampled heartbeats, nearest center and euclidean distance [31].

### 2.1.3 Algorithms based on Hybrid Features

There are a few algorithms that use non-fiducial features for pruning the match space and fiducial features for the final classification while there are others that combine fiducial features with non-fiducial features to create the feature set [11]. Example techniques used, based on hybrid features, are:

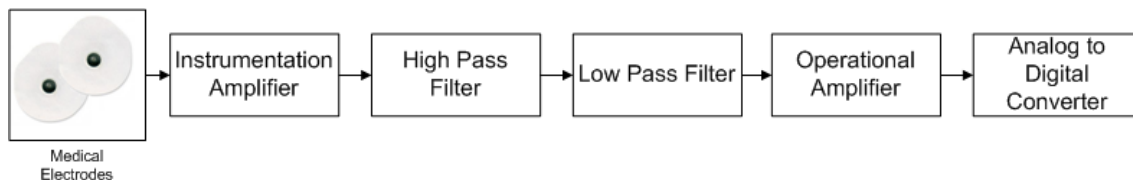


- Template matching based on cross correlation and decision-based neural network [32];
- Sub-sampled mean wave, feature selection context and nearest neighbour classifier [33] .

## 2.2 Acquisition

Contextualizing this work, as mentioned in the introductory chapter, the acquisition is performed using only two electrodes, one in each hand. Usually, recognition techniques (Table 2.1) use more than 3 electrodes to acquire the ECG signal. This generates a higher quality signal, compared to a Lead I acquisition, but not suitable for a portable system by its complexity and intrusion. The acquisition electronic module used is part of the BITalino [34, 35] project described later in subsection 4.2.2.

The hardware acquisition system can be represent by a block diagram, presented in Fig. 2.3. The first block is the instrumentation amplifier that is a differential amplifier suitable for use in biosignal acquisition. Its main characteristics include very low DC offset, low drift, low noise, very high open-loop gain, very high common-mode rejection ratio, and very high input impedances. Then the filters are used to remove unwanted noise from the signal acquired on the analysed subject and to remove the DC component of the signal generated mainly by unwanted movement of the members in contact with the electrodes. The high pass filter generally uses a cut-off frequency of 0.5 Hz and low pass filter generally uses a cut-off frequency of 250 Hz. Usually, the ECG signal contains information from 0.01 Hz to 250 Hz [14]. Finally the analogue to digital converter (ADC) translates the analogue signal to digital information, usually with a 10 to 12 bit precision.



**Fig. 2.3.** Block diagram of an generic ECG acquire system

## 2.3 Preprocessing: Segmentation and Filtering

The preprocessing phase is used to prepare the raw signal to be used at the proposed algorithm. The usual steps in this phase are down-sampling and filtering to peak detection and posterior segmentation. A very important step is the digital notch filter used to remove the power line interference. As for segmentation its an usual practice to take individual 700 msec segments aligned by the respective R-wave peak, beginning 200 msec prior to the peak. The segment (heart pulse) duration is chosen to ensure that all of the major components (P, Q, R, S, and T-waves of a single heartbeat) were included while minimizing the possibility of including portions

of adjacent beats. Each ECG heart pulse should be normalized by subtracting the sample mean of the pulse, and dividing by the sample standard deviation in order to cut-off abnormal QRS wave. In order to align the ECG segments to the peak of the R-wave, the peak has to be detected. Later on, the proposed approach will be described on Chap. 3.2. Fig. 2.4 describes de generic block diagram of the preprocessing phase.



**Fig. 2.4.** Block diagram of an generic ECG signal preprocessing

## 2.4 Feature Extraction

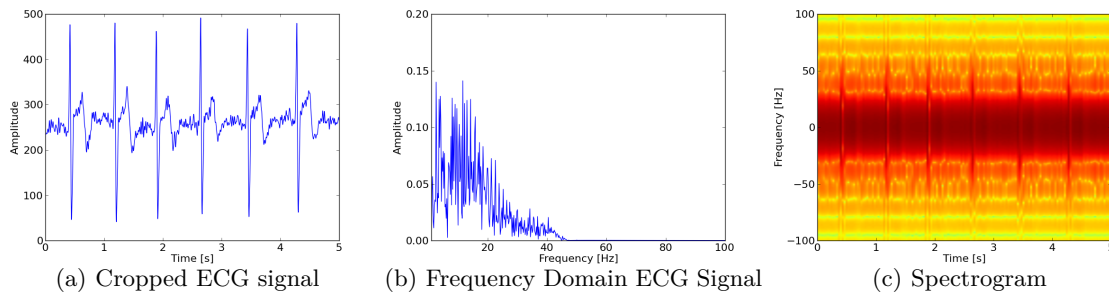
This component differs according to the approach. In the fiducial approach, features are extracted from each sample ECG signal. In non-fiducial approach, there are not extracted features but the sample ECG signal is used as a whole one characteristic. On the other hand, there are studies [29] for non-fiducial approaches, using this block as a quantizer which converts the samples into a set of characters (text). Hybrid approaches, like Odinaka's [18], the base model of feature selection used in this work, uses the heartbeat as a whole (non fiducial) to create a frequency characteristic and with that "frequency domain" ECG signal, features are extracted and used as evaluation (fiducial).

## 2.5 Classification

The main purpose of the classifier is to indicate if the acquired samples belong to a given subject. The most common way to perform a classification is based on the similarity between two sets of samples (samples and test samples of the model). The distance between sets may be used as the similarity measure. Small values of the similarity measure are interpreted as small distances between samples. Based on the type of classifier used, one can divide ECG recognition methodologies into seven groups:  $k$  nearest neighbours [36], nearest center [37], LDA [38], neural networks (NNs) [39], generative model classifiers (GMCs) [18], support vector machines (SVMs) [40], and others. Of these groups, the most frequently used in the ECG recognition literature are nearest centre, LDA, nearest neighbour and log-likelihood ratio (LLR) [11], being this the one used in this work, drawn from Odinaka method [18].

## Frequency-based ECG Recognition

The proposed ECG recognition algorithm uses the ECG frequency information of each person as the characteristic to be able to distinguish one from the others. This study was already been performed by Odinaka [18], and it is herein purposed innovations to his work in order to increase the general performance of the algorithm. It is a hybrid feature extraction since it uses the QRS peak as segmentation search point but after that the full heartbeat is used as a general frequency characteristic based on the means and variances of the signal frequency values, this is further explained in Section 3.3. Fig. 3.1, (a) and (b), illustrate a cropped ECG signal in the time and frequency domains, respectively. Composing the time and frequency information results on the often so-called spectrogram, presented in Fig. 3.1(c). All of these ECG signal dimensions have their characteristics that can be extracted for authentication and identification purposes.



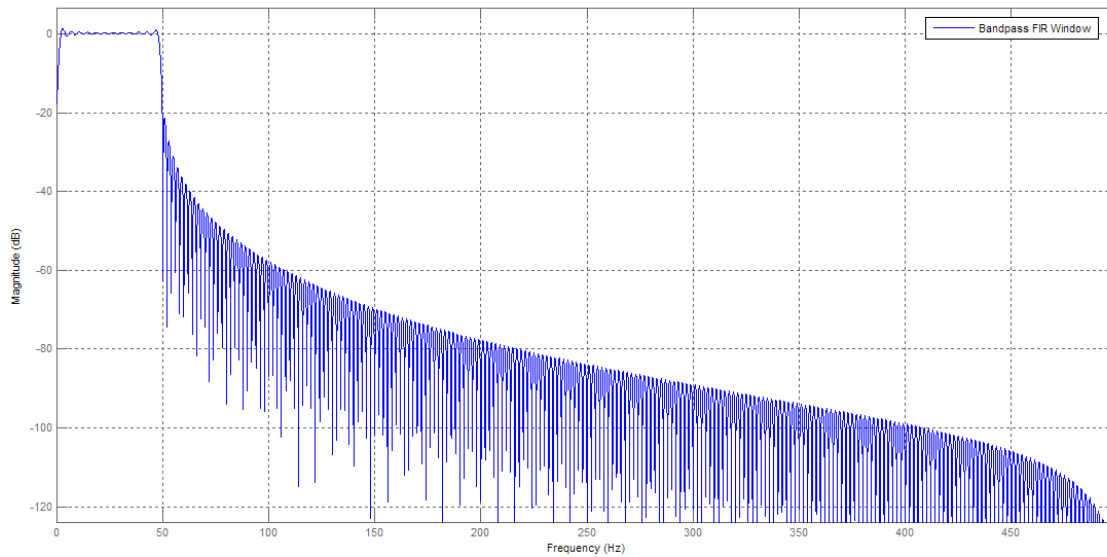
**Fig. 3.1.** Same user time-frequency analysis

In this chapter, all the reckoning system blocks, presented in Fig. 2.1, will be theoretical described and the solutions be given.

### 3.1 Filtering

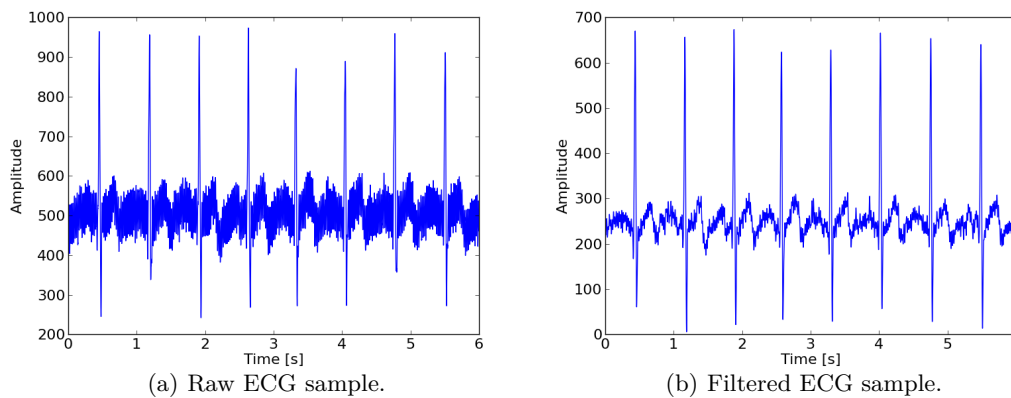
Since the aim is to develop a frequency dependent characteristic extractor, the cut-off frequencies of the filters have to be wisely chosen, in order to ensure no data loss but also rejecting unwanted noise away. The solutions available for the filter algorithm are:

- **Filtering by Direct Manipulation of the Fast Fourier Transform (FFT):** This approach gives complete freedom to control the frequency and phase response of the filter. There are two significant costs associated with implementing a filter in this fashion. The first problem is that computing the FFT of a signal can (depending on the sampling rate and time duration of the signal) be very computationally intensive. The second issue is that the entire signal must be obtained before the filtering begins, its not feasible to use this method for real time filtering [41].
- **Infinite Impulse Response Filtering (IIR):** These are digital filters must be implemented recursively because, theoretically, the response of these filters to an impulse never settles to zero. In practice, the impulse response of many IIR filters approaches zero asymptotically, and may actually reach zero in a finite number of samples due to the finite word length of digital computers. The frequency response function of a stable IIR filter is the Discrete Fourier Transform of the filter's impulse response. This filter phase is difficult to control and even with the advantage of low order coefficients to achieve a high resolution filter its not reliable to implement in real time because of his complex response.
- **Finite Impulse Response Filtering (FIR):** Known for the linear operators which have finite duration impulse responses. Such filters can be easily implemented by simply convolving the input signal with the impulse response. Since the impulse response is typically very short (perhaps just a few samples), this convolution can often be efficiently implemented directly without using the convolution theorem and the FFT. Finite impulse response filters are invariably stable because they have no recursive components (*i.e.*, no internal feedback in their algorithms) [41]. It's also trivial to make such a filter in real time with the only disadvantage that its needed a large minimum order do archive the desirable filtering.



**Fig. 3.2.** FIR filter magnitude response.

Keeping in mind the embedded use of the algorithm and the characteristics of the presented filters, a bandpass FIR filter is to be implemented with a five hundred filter order, Fig. 3.2. This feature adds an initial delay of five hundred samples in order to remove the filter transient response (0.5 seconds) and, on the other hand, it gives an cut-off frequency attenuation of 6dB (half the passband gain). The used cutoff frequencies are 1Hz and 49Hz. Therefore, the DC component is discarded and all the unwanted high frequencies (see section 2.2) and subsequently the main line interference (50Hz). Fig. 3.3 shows the result of the application of this filter to a ECG sample signal and the noise reduction is obvious.



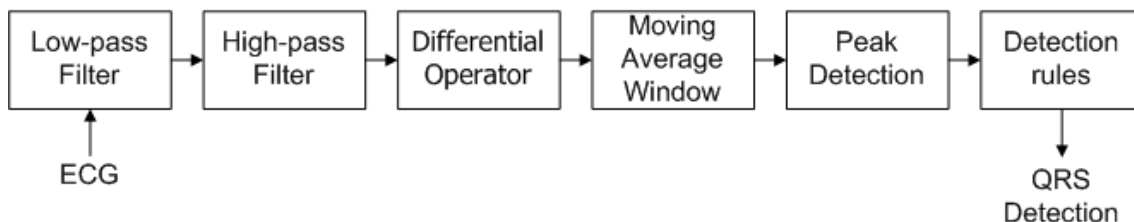
**Fig. 3.3.** Visual comparison between raw and filtered ECG samples.

## 3.2 Segmentation

Since heartbeat classification must be done using single heartbeats, the alignment of the detected ones must be as close as possible for the same subject so the comparison could be reliable. In order to achieve that alignment, a peak detection (QRS detection) algorithm must be implemented. In this work, two algorithms will be tested: Hamilton QRS detector [42] and Slope Sum Function (SSF) [43].

### 3.2.1 Hamilton

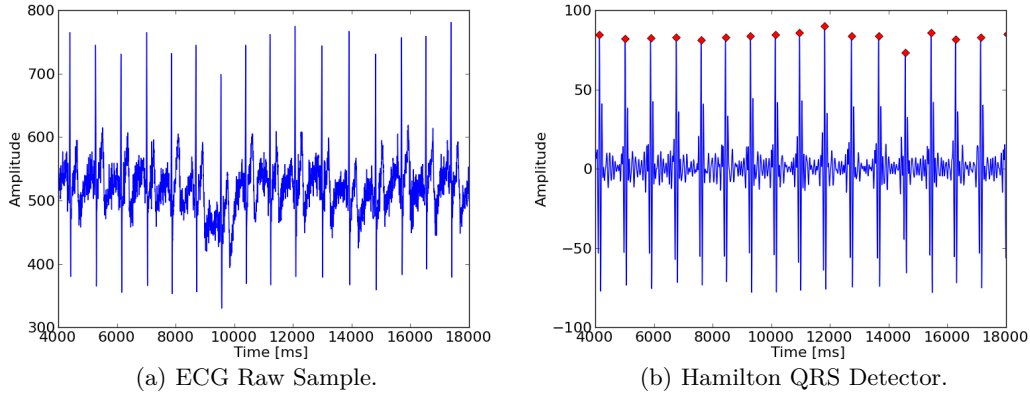
The segmentation step herein proposed is based on Hamilton work [44] for the QRS detection process. This QRS detector needs a preprocessing phase, presented in Fig. 3.4. The filter herein presented prepare the raw signal for the detection algorithm. The cut-off frequency of the filters are 16Hz and 8 Hz for low-pass and high-pass filters, respectively. The moving average windows have a 80 ms duration.



**Fig. 3.4.** Hamilton QRS detection operations

The basic detection rules for the beat detector are the following:

1. Ignore all peaks that precede or follow larger peaks by less than 200 ms.
2. If a peak occurs, check to see whether the ECG signal contained both positive and negative slopes. If not, the peak represents a baseline shift.
3. If the peak occurred within 360 ms of a previous detection and had a maximum slope less than half the maximum slope of the previous detection assume it is a T-wave.
4. If the peak is larger than the detection threshold call it a QRS complex, otherwise call it noise.
5. If an interval equal to 1.5 times the average R-to-R interval has elapsed since the most recent detection, within that interval there was a peak that was larger than half the detection threshold, and the peak followed the preceding detection by at least 360 ms, classify that peak as a QRS complex.



**Fig. 3.5.** Hamilton segmentation processing results.

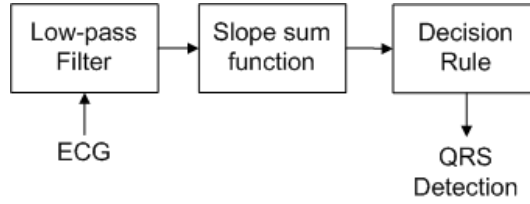
The detection threshold used in steps 4 and 5 using estimates of the QRS peak and noise peak heights. Every time a peak is classified as a QRS complex, it is added to a buffer containing the eight most recent QRS peaks. Every time a peak occurs that is not classified as a QRS complex, it is added to a buffer containing the eight most recent non-QRS peaks (noise peaks). The DT is set between the mean or median of the noise peak and QRS peak buffers according to the formula:

$$DT = ANP + TH(AQP - ANP) \quad (3.1)$$

where TH is the threshold coefficient (generally between 0.3125 and 0.475), ANP is the average noise peak and AQP is the average QRS peak. Similarly, the R-to-R interval estimate used in 5 is calculated as the median or mean of the last eight R-to-R intervals. Fig. 3.5 shows the result of this algorithm on a raw ECG signal.

### 3.2.2 Slope Sum Function (SSF)

Slope sum function was originally developed for detecting the onset of arterial blood pressure (ABP) pulses [43]. This work proposes the use of this algorithm for the detection of ECG's QRS wave. The motivation of this work is the on-the-fly processing algorithm offered by this detector. The algorithm employs a windowed and weighted slope sum function (SSF) to extract QRS waveform features from the heartbeat. Adaptive thresholding and search strategies are applied to the SSF signal to detect QRS pulses and to determine their peak.



**Fig. 3.6.** SSF QRS detection operations

As shown in Fig. 3.6, the algorithm consists of three components: a low-pass filter, a windowed and weighted slope sum function, and a decision rule.

- **Low-pass filter:** The purpose of the low pass filter is to suppress high frequency noise that might affect the QRS peak detection.
- **Slope sum function:** The purpose of the slope sum function is to enhance the upslope of the R pulse and to suppress the remainder of the electrocardiogram waveform. The windowed and weighted slope sum function at time  $i$ ,  $z_i$ , is defined as follows:

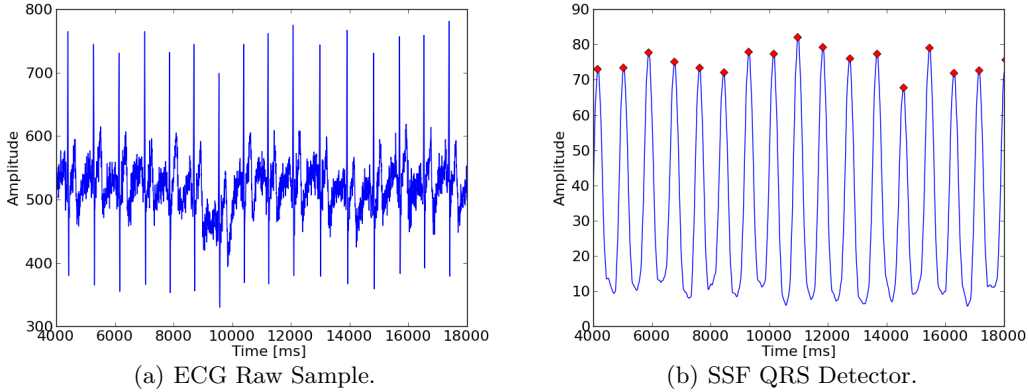
$$z_i = \sum_{k=i-w}^i \Delta u_k, \Delta u_k = \begin{cases} \Delta y_k & : \Delta y_k > 0 \\ 0 & : \Delta y_k \leq 0 \end{cases}$$

where  $w$  is the length of the analyzing window;  $1 + w \leq i \leq N$ ,  $N$  is the total number of heartbeats samples in the record;  $\Delta y_k = y_k - y_{k-1}$ , and  $y_k$  is the low-pass filtered ECG signal as defined above. To maximize the SSF,  $w$  is chosen approximately equal to the typical duration of the upslope of the R pulse. In the proposed algorithm,  $w = 300$  ms or 300 samples for the sampling frequency of 1000 Hz. The onset of the SSF pulse generally coincides with the onset of the QRS pulse as the SSF signal can only rise when the ECG signal (or noise not removed by filtering) rises. Since the SSF signal is a simpler signal to process, the pulse onset will be detected by processing the SSF signal on-the-fly, making it superb for real-time processing.

- **Decision rule:** This task is splitted into two: First, it is applied an adaptive thresholding to the SSF signal in order to detect SSF pulses of appropriate amplitude. Next, a local search strategy is employed around the detection point to confirm the detection and to identify the likely onset of the pulse. During the thresholding step, a threshold base value is established and is initialized at three times the mean SSF signal (averaged over the first five/ten seconds of the recording). The threshold base value is adaptively updated by the maximum SSF value for each SSF pulse detected. The actual threshold is taken to be 60% of the threshold base value. When the SSF signal crosses this threshold, the algorithm searches for the minimum and the maximum SSF values in a 100ms window preceding and succeeding the threshold-crossing point, respectively. The pulse detection is accepted only if the difference between the maximum and minimum exceeds a certain value; otherwise the pulse detection is rejected. When the pulse is accepted, the algorithm searches backward in time from the threshold-crossing point for the onset of the SSF pulse. The onset point is determined when the SSF



signal exceeds 1.0% of the maximum SSF value. The calculated QRS onset is adjusted to compensate for the low-pass filter's phase shift. Finally, to avoid double detection of the same pulse, a 300ms eye-closing (refractory) period is applied, during which no new pulse detection is initiated.



**Fig. 3.7.** SSF segmentation processing results.

This approach to QRS pulse onset detection is based on the transformation of a low-pass filtered ECG signal into a slope sum function signal, in which the initial upslope of the QRS wave form is enhanced and the remainder is suppressed. The transformation leaves the location of the pulse onset unaltered, except for the fixed filter delay, and detection of the pulse onset based on the slope sum function signal is straight forward. Fig. 3.7 demonstrates the result of this algorithm in an acquired ECG signal.

### 3.2.3 Segmentation Comparison

Both of the studied methods rely on preprocessing to grant a good QRS detection. The usage of software QRS detection algorithms in embedded devices requires the evaluation of the detection performance. Table 3.1 compares the two algorithms with eleven different users. The results show the peak detection and the true QRS wave form detection. Both scenarios have high success rate, with the Hamilton having a mean 91% success rate and SSF having 90% success rate. After considering both approaches, the crucial characteristic to compare is the real-time capacity and computational load. SSF algorithm is much lighter in computational load, with only one filter and threshold comparison and update. Since both approaches have approximately the same performance the SSF would be the better choice for on-the-fly processing.

**Table 3.1.** Performance comparison of the different segmentation algorithms.

User #	Hamilton Detections	Hamilton Valid Detections	SSF Detections	SSF Valid Detections	Total Heartbeats	Performance Ham./SFF (%)
1	32	29	40	31	32	91/97
2	42	40	40	40	42	95/95
3	48	39	48	33	39	100/85
4	36	35	37	35	37	96/95
5	28	27	29	27	28	96/96
6	54	42	29	29	32	76*/91
7	35	31	34	30	37	84/81
8	28	20	26	19	24	83/79
9	36	33	35	33	36	92/92
10	42	41	41	40	44	93/91
11	35	34	33	33	36	94/92

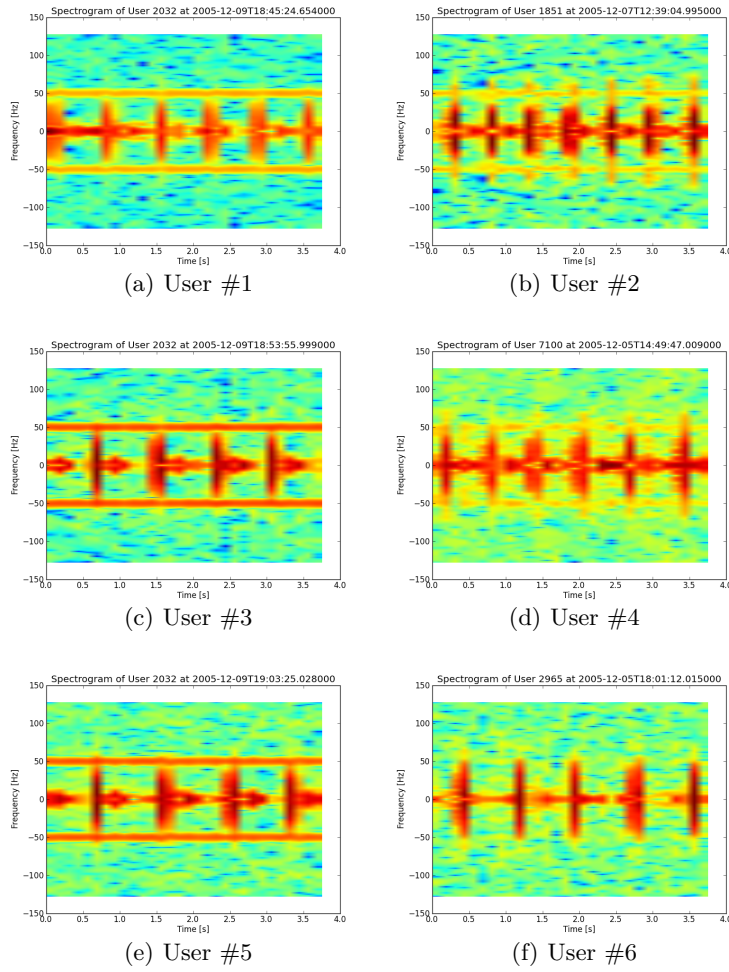
\*This value comes from false detections of heartbeats.

### 3.3 Feature Extraction and Classification: Odinaka’s Time-frequency Method

As for feature extraction and classification algorithm this thesis will focus on the work from Odinaka [18]. This work is an algorithm based on hybrid features since he needs fiducial features to segment the ECG sign but also uses all these segment to translate it to a score.

As already known by the current literature, ECG signals featured in their temporal domain have unique characteristics for each individual, making possible to identify any subject by ECG signal processing. Since the domain change only leads to a different perspective of the way the information is seen, its justifiable the use of the frequency domain to extract the same kind of unique characteristics used to the identification process.

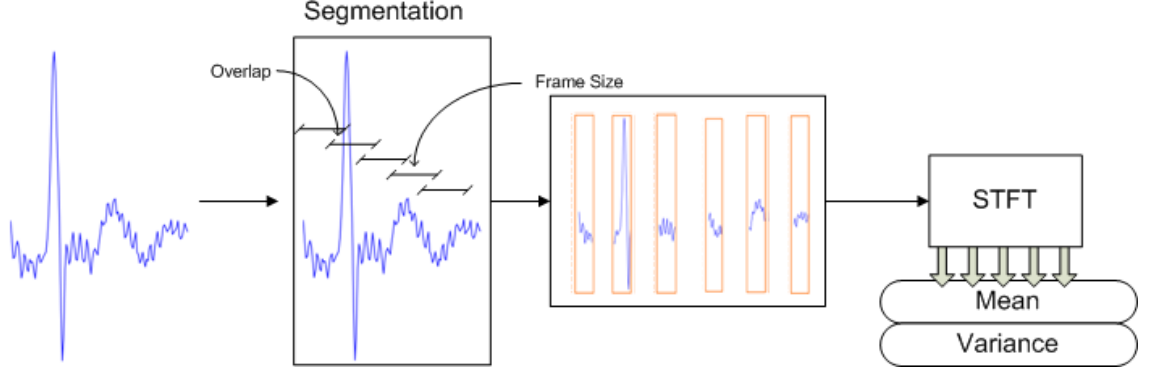
Fig. 3.8 shows us that, even at naked eye, the differences between the spectrogram of the same user are less expressible than between different subjects. This is a very prominent way to see the differences in the characteristics of the ECG signal in different persons.



**Fig. 3.8.** Spectrogram comparison between different users

### 3.3.1 Time-frequency Method

Odinaka [18] proposed a novel robust time-frequency method for ECG biometrics. On its original work, the method was applied to a large dataset of one lead ECG signals from 269 subjects, representing different demographic groups and health status. This work study, implement and deploy a system based on Odinaka [18] algorithm.



**Fig. 3.9.** Block diagram for Odinaka's time-frequency method

For each ECG pulse signal, a spectrogram is computed which is the logarithm of the square of the magnitude of the short-time Fourier transform (STFT) of a normalized ECG heart pulse.

Onidaka work use for the short-time Fourier transform a hamming window of size 64 ms, with an overlap of 54 ms (10 ms step time). After computing the STFT, the frequency content was truncated at 250Hz to reduce boundary effects. The spectrogram is then computed as the logarithm of the squared-magnitude of the truncated STFT and the data is shaped in a vector containing all the STFT segments results. This method is presented in Fig. 3.9.

In the same work the index of each point of the spectrogram is referred as a time-frequency bin. Thus each ECG heart pulse can be represented by  $L = 2048$  time-frequency components denoted as  $Y(l)$ . This number is obtained by the reshaped data, considering a 64 ms windows, resulting in a 32 sample frequency signal, ignoring the negative part of the spectrum, since the signal is real, and the 64 STFT that can be obtained in a 750 ms signal sampled at 1kHz with an overlap of 54 ms. For each  $l$ -th bin of the  $i$ -th subject, it is used the maximum likelihood (ML) estimates which are the sample means and variances denoted as  $\hat{\theta}_i = (\mu_{il}, \sigma_{il}^2)$ .

### Feature Selection and Classification

A effective away to select informative time-frequency bins for verification and recognition is using a robust feature selection method. The two key elements considered in this feature selection method are distinguishability and permanence. The feature should help distinguish the subject from a reasonably large subset of other subjects, and it should be stable across sessions. Let  $\mu_{il}$  and  $\sigma_{il}$  be mean and standard deviation of the  $l$ -th feature of the  $i$ -th subject. The  $l$ -th feature of the  $i$ -th subject is selected if the symmetric relative entropy, *i.e.*, the symmetric Kullback-Leibler divergence, between  $\mathcal{N}(\mu_{il}, \sigma_{il}^2)$  and the nominal distribution  $\mathcal{N}(\mu_{0l}, \sigma_{0l}^2)$  is larger than a threshold  $\kappa > 0$ , being  $(\mu_{0l}, \sigma_{0l}^2)$  the maximum likelihood estimate from all features of all subjects in the database. The Kullback-Leibler divergence is a non-symmetric measure of the difference between two probability distributions P and Q, defined by

$$D(p||q) = \int p \log \frac{p}{q}. \quad (3.2)$$

The symmetric relative entropy between the two densities is defined as

$$d(p, q) = D(p||q) + D(q||p) \quad (3.3)$$

For the Gaussian distributions used in this model, the symmetric relative entropy between  $\mathcal{N}(\mu_{il}, \sigma_{il}^2)$  and  $\mathcal{N}(\mu_{0l}, \sigma_{0l}^2)$  is

$$d(\hat{\theta}_i(l), \hat{\theta}_0(l)) = \frac{\sigma_{il}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{0l}^2} + \frac{\sigma_{0l}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{il}^2} - 1 \quad (3.4)$$

where the nominal model is obtained by using the spectrograms of all the subjects in the database and  $\hat{\theta}$  denotes the maximum likelihood estimate for the individual in test,  $\hat{\theta}_i(l)$ , and in the train database,  $\hat{\theta}_0(l)$ . Using the symmetric relative entropy for feature selection ensures that only those bins whose distributions are far from the nominal are selected for each subject, thereby ensuring distinguish-ability.

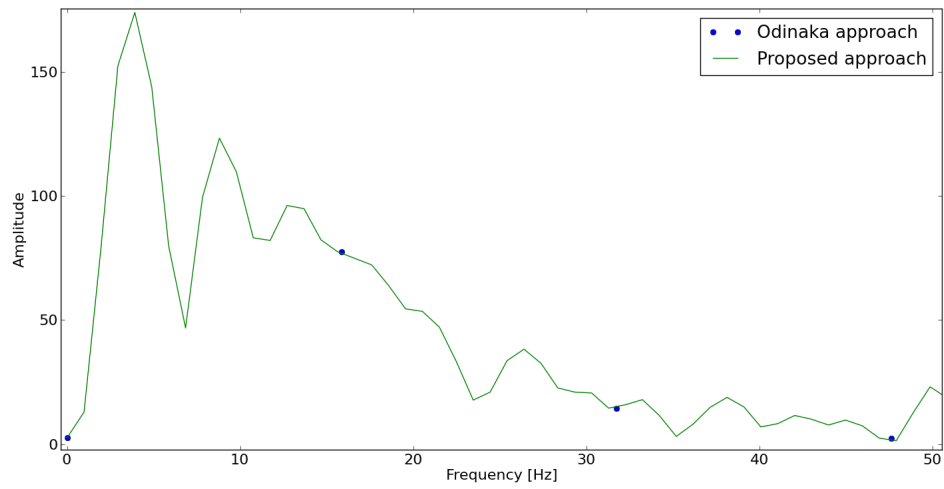
The score of a test heartbeat using the  $i$ -th subject's model is given by the log-likelihood ratio (LLR):

$$\Lambda = \sum \left[ \frac{p_i(Y(l)|\hat{\theta}_i(l))}{p_0(Y(l)|\hat{\theta}_0(l))} \right] I_{d(\theta_i(l), \theta_0(l)) > \kappa} \quad (3.5)$$

where  $I$  is the truth function indicating which time-frequency bins are selected;  $l$  is the index of the bins. For authentication, the LLR given in expression 3.5 is compared with a threshold  $\tau$ , so that if  $\Lambda > \tau$ , the heartbeat with the claimed identity is accepted, otherwise the heartbeat is rejected.

### 3.3.2 Proposed approach for the low resolution STFT

The main problem encountered on the Odinaka proposed method, when applied for the classification of low bandwidth ECG signals, was the low resolution offered by the STFT. Since this algorithm uses a 64 ms hamming window to run the STFT, the frequency resolution is one sample per 32 Hz at 1 kHz sampling frequency. As the signal is filtered at 40 Hz by the low-pass analogue filter all the frequency information present in the data is lost. The solution proposed here is an increase on the STFT resolution by increasing the number of points of the STFT and zero-padding the signal to meet the length requirements. With this approach, and cutting the frequency domain signal to 32 samples, the same length signal is achieved with a resolution of 1 sample per Hz.



**Fig. 3.10.** Difference between the two STFT methods of analysis of the same heartbeat

Fig. 3.10 exemplifies the difference between the low resolution SFTF and the SFTF with zero padding, from the same signal methods of evaluating the STFT used. This illustrates that the proposed zero padding increases the resolution. This will further increase the identification rate of the system when compared with Odinaka method.

## Embedded System Implementation

This chapter presents and describes the proposed embedded platform. The chapter starts with a comparative between embedded technologies and ends with the proposed prototype. All hardware solutions are explained as the peripherals used in the microcontroller. The software process is described as well as the solutions taken to develop the proposed algorithm.

### 4.1 Embedded Devices

Embedded platforms vary in many ways, used often depending on the usage, or project necessity. These devices can generally be divided in:

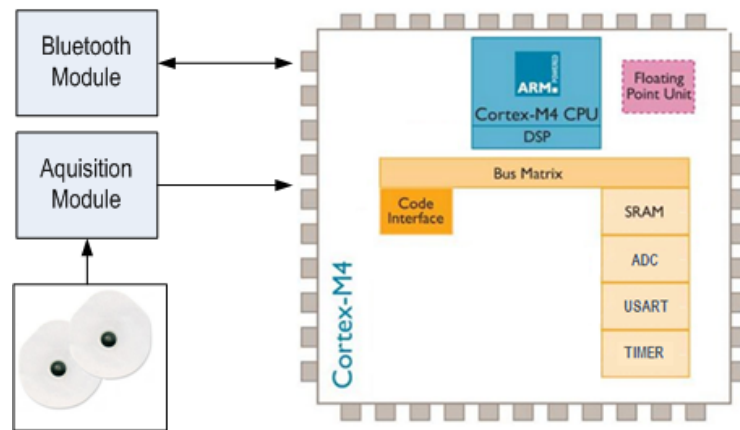
- A microprocessor is a multi-purpose, programmable, clock driven register and based electronic device. Many more microprocessors are part of embedded systems, providing digital control over myriad objects from appliances to automobiles to cellular phones and industrial process control [45];
- A MicroController (sometimes abbreviated  $\mu C$ ,  $\mu C$  or MCU) is a small computer on a single integrated circuit containing a processor core, memory, and programmable input/output peripherals. Microcontrollers incorporate all the features that are found in a microprocessor, however, it has also added features to make a complete microcomputer system on its own. Microcontrollers are designed for embedded applications, in contrast to the microprocessors used in personal computers or other general purpose applications due to on-chip (build-in) peripheral devices [45];
- A Digital Signal Processor (DSP) is a specialized microprocessor with an architecture optimized for the operational needs of digital signal processing;
- A field-programmable gate array (FPGA) is, informally thought, a 'blank slate' on which any digital circuit can be configured. Moreover, the desired functionality can be configured in the field. That is, after the device has been manufactured, installed in a product, or, in some cases, even after the product has been shipped to the consumer. In short, an FPGA provides programmable 'hardware' to embedded system developers [46].

- A application-specific integrated circuit (ASIC) can be defined as an integrated circuit designed for a particular application or end-use such as in a compact disc player or a telecommunications system. ASIC's are fully customized and have low costs but are designed for a final product due to is lack of reprogrammability.

ASIC's and FGPA's were discarded for the lack of reprogrammability and high costs, respectively. A DSP is specialized in data processing only and our system needs peripheral control and data storage, making it a unjustifiable solution. A microprocessor solution would need a construction of a fitting board with peripherals, so the chosen system, a development microcontroller is a all-in-one solution embedded system with a build-in microprocessor and all the needed peripherals. Fitting in these characteristics the development STM32F4DISCOVERY High-Performance Discovery Board is the solution herein proposed.

## 4.2 STM32F407VGT6 General Architecture

An ARM-Based Cortex4 32 bit RISC STM32F407VGT6, was chosen as the processor in our system. It works at 168MHZ, with characters of strong performance and low power consumption, real-time and low-cost. The processor includes: 1MB FLASH, 192KB+4KB RAM, and it will be using a bluetooth module used for communication with an auxiliary external visualization API. The system have the A/D converter with 12 bits resolution, and the fastest conversion up to  $0.41m\mu$ , with 3.6 V full-scale of the system. It also includes an Floating Point Unit (FPU) and a DSP inside the processor, making floating point mathematics faster than integers calculus. The system is powered by a external 5v power source (battery or USB power).



**Fig. 4.1.** Hardware block diagram of the system

Fig. 4.1 shows the processor peripherals and hardware used. The next subsections will describe each component and explain their use.



### 4.2.1 Bluetooth Module

Bluetooth is a way for devices to wireless communicate over short distances. The bluetooth hardware platform herein used is a Class II Bluetooth module (EGBT-045MS) with integrated USART protocol with a maximum bitrate transmission of 115200 baud per second (bps). Its powered by the embedded platform using his 5V power output, draws a maximum current peak of 100mA on full speed transmission and around 30mA in idle. In this project the bluetooth module is directly connected to the USART interface offered by the processor. This prototype uses Bluetooth communication for parameter configurations, like acquisition modality (between train and test scenarios) and allow the visualization of the acquired ECG signal. It also can be used as a result viewer, displaying the current authenticated or identified person.

### 4.2.2 Acquisition Module

The ECG acquisition module, is part of the BITalino [34, 35] project and is based on the voltage potential differential principle. Typically, the ECG signal acquired at the surface of the body is lower that 5mV and must be amplified to a level suitable for recording. This sensor amplifies and filters the signal with the parameters shown is Table 4.1.

Specification	Value
Filter	5 <sup>th</sup> order Butterworth band pass filter
Bandwidth	[0.5, 40]Hz.
Gain	1100

**Table 4.1.** Specifications of the BITalino ECG sensor.

The purpose of the filter is to cut the frequencies that are not needed for this study and unwanted noise, and in this case since the acquisition is performed "off-the-person", on the hands which are much more prone to noise, the bandwidth is more restrictive than on typical ECG sensors. Note that the signal is 1100 times amplified thus, high frequencies from external sources, DC offset from human movement, and main line interference are also substantially amplified. This filter will cope every one of this interferences and noise.

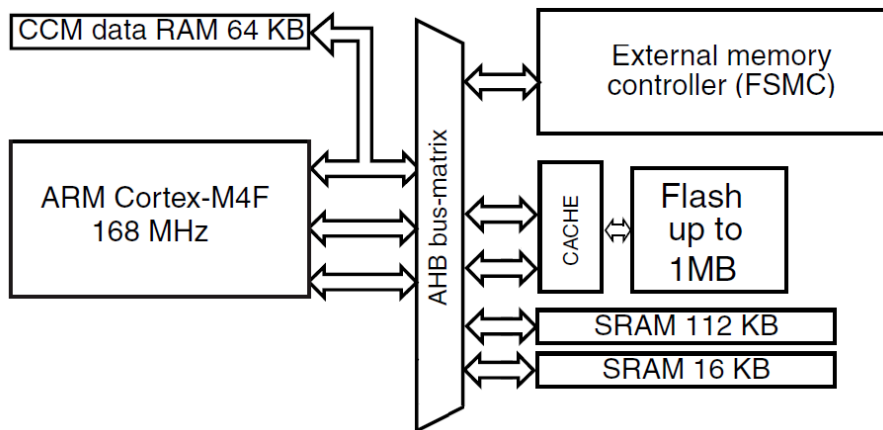
### 4.2.3 MCU Cortex Processor, Integrated DSP and FPU

The ARM Cortex-M4F processor is the latest generation of ARM processors for embedded systems [47]. It was developed to provide a low-cost platform that meets the needs of MCU implementation, with a reduced pin count and low-power consumption, while delivering outstanding computational performance and an advanced response to interrupts [47]. The ARM Cortex-M4F 32-bit RISC processor features exceptional code-efficiency, delivering the high-performance expected from an ARM core in the memory size usually associated with 8 and 16 bit devices. The processor supports a set of DSP instructions which allow efficient signal processing and

complex algorithm execution. Its single precision FPU (floating point unit) speeds up software development by using metalanguage development tools, while avoiding saturation [47].

#### 4.2.4 MCU Memory

A device storage space is important to keep code and data. Generally, in an embedded system, is divided in RAM and Flash memory. RAM is a volatile type of memory, which means that the data will be lost at device power off. As for Flash is a non-volatile storage unit capable of keep data without power source. In the hardware used, its available 1M Bytes of Flash memory and 196K Bytes of RAM memory, divided in a 64K Bytes block dedicated to the core (CCM, core coupled memory, providing performance equivalent to 0-wait) and two separated RAM modules of 112K Bytes and 16K Bytes, respectively. These blocks are separated to allow reading and writing at the same time by different peripherals or by the processor. For flash memory implementation a cache module must be used due to the difference of reading and writing speeds from the processor and the flash memory, being the last the slower one.

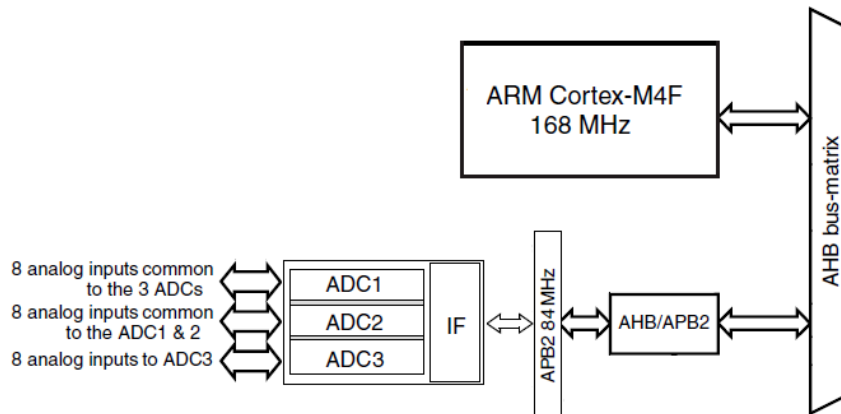


**Fig. 4.2.** MCU generic Memory block diagram, redrawn from [2].

The system also includes a Flexible static memory controller (FSMC) that allows possibility to add external memory up to a total of 4G Bytes of memory (maximum addressable memory). The 32-bit multi-AHB bus matrix interconnects all the masters (CPU) and the slaves (Flash memory, RAM, AHB peripherals) and ensures a seamless and efficient operation even when several high-speed peripherals work simultaneously. Fig. 4.2 shows the hardware placement and functionality of the described memory methodology. For this work the code and subjects train data are stored at flash memory because of his non-volatility and this way allowing system power off.

#### 4.2.5 MCU Analogue to Digital Converter

Three internal 12-bit analogue-to-digital converters are embedded and each ADC shares up to 16 external channels, performing conversions in the single-shot or scan mode. In scan mode, automatic conversion is performed on a selected group of analog inputs. Single-shot is the conversion type performed by the ADC is this prototype, using the timer as trigger.

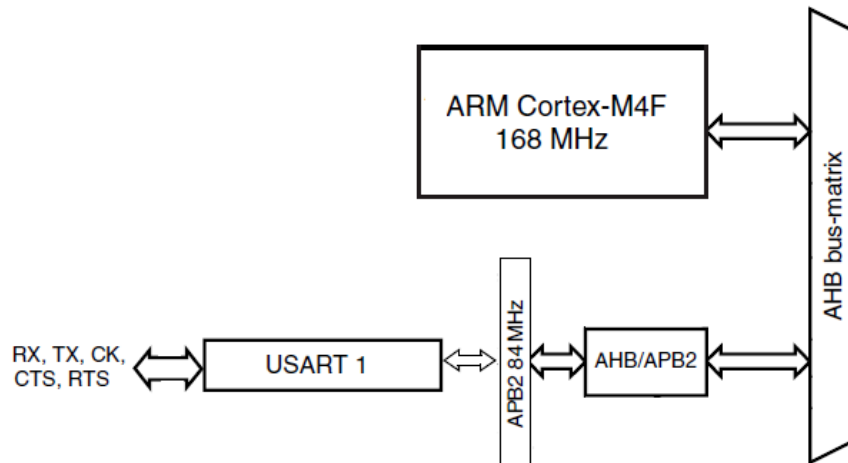


**Fig. 4.3.** MCU ADC block diagram, redrawn from [2].

The ADC's are connected to a high speed prescaler peripheral (APB2) that allow a maximum working speed of 84Mhz. Since this work aims a ADC sampling frequency of 1kHz, enough processing speed is available to achieve a precise measure. The precision will be measure in the next sections. Fig. 4.3 presents the hardware disposal of the ADC connections to buses and to the processor, highlighting that only one measure can be taken from each ADC at the same moment since only one communication channel is available.

#### 4.2.6 MCU USART

The STM32 embed four universal synchronous/asynchronous receiver transmitters (USART1, USART2, USART3 and USART6) and two universal asynchronous receiver transmitters (UART4 and UART5). These six interfaces provide asynchronous communication, multiprocessor communication mode and single-wire half-duplex communication mode. The USART1 and USART6 interfaces are able to communicate at speeds of up to 10.5 Mbit/s. The other available interfaces communicate at up to 5.25 Mbit/s. USART1, USART2, USART3 and USART6 also provide hardware management of the CTS and RTS signals.

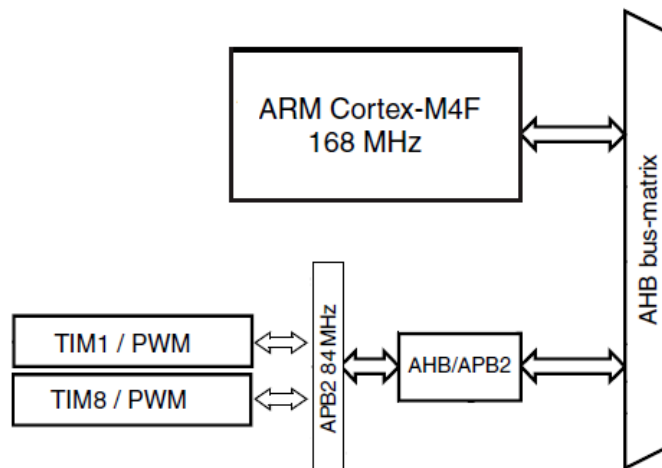


**Fig. 4.4.** MCU USART block diagram, redrawn from [2].

USART1 is used to communicate with the bluetooth module and allow asynchronous communication.

#### 4.2.7 MCU TIMER

The device include two advanced-control timers, eight general-purpose timers, two basic timers and two watchdog timers. To be able to sample the ECG signal, one general-purpose timer is used (TIM2).



**Fig. 4.5.** MCU TIMER block diagram, redrawn from [2].

The general-purpose timers consist of a 16-bit or 32-bit auto-reload counter driven by a programmable prescaler. They may be used for a variety of purposes, including measuring the pulse lengths of input signals (input capture) or generating output waveforms (output compare and PWM). Pulse lengths and waveform periods can be modulated from a few microseconds to several milliseconds using the timer prescaler and the RCC clock controller prescalers [2]. The timers are completely independent, and do not share any resources. They can be synchronized together. The proposed algorithm uses the TIM events to acquire a ADC sample with very high precision. Fig. 4.5 describes the general hardware diagram of the timer system. The timer is attached to APB2, capable of tic every 12.5 nanoseconds.

### 4.3 Software Framework

The framework of this biometric system is the software module that comprises a set of features that allow the execution of a real time authentication algorithm. Methods were first implemented in Python, a widely used general-purpose, high-level programming language that allow extended tests of each algorithm and support high amounts of data and after evaluated converted to C for running on the embedded system. Based on these objective, the software architecture relays on different modules, that combined generates a embedded application of a ECG acquisition and authentication algorithm. Fig. 4.6 represents the base algorithmic line, written in C, that the program follows, described as such:

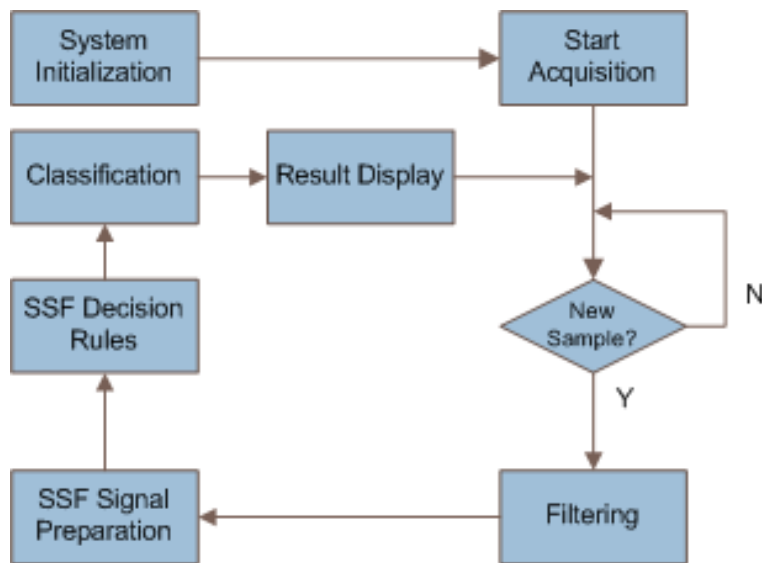


Fig. 4.6. System Software block diagram.

- **System Initialization:** In this block all the variables, peripherals and storage space are initialized and it is also defined the timing tick rate, ADC capture speed, USART baud rate

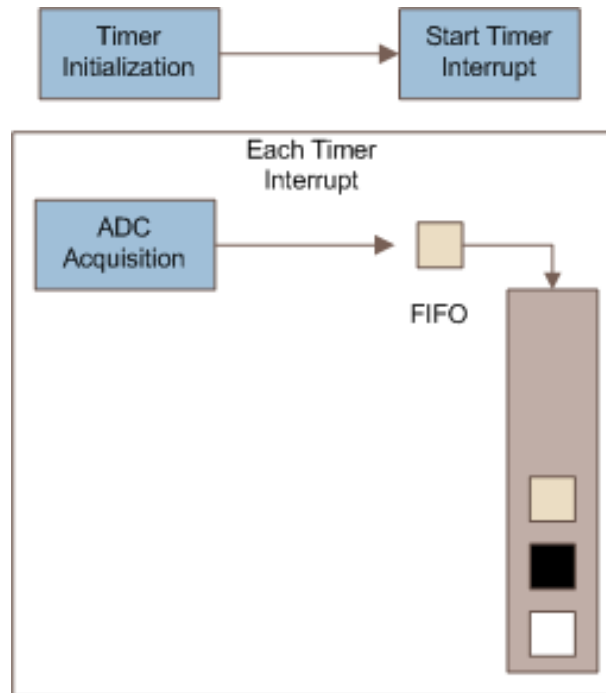
and FIFO's size. This is the first code to run after the embedded start-up and map the data of the system. The system only gets through the initialization on power on.

- **Acquisition Procedure:** The system will start the acquisition and the signal processing when a external system connected to the bluetooth send the start sequence. The start sequence, communication protocol and USART procedure will be described in the next subsections.
- **Filtering:** As mentioned before, two filter are needed, one for the peak detection (on the SSF) and another one for the feature extraction. In order to complete a real-time system, only one filter was implemented. A FIR 500-th order band-pass filter with a cutoff frequencies of [1, 49]Hz is implemented and the result signal is used as feature source and as SSF peak detector feed. The SSF function was adapted and implemented in order to use this type of signal, since it was originally designed to be used in a high filtered signal (band-pass [5, 15]Hz).
- **SSF Signal Preparation:** In this phase the ECG signal is processed in order to enhance the QRS peak and make it noticeable from the rest of the signal information.
- **SSF Decision Rules:** The decision of whether a peak is or not a valid QRS value is made here.
- **Classification:** If a valid peak is encountered, frequency characteristics are extracted from the windowed heartbeat and then compared with the features in the actual database.
- **Result Display:** Using the bluetooth communication set-up or the on-board LED's, this final step displays the result of the classification of the acquired ECG.

Most of the algorithm is parallelized with the help of interrupt triggers. The following subsections describe the parallel processing and detail the SSF implementation, feature selection, classification and communication protocol.

#### 4.3.1 Acquisition Software Architecture

After the acquisition begin a timer starts to run and executes a interrupt each millisecond. Fig. 4.7 describes the initialization set-up, and the interrupt work. This interrupt must have full priority for a coherent and persistence sampling rate. Each acquired sample his then added to a FIFO, in order to keep the samples ordered and stored. In normal execution (Filter and Peak Detection) this FIFO is always empty, meaning the processor is much faster to process the data then is the sampling rate. But in stressful occasions (FFT calculus) the processing time is bigger then a millisecond and the FIFO can reach up to 50 samples. The FIFO size is 500 samples just for precaution, since losing samples will destroy the authentication procedure.



**Fig. 4.7.** Timer Software block description.

A study was done to define the precision of the sampling frequency. Mainly this precision is defined by the jitter. Jitter is the undesired deviation from true periodicity of an assumed periodic signal, often in relation to a reference clock source. As the reference clock source used is an Agilent 33220A Function Waveform Generator with an harmonic distortion of -70dBc. The perfect jitter would be 0%, meaning that the sampling frequency is equal to the reference clock. Table 4.2 summarizes these tests and gives us a mean jitter of 0.0013%, being this value perfectly reasonable for frequency accuracy. Also frequency accuracy is shown with a mean of 0.00923%, meaning the deviation from the desirable frequency, 1000 Hz.

	Frequency [Hz]	Frequency Accuracy Rate [%]	Jitter [Hz/%]
Test #1	999.9077	0.00923	0.009/0.0009
Test #2	999.9092	0.00908	0.010/0.0010
Test #3	999.9048	0.00952	0.012/0.0012
Test #4	999.9092	0.00908	0.020/0.0020
<b>Mean</b>	999.9077	0.00923	0.013/0.0013

**Table 4.2.** Sampling rate test.

### 4.3.2 SSF Processing and Classification Software Architecture

The signal processing step for the SSF peak detection algorithm is presented in the fig. 4.8. The first step is a first derivative, that acts like a smooth low pass filter and discards the high frequency noise. Since the searched peak is the QRS, all the negative part of the signal is retired and replaced by 0. This can also be implemented as a module, increasing the noise around the peaks but adding additional down slopes that in some cases are more expressive than the QRS peak.

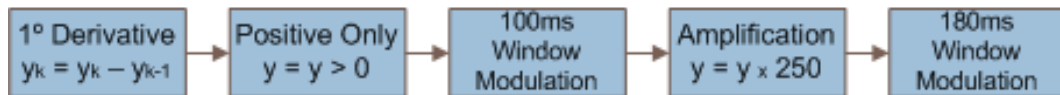


Fig. 4.8. Software block diagram of the SSF Signal preparation phase.

The following 100ms windows modulation makes each new sample grow depending on the size of the last 100 ms (100 samples at 1kHz). This time is the average QRS peak duration and thus making an amplification of all samples that are visual comparable to the desired slope. After the signal amplification step to replace and enhance the original signal dimensions another 180ms window modulation is fitted. With the same objective as the first one, but with a larger windows because of the QRS peak expansion that the first modulation has provided. This over again enhance the searched QRS ECG signal segment.

After the processing the signal feeds the peak search algorithm, as illustrated in fig. 4.9. For the first 5 seconds after the acquisition start the peak search algorithm is only calculating the used threshold for peak detection. As described in section 3.2.2, during the thresholding step, a threshold base value is established and is initialized at three times the mean SSF signal (averaged over the first 5 seconds of the recording). The threshold base value is adaptively updated by the maximum SSF value for each SSF pulse detected. The actual threshold is set to be 60% of the threshold base value. When the SSF processed signal crosses this threshold, the algorithm searches for the minimum and the maximum SSF values in a 150 ms-window preceding and succeeding the threshold-crossing point, respectively. The pulse detection is accepted only if the difference between the maximum and minimum exceeds a certain value; otherwise the pulse detection is rejected. After a pulse acceptance the signal is segmented in 700ms single heartbeats, 200ms preceding the peak and 500ms succeeding.



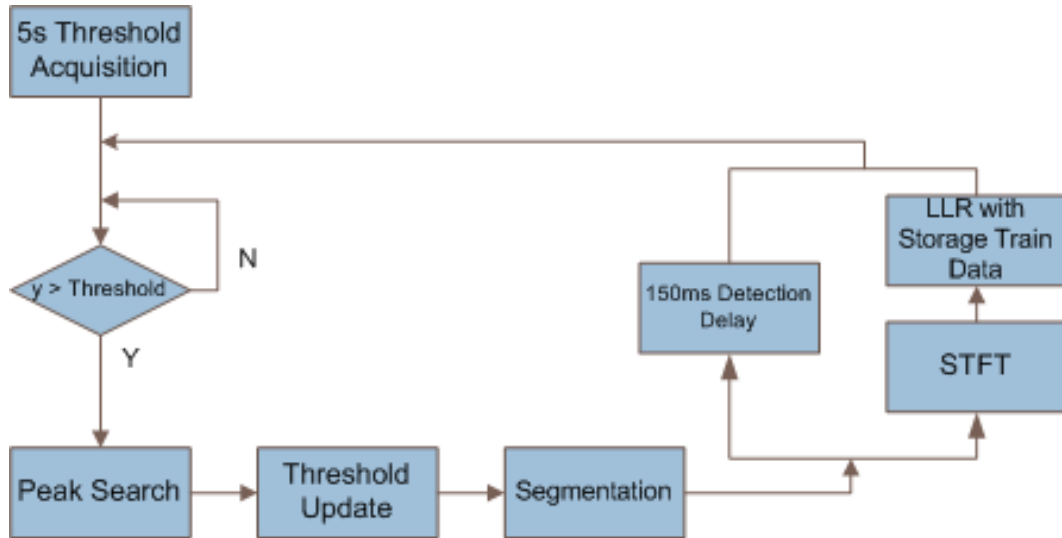


Fig. 4.9. Software block diagram of the peak detector and classifier.

Finally, to avoid double detection of the same pulse, a 150ms eye-closing (refractory) period is applied, during which no new pulse detection is initiated. In this period the feature extraction and classification algorithm start to process the segmented heartbeat. The STFT is computed with a 1024 point window for each 100ms of the 700ms segmented heartbeat (using zero padding). This means that 10 FFT's must be computed for of each signal. Since every 1024 point FFT uses 1.1ms of processing time, 10 will take 11ms being under the 150ms eye-closing period, so the delayed samples don't stack. After STFT computation it is calculated the maximum likelihood estimation which are the sample means and variances of the windows that compose the heartbeat. This extracted information act as features and are compared with the features stored in the database using the log-likelihood ratio (LLR) as score. As the score is computed the stored features are updated with the current extracted characteristics with a weighted average based on the score and the number of train heartbeats.

### 4.3.3 Bluetooth Communication Layer

Bluetooth is the wireless layer for the communication protocol in the embedded suite. Bluetooth provides the wireless connectivity that enables communication across diverse systems. The proposed packet provides a continuous communication, from the embedded system to the visualization system, lines of 6 data channels, 4 digital on/off bits, a cyclic redundancy check (CRC) for error-detection and a packed ID number. The proposed packet format is shown in Fig. 4.10.

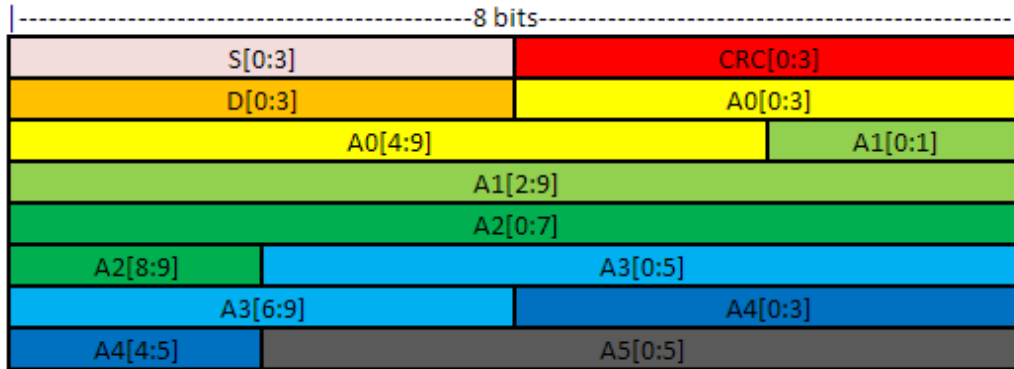


Fig. 4.10. Communication data packet structure.

Channels A0, A1, A2 and A3 provide a 10 bit data communication each, mainly used for signal transference. Channels A4 and A5 provide a lower bandwidth (6 bits) for lower resolution data. The protocol digital on/off bits are mainly used as flag announces, like report authentication results or report run-time errors.

The received transmissions from the visualization device can be one of the three commands, showed in Fig. 4.11. Its basically a start and stop acquisition command. Digital flag bits can also be sended to the embedded system using a command.

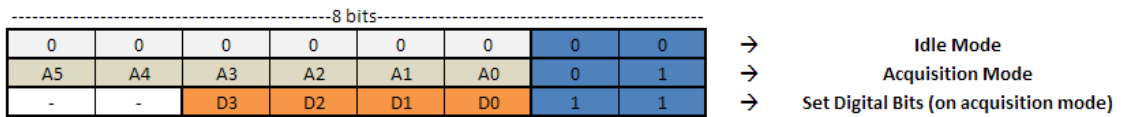


Fig. 4.11. Communication data packet structure.

USART Bluetooth communication defined characteristics are:

- **Baud rate:** 115200 baud per second, the fastest speed possible that can be used in the bluetooth module in use;
- **Data size:** A 8 data bits communication is used;
- **Stop bit:** Its used 1 stop bit;
- **Parity:** No parity is used in this communication;
- **Serial communication:** Full-duplex used, meaning that the module can receive and transmit data.

The bluetooth reception software implementation relay on a hardware interrupt generated by the USART peripheral when receiving data. When a byte reaches the bluetooth module this warns the USART peripheral that generate an software interrupt that is used to copy the transferred byte to a global system variable, available to the code. As for transmission, thus the

communication is full duplex the data is simply send to the bluetooth module which manage the bandwidth allocation to send the data without compromising the receptability of the system.

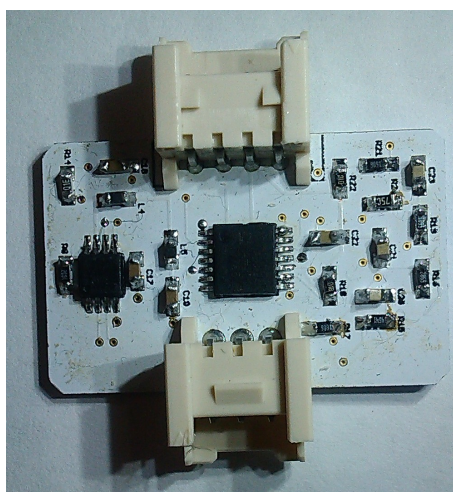
#### 4.4 Prototype

The prototype of the authentication system is composed by various hardware modules. This section presents the physical components of the system. Fig. 4.12 are the dry ECG sensing electrodes, made out of Ag/AgCl, commonly placed in both hands.



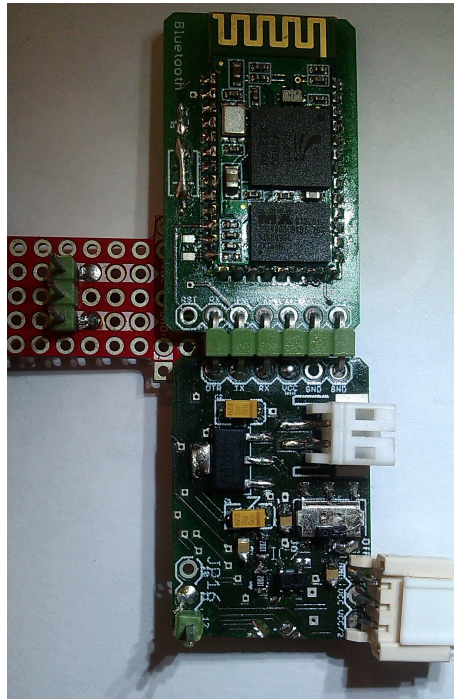
**Fig. 4.12.** Prototype ECG acquisition sensors.

Fig. 4.13 represents the BITalino ECG acquisition hardware. Top connector is the electrode interface and the bottom one as the output capture signal and the power source connection.



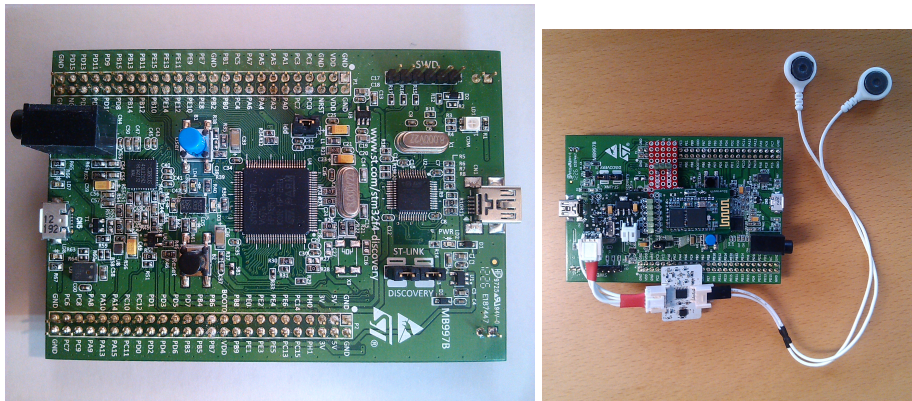
**Fig. 4.13.** BITalino acquisition hardware.

In Fig. 4.14 is represented the power source (bottom) for the acquisition hardware and for the bluetooth module, also presented in the figure (top). The bluetooth module directly connects to the power source and as is RX and TX signal on the left, for the MCU interface. On the bottom there is the ECG acquisition module interface for power and at the middle it is visible the power input connector, from the MCU.



**Fig. 4.14.** Bluetooth module and power supply.

Fig. 4.15 presents the prototype (on the right), composed by the STM32F4-Discovery board (alone on the left), bluetooth module and ECG sensor, used in the experiments.



(a) ARM STM32F4 Discovery Evaluation Board. (b) Prototype of the embedded system.

**Fig. 4.15.** Integrated Prototype and solo evaluation board.



## Experimental Evaluation

This chapter organizes the results obtained by applying the studied algorithm, by using a database of a previous study (HiMotion) [48] and also using the developed prototype as a source of signals to study. Both of these databases are tested and described. Herein it is described the used biometric evaluation metrics and explained some of the solutions taken during development based on practical tests. The chapter concludes with the final tests and the performance results of the system on identification and authentication task.

### 5.1 Biometric Evaluation

Performance evaluation of a biometric system allows determining the degree of accuracy of the system for operations authentication and personal identification. The level of performance is one of major factors defining the quality and acceptability of a Biometric system [49].

The most common metrics used for this evaluation are:

- **False Acceptance Rate (FAR):** acceptance rates of entities who are not really who they claim to be. False positive.
- **False Rejection Rate (FRR):** rejection rate of entities who are truly who they claim to be. False negative.
- **Equal Error Rate (EER):** corresponds to the value in which the FAR and FRR are equal.
- **ID Error:** error rate in identification.

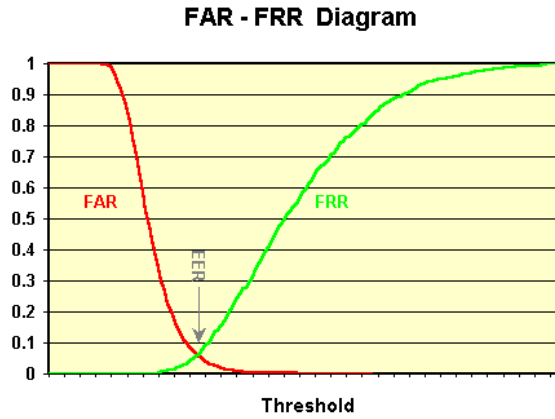
The confusion matrix in Table 5.1, used as the basis for obtaining a set of metrics, which is constituted by two rows and two columns. This table contains the values for: the true occurrences that the system accepted (correct, true positive), the true occurrences the system did not accept (error, false negative), the false occurrences that the system has not accepted (correct, true negative) and false occurrences that the system accepted (error, false positive).

**Table 5.1.** Confusion matrix.

		Analysis	
		True	False
Test	Accepted	TP	FP
	Rejected	FN	TN

\*TP = True Positive, FP = False Positive, FN = False Negative, TN = True Negative.

The FAR is obtained by summing the occurrences of false positives (FP) over the total number of cases analysed. Moreover, FRR is obtained by adding the true negative (TN) occurrences over the total number of cases analyzed. These values are calculated for a threshold value that should typically range between zero and one. An illustrative example of the curves of FAR and FRR obtained, are presented in Fig. 5.1.



**Fig. 5.1.** Illustration of the typical curves of error rates FAR and FRR which result in EER.

The equal error rate (EER) value results from the interception of the two rates FAR and FRR error. This point of intersection its the EER threshold, and it is the decision threshold to classify the occurrences. It also varies from zero to one, being zero the perfect test where all occurrences are true positives and true negatives.

## 5.2 Datasets

### 5.2.1 Himotion Database

The acquired signals in this database were obtained using an electrocardiogram setup with a triode electrode, placed in the 4th intercostal space in the mid clavicular line, "on-the-person" and on a setup much easier than the one evaluated on this thesis. This database will allow us to



validate all the method with signals with higher SNR than the ones acquired using the hands. The ECG recordings were performed during the execution of a cognitive task using a computer, and were part of a wider multi-modal physiological signal acquisition experiment, entitled Himotion [48], aiming studding emotional elicitation and personal identification. The signals under analysis on this paper, were acquired during a brain test where two grids with 800 digits were presented, where the goal is the identification of every consecutive pair of digits summing to ten. This task should be completed by each individual in 10 minutes (average time), and was designed to promote changes in the emotional state, namely stress.

The population used in this evaluation is composed of 27 subjects from which 18 were male (66%). The mean age was 23.4 (standard deviation 2.5) where the minimum age was 18 and the maximum age was 31. This recordings were sampled at 256 Hz. More details on the dataset used to evaluate the proposed approach are described on [33, 48].

### 5.2.2 Prototype Database

The dataset used to evaluate this approach was acquired using the proposed system. It is composed by 11 subjects, with two recording sessions per subject. The acquired signals were obtained following the recent trend "the off-the-person approach", where the ECG data is acquired at the fingers with dry Ag/AgCl electrodes. The ECG sensor consists of a custom, two lead differential sensor design with virtual ground, found in [16]. These acquisitions were performed in a closed room where the subjects were sitted in a chair. For the fist recording section the subjects were analysed after a 5 minutes rest period for and for the second recording section after a stair climbing.

## 5.3 Experimental Results

In this section a series of tests are conducted in order to evaluate and compare the proposed methods. All the tests were done using the same acquired signals, and with the same hardware, including software parameters. Summarizing, the following tests are performed:

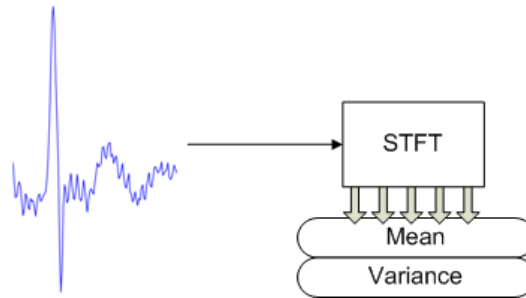
- Testing Odinaka's algorithm without segmentation and compare it with the proposed method with the same characteristics;
- Testing Odinaka's algorithm with the original parameters and compare it with the proposed method with the same characteristics;
- Testing the overlap size impact on the performance;
- Testing the frame size impact on the performance.

The performance evaluation results are shown in identification accuracy and equal error rate (EER). This performance is one of the key factors to define a quality and acceptability of a biometric system [49].

### 5.3.1 Himotion

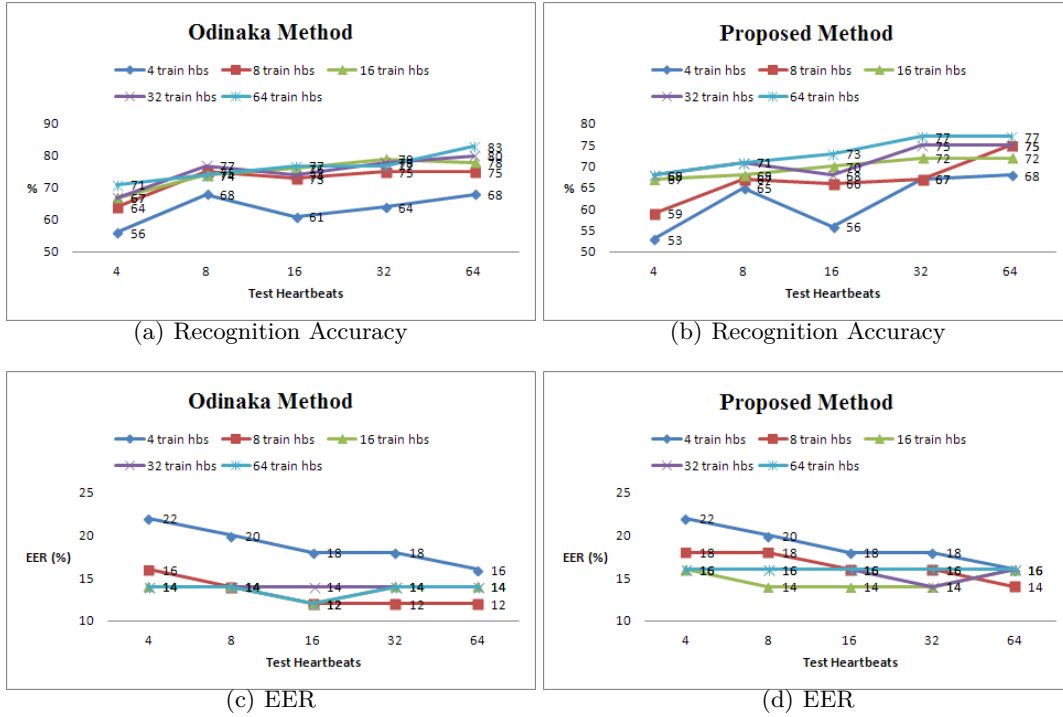
#### Methods without segmentation

For comparisons purposes, an evaluation of the Odinaka feature selection and classification method is performed without heartbeat segmentation (see Fig. 5.2). The EER and the recognition accuracy results are presented on Fig. 5.3 as a function of the number of heartbeats for train and test.



**Fig. 5.2.** Block diagram for Odinaka's method without segmentation

As shown in Fig. 5.3, the recognition accuracy are not good enough to build a viable system, although the equal error rate is fairly good regarding that is being using a direct heartbeat to be classified. It is also shown in this figure that in every case, the EER always drop and the recognition accuracy always increase, with increasing number of train and test heartbeats used.

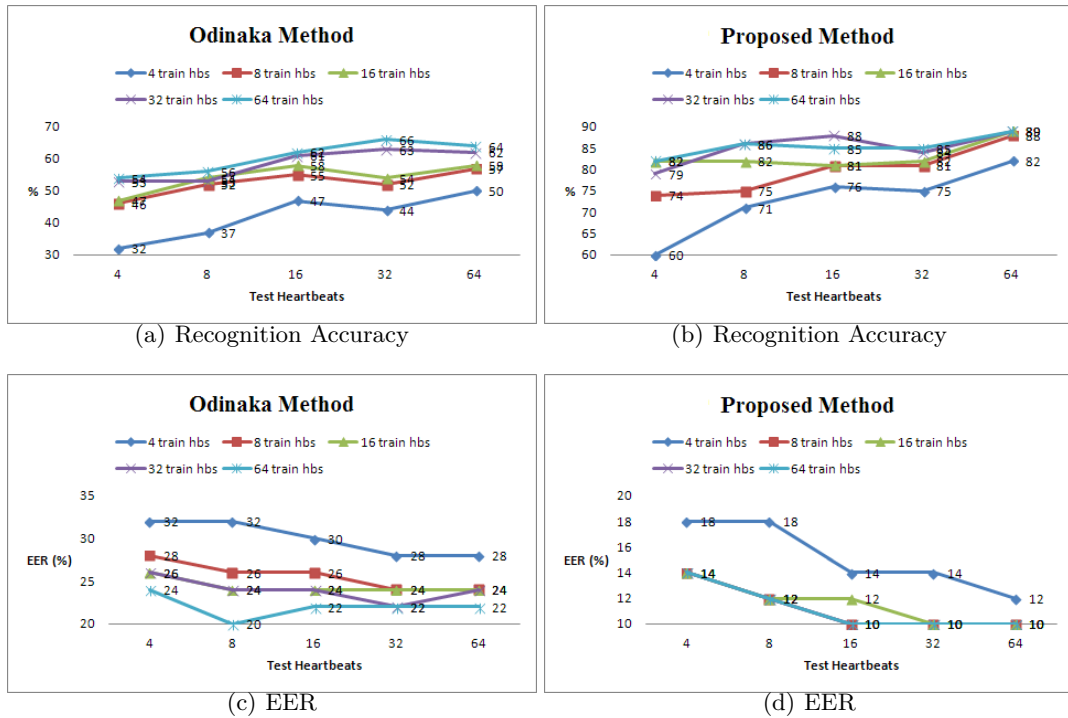


**Fig. 5.3.** EER and recognition accuracy curves for training on 4, 8, 16, 32, 64 heartbeats and testing on 4, 8, 16, 32, and 64 heartbeats, using the Odinaka method and the proposed method without segmentation for variable analysis

### Methods with segmentation and overlap

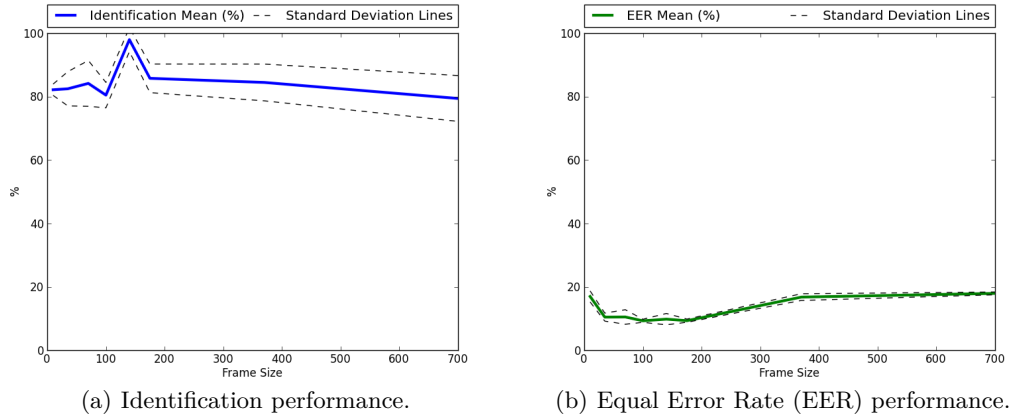
In order to compare the two different approaches to Odinaka’s method, each heart pulse computed the STFT with a Hamming window of size 64ms, with a overlap size of 54ms and a feature selection constant  $k$  of 1. To compute the custom high frequency resolution method it is used a 512 points Fast Fourier Transform (FFT) with a cut off frequency of 50 Hz, without feature selection. The Hamming windows, in this case, have a size of 90ms, with a overlap size of 40ms.

Fig. 5.4 shows the comparison of the two algorithms. Its clear that the custom high frequency resolution method has better results with this kind of low sampled signals. Other aspect is the consistency of the data, mostly independent to the number os heartbeats used to train or test, otherwise the normal method results have a high variance, with and high dependence on the heartbeats used.



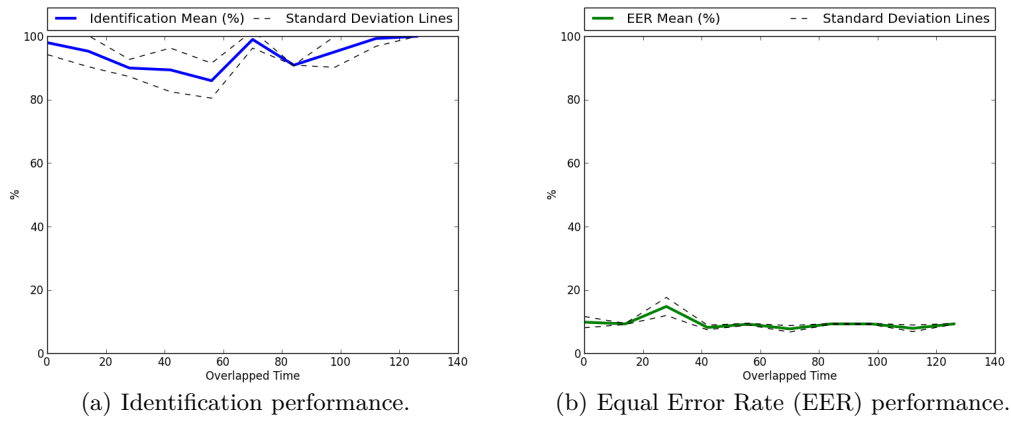
**Fig. 5.4.** EER and recognition accuracy curves for training on 4, 8, 16, 32, 64 heartbeats and testing on 4, 8, 16, 32, and 64 heartbeats, using the regular algorithm and the proposed approach with segmentation and overlap for variable analysis

A study has been made to determine the frame size and overlap time between frames, which results in terms of Equal Error Rate (EER) and identification performance are presented in Fig. 5.5 and Fig. 5.6. Frame size tests were performed without any overlap and overlap tests were performed with a frame size of 140ms, being this the top performance value. These tests were performed with 50 separated runs in order to create a mean and a variance for each variable (frame size and overlapped time). Regarding the experiment, the best solution is an 140ms frame size without overlap. Overlapping barely increase the performance and substantially increases processing time.



**Fig. 5.5.** Performance on frame size variability.

The STFT is applied to each of the 140ms window, leading to the creation of 50 frequency bins, totaling a vector with 250 features. The  $l$ -th feature corresponds to the STFT obtained over each segment window.

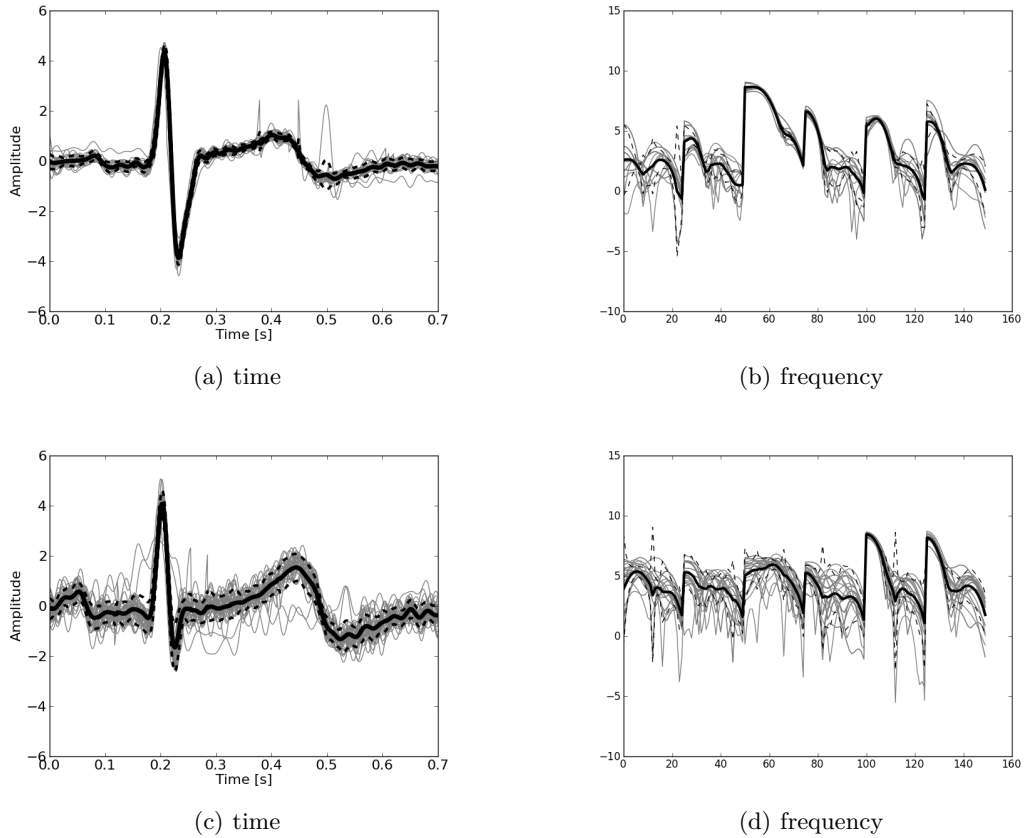


**Fig. 5.6.** Performance on overlap time between frames variability.

### 5.3.2 Embedded Platform Evaluation

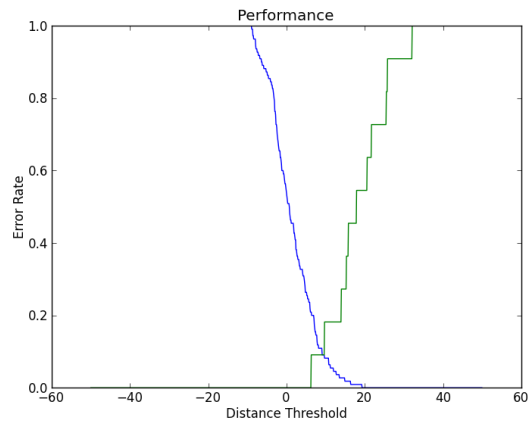
The features used in this work consist in frequency-domain representation. In Fig. 5.7 it is illustrated the potential of this representation, showing for two different users, the time (on the left) and frequency (on the right) domain representation. Observing both the figures, it is possible to distinguish visually the difference between both subjects. In the literature, frequency domain representation is considered more robust to heart-rhythm variation than the time domain

counterpart [11]. These signals were extracted using the embedded platform and posteriorly used as part of the test and train database.



**Fig. 5.7.** Comparison of time and frequency domain representation for two different users (users: Top for individual A and bottom for individual B.).

The performance evaluation over the entire dataset is summarized in Fig. 5.8, where the false acceptance rate (FAR) and the false rejection rate (FRR) curves are plotted in terms of the threshold of the system. Superimposing the equal error rate (EER) point, corresponding to the point where the FAR is equal to the FRR, it corresponds to  $EER=9.3\%$ . With this approach it's achieved a 100% identification rate with 30 seconds of train signals.



**Fig. 5.8.** FAR vs FRR curve.

These performances were achieved using the embedded platform setup without overlap time and with a frame size of 150 milliseconds. Comparing these results with the ones observed on the current used techniques [11], its clear that this method averages the results.





## Conclusions and Future Work

Biometrics based in behavioural characteristics are nowadays one of the major topics in technological development. The Electrocardiogram (ECG), which was in the past used only for clinical purposes, is now being used as a biometric indicator, aiming at a daily use in several common applications involving user authentication or recognition. The ECG identification/recognition state-of-the-art methods are based on the extraction of unique characteristics of the ECG signal capable of distinguishing a user from others and at the same time ensure no variation of these characteristics within the same individual.

The system herein proposed is composed by a hardware platform where a software based on these methodologies that acquire, validate and process ECG signals in order to identify or authenticate a set of individuals. The main software blocks of a reckoning systems are the pre-processing, the feature extraction and the classifier. These algorithms are further used in an embedded platform with hardware capable of acquiring an ECG. The conjunction of the hardware and software will allows an ubiquitous and portable reckoning system. The hardware architecture type, based on a ARM, allows real-time acquiring with a simple 2 lead placement, one in each upper limb. The acquisition modules filter and amplifies the ECG signal in order to be acquirable by the ADC of the microcontroller. The algorithm was implemented cohesively in order to keep the performance standards to real time.

The developed software components like filters, peak detectors, feature extractors, Fourier transforms and ADC sampling were evaluated in terms of its accuracy, reliability and performance regarding a biometric system and real time. The classification approach (non-fiducial) is based on the frequency domain details of ECG waveform. This has the advantage of not depending critically over details. Thus it can be obtained higher performances even with noisier signals. The classification is based on Odinaka's [18] work has guideline and with critical changes to the algorithm made it adequate to real-time.

To test the system two databases were used with different characteristics: -Himotion database, sampled at 256Hz, that includes the acquisition of ECG signals obtained from 24 individuals at rest using an electrode placed at V2 during 60 minutes for each user; -Database acquired by the designed system, sampled at 1000Hz and acquired by a two lead upper limbs placement for 60 seconds in each of the 11 users. Each single heartbeat is constituted by 700 samples.

The evaluation results obtained for the tests on the above mentioned databases reveal a personal identification error rate of 0.00% and an authentication rate of 9.3%. Between the two sets of data, the database created by this system obtained the best results. The hardware and software versatility has facilitated the performance of such tests and on retrieving the results.

As future work, some core functionalities may be implemented, allowing to explore different application scenarios:

- Using a mobile phone application to customize the system or to visualize the acquired signals.
- Integration of a removable memory to increase the database size in each system and to add the functionality of customization of the database in a PC.
- Integration of a LAN connection for data logging and security management.

As for the features implemented, it would be interesting to explore some alternatives:

- The implementation of different algorithms for segmentation, feature selection and classification.
- This solution with the use of novel dual-core microcontrollers would let the use of multi classification algorithms in real time.
- The use of other types of embedded systems, like FPGAs, would lead to better performance and thus more processing time for complex and effective algorithms.

The extent of features:

- Graphical interface for management and configuration of the authentication and identification process.
- Security solutions that enable the confidentiality of information, both in terms of data storage in the database as the communication between the various entities involved in the biometric system.

---

## References

1. Nobelprize.org, "The electrocardiogram, ecg," 2013.
2. STMicroelectronics group of companies, *UM1472 User Manual, STM32F4DISCOVERY, STM32F4 high-performance discovery*, Jan. 2012.
3. R. Vera-Rodriguez, R. P. Lewis, N. W. D. Evans, and J. S. D. Mason, "Optimisation of geometric and holistic feature extraction approaches for a footstep biometric verification system," in *International Summer School for Advanced Studies on Biometrics for Secure Authentication*, June 2007. Best Paper Award.
4. A. K. Jain, P. Flynn, and A. A. Ross, *Handbook of Biometrics*. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 2007.
5. N. P. Laboratory, "Uk scientists working to help grow european biometrics industry," 2013.
6. R. Chaturvedi, "Why biometric door access control systems are critical for any electronic security," 2012.
7. F. L. Ltd., "Fujitsu develops technology for world's first contactless palm vein pattern biometric authentication system," 2003.
8. I. Sandia Control Systems, "Products," 2004.
9. D. Ioannidis, D. Tzovaras, G. Mura, M. Ferro, G. Valenza, A. Tognetti, and G. Pioggia, "Gait and anthropometric profile biometrics: A step forward," *Second Generation Biometrics: The Ethical, Legal and Social Context*, p. 105–127, 2012.
10. A. Jain, P. Flynn, and A. Ross, *Handbook of Biometrics*. Springer, 2007.
11. I. Odinaka, P.-H. Lai, A. Kaplan, J. O'Sullivan, E. Sirevaag, and J. Rohrbaugh, "Ecg biometric recognition: A comparative analysis," *Information Forensics and Security, IEEE Transactions on*, vol. 7, pp. 1812–1824, dec. 2012.
12. F. Agraftoti, J. Gao, and D. Hatzinakos, *Biometrics*, ch. Heart Biometrics: Theory, Methods and Applications, Biometrics. InTech, 2011.
13. H. Silva, A. Lourenço, F. Canento, A. Fred, and N. Raposo, "ECG biometrics: Principles and applications," in *Proceeding of the 6th Conference on Bio-Inspired Systems and Signal Processing (BIOSIGNALS)*, 2013.
14. J. G. Webster, "*Basic Concepts of Medical Instrumentation*", in *Medical Instrumentation Application and Design*. Wiley, 4th ed., 2009.
15. M. R. Neuman, "*Biopotencial Amplifiers*", in *Medical Instrumentation – Application and Design*. Wiley, 4th ed., 2009.

16. H. Silva, A. Lourenço, R. L. Lourenço, P. L. Leite, D. Coutinho, and A. L. N. Fred, "Study and evaluation of a single differential sensor design based on electro-textile electrodes for ECG biometrics applications," in *IEEE Sensors*, pp. 1764–1767, October 2011.
17. A. Lourenço, Silva, and A. Fred, "ECG-based biometrics: A real time classification approach," in *Proceedings of the 22nd IEEE International Workshop on Machine Learning for Signal Processing*, 2012.
18. I. Odinaka, P.-H. Lai, A. Kaplan, J. O'Sullivan, E. Sirevaag, S. Kristjansson, A. Sheffield, and J. Rohrbaugh, "Ecg biometrics: A robust short-time frequency analysis," in *Information Forensics and Security (WIFS), 2010 IEEE International Workshop on*, pp. 1–6, dec. 2010.
19. L. Su, *CTO Freescale Semiconductor*. 2008.
20. A. Matos, J. Nascimento, and A. Lourenço, "Biometric recognition system using low bandwidth ecg signals," 2013.
21. A. Matos, J. Nascimento, and A. Lourenço, "Embedded system for ecg biometrics," 2013.
22. A. Matos, J. Nascimento, and A. Lourenço, "Embedded system for individual recognition based on ecg biometrics," 2013.
23. S. A. Israel, J. M. Irvine, A. Cheng, M. D. Wiederhold, and B. K. Wiederhold, "Ecg to identify individuals.," *Pattern Recognition*, vol. 38, no. 1, pp. 133–142, 2005.
24. Z. Zhang and D. Wei, "A new ecg identification method using bayes' theorem," in *TENCON 2006. 2006 IEEE Region 10 Conference*, pp. 1–4, 2006.
25. C. M. a. G.G.Molina, F.Bruekers, "Morphological synthesis of ecg signals for person authentication," *Proc. Eur. Signal Processing Conf., Poznan, Poland*, 2007.
26. F. Agrafioti and D. Hatzinakos, "Fusion of ECG sources for human identification," *IEEE 3rd International Symposium on Communications, Control and Signal Processing (ISCCSP)*, no. 1, pp. 133–142, 2008.
27. F. Agrafioti, F. Bui, and D. Hatzinakos, "Medical biometrics: The perils of ignoring time dependency," in *Biometrics: Theory, Applications, and Systems, 2009. BTAS '09. IEEE 3rd International Conference on*, pp. 1–6, 2009.
28. J. Yao and Y. Wan, "A wavelet method for biometric identification using wearable ecg sensors," in *Medical Devices and Biosensors, 2008. ISSS-MDBS 2008. 5th International Summer School and Symposium on*, pp. 297–300, 2008.
29. D. Coutinho, A. Fred, and M. Figueiredo, "One-lead ECG-based personal identification using zivmerhav cross parsing," in *20th Int. Conf. on Pattern Recognition (ICPR)*, pp. 3858–3861, aug. 2010.
30. C. Ye, M. Coimbra, and B. Kumar, "Investigation of human identification using two-lead electrocardiogram (ecg) signals," in *Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on*, pp. 1–8, 2010.
31. A. Lourenço, H. Silva, and A. Fred, "Unveiling the biometric potential of Finger-Based ECG signals," *Computational Intelligence and Neuroscience*, vol. 2011, 2011.
32. T. W. Shen, W. Tompkins, and Y. H. Hu, "One-lead ecg for identity verification," in *Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002. Proceedings of the Second Joint*, vol. 1, pp. 62–63 vol.1, 2002.
33. H. Silva, H. Gamboa, and A. Fred, "One lead ECG based human identification with feature subspace ensembles," in *5th Int Conf on Machine Learning and Data Mining*, 2007.
34. A. P. Alves, H. Silva, A. Lourenço, and A. Fred, "BITalino: A Biosignal Acquisition System based on Arduino," 2013.

35. J. Guerreiro, H. Silva, A. Lourenço, R. Martins, and A. Fred, "BITalino: A Multimodal platform for Physiological Computing," 2013.
36. N. Ghofrani and R. Bostani, "Reliable features for an eeg-based biometric system," in *Biomedical Engineering (ICBME), 2010 17th Iranian Conference of*, pp. 1–5, 2010.
37. A. D. C. Chan, M. Hamdy, A. Badre, and V. Badee, "Wavelet distance measure for person identification using electrocardiograms," *Instrumentation and Measurement, IEEE Transactions on*, vol. 57, no. 2, pp. 248–253, 2008.
38. K.-S. Kim, T.-H. Yoon, J.-W. Lee, D.-J. Kim, and H.-S. Koo, "A robust human identification by normalized time-domain features of electrocardiogram," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pp. 1114–1117, 2005.
39. H. Chen, K.-K. Tseng, F. Zeng, H.-N. Huang, and S.-Y. Tu, "A new eeg identification with neural network," in *Hybrid Intelligent Systems (HIS), 2012 12th International Conference on*, pp. 427–430, 2012.
40. R. Besrou, Z. Lachiri, and N. Ellouze, "Ecg beat classifier using support vector machine," in *Information and Communication Technologies: From Theory to Applications, 2008. ICTTA 2008. 3rd International Conference on*, pp. 1–5, 2008.
41. R. Aster and B. Borchers, "Digital filtering," 2011.
42. P. S. Hamilton and W. J. Tompkins, "Quantitative investigation of qrs detection rules using the mit/bih arrhythmia database," in *IEEE Transactions on Biomedical Engineering, VOL BME-33, NO. 12. DECEMBER 1986*, vol. BME-33, dec. 1986.
43. W. Zong, T. Heldt, G. Moody, and R. Mark, "An open-source algorithm to detect onset of arterial blood pressure pulses," in *Computers in Cardiology, 2003*, pp. 259–262, 2003.
44. P. S. Hamilton, "Open source eeg analysis software documentation," 2002.
45. D. Godse, *Microprocessor, Microcontroller & Applications*. Technical Publications, 2008.
46. R. Sass and A. G. Schmidt, *Embedded Systems Design with Platform FPGAs: Principles and Practices*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1st ed., 2010.
47. STMicroelectronics group of companies, *ARM Cortex-M4 32b MCU+FPU, 210DMIPS, up to 1MB Flash/192+4KB RAM, USB OTG HS/FS, Ethernet, 17 TIMs, 3 ADCs, 15 comm. interfaces and camera, Datasheet - production data*, May 2012.
48. H. Gamboa, H. Silva, and A. Fred, "Himotion: a new research resource for the study of behavior, cognition, and emotion," *Multimedia Tools and Applications*, pp. 1–31, 2013.
49. C. C. N. de Protecção de Dados, "Princípios sobre a utilização de dados biométricos no âmbito do controlo de acessos e de assiduidade," 2004.