INSTITUTO
UNIVERSITÁRIO
DE LISBOA

VAR-AS, Sustained Attention Detection System in the Learning Environment

Bárbara Nogueira da Costa

Master in Telecommunications and Computer Engineering

Supervisor:
Prof. Dr. Octavian Adrian Postolache, Associate Professor
Iscte-iul

Co- Supervisor:
Prof. Dr. John Fontenele Araujo, Titular Professor
Universidade Federal do Rio Grande do Norte

November, 2020

Acknowledgment

This Master's dissertation has received important support from which I am grateful. The encouragement, participation and collaboration with the professors that help me to realize this project.

First of all I express my sincere thanks to professor supervisor Octavian Postolache for his guidance and support during the thesis. I also thank Professor John Araujo for all his availability and help in the technical interpretation of the topic. It was an honor to work under the supervision of these scholars. I thank José Gouveia for the help of the final prototype of the project, with the assembly of all components on one board.

I would also like to acknowledge to Instituto de Telecomunicações, IT-IUL for providing all the necessary material for this project. Part of this work was supported by Fundação para a Ciência e Tecnologia, SmartLife Summer School, BI/SmartLife/2020, UIDB/50008/2020 and Instituto de Telecomunicações. I also thank Awesome project PTDC/CCI-INF/29234/2017 that through the exploitation of films for their emotional dimensions can be used for the educational purposes addressed in this dissertation. I would like to thank my colleagues in the university lab for their help and time spent during these months of research.

Finally I thank my family, parents and sister for their unconditional support and my boyfriend for all the motivation during this arduous process.

I especially dedicate this project to all those who directly or indirectly contributed to the success of this research.

To all my sincere thanks.

Resumo

Esta dissertação apresenta um sistema de monitorização da variabilidade da frequência cardíaca (VFC) através da Eletrocardiograma (ECG) e Fotoplestimografria (PPG) para a deteção do estado de atenção num ambiente de aprendizagem. Os signais de ECG e PPG foram adquiridos e processados através do desenvolvimento de um sistema embebido multi-microcontrolador. Ao extrair-se as ondas destes sinais, calcula-se a frequência cardíaca através dos intervalos de tempo entre os picos R para o eletrocardiograma e entre os batimentos para a fotopletismografia. Por fim, para poder indicar o nível da atenção da parte do utente adicionou-se um input em que o voluntário marca os períodos que considera estar mais atento. Estes dados são associados a uma marca temporal com resolução ma base de dados na nuvém. Após o armazenamento destes dados, analisa-se a VFC com base em algoritmos desenvolvidos com a ferramenta Matlab. Estes algoritmos permitem estudar a variabilidade cardíaca segundo os domínios do tempo, da frequência e como tambem foram consideradas medidas VFC não lineares. Por fim, adicionou-se um módulo para a medição da condutividade da pele, relacionando-a com a avaliação do nível de stress durante o processo de aprendizagem. Para comprovar a fiabilidade do sistema realizaram-se testes a diversos voluntários em ambientes reais de acordo com um protocolo estipulado. Estes registos foram analisados como ponto de partida para classificar situações de maior atenção do voluntário perante um cenário educativo.

Palavras chave: Sensores Inteligentes, Monitorização Cardíaca, Variabilidade Cardíaca, Atenção, Aprendizagem, Internet das Coisas.

Abstract

This dissertation presents a system for monitoring heart rate variability (HRV) by electrocardiogram (ECG) and photoplethysmography (PPG) for the detection of attention state in a learning environment. The ECG and PPG signs were acquired and processed through the development of a multi-microcontroller embedded system. When the waves of these signals are extracted, the heart rate is calculated through the time intervals between the R peaks for the electrocardiogram and between the beats for photopletismography. Finally, in order to indicate the level of attention on the part of the user, an input was added in which the volunteer marks the periods he or she considers to be most attentive. This data is associated with a millisecond resolution time stamp and sent in real time via Internet WiFi to a database in the cloud. After this data is stored, the HRV is analysed based on algorithms developed with the Matlab tool. These algorithms allow the study of cardiac variability according to time and frequency domains and how non-linear HRV measurements were also considered. Finally, a module for measuring skin conductivity was added, relating it to the analysis of the level of stress during the learning process. In order to prove the reliability of the system, several volunteers were tested in real environments according to a stipulated protocol. These records were analysed as a starting point to classify situations of greater attention of the volunteer in an educational scenario.

Keywords: Smart Sensors, Cardiac Monitoring, Cardiac Variability, Attention, Learning, Internet of Things (IoT).

Contents

List of Figures

List of Tables

Abbreviations

ANS	**A**utonomic **N**ervous **S**ystem (see page 6)
ECG	**E**lectro **C**ardio **G**ram (see page 2)
FFT	**F**ast **F**ourier **T**ransform (see page 40)
HF	**H**igh **F**requency (see page 9)
HRV	**H**eart **R**ate **V**ariability (see page 1)
IBI	**I**nter **B**eat **I**nterval (see page 35)
I2C	**I**nter **I**ntegrated **C**ircuit (see page 24)
I2S	**I**nter **I**C **S**ound (see page 24)
IoT	**I**nternet of **T**hings (see page 2)
LF	**L**ow **F**requency (see page 9)
OS	**O**perating **S**ystem (see page 19)
PNS	**P**arasympathetic **N**ervous **S**ystem (see page 6)
PPG	**P**hoto **P**lethysmo **G**ram (see page 10)
PSD	**P**ower **S**pectrum **D**ensity (see page 40)
RMSSD	**R**oot **M**ean **S**quare **S**uccessive **D**ifferences (see page 8)
RR	distance between peaks **R** (see page 7)
RRI	**R** **R** **I**nterval (see page 35)
RTC	**R**eal **T**ime **C**lock (see page 37)
Rx	**R**eceiver (see page 25)
SNS	**S**ympathetic **N**ervous **S**ystem (see page 6)
SPI	**S**erial **P**eripheral **I**nterface (see page 23)
Tx	**T**ransmitter (see page 25)
UART	**U**niversal **A**synchronous **R**eception **T**ransmission (see page 24)
VM	**V**ideo **M**otivation (see page 44)
VNM	**V**ideo **N**o **M**otivation (see page 44)

CHAPTER 1

Introduction

This dissertation arises from a previously developed work and aims to make it completer and more efficient. Measuring attention in a learning context is a challenge that is increasingly being addressed and is the focus of this dissertation, measured from the Variability of the Heart Rate (HRV).

1.1. Motivation

Nowadays, technology is an increasingly become a part of everyday life. As a result of the accentuated evolution of technology, the human being must adapt and keep up with the rapid changes. Despite becoming more and more dependent on technology, using it for knowledge is always a priority. In doing so, technology is added to studies and surveys always with the objective of improving human performance. In this case, the technology is correlated to the learning process and its analysis. It is a way of studying the learning of the human being that is also present every day and is essential for growth. Together with successful learning, the concept of attention emerges. How long can attention be maintained? This is the main question.

The impact of attention level can affect the whole learning process or even the role of everyone in society. Sustained attention is present in many activities of our daily lives. For the success of these activities it is necessary to maintain a certain level of attention. In most cases, it is not only necessary to maintain attention, but also to resist distraction caused by other factors. But keeping this focus for relatively long periods of time is not an easy task insofar as the level of attention decreases over time.

Time is the decisive factor not only in sustained attention but also, consequently, in the level of learning and performance. Learning is one of the activities in which attention plays a crucial role in retaining valuable information. These two concepts are currently being increasingly studied due to their impact on our lives. Until the last century, the functioning of the brain and intellect were still studied intuitively. However, with the rapid technological development new studies were arising. Nowadays, the attention level during the learning process can be estimated using different metrics including HRV measurement.. In other words, for the case of sustained attention and for a more objective methodology than common sense, the time without heart rate variation is analysed. For this reason, four HRV measures are studied, providing information about sustained attention and behavioral and emotional disorders. By measuring the HRV, the results illustrate the control of the parasympathetic system of the heart. However, HRV should not be compared from person to person as it is affected by various external and internal factors such as age, hormones and lifestyle.

In spite of that, the analysis of the above mentioned concepts should be done in a concrete and as objective way as possible. That is why more precise and optimized implementations are used. This way, a current challenge studied is the measurement of attention in a learning context, using objective and rigorous methods. Heart rate monitoring is one of the most effective and demanding healthcare applications of the IoT and has a major impact on medical research. Through the automation of IoT systems, these measurements are carried out quickly and efficiently. Thus, it is possible to study how behavior varies over time in order to improve adaptation to different situations.

1.2. Objectives

The purpose of this dissertation is the objective measurement of attention during the learning process based on a developed cardiac variability monitoring system. The first phase takes into account the study of the literature about cardiac variability, attention and success in the learning process. It is an important moment in order to understand the connection and influence between these concepts.

The development of embedded system and software capable of extracting information about the HRV. Regarding the hardware, it is represented by Electrocardiogram (ECG) and Photoplethysmography (PPG) measurement channels associated with cardiac activity measurement through a compatible Internet of Things (IoT) computation platform. This measurement is performed by the variation of time intervals between heartbeats.

After recording the calculated data, the metrics for attention analysis based on cardiac variability are calculated. It will be possible to have access to the evolution of attention over time according to the witnessed situation. Besides, it works as a biofeedback that can be obtained individually or in groups for specific cases. The main objective is always to obtain results that allow improving behavior in particular situations. In other words, knowing how and when our attention varies, it is easier to change our attitude and counteract it.

1.3. Scientific Contributions

The result of this research produced a functional prototype and a scientific paper, published at an international conference EPE2020 Organizing Committee International Conference and Exposition on Electrical and Power Engineering in October 2020. This project was also presented in 1st SmartLife IEEE IMS Workshop “Smart Sensing and Systems for Everyday Life” organized by ISCTE-IUL and Instituto de Telecomunicacoes Labs, September 2020.

1.4. Structure of the Dissertation

This dissertation includes five chapters, which are described below:

- Chapter 2 provides an overview of the essential literature concepts that highlight concepts useful for this project. Concepts such as autonomic nervous system, cardiac variability, ECG and PPG signals, learning experience and hardware.
- Chapter 3 describes the architecture of the system, namely the hardware expressed the Tx and Rx nodes.
- Chapter 4 concerns the software implemented at the level of the microcontroller and algorithms developed in Matlab.
- Chapter 5 presents the test results of real cases with volunteers according to the implemented protocol.
- Chapter 6 conclusion were the main achievement are discussed for volunteers as well as outlines future work that can be implemented to improve the system.

CHAPTER 2

State of the Art

This chapter is based on the research that is essential for the project's development. The first three sections concern theoretical concepts and how they relate to each other. That is, how HRV is related to learning issues and sustaining attention. In the following sections about IoT Healthcare systems, the hardware options are compared in order to choose the most suitable one. Finally, the last section presents similar projects that can help in some key points in the development of this project.

2.1. Human Behaviour: Attention

Since the late nineteenth century, attention has been the subject of study by psychologists and neuroscientists. This is one of the things that most affect each person's daily life. Thus, this attention capacity is strongly related to the perception of reality. According to the American philosopher William James, "at every moment, what we pay attention to is reality". The unconscious way of paying attention has an impact on the character and ethical behaviour. James also stated that geniuses are distinguished by their ability to voluntarily sustain attention. Attention was later defined as the complex interaction of various cortical and subcortical areas of the nervous system. Therefore, it was not considered a unitary process [**7**]. More recently, the attention is not considered a constant. On the contrary, it fluctuates from moment to moment [**19**].However, attention is also a fundamental aspect in cognition. In this case, it can be defined as the ability to generate and maintain a proper activation state for the correct processing of information. Thus, attention is subdivided according to the subject: [**43**]

- Internal or external depending on the origin of the stimuli;
- Voluntary or involuntary according to the attitude of the subject;
- Open or hidden if manifestation is motor or physiological;
- Divided or selective depending on subject interest;
- Through the sensations can be visual, spatial, auditory or temporal;
- Alternate or sustained attention according to the task change or continuity in the same task.

Sustained attention arises in the first year of life and continues to develop throughout childhood [**33**]. The attentional control is related to the ability to regulate the emotions. Thus, the best way to analyse the process of sustained attention is to evaluate it in contexts where it occurs and develops naturally [**4**]. In sustained attention, the cognitive element is responsible for activating certain neurocognitive processes in the body. This allows the human being to maintain attention or to remain vigilant to certain stimuli, extending this state for varying periods of time. This kind of attention is determined by physical characteristics of stimuli, number of stimuli, rhythm of presentation, temporal and spatial indeterminacy [**16**]. Some studies argue that sustained attention relates fixation on a focal stimulus in the presence of a peripheral distracting stimulus [**42**].

In addition to being an essential requirement for efficiently learning, sustained attention is very important for work safety [**5**]. Sustained attention is investigated according to the focus on the performance of a single task over time. Thus, it aims to explain the fluctuations caused in an individual and their ability to maintain this performance. The simplest way to measure these fluctuations is through momentary performance measurements [**19**]. Both cases, alternating or sustained attention, may change frequently due to mental disorders like attention deficit/ hyperactivity disorder, mood disorders like depression and mania, obsessive-compulsive disorder and even schizophrenia. In these cases, the difficulty lies in directing and maintaining attention to internal and external stimuli. This requires self-control in impulsive behaviour for emotional regulation. As noted above, emotion influences attention when it's directed at any stimulus or threat [**6**]. This influence can bring positive or negative affect. Along with tension (sleep, restlessness, patience and irritability), negative affect corresponds to anxiety and is also influenced by heart rate variability.

Since the 70's the sustained attention timeout has been studied. Johnstone and Percival (1976) conclude that sustained attention begins to decrease at 5 minutes and between 10 and 18 minutes. Few years later, according to Wilson and Korn (2007), attention decreases approximately 10 to 15 minutes. Bunce (2010) did some studies for 50 minutes classes. Then, he concluded that students do not pay attention continuously for 10 to 20 minutes.

2.2. Autonomic Nervous System

The autonomic nervous system (ANS) has two main divisions: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The healthy autonomic nervous system is flexible, dynamic and adaptable to the stimuli that receives.

The SNS divisions the function of the body and the preparation for action. In situations of stress, fear and emergency, SNS is activated and causes heart rate, blood pressure, and respiration rate to increase to deal with this alert state [**5**]. That's why the heart rate increases before this system is activated. By contrast, the PNS has the function of maintaining the state of rest, calming the level of stress. When in a relaxed state, the PNS is activated and causes heart rate, blood pressure and respiratory rate to decrease so that the body remains relaxed [**27**].

2.2.1. Cardiac Cycle

The dynamic balance between these two systems makes it possible to regulate the heart, i.e. the cardiac cycle. Shaffer (2014) defined the cardiac cycles as the events that occur in the heart from one heartbeat to the next and collectively. It consists of systole (ventricular contraction) and diastole (ventricular relaxation). The cardiac cycle of a normal individual is completed in approximately 0.8 seconds. Initially, during diastole, the atria and ventricles are relaxed. As the image below shows (Figure 2.1), atrial contraction is represented by the P wave has a maximum height and length of 2.5 [mm] and 110 [ms]. Thereafter, the duration of the Q wave may not exceed 0,02[sec], representing septal depolarization.

After contraction and atrial relaxation, ventricular contraction begins. On the ECG the depolarization of ventricular cells during the contraction is represented by QRS complex. The QRS amplitude measures the ventricular mass quantitatively and varies with age. the interval that also varies with age is the PR interval that reflects the time required for the propagation of the pulse. Finally, the T wave starts with ventricular relaxation, which corresponds to the re-polarization of the ventricles. The most frequent changes in the T wave reflect functional changes and are not related to cardiac diseases. However, the QT interval is inversely proportional to heart rate.

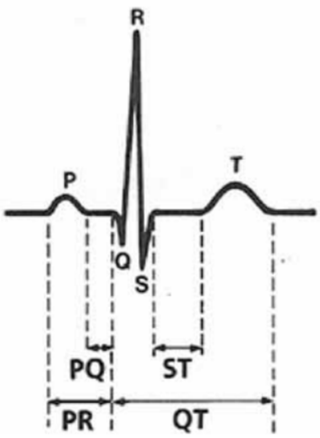


FIGURE 2.1. Cardiac cycle, source [**31**]

2.2.2. Heart Rate

Heart rate can be defined by the frequency and amplitude of the oscillating components [**27**].The RR variance, which represents the distance between peaks R, also decreases as age increases. As far as attention is concerned, sustained attention is characterized by a deceleration of heart rate (HR) and an increase in brain arousal and attention allocation capacity (Richards, 2008) [**41**].

2.2.2.1. *Heart Rate Variability.* The Heart Rate Variability is the result of interactions of the ANS and the mechanism of heart function [**21**]. Besides allowing to identify the predominance of SNS and PSNS, the HRV also helps to identify the physiological predisposition of the organism towards attention. The influence of HRV on attention and consequent cognitive processes is represented in Figure 2.2.

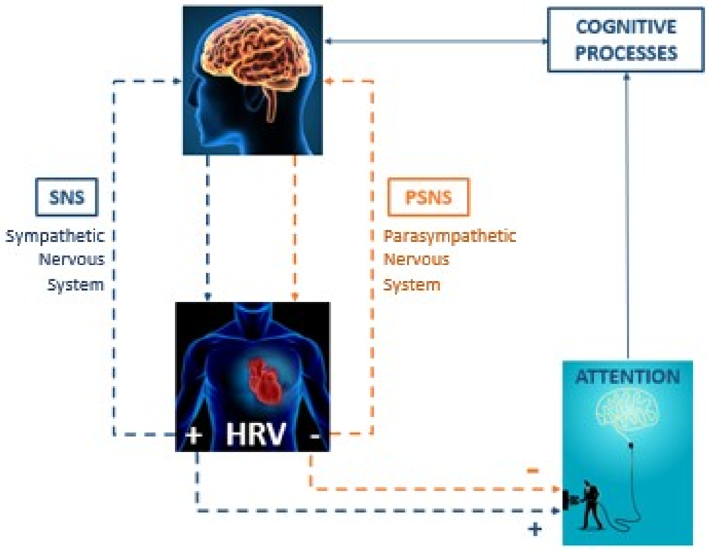


FIGURE 2.2. The influence of HRV on attention, adapted from [**43**]

In biomedical sciences, the HRV method is used, which is based on data from an electrocardiogram (ECG) [**24**]. To observe and interpret the cardiac response to a stimulus, the HRV baseline values are compared with the HRV values during the exposure to the stimulus. However, resting HRV values vary from individual to individual [**23**]. These individual differences in HRV reflect the interactions between voluntary and conscious activities and the respective physiological events. This happens because these activities, which are carried out consciously, have their origin in the physiological processes that are mediated by the ANS. [**39**]. Consequently, by staying at rest and facing a combat or escape situation, the HRV reflects rapid physiological events such as increased heart rate and breathing rate. These events arise together with conscious and appropriate behavioural changes.

As previously mentioned, HRV evaluates the functioning of the autonomous regulation of the heart and the balance of the autonomous nervous system. According to Kubios, a software analysis of HRV, together with the sympathetic and parasympathetic nervous systems the breathing also influences the heart rate. That is, during the activation of the SNS the heart rate increases, which also corresponds to the inspiration phase. In this case, the HRV will have an inverse behaviour, decreasing. On the other hand, during the exhalation phase the heart rate decreases, the same happening when the PNS is activated. In this scenario, HRV will be greater. [**3**]

2.2.2.2. *HRV Analysis.* Related to heart rate variability, focus of this project, Aunque Griffiths (2017) also studied four measures that provide information about sustained attention and behavioural changes. Time domain measures are the simplest to calculate. The first one, Root Mean Square of the Successive Differences (RMSSD) that represents the root mean square of successive RR interval differences. That measure is the primary on time-domain and reflects the beat-to-beat variance in heart rate. The standard deviation algorithm is also used in this analysis. Another measure is the calculation of the number of pairs of successive NN intervals that differ by more than 50 ms. In this case, higher values indicate higher parasympathetic activity.

As far as the frequency domain is concerned, pure RR intervals are decomposed into their frequency constituents. According to the Figure 2.3, the oscillation of the signal is used to determine the interaction of the ANS.

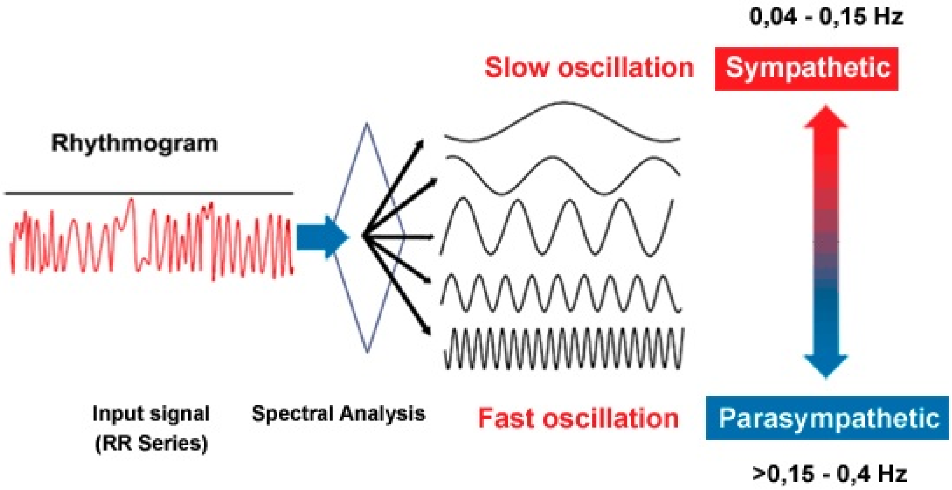


FIGURE 2.3. Frequency analysis and ANS, from [**14**]

The ANS FFT analysis includes Low Frequency LF (LF) corresponds to a frequency band between 0.04 and 0.15[Hz] and is usually recorded over a minimum 2 minutes period. LF indicates both sympathetic activity (SNS) and parasympathetic activity (PNS). In the other hand, the High Frequency (HF) that operates between 0.15 and 0.40[Hz] is called the respiratory band and is typically recorded over a minimum one-minute period. While the LF is related to the cardiac baroreflex activity, mechanism to regulate acute blood pressure changes, the HF is related to the parasympathetic nervous system (PNS) with respiratory cycle. The last frequency measure, the ration of LF to HF power aims to estimate the balance between SNS and PNS activity [**32**]. This frequency components are usually measured in absolute values (ms2), but in the case of HF and LF normalization units can also be used [**28**].

In addition to frequency and time measurements, non-linear analysis is also used in order to quantify the regularity of the data. The choice of these methods for analysing heart rate variability involves some aspects such as the type of performance, the time that lasts, whether it involves an active state or a rest state [**28**].

2.2.2.3. *ECG and PPG signals.* HRV values vary from person to person and the data usually come from an electrocardiogram (ECG).The ECG signals demonstrate the electrical activity of the heart. Thus, a typical ECG consists of the QRS complex and the P and T waves, with peak R as the main characteristic. The interval between two consecutive

R peaks allows the heart rate to be calculated. On the other hand, HRV can also be measured through the Photoplethysmogram (PPG) signal. The sign of a PPG represents the mechanical activity of the heart. In addition to measuring the rate of blood flow pumped by the heart, it also allows the measurement of oxygen saturation.This signal consists of two peaks representing systole and diastole.

ECG	***PPG***
Sensors read electrical signals resulting from cardiac activity	Sensors read signals that come from the light reflected by the pumping of blood flow during cardiac activity
Standard reference signal for heart rate measurement	Heart rate measurement by comparison with ECG reference signals
Heart rate variability extracted through R peak intervals	Heart rate variability correlated with pulse rate variation for long measurement periods
Heart rate accurately measured	Average heart rate measurements
Long periods (¿5min) for HRV measurements	Short periods for HRV measurements(RR intervals in milliseconds) measurements

Table 2.1. ECG and PPG comparison

Due to the difference between the peak intervals of these two waves, there is a delay between the QRS complex and the pulse wave, which is denominated Pulse Transit Time (PTT). According to Schäfer, when using the PPG measurement the most correct is to use the term Pulse Rate Variability (PRV) instead of HRV. This author also maintains that PRV is a sufficiently precise measure in relation to healthy individuals. However, there are factors that call into question the concordance between HRV and PRV such as physical and mental stress, and also active states involving movements. [**35**]

2.2.3. Skin Conductivity

The response of the sympathetic system, also known as "fight or flight", represents not only the functioning of the heart but also involves the preparation of action. Pupil dilation, increased heart rate and muscle contraction are some of the characteristics of this system. Thus, in situations of high stress, one of the fundamental hormones of this system emerges: the adrenaline. This hormone is released into the blood through the adrenal glands. Associated with this response, there is also sudomotor activity (SA). This activity is measured through the conductivity of the skin which considers the sum of the conductance through the skin tissue, considering the conductance resulting from the filling of sweat channels during the SA. [**40**].

As mentioned above, during the activation of the sympathetic nervous system, the conductivity of the skin increases due to the psychogenic sweating produced by the sweat glands distributed mostly in the hands. In this way, the amount of sweat produced varies the skin conductance response (SCR). Finally, a person's mental state can be reflected by the SCR. [**38**]. Alterations in the electrical characteristics of the skin due to sweat secretion culminate in electrodermal activity (EDA). In addition to this conductivity being a measure of electrodermal activity, it can also be used in tracking mental health problems caused by stress. [**1**].

2.3. Learning

As previously mentioned, the study of HRV allows the measurement of attention in an objective way through the interaction of these two systems. However, this measure can also be used to assess learning indirectly [**17**].

Over the years, the learning process has been an increasingly deepening theme. Ana Poppovic (1968) defined learning as a constant evolutionary process that implies a sequence of observable and real changes in the individual's behaviour in a global way and in the surrounding environment. A few years later, Traivers (1977) argued that learning was not a behaviour, but a permanent behaviour change influenced by environmental conditions. Shortly after, the acquisition of knowledge or expertise was the definition that Ross (1979) attributed to learning. Rapin (1982) also studies the concept of apprentice that is designed as an intelligent and flexible handler that: actively searches, organizes, integrates, stores and retrieves information. All this in a way adjusted to the cognitive structures.

Up till now, learning has been subject to different considerations. On the one hand, Ramón and Caial (1894) argue that the experience can cause changes in the brain throughout a person's life. Conversely, Luria (1966) states that the psychological process integrates a biological function with interactions of concrete neuronal units. Learning involves some basic integrations such as: psychodynamic functions that allow a hierarchical assimilation of what is observed and experienced by the organism; peripheral nervous system functions for symbolic learning; and central nervous system functions capable of storing, processing and processing information.

2.3.1. Behavioural and Cognitive Theories

As mentioned above, learning can be measured from the HRV in an indirect way. For that, there are behavioural and cognitive theories. Faced with behavioural theories, individuals may be learning a certain task and not executing the response at that time required by the experimenter. These behavioural theories encompass different types [**43**]. The first, self-regulated learning is guided by several factors such as metacognition, strategic action and motivation to learn. In general, it describes a process of planning, monitoring and evaluating personal progress as well as taking control and having autonomy. Secondly, free operating behaviour does not consider memory to explain learning. As a rule, the individual demonstrates an appropriate response followed by the presentation of an environmental stimulus.

Self-regulation is composed of cognitive, behavioural and emotional components and is characterized by the reciprocal interaction of conscious and reflective aspects of the person. with nonconscious, automatic and reactive aspects of emotional and physiological responses to stimulation (Blair and Raver, 2016; Blair and Ursache, 2011) [**4**].

2.3.2. Cognition

Therefore, information processing depends on cognition and emotional and behavioural development. Cognition is considered as the main indicator of the learning ability with the goal of "solving new problems" [**37**]. As a side note, cognitive theories arise relating the influence of the social environment on learning. In fact, learning is built on the relationship between pseudo-concepts and scientific concepts.

For the acquisition of new skills, i.e. learning, attention and memory play a crucial role [**37**]. In other words, learning can be associated with three theories: memory and intellectual operation; influence of the individual's internal factors; relationship between internal and external factors to the individual.

2.3.3. Performance

Taking the dynamic learning to the academic context, arises the concept of performance that is defined by the profile of skills, knowledge, attitudes and values developed by the student.

For a success performance, learning disabilities must be considered. Firstly, perceptual problems, visual and hearing discrimination can drastically affect the learning process. Consequently, emotional problems are also indicators of learning difficulties. After that, attention plays a crucial role in focusing and controlling distraction. In view of controlling cognitive activity, the learning strategies appear as sets of intentional, programmed and planned mental operations. Indeed, the set of strategies that a student uses to learn are called learning styles. Therefore, styles represent the way a person thinks and involve the processing of information [**43**].

2.4. IoT in Healthcare

Internet of Things (IoT) is defined as an object connected to the Internet. With the rapid evolution of technology, the development of these resources becomes increasingly accessible, useful and communicative. In this way, it appears as a facility for the human being and can be widely used in the areas of health and medicine. Alongside the concepts of embedded systems, communication and sensor networks, it is important to take into account aspects such as security, data management, compatibility and energy resources. There are several factors that make IoT devices vulnerable and susceptible to attack and malware. Hence the importance of data protection and proper data management.

With regard to the health area, we are witnessing the incorporation of wireless sensors in medical equipment in a network capable of communicating with other equipment, patients and hospitals. These IoT applications include continuous real-time monitoring, patient data management, and even error prevention in pharmaceuticals. The main focus of IoT medical devices is on disease prevention and control, reducing hospital costs, and especially increasing the quality of life of the population [**30**].

Regarding this project, the real time measurement of the HRV helps to evaluate the physiological status of a person and also contributes to the development of other studies based on this concept. That is, on the one hand, these IoT-based structures are fundamental to the diagnosis and management of cardiac diseases. On the other hand, by measuring the HRV in real time it is possible to study how it varies and influences other aspects of everyday life.

The next section presents the implementation of an HRV monitoring application based on an IoT system that includes a multi-microcontroller computation platform with Wi-Fi and BLE short range communication capabilities.

2.5. Hardware

Hardware resources refer to all physical devices used in a system. In addition to specifying a physical object, it also refers to its logical processing and technology used.

For the choice of hardware in the developed system it is essential to have in mind the characteristics and compatibility of equipment and protocols, without ever compromising efficiency.

2.5.1. Controlling Platforms

The control platforms have the ability to control the entire system and are considered the heart of the process operation. In addition to processing information, these platforms communicate and interact with other enterprise software.

For this project, it is important to take into account the simplicity of the board according to its level of performance. Arduino, ESP8266 and ESP32, the most commonly used platforms are analysed.

2.5.1.1. *Arduino.* Arduino is an open source platform based on software and hardware that are quite easy to use. These boards are capable of reading inputs and turning them into outputs. Using the Arduino programming language and the Arduino software (IDE), a set of instructions is sent to the microcontroller.It is also easy for users to adapt the board according to their needs and build it independently. This software runs on different operating systems (Mac, Windows and Linux) and simplifies the process of working with microcontrollers.Compared to other systems, Arduino has some advantages in terms of cost, clarity and flexibility of the programming environment and open source and extensible software and hardware [**11**].

There are several boards with different features but the most used and documented is the Arduino UNO.This microcontroller board is based on the ATmega328. It has 14 digital input/output pins, 6 analog inputs, a USB connection, a power connector, an ICSP header, a 16MHz quartz crystal and a reset button. It can be connected through a USB cable or through an AC to DC adapter or battery. It has 32KB of memory, 2KB of SRAM and 1KB of EEPROM. UNO makes use of the ATmega 12U2 as a USB to serial converter [**11**].

Figure 2.4. Arduino UNO board

2.5.1.2. *ESP8266.* What makes the ESP8266 different from other microcontrollers like Arduino is the inclusion of the wireless network. With consistent operation, this chip offers reliability and robustness as it provides a wide operating temperature range. ESP8266 consists of a 32-bit Tensilica processor with a maximum speed of 160MHz that enables high performance with energy efficiency. With an energy-saving architecture, it can operate in three different modes of operation: active mode, sleep mode and deep sleep mode. It also features antenna switches, low noise power and reception amplifiers, filters, and more. This board can be programmed through Arduino software (IDE) or even using MicroPython firmware. A disadvantage of this board is that it only supports the analogue reading in 1 of 17 GPIOs.

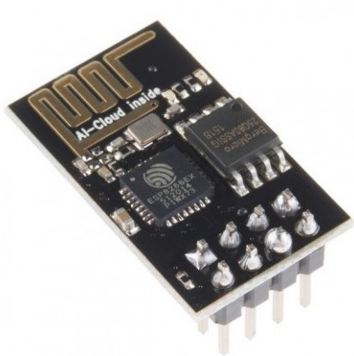


Figure 2.5. ESP8266 WiFi Module, source [**18**]

2.5.1.3. *ESP32.* The ESP32 is the ESP8266 successor. Although it is more expensive than ESP8266, ESP32 is more powerful. It is composed of more GPIOs and in addition to Wi-Fi also supports Bluetooth. With these features, this platform interacts with other systems through the SPI/SDIO or I2C/UART interfaces. ESP32 features ultra-low power consumption and is designed for mobile devices and IoT applications. In addition to the 34 GPIOs, it has the ability to assign several functions to the same pin. Despite the differences with ESP8266, it is programmed using the same software. But it is important to note that the ESP8266 code may not be compatible with ESP32. While no information is being sent, this board remains in deep sleep mode reducing approximately 99% of the current consumed. Thus, it has the ability to periodically wake up when a condition is detected.

FIGURE 2.6. ESP32 DevKitC-32D

The following table (Table 2.2) shows the differences between ESP8266 and ESP32. According to this table, ESP32 represents a good solution for low cost and energy consumption systems that does not compromise quality.

	ESP8266	**ESP32**
Architecture	32 bits	32 bits
Core number	1	2
Typical Frequency	80 MHz	160 MHz
Wi-Fi	HT20	HT40
Bluetooth	-	Bluetooth 4.2 and BLE
GPIO	17	34
SRAM	-	520 KB
FLASH	-	16 MB
ADC	10-bit	12-bit

TABLE 2.2. Differences between ESP8266 and ESP32

2.5.1.4. *Remarks.* The selection of the microcontroller must take into account not only the low power consumption but also the level of reliability. For a microcontroller with connectivity options, ESP32 is a great choice because of its speed from 160 [MHz] to 240 [MHz]. The implementation of WiFi MAC and TCP/IP protocols allows connectivity to most WiFi Routers and creation of an access point.

In general, minimal interaction with the host helps to manage energy and the time the service remains active. Finally, the biggest advantage over the previous model is the integration of Bluetooth Radio and Baseband which enables communication with mobile devices such as mobile phones and tablets present in the current market.

2.5.2. Sensors

A sensor is a device that has the ability to detect a physical phenomenon and measure it quantitatively. The transducers appear in conformity with the sensors. They differ from the sensors by converting the energy from one form to another.

2.5.2.1. *Pulse Sensor.* The Pulse Sensor is a plug-and-play heart rate sensor that attaches to a fingertip or earlobe. This sensor allows the pulse to be viewed in a real-time graph through an open source monitoring application [**34**].

On one side of the sensor is an LED and an ambient light sensor. The opposite side presents some circuits for signal amplification and noise reduction. The role of the LED is to emit the light that passes through the vein as it should be placed directly on top of one. That is, when the heart pumps the blood and this flow is detected, the ambient light sensor captures more light. By monitoring this flow it is also possible to analyze the heart beats by detecting the variation in light over time reflected by the blood [**12**].

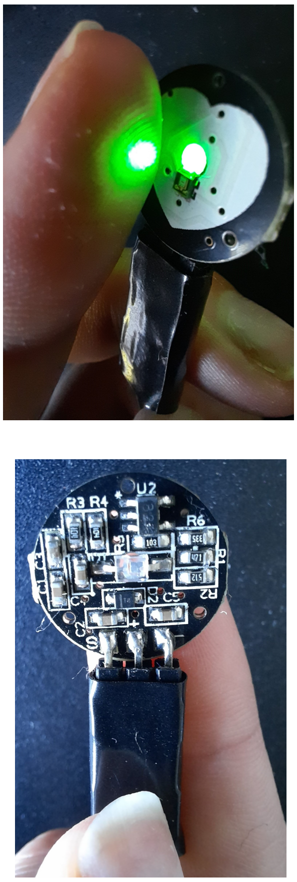


FIGURE 2.7. Pulse Sensor

2.5.2.2. *AD8232.* The AD8232 is an integrated front-end for heart rate monitoring. This device amplifies the ECG signal by filtering small biopotentials by electrode placement. The ECG waveform monitoring assumes a reading during the resting state, remaining relatively motionless. It also has an LED that turns on and off at the same time as the heart rate. The output signal can be easily acquired by a microcontroller or an analogue digital converter (ADC) [**8**].

This device can be used for several applications such as: activity heart rate monitors, portable ECG, gaming peripherals and biopotential signal acquisition.

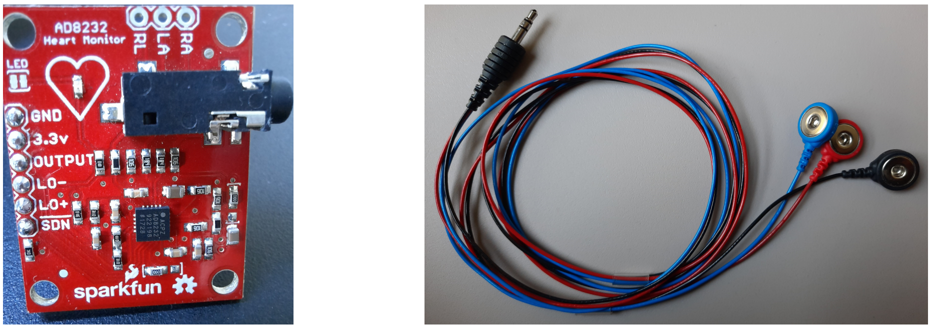


FIGURE 2.8. AD8232 Heart Rate Monitor

2.5.2.3. *Remarks.* With the first sensor mentioned, the Pulse Sensor, the heartbeat waveform is obtained in real time from which a PPG is obtained.

Conversely, the Heart Rate Monitor AD8232 detects the electrical activity of the heart through the ECG wave obtained at resting state. This technique is acquired in a channel for validation and comparison with PPG results.

2.5.3. Others components

2.5.3.1. *DS3231.* The DS3231 is a high-precision, low-power real-time clock that provides seconds, minutes, hours, days, month and year information. It also has a programmable square wave output signal used to improve its resolution.Thus, through synchronization with a 1Hz square wave, a resolution of milliseconds is obtained. The connection of this module to the microcontroller is simple and is done through the I2C pins. The device incorporates an integrated crystal oscillator with temperature compensation (TCXO) and a battery input. The integration of this oscillator increases the long-term accuracy of the device and with monitoring of the VCC status automatically switches to backup power if necessary.

In this project, this chip is used to identify the data through the associated date and time for correct and accurate reading.

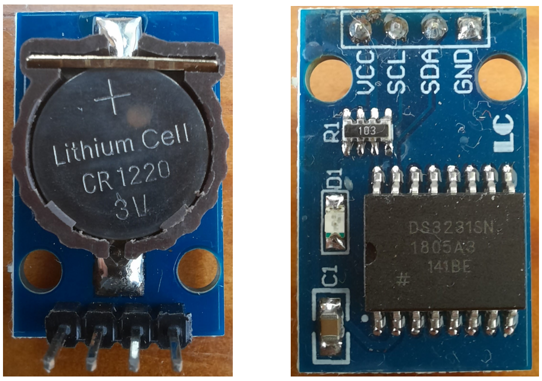


FIGURE 2.9. RTC DS3231

2.5.3.2. *ADS1015.* The AD1015 is a 12-bit analog-digital converter designed for easy and accurate implementation. This component already has a on-board reference and oscillator and the data is transmitted through an I2C compatible interface. The conversion rates can be up to 3300 samples per second (SPS) and it can operate in either a continuous conversion mode or a single-shot mode, reducing power consumption. With easy configuration, accurate measurements are obtained in a very accessible way.

Along with the I2C interface, this device also features an oscillator clock, internal voltage reference and a core with an adjustable gain. In this way, it allows the raw data to be collected through acquisition with as few noise as possible.

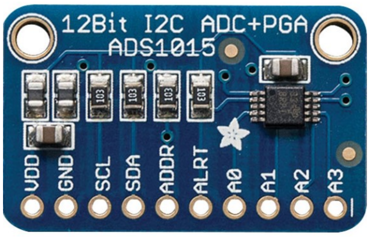


FIGURE 2.10. ADS1015 ADC 12bit

2.5.3.3. *Micro SD Card.* For this project a micro SD card reader and writer was used, which ensures an interface for most microcontrollers powered by 5[V] and 3.3[V]. This module communicates through an SPI communication protocol, storing and recovering data locally.

The micro SD memory card is non-volatile and stores gigabytes of data with a small physical size. This card appears alongside the microcontroller as it stores more data than the EEPROM. In this case, its function is to collect sensor data in specific situations.

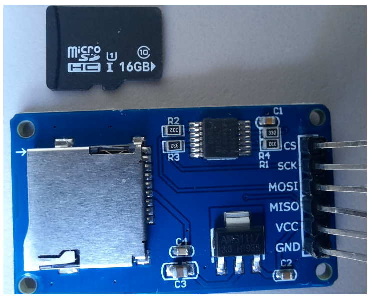


FIGURE 2.11. SD Card Adapter

2.6. Software

This chapter refers to the software chosen for the development of the embedded system and for the construction of the analysis algorithms. In addition to the justification of the choices, other alternatives are also highlighted.

2.6.1. Embedded software environment

Arduino IDE is an open-source development environment that allows writing C or C++ programs. This software runs on Linux, MAC and Windows operating systems where tasks are easily created for the microcontroller through scripts called Sketches. As it is a resource used by users around the world, there are many support guides, tutorials and even libraries in the cloud. In addition to its user-friendliness, it also provides the opportunity to create more complex processes through simple computer resources. Thus, it is a software compatible with several boards, requiring only a few changes to the libraries.

One of its best known alternatives is the integrated development environment for IoT, PlatformIO. This tool also supports multi-programs and library management. As Arduino IDE also runs on different operating systems but uses the Python language. However, it is possible to add the Arduino IDE plugin in development environments like Eclipse and Visual Studio. In the case of Eclipse, it supports different programming languages and has the features of the standard Arduino IDE. Microsoft Visual Studio, in addition to supporting Arduino libraries, also handles the Serial debug and creates graphics.

Despite the advantages of the alternatives presented above, Arduino IDE is the most accessible and supported software for creating the embedded system.

2.6.2. HRV analysis software environment

MATLAB is a numerical computing environment developed by Mathworks based on different languages such as C, C++, Java and Python. This computational tool enables the development and simulation of control algorithms with the help of additional higher level libraries. Besides the implementation of algorithms, it can manipulate matrices, arrange functions and data graphically and even create interfaces.

One hypothesis to this software is LabVIEW, a graphic programming language from National Instruments that has a front panel and block diagrams with the source code. This tool is used in data acquisition, control and industrial automation. It is easy to use when it comes to creating small applications, but for more complex programs it is necessary to understand how it works in more detail.

For the developed system, MATLAB is the interactive software that best fits the construction of advanced algorithms and real-time models.Although LabVIEW is a good choice for control operations, MATLAB is better for data manipulation in this particular case.

2.7. Mobile application

The development of a dashboard facilitates the understanding and analysis of the results obtained. The monitoring of these outputs must be visualized and transmitted efficiently. For this purpose, it is important to define its objective and frame it according to the target audience.Increasingly common, mobile applications are software applications programmed individually according to a specific objective. Initially, these applications were created for basic purposes such as e-mail, but with the advancement of technology they rapidly became everyday tools. These are used in devices such as smartphones and are developed according to an Operating System (OS). Currently, Android and iOS are the most widely used operating systems.

With the largest number of hardware and software developers, Android is an open-source operating system backed by Google. Based upon Linux, it can be developed with the Java programming language through the integrated development environment Android Studio.

iOS is an operating system originally developed by Apple for the iPhone and now also for the iPad. Apple does not give permission to any other hardware to run this OS. For the development of iOS applications it is necessary to have an Apple computer with, for example, Xcode capable of creating applications using the Swift programming language.

Taking into account that in November 2019 Android has about 75.88% of the world market share (Figure 2.12), the development of the application will be more suitable for this operating system.

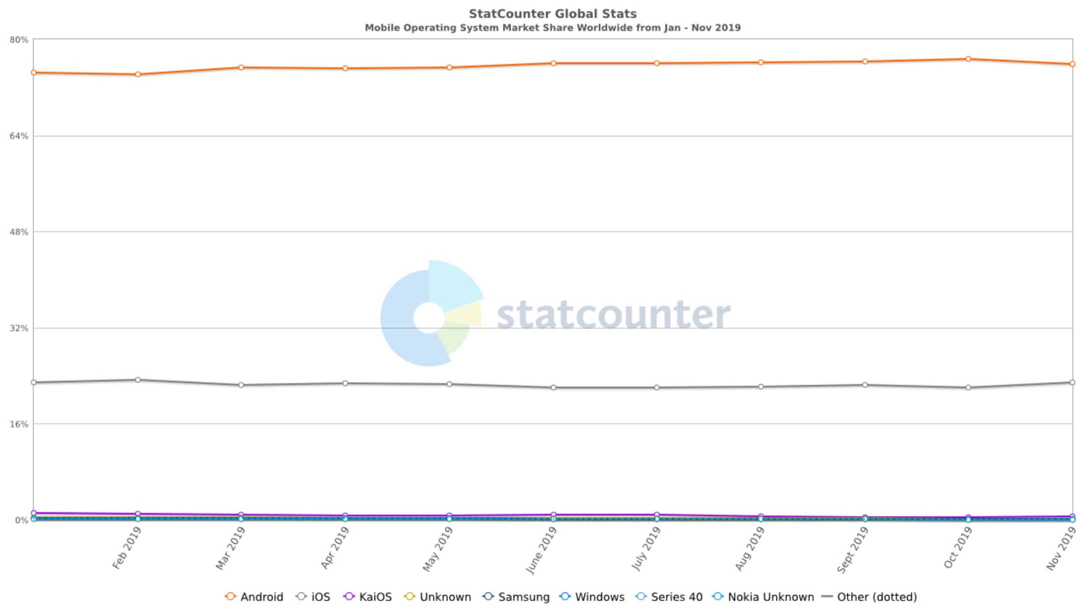


FIGURE 2.12. Mobile Operating System Market Share Worldwide, source [**15**]

The main objective of the developed application is to visualize the result of the analysis. Depending on the type of user, individual biofeedback or more connected users may be displayed, if applicable. In the case of a personal user, the aim is to improve attention and adaptation to different situations. For that reason, it is important to provide a graph with temporal evolution for a better perception of reality.

2.8. Related Work

Measuring attention in a learning context has increasingly become a challenge for researchers and professors. There are currently a number of projects that rely on HRV to measure this attention.

In [**43**], a system has been implemented that detects this variation across three domains: frequency, time and non-linear measures. The analysis was carried out during a 60-minute class, concluding that the university students maintain their attention only for the first 15 minutes of the class. However, this analysis also included the influence of personal characteristics such as chronotype, emotion and personality.

According to the authors in [**5**], the phases of sustained and non-sustained attention are classified based on HRV. In this case, this classification is based on ECG signals, where 98% accuracy was obtained. With this study it was possible to verify the activation of the sympathetic system at the time you need to be attentive to react to an event.

The authors in [**36**] calculated the HRV during an attention test that measures the Concentration Performance index and the Coefficient of Variation relative to sustained attention. This study demonstrated that the maintenance of attention is associated with a HRV at rest state, not influencing the attention's performance.

There are some IoT systems that measure HRV and they almost always arise in medical context, such as real-time cardiac monitoring [**26**]. Health data management is usually aimed at disease prevention and control. This proposal aims to monitor heart rate as a way to measure attention and then improve it during a learning situation.

CHAPTER 3

System Hardware

In this chapter, the first section describes not only the components used but also the system architecture. After the hardware description, the following section specifies the embedded system functionality and the type of communication implemented. After selecting the microcontroller used, the two systems, ECG and PPG, are collected simultaneously using the two cores of the microcontroller.

3.1. System Architecture

The implemented architecture is divided into four parts, being the device layer, the database, the algorithm analysis and finally the user interface. The first layer not only includes the acquisition of the PPG and ECG systems but also the processing at the microcontroller level. Section 3.2 describes this layer and explains the reason for adding extra components to the microcontroller. The hardware architecture is presented in Figure 3.1

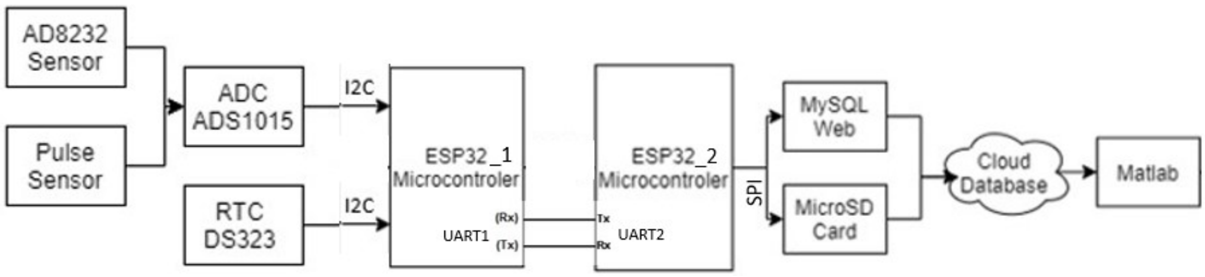


Figure 3.1. System Architecture

For the acquisition of ECG and PPG signals, a digital analogue converter with 12 bits of resolution was used. In this way, the SNR associated with implemented acquisition channel is improved.The sensors responsible for reading these signals communicate through an Serial Peripheral Interface (SPI) with the microcontroller which then processes the acquired signals. In this case, two microcontrollers are used since the first one performs the simultaneous acquisition of the two channels, requiring the two processing cores. Therefore, the second microcontroller is only responsible for sending the processed data and one core is mainly used for this task. The acquired samples are transferred from one microcontroller to the other by identifying the data individually with a date and time through a real time clock.

3.2. Device Layer

This layer comprises of devices, sensors and controllers and is responsible for collecting and processing data from the two sensors, PPG and ECG. For this, the ESP32 microcontroller was chosen, taking into account the level of reliability but also the power consumption.

3.2.1. Embedded Computation

ESP32 has the integrated Bluetooth and WiFi modules on board facilitating data transfer with the network. It is a dual-core device with 2 32-bit microprocessors, having the ability to run more complex programs simultaneously. In addition, it is capable of staying in deep sleep mode but with the wireless peripherals turned off. It also has the possibility to remain in light sleep mode as a way to save energy. In this case, the peripherals and CPU keep their internal state so that they can resume their operation. However, for this project it does not make sense to apply any of these modes since as the data are collected and sent straight to the database. In order for all components to be active, ESP32 will remain in the active state throughout the sensor reading. Although it is the most appropriate, it is the most inefficient mode with a higher power consumption, especially when the transmission is made via WiFi. The following table shows the features depending on the various power modes.

Power mode	**Active mode**	**Light sleep**	**Modem sleep**	**Deep sleep**
CPU	ON	PAUSE	ON	OFF
Wi-Fi/BT	ON	OFF	OFF	OFF
RTC	ON	ON	ON	ON
ULP	ON	ON	ON	ON/OFF

Table 3.1. Power modes and functionalities of ESP32

In this particular case, the active mode will be used as the system is only switched on for a period of time of less than 1h. This chip integrates a wealth of hardware peripherals including programmable GPIOs, touch sensors, ethernet MAC interface, motor PWM, hall sensor, high-speed SDIO / SPI, Universal Asynchronous Reception and Transmission (UART), Inter-IC Sound (I2C) and Inter-integrated-circuit (I2C). Of these various peripherals, only SPI, UART and I2C are used for communication with other devices. These communications will be explored with the sensor connections and other components in the implementation of the system. For a better understanding of all components integrated on the board, the image below shows the respective block diagram.

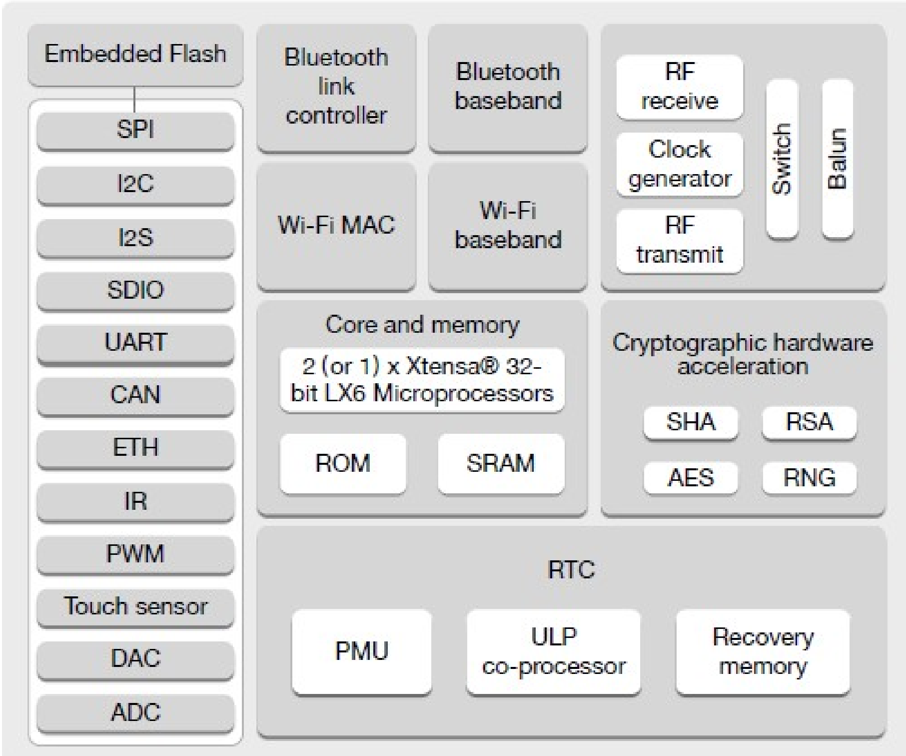


FIGURE 3.2. ESP32 internal component block diagram

This project can be divided into two segments each one with an ESP32, TX(transmitter) and RX (receiver). These names have been assigned due to the connection between them, as one works only as a transmitter and the other as a receiver. This makes it easier to distinguish them and refer to them later. The next sections specify each one respectively.

3.2.2. TX Node

For ESP32 TX, the acquisition and processing of PPG and ECG signals takes part. Obtaining pulse readings is quick and easy as the sensor combines an optical pulse sensor with amplification and noise cancellation circuits, consuming only 4mA to 5V. The pulse sensor detects the heartbeat through the variation of the light over the time. That is, the LED integrated in the sensor obtains the passage of light in the veins when the blood is pumped, capturing more light in those instants. For this flow passage to be perceptible it is necessary to place the sensor in areas that have a shorter distance to the blood vessels, such as the fingertips or earlobe. This operation can be monitored in two different modes. In this project the sensor emits a green light that passes to the blood vessels and is reflected back to a photo detector. However, there is also the transmission mode in which the photo detector is on the other side converting the measured light into an electrical signal. That is, the transmitter and receiver are aligned but one on each side of the finger. The following image shows the differences between the used reflected mode and the transmitted mode.

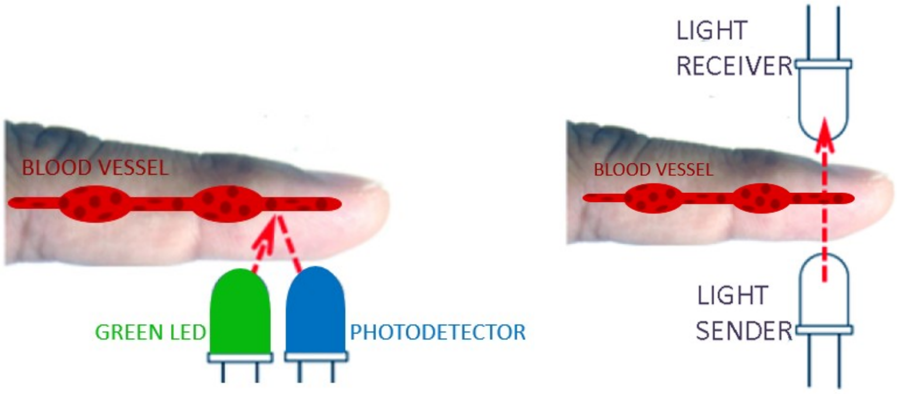


FIGURE 3.3. Reflected and Transmitted modes, adapted from [**22**]

To monitor the heart rate through the ECG wave the AD8232 sensor is used.Thus, three electrodes are placed in three different areas: one on the right side of the chest, one on the left side and the third on the right lower abdomen. It is through the electrodes that the electrical changes of the heart are detected. When this electrical activity is detected, a LED integrated in the module blinks according to the heart rate. As can be seen in the image below, the placement of the electrodes can be done in these two ways.

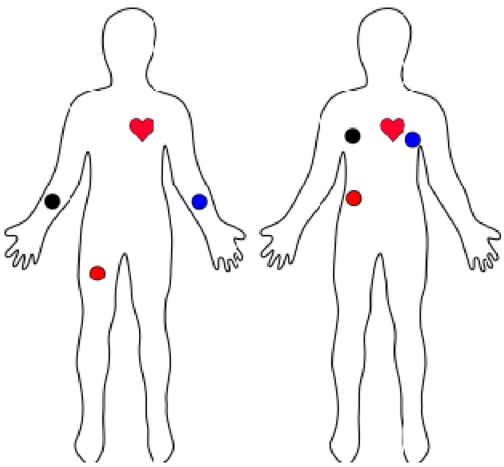


FIGURE 3.4. Electrode placement, source [**29**]

The acquired ECG signal provides different types of information. In addition to the heart rate, it is also possible to determine the quantity of electrical activity and the time it takes for the electrical wave to pass through the heart[**29**]. However, as the impulses generated by the other muscles may interfere with those generated by the heart, the acquisition of this signal is performed at resting state. This channel will serve as a comparison for the results obtained by the PPG signals since it is the standard reference signal for the measurement of heart rate. A table comparing the measurement of ECG and PPG signals is presented below (table 3.2).

Feature Description	ECG	PPG
Measurement type	Electrical	Optical
Sensor type	Electrodes	Photodiode
Can measure heart rate?	Yes	Yes
Diagnostic information	Yes	Yes
Minimum number of skin contacts required?	2	1
Number of ADC channels required	≥ 1	1

TABLE 3.2. ECG and PPG measurements, source [**9**]

The pressure wave of the cardiac cycle causes the expansion and contraction of blood vessels, giving a characteristic shape to the PPG wave. PPG measures the volume of arterial blood and when the pressure wave reaches the extremities corresponds to the peak of the PPG wave. As the period of this wave is repeated with each heart cycle, the heart rate can be calculated. While PPG provides information about pressure and blood flow, ECG provides information about the electrical activity of heart muscle tissue. In order for the blood to flow in the correct direction, the heart muscle cells must contract in the correct order. This sequence forms every portion of the ECG wave. When PPG and ECG signals are measured simultaneously they can be related since they have the same period. Although the PPG wave is delayed in relation to the ECG wave, both signals can determine the heart rate. The time difference between the R and systolic peak can be used for blood pressure estimation [**9**]. The next figure shows the two overlapping waves so that the delay between them is perceptible.

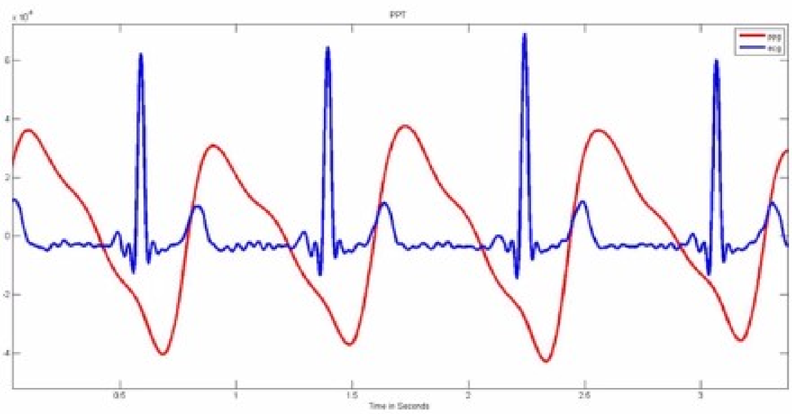


FIGURE 3.5. ECG and PPG waves, source [**9**]

These two signals are acquired by the external 12-bit ADC, ADS1015, in order to obtain a more accurate reading. Through the I2C interface, data is transferred to ESP32 at 3300 samples/second and then processed individually by each microcontroller core. In the case of the ADC present in ESP32 the measurements get more noisy when the WiFi is on. Therefore the use of an external ADC is preferable to the built-in ADC of microcontrollers.

A push button and an LED have been added for the user to mark the moments he considers the most motivating, i.e. that best capture the attention. If the user sees an interesting content, press the button that will light an LED. This marks the starting point of this moment of most attention, which will remain with the LED on. Finally, when the user considers that the content watched becomes tedious and loses attention, he presses the button again to turn off the LED. Therefore, as long as the LED remains on, it represents a period in which the user considers himself more attentive. On the other hand, while the LED is off it means that the user evaluates the moment as not motivating, losing the attention. This information is sent to the database associated with the other measured values including the timestamp.Thus, the data entered by the user in a subjective way can be compared with the data collected by the sensors. It will be a further aid in measuring the attention and evaluation of user behaviour and awareness.

After the signals were processed, a RTC DS3231 was added, communicating with ESP32 via an I2C interface.This real time clock includes a calendar and its purpose is to identify data that has just been processed. Thus the data are easily associated according to the corresponding seconds, minutes, hours, day, month and year. If necessary, it also has an on-board backup battery so that the data is stored in case of power failure. Initially the RTC DS1015 was used, but it only allowed resolution up to the second. As the ECG and PPG wave peaks occur mostly in less than 1 second, data were collected with the same associated time. This way a RTC DS8232 with resolution up to the millisecond was chosen. As mentioned in chapter 2, this RTC synchronizes a 1Hz square wave to obtain millisecond resolution.

The following figure represents the first schematic of the ESP32 transmitter, connected to the sensors and other components.

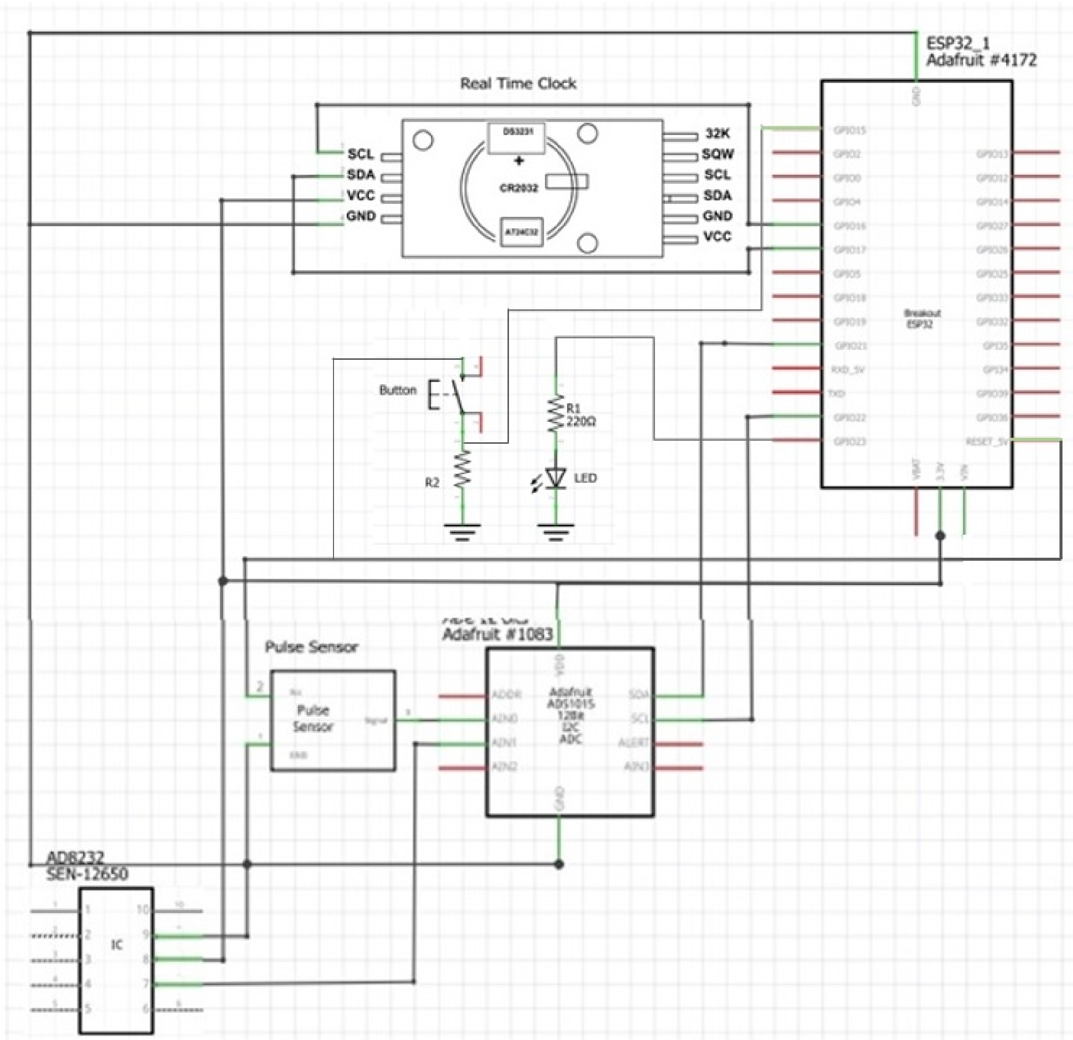


FIGURE 3.6. The TX node schematic

3.2.3. RX Node

The ESP32 RX connects easily to the TX microcontroller via the UART interface without the use of a clock. ESP32 supports three serial interfaces defined as UART0, UART1 and UART2. Although it is an asynchronous communication, it supports speeds up to 5Mbps. Even though it allows full-duplex communication, in this case only half-duplex data exchange from transmitter to receiver is used. For data to be transmitted between two UARTs, only two wires are used.The transmission UART transfers the data from the Tx pin to the Rx pin of the receiving UART.

After receiving the data, this microcontroller sends the data to the database using the WiFi module. If the connection fails, the data will be recorded locally on an SD card, preventing its loss. Through the SPI interface, an adapter for reading and writing to the micro SD card is connected to ESP32. Finally, a push button is added to indicate the end of the measurements. Therefore, it is the responsibility of the user to register this marking. The following figure represents the ESP32 RX layout, connected to the other components.

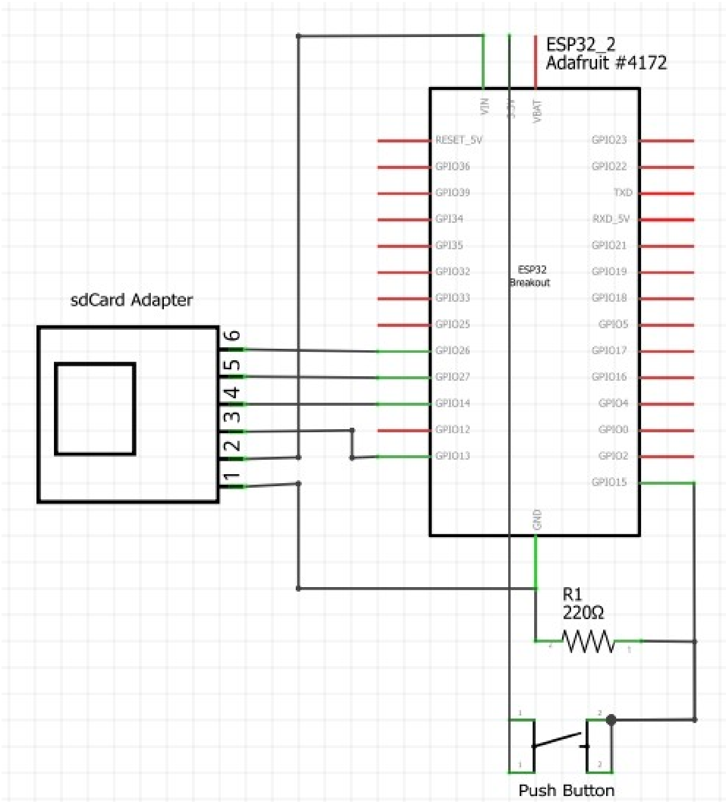


Figure 3.7. The Rx node schematic

Finally, there follows the image of the first prototype that corresponds to the union of the TX and RX nodes. At this stage the system was only implemented on the breadboard as shown in figure 3.8.

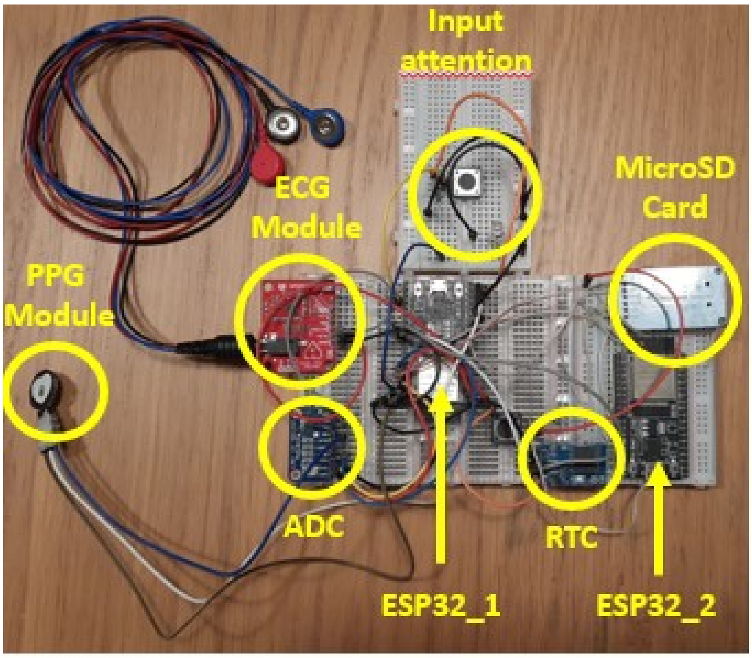


Figure 3.8. First prototype

The previous prototype did not yet have the skin conductivity module. This module was later inserted so that the system could count with a further measurement of the subject's condition. The skin conductivity system has been developed from scratch, which includes two jumpers for the choice of resistance values. This system includes an operational amplifier MCP6004 with 1 MHz Gain Bandwidth Product and Rail to Rail Input and Output. For that purpose, a low and continuous voltage is applied and through the electrodes in contact with the skin the continuous variation of the skin's electrical characteristics is measured. This variation provides an insight into how reactions to different stimuli can occur.

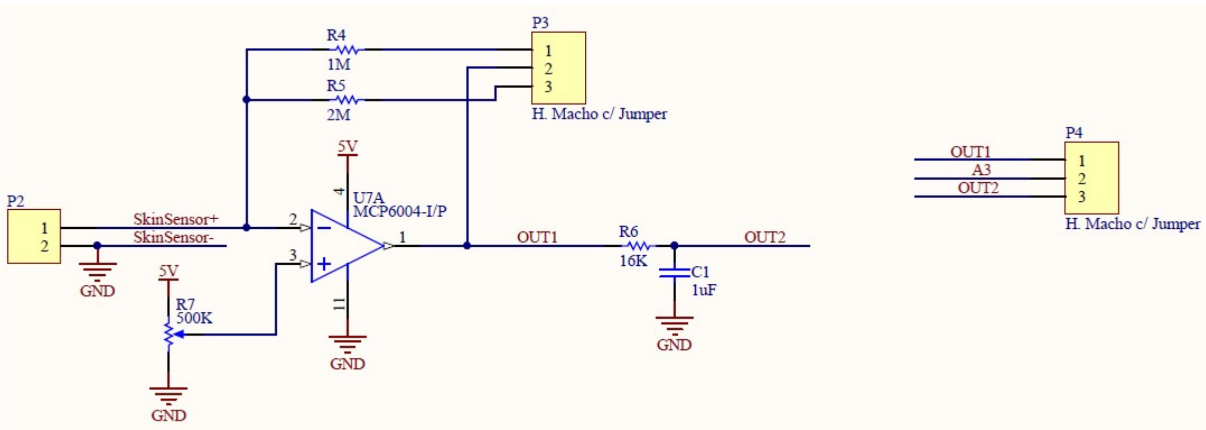


FIGURE 3.9. Skin conductivity schematic

The connection between two nodes through UART to transmit and receive serial data. UARTs have the same baud rate and data packet structure but no clock signal to synchronize the output. While TX UART converts parallel data into serial form, RX UART converts the serial data back into parallel data. Data flows from the transmitting UART Tx pin to the receiving UART Rx pin, where only Strings are sent and received. In this case, this connection is sufficient to withstand the transmission of the time interval between beats which is equivalent to a maximum of 25 bytes per String. A maximum of six Strings are sent per second (3 beats per second for the two signals, ECG and PPG) which is equivalent to 150 bytes per second. For each byte of data transmitted, ten bits are actually sent which correspond to one initial bit, eight data bits and one stop bit. The standard baud rate chosen was 9600 bps, which corresponds to 9600 bits per second or 9600 (9600/10) bytes per second. As can be verified, the 960 bytes per second that the connection supports is enough for the maximum transmission of 150 bytes per second of the system.

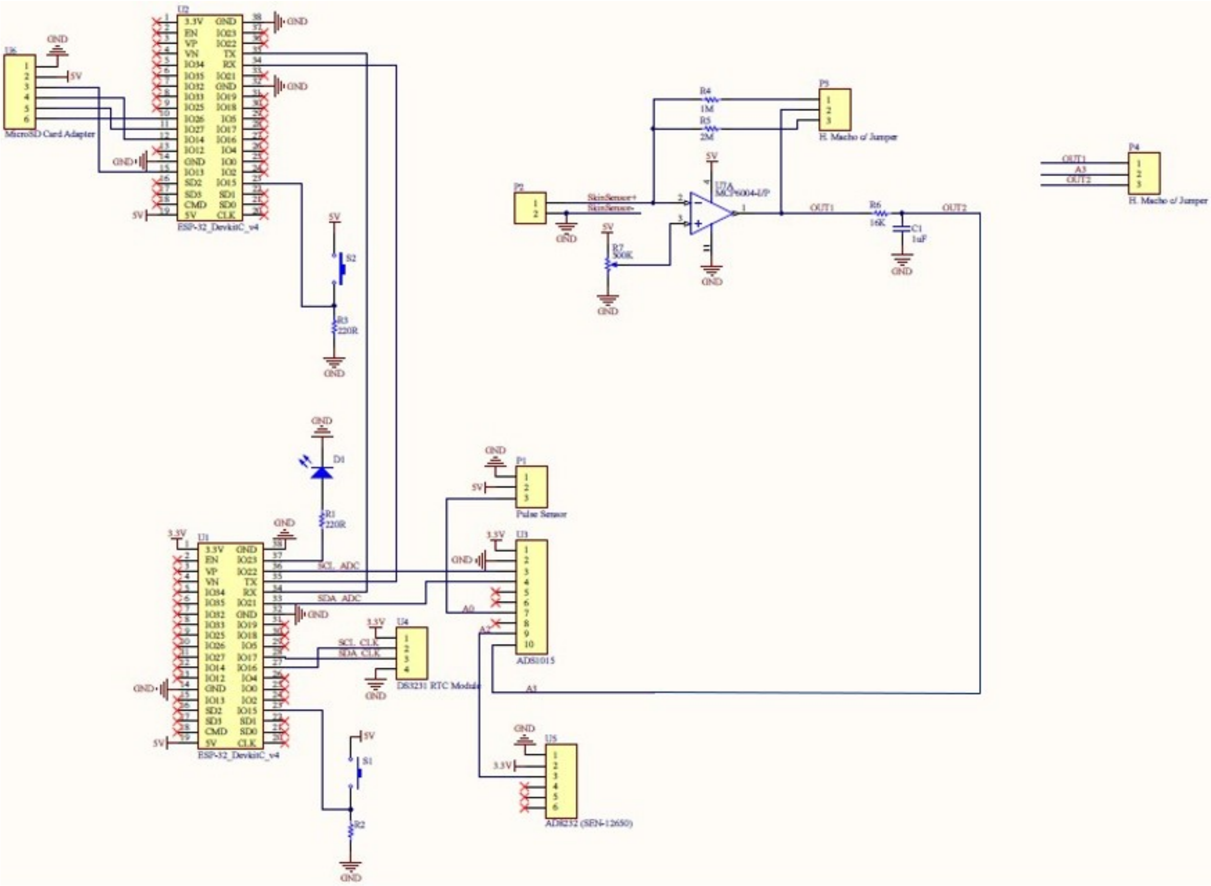


FIGURE 3.10. System schematic

To make the hardware as portable as possible, the complete system was welded on a 12x10cm board.

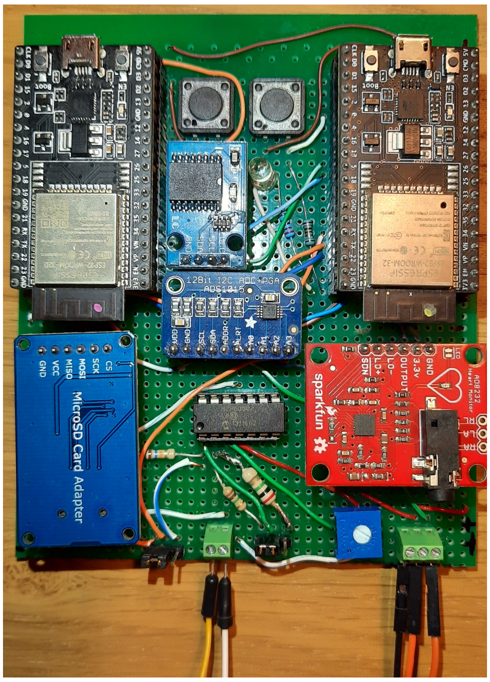


FIGURE 3.11. HRV monitor prototype

CHAPTER 4

System Software

After specifying the hardware and physical functionality of the system, this section covers the implemented software. First of all, much of the processing is done by the embedded system. Thus, after data collection, calculations are performed at the microcontroller level and only the essential ones are sent. After the data is transferred and stored, it is subsequently exported for detailed analysis.

Section 4.1.3 refers to the database layer and its connectivity during data processing and after storage. That is, the analysis using the algorithms specified in section 4.2. This analysis also includes the development of software for the algorithms being studied.

4.1. Embedded Software

It is considered an embedded system as it is developed for a specific task and has processing capability. This system has some associated peripherals that allow a permanent interaction with the environment. In addition to being a real-time system, the operation of the embedded software is autonomous and time-sensitive. Not only does it interact with sensors and actuators, the system also reacts to the user.In practice, the most usual approach to development is based on hardware because software is easier to handle.This means that after the microcontroller has been chosen, a version of the hardware is assembled and the software is developed under it. Finally, the integration of the developed software and hardware is carried out. For this reason, the hardware-software interfaces need to be designed together

Before the step-by-step explanation of the system activity, the flowchart below illustrates the general functioning of the system. This scheme only demonstrates the parallel acquisition of the ECG and PPG signals. The remaining features are specified later in this chapter.

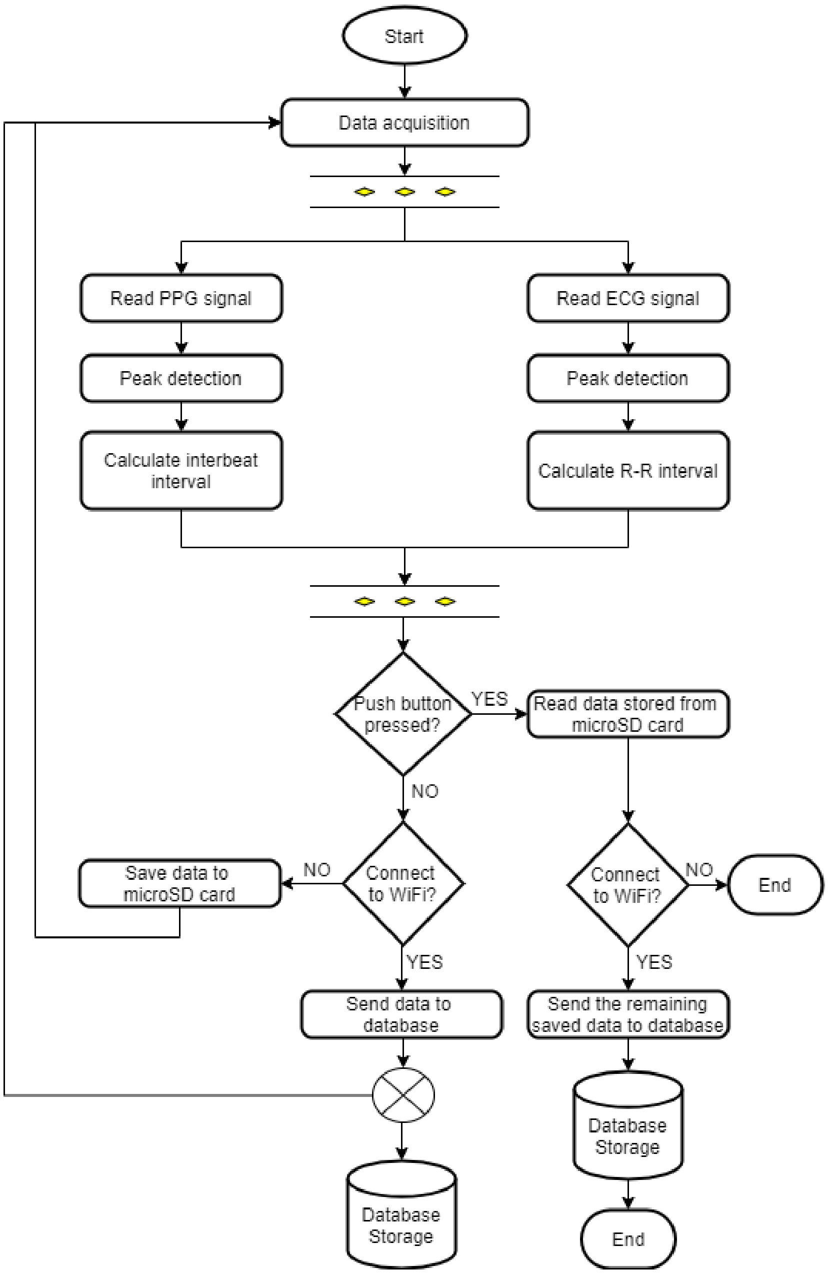


FIGURE 4.1. Software flowchart

4.1.1. Sensor data reading

Data is only collected by the TX node through two channels characterized by 12-bit ADC. For these measurements to be simultaneous, the two cores of the microcontroller are used: core 0 collects the PPG wave and core 1 the ECG wave. As the microcontroller has 2 Xtensa LX6 32-bit microprocessors, two tasks in parallel with the same priority are created.This real time operating system handle several tasks that run independently. The processor performs the tasks with the highest priority in the first place and for them to run at the same time they have the same priority. The implemented xTaskCreatePinnedToCore() function inserted in the setup() creates each task with its respective characteristics as shown in the following figure.

```
//create a task that will be executed in the Task1code() function
xTaskCreatePinnedToCore(
  Task1code,    /* Task function. */
  "Task1",      /* name of task. */
  10000,        /* Stack size of task */
  NULL,         /* parameter of the task */
  1,            /* priority of the task */
  &Task1,       /* Task handle to keep track of created task */
  0);           /* pin task to core 0 */

//create a task that will be executed in the Task2code() function
xTaskCreatePinnedToCore(
  Task2code,    /* Task function. */
  "Task2",      /* name of task. */
  10000,        /* Stack size of task */
  NULL,         /* parameter of the task */
  1,            /* priority of the task */
  &Task2,       /* Task handle to keep track of created task */
  1);           /* pin task to core 1 */
```

FIGURE 4.2. Code: tasks setup()

With this parallel and independent measurement, the waves are obtained as shown in the figure 4.3. The PPG wave is represented by the color red and the ECG wave by the color blue. For the ECG, only the interval between the R peaks of the QRS complexes is processed, called RR-Interval (RRI). In the PPG, the values of the intervals between beats and the respective amplitudes are extracted. In this case, the time value is called InterBeat Interval (IBI). For a clearer understanding of all these values, they are described in the following image.

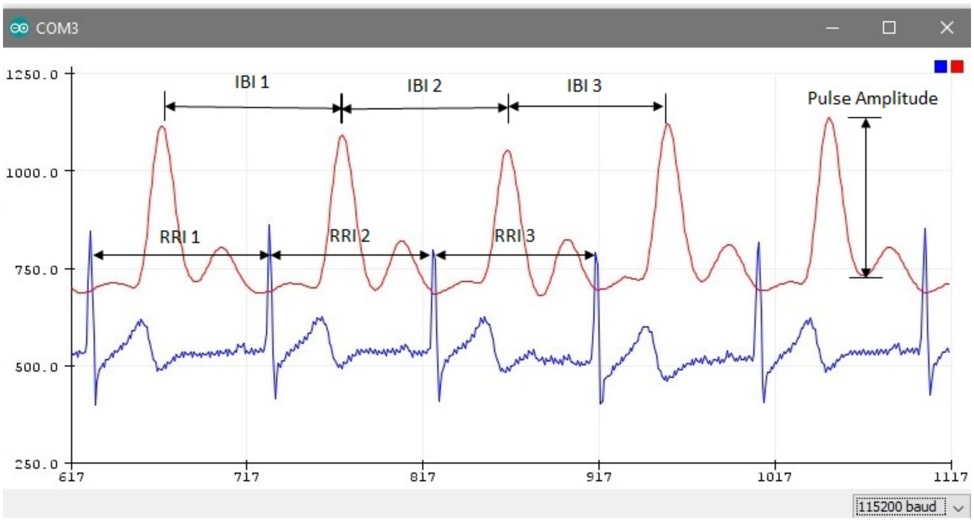


FIGURE 4.3. Simultaneous waves red=PPG, blue=ECG

4.1.2. Data processing

When reading the sign, it is checked whether the new value is higher than the previous one. If so, this value is saved as the new maximum. When the value stops increasing and becomes lower than before, it means that a peak has been found. To verify that this value is in the flat top of the peak, the comparisons are limited from a priori threshold value. Figure 4.5 illustrates this procedure in code for the ECG channel.The same applies for the PPG channel, differing the threshold value.

When the peak is discovered it is associated with its time stamp in order to calculate the difference with the time of the previous peak. This is how the time intervals between peaks are calculated, whether they are R or Beats. These values are measured in milliseconds. In these cases it is important to distinguish the peak that matters. In this project this problem is being solved for a defined minimum time until another peak is considered. In the case of PPG, the amplitude value of each peak is also extracted.

A flowchart for a better illustration of the peak detection algorithm for calculating the interval between them is presented below.

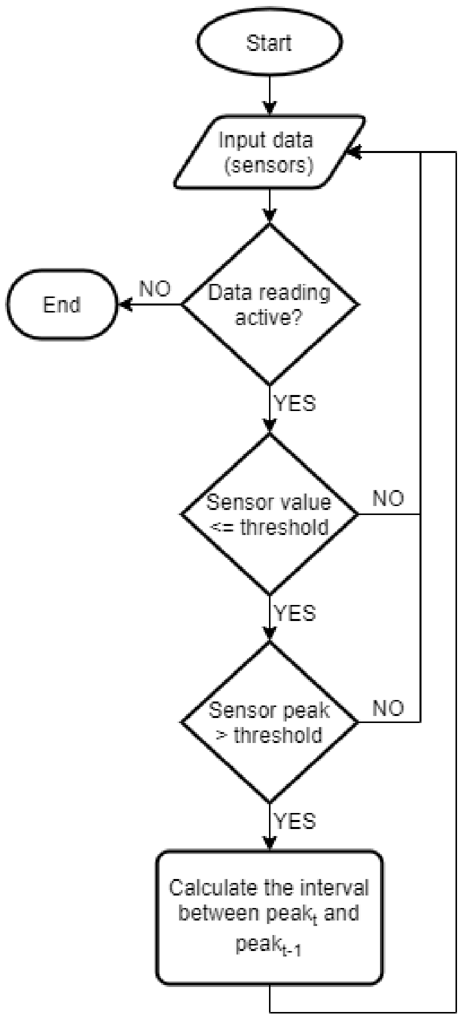


FIGURE 4.4. Peak detection flowchart

An excerpt of the code used in the Arduino IDE processed by the microcontroller is also presented.

```
for (;;)
{
  int16_t ECG_sensorValue = ads.readADC_SingleEnded(2);
  if (ECG_sensorValue > ECG_peakValue) {
    ECG_peakValue = ECG_sensorValue;
  }
  if (ECG_sensorValue <= ECG_threshold )
  {
    if (ECG_peakValue > ECG_threshold )
    {
      ECG_timer2 = ECG_timer1;
      ECG_timer1 = millis();
      rr_interval = ECG_timer1 - ECG_timer2;
      if (rr_interval > 450 )
      {
```

FIGURE 4.5. Code: peaks

The timestamp that is associated with the instant of peak discovery comes from a Real Time Clock (RTC). With RTC chosen (DS3231) you can decide on different frequencies of sub-second outputs. For a resolution of milliseconds, the 1Hz option is used to generate a square wave of synchronization. To control the total count of the seconds an interruption routine is still required.

4.1.3. Data transmission

After the two signals have been acquired and processed, the second esp32 serial is used to transmit the data to the RX node. This way, the UART communication is physically implemented through the input/output pins Rx and Tx. That is, data flows from the Tx pin of the UART transmitter to the Rx pin of the UART receiver. Despite being an asynchronous transmission, the introduction of time and hour by the RTC solves this problem.

The final purpose of the data is to be sent to the database in real time. That said, the microcontroller every 10 seconds tries to connect to the Internet via WiFi. If this condition is verified, i.e. connecting to the Internet, then the objective is achieved and the data is sent as the node receives it. If this connection fails, data is stored on the microSD card in such a way as to prevent data loss.

The end of the reading is signalled by a pressure button actuated at this instant. As opening, reading and closing the card dispenses some time, only at the end of this procedure is the data removed and sent to the database if there is Internet.This makes the system the most efficient when it comes to displaying data in real time.

The information transmitted from one node to the other has the format represented by the following.

P;584;1077;23:46:27:603;0
E;600;23:46:28:56;453
E;1008;23:46:29:168;469
P;2224;1053;23:46:29:827;1
E;1120;23:46:30:464;482
P;448;744;23:46:30:507;1

FIGURE 4.6. Serial data form

The letters E and P identify the ECG and PPG channels respectively. The next value is the interval between peaks and in the case of the PPG its amplitude is also added. Finally, the last value is the time calculated by the RTC at the TX node. The figure 4.6, in addition to representing the data transmitted in the serial is also how the data is stored on the micro SD card. The RX node decodes each line of the serial and sends it to the database according to table ECG or PPG. Each sign, ECG (table 4.1 and PPG (table 4.2), has its own table with the characteristics presented below.

User ID	**RR Interval**	**Date Time**	**Skin Conductivity**
0	600	23:46:28:56	453
0	1008	23:46:29:168	469
0	1120	23:46:30:464	482

TABLE 4.1. ECG Table

User ID	**Interbeat Interval**	**Amplitude**	**Date Time**	**Button Attention**
0	584	1077	23:46:27:603	0
0	2224	1053	23:46:29:827	1
0	448	744	23:46:30:507	1

TABLE 4.2. PPG Table

The database management process is performed through the phpMyAdmin web platform [**10**] where the MySQL data management is done over the Internet. In addition to simplicity, this tool allows access from any computer facilitating day-to-day transactions. With the user interface, SQL queries are also executed and data output is tested.

4.2. Data Analysis

After storing the results in the database, the process of analysis of the HRV is performed. To do this, linear algorithms were developed in the time and frequency domain. However, these methods of a stationary nature are insufficient in dynamic situations. Therefore, the data is also analysed through non-linear measurements. The next sections explain each of the algorithms developed in MATLAB.

4.2.1. Time Algorithms

The simplest methods of application in the study of HRV are the linear ones in the time domain. For the analysis of this method, the data are grouped in such a way that the records are at least 5 minutes long. The calculated variables are described below.

- RR Intervals: R-peak values of the ECG signal and beat intervals in the case of PPG.
- Heart Rate: heart rate over time for both ECG and PPG signals.
- SDNN: standard deviation of NN intervals calculated in 5-minute periods (ms); this parameter provides a quantification of the slow variations in variability [**44**]; subtract the simple average of the numbers from each interval by squaring the result. Then all the values are added together and divided by the number of values. Finally, the square root of the result is calculated. This is the formula for Population Standard Deviation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{4.1}$$

As the data are only samples, so as not to lose any accuracy, the Sample Standard Deviation is calculated. The difference with this formula is 'N-1' instead of 'N', called the Bessel's correction.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{4.2}$$

- RMSSD: square root of the mean squared differences of successive RR intervals calculated in 5-minute periods (ms); this parameter provides a quantification of the abrupt variations in variability. First we calculate the sum of each time difference between successive heartbeats squared. The result is the average before obtaining the square root of the total result.

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{4.3}$$

- NN50: Number of differences of successive NN intervals greater than 50 ms; and percentage between NN50 (pNN50) and the total number of successive NN intervals.

4.2.2. Frequency Algorithms

The heart rate is conditioned by stimuli received by the Autonomous Nervous System which may be of intrinsic or extrinsic nature. The intrinsic stimuli are related to the emotional state of the individual, while the extrinsic ones come from factors of the environment around him. For the analysis of this domain, after collecting the RR intervals, the RR wave is interpolated in order to obtain a continuous signal in time. In this way, the RR signal spectrum and a precise estimation of the Power Spectral Density (PSD) through the Fast Fourier Transform (FFT) are obtained [**25**].

The following figure shows the code that allows PSD calculation, whose graphical result is represented by figure 4.7. First, the fixed space for the interpolation is defined which is twice as small as the value of the minimum interval. After interpolation using the spline function, the absolute values of the FFT are calculated. Finally, the power is calculated for each normalised frequency component.

```
y=y-mean(y); %DC component strip (average)
T0 = x(length(x)); %total duration in milliseconds
Dist_min = min(diff(x)); %[ms]
Freq_max = 1/(Dist_min/1000); %[Hz]

Ts = Dist_min/2; %fixed space [ms]
Fs = Freq_max*2; %[Hz]
xx = 0:Ts:T0;
s = spline(x,y,xx); % is a soft PCHIP that continuously varies
L=length(s);
NFFT=1024;
Xf=fft(s,NFFT);
subplot(3,4,9);
plot(abs(Xf));  % FFT graph
title('FFT');
Px=Xf.*conj(Xf)/(NFFT*L); %Power of each frequency component
fVals=Fs*(0:NFFT/2-1)/NFFT;
subplot(3,4,10);
plot(fVals/Fs,Px(1:NFFT/2),'b','LineSmoothing','on','LineWidth',1);
title('One Sided Power Spectral Density');
xlabel('Frequency (Hz)')
ylabel('PSD');
```

FIGURE 4.7. PSD calculation code

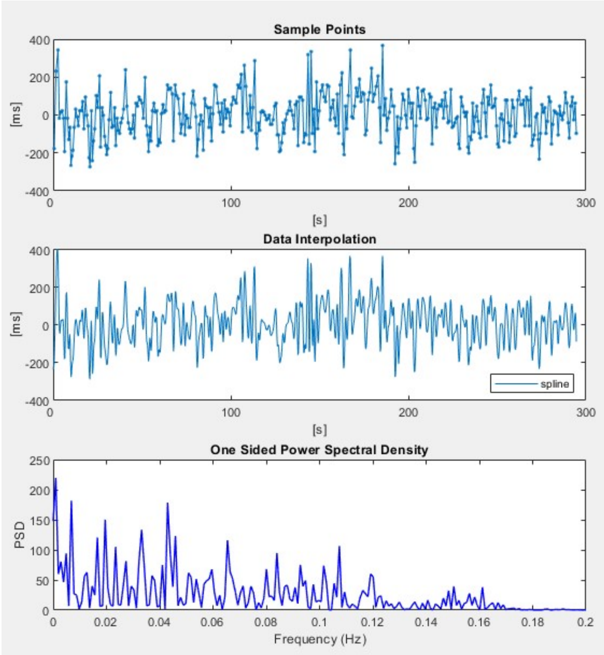


FIGURE 4.8. PSD calculation graphically (Top chart: sample points of RR intervals, Middle chart: RR intervals interpolation, Bottom chart: PSD of RR intervals interpolation

FFT is one of the methods that allows to obtain a representation of the power spectrum of a series of data. In this way, the power of specific frequencies in a signal can be isolated and quantified. After calculating the PSD graph, the objective is to divide it into bands represented by the three colors:

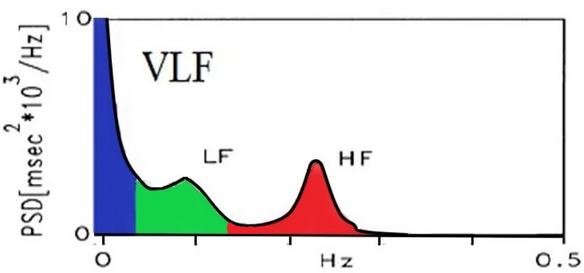


FIGURE 4.9. PSD division, adpated from [**13**]

Frequency Band	Interval	ANS relation
VLF:very-low-frequency band	Up to 0.04 Hz	*(not related)*
LF: low-frequency band	Between 0.04 and 0.15Hz	Influenced by the PNS
HF: high-frequency band	Between 0.15 and 0.4Hz	Influenced by the SNS
LF/HF: ratio of low to high frequency power	*(not related)*	Sympathetic and parasympathetic balance index

TABLE 4.3. Total spectral power band division

The *trapz* and *area* functions of MATLAB are used to calculate the areas associated with different frequency bands. After defining the limits of the bands, the area that the PSD function covers within these limits is calculated. The following figure provides the code for the calculation of the area that corresponds to the High Frequency band. In this way, the figure 4.10 represents the color graphic according to the 3 areas defined before.

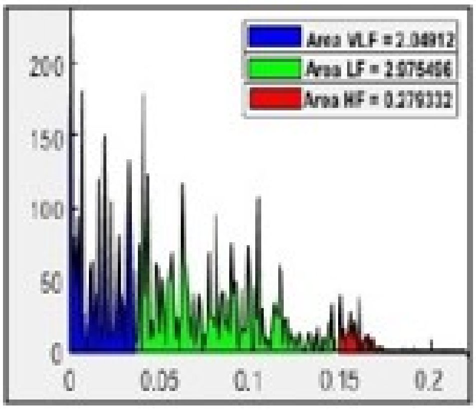


FIGURE 4.10. PSD frequency bands

By calculating the total area of the PSD graph, the percentage of the low and high frequency bands is determined. With these results the following can be inferred that high %LF and low %HF correspond to cases of high stress. In contrast, low %LF and high %HF represents low stress situations. The lower the LF/HF value the better the performance and the attention of the user.

4.2.3. Non-linear Algorithms

Since linear methods of a stationary nature are insufficient for the study of dynamic factors, non-linear methods are used. These methods characterize unbalanced and non-periodic systems such as the cardiovascular system, with the presence of dynamic variables that directly influence HR [**25**].

- Detrended Fluctuation Analysis (DFA): this measure quantifies the occurrence or not of the correlation over time scales using exponents of scale. This measure quantifies the fractal property of time series of RR intervals. Through the result of the coefficient, it is possible to detect anomalies present in a subject [**20**]. In order to describe the "roughness" of the series, it is divided into blocks of equal size for which its tendency is calculated by the method of least squares. The following figure is an example of the trend line that best fits the 5min ECG data. This statistical procedure finds the best fit for a set of data points as can be seen in figure4.11.

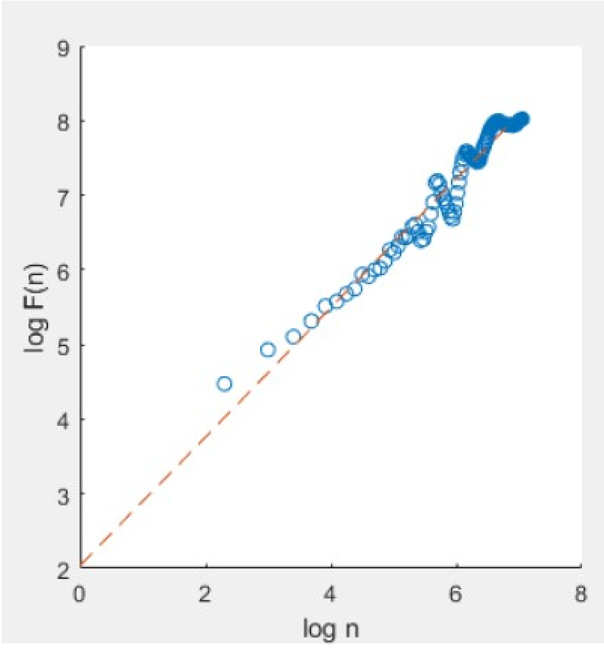


FIGURE 4.11. Least squares method

Finally, the slope of the adjusted straight line which is the exponent of scale, α, is calculated.

α	Description
0¡α¡0.5	large and small intervals are more likely to alternate
0.5¡α¡1.0	large/small interval is more likely to be followed by a large/small interval
α=1.0	noise 1/f
α=1.5	Brown noise

TABLE 4.4. Exponent of scale analysis

- Approximate Entropy (ApEn): this measure or metric express the changes that occur in an experimental time series. It returns a non-negative number for the series that the higher the value, the greater the complexity, that is, the irregularity of the data [**20**]. Entropy is directly associated with the quantity of information contained in a message. In other words, a message with a higher probability has a lower entropy. The ApEn result is a positive value that the closer to 0 it refers to a series with high regularity. By contrast, if the value is further from 0 it means that the series has few repetitive patterns.
- Sample Entropy (SampEn): negative natural logarithm of the conditional probability of two similar subseries. In addition to eliminating the self-matches count, it corresponds to the sum of the conditional probabilities. Contrary to the approximate entropy that concerns the logarithm of each individual conditional property [**25**]. This algorithm presents a more robust evolution of the regularity of the series, but it is interpreted in the same way as ApEn.

```
m=2; %subseries length, for clinical data m is to be set at 2 or 3
r=0.2*std(Y2); %tolerance: between 0.1 and 0.25 times the standard deviation of the data
SampEn = sampen(Y2, m, r, 'chebychev');
```

FIGURE 4.12. Parameters for entropy calculation

These entropy-related algorithms are very sensitive to input parameters. Thus, two input parameters are defined, m and r (see figure 4.12. The parameter m is an integer value that corresponds to the length of the subseries and for clinical data m is to be set at 2 or 3. The parameter r is an actual positive number which represents the tolerance between 0.1 and 0.25 times the standard deviation of the data for both signals (ECG and PPG).

According to the authors in [**20**],the high HRV corresponds to a good adaptability of the functions of the organism, namely the ANS. Thus, with a good functioning of the autonomic control mechanisms it reflects a healthy individual. On the other hand, the low HRV indicates abnormal or insufficient adaptability of the ANS, allowing the presence of physiological malfunction.

4.3. Attention Assessment Protocol

In order to evaluate the attention in a more objective way, all the volunteers watch two videos and reply to a questionnaire at the end of each one. The protocol used is described below.

(1) Random selection of the sequence of the videos. At this point one of the following sequences is chosen:
  - Sequence A: first the Video Motivation (VM) and then the Video No_Motivation (VNM);
  - Sequence B: first the Video No_Motivation (VNM) and then the Video Motivation (VM);

(2) The sensors are placed on the volunteer. Thus, the PPG sensor on the finger and the electrodes of the ECG module as shown in figure 3.4.

(3) It is explained to the volunteer that he will watch two videos and that at the end of each one he will have to answer some questions about the quality of the video he has just watched. For an initial level of attention it is essential to approach the theme of the video which will be on Sleep Disorders.

(4) The HRV registration system is connected by presenting the first video, according to the sequence selected previously. Afterwards, the questionnaire is presented to the volunteer, and the system is switched off.

(5) The HRV registration system is reconnected by presenting the second video, according to the sequence selected previously. Afterwards, the questionnaire is presented to the volunteer, and the system is switched off.

QUESTIONNAIRE:

- Q1: Is the subject of the video interesting?
  [0=not interesting, 10=very interesting]
- Q2: What score do you give to the quality of the video?
  [0=very bad, 10=very good]
- Q3: How much attention do you think you kept during the video?
  [0=not attentive, 10=very attentive]

In order for the Motivation video to attract more attention, it is performed with movement on the pointer screen and the presence of body language. As can be seen in the following two figures (4.13 and 4.14), the presence of body movement and the pointer interact more with the user.

FIGURE 4.13. Video Motivation with corporal language

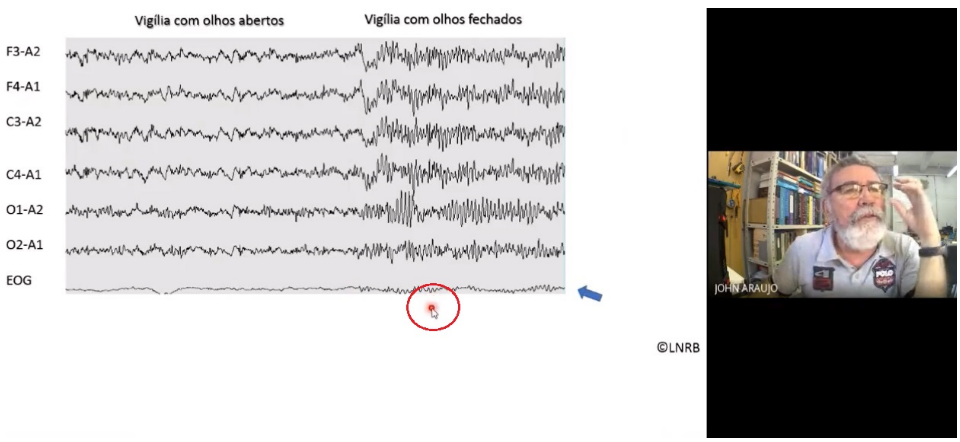


FIGURE 4.14. Video Motivation with pointer screen

While the video No_Motivation reads the slide texts with a monotonous tone of voice. In this case, there is no interaction with the user as can be seen in the figure 4.15.

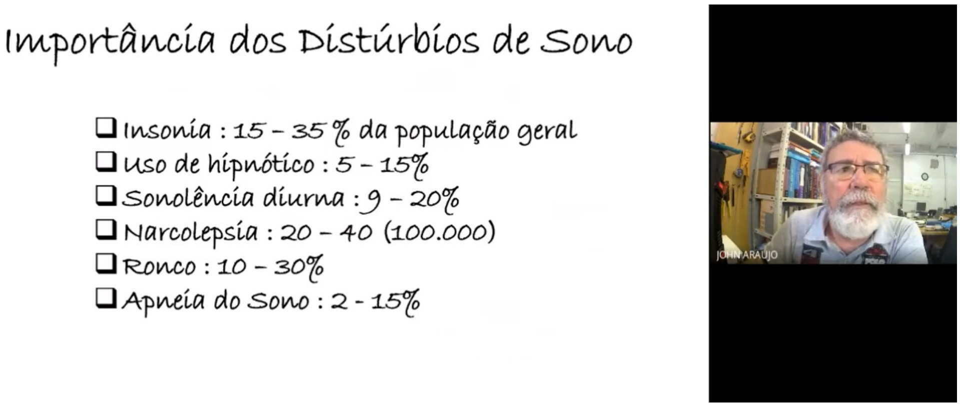


FIGURE 4.15. Video No Motivation

CHAPTER 5

Results and Discussion

This chapter presents some obtained experimental results obtained by the system. Firstly, the analysis of the signals of ECG and PPG sensors is presented through graphs and tables for an easy understanding of the system behaviour. The performance of the system is also evaluated by the concordance of results.

5.1. Sensing data analysis

The system was tested in a laboratory with 12 volunteers, most of them aged between 20 and 25 years. The steps of the protocol 4.3 were followed, from the random assignment of the video sequence to the HRV registration of the two videos with the completion of the respective questionnaire. As mentioned above, the videos were evaluated on a scale of zero to ten according to questions 1, 2 and 3 of the Questionnaire 4.3. Thus, the VM had an average of 7.8 while the VNM had an average of only 5.78 of the three questions asked. These values correspond to the expected result since the VM was performed in a way to motivate the user, attracting his attention.

After collecting the data, the program developed in MATLAB will fetch the data stored in the database based on the user ID. Each id corresponds to a single video and the analysis graphically returns the IBI and IRR comparison, the amplitude of the pulse wave peaks and the user's attention input. These results are then analysed in the three areas, time, frequency and non-linear measures.

5.1.1. Volunteer ID02

Next are the results of a male user aged between 20 and 25. The sequence B is assigned, which first visualizes the VNM and only then the VM.

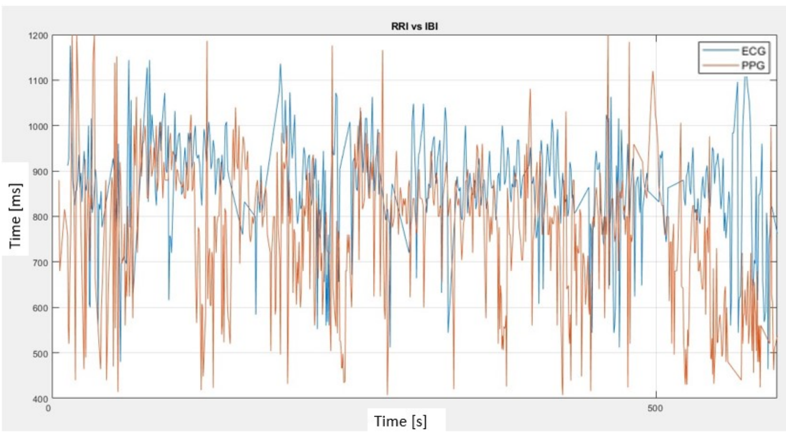


FIGURE 5.1. RRI vs IBI, VM (ID02)

The first graph 5.1 shows the difference of the intervals between RR peaks for the ECG signal and interbeat for the PPG signal. Even though PPG is a less intrusive measurement technique than ECG, for some cases studied the correlation between these two signals for HRV estimation is not so linear. For the collected PPG signal to be accurate, one of the solutions it would be the application of machine learning methods to test the measurement local as well as the contact force of the sensor and even the wavelengths of the LED present in the sensor [**2**]. In this case, the PPG signal is used for validation and redundancy.

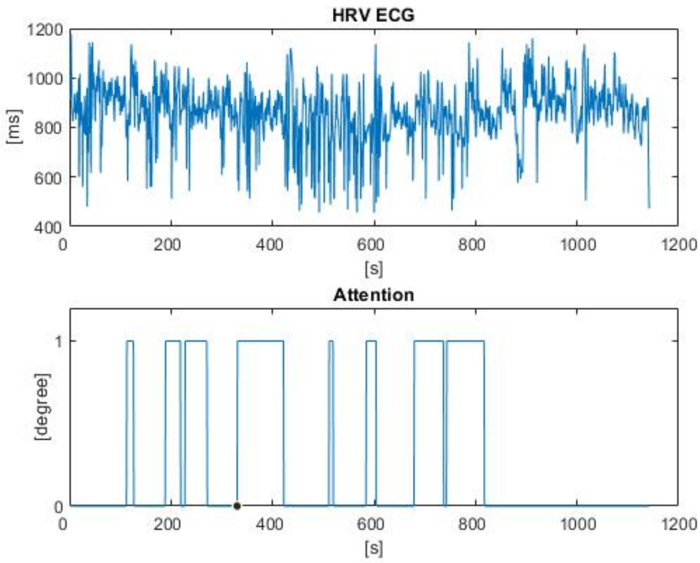


FIGURE 5.2. RR intervals and attention input, VM (ID02)

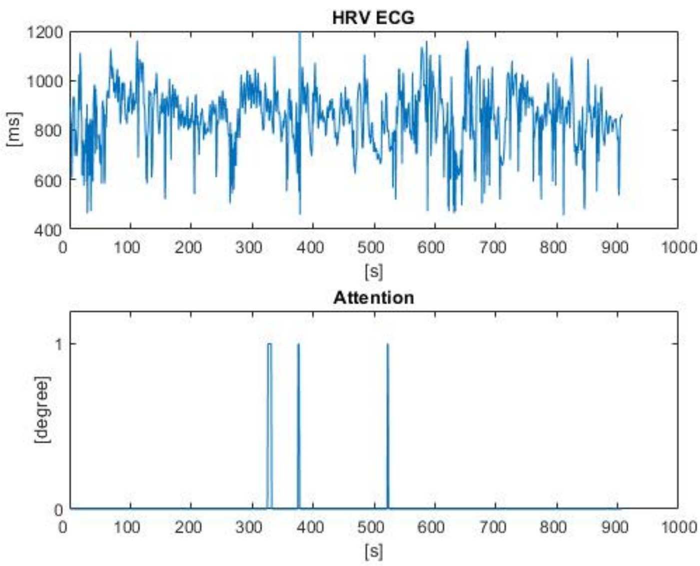


FIGURE 5.3. RR intervals and attention input, VNM (ID02)

The last two graphs 5.2 and 5.3 relate the moments of most attention marked by the volunteer to the intervals between beats. With this input it is possible to subjectively relate the most motivating moments that captured the most attention of the user with the heart rate. In this case, the user considered the most attentive moments those with the highest IBI and RRI variation. On the other hand, at the end of the measurement the cardiac variability tends to decrease as well as the attention inputs. In this way, this variable introduced by the user is in conformity with the HRV.

The VNM was made in a way that became demotivating and less interesting to the user. The graphic result (5.3) already allows to visualize a smaller variability compared to the VM (5.2). Thus, these three graphics are in agreement with the objective of the video.

5.1.2. Volunteer ID07

Next is the result of another volunteer.

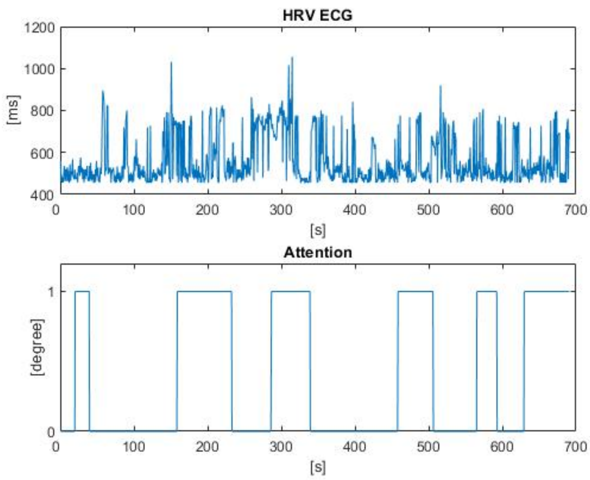


FIGURE 5.4. HRV and attention input, VM (ID07)

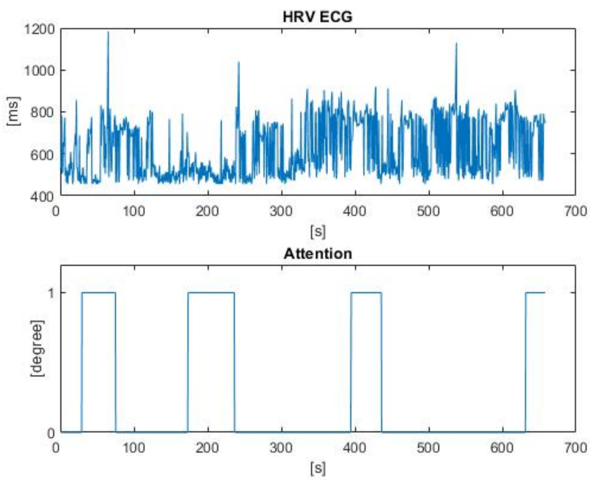


FIGURE 5.5. HRV and attention input, VNM (ID07)

In the graphs above, the user's input allows to check the type of video displayed. That is,Fig 5.4 refers to the motivating video as it presents a greater number of periods of attention. For HRV, the moments without attention input take place in phases with lower HRV like the first 150 [s], and around 400 [s] in Fig 5.4. The HRV graph in Fig 5.5 does not show these moments so clearly. In this case, the data collected from the ECG have small failures in the detection of R peaks, which makes the display of RRI with abrupt differences between waves.

From Fig. 5.6, the amplitude values indicate changes in blood flow volume at the point of measurement. Therefore, smaller amplitude values refer to lower pulsations of blood volume.

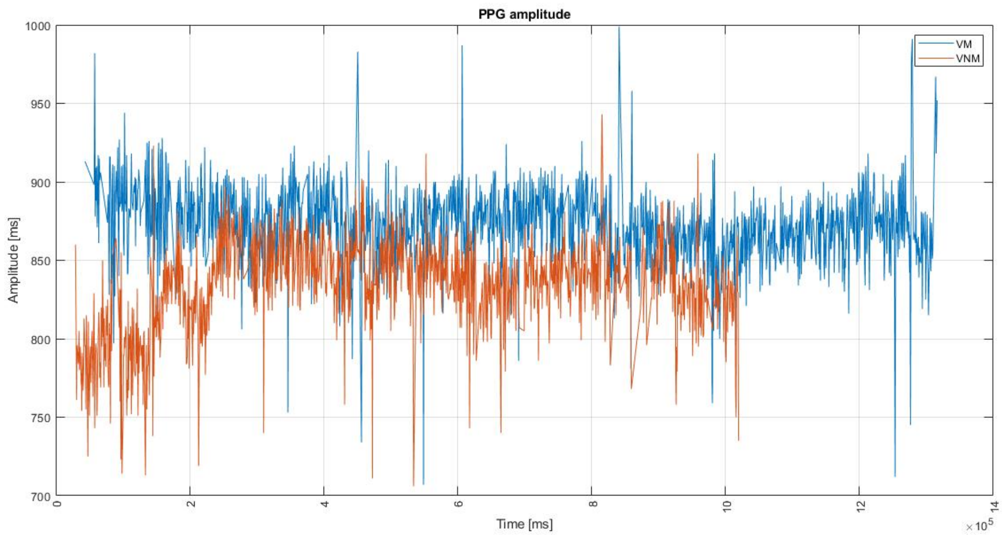


FIGURE 5.6. Peak wave amplitude PPG (ID07)

Although the reduction in the amplitude of the PPG signal could be related to the loss of blood pressure, to extract more concrete conclusions it was necessary to implement analysis algorithms. For this, it is necessary to have more knowledge about respiratory parameters, which goes beyond the main theme of this project. In order to be a work to be developed in the future, this amplitude is still obtained in a primitive form.

5.1.3. Results of 5 volunteers

The next graphs evaluate the results of five random volunteers. Initially the RRI values for Video Motivation and Video No Motivation are compared.

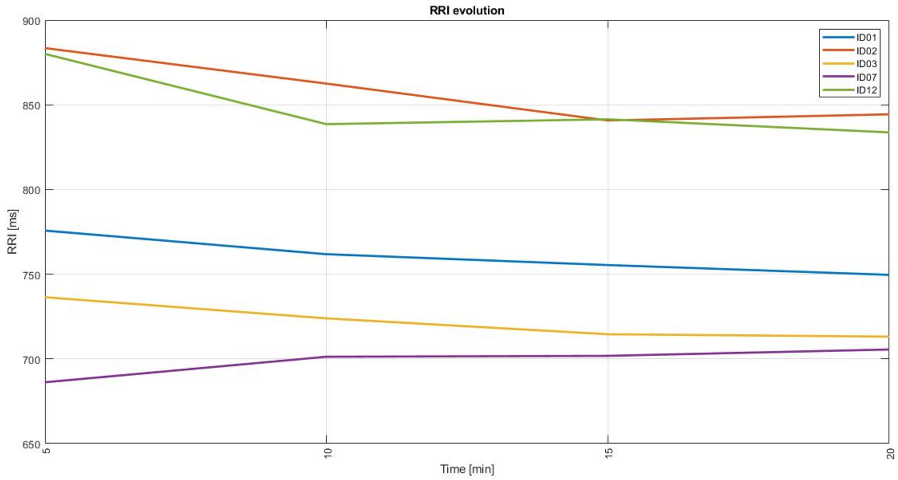


FIGURE 5.7. RRI evolution, VM

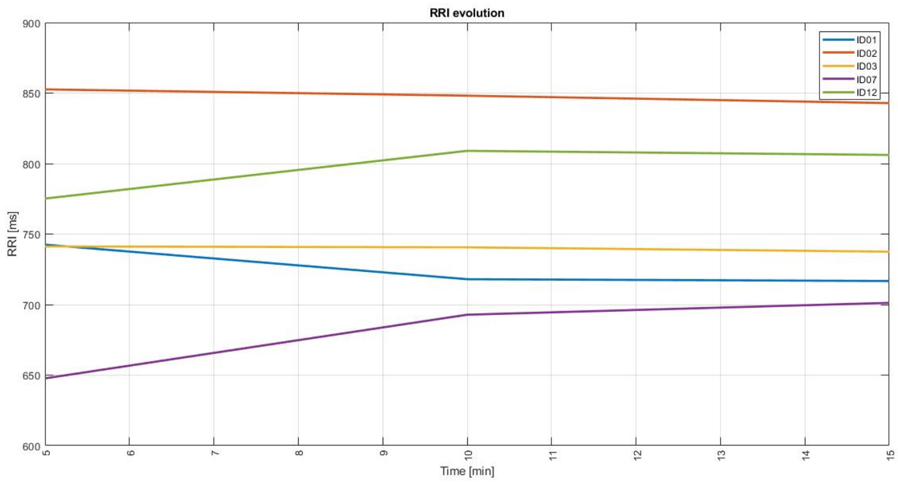


FIGURE 5.8. RRI evolution, VNM

The greatest variation in these intervals occurs in the first 10 minutes. For the selected volunteers, from 15min these values stabilize, corresponding to a lower HRV at the end of the learning experience. It is also noted that the initial RRI values are higher for Video Motivation (figure 5.7. In this analysis the most important are not the RRI values but their variation over time. While in VM we see lines with slope, i.e. variation of values, in VNM (figure 5.8 we see practically straight lines corresponding to a lower HRV value and consequently performance.

The results of the algorithms RMSSD, SD and pNN50 are presented below.

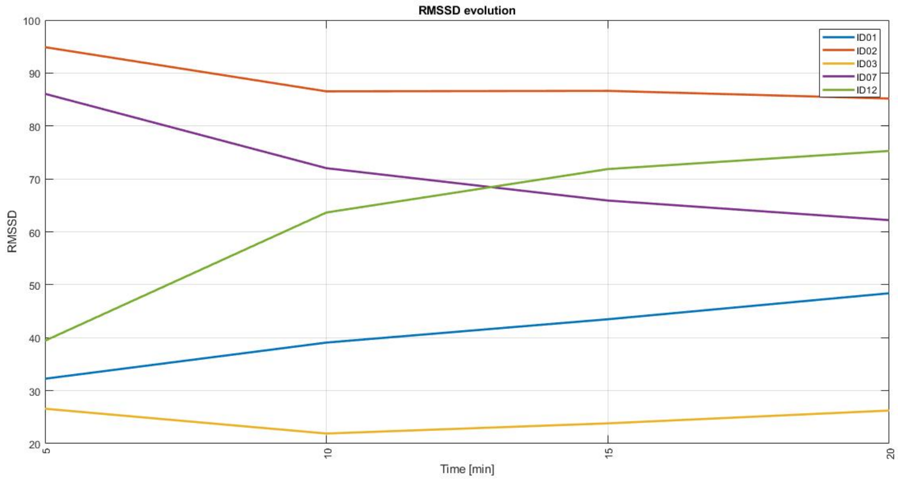


FIGURE 5.9. RMSSD evolution, VM

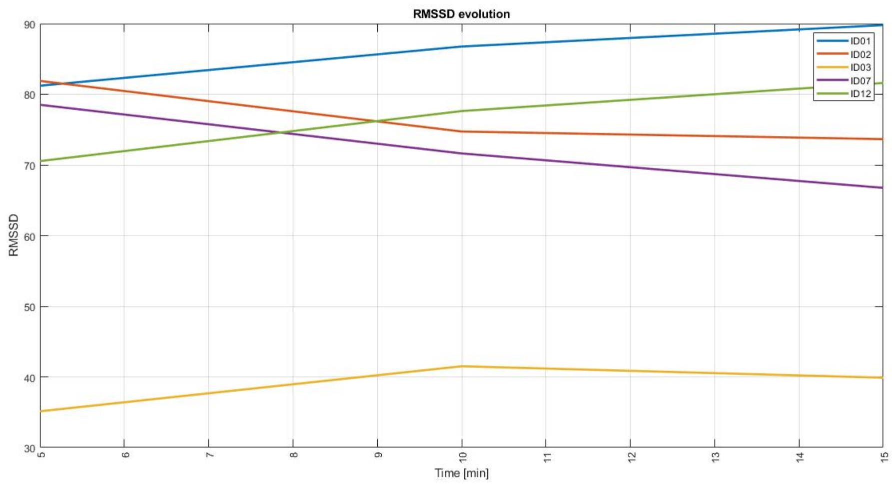


FIGURE 5.10. RMSSD evolution, VNM

In the time domain, the RMSSD algorithm is a key marker for the evaluation of vagal activity. This means that a low RMSSD value corresponds to a poorer mediated vagal variability. For a comparison of the two videos, the difference between the initial and final RMSSD value is calculated. The delta RMSSD ($RMSSD_{final} - RMSSD_{inicial}$) is higher for VM than for VNM video. This higher value means a change from a sympathetic derivation of ANS predominance to a parasympathetic derivation of ANS predominance. This change occurs in a more smooth way in VNM. In addition, the highest RMSSD delta value for the VM is visually proven through the highest slope of the line.

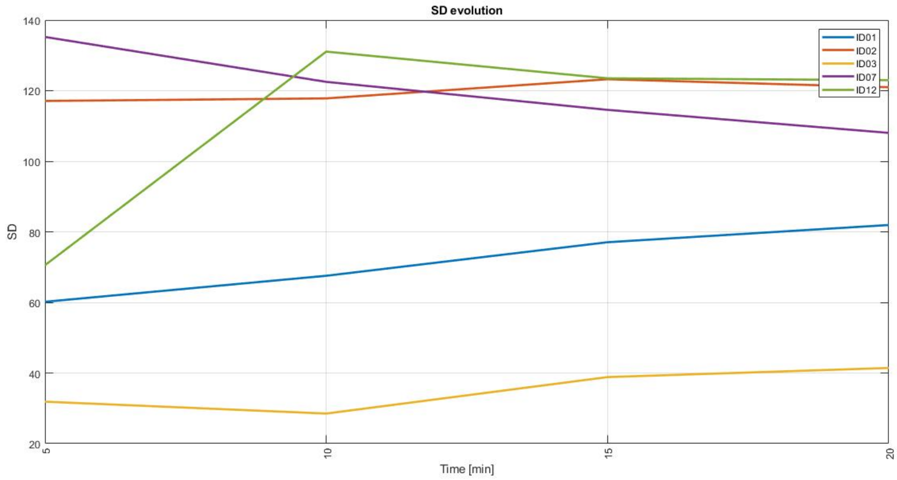


FIGURE 5.11. SD evolution, VM

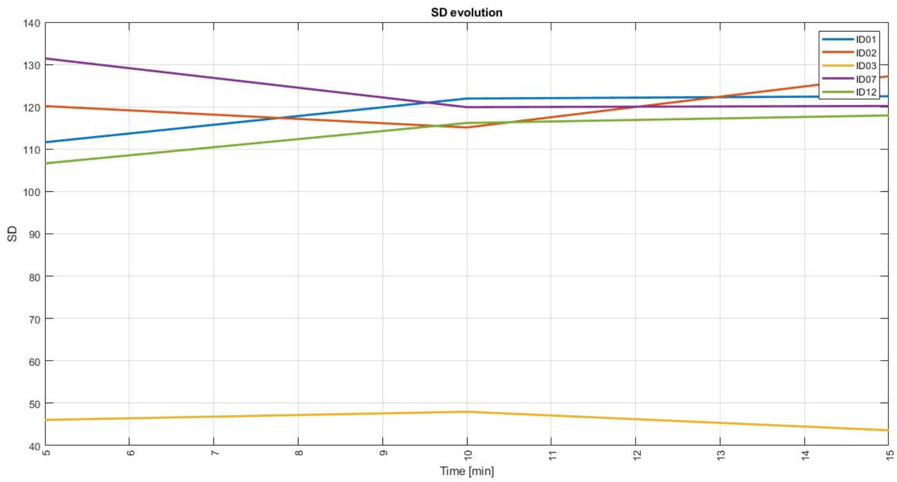


FIGURE 5.12. SD evolution, VNM

he SD parameter provides a quantification of slow variability variations. A high standard deviation value indicates that the data points are spread far from the mean. While a small standard deviation value indicates that the data points are grouped near the mean. It can be seen that the VM has a higher variation of the SD parameter, which corresponds to a higher HRV compared to the VNM (5.12).And for VM (5.11), in 80% of cases this parameter tends to increase mainly in the first 10min, the more attentive phase of volunteers.

Next, the successive NN intervals of more than 50 milliseconds (Pnn50) algorithm is analyzed, which directly reflects HRV because the more a RR interval differs from the previous one, the more cardiac variability.

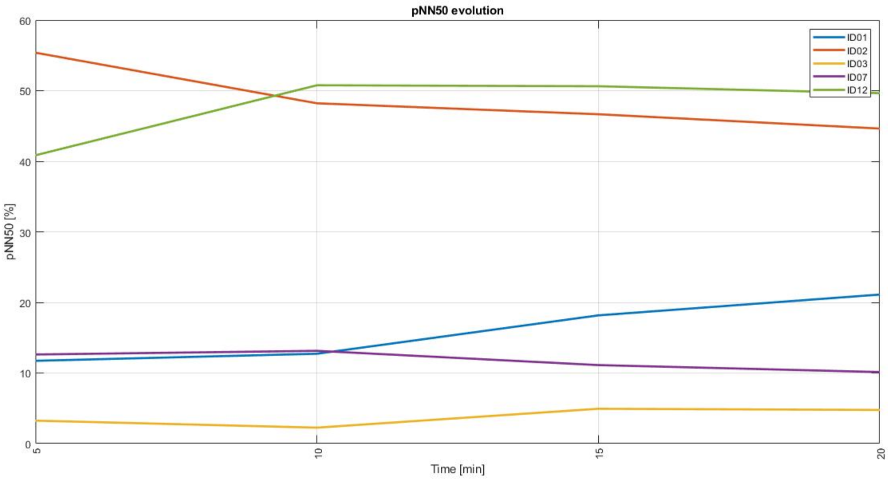


FIGURE 5.13. pNN50 evolution, VM

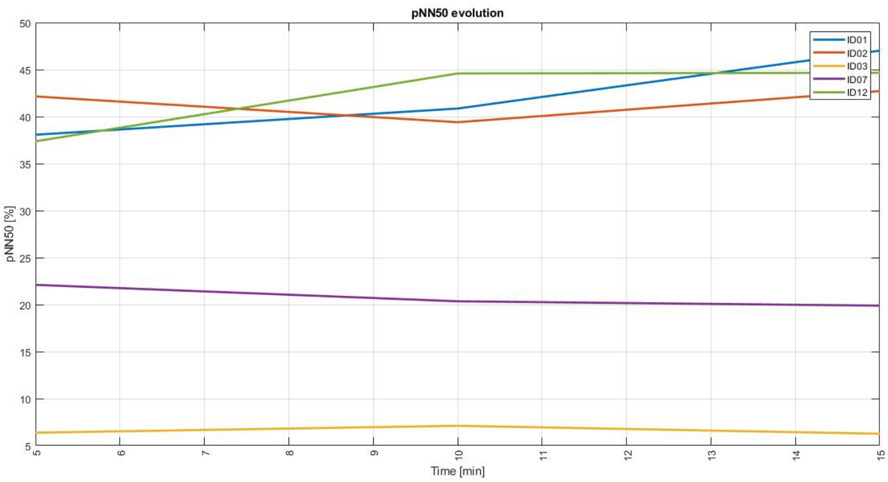


FIGURE 5.14. pNN50 evolution, VNM

In 80% of cases, this percentage increases more sharply in the first 10min of the learning experience. From that moment until about 10min, the growth of this parameter is lower. It tends to stabilize more and more over time. Again, the highest cardiac variability is represented by the higher pNN50 value for the VM (5.13.

HRV analysis in frequency domain was carried out and the obtained results are presented in Figure 5.15. It has an overlap of 20 seconds every minute, hence a higher number of results. That is, the second minute does not start at 2'00", but 1'40" and ends 1 minute later (at 2'40").

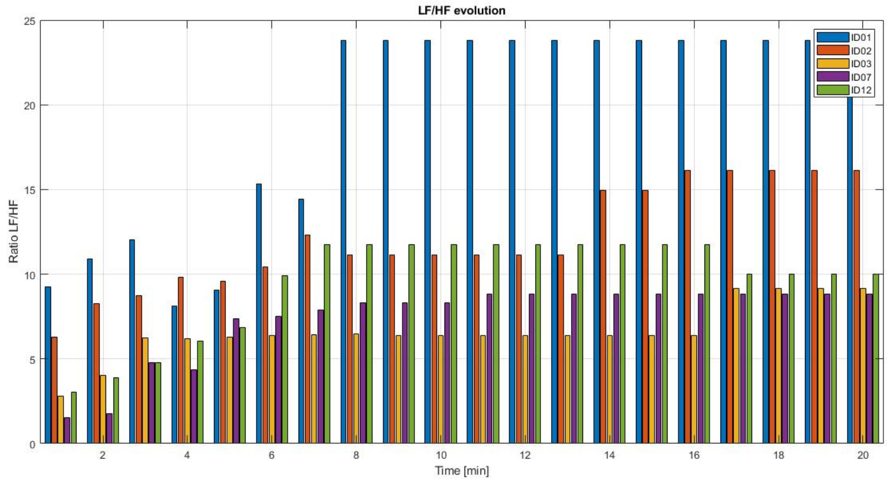


FIGURE 5.15. LF/HF evolution VM

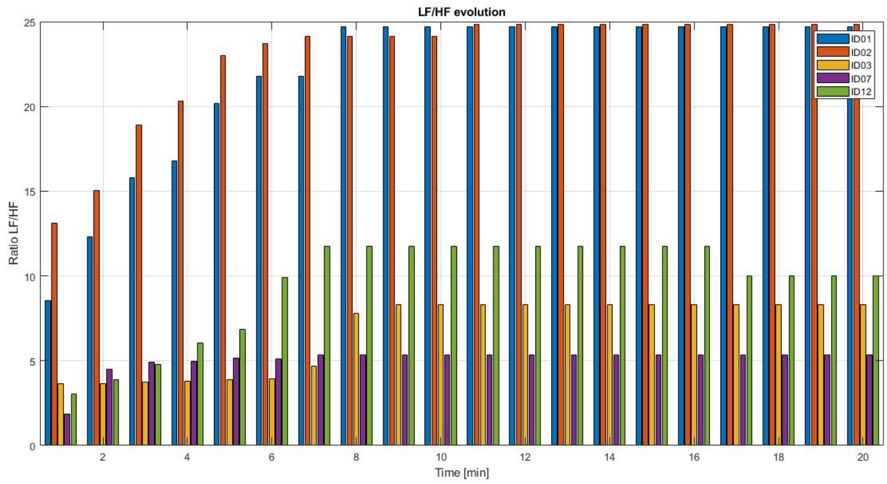


FIGURE 5.16. LF/HF evolution VNM

According to these results, the LF/HF values are lower in the first measurement phase and stabilize in the following minutes. As mentioned above, performance during a learning environment varies inversely with the LF/HF ratio. That is, the lower the LF/HF value the better the performance and the attention of the user. That said, this ratio considers that the less attentive moments occurred in the final phase of the learning experience which corresponds to the lower number of user attention inputs.

Visually, it is quite visible that the VM (5.17 has lower values for the LF/HF parameter. As the LF/HF ratio values reach their maximums earlier, this means that the worst performance also happens early. Once again it is proven that the user loses interest in the video more quickly.

FIGURE 5.17. Example of LF/HF evolution (ID02)

The next graph presents the HRV non-linear measure. Non-linear measures allow an evaluation in terms of the correlation between the RR intervals series, as is the case with the DFA algorithm.

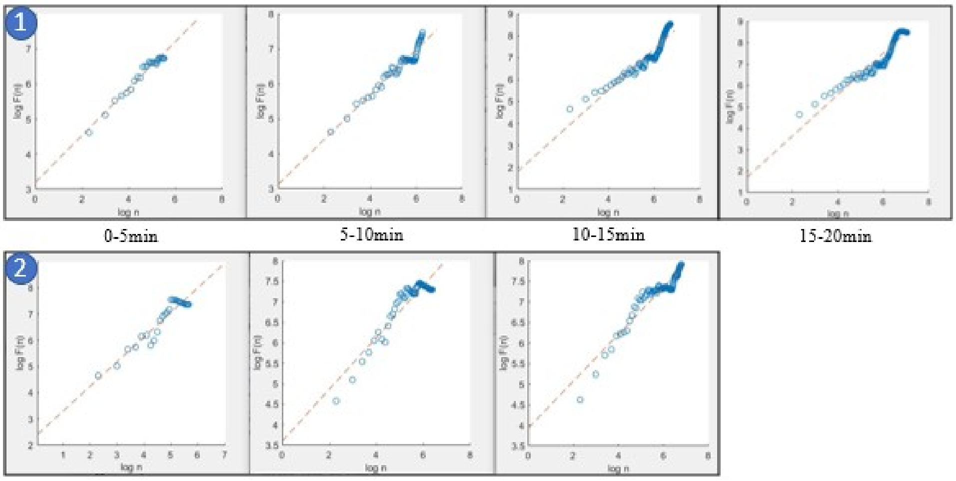


FIGURE 5.18. Example of DFA evolution,1:VM, 2:VNM (ID02)

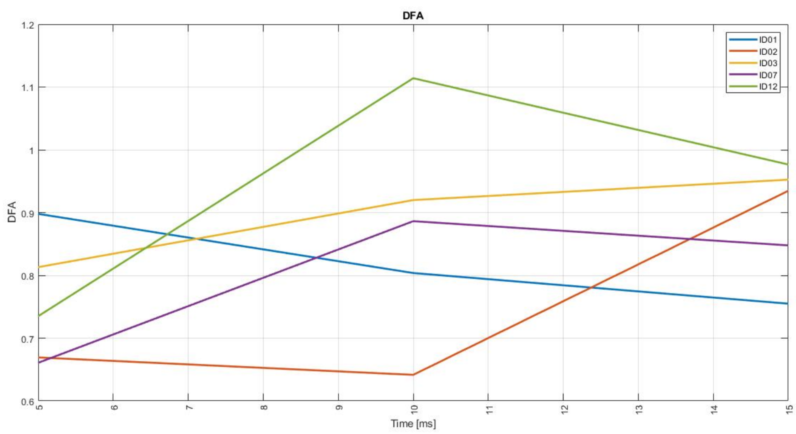


FIGURE 5.19. DFA evolution, VM

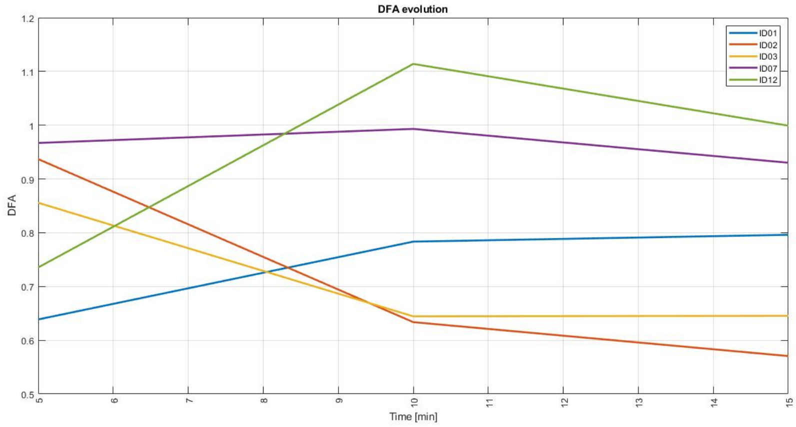


FIGURE 5.20. DFA evolution, VNM

A higher DFA value is related to a higher correlation between the ranges of data collected. That means, the higher the DFA values express the lower cardiac variability. Although volunteers have some differences in this parameter, VM (figure 5.19) has lower values than VNM (figure 5.20). This is in accordance with the above mentioned because the DFA algorithm is inversely proportional to cardiac variability. If the DFA values increase with time, it means that the attention is less at those moments.

Another measure is entropy, which is directly proportional to the amount of information in a message. Below are two graphs with the DFA results of five volunteers divided by type of video.

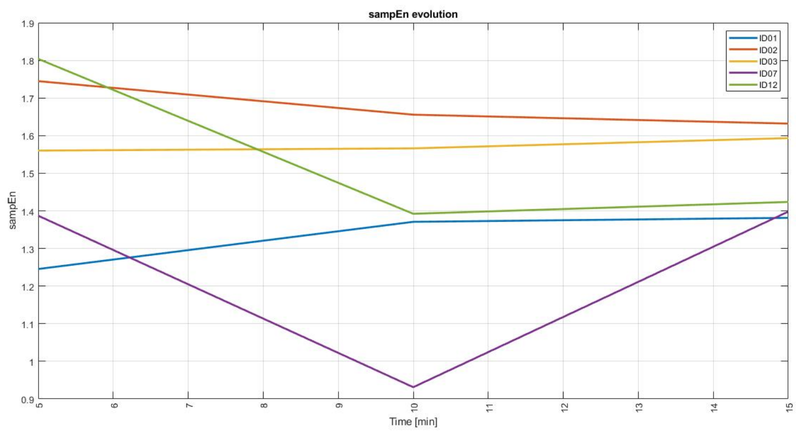


FIGURE 5.21. SampEn evolution, VM

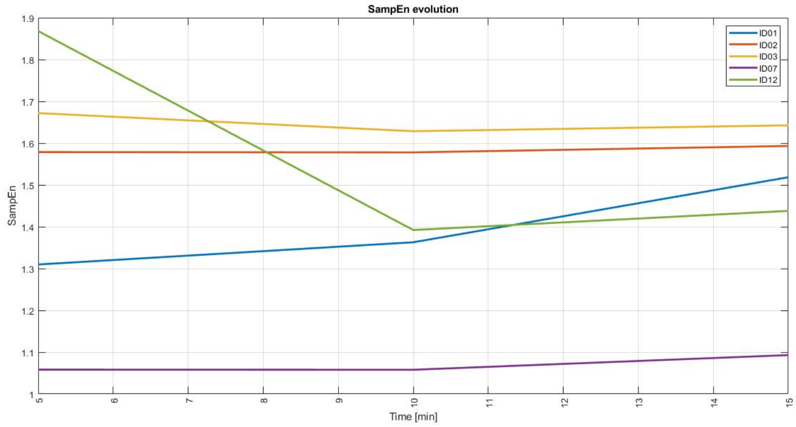


FIGURE 5.22. SampEn evolution, VNM

The closer the entropy value is to zero, the more regular the series, i.e. less variability. If the entropy value deviates from zero, the series becomes more irregular considering a higher HRV. In 60% of the cases presented, the value of this parameter is higher for VM (figure 5.21) than for VNM (figure 5.22). Of all the algorithms analysed, this is the parameter with the least differences between the two videos. For entropy, 10min represents a turning point for all the volunteers.

The results of these volunteers are not very similar since each person reacts differently to learning stimuli. Despite the distinctions, both reacted positively to the type of video they watched. In other words, they were more attentive to the VM. However, the periods when they were most attentive were not at the same time. Even so, the algorithms in the different domains provide results in agreement which allowed to identify these moments of attention.

The tests of the remaining volunteers had similar results to those mentioned above. As it is not possible to make a detailed analysis of each of them, five examples were chosen. For all these cases, the results were quite explicit as to the degree of motivation. That is, for all of them it was distinguished whether the volunteer was watching the VM or the VNM.

5.1.4. Volunteer ID12 with skin conductivity test

Previous tests did not show any results on skin conductivity as this module was only included in the system at a final stage. Although the study of this parameter has not been deepened, the following results are obtained from a volunteer tested with the whole system working (measurement of ECG and PPG signals and skin conductivity).

The following graph relates skin conductivity to heart rate variability.

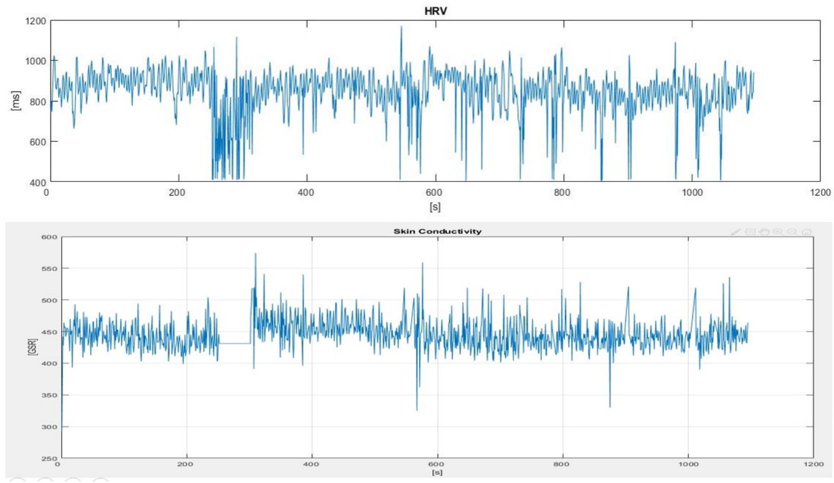


FIGURE 5.23. Skin conductivity, VM (ID12)

What is most striking in these graphs is the similarity of the saturation peaks. Lower heart rate values lead to saturation of the skin conductivity values in the same instants of time. On the other hand, the conductivity measurement does not correspond to a complete reading in time. That is, values are sent at the instant when an R peak is detected in the ECG signal.

In this case, as the skin conductivity value has little change in the voltage values, it becomes difficult to make a continuous analysis over time. In order for the reading to be as accurate as possible, it was necessary to send the conductivity value continuously and not every 800 ms on average. As can be seen from the graph below 5.24, even in a shorter time window, the variation in conductivity does not allow conclusions to be made regarding its evolution over time 5.24.

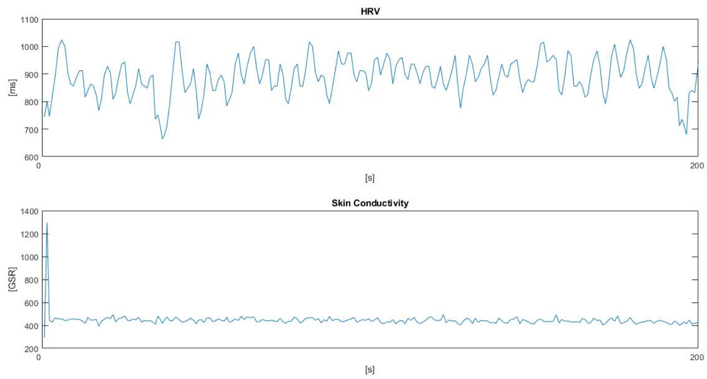


FIGURE 5.24. Skin conductivity 2, VM (ID12)

In order to see the difference in the measurement of this parameter continuously over time, the image below is shown. This graph represents the signal obtained in a simple conductivity measurement. The difference in the continuously measured signal is well visible on the figure 5.25 and would be the most correct way to read and study the variation of this parameter.

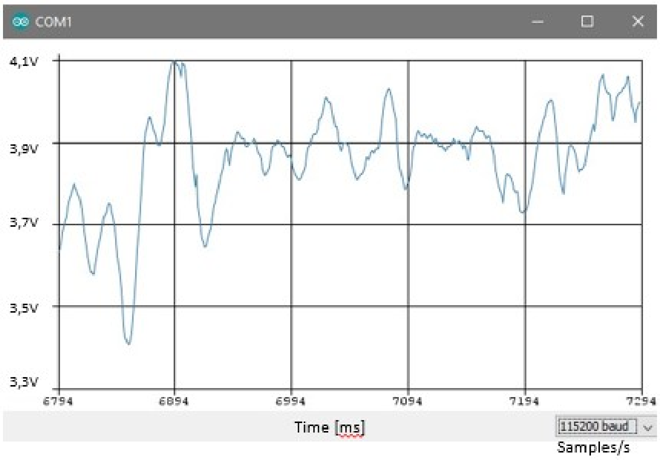


Figure 5.25. Skin conductivity

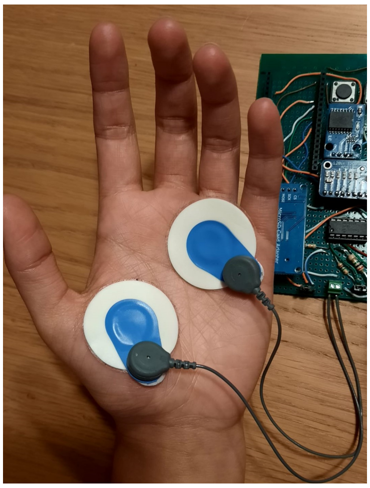


Figure 5.26. Electrodes skin conductivity

Two electrodes were placed in contact with the skin in the hand and that result was obtained. The measured electrical signals are strongly influenced by the choice of electrodes. Sweating is also a phenomenon to be considered in this measurement. As sweating is controlled by the sympathetic nervous system, when this system is highly excited, the activity of the sweat glands also increases, which increases the conductance of the skin. The measurement of this voltage varies depending on the location of the electrodes, as well as changes in temperature and humidity. This study is quite complex and requires a great knowledge of all the factors that make the measurement of conductivity vulnerable. Given the instability of this system in measuring skin conductivity, this is a starting point for further research relating this parameter to HRV.

5.1.5. Volunteer ID03

Next are the results of a female user aged between 50 and 55. Although the age difference is not a focus of this project, it is important to highlight the adaptation of the system to different conditions.

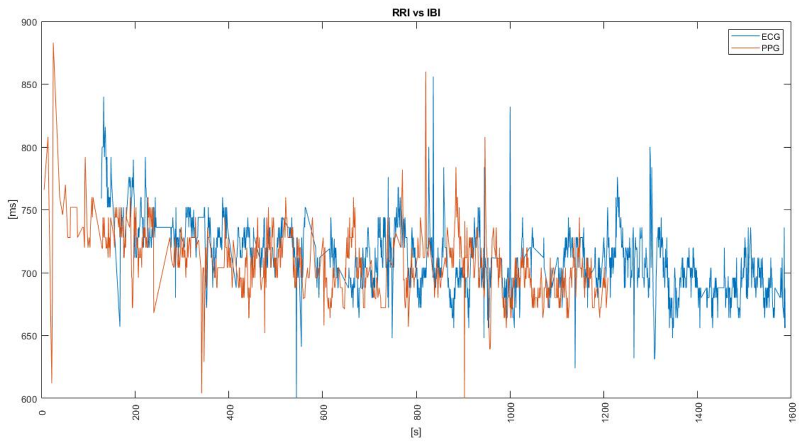


FIGURE 5.27. RRI vs IBI, VM (ID03)

The differences in the graphical results are immediately observed when compared with previous cases of 20-25 years. Comparing the ECG and PPG signals, the RRI and IBI intervals have a similar behaviour but differ by approximately 100 [ms].

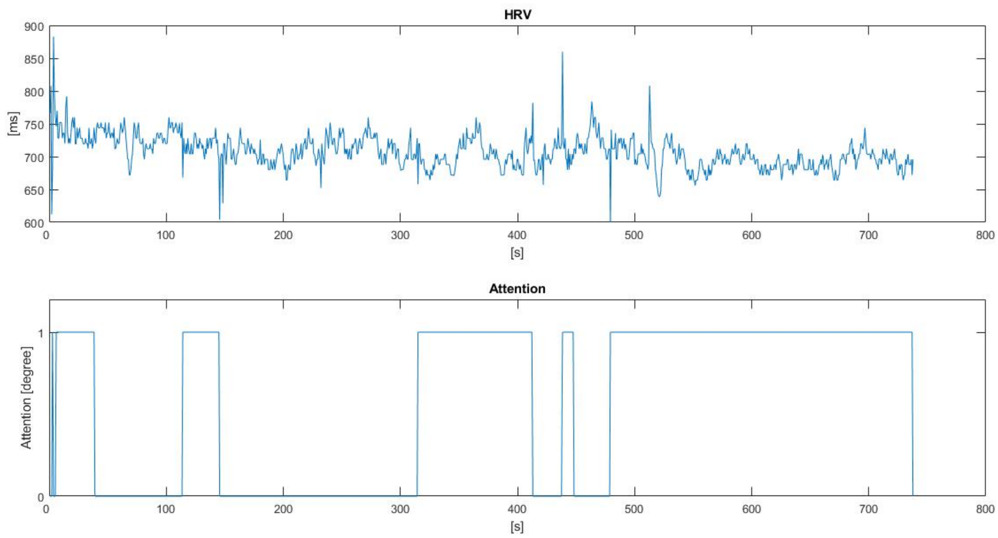


FIGURE 5.28. HRV and attention input, VM (ID03)

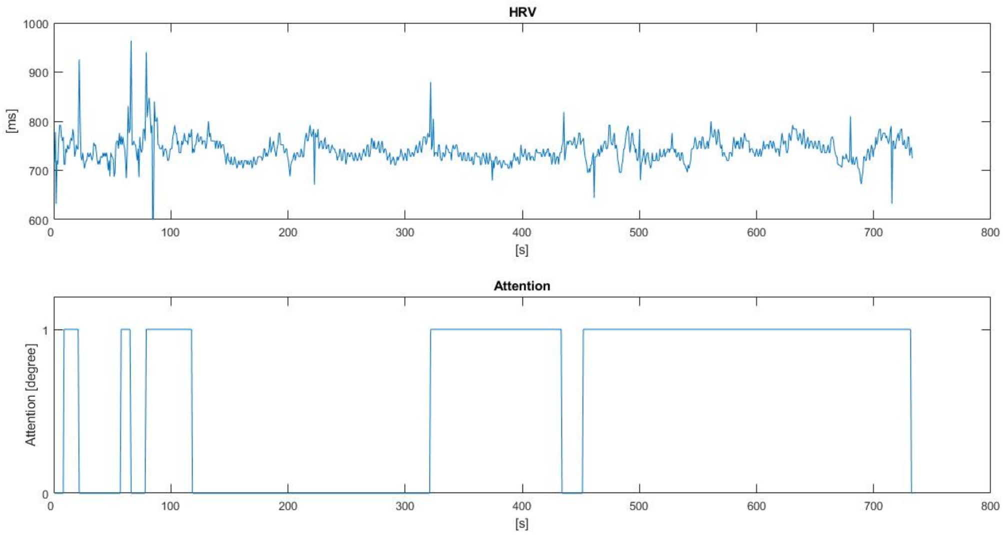


FIGURE 5.29. HRV and attention input, VNM (ID03)

In relation to graphics Fig 5.28 and Fig 5.29, the number of attention inputs does not differ so much from one video to another, but the difference in the duration of these more attentive periods is notorious. In other words, the non-motivating video has shorter periods of attention.

The tests were conducted by volunteers whose academic degree or similar. In this case, a possible comparison of the degree of attention taking into account this age difference requires further study. The heart variability of a 50-year-old is not the same as at 20. The predisposition for viewing videos with educational content is also not the same for these two cases. Therefore attention cannot be assessed in the same way. The testing of this volunteer serves to underline the capability of the system to acquire ECG, and PPG and to quantify the attention level based on HRV parameters associated to different types of algorithms.

CHAPTER 6

Conclusions and Future Work

6.1. Conclusions

The great advantage of this project is to estimate the level of attention by a non-invasive method. Initially this system was only designed to measure the ECG signal and to make it more complete the simultaneous reading of the PPG signal was added. This two signals can be used to extract information about attention but also to provide higher reliability for the system through redundancy. In this way, it was necessary to deepen the knowledge about the functionalities of the microcontroller so that the parallel reading synchronous signal acquisition (parallel reading) was carried out. The choice of sensors has helped the acquisition of the physiological signals as they already include some primary processing including noise reduction. The fact that the data is processed at the microcontroller level is also advantageous to reduce the amount of the data transmitted through Wi-Fi. Thus, instead of sending the complete waves to the database, only the RR intervals and timestamp are sent to calculate the heart rate variability algorithms.

Matlab automatically fetches the data stored in the database at any time by selecting the user number and the measured signal. Thus, the results of the algorithms are saved in images (graphs) and excel files (tables). It is also concluded that using a shorter sampling rate (1min) for HRV assessment is more advantageous.

The algorithms developed in Matlab successfully determined the periods of greatest attention when compared to the periods marked by the volunteer as the most attentive. Thus, the system is validated by this parameter inserted and by the fact that it is in agreement with the various volunteers tested. For all of them, the periods of most attention are strongly related to the periods with highest HRV. Although the attention input is related to the motivating content of the video, it has been proven in most cases that volunteers maintain their highest state of attention in the first 10 minutes. This timing is in line with the literature of chapter 2 which generally refers to the most attentive state during a learning environment up to the first 10 or 20 minutes. Again for all tested volunteers, the lowest degree of motivation occurs in the middle of the learning experience. This period is also equivalent to the phase of least visible cardiac variability in the graphs of chapter 5.

To analyse HRV based on ECG signal, readings must be at least 5min, while periods longer than 10min for PPG do not correspond to a correct analysis of cardiac variability.

Some failures were felt in the system due to the state of activation of volunteers. Failures in PPG readings are based on incorrect positioning and finger contact at the sensor. The errors in the ECG readings are again due to the movements of the volunteer or the lack of contact of the electrodes with the skin. As sweat is also a factor influencing the measurements it is very important that the volunteer remains at rest.

Regarding the more complex study of skin conductivity, it was carried out only in a more superficial form since it requires more specialised knowledge. It was not an initial goal, but it was implemented to make this system more complete by having one more parameter that would help us measure the impact of the autonomous nervous system in a learning environment. To be correctly implemented it was necessary to rethink the whole project from reading to signal processing. As in the final phase it would not make sense to change this whole process, it remains a theme to be explored further in the future.

6.2. Future work

In order to reaffirm the success of this system it was necessary to test more volunteers. Due to the current situation of the Covid-19 world pandemic, only 12 tests were carried out. In addition to the number of volunteers, it would be important to test the system for different age groups and academic degrees. Thus, with a larger number of results it would be interesting to use Machine Learning to train models and detect the different states of attention over time. Regarding system failures, some improvements would help to make it more adaptive. One way to avoid the sensor reading failures would be to develop algorithms that minimize the noise of sensor readings. Thus, adding filters to remove some unwanted components of the acquired signal caused by motion artefacts or respiration. Another factor to improve signal acquisition is the peak detection threshold chosen a priori. This limit must be adaptable to the signals, i.e. decrease or increase the value according to the changes in waves. Finally, the user interface that would be implemented in a mobile or web application may be implemented. A future work would be to study how the results of this system could be presented to the user in a simple and intuitive way.

References

[1] R. Amin and T. Faghih Rose. Robust inference of autonomic nervous system activation using skin conductance measurements: A multi-channel sparse system identification approach. *IEEE Access*, 7:173419–173437, 2019.

[2] T. Aslanidis, N. Aimie-Salleh, N. Ghani, N Hasanudin, and S. Shafie. Heart rate variability recording system using photoplethysmography sensor. In Theodoros Aslanidis, editor, *Autonomic Nervous System Monitoring - Heart Rate Variability*. IntechOpen, 2020.

[3] J. Berntson, G.and Bigger, D. Eckberg, P. Grossman, P. Kaufmann, M. Malik, H. Nagaraja, S. Porges, P. Saul, P. Stone, and M. van der Molen. Heart rate variability: Origins, methods, and interpretive caveats. *Psychophysiology*, 34:48–623, 1997.

[4] A. Brandes-Aitken, S. Braren, M. Swingler, K. Voegtline, and C. Blair. Sustained attention in infancy: A foundation for the development of multiple aspects of self-regulation for children in poverty. *Journal of Experimental Child Psychology*, 184:192–209, 2019.

[5] C.Y. Chen, C.J. Wang, E. L. Chen, C.K. Wu, Y. K. Yang, J.S. Wang, and P.C. Chung. Detecting sustained attention during cognitive work using heart rate variability. *Sixth International Conference On*, pages 372–375, 2010.

[6] J. Cisler and E. Koster. Mechanisms of attentional biases towards threat in anxiety disorders: an integrative review. *Clin. Psychol. Rev*, 30:203–216, 2010.

[7] R.A. Cohen, S.S Salloway, and T.Z. Zawacki. Aspectos neuropsiquiátricos dos transtornos de atenção. *In: YUDOFSKY, S. C; HALES, R.E. Neuropsiquiatria e Neurociência na Prática Clínica*, pages 416–445, 2006.

[8] SparkFun Electronics ©. Sparkfun single lead heart rate monitor - ad8232. `https://www.sparkfun.com/products/12650`. Online; Accessed: 2019-11-28.

[9] ©1995-2020 Texas Instruments Incorporated. How to measure ecg - ecg vs. ppg. `https://training.ti.com/how-measure-ecg-ecg-vs-ppg`. Online; Accessed: 2020-04-08.

[10] ©2003 2020 phpMyAdmin contributors. Bringing mysql to the web. `https://www.phpmyadmin.net/`. Online; Accessed: 2020-02.

[11] Arduino ©2019. Arduino. `https://www.arduino.cc/`. Online; Accessed: 2019-11-17.

[12] Components 101 ©2019. Pulse sensor. `https://components101.com/sensors/pulse-sensor`. Online; Accessed: 2019-11-18.

[13] ©2019 by Sun Scientific Corporation.& Taiwan Scientific Corporation. Hrv & ans. `https://www.answatch.com/hrv-ans`. Online; Accessed: 2020-06-23.

[14] ©2020 Commit GmbH. Hrv measuring parameter. `https://www.ans-analysis.com/hrv/hrv-measuring-parameter.html`. Online; Accessed: 2020-06-23.

[15] ©StatCounter 1999-2019. Mobile operating system market share worldwide. `https://gs.statcounter.com/os-market-share/mobile/worldwide#monthly-201901-201911`. Online; Accessed: 2019-11-20.

[16] M. Cuervo and M. Quijano. Las alteraciones de la atención y su rehabilitación en trauma craneoencefálico. *Revista pensamiento psicológico*, 4:167–182, 2008.

[17] LC. De Abreu. Variabilidade da frequência cardíaca como marcador funcional do desenvolvimento. *Journal of Human Growth and Development,*, 22:279–282, 2012.

[18] PTRobotics Especialista em Componentes Electrónicos. Wifi module - esp8266. `https://www.ptrobotics.com/wifi/3498-wifi-module-esp8266.html`. Online; Accessed: 2019-11-17.

[19] M. Esterman and D. Rothlein. Models of sustained attention. *Current Opinion in Psychology*, 29:174–180, 2019.

[20] M. T. Ferreira, M. Messias, L. C. M. Vandereli, and C. M. Pastre. Caracterização do comportamento caótico da variabilidade da frequência cardíaca (vfc) em jovens saudáveis. *International Journal of Scientific and Research Publications*, 11:141–150, 2010.

[21] A. Fonfría, R. Poy, P. Segarra, R. López, A. Esteller, C. Ventura, and J. Moltó. Variabilidad de la tasa cardíaca (hrv) y regulación emocional. *Fórum de recerca*, 16:903–013, 2011.

[22] T.K. Hareendran. Heart rate sensor. `https://www.electroschematics.com/heart-rate-sensor/`. Online; Accessed: 2020-04-08.

[23] B. Kuch, T. Parvanov, H.W. Hense, J. Axmann, and H.D. Bolte. Short-period heart rate variability in the general population as compared to patients with acute myocardial infarction from the same source population. *Ann Noninvasive Electrocardiol*, 9:113–120, 2004.

[24] S. Laborde, E. Mosley, and J.F. Thayer. Cardiac vagal tone in psychophysiological research – recommendations for experiment planning, data analysis, and data reporting. *Frontiers in psychology*, 2017.

[25] Hugo Machado. *Análise da variabilidade da frequência cardíaca usando métodos não lineares*. PhD thesis, Faculdade de Engenharia da Universidade do Porto, 2018.

[26] A. Majumder, M. Elsaadany, J. Izaguirre, and D. Ucci. A real-time cardiac monitoring using a multisensory smart iot system. *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)*, 2:281–287, 2019.

[27] A. Malliani, M. Pagani, F. Lombardi, and S. Cerutti. Cardiovascular neural regulation explored in the frequency domain. *Circulation*, 84:482–492, 1991.

[28] V. R. F. S. Maraes, D. V. A. Carreiro, and N. B. H. Barbosa. Study of heart rate variability of university trained at rest and exercise. *Pan American Health Care Exchanges*, pages 1–5, 2013.

[29] C. Mehak and K. Manik. Real time ecg monitoring system based on internet of things (iot). *International Journal of Scientific and Research Publications*, 7:547–550, 2017.

[30] S. Mishra and A. Rasool. Iot health care monitoring and tracking: A survey. *Proceedings of the International Conference on Trends in Electronics and Informatics, ICOEI 2019*, pages 1052–1057, 2019.

[31] Park Myung and Guntheroth Warren. *How to Read Pediatric ECGs*. Mosby, 2006.

[32] T. Obo, D. Takaguchi, D. Katagami, J. Sone, T. Tomoto, Y. Ogai, and Y. Udagawa. Heartbeat detection based on pulse neuron model for heart rate variability analysis. *2019 International Joint Conference on Neural Networks, Neural Networks, 2019 International Joint Conference On*, pages 1–6, 2019.

[33] G.D. Reynolds and A.C. Romano. The development of attention systems and working memory in infancy. *Frontiers in Systems Neuroscience*, 2015.

[34] Generation Robots. Pulse sensor getting started guide. `https://www.generationrobots.com/media/DetecteurDePoulsAmplifie/PulseSensorAmpedGettingStartedGuide.pdf`. Online; Accessed: 2019-11-17.

[35] A. Schäfer and J. Vagedes. How accurate is pulse rate variability as an estimate of heart rate variability? *International journal of cardiology*, 166, 2012.

[36] A. Siennicka, D.S. Quintana, P. Fedurek, A. Wijata, B. Paleczny, B. Ponikowska, and D.P. Danel. Resting heart rate variability, attention and attention maintenance in young adults. *International Journal of Psychophysiology*, 143:126–131, 2019.

[37] C. M. Siqueira and J. Gurgel-Giannetti. Mau desempenho escolar: uma visão atual. *Revista Da Associação Médica Brasileira*, 57:78–87, 2011.

[38] N. Tateyama, K. Ueda, and M. Nakao. Development of an active sensing system for distress detection using skin conductance response. In *2019 8th International Conference on Affective Computing and Intelligent Interaction (ACII)*, 2019.

[39] J.F. Thayer, M. Ahs, F.and Fredrikson, J.J. Sollers, and T.D. Wager. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. *Neuroscience & Biobehavioral Reviews*, 36:747–756, 2012.

[40] C. Tronstad, O. Elvebakk, H. Kalvøy, M. Bjørgaas, and O. Martinsen. Detection of sympathoadrenal discharge by parameterisation of skin conductance and ecg measurement. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2017.

[41] W. Xie, B. M. Mallin, and J. E. Richards. Development of infant sustained attention and its relation to eeg oscillations: an eeg and cortical source analysis study. *Developmental Science*, 21:1–16, 2018.

[42] W. Xie and J. E. Richards. Effects of interstimulus intervals on behavioral, heart rate, and event-related potential indices of infant engagement and sustained attention. *Psychophysiology*, 53:1128–1142, 2016.

[43] U. Ávila. *Atenção Sustentada na sala de aula: modulação da personalidade, emoção e cronotipo.* PhD thesis, Universidade Federal do Rio Grande do Norte, 2019.

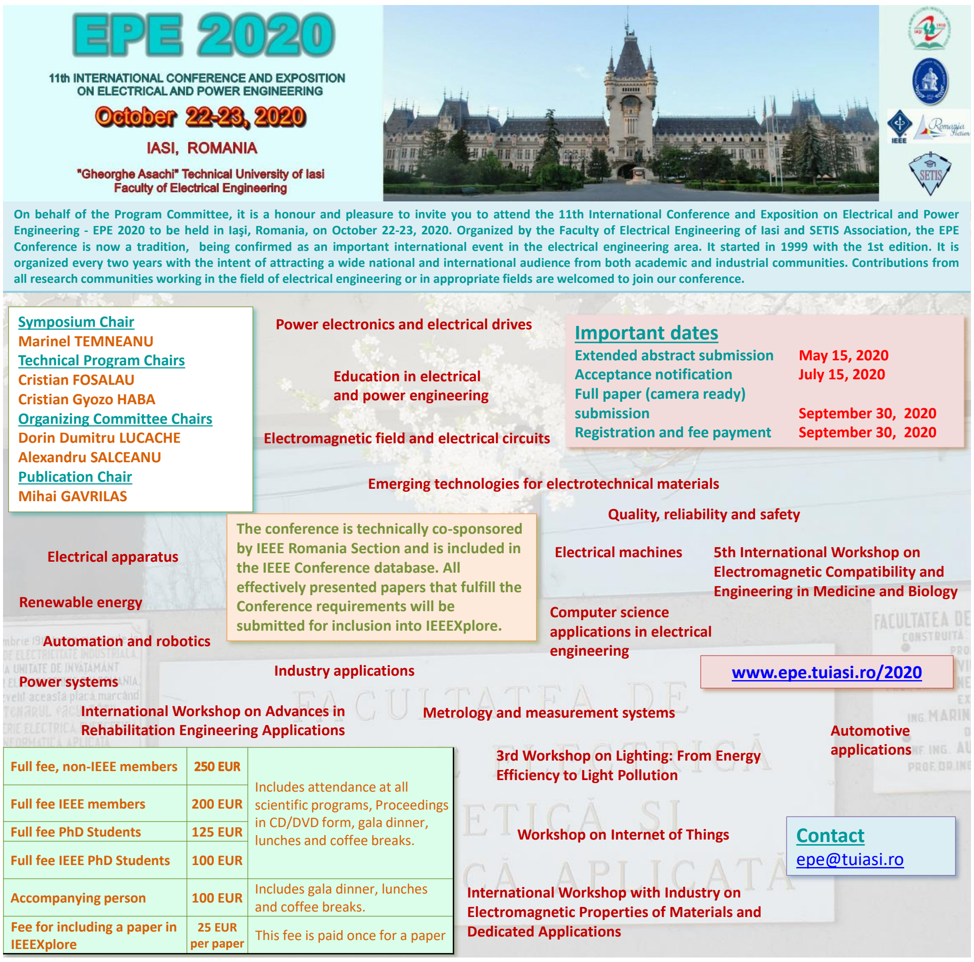
[44] Ubaldo Ávila. *Atenção Sustentada na sala de aula: modulação da personalidade, emoção e cronotipo.* PhD thesis, Universidade Federal do Rio Grande do Norte, 2019.

Appendices

APPENDIX A

Published Paper

This article, entitled “Sustained attention detection system in learning environments”, was accepted at the 11th International Conference and Exposition of Electrical and Power Engineering, in October 22-23, 2020.



Sustained attention detection system in learning environments

Bárbara Nogueira da Costa
Iscte - Instituto Universitário de Lisboa
Lisbon, Portugal
Barbara_Costa@iscte-iul.pt

Octavian Postolache
Iscte - Instituto Universitário de Lisboa and Instituto de Telecomunicações
Lisbon, Portugal
Octavian.Adrian.Postolache@iscte-iul.pt

John Araujo
Laboratório de Neurobiologia e Ritmicidade Biológica
Departamento de Fisiologia - CB - UFRN
Natal, Brasil
johnfontenelearaujo@gmail.com

***Abstract*—The article presents a heart rate variability monitoring system for the detection of attention status during learning. Using a developed embedded 2-channel system, ECG and PPG signals are collected simultaneously. After extraction of the waves of these signals the heart rate is calculated through the intervals between the peaks. These results are then sent in real time to a database in the cloud. Subsequently, HRV is analysed based on Matlab implemented algorithms considering time and frequency domains as so as non-linear measures. Several tests were carried out and the recorded results were analysed as the starting point to classify situations that capture the state of attention.)**

Keywords—smart sensor, attention, learning, heart rate, cardiac monitoring, internet of things (IoT)

I. INTRODUCTION

Nowadays the technology has been evolving faster and faster and is used on a large scale to improve human knowledge. In order to improve human performance, the concept of attention arises. The concept of attention can be studied in various environments, while driving, a film or even a game. But in this case, it is based on a learning environment and the following question arises: "How long can you keep your attention on a learning process?".

Maintaining focus during certain periods of time also considers resistance to distracting factors. Thus, attention is no longer considered a unitary and constant process but is influenced by each moment. The theme of attention can be divided into several sub-themes, one of which is sustained attention. During sustained attention the human being remains vigilant to a certain stimulus, maintaining the attention for a certain time period [1]. In a 2010 study, Bunce analysed human behaviour in 50min classes, particularly attention, concluding that students do not maintain attention for periods of 10 to 20 minutes. Attention can be influenced positively or negatively by many factors such as emotion. . The concept of attention can be studied in various environments, while driving, a film or even a game. But in this case it is based on a learning environment and the following question arises: [2] One of the negative factors is anxiety affecting Heart Rate Variability (HRV). Today attention can be estimated in indirect way through the HRV. This measurement must be carried out in an objective way so that it can illustrate the regulation of the heart which is based on dynamic equilibrium of the autonomic nervous system (ANS) and the regulation of the heart [3]. This system is composed of the sympathetic nervous system (SNS) and parasympathetic system (PNS). The SNS characterizes the functioning of the body and the state of preparation for action. When it is activated it increases the heart rate, respiratory rate and blood pressure in order to be able to cope with the alert state [4]. On the other hand, the PNS represents the state of rest by decreasing all these factors so that the body remains relaxed [5]. The subject of heart regulation implies the knowledge of the cardiac cycle. A normal cardiac cycle lasts 0.8 seconds and consists of ventricular contraction and relaxation, i.e., systole and diastole respectively. Therefore, heart rate monitoring plays a key role in rigorous health application and current medical research.

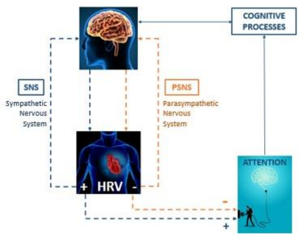


Fig. 1 - The influence of HRV on attention, adapted from [5]

Both attention and cognitive processes are influenced by HRV as seen in the figure above. Thus, the main objective of this work is the development of a system that measures the level of attention in a learning process based on monitoring cardiac variability. After the study phase of the literature on the concepts mentioned above, there follows the development of an embedded system capable of extracting information about heart rate variability. For that, the system reads two signals: Electrocardiogram (ECG) and Photoplethysmography (PPG). In both signals, the variation of the time intervals between heartbeats is measured. The ECG signals express the electrical activity of the heart. Thus, a typical ECG consists of the QRS complex and the P and T waves, with peak R as the main characteristic. The interval between two consecutive R peaks allows the heart rate to be calculated. On the other hand, the sign of a photoplethysmography (PPG) represents the mechanical activity of the heart. In addition to measuring the rate of blood flow pumped by the heart, it also allows the measurement of oxygen saturation [6].

First the system architecture, including hardware and system design, is explained. Then, the methods and technologies used are listed below. Finally, based on the implemented protocols and performed tests the obtained results are compared to validate the capabilities of the proposed system.

II. Related Work

The Internet of Things (IoT) is a set of devices capable of communicating with each other, controlling actions and processing data. Today this topic often arises in relation to health and medicine through real-time monitoring and patient data management applications. Observation, communication and data application are some of the benefits of IoT. It is currently widely used in the medical and health care field. With the strong evolution of technology, this intellectual system will tend towards the future development of health resources. Considering this implementation, HRV's real-time analysis allows us to evaluate a person's psychological state, including attention. Currently, in the learning context, some projects have been carried out that are based on HRV as a measure of attention.

Ubaldo Enrique et al presented in [2]a study regarding the attention of university students in classes of 60min. This study was also complemented by the influence of human characteristics such as personality, emotion and chronotype. The chronotype influences sustained attention not only in the first few minutes but throughout the entire class. The HRV metrics allow the analysis in the domains of frequency, time and non-linear measures. Finally, it was concluded that university students only maintain their attention for the first 15min of a 60min class. In [4] the authors have been used HRV to classify the phases of sustained and non-sustained attention. In this case, they analysed the activation of the sympathetic system through ECG signals where 98% accuracy was obtained. Complementing, according to the authors in [7], sustained attention is associated to a state of rest. For this, the HRV was measured during tests that result in a Concentration Performance index and a Coefficient of Variation of sustained attention. In a medical context there are several IoT systems that are doing cardiac monitoring [8]. Usually the management of these health data is designed to monitor the health status and sometimes prevent some disease. More and more we are confronted with devices that, besides the pulse and heart rate, already allow us to perform an ECG quite easily. This is the case of some smart watches like Apple Watch Series 4 that bring ECG measurement to the spotlight. Recently, the Samsung Galaxy Watch Active 2 model also comes with an ECG report and Stress Level Meter that calculates stress through heart rate variability.

In this project the two systems, ECG and PPG, are used in a comparative way to achieve more precise results and to have a validation channel. According to Schäfer, when analysing the PPG signal, HRV is measured by the interval between the pulse waves known as Pulse Rate Variability (PRV). The option of heart variability measured by pulse wave simplifies the ambulatory monitoring of HRV. [9]. The next section describes the used components and the system architecture.

III. System Description

The functionality of the embedded system is explained from the choice of microcontroller and sensors to the type of communication implemented. The following image (Fig.2) schematizes the hardware system architecture, the cardiac status monitoring.

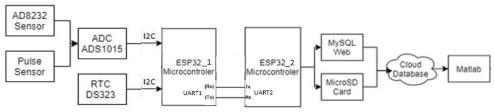


Fig. 2 –Distributed computation of cardiac status monitoring

In the device layer, the computation platform ADC1015 with analog input channels are used, ECG and PPG. The ECG and PPG sensing module are characterized by analog outputs, the output voltage VECG and VPPG being converted in a digital form using 12-bit Analog-Digital Converter (ADC). With the built-in ADC in ESP32, the measurements obtained are noisier. In this way, better resolutions are obtained with an external device. Thus, through the SPI interface the digital values for ECG and PPG signals are delivered to ESP32 computation platform. The digital signal processing for the acquired signals is done at the microcontrollers level (ESP32_1 and ESP32_2). On the level of ESP32_1, as the Wi-Fi module conflicts with parallel processing, it was necessary to add another device to resolve the data transmission via Wireless. In order to collect ECG and PPG signals at the same time, the microcontroller's multicore option was chosen. But with this option, the WiFi module no longer works correctly. In this case two are used, one to process the received signals and the other to forward the results to the database or store on the SD card. However, during the processing phase, the results are identified with a date and time via the Real Time Clock (RTC) chip with high precision and low power consumption. The reason why another microcontroller is needed is that the first one needs two cores to perform simultaneous acquisition of ECG and PPG. After the data is transferred from ESP32_1 to the ESP32_2, ESP32_2 connected the Internet via Wi-Fi and it sends the processed data to the cloud database. After the storage in the database, the HRV is analysed through specific algorithms that were developed in MATLAB. The HRV analysis includes time, frequency and non-linear analysis.

A. Hardware

The microcontroller was selected considering the following requirements: low power consumption and wireless communication capabilities. The Arduino platform could be a choice if a wireless communication shield is considered too. The compact ESP32 computation platform characterized by Wi-Fi and Bluetooth communication interfaces was considered. This platform has been designed for mobile devices and IoT applications and can remain in sleep mode until it is awakened periodically when a condition is detected. As previously mentioned, ESP32 can run more complex programs because it is characterized by two processing cores with 520KBytes of SRAM memory. In this work, Serial Peripheral Interface (SPI), Universal Asynchronous Reception and Transmission (UART) and Inter-integrated-circuit (I^2C) interfaces are used for communication with the other devices such as ADC and RTC. Through the I^2C interface, data is transferred from the external 12-bit ADC, ADS1015, to the microcontroller. This device is characterized by high accuracy and stability comparing with ESP32 ADC, for this reason has been added to the system. ECG and PPG signals arrive at the ADC, which are then processed individually by each microcontroller core, one for the ECG module and another for the PPG module.

The Pulse Sensor is a plug-and-play heart rate sensor that is attached to a fingertip or earlobe. Using this sensor, it is possible to extract information about the cardiac activity through the pulse wave (PPG signal). On one side of the sensor is an LED and an ambient light sensor. The role of the LED is to emit the light that passes through the vein as it should be placed directly on top of one. That is, when the heart pumps the blood and this flow is detected, the ambient light sensor captures more light. To monitor the cardiac activity associated with heart control an AD8232 module is used. The sensor provides the ECG signal. By placing the electrodes in three different areas, one on the right side of the chest, one on the left side and the third on the right lower abdomen, the signal is obtained. The signal acquisition is carried out by the microcontroller's analog-to-digital converter (ADC) or by an external ADC connected to the microcontroller through I2C. The Heart Rate Monitor AD8232 detects the electrical activity of the heart through the ECG wave obtained at resting state. The signal acquisition for the volunteer resting status to avoid motion artefacts. The heart rate (HR_{ECG}) extracted from ECG signal can be compared with HR_{PPG} from PPG signals.

The motivation level can be signalled by the volunteer during the learning experience pressing a button for high motivation that switch on a LED. During the period of most attention, the LED will remain on. For lower motivation when the volunteer is losing his attention, he can press the button again to turn off the LED that will remain off until another click. Associated with a time stamp this information is sent to the database, helping to measure the attention and evaluate the user's behaviour. After ESP32_1 received the acquired samples, RTC DS3231 assigns the time value to the samples. The RTC provide the time and date information for each sample. In this implementation the RTC is connected to the microcontroller UART port, providing information of seconds, minutes, hours, days, month and year for each sample. The resolution of milliseconds is obtained selecting 1 kHz DS3231 sub-second output frequency. To prevent the lost samples due to Internet connection failure the samples are always stored locally on SD card. Through an SPI interface, an adapter is added to the ESP32_2 that allows reading and writing on a micro SD card. Time to time the data is synchronized to the remote database. Considering that ESP32 presents two computation cores the synchronized processes makes the Wi-Fi module to fail time to time. The connection between ESP32_1 and ESP32_2 is made through the UART interface. The selected data transmission speed, was set to 115200 bits/s. Finally, a push button is added to mark the end of system measurements. The first prototype of the system is presented in Figure 3.

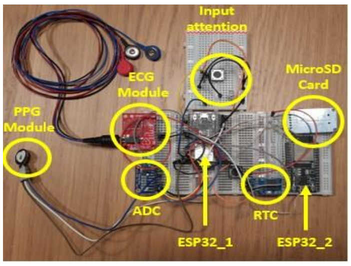


Fig. 3 – Prototype of hardware setup

B. Software: Acquisition and Primary Processing

Together the implemented and testes hardware the software represents an important component of the system. Thus, in this section it is presented the implemented software associated with signal acquisition, primary digital signal processing and data analysis. The embedded processing is performed at the microcontroller level programmed through the Arduino Integrated Development Environment (IDE). This open source software was used to write and upload programs for the developed system based on ESP32. The physiological signals provided by the PPG and ECG measurement channels are collected through the ADC with 12bits of resolution. To perform simultaneous acquisition two cores of ESP32 are used, thus, two independent tasks are created by setting the microcontroller in multitasking mode, where is chosen the microcontroller core for each task. In the next phase, to calculate the HRV it is necessary to extract the time location of the PPG and ECG wave peaks.

For peak detection, threshold methods are efficient in computing especially if this value is set a priori as is the case. For this parameter to be adaptive to the limits of each wave it is more difficult to solve. Again, an adaptive threshold recognizes more R peaks in the case of the ECG signal.[10] To do this a threshold value was setting up depending on the sensor chosen in order to isolate the peaks corresponding to the QRS complex. As the signal reading is received, the current peak value and the set threshold are compared. The same applies to the PPG signal, detecting the peak that represents systole. After determining the peak value, the time interval between consecutive peaks is calculated. The Figure 4 clarifies the peak detection algorithm implemented.

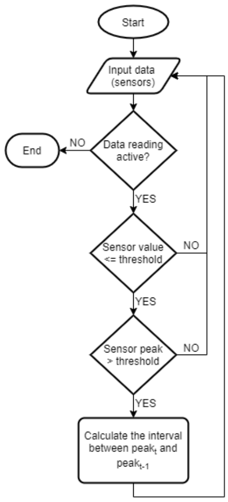


Fig. 4 Peak detection flowchart

For the PPG signal the Inter-Beat Interval (IBI) is calculated between each pulse corresponding to the systole. For the ECG signal the RR Interval (RRI) is calculated, which corresponds to the interval between the R peaks of the wave. In this way, the two waves are obtained in the same temporal instant as seen in the Fig. 5.

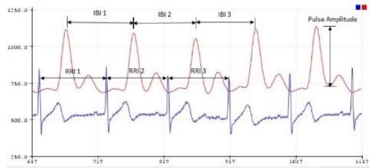


Fig. 5 – PPG and ECG signals: Red wave: PPG; Blue wave: ECG

After the calculation of each interval, as mentioned above, the time stamp is associated with each sample with a millisecond resolution. The result is then transferred to the ESP32_2 and sent to the MySQL database through Internet connectivity (Wi-Fi). The system checks the Internet connection and if it fails the data are stored on the SD card. This verification is performed at pre-defined time intervals of 10 seconds, to ensure that the data is sent or stored. To signalize the end of measurement session the user might press the "END of Measurement" button.

C. *Software: Data Analysis*

Real-time HRV measurement helps to evaluate a person's physiological state and helps to study how it varies in aspects of daily life such as the state of attention during a learning activity. The analysis of cardiac variability was carried out considering different HRV metrics. The HRV analysis requires more than five minutes of ECG recording time with physical and mental states within normality [11]. With a minimum of 5min of recording, the intervals between peaks and consequently the heart rate in bpm are calculated. The HRV based on Sample Standard Deviation (SSD) is then calculated using the formula:

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{1}$$

The parameter x_i represents the value of each time interval, IBI or IRR, and $\bar{x}$ the mean of all these intervals This parameter provides a quantification of the slow variations in variability.[2] Another method that provides a quantification of the abrupt variations in variability. Is square root of the mean squared differences of successive RR intervals (RMSSD). Its formula is as follows:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \tag{2}$$

To finish the algorithms of this method, it is also calculated the number of differences of successive NN intervals greater than 50 milliseconds and its percentage. That is, if the N interval is more than 50ms apart from the N-1 interval. As the heart rate is conditioned by stimuli from autonomous nervous system, it is necessary to analyse its components in the frequency domain. For this, the acquired signals, time intervals between ECG and PPG signal peaks form a non-continuous signal in time. Interpolation is done in order to sample the signal uniformly because the RRI or IBI distances are not uniformly sampled (equal distances between the samples). Interpolation is performed to sample the signal uniformly because the distance RRI or IBI do not have equal distance between the samples. After that, the spectrum of that signal is obtained through the Fast Fourier Transform (FFT)[12] . The definition of the Fourier Transform is based on the formula:

$$V(f) = F[v(t)] = \int_{-\infty}^{\infty} v(t)e^{-j2\pi ft}dt \tag{3}$$

Since N represents the signal length, the Discrete Fourier Transform (DFT) requires N^2 operations while FFT requires $N*\log_2(N)$. The FFT takes advantage of symmetry in sinusoidal waves. It is a great algorithm when the signal has a finite number of frequency components. The PSD analyses random vibration signals, multiplying the FFT amplitude by its conjugated complex and normalizing it. That is, the PSD describes the distribution of the signal power according to the frequency. [13]

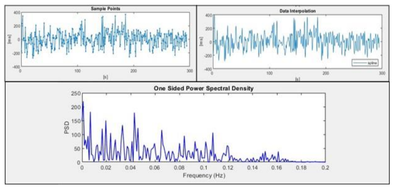
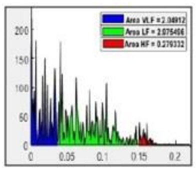


Fig. 6 Step-by-step PSD calculation

After calculating the Power Spectral Density (PSD), the graph is divided into three frequency bands:



Very low frequency band (VLF), up to 0.04Hz;

Low frequency band (LF), between 0.04 and 0.15Hz;

High frequency band (HF), between 0.15 and 0.4Hz.

Fig. 7 Division of PSD in frequency bands

Thus, it can be inferred that high values of LF component and low values of HF component [%] correspond to cases of high stress. The opposite corresponds to low stress situations. Also, according to [2], the higher LF/HF ratio during sustained attention is associated with poorer performance.

Since stationary methods are not enough for the study of dynamic factors, non-linear methods are used. In this way, one begins by calculating the measure Detrended Fluctuation Analysis (DFA). This method quantifies the presence of correlation in the records collected, describing the dynamics associated with factors that influence heart rate. [11] For this case study, it quantifies the fractal property of the RR interval series. Entropy is the other measure calculated in this domain and is divided into two variants, Approximate Entropy (ApEn) and Sample Entropy (SampEn). The ApEn calculates the conditional probability of two consecutive and similar sequences remaining similar when one more consecutive point is included. SampEn does not account for self-matches, solving some limitations of the approximate entropy.[14] Entropy is associated with the amount of information present in a message. If the HRV is low, it means the heart rate varies slightly. Thus, the record of the respective ECG contains little information and is associated with low entropy. The opposite occurs for a higher HRV. [12] The results of entropy are analysed according to TABLE 1.

TABLE 1. ANALYSIS OF ENTROPY RESULTS

Healthy	Unhealthy
Higher HRV	Lower HRV
Greater adaptation	Lower adaptation
HRV sign with more information	HRV sign with less information
Higher entropy	Lower entropy

D. Attention Assessment Protocol

For a more objective assessment of attention, all volunteers watch two videos in random order and answer a questionnaire at the end of each one. One of the videos has the presence of movement on the pointer screen and body language. While in the other one the slide texts are read with a monotonous tone of voice. The protocol used is described below. Firstly, the random selection of the sequence of the videos is made. Sequence A: Video Motivation (VM) and then Video No-Motivation (VNM); Sequence B: Video No-Motivation (VNM) and then Video Motivation (VM). Secondly, the sensors are placed on the volunteer. Thus, the PPG sensor on the finger and the electrodes of the ECG module. For an initial level of attention, it is explained to the volunteer that he will watch two videos about Sleep Disorders. After that, the HRV registration system is connected by presenting the first video, according to the sequence selected previously. Afterwards, the system is switched off. The same procedure applies to the second video.

IV. Results

The system has been tested in the laboratory with 12 users, most of them aged between 20 and 25 years. The protocol mentioned above was successfully followed with random assignment of the video sequence. The next results are from the signal collected from the volunteer 2. Matlab graphs show the evolution of IBI and IRR over time and compared to the subject's attention input.

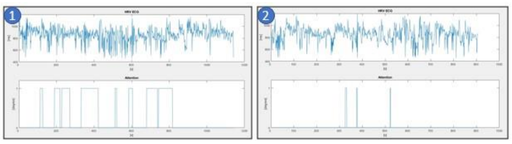


Fig. 8 HRV ECG and attention degree, 1-VM, 2-VNM

Through the attention input given by the subject, it is concluded that moments of greater attention correspond to greater HRV, i.e. more IBI and RRI variations. As time goes by, the HRV decreases and so do the inputs of the moments of attention. In the case of the VNM, there is graphically less variability. Also, the signalling of the degree of attention corresponds to fewer phases of higher HRV and consequently more attention. Thus, the smallest phases of attention are justified by the unmotivating and captivating video.

Compared to the ECG, the PPG signal is inaccurate in assessing heart rate variability. In this case, the PPG signal is used for validation and redundancy.

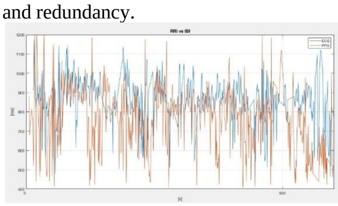


Fig. 9 RRI and IBI comparison, VM

TABLE 2. TIME ALGORITHMS VALUES

Signal	Algorithm	0-5min	5-10min	10-15min	15-20min
Motivation Video	RRI	883	862	840	844
	HR	69	71	73	73
	SD	117	118	123	121
	RMSSD	95	87	86	85
	Pnn50	55	48	47	45
No Motivation Video	RRI	852	848	842	-
	HR	72	72	73	-
	SD	120	115	127	-
	RMSSD	82	75	74	-
	Pnn50	42	39	43	-

In relation to time domain algorithms, RMSSD is a key marker for vagal activity, i.e. low RMSSD mean poor vagal mediated HRV. As the RMSSD value decreases over time it also proves that at the end of the measurement the attention is reduced. The same is true for the percentage differences in successive intervals of more than 50 milliseconds (pNN50). Again, short distances in time between beats means lower HRV and consequently less attention. For a comparison of the two videos, the difference between the initial and final RMSSD value is calculated. Thus, it is concluded that for the VM the delta RMSSD is greater than for the VNM. The higher delta value is due to a shift from sympathetic to parasympathetic predominance. While during the VNM viewing this change did not occur. The NN50 percentage changes little reflecting also less heart variability.

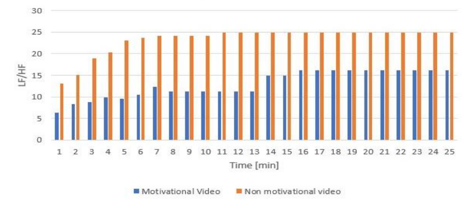


Fig. 10 – Users' LF/HF evolution for motivational and non-motivational video

The frequency analysis has an overlap of 20 seconds every one minute, with a minimum measurement of 5min. Following these results, the LF/HF value is lower in the first part of the measurement stabilizing in the following minutes and ending with a high value. As mentioned before, the higher the LF/HF ratio, the poorer the performance during a learning environment. Therefore, it is concluded again that the less attentive moments occurred at the end of the lesson (learning experience). In the non-motivation video, the LF/HF values reach their maximums earlier, corresponding to an earlier worse performance.

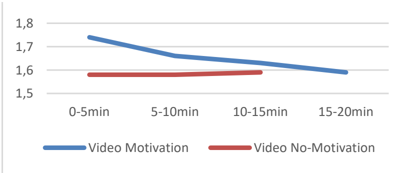


Fig. 11 - SampEn evolution

If the entropy value is closer to zero it means that the series is more regular, with less variation in the intervals between waves. On the other hand, when the value of the entropy moves away from zero, it means that the series are more irregular, i.e. higher HRV. The graph shows a decrease in entropy, which shows a loss of attention over time to MV.

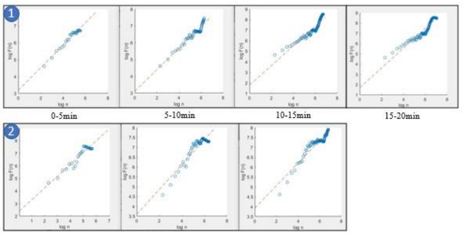


Fig. 12 DFA evolution, 1-VM (20min), 2-VNM (15min)

In non-linear measures, the slope of the line determines the exponent of scale that indicates similarity. It is considered that DFA values closer to 1 means a higher correlation between the collected data, thus a lower HRV. If the DFA exponent tends to decrease to zero, it indicates loss of correlations and thus higher HRV. If this parameter is less than 1/2 it means anti-correlation, and if it is greater than 1/2 it means that the series is correlated. In this situation, the DFA values increase with time, which reflects the loss of attention at the end of the learning experience, that can be seen in Fig.12.

V. Conclusions and future work

This project has the advantage of evaluating attention by a non-intrusive method. It was possible to determine the periods of most attention through the developed algorithms that successfully corresponded to the subject's degree of attention input. In this way, the volunteer validates the system indicating his state of attention. This has shown that the most attentive periods are strongly related to the periods with higher HRV. One of the limitations was the number of volunteers tested which should be greater in future work to reassert the success of the system. Failures in PPG readings concern incorrect positioning and contact of the finger with the sensor and consequently movement; sweating also affects measurements. Errors in the ECG reading are due to the subject's movements or, if this happens, the electrodes are no longer in contact with the skin. So it is important that the subject remains at rest for better contact with the sensors. One way to avoid these failures would be to develop algorithms that minimise the noise from sensor readings. As well as the threshold for peak detection chosen a priori should be adaptive to the different types of waves.

Acknowledgment

This wok was supported by Fundação para a Ciência e Tecnologia, SmartLife Summer School, BI/SmartLife/2020, UIDB/50008/2020 and Instituto de Telecomunicações,

References

[1] M. T. Cuervo e M. C. Quijano, «Las alteraciones de la atención y su rehabilitación en trauma craneoencefálico», *Pensamiento Psicológico*, vol. 4, n. 11, pp. 167–182, 2008.

[2] Ubaldo Enrique Rodriguez de Ávila, «Atenção Sustentada na sala de aula: modulação da personalidade, emoção e cronotipo.», Universidade Federal do Rio Grande do Norte, NATAL/RN, 2019.

[3] A. Fonfría *et al.*, «Variabilidad de la tasa cardíaca (HRV) y regulación emocional», *FÒRUM DE RECERCA*.

[4] C.-Y. Chen *et al.*, «Detecting Sustained Attention during Cognitive Work Using Heart Rate Variability», em *2010 Sixth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, Darmstadt, Germany, Out. 2010, pp. 372–375, doi: 10.1109/IIHMSP.2010.187.

[5] A. Malliani, M. Pagani, F. Lombardi, e S. Cerutti, «Cardiovascular neural regulation explored in the frequency domain.», *Circulation*, vol. 84, n. 2, pp. 482–492, Ago. 1991, doi: 10.1161/01.CIR.84.2.482.

[6] G. Lu, F. Yang, J. A. Taylor, e J. F. Stein, «A comparison of photoplethysmography and ECG recording to analyse heart rate variability in healthy subjects», *J. Med. Eng. Technol.*, vol. 33, n. 8, pp. 634–641, Nov. 2009, doi: 10.3109/03091900903150998.

[7] A. Siennicka *et al.*, «Resting heart rate variability, attention and attention maintenance in young adults», *Int. J. Psychophysiol.*, vol. 143, pp. 126–131, Set. 2019, doi: 10.1016/j.ijpsycho.2019.06.017.

[8] A. J. Majumder, M. Elsaadany, J. A. Izaguirre, e D. R. Ucci, «A Real-Time Cardiac Monitoring using a Multisensory Smart IoT System», em *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)*, Milwaukee, WI, USA, Jul. 2019, pp. 281–287, doi: 10.1109/COMPSAC.2019.10220.

[9] A. Schäfer e J. Vagedes, «How accurate is pulse rate variability as an estimate of heart rate variability?», *Int. J. Cardiol.*, vol. 166, n. 1, pp. 15–29, Jun. 2013, doi: 10.1016/j.ijcard.2012.03.119.

[10] Q. Qin, J. Li, Y. Yue, e C. Liu, «An Adaptive and Time-Efficient ECG R-Peak Detection Algorithm», *J. Healthc. Eng.*, vol. 2017, pp. 1–14, 2017, doi: 10.1155/2017/5980541.

[11] I. Reyes, H. Nazeran, M. Franco, e E. Haltiwanger, «Wireless photoplethysmographic device for heart rate variability signal acquisition and analysis», em *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Diego, CA, Ago. 2012, pp. 2092–2095, doi: 10.1109/EMBC.2012.6346372.

[12] H. Machado, «Análise da variabilidade da frequência cardíaca usando métodos não lineares», Faculdade de Engenharia Universidade do Porto, 2018.

[13] S. Hanly, «Vibration Analysis: FFT, PSD, and Spectrogram Basics». https://blog.endaq.com/vibration-analysis-fft-psd-and-spectrogram#fft (acedido Ago. 06, 2020).

[14] T. Ferreira, «Construção de um modelo utilizando a Análise Discriminante para a deteção de Acidemia Fetal», Faculdade de Ciências da Universidade do Porto, 2018.

[15] M. Elgendi, «On the Analysis of Fingertip Photoplethysmogram Signals», *Curr. Cardiol. Rev.*, vol. 8, n. 1, pp. 14–25, Jun. 2012, doi: 10.2174/157340312801215782.

APPENDIX B

Volunteers tests

Seq	Age	ID	Gender	Video	Id_video	Q1	Q2	Q3	Average
A	20-25	ID01	F	VM	4	8	8	8	8.00
				VNM	5	8	3	4	5.00
B	20-25	ID02	M	VNM	6	4	3	4	3.67
				VM	7	8	8	8	8.00
B	50-55	ID03	F	VNM	8	6	6	5	5.67
				VM	9	7	8	8	7.67
A	50-55	ID04	M	VM	10	6	5	5	5.33
				VNM	11	6	5	3	4.67
A	20-25	ID05	F	VM	12	8	8	6	7.33
				VNM	13	8	8	5	7.00
A	20-25	ID06	F	VM	14	9	6	7	7.33
				VNM	15	9	7	5	7.00
B	20-25	ID07	F	VNM	16	6	3	2	3.67
				VM	17	8	4	6	6.00
B	20-25	ID08	M	VNM	18	8	7	8	7.67
				VM	19	8	9	9	8.67
A	20-25	ID09	M	VM	20	8	7	6	7.00
				VNM	21	5	6	5	5.33
B	20-25	ID10	M	VNM	22	8	8	7	7.67
				VM	23	9	9	9	9.00
B	20-25	ID11	F	VNM	24	9	8	7	8.00
				VM	25	10	8	8	8.67
A	20-25	ID12	F	VM	26	8	5	8	7.00
				VNM	27	4	4	4	4.00

Avg Mot:	7.50
Avg No_Mot:	5.78

Number users: 12

Q1: Is the subject of the video interesting?
Q2: What score do you give to the quality of the video?
Q3: How much attention do you think you kept during the video?

Random: 1 0 = Sequence A
1 = Sequance B