

Faculdade de Engenharia da Universidade do Porto



**SHRAM-Smart Heart Rate and Activity
Measurement**

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Abstract

Nowadays people are more concerned and conscious about the impact that lifestyle might have on their own health and well-being. Further, a huge interest for smartphones and wearables has been verified over the past few years. Their versatility and portability make them a consideration for people who want to decrease visits to the doctors and remotely monitoring themselves, in a comfortable and practical way. The heart rate changes according to the type of activities being performed, levels of stress and anxiety, nutrition and internal factors such as the respiration mechanism. However, some of them can be abnormal and indicative of cardiac or neurologic diseases and disturbances. Living in a society where everybody is busy and lives in a rush and under stress, heart rate irregularities may occur without noticing, with negative consequences on health. They can be present at all times or occur randomly during the day, so they might not be detected in standard exams such as ECG (Electrocardiography).

This work aims to study if it is viable to use a wearable device system for continuous heart rate monitoring in a daily basis, in combination with activity monitoring, to improve current activity related features and detect abnormalities that other way might go unnoticed. For this, a heart rate validity measurement test was performed, with 8 volunteers between 22-30 years old, in which the Fitbit Surge smartwatch was tested against the Zephyr Bioharness 3 chest strap within different activities. Furthermore, the application of heart rate variability analysis techniques and the study of how their patterns are related with the activities being performed was also a focus theme. For this public datasets (PAMAP and PAMAP2) and also the datasets acquired during the validity test mentioned above were used. Besides this, a study of how the heart rate data and its features can be used to improve activity monitoring analysis, especially the energy expenditure estimation, was accomplished, using a dataset from a previous work. This dataset includes data from 13 subjects, with an average age of 33 ± 9 years, wearing a heart rate chest strap monitor and performing a stress test in which the energy expenditure was measured through indirect calorimetry and also through an activity based model, which in turn used accelerometer data provided by the smartphone's accelerometer that was located in the subject's belt. The energy expenditure values provided by the model that combines both activity and heart rate data, the activity based model and heart rate model were evaluated against the results provided by the indirect calorimetry. Finally, a system that monitors both activity and heart rate was built as a proof of concept, in which the activity monitoring is performed by an already developed system that captures the smartphone accelerometer data, classifying the activity through Machine Learning techniques and computing its main features, and the heart rate is monitored through a smartwatch wearable device.

The results obtained suggest that smartwatches, although at the moment they are not the ideal monitoring device for an exigent heart rate monitoring that is requested by

cardiac patients, are suitable to behave as activity and heart rate trackers and guide common users to follow an healthy lifestyle, taking into account the validity test results (reliability=75.39%, accuracy=93.80%, mean error=4.21 BPM, mean absolute error=7.22 BPM). Further, the study allowed to better perceive the heart rate variability patterns and how they depend on the type of activity performed, and that the energy expenditure is more accurate and reliable when both activity and heart rate data are combined, where the best result achieved a NRMSE of 19.9%. Hence, current generation of smartwatches, although it presents some limitations, represents a valuable tool that can revolutionize the way the healthcare is currently provided, by enabling continuous monitoring of the user's health status and helping following a healthy lifestyle.

Keywords: Heart Rate Monitoring; Activity Monitoring; Heart Rate Variability; Energy Expenditure; Smartwatch

Resumo

Atualmente, as pessoas estão mais conscientes acerca do impacto que o estilo de vida pode ter na sua saúde e bem-estar. Por outro lado, tem-se verificado uma enorme adesão a smartphones e wearables, que permitem aos seus utilizadores, de forma confortável e prática, monitorizar-se de forma remota e, assim, diminuir as consultas médicas. A frequência cardíaca varia dependendo do tipo de atividades realizadas, níveis de stress, nutrição e também factores internos como a respiração. Contudo, algumas destas variações podem ser anormais ou indicativas de doenças cardíacas, neurológicas ou outros distúrbios. Numa sociedade cada vez mais ocupada e dominada pelo stress, podem ocorrer irregularidades na frequência cardíaca sem qualquer percepção, frequentemente ou aleatoriamente ao longo do dia, e com consequências negativas na saúde, podendo não ser detectadas em exames standard como o ECG.

Este projecto tem como objectivo determinar se é viável usar um sistema wearable para monitorizar diariamente e continuamente a frequência cardíaca, em combinação com monitorização de atividade, no sentido de melhorar as atuais características de atividade e detectar anormalidades que, de outra forma, não seriam detectadas. Para isso, um teste de validação da medição de frequência cardíaca foi executado, com 8 participantes entre os 22 e 30 anos de idade, no qual o smartwatch Fitbit Surge foi testado em relação a uma fita cardíaca Zehpyr Bioharness 3, durante diferentes atividades. A análise da variabilidade da frequência cardíaca e a forma como os seus padrões se relacionam com o tipo de atividade executada foi também um tema de foco. Neste sentido foram utilizados datasets públicos (PAMAP and PAMAP2) e também os datasets recolhidos durante o teste de validação referido anteriormente. Para além disso, foi estudada a forma como a frequência cardíaca e as suas características podem melhorar a análise de monitorização de atividade, especialmente no que diz respeito à estimação do dispêndio de energia, no qual foi utilizado um dataset de um trabalho anterior. Este dataset inclui dados de 13 indivíduos, com idade média de 33 ± 9 anos, que realizaram um teste de esforço, no qual foi registada a frequência cardíaca e o dispêndio de energia foi medido por calorimetria indirecta e também usando um modelo baseado na atividade, que usou os dados do acelerómetro do smartphone que os sujeitos usavam no cinto. Os valores de estimação de energia fornecidos pelo modelo que combina ambos os dados de frequência cardíaca e atividade, pelo modelo baseado na atividade e pelo modelo baseado na frequência cardíaca foram comparados com os valores fornecidos por calorimetria indirecta. Finalmente, foi desenvolvido um sistema que monitoriza a frequência cardíaca e atividade, como prova de conceito. A monitorização de atividade é executada por um sistema que recebe os dados do acelerómetro de um smartphone, classificando a actividade e calculando as suas principais características, e a frequência cardíaca é monitorizada por meio de um smartwatch.

Os resultados obtidos sugerem que os smartwatches, apesar de neste momento não

serem precisos o suficiente para monitorizar exigentemente doentes cardíacos, são a ferramenta ideal para monitorizar indivíduos comuns e ajudá-los a seguir uma vida saudável, tendo em conta os resultados do teste de validação (reliability=75.39%, accuracy=93.80%, mean error=4.21 BPM, mean absolute error=7.22 BPM). Permitiu também compreender melhor os padrões de variabilidade de frequência cardíaca e como estes dependem do tipo de atividade executada, e que a estimação do dispêndio de energia é, de facto, mais confiável quando os dados de atividade e frequência cardíaca são combinados, tendo-se obtido como melhor resultado um NRMSE de 19,9%. Em suma, apesar de os atuais smartwatches apresentarem algumas limitações, representam uma ferramenta valiosa que pode revolucionar a forma como os cuidados médicos são prestados, ao permitir uma monitorização contínua e ajudar os utilizadores a seguir um estilo de vida saudável.

Keywords: Monitorização da Frequência Cardíaca; Monitorização de Atividade; Variabilidade da Frequência Cardíaca; Dispêndio de Energia; Smartwatch

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Abbreviations

ANS	Autonomous Nervous System
BPM	Beats per Minute
CRF	Cardiorespiratory Fitness Level
ECG	Electrocardiography
EE	Energy Expenditure
FEUP	Faculdade de Engenharia da Universidade do Porto
FhP-AICOS	Fraunhofer Portugal Research Center for Assistive Information and Communication Solutions
HF	High Frequencies
HRaS	Heart Rate above Sleep
HRDF	Heart Rate Deflection Point
HRmax	Maximum Heart Rate
HRreserve	Heart Rate reserve
HRV	Heart Rate Variability
IMU	Inertial Measurement Unit
IBI	Inter-beat Interval
IR	Infra-Red
LF	Low Frequencies
METS	Metabolic Equivalent
PNS	Parasympathetic Nervous System
PPG	Photoplethysmography
RMSSD	Root Mean Square of the Successive Differences
SDANN	Standard Deviation of Sequential Five-Minute Inter-beat Interval Means
SDNN	Standard deviation of Inter-beat intervals
SNS	Sympathetic Nervous System
VLF	Very Low Frequencies
VO ₂	Volume of O ₂
VO ₂ max	Maximum Volume of O ₂

Chapter 1

Introduction

1.1. Motivation

Nowadays people are more concerned and conscious about the impact that lifestyle has on their own health and well-being, taking into account the relation between lifestyle, stress and diseases. Additionally, coronary artery diseases, depression and emotional exhaustion are diseases and problems that are related to the lifestyle an individual chooses to take. At the same time, it has been observed a huge adhesion to smartphones and wearables over the past few years. Their versatility and portability make them a considerable option for people who want to decrease visits to the doctors and remotely monitoring themselves.

With the aging of the population, which is even more busy and with stressful lives, and the increasing of chronic diseases and psychological disturbances, the continuous heart rate and activity monitoring became fundamental to increase the quality of life of people, maintaining their independence. This is possible due to the great contribute given by the wearable technology that has been developed in the past few years, comfortable and practical for daily use.

Clinical assessment might be performed from the heart rate signal and activity monitoring. It provides data for a detailed analysis of the activities and possible abnormalities identification, as for example risk factors related to serious pathologies, by analysing changes in the monitored variable caused by body reaction to specific stressful events.

1.2. Problem Statement and Objectives

Heart Rate monitoring, besides being important for athletes and exercisers, to control and improve exercising, is also relevant for a daily basis use.

The heart is the reflex of an individual's health status, and through its continuous monitoring, changes can be detected. These changes are derived from the type of activities done, levels of stress and anxiety, nutrition and internal factors such as the respiration mechanism. However, some of them can be abnormal and indicative of cardiac or neurological diseases and disturbances. Living in a society where everybody is busy and lives in a rush and under stress, heart rate irregularities might occur without noticing, with negative consequences on health. They can be present at all times or occur randomly during the day, so they might not be detected in standard exams such as ECG. The Holter monitor might be an alternative, but it can represent a serious discomfort, though.

Since current wearable devices include heart rate sensors, perform activity monitoring and it has been observed an increasing of their use and popularity over the past few years, both heart rate and activity data might be both used to improve current monitoring algorithms. This will allow the combination between heart rate data and the physical activity monitoring in order to assess the user personal physical behaviour during the day, allowing the detection of some anomalies, whether cardiac or psychological, avoid potential harmful events and understand the personal context of the user. Hence, the main goal is to study if wearable devices are suitable for heart rate monitoring in a daily basis, and develop a proof of concept system that performs a combined heart rate and activity monitoring analysis that generates alerts for abnormal heart rates. This way, it will be possible to combine heart rate and activity data, in order to detect some possible abnormal events and to realize the user quotidian context.

1.3. Project

This work aims to study if it is viable to use wearable devices for continuous heart rate monitoring and analysis, in combination with activity monitoring, and improve activity related features with the heart rate variability. Further, a great focus was made in the study of the inter-combination between energy expenditure, speed and workload, activity features and heart rate. A system was built as proof of concept, which monitors both activity and heart rate. The activity monitoring is performed by an already developed system that captures the smartphone accelerometer data and classifies the activity through Machine Learning techniques (sitting, staying, lying, walking, running, cycling, tilting) and computes its features. In turn, the heart rate is monitored through a smartwatch wearable device.

The project includes two main areas of research. The possibility of using a wearable device, mainly a smartwatch, for heart rate monitoring, comparing its performance with currently used devices, in this case a chest strap, was evaluated. For this, a heart rate validity measurement test was performed, with 8 participants within a range of 22-30 years old. The Fitbit Surge smartwatch was tested against the Zephyr Bioharness 3 chest strap within different activities, which were manually annotated and recorded by a developed system that includes an accelerometer and a recorder application that saves its data, in a supervised laboratory environment. Furthermore, the application of heart rate variability techniques and how their patterns are related with the activities being performed was focused, in which public dataset (PAMAP and PAMAP2) and also the dataset acquired during the validity test previously mentioned were used. Besides this, another topic included the study of how the heart rate data and its features can be used to improve activity monitoring analysis, especially the energy expenditure estimation. For this, a dataset from a previous work, which includes data from 13 subjects, with an average age of 33 ± 9 years, wearing a heart rate chest strap monitor and performing a stress test was used. In this test, the energy expenditure was measured through indirect calorimetry and also through an activity based model, which used accelerometer data provided by the smartphone's accelerometer that was located in the subject's belt. A model that combines both activity and heart rate and another model that uses only the heart rate data were applied on this dataset. Hence, the results obtained by the heart rate and activity model, the activity based model and heart rate model were evaluated against the results provided by the indirect calorimetry.

This project mainly contributed to better understand the real potential of current wearable devices to improve people lives, by enabling comfortable continuous activity and heart rate monitoring, which is determinant to take a healthy lifestyle and avoid long-term health problems, either due to abnormal heart rate values, inactivity or stress. It allowed to realize that smartwatches, although they are not the ideal monitoring device for an exigent heart rate monitoring that is requested by cardiac patients yet, are suitable to behave as activity and heart rate trackers and guide the users to follow an healthy lifestyle. Further, it

allowed to better perceive the relationship between heart rate and activity, namely the heart rate variability patterns, and that the energy expenditure is more accurate and reliable when both activity and heart rate data are combined. In short, this study demonstrated that current generation of smartwatches, although they present some limitations, they represent a valuable tool that can revolutionize the way healthcare is currently provided, by enabling continuous monitoring the health status of the user and giving feedbacks.

This study was performed using PyCharm and MatLab® R2013a, for the data processing and evaluation. The Android Studio was used to develop the proof of concept system.

1.4. Overview of Dissertation

This dissertation includes four chapters, besides this Introduction. Chapter 2 includes an explanation of the main concepts related with the heart rate, its variability, main applications and measurement methods. Further, activity monitoring concepts and Machine Learning Technology are also described in detail. Besides, it includes a state of the art review related with measurement and monitoring systems, mainly heart rate measurement devices and heart rate and activity monitoring systems. In Chapter 3, the research methodology approach is described in detail, whose results are presented and discussed in Chapter 4. Finally, Chapter 5 summarizes the major achievements and conclusions related with the dissertation, with some improvements and future work suggestions.

Chapter 2

Literature Review

2.1. Heart Rate

Cardiac cycle starts spontaneously from the sinoatrial node of the heart, located at the right atria, due to depolarizing pacemaker cells. From these cells, the electrical signal spreads through the atria, causing both of them to contract, and then the atrioventricular node is activated, followed by the ventricles, leading to their contraction due to the impulse's spread over the heart muscle. After the heart pumps the blood into the arteries, the ventricles repolarize and the heart fills with blood, relaxing. The period of relaxation is called diastole and the period of contraction is designated as systole (Hall, 2010).

Heart rate is, thus, known as the speed of the heartbeat and it is described as the number of contractions of the heart per unit of time, generally in beats per minute (BPM).

The depolarization rate of the pacemaker cells is controlled by the autonomous nervous system (ANS), through its two separate branches, the sympathetic nervous system (SNS) and parasympathetic nervous system (PNS), which have opposite effects on the heart. The SNS stimulates the heart, increasing the heart rate, whereas the PNS inhibits the heart functions, leading to lower heart rates. This way, a balance between the SNS and PNS is required in order to the cardiovascular system to adapt to several different body requirements and maintain equilibrium. Figure 1 (Marieb & Hoehn, 2007) reflects the autonomic innervation of the heart.

The baroreflex system is an important regulation system based on baroreceptors, which are specialized neurons that continuously sense arterial pressure, located in the heart, arteries and vessels. This homeostatic mechanism allows the blood pressure to be nearly constant, through a degenerative feedback loop, in which a high blood pressure causes the heart rate to decrease, so the pressure can decline. In turn, a lower blood pressure decreases the baroreflex system's activation, which causes the heart rate to increase and, this way, restores blood pressure. The cyclic changes in arterial blood pressure due to the baroreflex control system are designated Mayer waves (Myers et al., 2001).

The heart rate is also affected by the respiration mechanism. During the inspiration the heart rate increases and it decreases during expiration, due to direct SNS and PNS stimulation. Moreover, during respiration cycle the intra-thoracic pressure changes, which results in blood pressure changes and, consequently, baroreflex system activation. This continuous balance between cardiovascular system and autonomous nervous system results in varying heart rate.

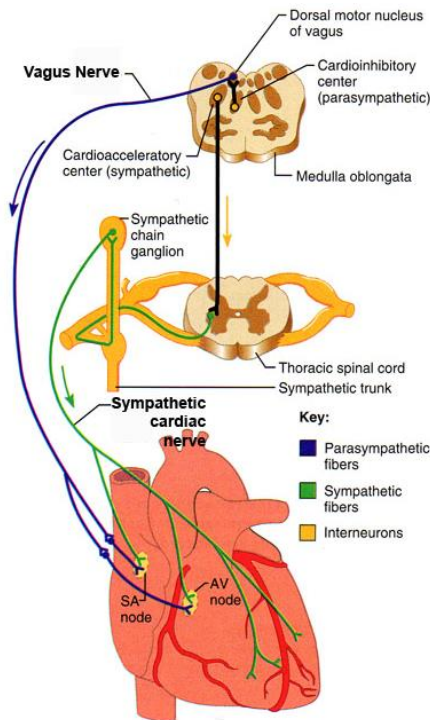


Figure 1: Autonomic innervation of the heart (Marieb & Hoehn, 2007).

The heart rate has a huge impact on the cardiac output, which represents the volume of blood that is pumped by the heart, in one minute (L/min) (Vincent, 2008). The cardiac output is an important indicator of how efficient the heart can meet the body needs. The stroke volume refers to the quantity of blood pumped out of the left ventricle with every heartbeat. The product between the stroke volume and heart rate equals the cardiac output. Thus, cardiac output is influenced by the heart rate, because the higher is the frequency the heart contracts with, the higher the cardiac output. However, if the heart rate increases too much, the amount of blood that fills the heart during the diastole will be lower and, consequently, less is the amount of blood that the heart pumps for the all body with every beat. In turn, the efficiency of the heart decreases.

The heart rate is mainly affected by the autonomic nervous system, hormones, fitness level condition and also by the age.

The normal heart rate value is strongly dependent on the person's age, gender, size, heart conditions, physical capacity and also the activity in cause, whether the person is sitting, walking or doing other challenging or stressful activity. Even emotions have a huge impact on heart rate value. The heart rate can vary according to the body's physical requirements, in order to maintain equilibrium between the needs, oxygen and nutrients delivery and carbon dioxide excretion.

The basal heart rate (resting heart rate) is typically defined as the heart rate value when the person is awake, under neutral temperature environment and not subjected to any exertion, stimulation or stress. A heart rate between 60 and 100 beats per minute is considered normal for a resting adult (Association, 2015). It must be highlighted that people in excellent physical condition such as athletes have lower resting heart rate values. A resting heart rate slower than 60 beats per minute is said to be bradycardiac and a rate faster than 100 beats per minute is said to be tachycardiac. When the heart contracts following an inconsistent pattern, it is said that the individual suffers from an arrhythmia, although he might not present any symptom.

The maximum heart rate (HRmax), which corresponds to the highest heart rate a person can achieve without severe sequelae, normally decreases with age. This value is often

estimated through formulas, being the most cited the one proposed by Dr. William Haskell and Dr. Samuel Fox (Simon, 2004):

$$HR_{max} = 220 - age \quad (2.1)$$

During exercising, the desired range of values differs a lot, and is based mostly on age and the activity's intensity, expressed in percentage. For example, for a 50-70% intensity physical exercise a 22 years old person, who has a HRmax of 198 beats per minute should present a heart rate between 99 and 139 BPM. This is useful to control the effort done during any physical activity.

$$50\% \text{ intensity: } (220-22) \times 0,50 = 99 \text{ BPM} \quad (2.2)$$

$$70\% \text{ intensity: } (220-22) \times 0,70 = 139 \text{ BPM} \quad (2.3)$$

The reduction that heart rate suffers between the peak achievement during exercise and after a cool down period of fixed time, is designated as heart rate recovery. A high reduction in heart rate after some exercise during the fixed period is highly associated with a high physical condition. People with low heart rate recovery values present an increased risk of death (Watanabe et al., 2001).

The heart rate is a non-stationary signal, and its variation includes indicators of current disease or warnings about impending cardiac diseases. All parameters of cardiac function, including heart rate, conduction, force of contraction and relaxation, reflect the net balance between an inhibitory parasympathetic influence and an excitatory sympathetic influence.

In general, a low heart rate variability reflects the depletion of the autonomous nervous system, either due to the aging, chronic stress, depression or other pathologies. The heart rate value itself influence heart rate variability. When the sympathetic activity increases, the heart rate rises and the range of variability that can be measured is smaller. In turn, when the parasympathetic activity increases, the inter-beat interval duration is higher and so is the range of variability that can be measured (Nieminen et al., 2007).

There are several factors that influence the heart rate, from the individual factors, such as age, gender, body mass index and physical condition, to the physiological factors, such as breathing frequency, blood pressure, hydration, nutrition or drugs and environmental factors such as the temperature or altitude (Achten & Jeukendrup, 2003; Parati & Di Renzo, 2003).

The age influences the maximum heart rate value that an individual can achieve, as described by the formula suggested by Fox (Simon, 2004). The age also influences the heart rate variability. As the individual gets older, the heart rate variability will also present lower values. Time domain parameters such as SDNN, coefficient of variation, SDANN, RMSSD and pNN50, which quantify the variability of an inter-beat interval time series, are inversely related to age for both genders.

The physical condition, which is influenced by exercise habits, determines the lower heart rate value that an individual can achieve. It is known that a trained heart is more efficient, and therefore, it needs to contract less times than a non-trained heart. The life style an individual takes has also an important role in the cardiovascular system and its variability. As for example, work stress has repeatedly been associated with an increased risk for cardiovascular disease.

Factors such as high ambient temperature, high humidity, and emotional stress will cause an increase in heart rate without a significant rise in oxygen consumption, which is also affected by the muscle mass of each individual (Achten & Jeukendrup, 2003).

Posture also influences the heart rate. When a subject transits from sit to stand, the heart rate increases due to the baroreflex system, which is activated due to the decrease in the blood pressure (Olufsen et al., 2008).

Regarding the environmental conditions, there are some factors that can also influence the heart rate and its behaviour. For instance, when a physical activity is performed in hot or dehydration conditions, the heat loss mechanisms become less efficient and core temperature increases, which leads to higher heart rate values at the same exercise intensities, overestimating the exercise's intensity (Achten & Jeukendrup, 2003). In turn, during exercise in cold environments the heart rate will be very similar to that in warm conditions, although the oxygen volume consumption will be higher. Therefore, the heart rate value will underestimate the intensity of exercise (Achten & Jeukendrup, 2003). Performing exercise at altitude will cause the heart rate to increase, due to the reduced partial level, compared to the sea level. However, when the individuals stay at altitude for a long time, some adjustments in the body take place (Achten & Jeukendrup, 2003).

Regarding the external factors, nutrition and drugs influence the heart rate. For instance, caffeine and nicotine stimulate the nervous system, increasing the heart rate. Equally, the presence of catecholamine, such as epinephrine and norepinephrine, and thyroid hormones increase the heart rate (Smith et al., 1977). In turn, beta blockers and calcium channel blockers have an opposite effect, decreasing the heart rate (Bangalore et al., 2008).

2.3. Heart Rate Measurement

Besides the manual measurement, there are other methods to detect heartbeats and measure the number of contractions that the heart performs in a specific unit of time.

The electrical activity of the heart can be acquired through biopotential electrodes, as is used in the typical Electrocardiogram exam. Blood plethysmography is the measurement of changes in volume of blood in the capillaries. The fluctuations of blood flow can be detected through several methods such as changes in light absorption (photoplethysmography) and detection of changes in electrical resistance (impedance plethysmography). Since the blood flow is proportional to the cardiac cycle, being higher during the systole, optical sensor can measure indirectly the heart rate, through the measurement of the light absorbed and reflected by the blood. Following the same logic, bioimpedance sensor can also be used to measure heart rate through the measurement of skin resistance, assuming that it is also proportional to the blood flow and, consequently, to the heart activity. Finally, the cyclic activity of the heart exerts blood pressure changes along the blood vessels wall and, consequently, the vessels pulsate in the rhythm of the heart, which can be detected with pressure sensors.

2.3.1. Electrocardiography

The mechanism of electric conductivity in the body involves ions as charge carriers and, thus, collecting the signal involves interacting with these ionic charge carriers, transducing ionic currents into electric currents, carried by electrons. Electrodes carry out this transducing function and they are, in their simplest form, metallic conductors in contact with the skin.

Biopotential electrodes used to capture cardiac electrical signal are placed on the skin. The integrity of the skin is not compromised when these electrodes are applied. These can be wet and dry depending on the use or not of an electrolyte. An ECG signal, captured through biopotential electrodes, is represented in Figure 2 (Kumar, 2011). This signal provides a clear waveform, which allows excluding heartbeats that are not originated in sinoatrial node, and several segments can be distinguished. The P wave represents the depolarization of the atria, whereas the PR interval consists on the time that the electrical impulse takes to travel from the sinoatrial node to the atrioventricular node. The QRS complex represents the ventricular depolarization and the ST segment represents the time when the ventricles are depolarized. In turn, the T wave represents the repolarization of the ventricles. The heart rate is calculated

through the inverse of time between two QRS complexes, which corresponds to the time between two heartbeats.

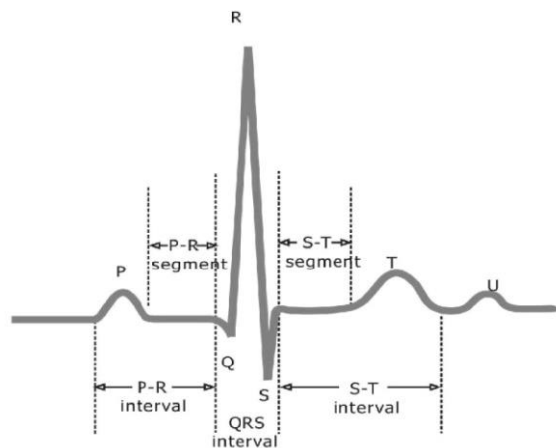


Figure 2: ECG signal (Kumar, 2011).

2.3.2. Photoplethysmography

Photoplethysmography sensors can be based on the light transmission principle, usually applied on the finger or earlobe, or based on principle of reflection, for wrist application. In the first one, the emission module and the photo-detector are placed on opposite sites but accurately adjusted and aligned so the signal is well captured by the detector. When based on the reflection principle, both the emission module and the detector are placed on the same site. The system is basically composed by an emission module, normally infrared LEDs, a reception module, generally a photodiode that converts the optical signal into current, a trans-impedance amplifier that converts the current signal into tension, and an analog signal processing module, responsible for the signal amplification and filtering. Usually, a band-pass filter is used to remove the DC component and the high frequency noise to the signal.

Infrared LEDs usually own a very narrow bandwidth spectrum, with a wavelength between 850-950 nm, which cover the maximum absorption by the oxyhemoglobine.

For a rigorous and accurate monitoring it is necessary to take into account the dynamic behaviour intrinsic to the physiologic parameters of interest. Therefore, it is fundamental that the analysis is done over signals acquired in a continuous way, since it provides information that allows to minutely describing the variations suffered by the parameters throughout the monitoring time. The heart rate monitoring through the wrist using bracelets or watches has been demonstrated to be very challenging since it offers a comfort monitoring, biofeedback and visual system regarding to the health state of the user.

Heart rate measurement can be done assuming the photoplethysmography principle, this is, the measurement of blood flux variations using an optical method. The sensors measure the quantity of infrared light that is absorbed or reflected by the blood, taking into account the existing relation between the vessels volume, blood pressure and volume (Tamura et al., 2014). However, the sensors must be placed on spots with high perfusion and low number of surrounding tissues. The cardiac cycle has two phases: the diastole, when the blood flows from the vessels to the atria and the vessels volume and pressure reach the lowest value, and the systole, when the blood is pumped by the ventricles to the all body, leading to the increase of the volume/pressure in the vessels. Therefore, light absorption or reflection will be higher during systole.

Bones, skin, tissues, venous blood and non-pulsatile blood are the main responsible for the continuous light absorption, which corresponds to the DC component of the signal (Utami et al., 2013). The variation of the optical signal, the AC component, is due to changes in blood flux. Furthermore, the spatial orientation of red blood cells also influences the photoplethysmography, because they adopt a perpendicular position relative to the blood flux

during the systole and a parallel position during diastole (Kyriacou, 2001). Thus, during the systole, the optical path is bigger and, consequently, also the light absorption. The instant heart rate can be calculated from the inverse of the time between cardiac cycles.

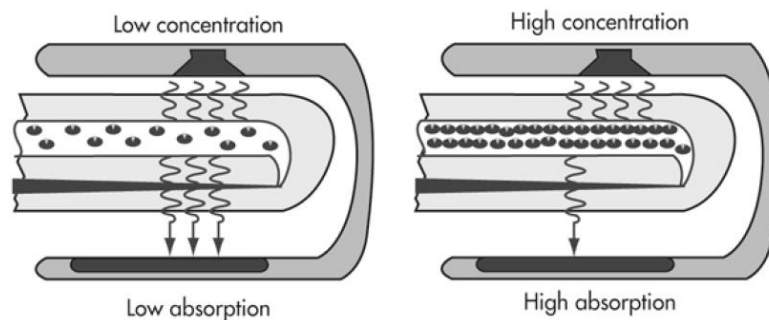


Figure 3: Photoplethysmography transmission principle (Utami et al., 2013).

Light propagation might be affected by different factors, making difficult to obtain a reliable optical heart rate monitoring (Delgado-Gonzalo et al., 2015b). The human skin is a complex and non-homogeneous structure and thus, a small change in the sensor-skin contact might lead to significant changes in the light propagation pathway. Therefore, it is very prone to movement artefacts. Moreover, even physiology, such as temperature control mechanism, causes peripheral vascular dilatation and constriction, depending on the environmental temperature or body heat production. This makes the volume of both blood, close to skin and the one depth, to vary depending on external conditions and individuals. Furthermore, there are some differences in the skin and tissue structures, namely the thickness of the layers and the amount of melanin between different persons. Thus, both the optimal measurement depth and the strength of the signal as well depend on the individuals since the different components of the tissue present different optical properties, longer wavelengths, such as infrared light (IR), penetrate deeper into the tissue than short wavelengths, such as green light. However, decreasing the distance between the LED and the photo-detector reduces the average light propagation path. Furthermore, the larger the measurement area is, more prone to movement artefacts the measurement is. It should be taken into account that reducing the weight of the sensing device reduces forces caused by the movement. Using light to measure a pulse is relatively straightforward when a person is at rest, but becomes challenging when the subject moves around. Ambient light, as well as the movement of the person's muscles, tendons and capillaries, can all interfere with the measurements.

2.3.3. Impedance Plethysmography

Impedance plethysmography detects changing tissue volumes in the body, based on the measurement of electric impedance at the body surface, i.e., the resistance to the passage of an electrical current (Khalil et al., 2014). The electrodes used are similar to the ones used in electrocardiography. The electrodes send small electrical currents through the skin and measure the tissue's resistance to calculate how many times the heart contracts in one minute. The sensor measures impedance changes within the body, namely the changes that occur due to volume of blood flowing. Blood has a relatively high conductance when compared to other tissues such as muscle or fat and thus, the arteries expansion at systole produce an increase in overall conductance in the region through which it passes. In the wrist, for example, two main arteries supply blood to the hand, the radial and the ulnar. Thus, it is expected that a resistance change occur due to blood flow through these arteries. This can be observed in Figure 4 (Bera, 2014). Measurement of resistance is theoretically simple to achieve, using Ohm's law. The potential measured in response to the constant current that passes through the tissue is then proportional to the characteristic impedance of the tissue (Khalil et al., 2014). Therefore, the

magnitude of the impedance acts as a resistance, giving the drop in voltage amplitude across an impedance Z for a given current.

$$Z = \frac{\text{Voltage Drop}}{\text{Current}} \text{ Ohm } (\Omega) \quad (2.4)$$

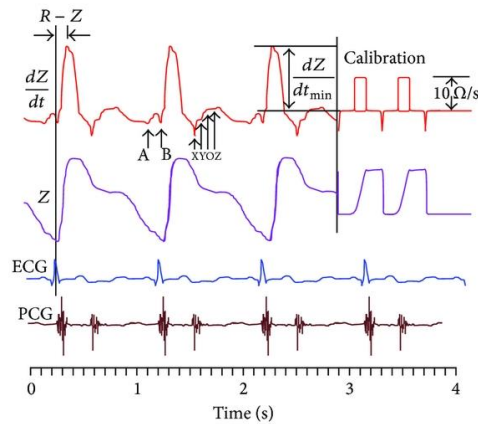


Figure 4: Comparison between ECG, PPG and Bioimpedance signals, for heart rate measurement purposes (Bera, 2014).

2.3.4. Blood Pressure Measurement

For each cardiac cycle the blood pressure varies between the systolic pressure, which corresponds to the maximal pressure in the arteries when the ventricles contract, and diastolic pressure, which is the minimum pressure exerted on the arteries when the ventricles fill with blood. Therefore, the pressure exerted on the blood vessels wall changes proportionally to the heart's cycle. Thus, the blood vessels pulsate in rhythm to heart's cycle, which can be detected with pressure sensors placed at specific places on the human body. This is the principle used by automatic blood pressure monitors to detect the heart pulse. The heart rate can be calculated through the inverse of time between consequent systolic pressures (Kumar, 2011).

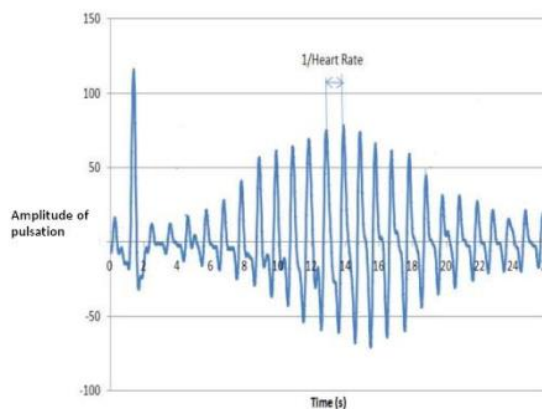


Figure 5: Blood Pressure Signal (Kumar, 2011).

2.4. Heart rate variability

Heart rate variability (HRV) is the physiological phenomenon of variation in the time interval between heartbeats, as it can be observed in Figure 6 (Sjövall, 2015). Heart rate variability data analyses non-stationary characteristics of the heart rate signal.

Its variation may contain indicators of current diseases or warnings about possible cardiac diseases, psychological syndromes or even neurologic disturbances. These indicators

may be present at all times or may occur randomly during certain intervals of the day. Thus, heart rate variability is a reliable reflection of many physiological factors that modulate the normal rhythm of the heart. In fact, it provides a powerful method of observing the equilibrium between the sympathetic and parasympathetic nervous systems and, consequently, the heart's ability to adapt to changing circumstances by detecting and quickly responding to unpredictable stimuli (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). The greater the HRV, the better the heart can keep up with changes and, therefore, the healthier is the individual.

The heart rate varies during different activities and postures, according to age and gender. Reduced levels of resting heart rate are commonly observed in athletes due to the training effect on cardiovascular system.

During dynamic exercise, the heart rate increases due to both sympathetic and parasympathetic systems, depending on the exercise intensity. The heart rate increases according to the intensity of exercising.

Stress is the body's physical and mental response to real or perceived challenges in real life, so it can be caused by internal factors related to body's status, and external factors related social-life events.

Heart rate variability is, thus, a biological marker that characterizes the way a person experiences and regulates emotions, like facing a challenge in quotidian, fear, stress, and fury or panic situations. Whenever an individual is confronted with potential dangers or stressful conditions, a fight-or-flight response is activated by the autonomous nervous system, which leads to heart rate shooting, puffy breathing, muscles stiffening, and a feelings cascade unfolding. The sympathetic branch of the nervous system mediates this response, with hormone secretions.

The heart response to sympathetic stimulation is relatively slow, taking about 5 seconds to increase the heart rate since the beginning of the stimulation, and takes almost 30 seconds to reach its peak (Gorman & Sloan, 2000). In turn, the heart response time to parasympathetic stimulation is very fast, taking about one or two heartbeats before the heart slows down to the minimum value proportional to the level of stimulation, depending on the phase of heart cycle at the moment of the stimulus (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

Hence, heart variability analysis can be used to assess autonomous nervous system function. Low HRV is generally interpreted as a consequence of higher sympathetic nervous system activity, associated with stress, overtraining and inflammation. A high HRV indicates dominance of the parasympathetic response, the ANS branch that promotes relaxation, sleep and recovery. High heart rate variability or instability caused by arrhythmias or nervous system disturbances is detrimental to efficient physiological functioning and energy utilization. However, little variation is characteristic of age-related system depletion, chronic stress, pathologies or inadequate functioning of the self-regulatory control systems (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). HVR is an overall measure of cardiac health status and it can also denounce psychological diseases and disturbances. It is the measurement of the complex interaction between the brain, heart and other systems in the body. It is important to note that stress is not always harmful, because it might be caused by joyful experiences. However, it can have negative impact on health when it experienced for long periods of time. The heart must experience a recovery time after its activity peak, to overcome the effect of stress.

Inter-beat intervals can be represented on a tachogram, in which the x-axis plots the number of the beat and y-axis plots the intervals time, as shown in Figure 7 (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

Studies suggested that individuals with depression or anxiety disorders present decreased HRV, resulting in a higher risk of cardiovascular diseases (Gorman & Sloan, 2000). Moreover, low heart variability is a powerful predictor of sudden cardiac death (Gorman &

Sloan, 2000).

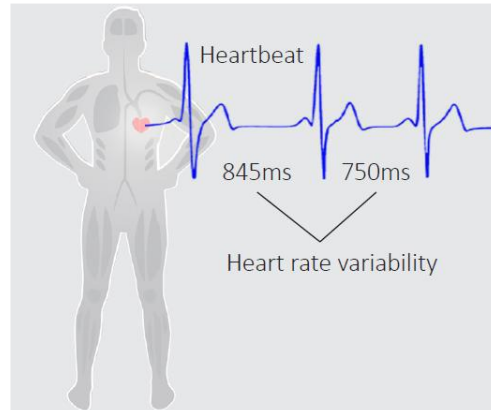


Figure 6: Heart Rate Variability (Sjövall, 2015).

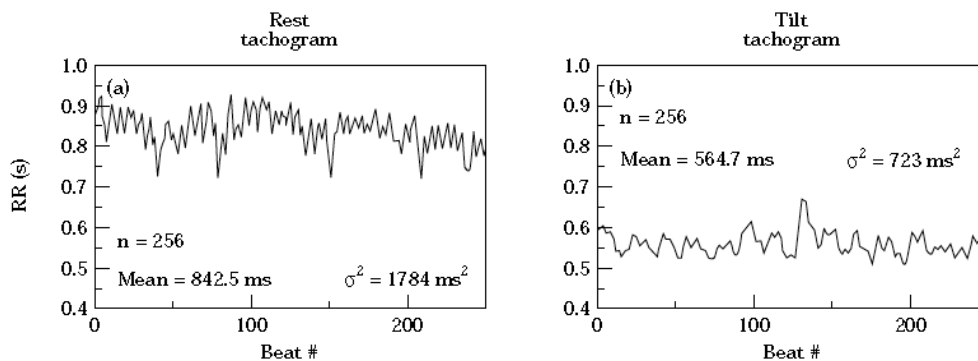


Figure 7: Tachogram examples (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

There is a variety of factors that affect HRV, including hormonal reactions, metabolic processes, physical activity, cognitive processes and stress or emotional reactions, alcohol and drugs consumption, nutrition and illness. A decrease in the HRV occurs with increasing age, due to the decline in efferent vagal cardiac tone. The inter-beat variation in heart rate has been demonstrated to be a function of conditioning status in young subjects. A simple autonomic provocation consists in an active change of posture from supine to standing. This results in a shift of blood away from the chest to venous system below the diaphragm, usually referred to as venous pooling. Almost invariably in all healthy volunteers, an increase in heart rate is the result.

The cardiovascular adjustments in exercise represent a combination and integration of neural factors such as activation of sympathetic nervous system, reflexes in the contracting muscles and baroreflex, and chemical factors. When exercise stops the heart rate suffers an abrupt decrease and parasympathetic activity is enhanced.

Moreover, the heart rate variability is dependent on the level of heart rate itself. The inter-beat interval has a nonlinear inverse relation with the heart rate value. The higher the heart rate the shorter the inter-beat interval and shorter intervals usually present less variation (Nieminen et al., 2007).

2.4.1. Inter-beat Interval Extraction and Pre-processing

The heart rate variability time series can be derived through the heart rate data provided by a smartwatch, taking into account the time when the heart rate value was measured and the time relationship between heart rate and inter-beat interval.

Pre-processing of inter-beat interval time series data is frequently required before heart rate variability analysis, in order to reduce analysis errors. Some of the inter-beat interval

pre-processing methods are ectopic beat and interval correction and inter-beat interval resampling (Ramshur, 2010). An abnormal inter-beat interval can occur due to a false or missed beat. These are considered ectopic beats and can be detected using several techniques, such as assuming that any interval that change more than a defined percentage (normally 20%) from the previous one. These ectopic beats can be replaced by the mean or median value of the some defined neighbours inter-beat intervals centred on the ectopic interval (Ramshur, 2010). Another option is to use cubic spline interpolation to replace these ectopic beats or simply removed them (Clifford, 2002; Medeiros, 2010; Ramshur, 2010).

The time series constructed from all the available heart rate values measured by the smartwatch are, clearly, not exactly equivalent to the time series extracted by an ECG signal, but they are also not equidistantly sampled, which has to be taken into account before frequency-domain analysis so additional harmonics are not introduced into the power spectrum. A common approach is to use interpolation methods for converting the non-equidistantly sampled inter-beat interval function to equidistantly sampled, such as the cubic spline or linear interpolation (Ramshur, 2010).

All the HRV parameters are calculated on inter-beat intervals, caused by normal heart contractions paced by sinus depolarization. HRV can be described by both time and frequency domain analysis measures. These are calculated from recordings with durations about 5 minutes for short-term recordings and 24 hour for long-term recordings (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

2.4.2. Time Domain Analysis

Time Domain heart rate variability analysis parameters can be classified as statistical or geometric, depending if the analysis is performed through statistical or geometric patterns.

Statistical HRV indices are calculated on a beat-to-beat basis and are based on Euclidean root-mean square (rms) metrics.

Time domain analysis includes the mean inter-beat intervals duration and statistical measures of the variance (Gorman & Sloan, 2000; Medicore, n.d.; Schubert et al., 2009; Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

\bar{I} represents the mean of inter-beat intervals, where N represents the total number of the inter-beat intervals and I_i the interval itself:

$$\bar{I} = \frac{1}{N} \sum_{i=1}^N I_i \text{ (ms)} \quad (2.5)$$

SDNN is the standard deviation of the inter-beat interval, calculated as the square root of their variance. It reflects all the cyclic components of the variability of the intervals. SDNN values should be compared taking into account the length recording. Low SDNN values indicate low heart rate variability. Hence, this measure is calculated as follows:

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (I_i - \bar{I})^2} \text{ (ms)} \quad (2.6)$$

SDNN index is designated as the mean of all the 5-minute of inter-beat intervals standard deviations during a 24 hours period (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996), whereas the SDANN is the standard deviation itself. N5 is the total number of 5 minute sections of inter-beat intervals during a 24 hours period, \bar{I}_5^i is the mean of inter-beat intervals in a 5 minute section and $\bar{\bar{I}}_5$ is the mean of all the means of inter-beat intervals in all the 5 minute section. The SDNN index and SDANN are calculated as follows:

$$SDNN_{ind} = \frac{1}{N_5} \sum_{i=1}^{N_5} SDNN_i \text{ (ms)} \quad (2.7)$$

$$SDANN = \sqrt{\frac{1}{N_5 - 1} \sum_{i=1}^{N_5} (\bar{I}_{5^i} - \bar{\bar{I}}_5)^2} \text{ (ms)} \quad (2.8)$$

RMSSD (root mean square of successive differences) estimates high-frequency variations in heart in short-term recordings and, thus, the regulation of the heart by parasympathetic nervous system and reflexion of vagal tone:

$$RMSSD = \sqrt{\frac{1}{N - 1} \sum_{i=1}^{N-1} (I_{i+1} - I_i)^2} \text{ (ms)} \quad (2.9)$$

Another popular measure is pNN50, which represents the percentage of differences between adjacent inter-beat intervals that differ more than 50 milliseconds. NN50 represents the number of differences between adjacent inter-beat intervals that differ more than 50 ms. The pNN50 parameter is calculated as follows:

$$pNN50 = \frac{NN50}{N} \times 100 \text{ (\%)} \quad (2.10)$$

pNN50 is a quantification of the relative frequency of high beat-to-beat interval changes, and it is strongly correlated with other ANS activity measures such as spectrum power and RMSSD. This measure can be also applied by changing the time varying between intervals to lower values and, then, increasing the variability resolution, as is the case of the pNN20.

Further, the coefficient of variation gives a global measure of the heart rate variability in time-domain, and it is defined as the ratio between the standard deviation of inter-beat intervals and the average inter-beat interval duration:

$$CV = \frac{SDNN}{\bar{I}} \times 100 \text{ (\%)} \quad (2.11)$$

The inter-beat interval time series can also provide a geometric pattern of variability, such as the sample density distribution of inter-beat intervals durations or the sample density distribution of differences between adjacent inter-beat intervals. Geometric heart rate variability measures are calculated from the geometric pattern characteristic of the inter-beat interval time series, being the histogram the most common pattern used. Taking into account the histogram, two measures might be calculated such as the HRV triangular index (HRVti) and the triangular interpolation of the inter-beat intervals histogram (TINN).

Geometric methods are advantageous because of their relative insensitivity to the analytical quality of the series of inter-beat intervals. However, a reasonable number of inter-beat intervals to construct the geometric pattern is needed.

HRV triangular index (HRVti) is calculated dividing the area integral of the density distribution of the IBI series by the maximum value present in the density distribution, i.e., the total number of inter-beat intervals divided by the maximal height of the IBI series histogram (the most frequent Inter-beat interval) (Medeiros, 2010; Ramshur, 2010):

$$HRVti = \frac{N_{IBI}}{\text{Maximum of the density distribution}} \quad (2.12)$$

Triangular Interpolation of the histogram of the inter-beat intervals (TINN) is calculated by approximating the inter-beat intervals distribution to an isosceles triangle and measuring the width of the unequal side (the base). It is the baseline width of the distribution measured as a base of a triangle approximating the inter-beat intervals interval distribution, where the triangle is found through the minimum square difference (Medeiros, 2010; Ramshur, 2010).

2.4.3. Frequency Domain

Frequency domain analysis measures and describes power spectral density, i.e., finds out the power of different frequency bands in the signal. This requires a spectral analysis, representing the HRV data into frequency over time, as a combination of sine and cosine waves, which requires a Fourier transform approach (Gorman & Sloan, 2000; Medicore, n.d.; Ramshur, 2010; Schubert et al., 2009; Tarvainen, 2014; Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

Spectral analysis is thought to provide an understanding on the effects of sympathetic and parasympathetic nervous system on the heart rate variability. Three main components are usually analysed through the spectrum: very low frequencies, which are known to represent fluctuations that occur slowly and are possible due to circadian rhythms, peripheral vasomotor and thermoregulatory influences; low frequencies, which are dependent on sympathetic tone due to the baroreceptor activity; high frequencies, which are indicative of vagal activity.

The HF power is considered a reliable marker of vagal control of the heart rate, whether the LF is indicative of sympathetic activity although it also is influenced by the parasympathetic nervous system. Therefore, a change in LF power cannot be assumed as an indicator of alterations in sympathetic cardiac control. The LF/HF ratio has been considered as an index of the sympathovagal modulation of the sinoatrial node. Therefore, LF/HF ratio indicates overall balance between SNS and PNS. High values indicate sympathetic activity dominance or reduced parasympathetic activity. Total power reflects overall variance of the signal, and thus, the autonomic activity where SNS activity is a primary contributor. As aforementioned, the most popular bands used to divide the signal are frequencies lower than 0.04 Hz, known as very low frequencies (VLF), frequencies between 0.04 Hz and 0.15 HZ, designated as low frequencies (LF) and frequencies between 0.15 Hz and 0.40 Hz, denoted as high frequencies (HF) (Medicore, n.d.; Schubert et al., 2009; Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

This frequency analysis can be verified in Figure 8 (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996). Frequency domain variables represent essentially the fluctuations in the balance of the autonomous nervous system, and their interpretations consider the balance between the SNS and the PNS. Very low frequencies reflect the activity of slow mechanisms of sympathetic function. Low frequencies reflect modulations of both the SNS and PNS. Generally is indicative of sympathetic activity. People with exaggerated sympathetic activity as occurs in disturbed patients, present stronger LF fluctuations that in healthy subjects. PNS influence is represented by low frequencies during deep breathing or very low respiration rate. LF values can be high when a subject is in relaxation. High frequencies reflect parasympathetic activity and also the respiratory phenomenon (heart rate higher during inhalation and lower during exhalation).

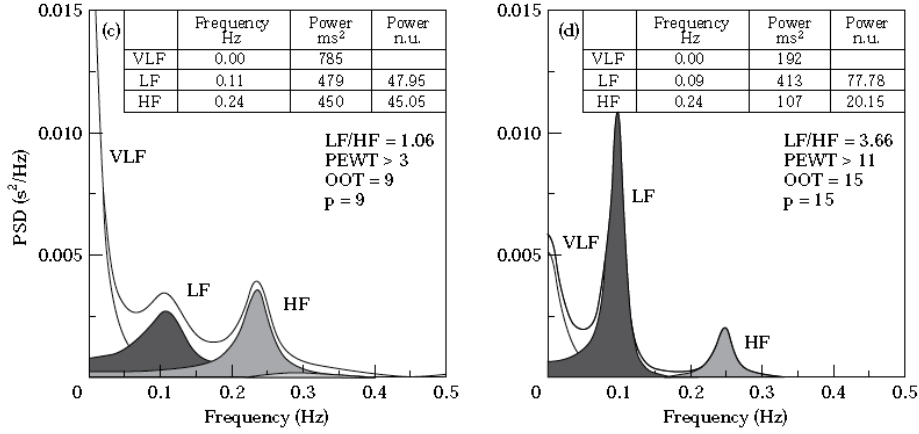


Figure 8: Frequency spectrum analysis (Task Force of the European Society of Cardiology the North American Society of Pacing Electrophysiology, 1996).

2.4.4. Time-Frequency Analysis

The spectral analysis assumes that the data series is stationary. However, statistical properties in both time- and frequency-domain of heart rate variability are known to vary over time (Dekker et al., 2000; Medcore, n.d.; Ramshur, 2010). The HRV analysis in the frequency domain yields information about how the IBI signal power is distributed in the frequency domain but it does not provide an insight into the temporal evolution of the spectrum. Statistics measured in a specific period of time interval of HRV probably differ from those measured in the next time interval and from those measured in the entire time provided by the sum of the two periods. The power spectral density does not reveal the frequency components in time and the instantaneous power does not show the time components in frequency, i.e., the information about how the frequency changes over time is lost.

In this analysis both time and frequency information can be combined to provide a deeper insight. Similarly to the frequency-domain analysis, time-frequency HRV analysis also quantifies VLF, LF, and HF related measures. The most common methods of time-frequency analysis used are the windowed Fourier transform, also called short-time Fourier transform, wavelet transforms, windowed periodograms and Wigner-Ville distribution.

The short-time Fourier transform STFT is a classical time-frequency transform to analyse time-related spectral characteristics. The usefulness of STFT is based on the data stationarity in the observed window and the selection of window length in STFT includes a trade-off between time and frequency resolutions. In this method, a complex window $w(t)$, centered around the time origin $t = 0$, is shifted in equal steps along the time axis, and the Fourier transform of the data segment of the signal within the time-window is computed (Chan et al., 2001). In short, the waveform is divided into a number of short segments, assumed as stationary, and the Fourier Transform is computed on a window of data that slides along the time axis.

$$\text{Continuous STFT } s(t) = STFT(t, f) = \int_{-\infty}^{+\infty} s(\tau)w(\tau - t)e^{-2\pi jf\tau} d\tau \quad (2.13)$$

$$\text{Discrete STFT } s(n) = STFT(m, f) = \sum_{n=0}^{N-1} s(n - m)w(n) e^{-2\pi jfn} \quad (2.14)$$

The short-time Fourier window can give a localized measure of the spectral density, although the choice of the window size might be determinant due to the trade-off between the time resolution and frequency resolution, since they are constant along the entire time-frequency plane. A wide time-window yields a poor time-resolution and a good frequency-

resolution, whereas a narrow time-window yields a good time resolution and a poor frequency-resolution. In the computation of the short-time Fourier transform, both the time and the frequency-resolution of the time-frequency plane are dependent on the chosen time-window since, as referred before, the time and frequency-resolutions are fixed throughout the entire time-frequency plane. A signal consisting of abrupt changes of short duration superimposed on slow components with long periods, can be analysed with a short time-window, which is optimal to discriminate the transient events, or it can be analysed with a long time-window, which in turn is great to discriminate the slow frequency components. However, with the short-time Fourier transform it cannot be analysed with both simultaneously (Steenis, 2002).

In contrast, the Wavelet Transform can be applied on non-stationary signals and uses a short window at high frequencies and a long window at low frequencies, overcoming the resolution problem. The Wavelet Transform decomposes the signal into a series of base functions denominated wavelets, which are expansions or contractions of a prototype wavelet that might be understood as band-pass filter. Therefore, the signal is expressed as a combination of wavelets and the signal decomposition provides wavelets coefficients. The signal can be reconstructed through the linear reconstruction of the wavelets functions, taking into account the coefficients. There are several types of Wavelet Transforms, which should be chosen according to the features of the signal to be processed. When the signal to be analysed is continuous the Continuous Wavelet Transform should be used, whereas the Discrete Wavelet Transform should be used when the signal is discrete (Chan et al., 2001).

$$WT(\tau, a) = \frac{1}{\sqrt{a}} \int s(t) \frac{1}{\sqrt{a}} \Psi^* \left[\frac{t - \tau}{a} \right] dt \quad (2.15)$$

τ represents the time delay whereas a represents the scale factor. As a smaller scale parameter is selected, the more contracted in time is the associated wavelet function, which means it can catch fast changing characteristics in the signal, giving better time resolution for high frequency components. The wavelet coefficients $WT(\tau, a)$ describe the correlation between the signal $s(t)$ and the wavelet at various translations and scales. For a larger scale parameter, the wavelet is wide enough to cover slow-varying components, which by the frequency resolution is good for low frequency components. In the case of the Discrete Wavelet Transform, the scaling and translations are done in a less smooth or more discrete manner. The dilation function is often represented as a tree of low and high pass filters (Chan et al., 2001). Ψ^* is the complex conjugate of the mother wavelet.

The windowed power spectrum is an extension of the basic power spectrum density, where the data is divided into consecutive segments or windows, which might be overlapped or not. The power spectrum density is then computed for each segment, using a nonparametric estimation. Plotting PSD values onto a two-dimensional plane with frequency and time as the vertical and horizontal axes, respectively, produces a spectrogram. The windowed periodogram can use other techniques to compute the PSD, as Burg periodogram and the windowed Lomb-Scargle periodogram (Ramshur, 2010). In the case of the windowed Burg periodogram, which corresponds to an autoregressive method, the entire data series is first resampled and then divided into segments of equal lengths. Finally, the PSD is computed for each segment using the Burg periodogram, which estimates the power spectral density by fitting an autoregressive model to the signal by minimizing the forward and backward prediction errors. Autoregressive spectral estimation methods differ from non-parametric methods since they do not estimate directly the power spectrum density but they attempt to model the data. In turn, the windowed Lomb-Scargle periodogram is computed similarly, although this method does not require the resampling step, using non-uniformly sampled data. The data is also divided into segments of equal lengths of time and the Lomb-Scargle Periodogram for each segment is computed, which estimates the frequency spectrum by performing a least squares fit of sinusoids to the data (Ramshur, 2010).

$$P_{LS}(f) = \frac{1}{2\sigma^2} \left(\frac{|\sum_{n=1}^N (s(t_n) - \bar{s}) \cos(2\pi f(t_n - \tau))|^2}{\sum_{n=1}^N \cos^2(2\pi f(t_n - \tau))} + \frac{|\sum_{n=1}^N (s(t_n) - \bar{s}) \sin(2\pi f(t_n - \tau))|^2}{\sum_{n=1}^N \sin^2(2\pi f(t_n - \tau))} \right) \quad (2.16)$$

In 2.16, \bar{s} represents the mean and σ^2 represents the variance of the time series, whereas the τ is a time frequency time delay that makes the periodogram insensitive to time shift.

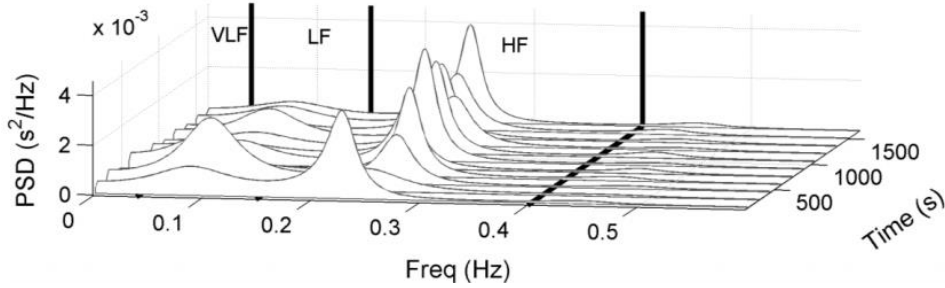


Figure 9: Example of a power spectrum density versus time (Ramshur, 2010).

The Wigner-Ville Distribution is capable of interpreting the time-varying characteristic of the signal without the compromise between time and frequency resolution. This methodology was the pioneer in the performance of time-frequency analysis. The spectrum of the Wigner-Ville transform is calculated through the following formula, where $s(t)$ represents the stochastic process to consider, $s^*(t)$ presents the complex conjugate, t is time, f is the frequency and τ the time delay (Chan et al., 2001; Ramshur, 2010; Steenis, 2002).

$$WVD(t, f) = \int s\left(t + \frac{\tau}{2}\right) s^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (2.17)$$

This distribution preserves the time and frequency translations. To calculate the spectrum in a specific time t , a multiplication between a signal portion immediately before and a signal portion immediately after is done, where both portions must be equal (Steenis, 2002). The Wigner-Ville distribution is interpreted as a power spectral density function that represents the power of the signal $x(t)$ for each point (t, f) of the time-frequency plane.

2.4.5. Non-Linear Analysis

Non-linear methods make use of chaos theory to describe non-linear properties of heart rate fluctuations, providing a more sensitive way to characterize the cardiovascular system behaviour (Clifford, 2002; Tarvainen, 2014).

One of the most used non-linear features is the Poincaré Plot. This method is a graphical representation of the correlation between consecutive inter-beat intervals and it is created by plotting all the inter-beat intervals in two dimensional system, where two adjacent intervals represent one point in the plot. The first interval represents the x-coordinate and the second interval represents the y-coordinate (Ramshur, 2010; Tarvainen, 2014). The shape of the plot is the essential feature and it commonly parameterized by fitting an ellipse to the plot. The standard deviation of the points perpendicular to the line described as SD1 (line of identity $y=x$) describes short-term variability, whereas the standard deviation of the points perpendicular to the line described as SD2 (line of identity $y=x$) describes long-term variability. The area of the ellipse represents the total variability (Medeiros, 2010; Ramshur, 2010; Tarvainen, 2014).

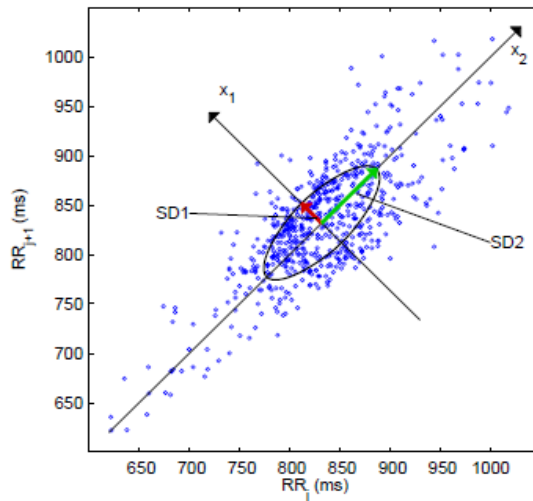


Figure 10: Poincaré Plot example (Tarvainen, 2014).

2.5. Heart Rate Applications

Heart rate data has a huge clinical value since it reflects the overall health status and physical condition of an individual. The continuous monitoring of heart rate allows performing a lifestyle assessment, through the analysis of heart rate variability. Its analysis enables detecting daily periods of stress and recovery, what caused the periods of stress and, consequently, it is possible to infer about the heart and autonomous nervous system health status. Along with the data provided by activity measurement, it can be evaluated if a specific heart rate value is abnormal or not, depending on the activity level being performed. Both activity and heart rate data can be analysed in order improve the user quality of life and help him to understand his current well-being, how daily habits and routines affect him, detect abnormalities such as heart rate increase due to psychological problems or exaggerated fears, excessive heart effort when doing normal daily activities such as climbing stairs, which denounces a weak physical status. It allows the identification of stress factors, and early warnings signs of conflict, overload, and burnout before more serious problems occur. It is important to underline that it is assumed that any physical activity has certain duration and during it cardiac activity is increased. It might be useful that the monitor user is provided with a diary to record some events during the day, such as challenging tasks, alcohol consumption or few hours of sleep.

The accelerometer data improves the ability of the analysis to recognize whether an increased activation level in the body is caused by mental stress or physical activity. This improves the accuracy especially with unfit people, with whom even slight activation can increase the heart rate significantly, and also with very fit people, who typically do not show much of a heart rate reaction to light exercise.

Continuous heart rate monitoring allows continuous supervising at any environment, without hospitalization or clinical appointments. Further, heart rate data can be used to assess physical capability (fitness level), assuming that the heart rate increasing is proportional to the physical effort and activity speed. This is especially important for athletes and sports practitioners, but has also interest for inactive, elderly people and cardiac rehabilitation patients. It has also interest for the detection of arrhythmias, as occurs in the case of high heart rate variability but low physical activity during the day.

The heart rate monitoring is very important to avoid excessive training components such as the frequency of exercise sessions, its durations and intensity, so the performance is not deteriorated and overtraining syndrome is not developed (Achten & Jeukendrup, 2003). The intensity of each exercise session is usually defined as the amount of energy expended per minute to perform a certain task, which currently available methods are not suitable for non-

laboratory occasions. Therefore, the heart rate is used to evaluate the intensity of exercise and, consequently, to determine the effect of a training session, using the heart rate reserve. The heart rate shows an almost linear relationship with the volume of oxygen at submaximal intensities, so it can be used to estimate the exercise intensity, although this relationship is individual and should be determined for each person (Achten & Jeukendrup, 2003; Altini, 2015).

Heart efficiency might also be evaluated. By definition, increasing the heart rate increases the cardiac output, because there is major number of stroke volumes of blood being released into the system. This occurs as long as the heart is given enough diastole time to fill the heart with the same volume. However, if the heart rate becomes excessively high, the heart may not have enough time to properly fill with blood between beats, which leads to a decreased cardiac output. This is not desirable for athletes in high physical effort because it means that the fatigue will overcome very soon. The heart is a muscle as any other and thus, it can be trained in order to increase its efficiency, which makes the heart rate useful to evaluate the progress of physical activity status.

Moreover, heart rate data is already used to estimate energy expenditure, along with the acceleration data. The incorporation of the heart rate data in activity-specific regression equation showed consistent improvements in energy expenditure estimation (Albinali et al., 2010; Altini et al., 2012; Ceesay et al., 1988; Ltd., 2012). Acceleration reflects a relation between motion and energy expenditure, whereas heart rate shows a strong correlation between energy expenditure and oxygen consumption. However, heart rate during an activity is specific to a person since it depends on the individual's cardiorespiratory fitness level. Therefore, the heart rate should be normalized according to each individual's fitness level, using normalization parameters at individual level (individual calibration). It is very important to realize that the heart rate is affected not only by the activities such as walking or running, but also by work or social interactions. Thus, the heart rate normalization for energy expenditure estimation must be recognized and interpreted according to the situation in which the activities are performed. Some studies have suggested algorithms for individual calibration of heart rate, motivated by the substantial inter-individual differences between heart rate and energy expenditure due to cardiorespiratory fitness level (Altini et al., 2013, 2015).

Estimating energy expenditure from heart rate is relatively cheap and easy to perform. When the heart rate is used to estimate the volume of oxygen or energy expenditure, a linear relationship between the heart rate and oxygen volume consumption is assumed. Although this is true for a large range of intensities, during very low and very high intensities the relationship becomes non-linear. At rest, slight movements can increase the heart rate, while energy expenditure remains almost the same. In addition, the estimation of energy expenditure from the heart rate is sport-specific. It has been well documented that the type of physical activity and posture can influence the relationship between heart rate and energy expenditure and can therefore affect the energy estimation (Achten & Jeukendrup, 2003; Altini, 2015). During intermittent exercise, the relationship between the heart rate and energy expenditure might not be as accurate. This occurs because the heart rate responds relatively slowly to changes in work effort. A sudden increase in work effort will not immediately result in heart rate increase that would be observed at that exercise intensity after body's adaptation. Similarly, when the work effort is decreased, the heart rate will remain elevated for some time and only gradually return to the heart rate value observed during steady-state conditions at this lower work intensity (Achten & Jeukendrup, 2003).

The heart rate and its variability has been greatly used for stress state detection. Stress consists in a psychological response to a certain physical, emotional and physical event that a person faces and it is known as 'fight-or-flight' or acute stress. Physiologically, it consists in the secretion of hormones such as adrenaline and cortisol into the body's blood stream (Alexandratos, 2014). These hormones intensify the individual's concentration, increase alertness and provide extra energy. Despite the fact that stress alert the person to eventual dangerous events, long periods of stress can be very harmful for the health as and it can lead

to various conditions like cardiovascular disease, obesity or depression and anxiety disorders (Alexandratos, 2014). Despite the complexity of measuring the stress level directly, it is quite possible to annotate stressful events and relate them to physiological signal changes that can be easily measured, such as the heart rate or electrodermal activity (Alexandratos, 2014; Liu & Ulrich, 2014). Thus, it is important to measure physiological signals accurately anytime and anywhere. There is a balance between the two branches of the autonomous nervous system under normal situations, placing the body in a state of homeostasis. However, under a state of mental stress, this balance is altered and several physical changes might occur in the human body. These include increased heart rate, faster breathing and increased sweating due to the higher activity of sympathetic branch. Therefore, HRV can be used to detect the change in system balance as measures of mental activity and mental stress. During stress conditions, it is expected that SDNN, RMSSD, pNN50, Total Power, HFnorm decrease and that LFnorm and LF/HF increase (Alexandratos, 2014; Dennis et al., 2014; Yang et al., 2008).

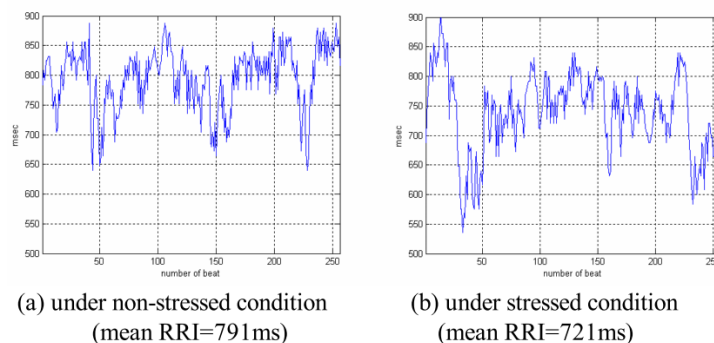


Figure 11: Tachograms under non-stress situation and under stress (Yang et al., 2008).

As referred, several studies have reported reduced heart rate variability in patients with anxiety disorders and chronic or post-traumatic stress, due to the autonomic nervous system alterations. This represents a higher risk of developing a cardiovascular disease (Liu & Ulrich, 2014; Yang et al., 2008). Therefore, a real-time personal stress monitor can be a powerful tool by providing meaningful information about the user stress level at anytime and anywhere. A real-time system that monitors the user's heart, suitable for stress state detection, arrhythmia detection and heart rhythm classification was developed (Pierleoni et al., 2014). This system includes a Zephyr HxM-BT device and a smartphone, where the data packages are transmitted at a frequency of 1 Hz to the smartphone. The stress state detection, due to emotional stress occurrence, is based on the heart rate variability analysis, through the computation of time-domain parameters over an appropriate data acquisition window, including the SDNN, RMSSD, pNN50 and average heart rate. The window used has a standard duration of 5 minutes. According to (Andreoli et al., 2010), the stress state was reached every time at least three of the four values exceeded the correspondent established thresholds (Yang et al., 2008). This analysis is possible since the heart rate monitor acquires continuously the cardiac activity, which means that all of the heart beats are included in the algorithm.

Table 1: Time-Domain HRV parameters thresholds for stress state detection (5 minutes recording) (Yang et al., 2008).

HRV feature	Threshold
Mean HR	higher than 85 BPM
pNN50	lower than 7%
SDNN	lower than 55 msec
RMSSD	lower than 45 msec

2.6. Activity Measurement

Physical activity is any body movement promoted by the skeletal muscles, which results in energy expenditure (Westerterp, 2013), and it can be measured through an inertial measurement unit (IMU) that includes sensors such as accelerometers, gyroscopes and magnetometers. Physical activity can be characterized by its duration, frequency and intensity.

Activity monitoring is deeply related with motion-aware systems that classify the activity being performed by an individual and compute valuable features that are representative of the activity level and intensity. Accelerometers are the most broadly used sensor to activity monitoring. They can be uni-axial if they can measure acceleration in just one direction, or tri-axial, if they measure movement acceleration, on vertical, anterior-posterior and lateral-medial axes, in m/s^2 in SI (International System). They are small and low energy consumption sensors and allows distinguishing between a continuous and intermittent activity and also its frequency. Through their data it is possible to extract velocity and distance values. Velocity can be calculated through the integral over time of the acceleration and, in turn, distance is defined as the integral over time of the velocity. However, practically, the acceleration integration over time to obtain velocity brings a considerable error to the measure. Other option consists in use the number of steps and multiply them by the step's length, and posteriorly divide the result by the time's window (Aguiar et al., 2014). Magnetometers measure the magnetic field in the X, Y and Z-axes, mostly used to assist calibration against orientation guidance and calculate an absolute direction, relative to the earth coordinate system (Figueira, 2015). In turn, gyroscopes measure angular velocities of an object in rad/s or degrees/s, along each one of the three axes, being used to estimate the orientation, based on the principles of the conservation of momentum.

Activity monitoring performed by smartphones and smartwatches use essentially data from accelerometers and gyroscopes to identify activity patterns and daily activities such as sitting, lying, walking and general transitions (Cerqueira da Silva, 2013). Furthermore, barometers have been recently included in smartphones, in order to help the GPS sensor to correct the altitude measurement. Barometers measure the atmospheric pressure from its height, which changes with the distance above or below the sea level. This way, smartphones can track elevation gained or measure stairs climbed, improving activities recognition.

Activity recognition is considered a machine learning problem, using techniques based on probabilistic and statistical arguments. This process begins with gathering the raw data through motion sensors, followed by its pre-processing in order to remove artefacts and noise, where it is segmented into its components. Then, segments of long stillness or interchanging between movements are excluded. Once the components are representative of the physical activity performed, features are extracted. These features are measurable properties that enable the characterization of the movement and they must be selected and analysed in order to extract relevant and sufficient information for the classification step. However, its number should not be too large in order to the data not became scarce relatively to the features dimensionality and, therefore, not increasing exaggeratedly the computational cost. The data can be analysed in time or frequency domain, where the last one can be obtained through the application of mathematical operator such as transforms, as for the example the Fourier Transform. The algorithm, based on the extracted features, performs the classification of the segments in order to identify activities. There are several machine learning approaches that might be employed for pattern recognition. The algorithms may be supervised or non-supervised, although supervised are the most broadly used in the field of activity monitoring (Figueira, 2015). The supervised algorithms include a training phase and a test phase. The training phase include the classifier selection (Neural Networks, Decision Trees, Support Vector Machine, Bayesian, K-Nearest Neighbours, for example), and its training using a labelled dataset, i.e., objects of data with known class and features, in order to create a model to

classify unlabelled objects of data. The test phase is used to evaluate the algorithm performance, through confusion matrices, measurement of accuracy, precision and F-Measure.



Figure 12: Schematic representation of machine learning process.

Current activity measurements include features such as distance walked, speed, number of steps, calorie consumption and hours of sleep. Speed is a metric that is usually defined by the distance performed during a specific interval and characterize the activity's intensity or workload. Energy expenditure is an important metric used to evaluate the quality and progress of individual training and is frequently assessed along with energy intake for weight management purposes. The assessment of this feature in real life has become very important because it might help to identify inactive lifestyles. It can be estimated using METs (metabolic equivalents) values for the quantification of the extent of activity intensity, using linear regression (Carneiro et al., 2015). The accelerations are converted into "activity counts" per defined period of time, which are then converted to METS. Ryu et al (Ryu et al., 2008) presented also an approach to estimate the METS, depending on the activity recognition and the walking or running speed. Other methods were proposed based on linear regression derived from the data collected by the motion sensors, one using the speed and the other using the feature root mean square of the magnitude of the accelerometer signal (Carneiro et al., 2015).

This data has huge applicability in the detection of dangerous situation in a person's lifestyle, especially for elderly and disabled people, assessment of individual's degree of functional ability and also for active and healthy lifestyle promotion (Machado, 2013). Therefore, these data analysis might be enriched by heart rate data and its variability, allowing to make a more reliable and valuable analysis.

2.7. Heart Rate and Activity Monitoring

2.7.1. Physical Activities and their heart rate variability patterns

Physiological signals present a nonlinear behaviour. The heart rate unexpectedly changes depending on the exercise's intensity and its variation also differs among individuals, depending on the physical condition of each individual. A low heart rate variability and/or increased heart rate usually indicates alterations of autonomic activity characterized by sympathetic nervous system activity and/or vagal withdrawal. Parasympathetic nervous system which regulates the vagal tone is dominant during relaxed state and sleeping activity. In turn, vagal activity decreases during exercise and is eventually absent, while sympathetic activity dominates. Sympathetic nervous system can also be triggered by anxiety, stress, depression and fatigue. Since sympathetic nervous system could be triggered due to either physical or mental factors, movement state information should be incorporated for a more reliable and significant analysis (Bidargaddi et al., 2008). Moreover, clinical significance of movement activity information can be assessed by interpreting the heart rate and its variability.

An active state is characterized by high heart rate values and low heart rate variability, due to increased sympathetic activity caused by exercise (Bidargaddi et al., 2008). The presence of high heart rate values and low heart rate variability in an inactive state indicates that the sympathetic activity could be triggered by stress and fatigue. Therefore, activity

information plays a critical role in differentiating these two possibilities. Increased parasympathetic activity leading to relaxed state in inactive state is characterized by high heart rate variability and low heart rate values. However, low heart rate values and heart rate variability can also be observed in an inactive state, which indicates higher sympathetic activity but the presence of low heart rate values at the same time (Bidargaddi et al., 2008). Combining heart rate values, heart rate variability and movement activity data allows to discriminate between normal and abnormal physiological state and autonomic function (Bidargaddi et al., 2008).

The increase in heart rate during exercise is the main mechanism by which cardiac output is increased to meet the demands of working skeletal muscle. During early exercise, heart rate rises because of a central withdrawal of parasympathetic tone, until it achieves a steady state that corresponds to the optimal heart rate value for meeting the circulatory demands at that specific work rate (Lauer, 2001). The heart rate fall that occurs immediately after exercise, or heart rate recovery, is thought to be due to rapid central vagal reactivation. During the recovery, heart rate decreases gradually but it does not achieve pre-exercise values within several minutes after exercise. The rate of decrease in heart beat frequency and the recovery time duration after intense exercise are commonly used as indicators of cardiovascular fitness level (Lauer, 2001). The combination between physical activity monitoring and heart rate analysis is important for physical activity applications as an additional information of the human physical behaviour during the day. It could also be used to trigger alarms in case of abnormal heart rate values that have a negative impact on the person's health. The combination between activity and heart rate is also important to perceive some heart rate patterns that are influenced by physical activity.

Other works have been performed to study the heart rate usefulness to better characterize and distinguish different activities. A real-time algorithm for automatic recognition of not only physical activities, but also their intensities, using five tri-axial wireless accelerometers and a wireless heart rate monitor was presented (Emmanuel Munguia Tapia et al., 2007). The heart rate is a useful measure since it correlates with energy expenditure for aerobic exercise. However, alone its value provides little information about the activity type being performed, and it is influenced by other factors such as emotional states, ambient temperature, and fitness level. In this study, they concluded that the heart rate has little discrimination power, even when normalized.

Moreover, the possibility of discriminating between normal and abnormal physiological state based on heart rate, its variability and movement activity information was studied (Bidargaddi et al., 2008). By applying k-means clustering on heart rate, heart rate variability and movement information obtained from cardiac patients, three different clusters were obtained in inactive state and one cluster in active state. Two of the clusters that were found in inactive state were characterized by high heart rate values and low heart rate variability, and both low heart rate variability and heart rate values, which could be inferred as pathological with abnormal autonomic function. Furthermore, activity information was significant in differentiating between the normal cluster found in active state and the abnormal cluster found in inactive state, both with low heart rate variability. In this study, it was found out that the activity information must be taken into account while interpreting heart rate values and its variability. As observed in Figure 13, the clusters obtained can be well characterized. Cluster 1 falls in the inactive state and presents low heart rate values and high HRV, which is a characteristic feature of relaxed state, induced by high parasympathetic activity. Cluster 2, which again falls in the inactive zone, has both low heart rate values and HRV, which indicates increased sympathetic activity. In this case, since the heart rate values are low, further clinical investigation and analysis is needed. Clusters 3 and 4 have similar characteristic features of high heart rate values and low HRV. High heart rate values and reduced HRV is characteristic of high sympathetic activity. As above mentioned, sympathetic activity could be induced by physical activity or due to stress, fatigue, depression or other

psychological factors. The sympathetic activity in Cluster 3 is activated by physical activity since it belongs to an active state. However, the Cluster 4 belongs to an inactive state, which could indicate the presence of stress and fatigue due to the high sympathetic activity. Therefore, movement activity information is essential to differentiate between these two situations.

Further, a system that combines acceleration data with vital signs to achieve highly accurate activity recognition was developed (Lara et al., 2012). This system recognizes five activities: walking, running, sitting, ascending, and descending stairs. After evaluating eight different classifiers and three different time window sizes, the results showed an overall accuracy of 95.7%, which is higher than other approaches under similar conditions, indicating that vital signs are useful to discriminate between certain activities.

Finally, the mean heart rate proved to be a determinant feature for activity classification (Maguire & Frisby, 2009). In this study classification accuracy increased about 5.28% and it was possible to correctly identifying 6 common activities when using combined heart and accelerometer data.

As above mentioned, there are heart rate variability patterns and heart rate values ranges that might distinguish between rest activities and dynamic activities. Therefore, applying heart rate variability analysis to the heart rate signal should help on activity distinction.

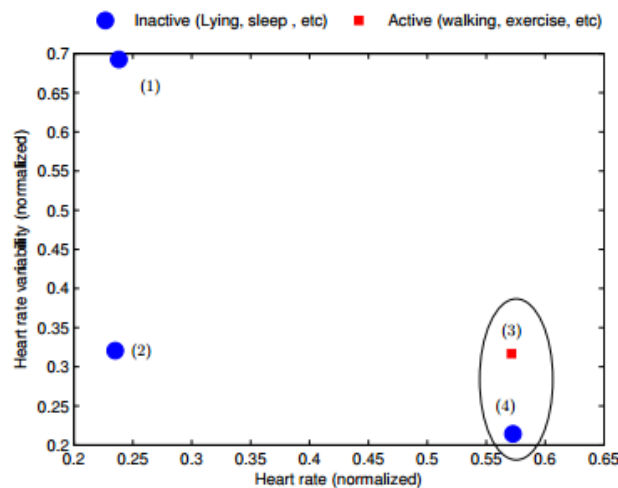


Figure 13: Different Activity clusters obtained in (Bidargaddi et al., 2008).

2.7.2. Heart Rate, Speed and Activity Relationship

Moreover, it is known that the heart rate is closely related to the rate of change of oxygen uptake (Bodner & Rhodes, 2000; Vachon et al., 1999). As exercise intensity increases so does the rate of change of oxygen uptake. This rate of increase is determined by the rate at which oxygen is transported to the tissues, the blood's oxygen carrying capacity and the amount of oxygen extracted from the blood. Therefore, the heart rate, and the cardiac output, increase in a rectilinear relationship with the increasing workload, until the maximum exercise performance is reached. The myocardial cells are capable of contracting at over 300 BPM but the rate of 210 BPM is rarely exceeded because a faster heart rate would not be beneficial, since there would be inadequate time for ventricular filling (Plowman & Smith, 2013). Hence, the heart would become inefficient.

A correlation and a linear relationship is verified between the activity workload, or speed, and the heart rate, because the oxygen demand linearly increases with the workload until the anaerobic deflection point is reached. The heart rate, which is the limiting factor of these three variables, increases so that oxygen can be delivered to the body. When the heart rate reaches its maximum, the volume of oxygen that can be consumed by the body also reaches

its maximum. This is called VO_2 max and, at this point the volume of oxygen consumed is equal to the volume of CO_2 exhaled. Moreover, there can be no further increase in exercise intensity, heart rate, or VO_2 max. When the subject starts to produce energy anaerobically, it is said that the Conconi point, or heart rate deflection point, was achieved. Moreover, a plateau is reached due to proximity to the maximum heart rate (Vachon et al., 1999). The heart rate deflection point evidences the decrease in the slope of the linear relationship between heart rate and physical effort. This is visually manifested as a curvilinear response in the graphic power-heart rate (Figure 14) and it is usually observed in the range of 88 to 94% of maximum heart rate that the individual can achieve (Bodner & Rhodes, 2000).

An increase of the heart rate value due to a decrease in vagal outflow is an immediate response of the cardiovascular system to exercise. This increase is followed by an increase in sympathetic outflow to the heart and systemic blood vessels. During dynamic exercise, heart rate increases linearly with workload and VO_2 . But during low intensity levels of exercise and at a constant work rate, heart rate will reach steady state within several minutes. Further, as the workload increases, the time necessary for the heart rate to stabilize will progressively lengthen. Under submaximal load the heart rate increases linearly with the increase of the exercise intensity, which is usually defined as the speed, if the activity performed is walking, running or cycling, and with the oxygen uptake.

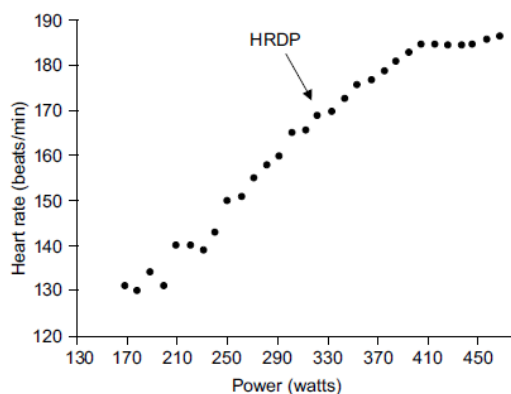


Figure 14: Relationship between Speed and heart rate (Bodner & Rhodes, 2000).

2.7.3. Energy Expenditure and heart rate relationship

Regarding the relationship between energy expenditure and heart rate, there are some concepts that should be studied. Energy Expenditure (EE) consists in the sum of internal heat produced as basal metabolic rate and thermic effect of nutrients processing, and also external work, measured by physical activity level (Altini, 2015). It is usually estimated through indirect calorimetry. In this method, the oxygen consumption and carbon dioxide production are monitored for a certain period of time.

There is a linear relationship between heart rate and energy expenditure that allows to detect changes in physical effort. However, studies have shown that it is difficult to monitor physical activity and EE using only heart rate data (E M Tapia, 2008). The accuracy of such monitoring increases when individual calibration is performed establishing a relationship between the heart rate and energy expenditure equations, because different fitness levels between humans lead to different heart rate values for the same activity level and also because variation occurs due to emotional states or stress (Stankevičius & Marozas, 2013).

Energy expenditure is the most common parameter used to quantify physical activity, and it is typically estimated using acceleration and heart rate sensors. Acceleration reflects a relation between motion and EE, while the heart rate shows a strong correlation with EE via the relation of EE and oxygen consumption. However, the heart rate value during an activity is specific to a person since it depends on the individual's cardiorespiratory fitness level (CRF).

Therefore, EE estimation based on heart rate typically requires individual calibration, since an individual with higher CRF will have a lower heart rate during exercise, compared to an individual with low CRF. CRF is defined as the ability of the circulatory and respiratory systems to satisfy the body's need by supplying oxygen during sustained physical activity, and it is among the most important determinants of health and wellbeing (Altini, 2015).

Motion sensors were the first wearable sensors to be employed in order to estimate energy expenditure. Using accelerometers, researchers tried to quantify physical activity and EE in different modalities, by exploiting the relation between whole body motion as measured by accelerometers and EE, and then, by using accelerometers to distinguish activity types and then develop activity specific EE models (Altini, 2015). Several methods have been studied recently related to assign specific MET values to each one of the group of activities and use anthropometric features or other static features to personalize the activity-specific models for different individuals or groups of individuals or apply a regression equation for each activity classified extending counts-based approaches to multiple group of activities. The regression models typically use accelerometer features, heart rate and anthropometric characteristics as independent variables (Altini, 2015). Estimating the oxygen volume and subsequently energy expenditure from heart rate presents some advantages, compared to established metabolic equations, since the heart rate changes during exercise reflect the volume of oxygen whereas metabolic equations assume a fixed expenditure rate for a specific intensity.

For the estimation to be specific of each individual, the relationship between the oxygen volume and heart rate should be determined. Although currently there are some studies regarding individual calibration methods without performing a test in laboratory environments, but using the accelerometer and heart rate data itself do determine a normalization factor (Altini et al., 2014, 2016), the usual methodology requires the individual to complete a progressive exercise test in a laboratory environment. During the test, the heart rate is simultaneously measured along with indirect calorimetry to estimate energy expenditure. It is required that the maximal oxygen volume and resting oxygen volume are determined, along with the resting and maximal heart rate. Posteriorly, the volume of oxygen per beat above the rest should be determined, dividing the $\dot{V}O_2$ reserve by the Heart Rate reserve to yield a $\dot{V}O_2$ -pulse coefficient, and multiplied by the number of heart beats above rest, which indicates of exercise's intensity, to derive the oxygen volume per minute. Finally, it is added the oxygen volume at rest, the result is multiplied by the ratio of kcal per one litter of oxygen, and then multiplied by the total minutes of the exercise with the same intensity (Pettitt et al., 2007).

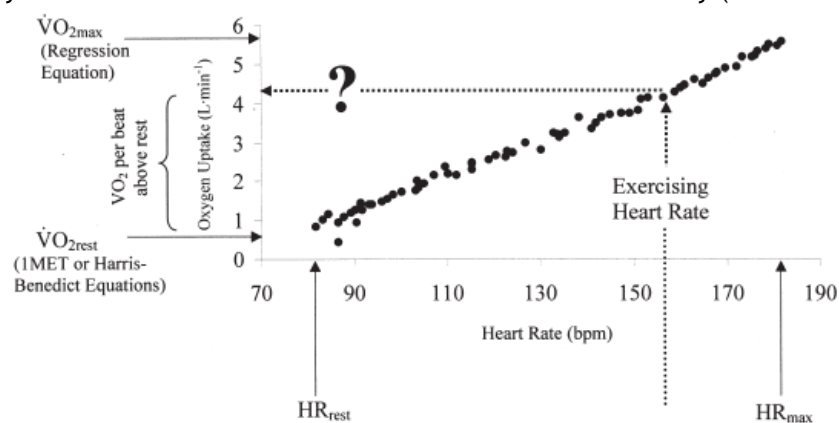


Figure 15: Energy Expenditure estimation model (Pettitt et al., 2007).

Furthermore, heart rate monitors have proved to be accurate for moderate to vigorous activities. In turn, during lower intensity activities, other factors might be determinant on the heart rate and independent of any change in oxygen uptake. These factors include stress, emotions, caffeine intake, ambient temperature or even illness (Andre & Wolf, 2007).

Heart rate monitoring provides an objective and effective method to monitor the

intensity, duration, and frequency of daily activities using a physiological parameter that represents the exercise intensity and cardiovascular adaptation to it. The heart rate reflects relative stress placed on the cardiopulmonary system during physical activity. However, it can also be elevated by emotions, stress and mental activity. Hence, the simultaneous use of the heart rate value and motion sensors data provides a more accurate prediction of energy expenditure, compared with the use of heart rate or motion sensors independently.

As it can be observed in Figure 16, the heart rate is as higher as the physical effort required by the physical activity performed, which is confirmed by the energy expenditure per minute in each activity type. In general, the energy expenditure is as higher as the heart rate value in each activity, due to the also higher oxygen intake demanding required by high physical effort. The heart rate is highly correlated with energy expenditure during moderate and vigorous activities such as walking, running and biking. But during lying or sedentary activities, this relationship is weaker.

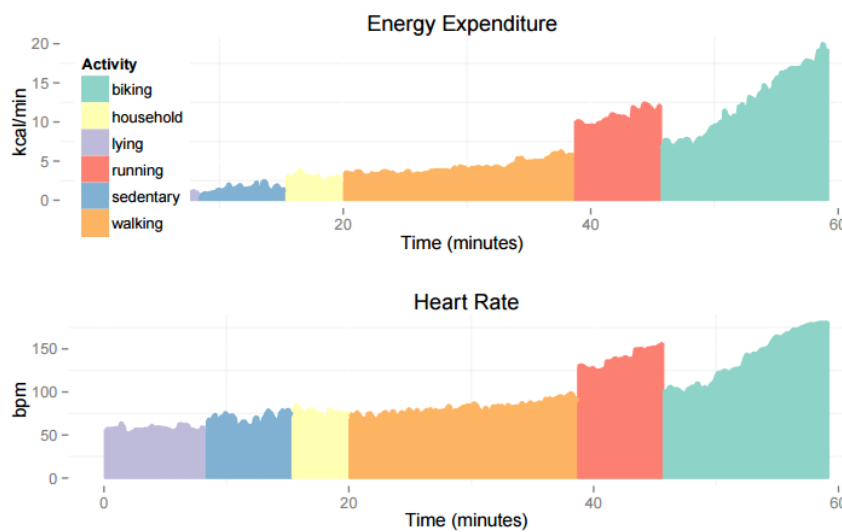


Figure 16: Relationship between heart rate and different physical activities (Altini, 2015).

2.8. Measurement and Monitoring Systems

2.8.1. Heart Rate Monitors

Heart rate monitors are monitoring devices that allow measuring heart rate in real time or recording the heart rate for later analysis. They have a huge clinical applicability, since they enable to infer about the clinical state of the person. Furthermore, they also have an immeasurable impact on sports field, because they provide immediate feedback on how hard the person is working out so that adjustments can be made to get the greatest benefit from exercising. Since the heart rate is a useful indicator of physiological adaptation and intensity of effort, its monitoring is very important for cardiovascular fitness assessment and training programs. Nowadays there are plenty of devices that measure the heart rate, from typical ECG to current wearables such as smart vest or smartwatches. These devices differ essentially by the heart rate measurement mechanism: the ECG, Holter monitors and chest straps rely on biopotential mechanism, smartwatches and bracelets rely on photoplethysmography or bioimpedance mechanisms, oximeters rely on photoplethysmography mechanisms and blood pressure monitors rely on pressure method.

The electrocardiograph (ECG) and Holter monitoring devices have been demonstrated to be accurate, but not feasible for use in field settings due to cost, size and complexity of operation (Jain & Tiwari, 2014). The ECG is the current gold standard approach for heart rate measuring, but requires a hospital visit, sticky gels and uncomfortable electrodes attached to

the skin. In turn, portable heart rate monitors emerged as portable ECG like Holter, wireless chest straps that send data to a monitor worn on the wrist, ECG electrodes built-in in vests, pulse monitors worn on the wrist such as watches or bracelets, and even worn on the ear as earbuds. The Holter monitor uses biopotential electrodes incorporated in gel patches that are placed on the chest.

Nowadays, smart vests, smartwatches and bracelets, besides the heart monitoring, also include activity tracking, so both data can be combined to do a more reliable clinical/fitness analysis. However, studies have demonstrated that wrist-based heart rate monitoring is not as reliable as the ECG or even the chest straps (Parak & Korhonen, 2014a; Richmond, 2015).

The chest straps that connect to sports-watch models allow the continuous tracking of heart rate by sending the information to a monitor worn on the wrist. It is advisable to moisture the electrodes placed on the chest strap in order to conduct the signal. Chest-strap heart rate monitors can be a burden to participants because of the constriction required across the chest to maintain good skin contact. Electrode-based heart monitors are difficult to wear, as placement, skin treatment, and irritation can be significant issues and detriments to long-term wear. Current sports watches and fitness trackers provide target zones in order to the user control physical effort and can also include other activity features such as calorie counters, speed and distance monitors, lap counters, recovery heart rate and time spent in the target zone. Gym equipment such as treadmills, elliptical machines, stationary bikes and stair climbers are also equipped with pulse monitors based on biopotential sensors, however they are not so accurate. Everyone, from at risk heart people, injury-rehabilitation patients, athletes, sports amateurs and healthy life style people can benefit from continuous heart rate monitoring. Heart patients can prevent potential life-threatening heart attacks by using heart rate monitors to protect themselves.

Heart rate sensors included by the majority of smartwatches work via photoplethysmography, where each signal's pulse peak can be interpreted as an R wave with good accuracy. However, they present some limitations such as the need to recharge the battery, limiting the potential monitoring time. Furthermore, individual skin's characteristics such as the pigmentation, existence of tattoos, temperature, variations in skin pressure or even hairiness, allied to fluctuations in oxygen levels or movement artefacts can all affect readings that are performed via PPG (Carpenter & Frontera, 2016). Current smartwatches, although they represent a great tool for heart rate monitoring, they do not enable arrhythmia detection yet, since they do not incorporate ECG features such as P wave and P-R interval, which are important features to detect arrhythmias (Carpenter & Frontera, 2016). Further, they do not provide, for third parties applications, the all beat-a-beat heart rate signal, but the heart rate at a specific time, which does not provide a constant rhythm analysis

The market for consumer wearable devices is popular and continues to grow. Besides this, these gadgets presents a great potential utility to be used by cardiovascular patients (Hickey & Freedson, 2016). Wearable devices may provide opportunities to overcome limitations of self-reported activity and also provide a driver for sedentary behaviour change. These devices can be used to track physical activity behaviour as an outcome after different treatments and also to be used as encouragement to be more active and prevent cardiovascular diseases. However, it must be determined which features of the devices are the most effective in changing the lifestyle behaviour. These wearables present a huge potential to improve the healthcare system and treatment providers. For instance, it was reported the use of Fitbit Charge HR to determine the onset time of a patient's arrhythmia and guide his emergency department management (Rudner et al., 2016). Although they cannot identify arrhythmias yet but only the pulse rate, they can detect heart rate abnormalities, which in turn can guide the clinician in designing further evaluation strategies using more sophisticated instrumentation. Hence, they are devices with a great potential, which in the future will be highly accurate to behave as a medical helping tool and the current limitations will be outdated and, taking into account the technology development speed, very probably with the possibility to perform non-

invasive detection of cardiac arrhythmias (Carpenter & Frontera, 2016).

The heart rate devices differ on the heart rate measurement method used, included activity and heart rate variability features and also on the easiness and using comfort. In a previous work, the Dissertation Preparation Monography, these devices were already analysed in detail, taking into account their main attributes and capabilities. Hence, the main products that are available in the market can be consulted in that work.

2.8.2. Heart Rate and Activity Monitoring Systems

Accelerometers and heart rate monitors have been combined to improve the accuracy and precision with which Energy Expenditure can be predicted, measure of physical fitness by combining the heart rate values with body movement. Nowadays, the energy expenditure estimation is a very valued feature by the consumers when they attempt to buy a wearable device for activity monitoring. However, the models included in these devices might not be as reliable as desirable. The validity of total energy expenditure estimates of several wearable devices, against the gold standard metabolic chamber method and doubly labelled water (DLW) methods, was assessed through an accuracy test, with 19 healthy volunteers (Murakami et al., 2016). The total energy expenditure was measured using 12 different wearable devices, which differ in the energy estimation method, depending if they include heart rate sensor or not, and also the wearing method. The results showed that the measurements from the devices, for a standardized day, were higher than the metabolic chamber but blower than the values provided by the DLW. In short, the wearable devices tested were able to rank daily total energy expenditure between individuals, but absolute values differed widely among devices and varied significantly from the gold standard measures. Furthermore, they all underestimated total energy expenditure and the large variance observed among the values measured by the devices may be associated with posture detection and also periods of not wearing the devices. With this study it was concluded that majority of wearable devices do not produce a valid measure of total energy expenditure.

Nevertheless, heart rate and activity monitoring features are currently combined in several systems that are available on the market. These sensor fusion systems present advantages when compared to activity monitoring systems. For instance, low motion might indicate rest or it might indicate physical activity using a part of the body far from the accelerometer. In turn, moderate motion might indicate physical activity or it might indicate riding in a moving vehicle on a rough road. By adding another variable, such as heart rate, these different contexts can be disambiguated, since subjects at rest will typically have lower heart rates than those performing low-motion physical activity. By taking advantage of the science of data fusion, multi-sensor systems typically achieve higher accuracies than single sensor systems while typically keeping overall costs moderate. Further, the heart rate logging might be used for different purposes, mainly for clinical or fitness purposes, although they are related. Heart rate data from biopotential sensors, characteristics of the ECG, existent in smart vests and Holter monitor, are currently used for clinical purposes, especially for arrhythmia's detection and cardiac rehabilitation.

Firstbeat¹, a Finnish company, has developed a strong tool for heart rate analysis that enables the creation of a user's physiology model, in order to improve well-being (Wellness Service) or training effect (Sports Service), depending on the purpose. In both cases, Firstbeat Bodyguard 2² records the data. In the Sports Service, the tool is suitable for athletes and coaches, providing tools for optimizing training load and recovery. It detects VO₂max from a freely performed workout, based on the heart rate response and external workload, with high accuracy, in this case walking at a considerable speed. This parameter represents the maximum

¹ <http://www.firstbeat.com/>

² <http://shop.firstbeat.com/all-products/bodyguard.html#.V2qWWLgrLIU>

volume of oxygen the body can consume in one minute, and it is an important measure of fitness condition. Firstbeat's VO_2 max algorithm uses real life running, walking or cycling data, analysing the relationship between the heart rate and the speed. It can be used to evaluate fitness improvement over time and compare results with age-gender reference. The exercise impact on the body is also estimated, based on user profile, duration and intensity of the workout. Anaerobic threshold is the highest workload at which the body is able to achieve a steady-state condition, so the lactic acid accumulation and removal are in equilibrium. This threshold is estimated through the relation between heart rate and speed and heart rate variability as well, using sophisticated data modelling methods. Energy expenditure is calculated through heart rate data, respiration rate and VO_2 , which, in turn, is derived from heart rate. Daily performance, recovery time are also calculated to optimize training. In the Wellness Service, the tool is used for lifestyle assessment and thus, measures daily periods of stress and recovery, creating a detailed report. This allows avoiding exaggerated stress and its negative consequences on health, by detecting its causes, and promotes the user to find a balance between stressful and relaxing activities. It analyses periods of stress and recovery, hours of sleep, hours of physical activity and energy expenditure. These assessments are done for a 3 days period, with previous personal information from a pre-questionnaire. Currently, daily basis heart rate devices such as smartwatches and bracelets enable continuous heart rate measurement and, thus, heart rate logging. They usually include an app where the user is allowed to see the heart rate logging throughout the day and the time in each heart rate zone, along with other activity measures like distance, speed, steps walked, oxygen consumption, calories burnt and even sleep patterns. These data is analysed for well-being and fitness purposes. Firstbeat tool has been adopted by smartwatches and bracelets brands (Sony, Suunto, Garmin and Samsung) so the users can improve their fitness experience, well-being and find a balance between stress and recovery. However, the main focus is on fitness improvement.

Within the PAMAP³ project, a Mobile and unobtrusive platform that enables the accurate monitoring of physical activities in daily life, which is posteriorly integrated into a healthcare system that supports out-of-hospital services, was developed (Reiss et al., 2012). The main purpose of this mobile platform is the monitoring of the user's daily activities by collecting and processing sensory data, and also giving instant feedback to the user. The main goals of an aerobic activity monitoring system consist in analysing what activity the user performed, for how long and with what intensity. For that, the system presents three IMUs, placed on the hand, chest and shoe, and a chest strap heart rate monitor, which can be quite uncomfortable for a daily use.

This data enables the detection of daily activities such as sitting/standing, lying, cycling, run, walking or Nordic walking and "other" activities, that cover all the other transition actions between the ones with interest. The physical effort associated to each activity is primarily established, categorizing each one as light, moderate or vigorous. Therefore, the total time spent doing activities with a certain intensity is the time spent doing the activities labelled with that same intensity. Due to the available heart rate information, the mobile application allows defining a specific heart rate value, which if it is exceeded, an alarm is initiated. Besides this, it provides a summary of how much time the user spent in different heart rate zones, taking into account the normalization of the heart rate according to the rest and maximum values, i.e., an activity summary with the detailed activities performed and the associated physical effort. These summaries can be observed in Figure 17.

³ <http://www.pamap.org/index.html>

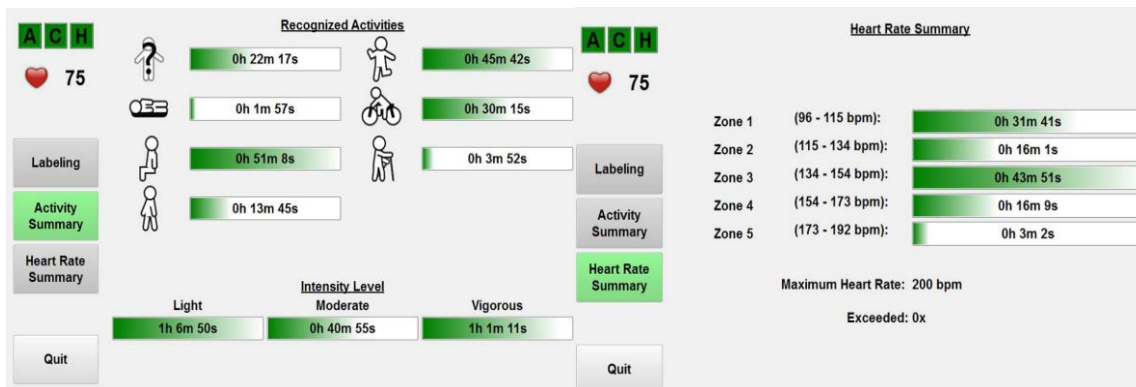


Figure 17: Example of the heart rate summary provided by the application (Reiss et al., 2012).

Heart rate and activity monitoring has led to technology evolution. Recently, Bosch Sensortec⁴ launched two sensor hubs to collect vital signals based on heart rate and motion evaluation for fitness and well-being applications. These allow integrating data from different sensors and process them, which promotes battery consumption and improves performance. A third party company, the Firstbeat Company, provides the analytic software on-chip. The two chips, BHV250 and BHV160, integrate 3 and 6-axis inertial MEMS sensors, accelerometer, and the BHV160 also includes a gyroscope. The devices are Android-Wear compatible and they were specifically designed for sensor based always-on applications in wearable devices such as smartwatches, fitness wristbands, earphones, smart shoes and textiles. Hence, they are an ideal all-in-one-solution for sensor based applications such as fitness level and training effect analysis, sleep quality and body stress, tracking of physical activity and calorie consumption based on Firstbeat's powerful vital analytics algorithms, and also sensor features like activity and gesture recognition. The system can be used to measure relevant body parameters in e-health and telemedicine monitoring projects, where healthcare providers can monitor the progress of their patients through an e-health portal.

The ECG Necklace⁵ device is a smart biomedical sensor that measures the ECG signal and also activity parameters from the human body, through two leads and a small device. This can analyse the signals in real time and transmit them to a user interface wirelessly. This technology is specifically designed for healthcare and research applications, measure relevant body parameters in e-health and telemedicine monitoring projects. The data provided by the system can be translated by algorithms into meaningful information for use in an app on a smartphone.

The Kyma μ -cor⁶ is a system for monitoring of patients with chronic cardiac illnesses. Attached to the patients' torso, it measures fluid trends in the thoracic region, performs heart and breathing rate measurement and also activity and body posture analysis.

Rejiva⁷ is a wireless ECG based telemedicine and biofeedback patch that captures overall health, manages stress, tracks sleep and energy level. It measures ECG, Heart Rate and its variability, respiratory rate, sleep position, breathing Index, and energy Level to analyse the state of the Autonomic Nervous System.

SecuraFone⁸ is a device that combines remote monitoring of vital signs with GPS tracking and emergency response to deliver an individualized mobile health solution. It includes system-on-a-chip semiconductors, accelerometers, cloud-based computing and an app with a dashboard, where the user can understand the vital signs acquired by the SecuraPatch, which

⁴ https://www.bosch-sensortec.com/bst/products/all_products/bhv160

⁵ <http://www.maastrichtinstruments.nl/portfolio/ecg-necklace-body-area-network/>

⁶ <http://www.kyma-med.com/tech/solutions.html>

⁷ <https://rijjuven.com/>

⁸ <http://www.securafone.com/home/>

is a wireless adhesive sensor that includes heart rate, respiration rate, body posture and temperature sensors. The SecuraFone Health can be configured to allow the caregiving team to access both real-time and historical data and to work with a 24/7 monitoring company that provides near-immediate emergency response to health and other events.

Released in the end of 2015 by Reassure Analytics, CareMind⁹ is a new smartphone app that allows tracking the vitals of an elderly, making use of Fitbit Surge smartwatch. It takes advantage of Fitbit's ability to share information with paired devices over Bluetooth connections to transmit activity levels, sleep and heart-rate patterns. This app can convey this information in something like real time, allowing it to send out alerts during some health crises and provide other notifications, making it ideal for cardiac patients and elderly. It allows to know the user heart rate, the time they woke up, last time they moved and also the number of steps taken. It alerts when the heart rate is too low or too high, when the user has not moved for a long period of time, when abnormal sleep patterns are detected or there is a high risk of falling. The frequency with which the users sync the Fitbit will determine how often their data will refresh in the CareMind app. If the users have an Apple smartphone, it will periodically sync when the Fitbit and iPhone are near each other, but may require the user to occasionally open the Fitbit app. If they are using an Android smartphone, the Fitbit and their Android smartphone will automatically sync every 15 mins throughout the day as long as the devices are near each other.

Olive¹⁰ is a bracelet, still in project phase, that uses a number of indicators to see if the user is under stress and how much, such as the heart rate, skin endurance, muscle tension and trends in skin temperature. It also analyses daily physical activities to see if they contribute to the stress, such as sleep or even exposure to light. When the bracelet detects higher than normal stress levels, it notifies the wearer through haptic feedback or LED lights on the wrist.

Imec's health patch system¹¹ consists on an imec's breakthrough health patch with a dedicated software. It includes an innovative approach to measuring accurate energy expenditure, computing the person's individual cardiorespiratory fitness level to continuously calibrate the activity monitoring. It deduces the wearer's cardiorespiratory fitness level from the heart rates at rest and during walking. The system stores the heart rate at rest and while walking (including walking speed). The normalization factor is recalculated every day, using the median values of the last week of heart rate data. That way, changes in cardiorespiratory fitness will be automatically reflected in changes in the normalized heart rate. This will at all times ensure an accurate monitoring of the energy expenditure.

⁹ <http://www.caremindapp.com/>

¹⁰ <https://www.indiegogo.com/projects/olive-a-wearable-to-manage-stress#/>

¹¹ http://www2.imec.be/be_en/research/wearable-health-monitoring.html

Chapter 3

Research Methodology

3.1. System Architecture

Monitoring means to be aware of the state of a specific system, observing a situation or condition for any changes which may occur over time. Cardiac monitoring usually refers to continuous electrocardiography with assessment of the patient's condition relative to their cardiac rhythm.

This project aims to develop a system, as proof of concept, which allows both activity and heart rate monitoring, in a daily basis, in order to study the inter-combination between energy expenditure, speed or workload, activity and heart rate and generate alerts for abnormal heart rates. There are already plenty of devices developed for heart rate monitoring purposes, using as heart rate monitor ECG patches or chest straps, which are very uncomfortable and difficult to use in the quotidian. Therefore, the heart rate monitor should be comfortable and highly accurate, preferentially positioned at the wrist as a bracelet, in order to be comfortable enough to be used during all day.

The activity data will be provided by the MoverLib (Teixeira et al., 2011), which is a Fraunhofer component that allows falls and activity monitoring that receives data from a smartphone's built-in accelerometer, and classifies the type of activity being performed and its main characteristics, such as energy expended, distance, number of steps performed and speed. On the other hand, the smartwatch provides the heart rate data, acquired continuously from the wrist.

The combination of both data is important for physical activity applications as an additional information of the human physical behaviour during the day. It could also be used to trigger alarms in case of abnormal heart rate values that have a negative impact on the person's health. It is also important to perceive some heart rate patterns that are influenced by physical activity. Taking into account the heart rate applications and its potential to improve activity monitoring, several system requirements were defined. The system should analyse the heart rate variability along the day and relate it to the activities and physical effort performed, studying the correlation between the energy expenditure, speed, physical effort and even stress with heart rate patterns and the autonomic nervous system balance. It should also evaluate the physical effort and the type of activity being performed, detecting if the heart rate is not normal for the physical effort required, detect abnormal situations and generate alerts for emergency situations. Besides this, it can also perform a daily summary with the time

spent in each cardiac zone, and the main activity and heart rate characteristics along the day.

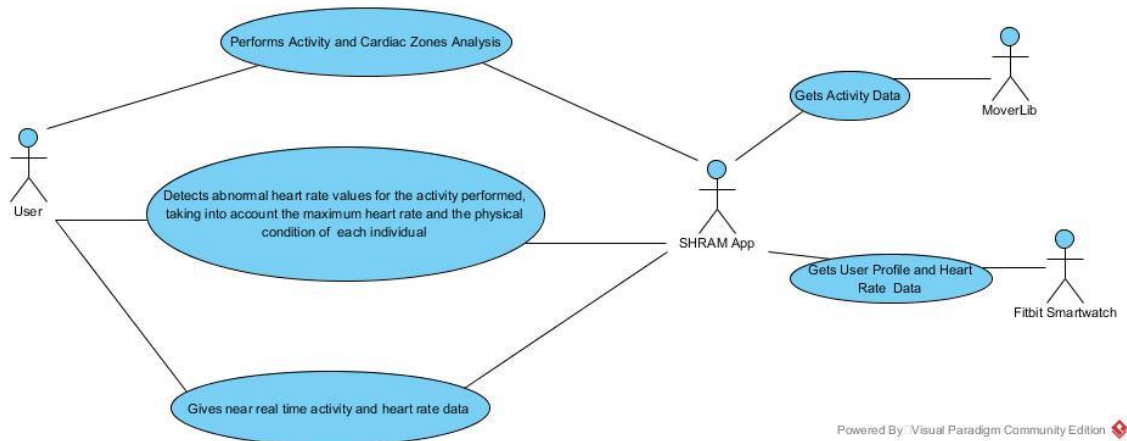


Figure 18: System Use Case Diagram.

3.1.1. Hardware

The system requires a heart rate monitor that is comfortable and accurate at the same time, preferentially positioned at the wrist. Moreover, it is desired that the monitor is capable of continuously reading the heart rate, in order to acquire all the important information. Further, the device should enable easy access to the all acquired data and the development of third parties applications.

Taking into account the smartwatches and bracelets that are available on the market and according to preliminary tests performed in the previous work related with the Preparation of Dissertation Monography, which evaluated the precision and reliability of the smartwatches Fitbit Surge¹², Samsung Gear S, Moto 360 and LG Watch R¹³, the main choice fell within the Fitbit Surge as heart rate monitor. Further, other features were taken into account in this choice, as the possibility to access the heart rate and other activity features data, and mainly the almost constant reading frequency. In turn, the other tested smartwatches provided a very low and non-constant reading frequency, which is not suitable for continuous heart rate monitoring because a lot of valuable heart rate information is lost.

The Fitbit Surge is a smartwatch that measures the heart rate through the photoplethysmography principle. Its LED emits light that reflects onto the skin to detect blood volume changes due to the cardiac cycle. It also tracks the number of steps taken, distance performed, calories burned, floors climbed, active minutes, hours slept and the time spent in each heart rate zone. The heart rate zone is defined using the estimated maximum heart rate (220-age): the Peak zone corresponds to heart rate values greater than 85% of HRmax; the Cardio zone corresponds to values between 70% and 84% of HRmax; the Fat Burn zone includes heart rate values between 50 and 69% of HRmax and finally; the Out of Range zone includes heart rate values below 50% of HRmax. The watch includes several sensors such as 3-axis accelerometer, which measures motion patterns and determines the steps taken, distance travelled, calories burned, active minutes and quality of sleep, an altimeter, which measures floors climbed, GPS, Bluetooth 4.0, an optical heart rate sensor, 3-axis gyroscope and 3-axis magnetometer. Fitbit Surge holds detailed minute-by-minute information for the most recent 7 days, and 30 days of daily summaries. The heart rate data can be stored at one-second intervals resolution during exercise tracking and at five-second intervals at all other times.

The Fitbit has an application programming interface that allows developers to interact with Fitbit data in their own applications, products or services. This data can be personal or

¹² <https://www.fitbit.com/surge>

¹³ <http://www.lg.com/us/smart-watches/lg-W110-lg-watch-r>

from other users. Any developer can build an application to access a Fitbit user's data on their behalf, if the application is registered and authorized by the users to access the data. This is useful, for instance, to help a doctor tracking the patient's health and behaviour throughout the day, by accessing his heart rate and other activity features. The Fitbit Web API uses the OAuth 2.0 protocol for user authorization, which enables applications to obtain limited access to user accounts on an HTTP service. The implicit code grant method is preferable over the authorization code grant flow since the token has a higher lifetime, which does not require a constant authorization by the user. The developed application redirects the user to Fitbit's authorization page. Upon user consent, Fitbit redirects the user back to the application's redirect URL with an access token as a URL fragment. In turn, the application stores the access token, which will be used to make requests to the Fitbit API. This token has a limited validation time of one year, therefore, each time the token is expired the application must refresh the access token.

The smartwatch saves the heart rate data with a variable frequency, from every 1 to 20 seconds, depending on the activity and effort required from the watch system. Therefore, the acquirement frequency cannot be defined, which becomes the data coordination such a challenge.

To access the data acquired by the smartwatch, a specific library was built, with different classes to get specific structured JSON data objects from the server. It enables the access to data saved at one second level resolution, called intraday time series, daily summaries, which include a summary and list of a user's activities and activity log entries for a given day, or even the user's profile data, including personal information such as birthdate, gender or height, among other features.

The tracker syncs with Fitbit Server every 15 minutes if network connection is available and new data has been pushed. The tracker syncs with the Fitbit app every time the app is opened, or periodically throughout the day if the all-day sync option is turned on.

The Fitbit Surge measures energy expenditure taking into account the basal metabolic rate, which is the rate at which an individual burns calories at rest in order to maintain body's functions such as breathing, heartbeat, brain activity or digestion. This is estimated based on the individual's gender, age, height and also weight. Further, the estimation of calories burnt takes also into account the activity recorder by the tracker, heart rate and other activities that might be logged into the system manually. The Fitbit Surge owns the PurePulse technology, developed by Fitbit, which uses heart rate data, when available, to more accurately estimating energy expenditure.

Several studies have been performed to assess the Fitbit reliability, either in activity or heart rate monitoring (Alharbi et al., 2016; Jo & Dolezal, 2016; Paul et al., 2015).

Cardiovascular researchers from the University of Sydney have found that Fitbit is a valid and reliable way of monitoring physical activity for cardiac patients (Alharbi et al., 2016). They discovered that Fitbit accurately identified whether patients met physical activity guideline recommendations, such as number of steps per day, offering valuable data for clinicians and researchers working in cardiac rehabilitation programs to monitor, evaluate and encourage their patient's physical activity levels. It is important to assess physical activity in cardiac rehabilitation participants because they are more likely to have lower levels of activity. These individuals are often of older age and have conditions that cause symptoms such as chest discomfort, dizziness, shortness of breath and leg or arm discomfort. Therefore, Fitbit devices might be perfect to use in this population to help tracking their physical activity and to motivate sustained changes in moderate-intensity exercise.

Moreover, physical activity features such as daily step counts and moderate vigorous minutes, measured though Fitbit-Flex¹⁴, which does not include heart rate monitor but includes

¹⁴ <https://www.fitbit.com/flex>

the same method to count steps and active minutes as the Fitbit Surge, were compared against Actigraph¹⁵ accelerometer (Alharbi et al., 2016). The results showed that Fitbit device was significantly correlated with Actigraph in measuring step counts and active minutes of light activity, moderate activity and moderate to vigorous physical activity. However it seemed to progressively overestimating the step count as the number of steps increased, which might be due the manufacturer definition of the intensity cut-off points or the placement of Fitbit on the wrist rather than the waist. Fitbit was also correlated with Actigraph for measuring all active minutes except during vigorous activity. Another work concluded that Fitbit was a valid, reliable and inexpensive alternative device for activity monitoring, suitable to predict attainment of physical activity guideline recommendations and monitoring physical activity in cardiac patients (Paul et al., 2015). Although some overestimation in step counter and active minutes might occurred, it was capable of continuously monitoring free-living conditions and providing valuable physical activity data for clinicians, individuals and researchers to track physical activity levels.

Furthermore, the validity of the Fitbit Charge HR, which include the optical heart rate monitor, was evaluated (Militara et al., 2015). In this work, the possibility of the smart gadget Fitbit Charge HR being suitable for self-management and daily feedback in type 2 diabetes patients was studied. For that, researchers compared the heart rate monitoring values and the calories burnt, distance and speed against RunKeeper¹⁶, which is a mobile application that uses the phone's built in accelerometer and GPS to track data. They concluded that the device presented an acceptable accuracy for the investigation. In a different study, the Fitbit Surge and Fitbit Charge HR were evaluated against a Zephyr Bioharness chest strap (Jo & Dolezal, 2016), as performed in Chapter3. However, the obtained results were not positive. They concluded that the PurePulse technology exhibited an aggregate mean bias of 8.9 BPM and a mean absolute differential of 13.9 BPM when compared against Zephyr. Further, during higher exercise intensities, the mean bias was -16.8 and the mean absolute difference increased to 19.2 BPM.

Currently, there are several apps for daily monitoring that use Fitbit tracker to assess physical activity and also heart rate, as is the case of CareMind, as referred in Chapter 2.8.2.

However, it has to be taken into account that Fitbit trackers are designed to provide meaningful data to users and help them reach their health and fitness goals, and are not intended to be scientific or medical devices.

Besides the heart rate monitor, the system requires a smartphone with built-in sensor such as accelerometer, in order to acquire activity data that will be analysed and used to classify the activity being performed.

Since the Fitbit does not allow to access the data in real-time, the possibility of using an Android Wear smartwatch was tested. However, none of the tested devices, which included Moto 360 and LG watch R, showed an acceptable behaviour. Further, it is not possible to establish a suitable and constant reading rate to perform a continuous monitoring with these devices.

3.1.2. Software

The activity monitoring will be performed by a developed library denominated Mover Lib. This library, developed by Fraunhofer AICOS, is useful for applications that are inserted in a lifestyle category, enabling activity level tracking and also helping the user to become more active.

The Mover Lib reads data from the smartphone's accelerometer, classifying ambulatory activities and postures of the user in real-time. It also computes the number of steps and speed

¹⁵ <http://actigraphcorp.com/>

¹⁶ <https://runkeeper.com/>

of walking or running activities. The signals usually present a fixed sample frequency of 33.33 Hz but when it is detected that the user is motionless, the sampling frequency is drastically decreased to 4 Hz (Aguiar et al., 2014; Teixeira et al., 2011). The output provided by the 3-axis accelerometer of the smartphone is a continuous stream of acceleration vectors that is divided into segments of 5 seconds, using a total of 28 different signal components in the analysis and activity classification. For each signal component several features are calculated such as mean, median, maximum, minimum, root mean square, standard deviation, median deviation, interquartile range, energy, entropy, skewness and kurtosis are computed, making a total of 336 features for each time window (Aguiar et al., 2014).

Currently, this system includes an energy expenditure estimation model that was validated against indirect calorimetry (Carneiro et al., 2015). The Indirect calorimetry is a standard measurement method of energy expenditure and it is based on the indirect measure of the heat expended by nutrients oxidation, which in turn is estimated by monitoring oxygen consumption and carbon dioxide production during a period of time. It consists in the collection of the inspired and expired gas, quantifying the volume and concentration of inspired oxygen and carbon dioxide (Carneiro et al., 2015). The energy expenditure model has been introduced by (Ryu et al., 2008) and it consists of two linear regressions of Metabolic Equivalents (METs) based on speed, one for walking and another for running. Thus, once a time window is classified as walking or running, a peak detector based step counter algorithm is executed in order to compute the total number of steps performed, from which speed is computed. Once an activity is classified, energy expenditure is calculated based on the activity recognition result, whose values of METs are computed from the equations in Table 2.

Table 2: METS Estimation per activity type.

Activity	METS
Run	$0.00558 \left(\frac{kcal}{kg \times km} \right) \times speed \left(\frac{km}{h} \right) - 4.7 \left(\frac{kcal}{kg \times h} \right)$
Walk	$0.00163 \left(\frac{kcal}{kg \times km} \right) \times speed \left(\frac{km}{h} \right) + 1.2 \left(\frac{kcal}{kg \times h} \right)$
Stand	<i>Between 1.2 and 2.3</i> $\left(\frac{kcal}{kg \times h} \right)$
Sit	<i>Between 1.0 and 2.0</i> $\left(\frac{kcal}{kg \times h} \right)$
Lay	<i>Between 0.95 and 1.3</i> $\left(\frac{kcal}{kg \times h} \right)$

The METS value of the postures vary linearly with the standard deviation of the accelerometer magnitude in a defined range of values. The energy expenditure estimation is calculated using the METS values, using the formula (3.1).

$$Energy\ Expenditure\ (kcal) = 1.05 \times METS \left(\frac{kcal}{kg \times h} \right) \times Duration\ (h) \times Weight(kg) \quad (3.1)$$

As reported in (Carneiro et al., 2015) the actual model that is implemented does not adjust correctly the values of METs to the speed, even the real speed given is used instead of the calculated through the accelerometer data (Carneiro et al., 2015). Moreover, for high speed levels the step counter and stride length algorithms implemented do not allow enough speed estimation accuracy.

Besides the Mover Library, the Fitbit App is required in order to synchronize the smartwatch data with the Fitbit Server.

Besides all the valuable data and advantages that the heart rate monitoring brings, allied to the activity monitoring, if a thorough analysis is performed to the current activity monitoring, some potential improvements can be detected. The heart rate data could be used to improve energy expenditure estimation, since it is proved that the combination of both activity and heart rate data leads to a better estimation than using just activity or heart rate data alone (Albinali et al., 2010; Altini et al., 2012). Further, it is desirable that a bigger number of different activities can be distinguished. For instance, the current system cannot distinguish between walking and ascending or descending stairs, which are entirely different activities. However, they are all interpreted as walking activities and the same MET value is attributed, although the physical effort required and the energy expenditure in each activity are completely different. Further, the heart rate data could be used to avoid abnormal heart rate values for the considered normal effort required by the activity performed, by comparing the normalized heart rate value with the range of normal values established for each activity type. Hence, the developed system constitution is represented in Figure 19.

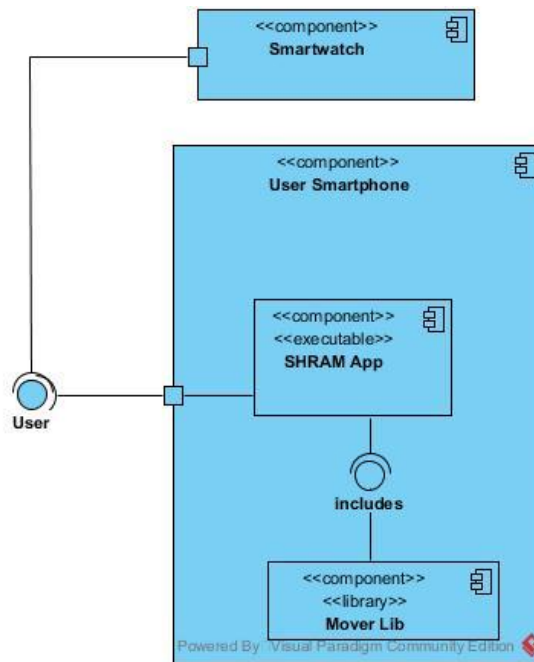


Figure 19: Component Diagram.

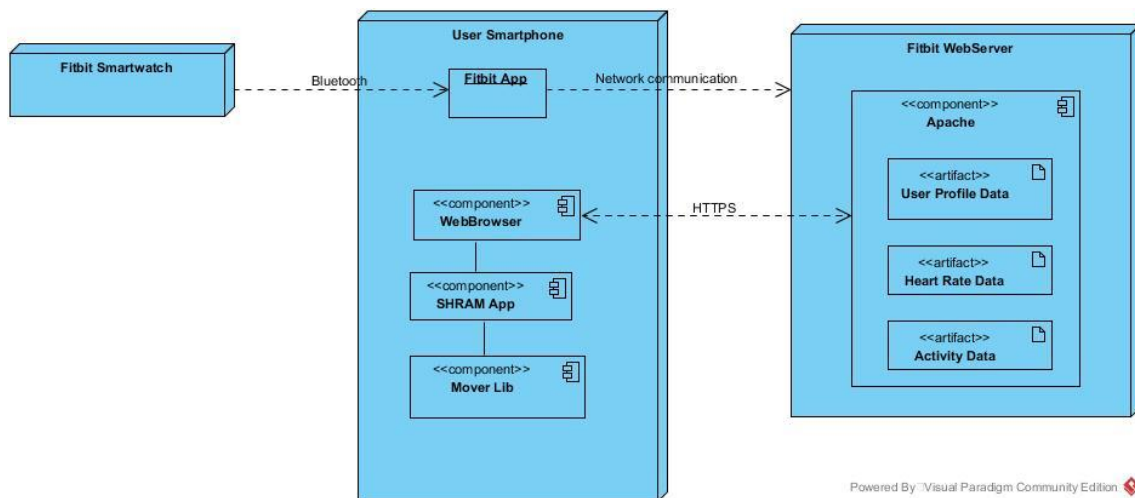


Figure 20: System Deployment Diagram.

The system behaviour is represented on Figure 20. The Fitbit Surge sends the data to the Fitbit Application, which in turn, syncs the data with the Fitbit webserver, if the network communication is available. This data includes activity, heart rate and also personal user's data. The developed app, which includes the Mover Lib to monitor and classify the activity performed by the user, access the Fitbit data through HTTPS requests to the Fitbit Webserver. For that, previous user's authorization procedure should be performed, to get the access token needed to access the user's data stored in the webserver, as represented in Figure 20.

A service is responsible for gathering the data provided by the activity monitoring system and also by the smartwatch. The activity data is acquired every 5 seconds, using the Mover Lib, and it includes the activity classification, speed, distance, number of steps and also the energy expenditure, for the correspondent window. In turn, the access to the heart rate data is limited by the existence of network communication and synchronization method between the smartwatch and the webserver.

3.2. Smartwatch Heart Rate measurement validity

The use of wearable technologies has become increasingly popular among the common population and it is expected that about 99 million wearable fitness bands will be sold in 2019 (El-Amrawy & Nounou, 2015).

Nowadays, wearable activity trackers use photoplethysmography (PPG) techniques to measure heart rate, which is a non-invasive method for the heart rate detection and it is connected with the optical properties of vascular tissue using LEDs. Therefore PPG sensors use LED lights to shine directly into the skin and interact with changes in the blood volume (Delgado-Gonzalo et al., 2015b). The heart rate is determined based on that blood flow through the artery is inversely related to the amount of light refracted or absorbed, dependent on the site that the light detector is placed. PPG techniques using optical LED blood flow sensors have allowed heart rate monitoring devices to become increasingly popular, with many new models entering the market each year. The healthcare system is experiencing a revolution because of the use of these devices to provide a convenient continuous feedback. In turn, chest strap heart rate monitors, based on electrocardiography, have been considered as the standard for sports heart rate monitoring. These monitors typically have a correlation higher than 0.90 and a standard estimation error lower than 5 BPM during rest and moderate activity, which is considered sufficient for consumer sports use (Terbizan & Dolezal, 2002). However, they cause discomfort and complication of use, which has limited their popularity among consumers.

Given the huge influx, interest, money and also the great potential that these devices present for the medical applications, validated research is needed to ensure that activity monitors accurately measure the heart rate under resting, light, moderate, and vigorous intensity conditions, because there has been little evaluation of their use, accuracy and precision.

Similar works have been performed in order to access the smartwatches reliability, either the activity or the heart rate monitoring (Delgado-Gonzalo et al., 2015a, 2015b; El-Amrawy & Nounou, 2015; Haavikko, 2014; Stahl et al., 2016).

Researchers have tested several smartwatches (Scosche Rhythm¹⁷, Mio Alpha, Fitbit Charge HR¹⁸, TomTom Runner Cardio¹⁹, Microsoft Band²⁰ and Basis Peak²¹) against the chest

¹⁷ <http://www.scosche.com/rhythm+>

¹⁸ <https://www.fitbit.com/chargehr>

¹⁹ https://www.tomtom.com/pt_pt/sports/running/products/runner-sport-gps-watch/all-black/

²⁰ <https://www.microsoft.com/microsoft-band/en-us>

²¹ <http://www.mybasis.com/>

strap Polar RS400²² (Stahl et al., 2016). Fifty volunteers with age between 19 and 45 years old and sports habits were recruited. The devices were programmed with the participants' personal data before the protocol start. The protocol included a rest phase, where the heart rate was recorded every minute for 3 min, in the beginning and at the end. A treadmill phase was performed between the rest phases, which included walking and running at 3.2, 4.8, 6.4, 8.0, 9.6 and 4.8 km/h for 5 min at each speed. A good criterion validity was found between all the monitors and the Polar HR monitor that was used as reference. Specially, the Fitbit Charge presented a mean of 105.00 ± 30.6 BPM, compared with 109.06 ± 29.3 BPM presented by the criterion measure. The highest percentage of error occurred, however, in the Fitbit Charge HR in the 3.2 (9.99%) and 6.4 km/h (10.06%) walking phase, respectively.

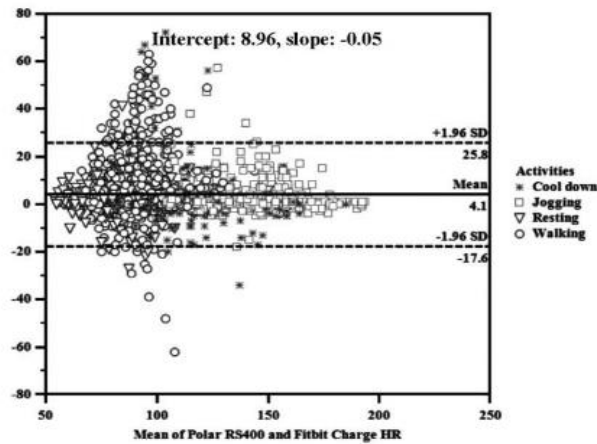


Figure 21: Bland-Altman plot obtained in (Stahl et al., 2016).

In another fitness trackers and smartwatches proved to be accurate for tracking step counts and heart rate (El-Amrawy & Nounou, 2015). The protocol included walking 200, 500 and 1000 steps, which corresponded to thirty heart rate measurements, and each set was repeated 40 times. For this study, four healthy adults aged between 22 and 36 years old, were recruited. The positive controls used were a tally counter and Onyx Vantage 9590²³, for the step counting and heart rate, respectively. In this study, the accuracy and precision were calculated. Accuracy was defined as the closeness of measured values to the positive control, i.e., the percent by which measurements deviated from the average. In turn, the precision was defined as the coefficient of variability between the repeated measurements for each tracker. The accuracy and precision ranged from 99.9% (Apple Watch²⁴) to 92.8% (Moto 360²⁵) for accuracy and from 5.9% (Apple Watch) to 29.6% (Samsung Gear S²⁶) for precision. In general, the devices tested were found to be relatively accurate and beneficial, helping solving many health problems.

²² http://www.polar.com/en/products/earlier_products/RS400
²³ <http://www.nonin.com/Finger-Pulse-Oximeter/Onyx-Vantage-9590>
²⁴ <http://www.apple.com/watch/health-and-fitness/>
²⁵ <http://www.motorola.com/us/products/moto-360>
²⁶ <http://www.samsung.com/global/microsite/gears/>

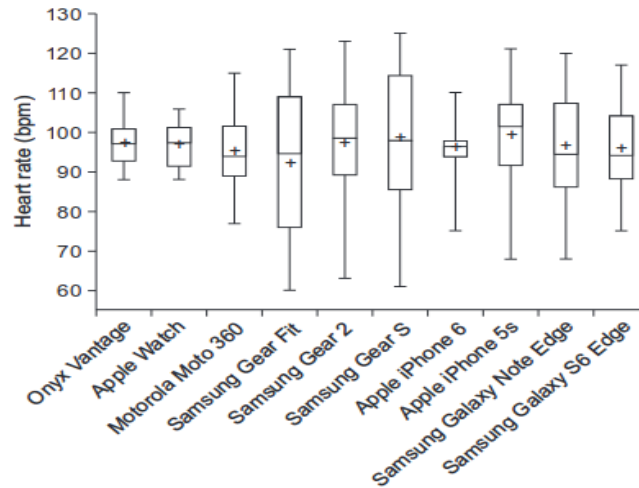


Figure 22: Results obtained in (El-Amrawy & Nounou, 2015).

The accuracy and reliability of PulseOn²⁷ technology was evaluated against ECG-derived heart rate in laboratory conditions during a wide range of physical activities and also during outdoor sports (Delgado-Gonzalo et al., 2015b). They also compared the performance to another on-the-shelf wrist-worn consumer product Mio LINK. The results showed a PulseOn reliability of about 94.5%, which was defined as the % of time with error <10 BPM, and an accuracy of 96.6%. In turn, the Mio Link²⁸ 86.6% and 94.4%, for reliability and accuracy, respectively. The results showed that PulseOn smartwatch provides reliability and accuracy similar to traditional chest strap ECG HR monitors during cardiovascular exercise. All data was linearly interpolated to the match PulseOn's HR monitor operation frequency and averaged over 5seconds windows. This device's performance was also tested in another work, under controlled laboratory conditions with 20 subjects (Haavikko, 2014). A Polar heart rate chest strap and a Firstbeat Bodyguard 2²⁹ Holter monitor were used as reference. Before the protocol, the devices were set up, but also there was a three-minute waiting period after all the devices were turned on. The protocol included periods of rest and activities of varying intensities such as walking and running at different speeds and cycling. To make the readings comparable, the average heart rate value over a five second time window was taken to represent the device over time. Here, the results showed that the PulseOn device had a good accuracy, being in the same heart rate zones as the reference device, and the calculated errors were decent enough since the device showed correct readings during most part of the test. In this study, the reliability measure was defined as the percentage of number of data point pairs where the error between the PulseOn device and the reference is less than 5 or 10 beats per minute. The PulseOn device presented an average reliability value of 90.40%.

Finally, the performance of Mio Alpha and Scosche Rhythm against an ECG reference, with a similar protocol, was also evaluated (Parak & Korhonen, 2014b). Their results showed that the devices had reliability values of 87.49 % and 86.26 %, and mean absolute errors of 4.43 BPM and 6.82 BPM, respectively. In the processing phase, the signals were smoothed by a moving average of 5 seconds window.

²⁷ <http://euro.pulseon.com/support>

²⁸ <http://www.mioglobal.com/Mio-Link-heart-rate-wristband/Product.aspx>

²⁹ <http://shop.firstbeat.com/all-products/bodyguard.html#.V103VfkrLIU>

3.2.1. Material and Methods

The smartwatch tested was the Fitbit Surge, since it was the chosen heart rate monitor to include in the proof of concept developed system and there is little investigation about its heart rate monitoring validity and error. As comparison device, the Zephyr Bioharness 3³⁰ was the chosen due its validity against a 3-Lead ECG (Johnstone et al., 2012; Systems, 2012). The Bioharness 3 was worn against the skin by each participant via an elasticated strap attached around the chest. The monitoring device attaches on to the strap and acts a data logger or transmitter, measuring five variables simultaneously. Before the beginning of every test, the chest strap was adjusted to the subject's chest perimeter. The smartwatch was used on the left wrist. A visual inspection of the wrist and forearm was conducted so the watch was correctly fitted, according to the manual specifications.

Table 3: Zephyr Bioharness Accuracy (Zephyr, 2012).

Accuracy (BPM)	Activity Level	% of time	Max deviation (BPM)
±1	Laboratory - ECG emulator	100	1
±2	Low activity (static)	99	5
±3	Moderate activity (walk/jog)	95	5
±3	High activity (run)	95	10

The test included rest and different dynamic intensities, in order to simulate daily activities (Table 5). Furthermore, the protocol was repeated on another day, in order to ensure repeatability. The activities were manually annotated and the volunteers also used a system solution that includes an accelerometer and a recorder application that saves this data to posteriorly analysis. The heart rate at rest was considered as the minimum heart rate achieved in the first sitting task, in order to set the baseline. The Zephyr Bioharness 3 saves the heart rate data at frequency of 1 Hz. In turn, the Fitbit Surge saves the data at a variable frequency from 1/3 to 1 Hz. Therefore, both signals were synchronized through the timestamp and only the data whose timestamp was present in both signals was taken into account.

The test group, with an average age of 25.6 ± 2.1 years old, consisted on N=8 healthy volunteers, from which 5 are men and 3 are women (see Table I).

The heart rate signals analysis was performed using Pycharm IDE. Bland Altman analysis was performed using IBM-IPSS version 23.

Table 4: Subjects' characterization.

Subjects	Gender	Age	HR max	HR rest
Subject 1	M	29	191	75
Subject 2	M	29	191	54
Subject 3	M	26	194	80
Subject 4	F	23	197	62
Subject 5	M	27	193	61
Subject 6	M	24	196	48
Subject 7	F	25	195	70
Subject 8	F	22	198	74

³⁰ <https://www.zephyranywhere.com/products/bioharness-3>

3.2.2. Evaluation

The heart rate measurement performance was estimated by the device's accuracy and reliability. Reliability, was considered as the % of samples in which the absolute error is smaller than 10 BPM, whereas the accuracy consisted in the complement of the relative error (i.e., 100% - mean absolute percentage error). The reliability provides a measure of the amount of time the system is working within an acceptable confidence interval. The 10 BPM error threshold was chosen to represent a level that is adequate for consumer sports device for typical recreational use, providing the error committed by the system at any time (Delgado-Gonzalo et al., 2015b). The concordance analysis was performed with the application of a 5 seconds moving average window, as referenced in (Delgado-Gonzalo et al., 2015b; Parak & Korhonen, 2014b). For that, the Fitbit Surge signal was linearly interpolated to overcome the non-constant reading frequency.

According to (Bland & Altman, 1999), methods that are designed to measure the same parameter must have good correlation, which is not synonymous of agreement. The correlation coefficient does not assess agreement but association, which is very different. Perfect agreement occurs when both measurements lie perfectly along the line of equality. In turn, poor agreement can produce quite high correlation. Agreement between two different methods of clinical measurement can be quantified using the differences between measurements using the two methods on the same subjects. The 95% limits of agreement are estimated by mean difference ± 1.96 standard deviation of the differences, and they provide an interval within which 95% of differences between measurements by the two methods are expected to lie (Bland & Altman, 1999). In the case of a reliable measure, 95% of the value points should lie between these limits.

The relative reliability between test and retest was evaluated with Intra-Class Coefficient (ICC) model (3, k), as defined in (Shrout & Fleiss, 1979), which takes both systematic and random errors in the data into account and uses the mean scores of repeated tests as evaluation score. Hence, and as referenced in (Bruton et al., 2000), ICC scores equal or larger than 0.75 correspond to an excellent relative reliability, an ICC score between 0.4 and 0.75 is known to correspond to a good relative reliability and finally, an ICC score lower than 0.4 is considered as poor relative reliability

The visual assessment of reliability was carried out using Bland-Altman plots: the plot of the average of two measurements by the difference among two measurements provides a qualitative estimate of absolute reliability. Mean differences should be close to zero to demonstrate agreement.

Table 5: Testing Laboratory Protocol and durations.

Protocol Task	Duration (min)	Starting time
Sitting at rest	1	00:00
Standing still	1	01:00
Walking 3.5 km/h 0% inclination	2	02:00
Walking 3.5 km/h 10% inclination	2	04:00
Walking 5 km/h 10% inclination	2	06:00
Running 8 km/h 0% inclination	2	08:00
Running 8 km/h 10% inclination	2	10:00
Sitting at rest	1	12:00
Ascending Stairs	0,5	13:00
Descending Stairs	0,5	13:30
Total Duration	14	

3.3. Datasets

In order to study the relationship between the heart rate variability patterns and the activity being performed, speed and energy expenditure, public datasets and some acquired datasets were used, with different purposes and methods.

The public datasets used, which included both activity and heart rate data, were PAMAP and PAMAP2. The PAMAP dataset was recorded with an early system prototype developed in the PAMAP (Physical Activity Monitoring for Aging People) project, in August 2010, where wired 3D-IMUs and a heart rate monitor were used as sensors ("PAMAP.ORG," n.d.). Eight volunteers, with an average age of 27.9 ± 1.9 and from which 7 are men and 1 is woman, were subjected to a predefined data collection protocol of about one hour each, which makes approximately 8 hours of data that was collected. In turn, the PAMAP2 dataset was recorded in autumn 2011. It includes data from 9 volunteers subjects, with an average age of 27.2 ± 2.7 and from which 8 are men and 1 is woman, wearing 3 IMUs³¹ and a heart rate monitor³², and performing 18 different activities. Over 10 hours of data were collected altogether, from which nearly 8 hours were labelled as one of different 18 activities. Both datasets have been made publicly available for research purposes, and can be downloaded³³. These datasets include outdoor activities, such as walking, running, cycling, playing soccer and rope jumping, and also indoor activities such as lying, sitting, standing, vacuum cleaning, ironing and ascending/descending five flights of stairs. It also includes transient activities that consist in going from one location to the next activity's location, waiting for the preparation of some equipment. The detailed description of each activity performed is presented in Table B1.

In order to study the possibility to use the smartwatch heart rate signal to infer about stress states, three subjects, aged between 22 and 25 years old, wore the Fitbit smartwatch and a smartphone, to record the heart rate and the activity data, respectively, during several days, in order to record some possible stressful daily situations. The heart rate data was posteriorly accessed through the developed API protocol library, which enables the access to the heart rate data that the Fitbit syncs to its server. To record the activity data, it was used an application that records the accelerometer data that was already developed at Fraunhofer, in order to create an annotated dataset. This data was posteriorly analysed by a proper library that classified the activities. The smartphone was always placed on the pocket and the recording was performed with an execution with 5 seconds delay before starting, to enable the users to place the phone in the pocket and stabilize it. Both data was synchronized through the timestamp. Daily basis activities were performed and stressful situations were manually annotated. These last include work, car traffic or public presentations.

In order to study the combination between heart rate and energy expenditure, it was also used a dataset acquired during a previous validation procedure (Carneiro et al., 2015). In this test, three models were compared with indirect calorimetry outputs of energy expenditure during an incremental speed treadmill protocol. During the test, it was measured the maximum volume of oxygen consumption, accelerometer and heart rate data. The method used as ground truth was the indirect calorimetry, with the oximeter Jaeger Oxycon Pro Metabolic Cart TM34, which measures the concentration of expiration gases in intervals of 5 seconds. The performed protocol consisted in a maximal incremental treadmill protocol starting with a 2 minutes warm-up phase at 4 km/h, followed by speed increase to 6 km/h for 1 minute and subsequent increases of 1 km/h, each level lasting for 1 minute. The tests were carried out using one

³¹ <http://trivisio.com/index.php/products/motiontracking/colibriwireless>

³² http://bm-innovations.com/index.php/shop_products.html

³³ <http://www.pamap.org/index.html>

³⁴ <http://www.carefusion.com/our-products/respiratory-care/metabolic-carts/oxycon-mobile-device>

smartphone attached to the left side of the belt and another to the right side of the belt of each subject. Further, during the tests the subjects also wore an oronasal mask 7450 Series V2 Mask35 with flow sensor for gas collection and analysis. The heart rate data was acquired through the chest strap Polar Wearlink36, which was sent through Bluetooth and synchronized with the oximeter data. Each subject performed the test on the treadmill until volitional exhaustion was reached. The real number of steps was manually annotated using a tap counter application for smartphones and the total distance was obtained from the treadmill. Moreover, in order to differentiate between walk and run activities, the time when the subject started to run was manually annotated. The group was composed of 13 subjects, 12 females and 1 male, with an average age of 33.2 ± 9.1 years, average height of 161.2 ± 4.8 cm and an average weight of 56.2 ± 3.1 kg. The total number of samples were initially 26, two per subject, but one subject was rejected due to an interruption during the acquisition, resulting in 24 valid samples.

3.4. Heart Rate and Activity Analysis

3.4.1. Heart Rate Variability and activity patterns

The collected datasets, with heart rate and annotated activity data, were analysed using the standard heart rate variability measures, referenced in Chapter 2.4. This approach allowed to obtain more insights about the relationship between activity and heart rate and to detect potential heart rate variability patterns to discriminate activities.

The time-frequency domain analysis was performed using the MatLab® R2013a and the developed HRVAS tool box (Ramshur, 2010). The heart rate data was pre-processed, excluding ectopic beats, followed by a cubic spline interpolation at 2Hz, to assume equidistant sampling and calculate the spectrum directly from the inter-beat interval tachogram. The time-frequency transforms were applied using time windows from 30 to 60 seconds, depending on the activity performed, so the heart rate variability changes could be properly detected, and an overlap of 15 seconds. The time-frequency transforms applied included the Wavelet Transform and Lomb-Scargle Periodogram, as explained in Chapter 2.4.4.

Regarding the time-domain heart rate variability analysis, this one was performed using Pycharm. The calculated time-domain parameters included the RMSSD, SDNN, mean heart rate, mean inter-beat interval duration, as explained in Chapter 2.4.2, and mean variation speed between consecutive intervals. This last feature was calculated because the heart rate data provided by the smartwatch was not acquired at a constant frequency. Hence, in order to normalize the variation between consecutive intervals, the heart rate signal was resampled at a 1/3 Hz frequency, using cubic spline interpolation. Further, a sliding window of 100 samples, which corresponds to the standard 5 minutes short-term analysis, was applied to the signal, in order to capture the time domain heart rate variability behaviour over time.

For the stress state detection test, the same time-domain heart rate variability methodology was applied, so the algorithm proposed in (Yang et al., 2008) could be tested.

³⁵ http://www.rudolphkc.com/product_detail.php?id=181

³⁶ http://support.polar.com/us-en/support/Polar_WearLink___Transmitter_with_Bluetooth___Compatibility

3.4.2. Relationship between heart rate and energy expenditure

In order to confirm that the heart rate data is useful to estimate energy expenditure and that when combined with activity data, the estimation is improved, some already developed models were tested against the current model that is employed in the activity monitoring system.

The similarity between the results obtained by the algorithms and the reference values was determined by calculating the normalized root mean square error (NRMSE) value between the datasets. The NRMSE can be obtained by dividing the root mean square error (RMSE) by the mean of the observed data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{calc,i})^2}{n}} \quad (3.2)$$

$$NRMSE = \frac{RMSE}{\bar{X}_{obs}} \quad (3.3)$$

Since the dataset used to perform this study included already the computed energy expenditure estimation for each 5 seconds windows, instead of the raw accelerometer data, the algorithm chosen to combine the activity and heart rate data should allow including both data contribution by establishing a weight factor for each one. This way, the model already used for the energy expenditure estimation using smartphone's accelerometer could be combined with another model that uses the heart rate data.

Hence, in this procedure an energy expenditure estimation model through heart rate was combined with the activity based energy expenditure estimation model, which was suggested by (Ryu et al., 2008), following the branch model algorithm proposed by (Søren Brage et al., 2004) and adapted by camntech (Camntech, 2013; Crouter et al., 2008). In the case of using both activity and heart rate data, there is a heart rate value below which the linear relationship between heart rate and energy expenditure no longer holds. This is referred as the Flex Point and it has been used to distinguish between resting energy expenditure and energy expended during physical activity, and it was initially defined as the average of the highest heart rate value during rest and the lowest heart rate value during incremental exercise, performed during a treadmill test (Camntech, 2013). If the heart rate value is above this Flex Point, the energy expenditure is predicted using a regression line. A suggested multi-linear regression equation that was derived and expressed in terms of both activity counts and heart rate values is presented in Figure 23 (Søren Brage et al., 2004). P1, P2, P3 and P4 are weighting factors, X refers to the accelerometer counts, which is used to discriminate between activity and rest. Y and Z behave as heart rate thresholds in the presence and absence of activity, respectively. Y is used to discriminate between walking and running activities and Z is used to discriminate between the existence of movement or not during inactive states. During running the heart rate is a very reliable measure of energy expenditure whereas activity, measured by vertical acceleration, is less reliable since during running the latter does not increase linearly with speed. Further, when running at high speeds, the accelerometer usually reaches a maximum range value which leads to signal saturation. This is reflected by the high value of the weighting factor relative to the heart rate-energy expenditure relationship. In turn, the heart rate is a poor measure during resting activities whereas movement registration is more reliable, and this is reflected by a relatively low value of weighting factor relative to the heart rate-energy expenditure relationship. In boxes 2 and 3 movement and heart rate are equally weighted. The weight factors and the other parameters values were derived by walking and running on a treadmill in studies described in (S Brage et al., 2005; Crouter et al., 2008),

conducted with the Actiheart³⁷, and are currently included in the Actiheart energy expenditure analysis because they are believed to be reasonably valid for free living conditions (P1 value=0.9, P2 value=0.5, P3 value=0.5, P4 value=0.1). Further, transition HRaS, which is the average heart rate above sleeping between the highest walking and slowest jogging, was used to decide if equation 1 or 2 should be applied, was defined as 80 BPM (Crouter et al., 2008). The Y parameter was calculated by adding the transition HRaS to the sleeping heart rate.

Since the data provided did not include the heart rate measurement at rest but the age and the maximum oxygen volume, this one was estimated with a prediction equation, suggested by (Uth et al., 2004), using theoretical maximum heart rate value and the maximum oxygen volume consumption.

$$VO_2max \cong 15,3 \times \frac{HRmax}{HRrest} \quad (3.4)$$

This model was adapted, using the activity based model introduced by (Ryu et al., 2008) as the relationship between the activity and energy expenditure, and the model introduced by (Charlot et al., 2014) as the relationship between the heart rate and energy expenditure. Since the data used only includes walking and running activities, only the boxes 1 and 2, from the scheme, were used.

Other energy expenditure estimation models that use heart rate data were tested, as was the case of the case of the model proposed by (Keytel et al., 2005), with and without VO₂max, and the one proposed by Actiheart (Crouter et al., 2008). However, these algorithms showed a poor performance.

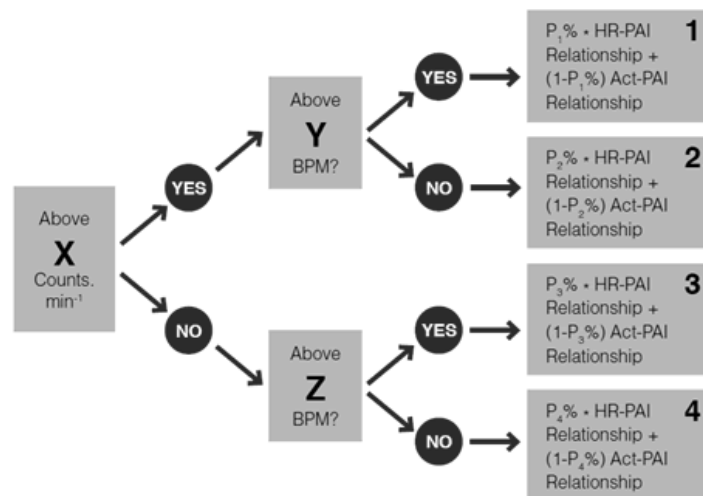


Figure 23: Branched equation model, suggested by (Søren Brage et al., 2004) and adapted by camntech (Camntech, 2013).

The model equation that was chosen to include in the combining method, and proposed by (Charlot et al., 2014), includes the heart rate value, height, weight, gender, resting heart rate and theoretical maximum heart rate, assuming that the heart rate at rest is an acceptable index of fitness level. According to the results obtained in (Charlot et al., 2014), the basic equation (3.5) proved to be accurate and to have a good correlation with indirect calorimetry. Besides this basic equation, Charlot et al. proposed also other equations that include parameters determined in laboratory environment, such as maximum oxygen volume, real maximum heart rate, running speed and speed at VO₂max (3.6). Although in the study performed by (Charlot et al., 2014) the equations that include running speed showed the best

³⁷ <https://www.camntech.com/products/actiheart/actiheart-overview>

performance, one of these equation does not include the heart rate value and the other had a worst performance when applied to the data, when compared to the basic model and the one which includes VO_{2max} data.

$$EE \left(\frac{Kcal}{h} \right) = 171,62 + 6,87 \times HR(bpm) + 3,99 \times Height(cm) + 2,30 \times Weight(kg) \\ - 1,39 \times Gender(1 = M, 2 = F) - 4,26 \times HR_{rest}(bpm) - 4,87 \times T \\ - HR_{max}(bpm) \quad (3.5)$$

$$EE \left(\frac{Kcal}{h} \right) = 738,90 + 6,89 \times HR(bpm) + 5,48 \times Weight(kg) - 2,81 \\ \times HR_{rest}(bpm) - 9,50 \times R - HR_{max}(bpm) + 32,31 \times S - VO_{2max} \quad (3.6)$$

Moreover, the same combined HR-activity based algorithm, but using the activity classification as method to decide which weight factors to attribute to each heart rate or accelerometer model, instead of using the heart rate above sleep (HRaS) value as threshold, was also tested.

Chapter 4

Results and Discussion

4.1. Smartwatch Heart Rate Validity Reliability Test

Since the heart rate data acquired does not follow a normal distribution, the Wilcoxon Signed Ranked Test, which is a non-parametric test for paired data, was applied on data, from all the participants, from both test and retest. Further, it was also evaluated the Pearson correlation. This analysis is depicted in Table 6.

Table 6: Evaluation of the statistical difference between Fitbit Surge and Zephyr Bioharness 3, using data from all the participants in test and retest.

Statistical Measure	Corr (r ²)	Wilcoxon test p-value
Value		
Test	0.95	p<0.05
Retest	0.96	p<0.05

The accuracy and reliability results, for each subject and also for test and retest, are presented in Table 7. The results regarding the test-retest reliability are presented in Table 8. The p-values computed in paired t-test, its 95% confidence interval boundaries and ICC scores to evaluate relative reliability are presented.

Table 7: Accuracy and Reliability results for each subject, for test and retest.

Subject	Accuracy (%)		Reliability (%)	
	test	retest	test	retest
1	90.66	95.45	54.98	71.73
2	94.38	95.90	85.20	93.85
3	97.34	95.04	97.26	84.30
4	89.40	89.82	36.80	47.98
5	96.62	92.38	92.10	55.49
6	96.22	95.03	95.64	89.17
7	96.98	94.23	92.04	72.34
8	91.62	91.73	52.64	84.64
Average	94.15	93.45	75.83	74.94

Table 8: Test-retest reliability of the accuracy and reliability assessments.

Assessments	Mean \pm SD Test	Mean \pm SD Retest	Mean \pm SD Diff	p- Value	95% CI of Diff		ICC
					Lower	Upper	
Accuracy	94.15 \pm 3.16	93.70 \pm 2.15	0.46 \pm 2.83	p>0.05	-1.91	2.82	0.65
Reliability	75.83 \pm 23.79	74.94 \pm 16.32	0.90 \pm 22.16	p>0.05	-17.63	19.42	0.61

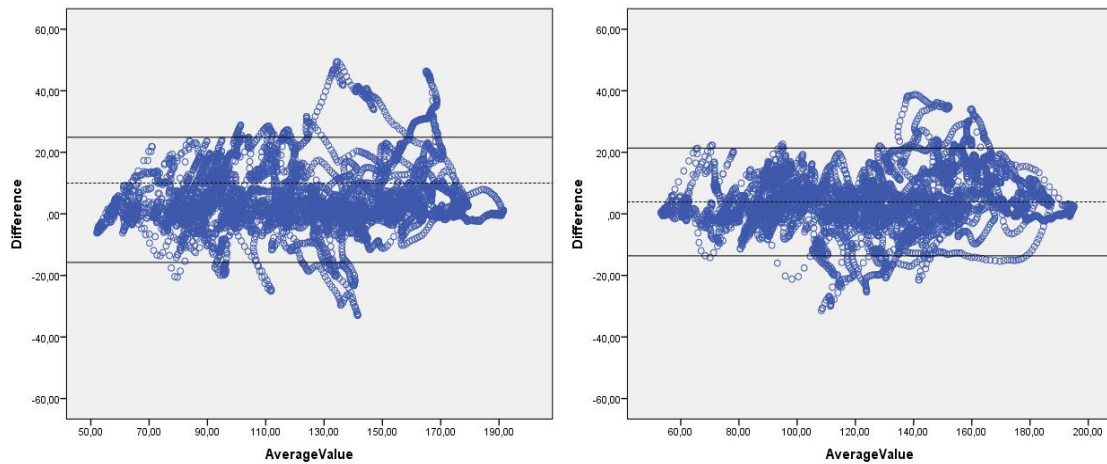


Figure 24: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' protocol data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. Left: test (N=7058). Right: retest (N=6885).

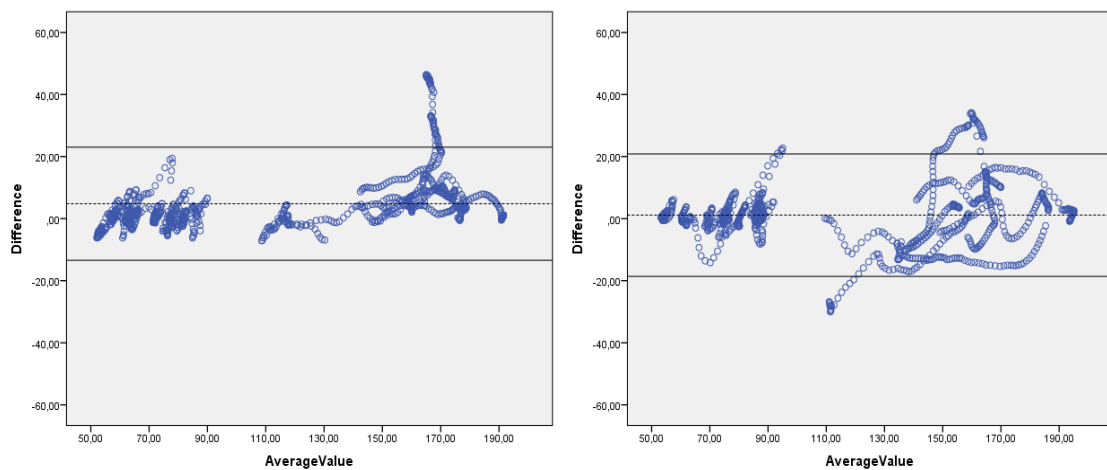


Figure 25: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' sitting data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. Left: test (N=920). Right: retest (N=870).

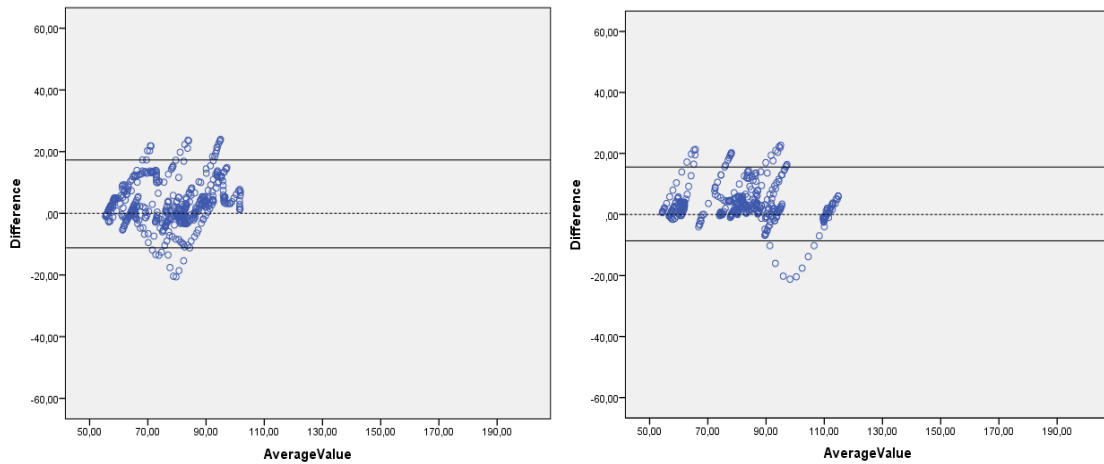


Figure 26: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' standing data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. **Left:** test (N=478). **Right:** retest (N=420).

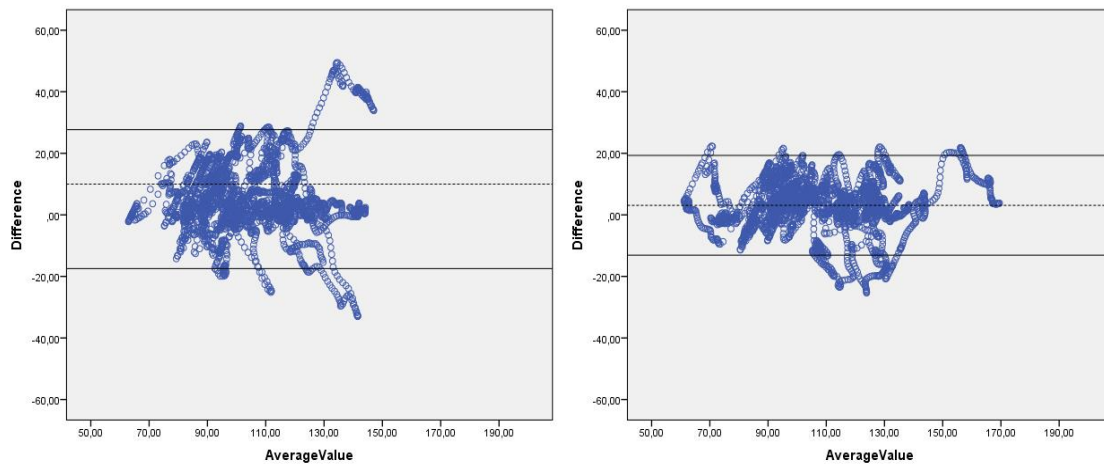


Figure 27: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' walking data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. **Left:** test (N=2880). **Right:** retest (N=2824).

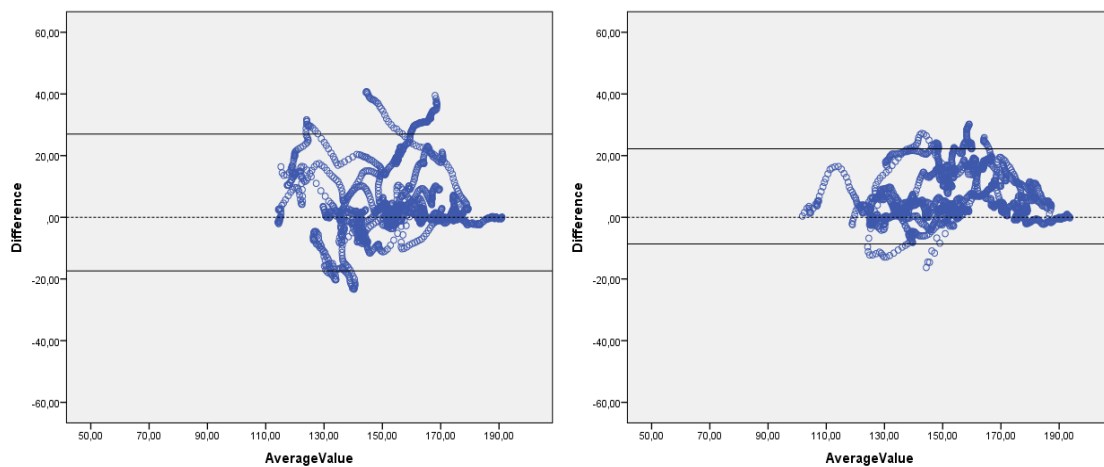


Figure 28: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' running data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. **Left:** test (N=1880). **Right:** retest (N=1920).

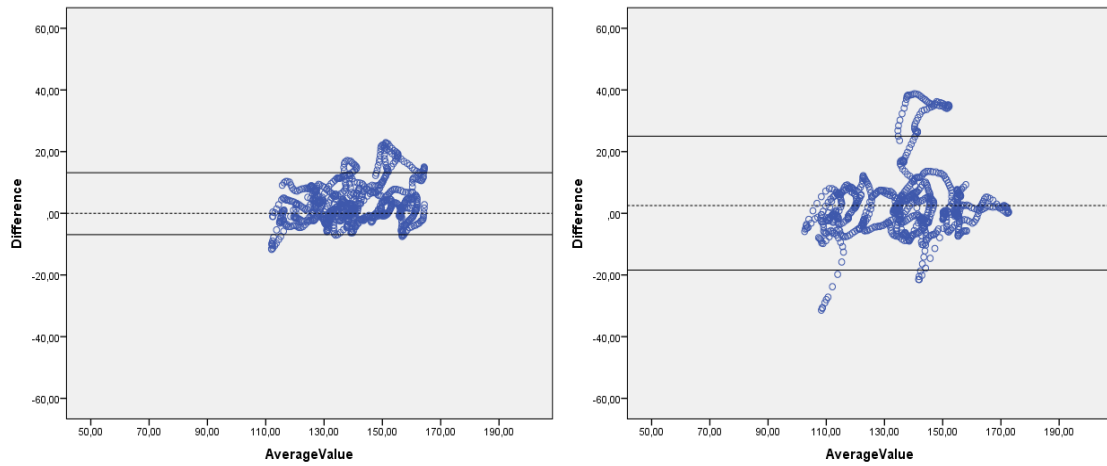


Figure 29: Bland-Altman plot comparing the chest strap-obtained RR intervals to the Fitbit-obtained RR intervals, for all the subjects' ascending and descending stairs data. The confidence interval $\mu \pm 1.96\sigma$ is represented by the dashed lines. **Left:** test (N=858). **Right:** retest (N=852).

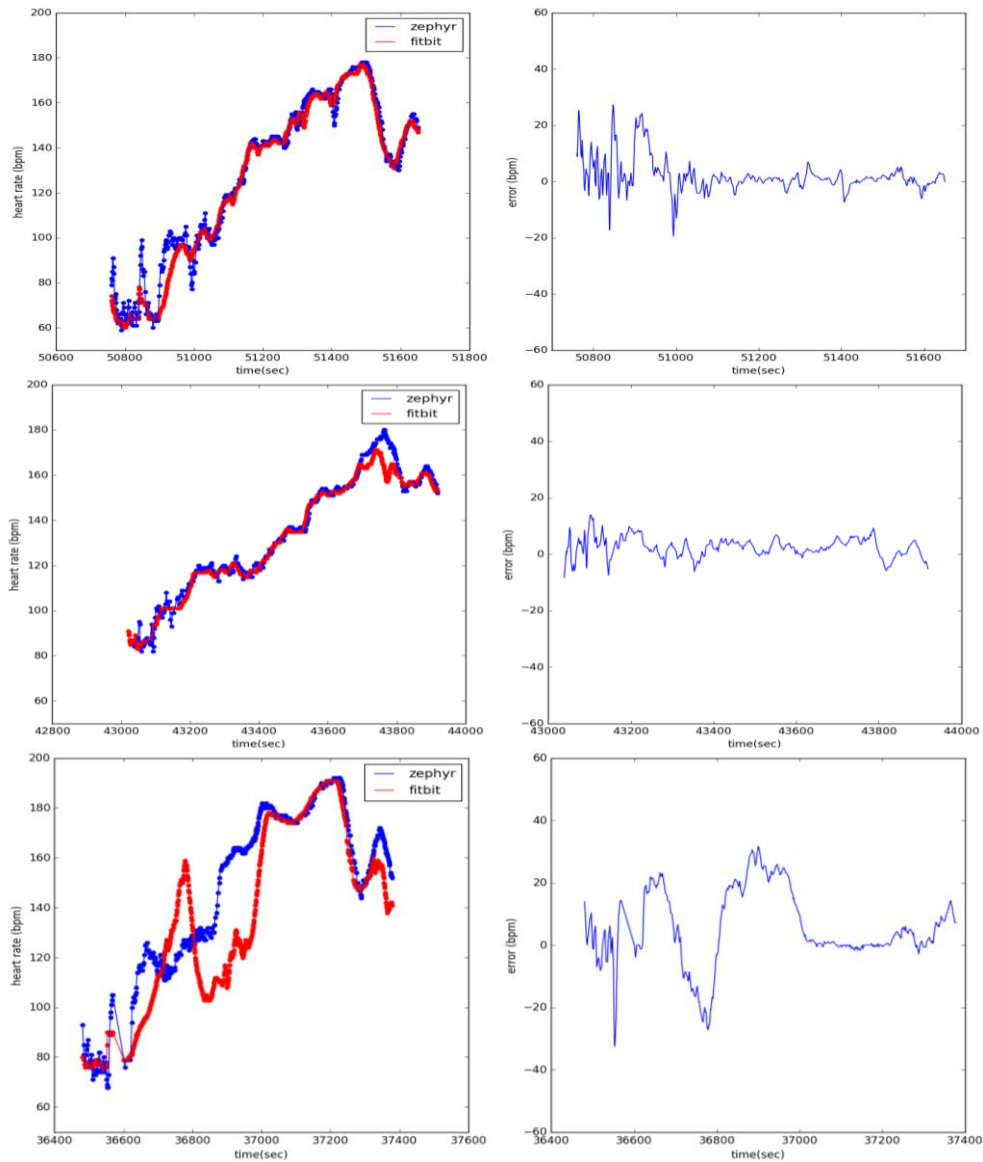


Figure 30: Some results obtained: Comparison between the chest strap and smartwatch heart rate signals. **Above:** Good performance. **Middle:** Good performance. **Bottom:** Failure.

Globally, the heart rate signal provided by the Fitbit Surge smartwatch was concordant with the signal provided by the chest strap.

Figure 30 evidences some of the obtained results per subject, while the Table A1 and Table A2 present the results per both subject and activity type. In average the accuracy of the smartwatch was acceptable for the tested subjects, although the reliability should be better in some cases. Figure 30 compares some of the signals provided by the chest strap and the smartwatch for three of the participants of this study. In the majority of the cases the signals are practically concordant with the chest strap. However, there are cases where the error between the two signals is not acceptable for reliability purposes.

As observed, although the Pearson Correlation coefficients reached 0.95 and 0.96 in test and retest, respectively, when applying the Wilcoxon Signed Rank statistical test for a significance level of 5%, there are significant differences between the values provided by the chest strap and the smartwatch.

Figure 24 shows the Bland-Altman plots with all the subjects' protocol data, while Figure 25, Figure 26, Figure 27, Figure 28 and Figure 29 show the Bland-Altman plots with data relative to sitting, standing, walking, running and climbing/down stairs activity, respectively. Observing these plots, it can be concluded that the walking activity presented the greater dispersion. However, it must be noticed that the number of samples regarding the walking activity is the higher, and consequently, the most propitious to dispersion. Furthermore, and according to Bland-Altman, both devices agreed in most part of the tests, with the majority of data being between the 95% limits of agreement (Bland & Altman, 1999).

It should be noted that the chest strap signal presented high variance along the time. There are possible reasons for increased data variance from the Bioharness 3, mainly at higher velocities. The correct heart rate measurement using chest straps, with mounted biopotential electrodes, is reliant on a constant close connection with the performer's chest. It is posited that physical activity at higher velocities is associated with possible breaks in connection with the performer's chest, increasing movement artefacts linked to chest strap instability or noise, all of which may intermittently corrupt the heart rate data provided (Johnstone et al., 2012). Therefore, and although the chest straps are considered as a standard heart rate measure method in sports field, these motion artefacts should be taken into account. In turn, the optical sensor from the smartwatch is susceptible to outside light errors sources and the wrist blood vessels expression might vary with the subjects, being very prone to movement artefacts.

The results obtained in this study can be compared to results from other publications. The validity of seven commercial heart rate chest straps, including two Polar chest straps, which use the traditional measurement of electric potential on the skin surface, was assessed (Terbizan & Dolezal, 2002). Their measurements were performed in four different conditions for a duration of ten seconds, in which one was during rest, and the remaining three were on a treadmill. Their criterion for a valid measurement reading was that the correlation should be over 90 %, and the standard error of estimate less than 5 BPM. The results showed that none of the devices gave a valid reading according to these restrictions when it came to the fastest speed on the treadmill, which was about 9.6 km/h. Four of the devices, including the Polar chest straps, filled the criterions on the slower speeds and rest, and one of the devices was valid during the first two speeds, but failed during the rest period, and the remaining two measurement devices, failed to achieve the limits completely in any situation. Moreover, and as above mentioned, the performances of Mio Alpha and Scosche Rhythm were evaluated against an ECG reference with a similar measurement protocol (Parak & Korhonen, 2014b). Their results showed that the devices had 10 % reliabilities of 87.49% and 86.26%, and mean absolute errors of 4.43 BPM and 6.82 BPM, respectively. Taking other studies relative to other smartwatches, the results obtained in (Delgado-Gonzalo et al., 2015b) showed that the PulseOn's mean reliability was about 94.5% with an accuracy of 96.6%, opposed to 86.6% and 94.3% of Mio LINK. Furthermore, in another work it has also been studied the PulseOn accuracy and reliability, showing an average value of 90.40% for reliability (Haavikko, 2014). Comparing

the results obtained in this study, it can be concluded that the Fitbit Surge presented an accuracy similar to the presented in literature but a lower reliability (reliability=75.39%, accuracy=93.80%, mean error=4.21 BPM, mean absolute error=7.22 BPM). Although the mean error and mean absolute error are higher but close to the ones presented by (Delgado-Gonzalo et al., 2015a; Parak & Korhonen, 2014a) and the accuracy values are within the range present in literature, the reliability values are still below the values mentioned above.

As it can be observed, the individuals that showed poor results in the first tests, had also poor results in the retest. Hence, and regarding the test-retest results, a p-value of the paired t-test higher than 0.05 and the presence of zero value inside of the 95% CI indicate that there are no significant differences between the scores obtained in test and retest procedures. Both accuracy and reliability demonstrated good retest reliability with ICC of 0.65 and 0.61, respectively.

There are some reasons that might explain the difference, besides the obvious dissimilarities in the measuring technology, which include the measurement device to which the readings are compared. In (Delgado-Gonzalo et al., 2015b) and (Haavikko, 2014) the comparing device chosen was a Polar chest strap and in (Parak & Korhonen, 2014b) the results presented refer to Embla Titanium³⁸ multi-parameter wearable recorder. In this study, the Zephyr Bioharness 3 was chosen to be the comparing device, but we must keep in mind all the time that this reference doesn't tell the exact truth. Further, anatomical issues might also have influenced the results. Since the devices used were the same size for everyone, and although they give the user the possibility to adjust the size to the body, the volunteers that participated in the test present different morphologies. Hence, the devices might have adjusted better to some volunteer than others. Although the smartwatch positioning was carefully inspected, each volunteer placed on himself the chest strap, according to instructions present in the manual, which might represent an error source.

These results showed that the Fitbit Surge device had a good accuracy and acceptable reliability. It must be noticed that one reliability measure is acceptable depending on the purpose for which the device is intended to be used. In fact, this device is not suitable to behave as a medical device and to perform heart rate monitoring in cardiac patients, since the error that is associated with the smartwatch could make the difference in the patient's status. However, this reliability value could be acceptable for heart rate monitoring of people that intend to follow an active and healthy lifestyle. For this purpose, the values provided by the smartwatch can be very useful in order to provide the user an idea of its lifestyle assessment, taking always into account that these kind of devices are gadgets that were not built for medical purposes and that they might present, as expected, higher error values than the medical ones. Therefore, the calculated errors were decent enough to have the device showing correct readings most of the time during normal use. Moreover, the results show that the device provides results with some repeatability, giving, though, some credibility to use it in a daily basis.

The ideal device would be able to record the heart rate from any individual in every condition, which is an impossible task considering that each subject is a unique black box with many unknown parameters that should be known completely to get the perfect reading every time.

In average, the heart rate values were correlated, with differences up to 20 BPM, but with Fitbit showing a slightly lower heart rate value. Further, some problems were observed at sudden transitions of activity intensity, with the Fitbit responding a bit late to the pace change, and with high intensity activities, where in some cases it did not follow the heart rate increase to their peak values.

³⁸ <http://www.stowood.co.uk/Brochures/Embla%20Titanium%20Brochure.pdf>

The number of volunteers that have participated in this study is considered low, when compared to the number of volunteers in other similar tests (Delgado-Gonzalo et al., 2015b; Haavikko, 2014). Hence, the obtained results might not be sufficient to achieve a conclusive finding. However, if the failure cases were considered as outliers and if they were removed from the analysis, there would be a huge improvement on accuracy and reliability results on the both test and retest, increasing from and 93.8% to 95.42% and from 75.39% to 92.42%, respectively.

4.2. Heart Rate and Activity Patterns

4.2.1. Activity Distinction through heart rate variability

The performance of different activities, with also different intensities, leads to changes in heart rate and, consequently, in its variability. During dynamic exercising, the initial heart rate adjustment depends on the decrease in parasympathetic activity, whereas the subsequent increases are due to the increase in sympathetic activity. The modulation between the two nervous systems depends on the physical activity's intensity. Thus, some heart rate variability patterns, related to the activity being performed, might be detected.

The signal presented in Figure 31, regarding the execution of the protocol described in PAMAP, includes several activities with different intensities. In the image, it can be denoted one low intensity activity, corresponding to walking slow, three moderate intensity activities corresponding to walking, walking fast and cycling, and three very intense activities, corresponding to running, playing soccer and rope jumping. Therefore, the heart rate signal suffers great variability throughout the time.

The Wavelet Transform and periodogram denote the beginning of each activity with the intense presence of low frequencies, which correspond to sympathetic nervous system activity, because the heart rate suffers an abrupt increase to adapt to the body's needs, varying greatly. Further, higher frequencies can be also distinguished, although with lower intensity, corresponding to the recovering phases, when the heart rate decreases and the parasympathetic nervous system dominates. Further, an intense variation can be detected at the beginning of the signal, during the walking slow and walking activities. During this period, both very low frequencies and also higher frequencies are present. Hence, the abrupt increase that the heart rate suffers at the beginning of each intensity can be highlighted by very low frequencies. It can be also noted that before every abrupt heart rate increase, higher frequencies are highlighted due to the preceding recovery phase.

Regarding the time-domain heart rate variability over time, in Figure 33, and since in this case the window width is higher than the time that every activity transition takes to occur (the window's width is about five minutes and every activity takes about three minutes, followed by one minute break), the beginning of each activity cannot be highlighted. In turn, the global heart rate variability over time can be analysed. In fact, at the beginning of the signal the heart rate suffers a lot of variation, with the execution of three activities with different intensity levels. After the 1000 seconds, the heart rate variability decreases because, as it can be seen in the figure, the heart rate keeps within a smaller range of values, during the transition phases and the cycling activity that occurs between the running activities. After this occurrence, the heart rate variability returns to higher values, again due to the execution of three different activities with high intensity levels, in a cyclical way. In this case, and although the heart rate variability achieves higher values, these are still below the ones achieved at the beginning at the signal, because the intensity of each activity performed here is almost equivalent. This is observed with the RMSSD and SDNN behaviour throughout the time. Further, looking at the speed variation between consecutive inter-beat intervals it can be observed that it suffers also a lot of variation, achieving its minimum value during the transition phases and cycling activity that occur between the running activities.

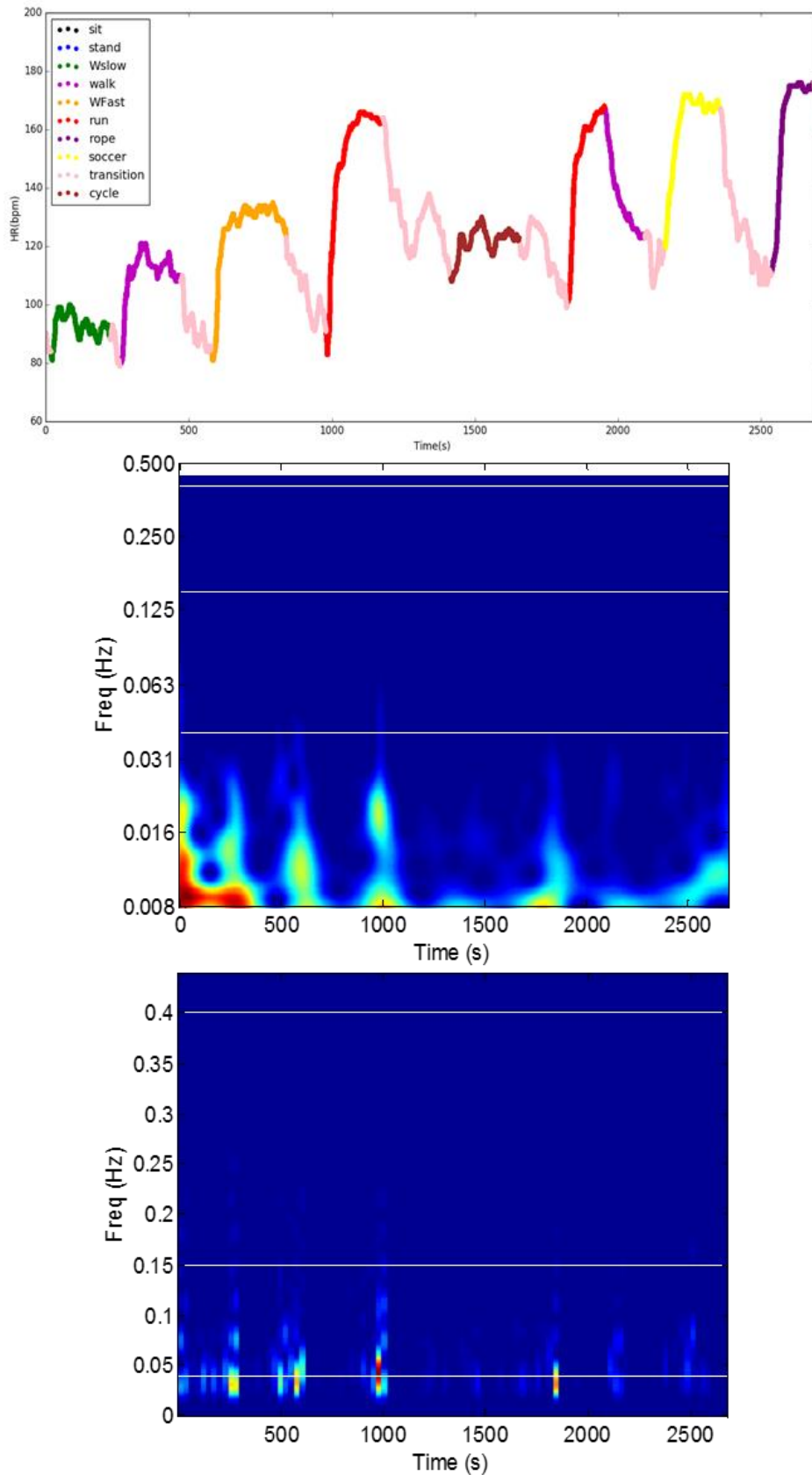


Figure 31: Time-Frequency Analysis of a heart rate signal acquired during PAMAP protocol. **Above:** Heart rate signal according to each activity. **Middle:** Wavelet Time-frequency Transform. **Bottom:** Periodogram.

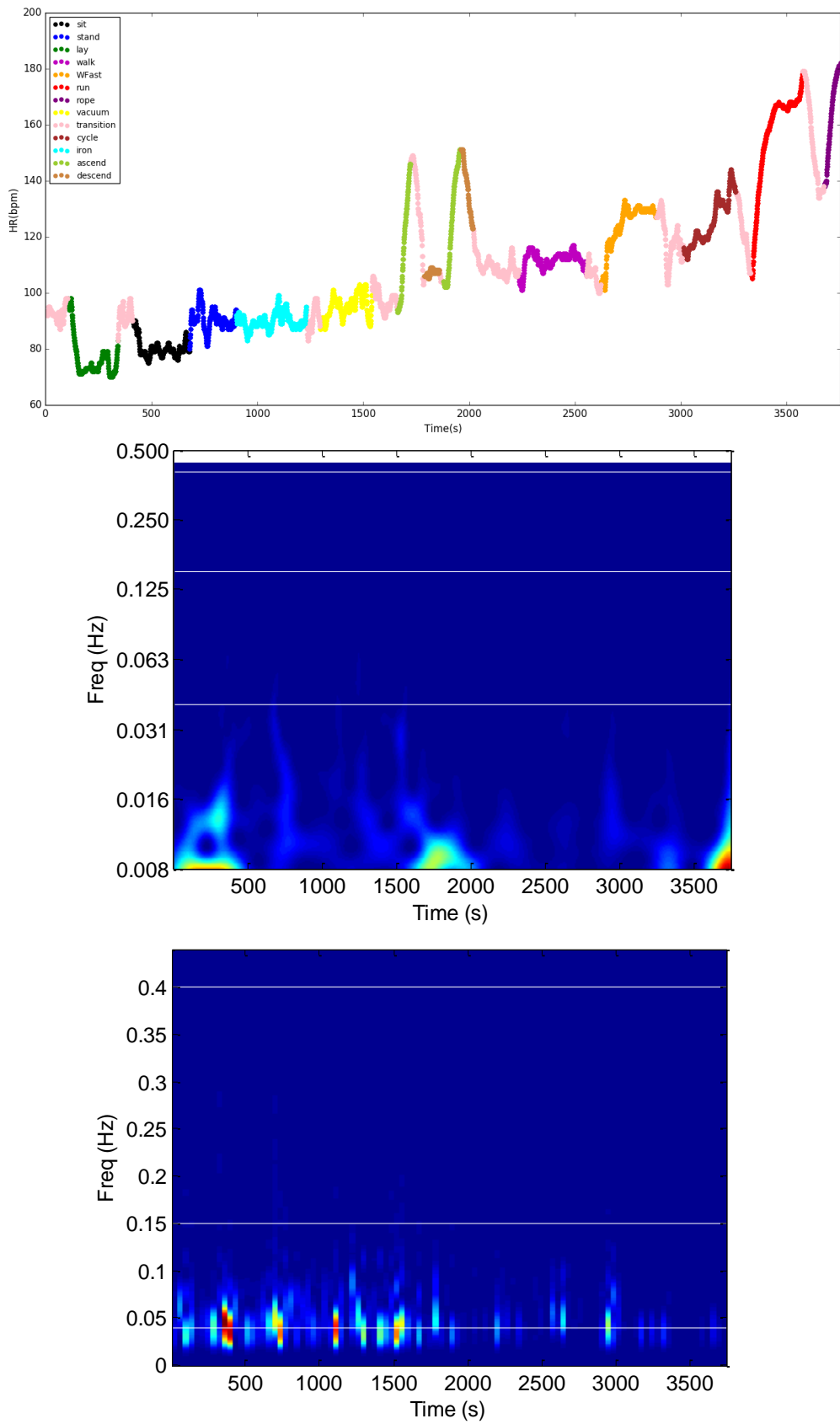


Figure 32: Time-Frequency Analysis of a heart rate signal acquired during PAMAP2 protocol. **Above:** Heart rate signal according to each activity. **Middle:** Wavelet Time-frequency Transform. **Bottom:** Periodogram.

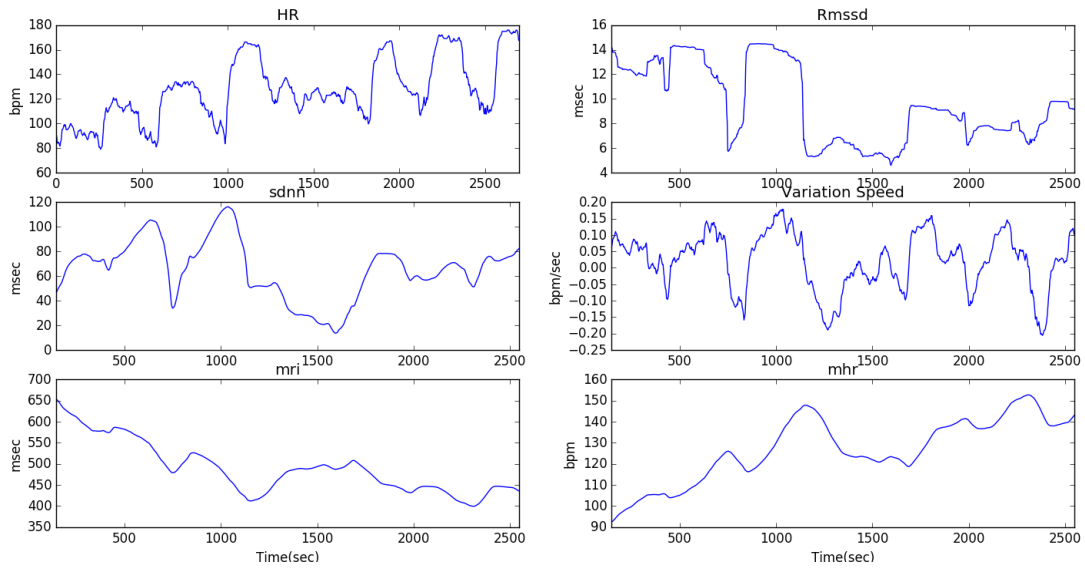


Figure 33: Time-Domain Heart Rate Variability analysis over time regarding PAMAP sample (HR-Heart Rate; RMSSD- Root Mean Square of the Successive Differences; SDNN-Standard Deviation of inter-beat intervals; Variation speed-Mean Variation speed between consecutive intervals; mri-mean inter-beat intervals duration; mhr-mean heart rate).

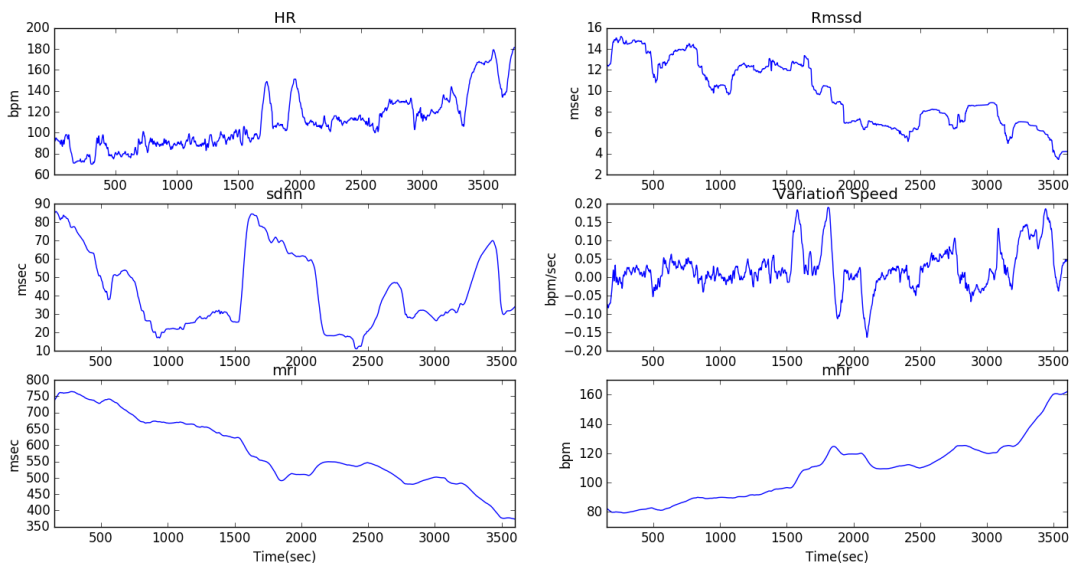


Figure 34: Time-domain Heart Rate variability over time regarding PAMAP2 sample (HR-Heart Rate; RMSSD- Root Mean Square of the Successive Differences; SDNN-Standard Deviation of inter-beat intervals; Variation speed-Mean Variation speed between consecutive intervals; mri-mean inter-beat intervals duration; mhr-mean heart rate).

The signal presented in Figure 32, regarding the execution of the protocol described in PAMAP2, also includes several activities with different intensities. The majority of the activities are low intense activities, corresponding to lying, sitting and standing. It also includes moderate intensity activities corresponding to ironing and vacuuming and intense activities, which correspond to walking, ascending and descending stairs, running, walking fast, cycling and rope jumping. The beginning of each activity that is characterized by an intense increase of heart rate is distinguished in the spectrums with the presence of low frequencies. During the low and moderate intensity activities, the heart rate suffers great variability, which is denoted by some higher frequencies, during their execution, and also by a highlighted region in the spectrums, as it is observed from the beginning until the 2000 seconds.

The Figure 34 depicts the time-domain heart rate variability features along the time. Once again, the windows' width applied is higher than the activities duration, whereby the beginning of each activity is not highlighted as occur in the time-frequency analysis. In turn, the global variability of the signal is analysed. Similarly to the previous signal, the higher variability occurs when different activities with high intensity are performed in an alternated way, separated by transition phases or low intensity activities. In the beginning the heart rate suffers high variability during the transition from lying to sitting position, with some higher intensity level transition phases that occurs between them and previously to the lying activity. Further, the heart rate variability decreases from this point, and but it keeps within high levels of variability since the activities performed are characterized by low intensity levels and, therefore, the heart rate value can vary greatly. Regarding this observation, the RMSSD and SDNN present a different behaviour, since the SDNN analyses the variation of each interval comparing to the mean interval duration of each window, but the RMSSD compares the variability relative to the previous interval duration. Hence, during these low intensity activities, the SDNN reports a lower heart rate variability, comparing to rest of the signal because the mean interval duration of the window is very similar to the heart rate values observed, but the RMSSD reports a high heart rate variability when it is analysed the variability comparatively to consecutive intervals. This situation keeps from the sitting position until the ascending stairs activity is performed twice, separated by a low intensity transition phase and descending stairs. After this, one moderate intensity activity is performed, followed by two more intense activities (walking fast and cycling). Hence, this transition from walking to walking fast causes a higher heart rate variability, which is decreased soon after because the cycling activity presents an intensity similar to the walking fast activity. Finally, the heart rate variability increases again due to execution of an activity with high intensity levels. This is depicted by the RMSSD and SDNN behaviour throughout the time. The speed variation between consecutive inter-beat intervals also corroborates this analysis, since it suffers some variability at the beginning, followed by a period in which it keeps almost unchanged, and then a period of great variability.

The signals presented in Figure 35 and Figure 37 correspond to heart rate signal of two of the volunteers that participated in the Fitbit Surge validity test. At the beginning, during the transition from sitting to standing position, the heart rate suffers a considerable variability, due to the body's adaptation to the pressure change. This is highlighted in the spectrum with the intense presence of low frequencies. Once again, the transition from one activity to another can be distinguished by the presence of low frequencies in the spectrums. Further, during low and moderate intensity activities the spectrum denote the presence of higher frequencies, due to higher variability suffered by the heart rate signal. During these activities, the heart rate variability is higher, which is reflected by the spectrums content, considerably bigger than the remaining signal.

Regarding the time-domain heart rate variability analysis, throughout the time, represented in Figure 36 and Figure 38, it can be observed that as the intensity of the activity performed increases, the heart rate variability decreases, denoted by both RMSSD and SDNN, which corroborates the HRV theory present in literature, that refers that the higher the heart rate the shorter the inter-beat interval and shorter intervals usually present less variation (Nieminen et al., 2007). Further, also the speed variation between consecutive inter-beat intervals suffers some variability, although it keeps positive since from the beginning until the end of the running activity. This parameter achieves higher values when the transition from one activity to another occurs. When the body starts to adapt to the exercise requirements, the speed decreases, until a new high intensity level activity begins.

Thus, comparing the heart rate variability analysis and patterns that were observed in the samples taken from the PAMAP and PAMAP2 and the ones taken from the Fitbit Surge validity test, it was observed that similar conclusions and patterns were found, despites the signal sampling frequency difference of each device.

It can be concluded that low frequencies are influenced by both sympathetic and parasympathetic branches, although they are mainly associated with sympathetic activity. LF/HF ratio increases with the increase of the heart rate, during stress, exercise or mental tasks and emotions, when the sympathetic activity predominates. Moreover, the heart rate variability tends to decrease as the exercise intensity increases.

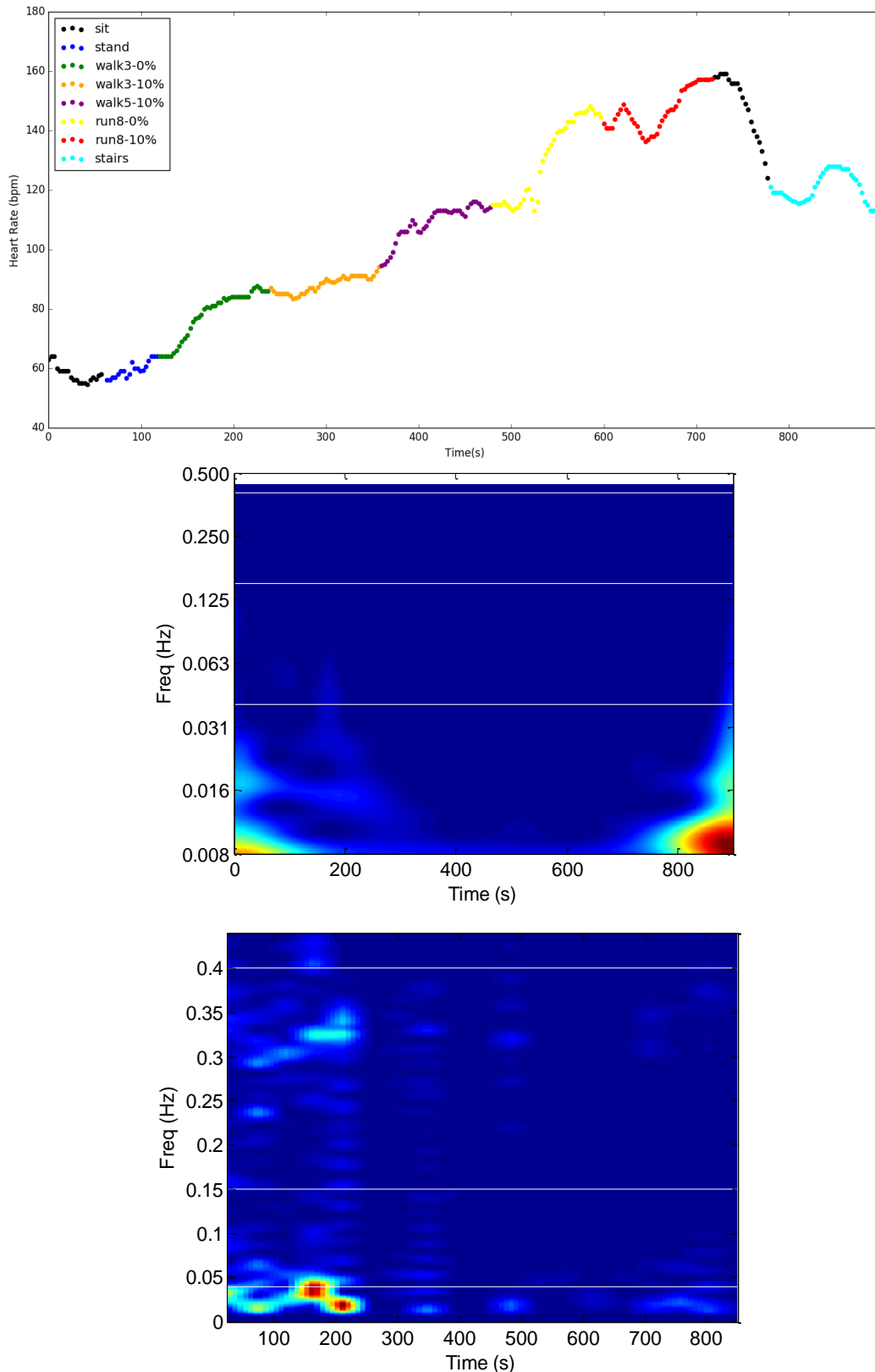


Figure 35: Time-Frequency Analysis of a heart rate signal acquired during Fitbit validity test. Above: Inter-beat interval signal. Middle: Wavelet Time-frequency Transform. Bottom: Periodogram.

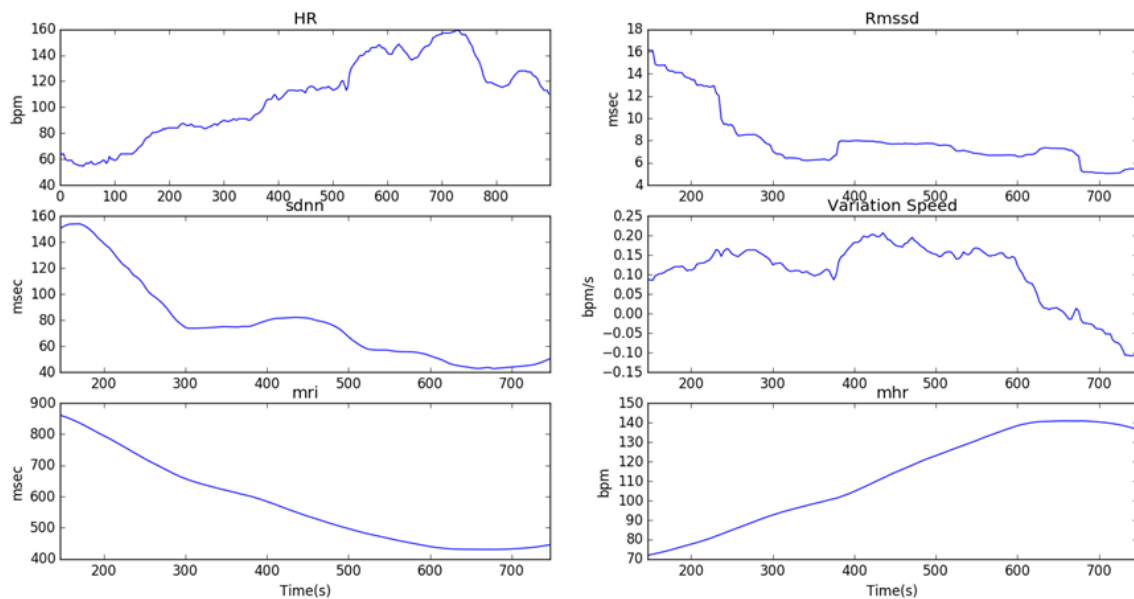


Figure 36: Time-domain Heart Rate variability over time regarding one Fitbit Surge validity test sample, represented in Figure 35 (HR-Heart Rate; RMSSD- Root Mean Square of the Successive Differences; SDNN-Standard Deviation of inter-beat intervals; Variation speed-Mean Variation speed between consecutive intervals; mri-mean inter-beat intervals duration; mhr-mean heart rate).

A normal increase in heart rate during exercise and the ability to slow it in the immediate post-exercise phase are dependent on the autonomic nervous system and the ability of the cardiac conduction tissue to normally propagate the electrical impulse. The shortening of the inter-beat intervals in dynamic activities would account for a reduced beat-to-beat variability in the low frequencies band.

Thus, the time-frequency analysis is a great tool to differentiate the activity type being performed in time, although it cannot be used as activity classification or differentiation approach. It can distinguish rest activities, characterized by low heart rate values and high heart rate variability, continuous intense exercising, characterized by high heart rate values and no considerable variation during its performance, and interval exercising, characterized by great heart rate variability.

Further, the analysis performed is dependent on the trade-off that is performed between the window's width that is applied and the activity duration. This will be determinant on the results of the heart rate variability analysis, namely if will allow distinguish the transition from one activity to another, or if it will give an overall measure of the global heart rate variability throughout the time. Nevertheless, and although the heart rate variability performed with a heart rate signal provided by a chest strap or a smartwatch might not be equivalent to one that is performed with the signal provided by an ECG, since some information is lost due to the resampling frequency, similar conclusions can be taken from the analysis that is executed. Hence, the signal provided by this kind of wearables is still important to analyse some heart rate variability patterns, according to the activity type performed, which gives useful information about how the nervous system and consequent heart rate modulation behaves with the performance of different intensity levels activity.

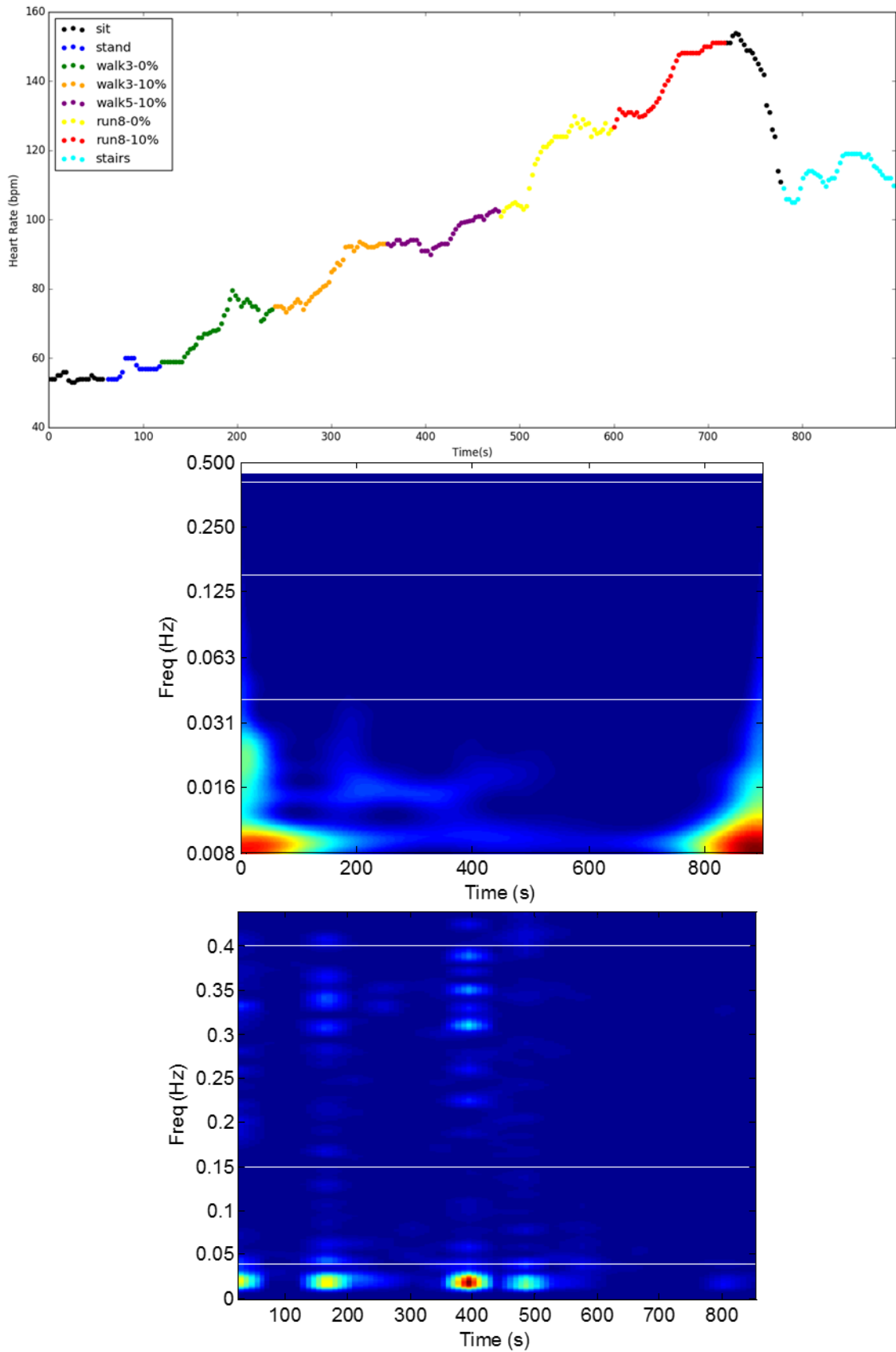


Figure 37: Time-Frequency Analysis of a heart rate signal acquired during Fitbit validity test. **Above:** Inter-beat interval signal. **Middle:** Wavelet Time-frequency Transform. **Bottom:** Periodogram.

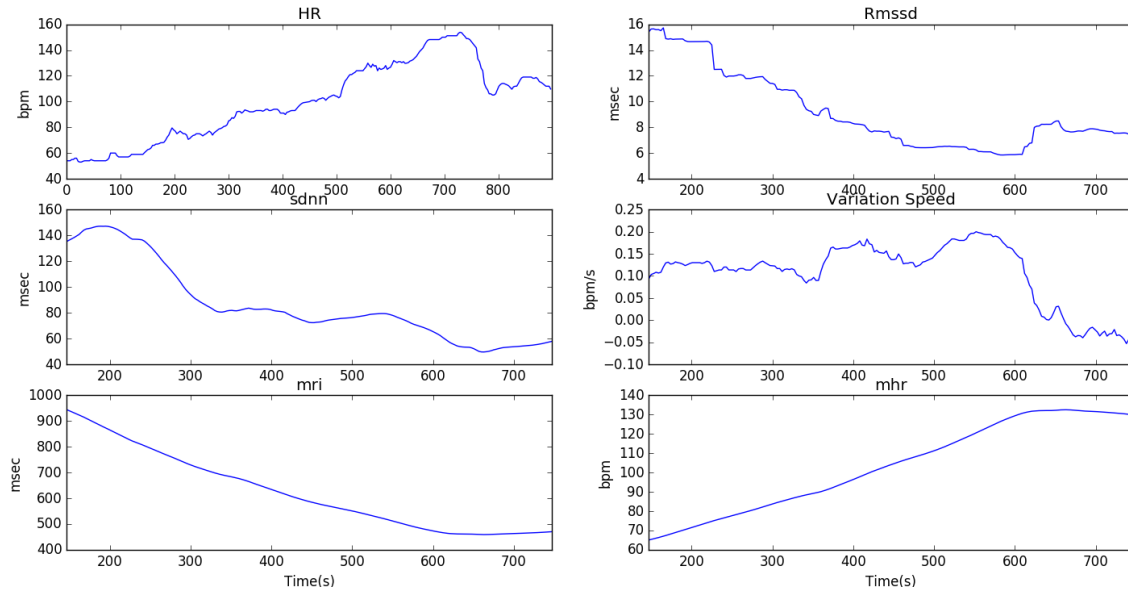


Figure 38: Time-domain Heart Rate Variability analysis over time regarding one Fitbit Surge validity test sample, represented in Figure 37(HR-Heart Rate; RMSSD- Root Mean Square of the Successive Differences; SDNN-Standard Deviation of inter-beat intervals; Variation speed-Mean Variation speed between consecutive intervals; mri-mean inter-beat intervals duration; mhr-mean heart rate).

In order to avoid excessive physical effort and cross a specific heart rate value that could be harmful to the health, taking into account the activity being performed, the monitoring of the heart rate could be very useful. Therefore, for each type of activity should be determined the heart rate values range considered normal or healthy. These heart rate, though, should be applicable to every individual with any fitness level condition and age. Therefore, the heart rate values ranges should be normalized, against the maximum heart rate value that the individual can reach and also the minimum heart rate value, normally considered as the heart rate at rest, using the formula:

$$\%HRreserve = \frac{(HR - HR_{rest})}{(HR_{max} - HR_{rest})} \times 100 \quad (4.1)$$

To estimate the HR_{max}, an age-predicted estimate equation can be utilized, suggested by Fox (220-age) (Simon, 2004), although its validity might be questionable because it was developed through clinical observations and not through rigorous research methodology.

Taking into account the relationship between the activity demanding and the instantaneous heart rate (an increase in workload should be reflected in a proportional increase in the heart rate value), abnormal heart rate values might be determined, comparing the values with the activity being performed. Therefore, for each type of activity that can be distinguished should be assigned a range of values that can be interpreted as normal or healthy, according to the physical effort that it requires.

Researchers have studied the cardiac response for different types of activity (Tamaki et al., 1987). In this work, eighteen healthy volunteers with an average age of 31 years old, performed different daily activities, including sitting quietly for 10 minutes, where the heart rate at rest where measured, standing still for two minutes, walking briskly in a firm surface for ten minutes and ascending 10 to 16 flights of stairs. Moreover, there are public datasets PAMAP and PAMAP2, which include the heart rate data of subjects performing a huge number of physical activities, including the heart rate at rest and maximum heart rate of each individual. It should be noted that when descending stairs, it should be taken into account if the ascending activity was performed right before. In negative case, the heart rate values that characterize the activity will be lower than in the positive case.

Observing the Table 13, and although there are little differences between the Fitbit and zephyr values, the obtained heart rate ranges are within the ranges reported in (Tamaki et al., 1987) and also in PAMAP and PAMAP2. However, the values obtained for ascending and descending stairs are higher than the ones reported in PAMAP and PAMAP2, due to the intense running activity that was performed before.

Table 9: Cardiac Responses reported by (Tamaki et al., 1987) (N=18).

Activity	%HRreserve	SD
Standing	9.65%	13.17%
Walking	21.93%	17.54%
Ascending Stairs	73.68%	18.43%

Table 10: Cardiac Responses obtained in public dataset PAMAP-outdoor activities.

Activity	%HRreserve	SD
Walking slow	17.37%	6.89%
Walking	28.71%	10.57%
Walking fast	39.02%	11.95%
Walking after running	54.79%	13.27%
Playing Soccer	80.12%	17.10%
Running	64.42%	17.57%
Cycling	40.85%	7.59%
Rope jumping	79.27%	17.66%

Table 11: Cardiac Responses obtained in public dataset PAMAP-indoor activities.

Activity	%HRreserve	SD
Laying	4.92%	4.20%
Sitting	8.57%	4.38%
Standing	15.79%	4.83%
Ascending Stairs	44.21%	17.63%
Descending Stairs	41.85%	17.67%

Table 12: Cardiac Responses in public dataset PAMAP2.

Activity	%HRreserve	SD
Laying	7.11%	7.12%
Sitting	10.37%	6.26%
Standing	17.50%	7.37%
Walking	36.88%	6.17%
Walking fast	45.33%	7.79%
Ascending Stairs	49.68%	16.35%
Descending Stairs	49.33%	18.50%
Running	70.89%	18.65%
Cycling	45.75%	7.51%

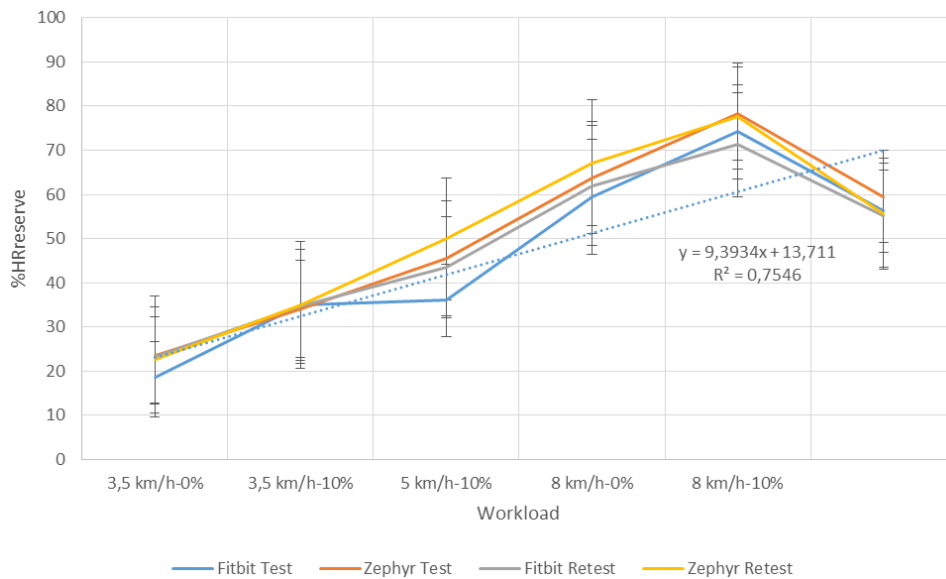


Figure 39: Cardiac responses for the Fitbit Surge validity test workload.

Table 13: Cardiac Responses obtained in Fitbit Surge validity test against Zephyr Bioharness.

Baseline (BPM)		65.50±9.25	
HR max (BPM)		194.38±2.13	
		Test	Retest
Sitting (%HRreserve)	Fitbit	3.44±2.54	5.63±8.85
	Zephyr	4.26±4.19	5.66±9.09
Standing (%HRreserve)	Fitbit	7.98±4.09	9.66±11.86
	Zephyr	10.32±7.40	11.91±11.94
Walking 3.5 km/h 0% (%HRreserve)	Fitbit	18.64±8.10	23.23±13.67
	Zephyr	23.46±11.01	22.53±9.69
Walking 3.5 km/h 10% (%HRreserve))	Fitbit	34.99±14.44	34.65±12.88
	Zephyr	34.13±10.99	35.03±12.56
Walking 5 km/h 10% (%HRreserve)	Fitbit	36.04±8.14	43.52±11.51
	Zephyr	45.61±13.04	49.93±13.82
Running 8km/h 0% (%HRmax)	Fitbit	59.50±12.99	62.01±13.61
	Zephyr	63.79±12.71	67.16±14.22
Running 8km/h 10% (%HRreserve)	Fitbit	74.16±10.67	71.31±11.80
	Zephyr	78.28±10.47	77.69±11.99
Ascending/Descending Stairs (%HRreserve)	Fitbit	56.20±9.24	55.26±11.80
	Zephyr	59.49±10.47	55.61±12.54

Table 14: T-Test results between Fitbit Surge and Zephyr Bioharness 3 cardiac responses, in test and retest.

	Corr (r ²)	Mean ± SD Diff	95% CI of Diff		p-value
			Lower	Upper	
Test	0.986	-4.21±3.34	-7.71	-0.70	p<0.05
Retest	0.993	-3.00±3.30	-6.48	0.49	p>0.05

The

Table 14 presents the results obtained when t-test was applied to the cardiac responses provided by Fitbit surge and Zephyr Bioharness 3, in both test and retest. Although the in test, some significant difference were found between the values provided by the Fitbit Surge and the Zephyr Bioharness, in the retest this does not occur. The p-value of the paired t-test higher than 0.05 and the presence of zero value inside of the 95% CI indicate that there are no significant differences between the scores by the Fitbit Surge and the Zephyr Bioharness in the retest.

Further, a linear relationship between the workload and the heart rate value, either by the chest strap or the smartwatch, was also verified, as denoted in Figure 39.

Taking account the values reported in the study performed by (Tamaki et al., 1987), the values reported in PAMAP and PAMAP2 and the values obtained in the Fitbit validity Test and retest, the following heart rate value range for each activity can be established and assumed as normal and healthy values.

Table 15: Heart rate values ranges assumed as healthy for each activity type.

Activity	Heart Rate range (%HRreserve)
Laying	0-10%
Sitting	5-15%
Standing	10-25%
Walking	15-45%
Running/Cycling	35-100%
Stairs	15-80%

These heart rate values ranges should be taken into account during heart rate and activity monitoring, either during rest or dynamic activities, so the user does not achieve heart rate values that might be harmful to the health or perform exaggerated physical effort comparing to the activity's intensity.

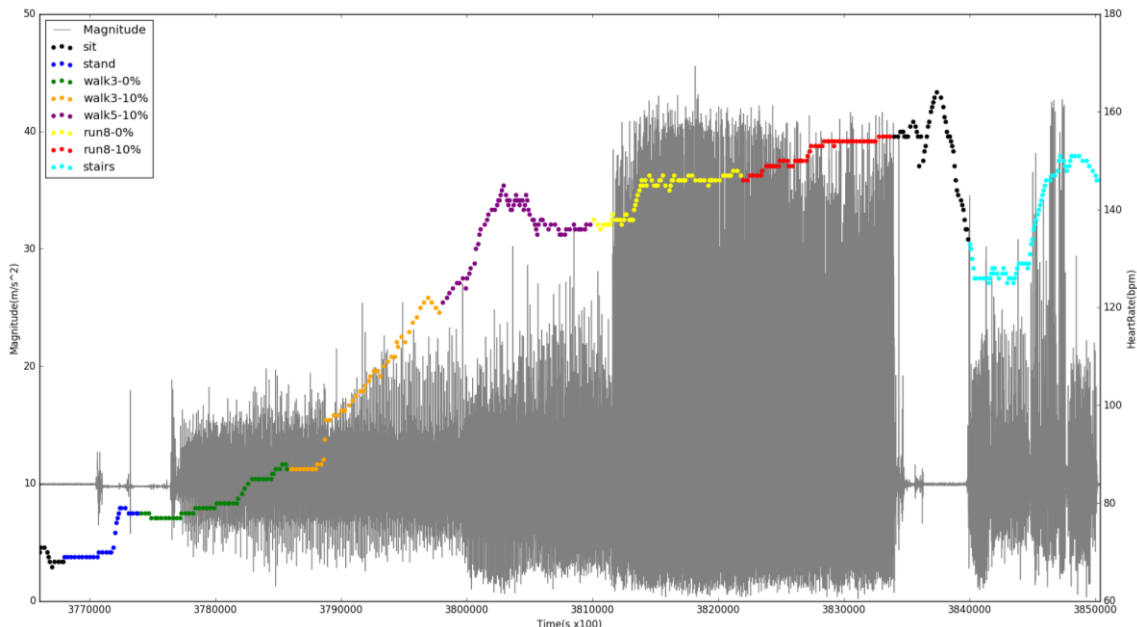


Figure 40 Relationship between heart rate and accelerometer's signal magnitude. The signal used is a sample from one of the volunteers that participated in the Fitbit Surge validity test.

Further, it can be confirmed that the heart rate response to physical effort is not instantaneous, but it responds relatively slowly to changes in physical effort. It is verified that a sudden increase in work effort will not immediately result in heart rate increase and when

the work effort is decreased, the heart rate remains elevated for some time and only gradually return to the rest values, as can be observed in Figure 40.

Moreover, it could be concluded that there is an almost linear relationship between the accelerometer's magnitude, which is representative of the activity's intensity level, and the heart rate. The higher the accelerometer's magnitude the higher the heart rate value. However, the accelerometer can also achieve a saturation state for very high speed levels (Carneiro et al., 2015), point from which this relation is no longer valid. It was observed that when the floor inclination changed from 0% to 10%, running at 8km/h, the accelerometer's magnitude slightly decreased, which might be due to the impact attenuation caused by the high inclination, since the vertical ground reaction force, and consequently the power absorption, is lower during sloped running (Gottschall & Kram, 2005).

4.2.2. Inter-combination between Heart Rate and Energy Expenditure, Speed and Activity

Table 16: Results obtained in the energy expenditure estimation study.

Energy Expenditure model		NRMSE	Corr (r^2)	Wilcoxon test p-value
Activity based (Ryu et al., 2008)		35.1%	0.88	p<0.05
Heart Rate- Basic Equation (Charlot et al., 2014)		23.5%	0.90	p<0.05
Heart Rate - $S \cdot VO_2/R \cdot HR_{max}$ (Charlot et al., 2014)		24.6%	0.90	p<0.05
Combined HR-Activity	Using HRaS	22.6%	0.90	p<0.05
	Using Activity Classification	19.9%	0.92	p>0.05

Combining the heart rate and activity data to estimate energy expenditure, there is an improvement of the results obtained with only activity based model.

Using the activity based model, with the equations proposed by (Ryu et al., 2008) to estimate energy expenditure, the NRMSE reaches 35.1% with a Pearson correlation coefficient of 0.88.

Using the basic heart rate model, proposed by (Charlot et al., 2014), the NRMSE reaches 23.5%, with a Pearson correlation coefficient of 0,90. In turn, the model that includes the real maximum heart rate value and the speed at which occurs the maximum oxygen volume consumption, but also proposed by the same author, reaches a NRMSE of 24.6% and a Pearson correlation coefficient of 0.90. Generally, although the errors might be acceptable, these models overestimates the energy expenditure, especially during walking, where the NRMSE achieves 43.2%. Otherwise, they underestimate the energy expenditure during very high speed running (above 14 km/h), where the NRMSE achieves 17.2%.

Since the data does not follow a normal distribution, the statistical test applied was the Wilcoxon Signed Rank Test, a non-parametric test for paired data. Applying the statistical test for a significance level of 5%, it can be confirmed that there are significant differences between the energy expenditure values obtained from the indirect calorimetry measurements and from the activity based model and both heart rate models.

In turn, combining the heart rate and activity based models, where the heart rate model is the one with the better performance (basic model), the NRMSE reaches 22.6%, with a Pearson correlation coefficient of 0.90.

Nevertheless, there is a significant improvement in energy expenditure estimation when activity and heart rate data are combined. However, there are still significant differences between the values obtained through indirect calorimetry and through the models that includes both heart rate and activity data. Nevertheless, this result can still be improved, by using

individual calibration procedures, as proposed by (Altini et al., 2013, 2015) and (Søren Brage et al., 2004, 2007), instead of using developed equations with group calibration, as occurs in these models.

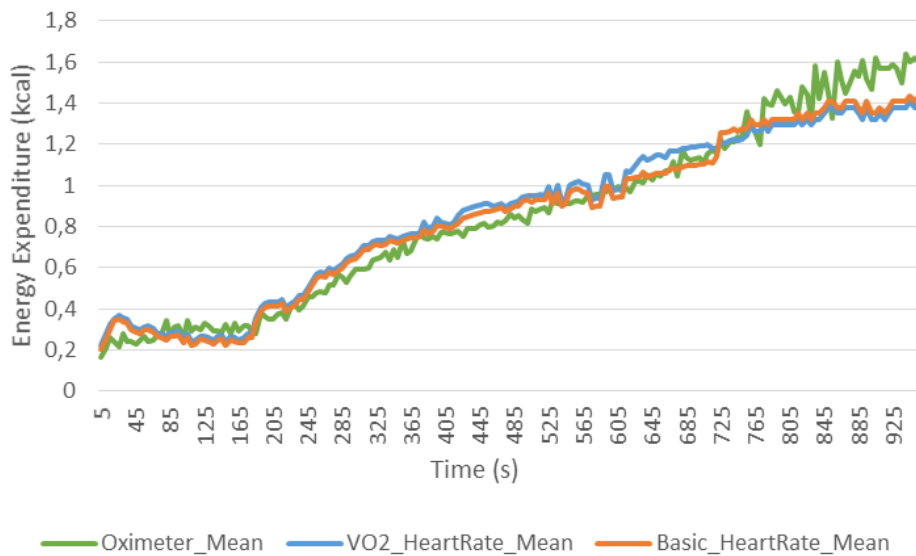


Figure 41: Average energy calculated, for all the participants. The green line represents the energy expenditure given by the oximeter, the orange line represents the through basic heart rate model and the blue line represents the energy calculated through the heart rate model that includes the speed at which occurs the VO_{2max} .

Otherwise, when using the activity classification as method to decide which weight factors should be attributed to each heart rate and accelerometer contribution, instead of using the HRAs as threshold, the NRMSE reaches 19.9%, with a Pearson correlation coefficient of 0.92. The results obtained here showed no significant differences comparative to the values provided by the indirect calorimetry. With this model the error is reduced during moderate to intense walking activity.

Further, the model applied showed a better performance during running, because it was initially derived to improve running energy estimation, although during its estimation it was also included the walking activity. The NRMSE achieves 32.4% and 16.25% for walking and running activities, respectively.

The average energy expenditure measured, for all the participants, through the oximeter, basic heart rate model, activity based model and combined heart rate-accelerometer model, using activity classification to establish the weight factors, are depicted in Figure 42. As observed, the model suggested by (Ryu et al., 2008), based on smartphone's accelerometer to classify the activity performed and calculate a MET value for each activity, gives acceptable energy expenditure values during walking. However, it overestimates the energy expenditure during running at moderate speed levels. In this model, it is observed a saturation phenomenon in the accelerometer signal for higher speed levels, which affects the performance of the step counter and distance calculator and, consequently, the calculated speed and energy estimation. In turn, when applying the combined heart rate and activity data model, there is great improvement when compared to the activity based model. However, although the energy expenditure estimation has improved for walking activity, this model still underestimate the energy expenditure for very high speed levels.

It should be noted that this study presents some limitations that extent to data that were missing due to monitor's instability or malfunctioning. Hence, some samples were excluded due to the missing heart rate values. However, just the null values were excluded, since they not allow the energy expenditure estimation, and all the other values, including the

ones corresponding to possible artefact movements or poor skin-contact were included in the analysis.

Thus, the combined heart rate-activity model that uses activity classification to attribute the weight factors to each heart rate and accelerometer contribution, is the most suitable method to estimate the energy expenditure using the accelerometer of the smartphone and activity classification and heart rate data. However, and although it has been proved that the heart rate data improves the heart rate estimation, the heart rate monitor to be used should be accurate and precise, in order to heart rate information not be lost because if this occurs, the total energy expenditure during the all measurement will be underestimated, as occurred in the present study.

Taking this study into account, it can be said that the use of a smartwatch to estimate energy expenditure through heart rate could be advantageous, since this variable improves energy expenditure estimation. However, depending on the device's accuracy and reliability, this can be verified or not, since if the heart rate value provided by the device is not even similar to the real one, the energy expenditure estimation will be also very distant from the real value.

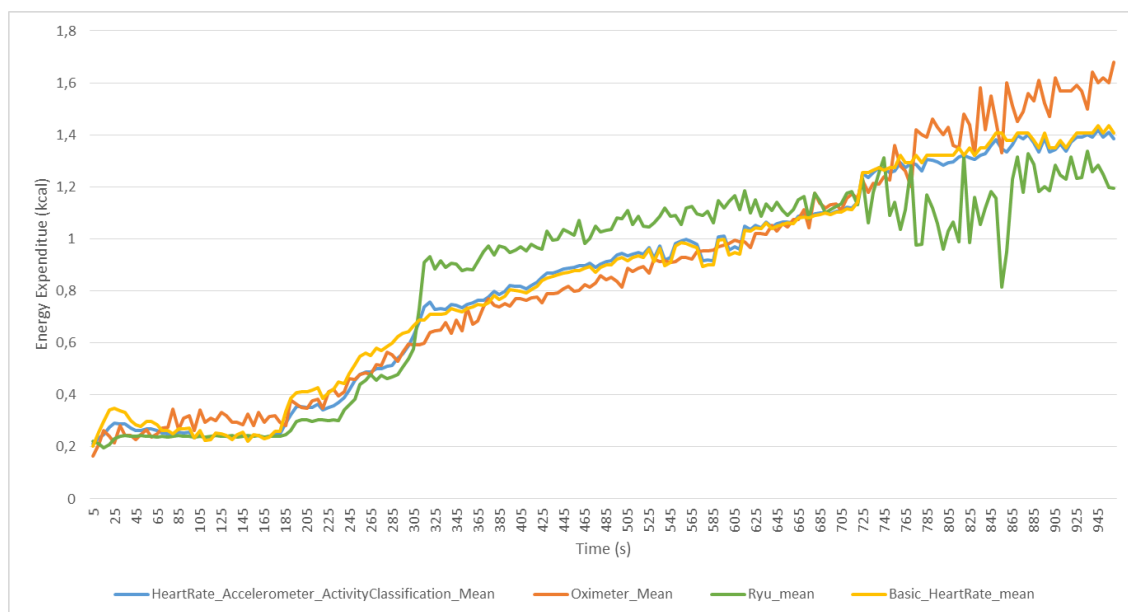


Figure 42: Average energy calculated, for all the participants. The orange line represents the energy expenditure given by the oximeter, the yellow line represents the energy calculated through basic heart rate model, the green line represents the energy expenditure given by (Ryu et al., 2008) and the blue line represents the energy calculated through the combination of both heart rate-activity model, that uses activity classification to establish the weight factors.

Further, with the same data, the linear relationship between speed and heart rate during submaximal intensity, which is referred in the literature (Bodner & Rhodes, 2000; Vachon et al., 1999), was verified. As observed in Figure 43, after the 13 km/h, this linear relationship is no longer present, due to the anaerobic threshold crossing (Heart Rate Deflection Point), when the range of 88% to 94% of the maximal heart rate is achieved (Bodner & Rhodes, 2000; Vachon et al., 1999). This almost linear relationship between the heart rate value and the speed, until the deflection point is reached, is depicted, with more detail, in Figure 44.

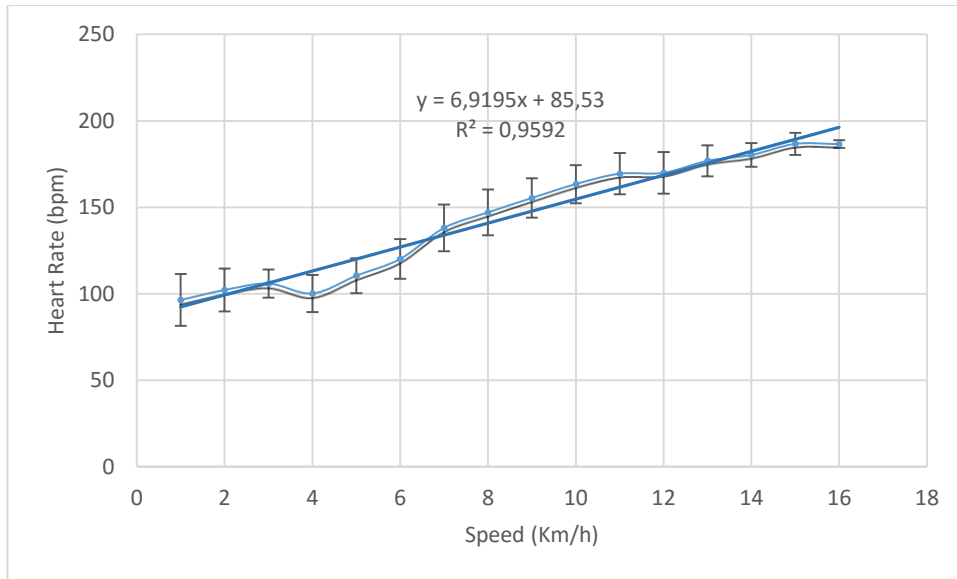


Figure 43: Relationship between heart rate and speed, using the data of all the participants. The heart rate values are the mean.

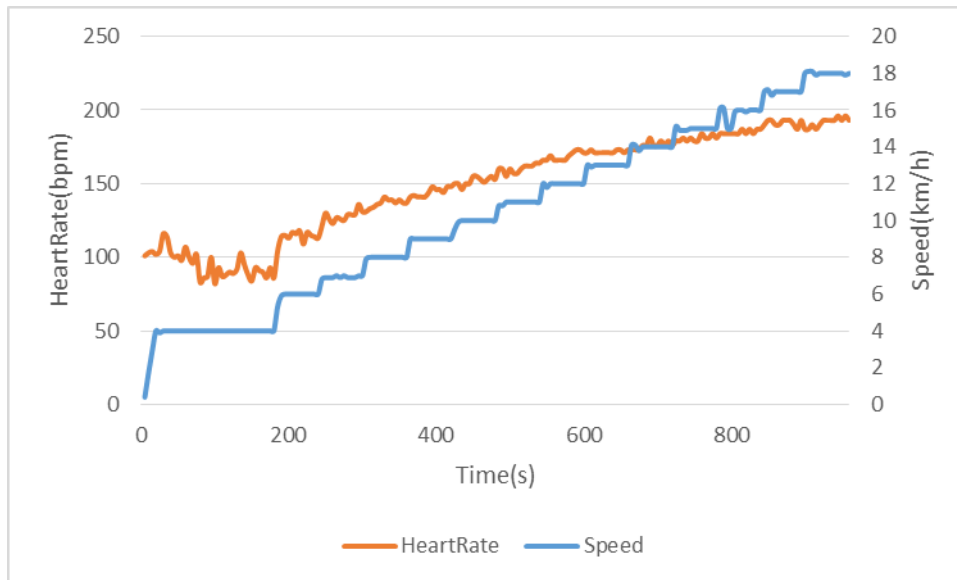


Figure 44: Relationship between the heart rate and speed, using the data of one of the participants.

4.2.3. Stress State Detection

Through the time-domain heart rate variability analysis throughout the time, it can be concluded that the algorithm proposed by (Pierleoni et al., 2014) is not suitable to be applied on the signal provided by the smartwatch, since the calculated time-domain HRV parameters are not comparable due to the very different sampling frequency. The proposed methodology intends to be applied on a heart rate signal that includes all the heart beats. In turn, the smartwatch does not accomplish this requirement, since it provides the heart rate at a specific timestamp.

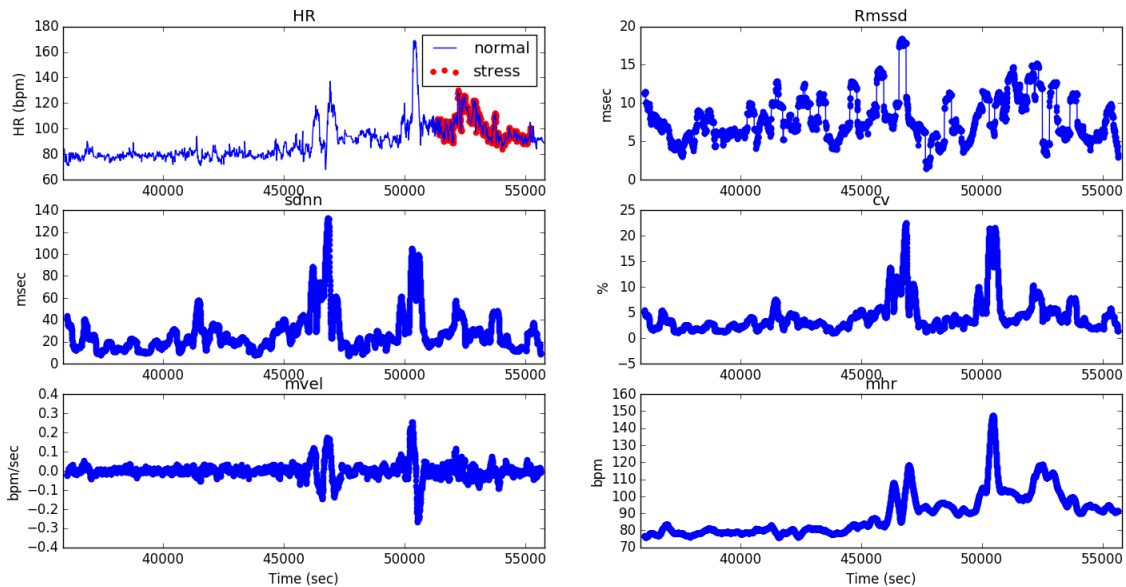


Figure 45: Time-domain HRV analysis of one of the stress state samples (HR-Heart Rate; RMSSD- Root Mean Square of the Successive Differences; SDNN-Standard Deviation of inter-beat intervals; Variation speed-Mean Variation speed between consecutive intervals; mri-mean inter-beat intervals duration; mhr-mean heart rate).

It was found out that, in all the samples that were analysed, the RMSSD is always below the established threshold (45msec). Besides this, both RMSSD and SDNN seem to behave oppositely comparing to the expected and referred on the literature. In fact, these parameters seem to suffer an increase when a stress state occur, due to the abrupt heart rate rising.

Further, the reported stressful situations were classified as such state in a subjective way, just taking into account the individual's feelings. Hence, and since a blood test should have been performed in order to detect the stress hormone serum cortisol, as reported in (Yang et al., 2008), allied to a low number of samples, this topic's goal was not achieved and more investigation is needed. In short, no conclusive findings were achieved about this topic.

4.3. Developed System Behaviour

As referenced in Chapter 3.1, in order to the application access the user data, the user must previously give authorization to do so. For that, on the first time the user experiences the application, he will be redirected to the authorization page, as described in Figure 46, so the application can get the access token needed to execute the data requests to the webserver. This is how the OAuth 2.0 protocol, adopted by Fitbit, works. Once the user authorizes the access, the access token provided has one year of lifetime. Hence, this procedure only needs to occur once a year.

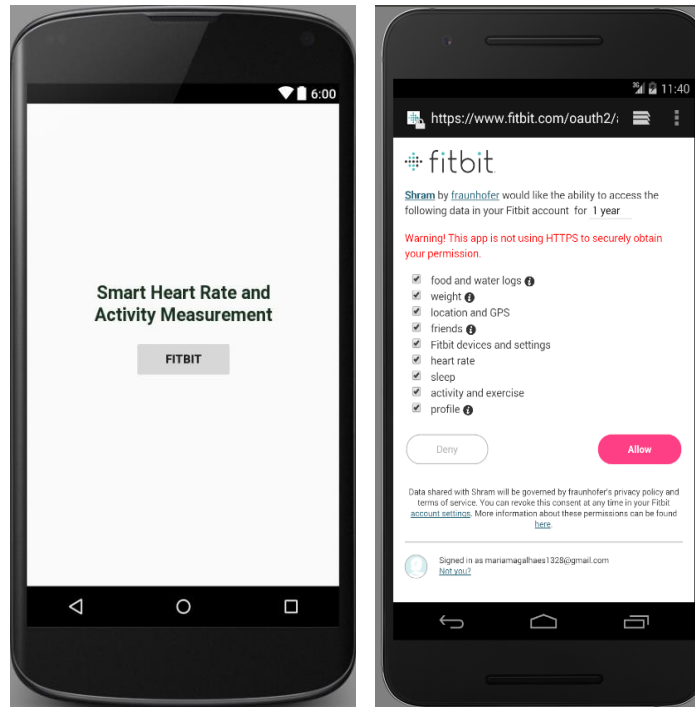


Figure 46: Application authorization procedure.

The application includes a main page that displays the main user's personal data, such as the name, birthdate and the heart rate value at rest. This last feature is important because it is an indicative of the individual fitness level and how it evolves throughout the time, since it is known that a low heart rate value at rest is indicative of a good physical condition. It also includes a detail panel that displays the activity performed in real-time, the number of steps performed, the energy expenditure, the number of active minutes so far, and also the maximum heart rate and the cardiac zone in which the user spent more time during the last data that was synchronized. The number of steps and energy expenditure is relative to the current day. Hence, every day these features are reinitialized. Further, it also displays the application menu, including the monitoring details regarding the heart rate and activity monitoring, abnormal events analysis and also the daily summary. The user might also opt by turn on the Threshold Mode, where a heart rate threshold is manually established by the user and every time this threshold is crossed, the application saves the event to alert the user. This is useful to give the user an idea of the ideal effort for every physical activity and how was his performance.

The heart rate and activity monitoring details include the detailed heart rate signal throughout the time of the current day, the time spent and the calories that were burned in each cardiac zone, which in turn is defined using the theoretical maximum heart rate value (% of the HRmax). Further, it includes the option to consult the number of active minutes along the day, depending on the activity's intensity performed: sedentary, lightly, fairly or very active. The user can also request the data of a specific day. The abnormal events option records the heart rate events along the day, which includes crossing the established threshold and abnormal heart rate values for the activity that is being performed, which could be indicative of stress or emergency situations. This analysis takes into account the type of activity being performed and the established range of healthy values, as referred in Chapter 4.2.1, and also if vigorous exercise was executed previously or not to a rest activity. In this case, it is expected to occur a recovery phase. Finally, the daily summary details the most important features that characterize each day, namely the maximum and minimum heart rate value achieved, the minutes spent in each activity, the number of steps and calories burnt. The number of active

minutes is compared with the goal suggested by the World Health Organization³⁹, which is about daily 30 active minutes. It also reports the number of abnormal events and the most active and stressful day so far. These are computed taking into account the day with the higher number of active minutes and stress events, respectively. For that, specific databases for each type of data were created.

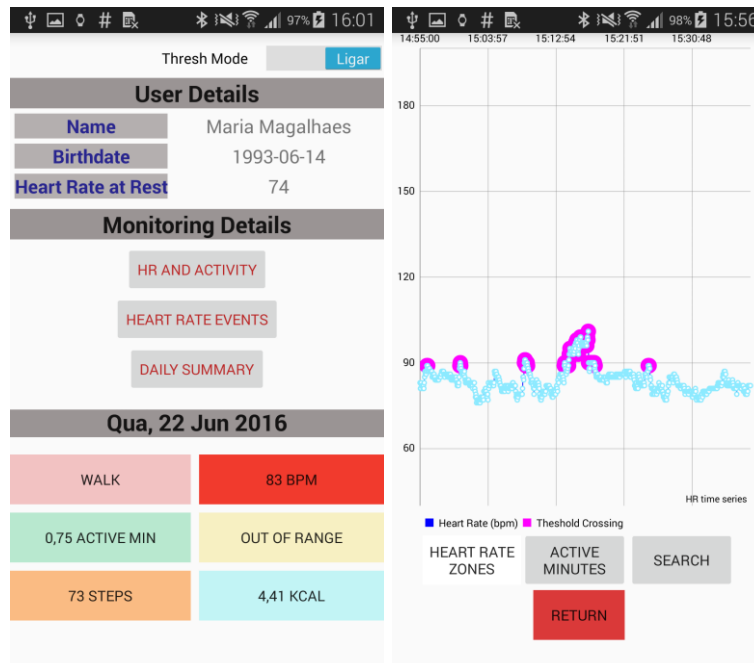


Figure 47: Main page and the heart rate signal plot, with the threshold crossing events signaled.

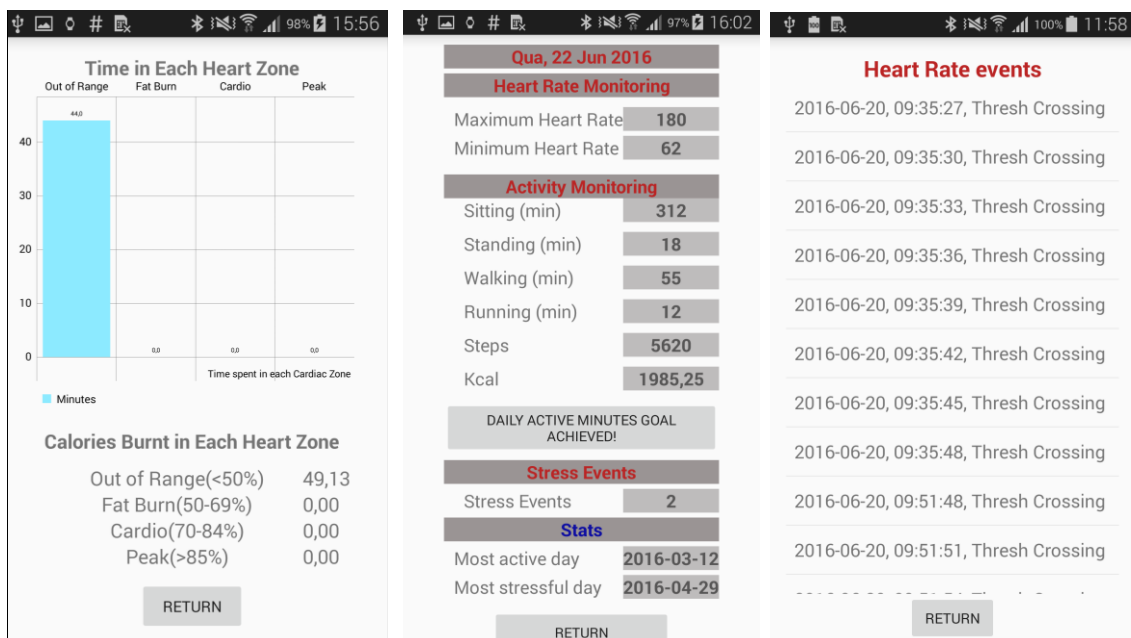


Figure 48: Left: The plot of the number of time and energy expenditure in each cardiac zone. Middle: Example of a daily summary. Right: Example of list of events, including thresholding crossing, stress events or abnormal heart rate values.

³⁹ http://www.who.int/dietphysicalactivity/factsheet_adults/en/

Although the developed system was not validated yet due to calendar issues, the data outputs that are provided to the user are intended to help him following a healthy lifestyle, keeping the heart rate within the range of values considered as normal and also giving an idea how the cardiorespiratory fitness level evolves throughout the time, through the heart rate at rest value and cardiac response to physical activity. Hence, the heart rate and activity data can be combined to give valuable information to the user and guide him to prevent long-term serious health problems, due to harmful heart rate values, inactive lifestyle and exaggerated stress during quotidian.

Chapter 5

Conclusions and Future Work

The heart rate corresponds to the number of times that the heart pumps blood through the blood vessel of the circulatory system in one minute, and it is very important to infer about the health status, being an important variable to keep on track by every person, from athletes, cardiac patients and common individuals. The heart rate variability reflects the physiological phenomenon of variation in the time interval between heartbeats. Its variation may contain indicators of current diseases or warnings about potential cardiac diseases, psychological disturbances or even neurological disturbances. These indicators may be present at all times or may occur randomly during certain intervals of the day. It reflects physiological factors that modulate the normal rhythm of the heart, providing a powerful method of observing the equilibrium between the sympathetic and parasympathetic nervous systems and, consequently, the heart's ability to adapt to changing circumstances.

Although there are plenty of devices that are capable of heart rate monitoring, such as the gold standard ECG, Holter monitors and blood pressure monitors, these devices are not suitable for daily basis use since they might be quite uncomfortable and difficult to use. Nevertheless, the wearable technology market is experiencing a huge growth and it is expected to expand even more during the next years. Current smartwatches and bracelets, which are daily basis accessories, already track the user activity, reporting several measures such as distance, speed, number steps performed, calories burned and also distinguishing between several different types of activities: walking/running, sitting and laying down. These are calculated through data acquired by built-in inertial sensors. These accessories might include an optical heart rate sensor, whose data is very useful for athletes, to control their effort during the workout and optimize the training. Its applicability has been used essentially for exercising purposes.

Therefore, one of the main goals of this project was to study if it is viable to a wearable device to continuously monitor the heart rate in a daily basis, and if when combined with activity monitoring, additional valuable data could be generated for analysis. Namely, if it allows inferring about the health status of the user and understanding the quotidian context and the impact that the lifestyle has on health. Further, it was also studied how the heart rate data could bring advantages to the activity monitoring, mainly, how both data and features can be combined in order to improve activity monitoring, especially the impact on heart rate variability patterns observed in different activities and how the heart rate data can enrich the energy expenditure estimation.

5.1. Achievements

The objectives of studying the viability of using a wearable device for continuous heart rate monitoring and how the heart rate data could be combined with activity data to perform a better analysis of the user's lifestyle and quotidian context were achieved.

A heart rate measurement validity test for the smartwatch Fitbit Surge was performed against a Zephyr Bioharness 3 chest strap. This smartwatch was chosen by taking into account a previous test that included other smartwatches such as the Moto360, LG Watch R and Samsung Gear S, and also the high popularity that this gadget has won among the healthy lifestyle and exercisers community⁴⁰. The test performed included a test and retest with eight volunteers with an average age of 25.6 ± 2.1 years old, including five men and three women. In average both heart rate signals provided by the chest strap and the smartwatch were concordant during the most part of the test and retest. However, there were some cases in which the error obtained were not acceptable for heart rate monitoring purposes. The walking and running activities were the ones with lowest reliability and bigger data dispersion, although they were the activities with higher samples. The accuracy achieved was within the values presented in literature but the reliability was quite lower than the expected (reliability=75.39%, accuracy=93.80%, mean error=4.21 BPM, mean absolute error=7.22 BPM). However, since the volunteers that performed the test were in lower number than the usual subjects number in these kind of tests, the data obtained might not be sufficient to achieve a conclusive finding. Further, the individuals that showed poor results in the test, had also poor results in the retest. Hence, regarding the test-retest results, a p-value of the paired t-test higher than 0.05 and the presence of zero value inside of the 95% CI indicates that there are no significant differences between the scores obtained in test and retest procedures. Both accuracy and reliability demonstrated good retest reliability with ICC of 0.65 and 0.61, respectively. The results showed that the Fitbit Surge device had a good accuracy and acceptable reliability, assuming that it is not supposed to the smartwatch acting like a medical device and that it has associated error that can or cannot be acceptable, depending on the purpose for which the device is intended to be used. Since the purpose is not performing heart rate monitoring in cardiac patients, the reliability value obtained can be acceptable for heart rate monitoring of people that intend to follow an active and healthy lifestyle. Moreover, the results show that the device provides results with some repeatability, giving, though, some credibility to use it in a daily basis. In average, the heart rate values were correlated, with differences up to 20 BPM, but with Fitbit showing a slightly lower heart rate value. Further, some problems were observed at sudden transitions of activity intensity, with the Fitbit responding a bit late to the pace change, and with high intensity activities, where in some cases it did not follow the heart rate increase to theirs peak values.

Regarding the heart rate variability patterns and the activity type being performed, some conclusions can be taken. When applying time-frequency transforms to the heart rate signal, the obtained spectrums can distinguish the beginning of each activity that causes an abrupt heart rate increase, when the window's width applied is sufficient and suitable for each activity's duration. Further, during low intensity and moderate activities, the presence of higher frequencies are highlighted, due to the greater variability presence. However, these patterns can distinguish between low intensity and intense activities, since although the first ones could also cause the abrupt heart rate increase and, therefore, will cause the presence of low frequencies in the spectrum, they also are characterized by some heart rate variability. Hence, also higher frequencies are present during these activities. Further, it was possible to confirm the almost linear relationship between the heart rate value and the activity's intensity

⁴⁰ <http://www.telegraph.co.uk/technology/news/12033656/Fitbit-is-the-most-popular-wearable-of-2015-as-sector-grows-almost-200pc.html>

level, which can be also confirmed by the accelerometer's magnitude. However, the accelerometer can also achieve a saturation state for high speed levels, from which this relationship is no longer valid. Nevertheless, it was also possible to infer about the range of healthy heart rate values that are considered normal to achieve during different activities, depending on its intensity and physical effort required. These are normalized heart rate values, against the maximum heart rate value and the heart rate at rest, so they can be suitable to apply on every individual, regardless the cardiorespiratory fitness level and age of each individual. These ranges are important for an efficient monitoring, giving the user a guide of which is healthy to perform or not, avoiding harmful heart rate values that can lead to serious long-term health problems and damages.

Combining the heart rate with activity data, which is provided by motion sensors such as the accelerometer, improves the accuracy of energy expenditure estimation, as is testified by the results obtained in the present study. The normalized root mean square error (NRMSE) decreased from about 35.1% to 23.5% when applying the heart rate model that includes individual parameters such as the heart rate at rest, height, weight, age and gender, instead of the activity based model. When combining both heart rate and activity models to estimate the energy expenditure, which consist in attributing weights factors to each specific model, the NRMSE reached 22.6%, when using the heart rate above sleep as threshold to decide the weights that are attributed to each heart rate and activity based model, and 19.9% when using the activity classification to do establish the weights of each model. Thus, the combined heart rate-activity model that uses activity classification to attribute the weight factors to each data, seemed to be, among the other tested models, the most suitable method to estimate the energy expenditure using the accelerometer of the smartphone, activity classification and heart rate data. Further, with the same data used in the energy estimation study, the linear relationship between speed and heart rate during submaximal intensity, which is referred in the literature (Bodner & Rhodes, 2000; Vachon et al., 1999), was verified. This data was relative to a stress test like protocol, and it was observed that after about the 13 km/h, this linear relationship is no longer present, due to the anaerobic threshold crossing.

In short, it can be concluded that the smartwatches are valuable devices that help people achieving a healthier lifestyle, by monitoring their activity. Although some of them do not include optical heart rate sensor, and the majority of those who include are not reliable and suitable for heart rate monitoring, the smartwatch studied in this project showed that it has a good accuracy and a median reliability and performs a continuous heart rate monitoring, although with a variable sampling frequency. Further, it allows the development of third parties applications, which current continuous smartwatches, such as Mio alpha and PulseOn, do not enable. However, they are not suitable for arrhythmia detection, due to the insufficient sampling frequency. Moreover, these kind of devices can be used to improve energy estimation methods, if they are accurate and reliable, and also used as a quotidian tool, to help people having a healthy lifestyle and not executing exaggerated efforts by monitoring their heart rate. The heart rate value is a valuable indicative of the cardiorespiratory fitness level, and its behaviour throughout the time gives an idea of how the physical condition evolves. The heart rate data provided can be used to improve current energy estimation methods used by activity monitoring systems, and also to improve both activity monitoring and activity classification, since there are different activities that are classified with the same label but characterized by different intensities and, therefore, different heart rate values, as is the case of walking and ascending stairs. Although it does not allow a real-time monitoring, due to the data synchronization frequency, this study serves as a proof of concept, with the certain that in the future this kind of technology will be improved and the real time monitoring through third parties application will be possible.

5.2. Future Work

Further development of this project would be of interest to improve the developed monitoring application that gives a relevant feedback about the user physical history. The main improvements of that could be applied to this project and future work were identified during its development.

Due to the positive results obtained in the energy expenditure estimation using both heart rate and accelerometer models, it should be integrated a model to estimate the energy expenditure that combines the heart rate data, provided by the smartwatch, and the accelerometer data, provided by the smartphone. This model could replace the activity based model (Ryu et al., 2008) that is currently being used by the developed system to estimate the energy expended.

One of the goals of this project was to combine heart rate and activity data to infer about the user's stress state detection, however, this goal was not achieved due to several reasons. Firstly, it was found that the stress state detection algorithms are based on the heart rate variability features and establishing some thresholds for each one, but the signal provided by the smartwatch is not suitable to apply these algorithms due to the lower sampling frequency. Further, the acquired data relative to this topic was considered low to achieve a conclusion about the adaptation and use of such device's heart rate signal to detect stress. Moreover, each stress state should be confirmed by a blood test for measuring the stress hormone serum cortisol. Hence, more investigation about this topic is needed.

Further, and since the developed system is a proof of concept and prototype, this can be largely improved. Firstly, the smartwatch that is currently being used with the system does not enable a real-time heart rate monitoring. Therefore, and since this is a very important feature, the smartwatch that is currently being used should be replaced by another that enables the continuous heart rate monitoring in real-time, and that is accurate and reliable enough at the same time. As studied, none of the Android Wear smartwatches with an optical heart rate sensor fulfil these requirements, since a suitable and constant reading frequency cannot be established. Hence, as soon as a smartwatch that completely fulfils these requirements be launched on the market, it should be considered the possibility of replacing the current heart rate monitor. Nevertheless, the data output display and data history should be improved, since it is important to the user that these aspects are as complete as possible and, currently, they are just prototypes. Further, the system performance must be tested and evaluated, in order to validate the algorithms and its behaviour, taking into account the purpose for which it was built.

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Appendix A

Fitbit Surge heart rate measurement validity test results

This appendix details the results regarding the reliability and accuracy measures, per subject and activity type, the mean errors and mean absolute error obtained per activity, and also other representative graphics that compare both heart rate signals provided by the zephyr Bioharness 3 and the Fitbit Surge.

Table A1: Reliability results per activity and subject.

Subject/ Activity	Sit		Stand		Walk		Run		Stairs	
	test	retest	test	retest	test	retest	test	retest	test	retest
1	100	79,50	76,27	86,66	17,78	48,89	80,83	85,42	60,34	100
2	100	96,61	50,85	86,66	78,06	91,11	94,17	95,42	98,18	100
3	86,87	73,79	81,36	80,00	100	77,50	100	95,83	100	100
4	65,25	100	91,52	81,66	29,44	48,33	6,67	30	64,66	20,69
5	93,22	61,86	77,97	11,67	87,50	59,17	98,33	11,67	100	66,67
6	100	30,00	84,75	NA	96,39	98,68	96,25	95,00	93,10	82,76
7	93,10	56,78	94,92	86,66	87,50	66,39	93,75	72,08	100	100
8	59,32	70,34	76,27	78,33	51,94	95,28	41,67	71,25	73,91	100
Average	87,22	71,11	79,24	73,10	68,58	73,34	75,99	69,64	86,27	83,76

NA-Not Available. Smartwatch was not responding.

Table A2: Accuracy Results per activity and subject.

Subject /Activity	Sit		Stand		Walk		Run		Stairs	
	test	retest	test	retest	test	retest	test	retest	test	retest
1	95,67	97,29	92,98	95,83	83,16	92,18	96,20	97,94	95,17	98,52
2	95,95	96,89	89,48	93,49	92,83	94,41	96,36	97,78	96,17	97,09
3	96,40	95,53	94,74	91,86	97,52	94,04	98,01	96,93	98,23	97,73
4	97,20	93,51	94,27	88,92	87,63	90,84	87,34	86,06	94,05	92,65
5	93,24	91,36	93,20	77,80	95,77	89,88	99,90	88,76	98,27	94,24
6	93,17	86,42	91,20	NA	96,41	95,69	97,16	97,39	96,92	92,55
7	97,99	93,67	95,16	95,17	96,08	92,77	97,98	95,43	98,07	96,86
8	97,84	93,22	93,58	90,52	89,78	92,26	91,30	89,76	95,10	94,74
Average	95,93	93,49	93,08	92,40	90,51	92,76	95,53	93,76	96,50	95,55

Table A3: Mean and Mean Absolute error observed.

Activity	Mean Error (BPM)		Mean Absolute Error (BPM)	
	Test	Retest	Test	Retest
global	4,55±10,37	3,88±8,93	7,43±8,55	7,01±6,76
sitting	4,80±9,29	0,80±10,19	6,09±8,51	6,86±7,57
standing	3,04±7,27	3,47±6,16	5,60±5,54	4,66±5,31
walking	5,11±11,52	3,10±8,27	8,61±9,20	6,88±5,55
running	4,81±11,32	6,78±7,88	8,09±9,26	7,61±7,08
stairs	3,12±6,43	3,29±11,07	5,13±4,98	7,40±8,87

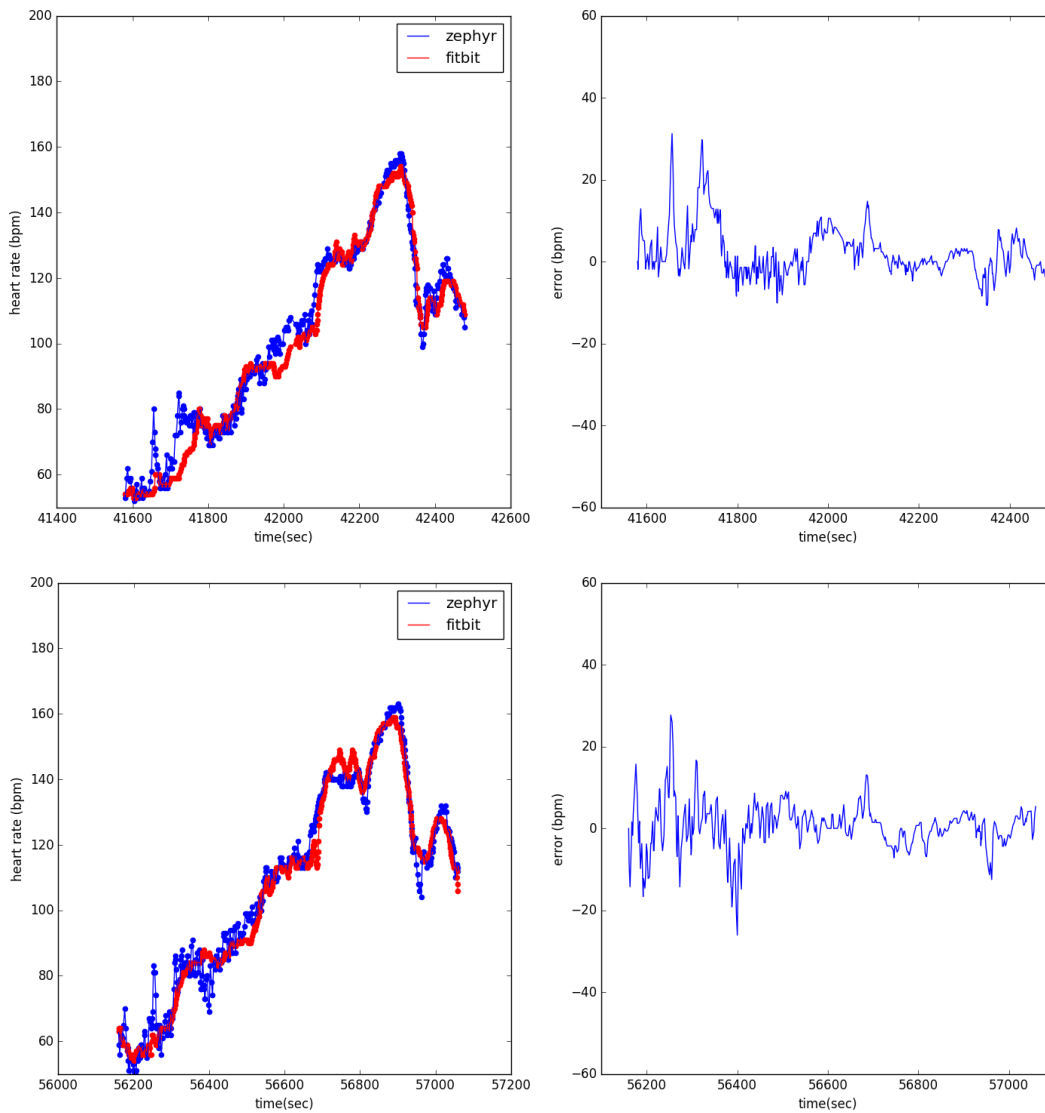


Figure A1: Other examples of results obtained in Fitbit Surge Validity test - Comparison between the chest strap and smartwatch heart rate signals.

Appendix B

PAMAP and PAMAP2 activities description

This appendix details the description of each activity that was included by the public datasets PAMAP and PAMAP2.

Table B1: Description of the activities performed on public datasets PAMAP and PAMAP2.

Activity	Description	
Laying	PAMAP	Lying quietly, doing nothing, but small movements such as changing the laying posture are acceptable.
	PAMAP2	
Sitting	PAMAP	Sitting in a chair, where writing, desk work or typing is allowed.
	PAMAP2	Sitting comfortably in a chair. Changing sitting postures is allowed.
Standing	PAMAP	Standing still, possibly talking and gesticulating.
	PAMAP2	
Walking	PAMAP	Walking outside with moderate to brisk pace, with a speed between 4 and 6km/h, on a firm surface.
	PAMAP2	
Walking slow	PAMAP	Walking at speed lower than 3,2 km/h, level ground, strolling, very slow.
Walking fast	PAMAP	Nordic Walking, performed outside on asphaltic terrain, using asphalt pads on the walking poles.
	PAMAP2	
Running	PAMAP	Jogging outside with a suitable speed for the individual subjects.
	PAMAP2	
Cycling	PAMAP	Bicycling at speed lower than 16.1 km/h, including leisure, riding to work or just for pleasure
	PAMAP2	Performed outside with a real bike with slow to moderate pace.
Ascending Stairs	PAMAP	Walking upstairs during 1 minute.
	PAMAP2	Performed in a building between the ground and the top floors, a distance of five floors had to be covered going upstairs
Descending Stairs	PAMAP	Walking downstairs during 1 minute
	PAMAP2	Performed in a building between the ground and the top floors, a distance of five floors had to be covered going downstairs
Rope jumping	PAMAP	Basic rope jump, where both feet jump at the same time over the rope, or the alternate foot rope jump, where alternate feet are used to jump off the ground.
	PAMAP2	
Playing Soccer	PAMAP	Playing 1 vs. 1 or 2 vs. 1, running with the ball, dribbling, passing the ball and shooting the ball.
	PAMAP2	

