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Non-invasive wearable sensing system for sleep disorder monitoring

Faculty of Sciences and Technology

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Mestrado em Engenharia Eletrónica
e Telecomunicações

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Declaração de autoria do trabalho

Declaro ser o autor deste trabalho, que é original e inédito. Autores e trabalhos consultados estão devidamente citados no texto e constam da listagem de referências incluída.

(Mauro Cruz Alberto)

Para quem acreditou em mim

"Whatever course you decide upon, there is always someone to tell you that you are wrong. There are always difficulties arising that tempt you to believe that your critics are right. To map out a course of action and follow it to an end requires courage."

Ralph Waldo Emerson

Acknowledgments

Aos meus pais, dedico este trabalho. Parece mentira, porém, está feito. E isto, porque vocês nunca desistiram de mim, nem mesmo quando eu não estava a dar provas de que era capaz de me elevar perante o desafio. A pessoa que entrou há sete anos na UAlg, não é a mesma de hoje e tudo porque tive a sorte de vos como progenitores. Obrigado por não desistirem de mim, e este trabalho é fruto da vossa educação e também de todo o afeto que recebi pela restante família (Irmã, Tios, Primos e Avós).

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Abstract

Keywords—sleep disorders; apnea; remote health monitoring; body sensor network;

This Master Thesis introduced a proposal of a remote sensory system for the detection of sleep disorders in geriatric outpatients. Although the most accurate solution would be an in-depth study in a sleep clinic, it is not a realistic environment for the elderly. The objective is that the patient stays at home, and without changing their daily routines, the clinicians get objective information in order to make a correct diagnosis of the sleep disorders. Sleep disorders are often classified as medical disorders corresponding to modifications on the sleep patterns and the amount of these modifications increase with age. However, regularly, these illnesses are undiagnosed, since is hard for the patients to explain the symptoms to the doctor. To achieve the proposed objective, we studied the polysomnography bio-signals that could be used to accurate reflect the sleep disorders occurrences. We designed a Body Sensor Network (BSN) to be divided into both movement assessment (Accelerometer and Gyroscope) and biomedical signals (EMG, ECG, PPG, GSR) evaluation. These signals, reflecting both breathing and cardiac activities, are processed by a specifically developed algorithm. The reduction of the number of sensors was also envisaged, and it was decided to use 3 biomedical sensors instead of the minimum of 22 sensors used by polysomnography. Thus, to offer better visualization of the recorded signals a software interface was developed to include the processing and visualization of the signals. To identify the sleep stage and apnea state, we settled an algorithm that processes both ECG and EMG. To validate this algorithm, it was decided to use two sources of data: PhysioNet data base containing ECG and EMG signals and data recorded by our BSN on volunteers. With this work, we were able to build a BSN capable of detecting a set of sleep disorders, without using any invasive method. The network provides reliable data, and using the developed interface, it helps elderly health providers to carry out an in-depth analysis of the information and to better identify sleep disorders.

Resumo

Keywords — distúrbios de sono; apneia; Monitoramento remoto da saúde; Rede de sensores corporais;

Este trabalho introduz uma proposta de uma monitorização remota de saúde para a deteção de desordens de sono em pacientes ambulatórios geriátricos. As desordens de sono são as condições que afetam a habilidade de dormir bem regularmente. Podem ser causadas por um problema de saúde ou por elevado *stress*. Embora a solução mais precisa seja um estudo aprofundado numa clínica de sono, este não corresponde a um cenário realista para os idosos, corrompendo os dados registados devido ao stress associado ao ambiente desconhecido. De modo a que o paciente não saia de sua casa e não altere as suas rotinas diárias, o sistema desenvolvido tem um uso simples que pode ser utilizado num ambiente amigável e seguro para o paciente. Isto irá providenciar informação objetiva aos clínicos, de modo a diagnosticar as desordens de sono de maneira correta, já que os pacientes por vezes têm dificuldade em explicar os sintomas aos médicos durante a consulta, o que vai provocar um elevado número de casos subdiagnosticados. O primeiro passo a tomar, de modo a criar um sistema de monitoramento remoto doméstico, é definir quais são os sinais a monitorizar. O primeiro sinal definido para ser alvo de monitoramento foi o Eletrocardiograma (ECG). A razão deve-se ao fato de este sinal já ter sido empregado em variadíssimos estudos relativos ao sono, em que os pesquisadores utilizam a *Heart Rate Variability* (HRV) para a deteção de apneias de sono (tanto no domínio do tempo ou frequência) e outros transtornos de sono. Neste trabalho vamos tentar identificar episódios de acoplamento cardiorrespiratório, ao analisar a HRV. O segundo sinal a ser eleito foi o Eletromiograma (EMG) proveniente do queixo. Este sinal foi escolhido, devido à correlação que tinha com o sinal ECG na presença de episódios de apneia obstrutivos. Este fenómeno deve-se à dificuldade que o paciente tem ao inspirar, pois como tem as vias respiratórias obstruídas, o ar não chega aos pulmões. Isto vai levar a um esforço extra por parte do paciente, que se vai traduzir num aumento de amplitude do sinal. Esta variação vai novamente aparecer dez ou

mais segundos depois, quando o ar voltar a entrar nos pulmões, e o paciente voltar a respirar normalmente. Para além de estes dois sinais biomédicos, também vamos monitorizar o sinal Fotopletismografia (PPG) e a resposta galvânica da pele (GSR). O PPG é usado para detetar as diferenças no volume do sangue, de modo a avaliar a circulação periférica enquanto que a resposta galvânica mede a condutividade da pele. Ambos os sinais apresentaram características distintivas na presença de apneia, e podem ser alvo de estudo detalhado em trabalhos futuros. Em termos de sinal de movimento, foram gravados e analisados os sinais do acelerómetros e giroscópios em dois locais distintos: na região do diafragma, de modo a obter dados que se possam correlacionar com doenças respiratórias relacionadas com o sono, e na coxa esquerda. Esta informação não vai ser utilizada minuciosamente no presente trabalho, mas no futuro irá ser empregada de modo a ser correlacionada com distúrbios do movimento do sono. Identificados os sinais a ser supervisionados e a informação proveniente, vai ser desenvolvido um algoritmo para diferenciar o estado de apneia obstrutiva (OSA) e o estado de sono normal (NS). No algoritmo proposto foi processado o sinal ECG de modo a obter a HRV. O nosso algoritmo foi baseado no domínio da frequência, dado que a literatura aponta como a forma mais adequada para revelar diferenças de episódios de apneia obstrutiva e sono normal [1]. Ao processar a HRV, obtemos as suas características, e é efetuada a densidade espetral de potência (PSD) na *Very Low Frequency* (VLF) *e High Frequency* (HF). Escolhemos estas duas bandas de frequência, porque está provado que são as melhores na distinção entre o estado de sono e o estado de apneia. No caso da VLF, o máximo em OSA é mais proeminente que no NS. Já o inverso ocorre na banda de HF, em que no estado NS, existe um pico que surge devido à arritmia do seio respiratório (RSA) e que normalmente tem o aspeto de uma curva gaussiana. Reconhecidas as diferenças entre os dois estados, são definidos *thresholds* para estado de apneia e estado de sono normal. Estes limites serão verificado por uma *Moving Average Window* com um tamanho de 60 segundos. No começo, o algoritmo vai desprezar os primeiro 60 segundos. Após este período, a janela média móvel vai fazer a PSD para HF e VLF e verifica se para ambos os resultados, o *threshold* é cumprido. Caso os limites sejam atingidos, a janela desloca-se 10 segundos, e aplica os mesmo método, durante os próximos 50 segundos, de modo a termos

os valores para 60 segundos. Após a recolha total de dados, é feita a média dos 60 segundos para as duas bandas de frequência. Se ambas atingirem o *threshold* definido, o intervalo é definido como OSA.

Para testar este algoritmo foram utilizadas duas bases de dados: a *PhysioNet*, que tem informação clinicamente anotada por médicos e é utilizada em diversos trabalhos nesta área, e também iremos testar na informação recolhida pela nossa rede de sensores.

Relativamente à base de dados da *PhysioNet*, os resultados obtidos foram bastante satisfatórios, com precisão a 87,8%, especificidade a 89,9% e sensibilidade a 86,3%. No caso dos sinais recolhidos pela rede de sensores proposta, foi escolhido um dos voluntários que já tinha sido previamente diagnósticos com apneia severa de modo a aumentar as nossas chances de encontrar episódios de apneia. Não foi possível definir valores para a precisão, especificidade e sensibilidade já que não temos um sinal de referência com anotações médicas, para compararmos com os resultados obtidos pelo nosso algoritmo. Em alguns intervalos que foram identificados como episódios de apneia, os sinais recolhidos foram verificados no domínio do tempo, e foram encontradas correlações entre o sinal HRV, EMG, acelerómetro e giroscópio, em que estes dois últimos são sinais obtidos oriundos do peito. De modo a aumentar a precisão do sistema proposto, o próximo passo vai ser incluir o sinal EMG no nosso sistema. Como foi observado em literatura previamente lida, é possível usar a PSD no sinal EMG, para diferenciar entre indivíduos com determinada patologia e indivíduos saudáveis [2]. Por isso aplicamos a PSD no sinal EMG, nos dois diferentes estados (NS e OSA) e obtivemos curvas semelhantes para ambos os estados, obtidas no sinal ECG. Tal fato deve-se provavelmente à componente respiratória que vai influenciar o sinal muscular obtido do queixo.

De modo a que os sinais sejam facilmente visualizados, também foi desenvolvida uma interface gráfica, na aplicação do Matlab™ GUIDE, que irá dar aos utilizadores acesso aos sinais gravados pela nossa rede de sensores, e possivelmente a aplicação do algoritmo proposto, para vermos em que pontos os episódios de apneia ocorreram.

Contents

List of Tables

List of Figures

List of Acronyms

ABG – Arterial Blood Gases

AHI – Apnea-Hypopnea Index

ANC – Adaptive Noise Correlation

ANS – Autonomic Nervous System

BPM – Beats Per Minute

BSN – Body Sensor Network

CVD – Cardiovascular Disease

ECG – Electrocardiogram

EEG – Electroencephalogram

EMG – Electromyogram

EOG – Electrooculogram

FSM – Finite State Machine

GSR – Galvanic Skin Response

HR – Heart Rate

HRV – Heart Rate Variability

ICA – Independent Component Analysis

iEMG – Intramuscular Electromyogram

LMS – Least Mean Square

MSLT – Multiple Sleep Latency Test

MU – Motor Unit

MUAPS – Motor Unit Action Potentials

NREM – Non Rapid Eye Movement

NS – Normal Sleep

OSA – Obstructive Sleep Apnea

PCA – Principle Component Analysis

PLMD – Periodic Limb Movement Disorder

PLMS – Periodic Limb Movement Sleep

PLMW – Periodic Limb Movement Wake

PMAF – Periodic Moving Average Filter

PRV – Pulse Rate Variability

PPG – Photoplethysmogram

PSG – Polysomnography

RDI – Respiratory Disturbance Index

REM – Rapid Eye Movement

RERA – Respiration Effort Related Arousal

RLS – Restless Leg Syndrome

RSA – Respiratory Sinus Arrhythmia

S_a0_2 – Oxygenated Haemoglobin

sEMG – Surface Electromyogram

SG – Savitsky-Golay

S_p0_2 – Oxygen Saturation

SRBD – Sleep Related Breathing Disorders

Chapter 1. Introduction

Great advances have been made in the area of intelligent homes and they are the result of the steady increase in interest in this topic. The goal of intelligent homes is to monitor the home with a non-invasive sensory system, reducing the maximum levels of intrusion and intervention, and to maintain the standard of privacy of the monitored person. This area could be of interest for different categories of end users as elderly people, people with specific pathologies, and athletes or healthy people that can be interested in home monitoring to check their health status. However, the increase in life expectancy and the aged people living independently, makes elderly people one of the main targets for these intelligent environments.

One health problem that is commonly underdiagnosed is the sleep disorders, mainly in the elderly people, since is difficult to explain properly the symptoms to the clinicians, making it difficult for them to do the correct diagnosis and treatment. This disorder is becoming an important aspect for health promotion and disease prevention because adequate and restful sleep is an essential part of a healthy lifestyle.

A Home Sensor Network (HSN) is composed of heterogeneous sensors, physiological parameters monitoring devices and smart home automation devices, which enables the implementation of health monitoring services. In addition, a number of tiny sensors, strategically placed in the human body, could be used for developing a Body Sensor Network (BSN) that can monitor various vital signs, providing real-time feedback to the user and the carers.

The proposal of this work is to develop two sensor networks (BSN and HSN), in order to help the diagnosis of sleep disorders in the elderly. As a first step towards achieving a home remote monitory system, this work introduces a BSN to monitor

various vital signals in order to collect enough information for sleep disorder diagnosis.

The thesis is organized as follow: Chapter 2 shows the background, providing the reader with the basic information about the topic of this thesis; Chapter 3 describes the proposed body sensor network, being referred the network layout, the bio-signals to be analysed, the signal processing algorithm and also the developed user interface to enable users visualizing the relevant signals; Chapter 4 presents the experiments that were carried out and results obtained when data from a public database and also from the proposed body sensor network are tested; and finally Chapter 5 includes the main contributions of this work and guidelines for future work.

Chapter 2. Background

This chapter introduces the main concepts related to this work. Section 2.1 describes the characterization of sleep disorders. It is useful to analyse these clinical disorders to understand how the sensors technical features can be used aiming at improving the elderly healthiness. The sleep states are also referred in this section. Section 2.2 describes the signals and instrumentation involved in sleep disorders assessment. Particular attention is paid to the characteristics of the signals so that a correct selection of sensors can be performed. Section 2.3 focuses on the major physiologic parameters that are required to be monitored by the sensors.

Section 2.4 includes the technology of body sensors networks available and their properties. This section summarizes the concept of activity monitoring and some ideas about how to monitor patients' activity during sleep, considering sleep disorders characterization. Finally, it is also mentioned the importance of the environment where the patient is.

2.1 Sleep disorders characterization

Good sleep is necessary for maintaining an optimal health status since sleep disorders affect hormone levels, mood and weight besides inducing other comorbidities. Because of its innate importance, sleep has been a research topic since the days before Christ. Ancients Egyptians analysed the meaning behind dreams and their symbols while the Greek philosopher Aristotle came up with the actual first scientific theory of sleep in 350 BC when he wrote: “a person awakes from sleep when digestion is complete ” [3]. He was wrong, but he was the pioneer of the sleep analysis.

Sleep disorders are classified as medical disorders, when the sleep patterns of a person suffer modifications. Sleep disorders affect any gender at any age. There exist different categories to classify sleep disorders, as shown in Table 2.1-1.
Sleep disorders have always been a target for studies. For instance, in [4] authors noticed that Obstructive Sleep Apnea (OSA) damages the brain because of oxygen depletion. Besides this deduction, they concluded that OSA has a more detrimental effect on women. In [5], the patient can stay at home being diagnosed for insomnia related problems, while the electrodes collect the data and send it to a smart device.

Turning our attention to the non-wearable systems, they are developed in order to reduce the intrusiveness, as in [6], where ultrasonic waves were transmitted across the airway, and recorded laterally across the neck, in an attempt to reduce intrusion. The researchers believed that the airway obstruction results in a change in the transmitted ultrasound signal, and that these changes are quantified to detect the airway occlusion.

Category	Definition	Examples
Hypersomnia	Causes a person to be excessively sleepy. They even can fall asleep in inconvenient situations.	Narcolepsy Idiopathic Hypersomnia Kleine-Levin Syndrome Insufficient Sleep Syndrome Long Sleeper
Sleep Related Breathing Disorder	Difficulty in breathing during sleep. Many variations of apnea belong to this category.	Obstructive Sleep Apnea Snoring Central Sleep Apnea Child Sleep Apnea Infant Sleep Apnea Sleep Related Groaning
Circadian Rhythm Sleep-Wake Disorder	In this case, sleep time is out of the standard. A patient with this disorder do not follow the normal sleep routines.	Delayed Sleep-Wake Phase Advanced Sleep-Wake Phase Irregular Delayed Sleep-Wake Rhythm Jet Lag, etc
Parasomnias	This group of sleep disorders involve unwanted events that occur while patient is falling asleep, sleeping or waking up.	Confusional Arousal Sleepwalking Sleep Terrors Bedwetting Sleep talking REM Sleep Behaviour Disorder, etc.
Sleep Movement Disorders	A condition that causes movement during or prior to sleep.	Restless Legs Syndrome Bruxism Sleep Leg Cramps Periodic Limb Movements Sleep Rhythmic Movement
Insomnias	Involves the inability to fall asleep or stay asleep.	Insomnia Short Sleeper Child Insomnia

Table 2.1-1. Summary of sleep states and their characterization

In [7], the authors proposed a system which perceives the difference between normal breathing and snoring using a wireless acoustic sensor to measure sounds, and the classification of all breathing episodes were implemented by a smartphone. Although the work in [8] is very intrusive, the authors propose a depth video and audio record using a camera during the patient sleep to extract as much information as possible.

Next subsections will detail the most common categories of sleep disorders and also recent studies aiming at the improvement on the detection of those illnesses. Additionally, we will also describe the sleeping stages.

2.1.1 Clinical sleep disorders characterization

In this sub-section, a characterization of the clinical sleep disorders is performed. The four categories presented are: sleep related breathing disorders (SRDB) – sleep apnea and snoring; insomnias, parasomnias and sleep movement disorders.

Sleep Apnea

Apnea is the suspension of breathing. During an apnea episode, there is no movement of the muscle of inhalation, and the volume of the lungs initially remains unchanged. When a reduced breathing due to partial obstruction of the airway happens for a specified length of time or longer it is called hypopnea.

If a patient is not breathing for at least a 10-second period and there is no effort to breathe for at least another 10 seconds it suffers from central apnea. Central apnea is due to the absence of air flowing into the lungs because the parasympathetic system ‘forgets’ to send the message of breathing to the diaphragm. When a breathing insufficiency is due to a mixture of no air flowing into the lungs for a 10 seconds period but the body is trying to breathe the disease is named mixed apnea. The extreme situation occurs for obstructive apnea (OSA). This is, the body is trying to breath but no air goes inside lungs for a period of at least 10 seconds due to complete obstruction of the pharyngeal airway. If the pharyngeal airway is only partially obstructed the disease is named obstructive hypopnea, as exhibited in Figure 2.1.1-1. All these different classes of breathing problems during sleep are quantified for sleep disorders evaluation.

Typically, the length of each apnea and hypopnea is calculated as the *mean* duration of the event, this is, as the ratio between the sum of the lengths of events of a given type and the number of events of that given type.

The Apnea-Hypopnea Index (AHI) represents the average number of episodes of apneas and hypopneas per hour that the patient has when he/she is sleeping [9].

This index is used to estimate the degree of the OSA syndrome. Normal AHI varies within 0 to 5, mild range when it varies from 6 to 15, moderate if the range is from 16 to 30; and if AHI is 31 or more it is classified as severe OSA. In [10] the authors state that severe OSA affect the quality of life and increase the risk for many diseases such as hypertension, poor mental and cognitive health, fragmented sleep, low blood oxygen levels, heart failure, myocardial infarction, and stroke.

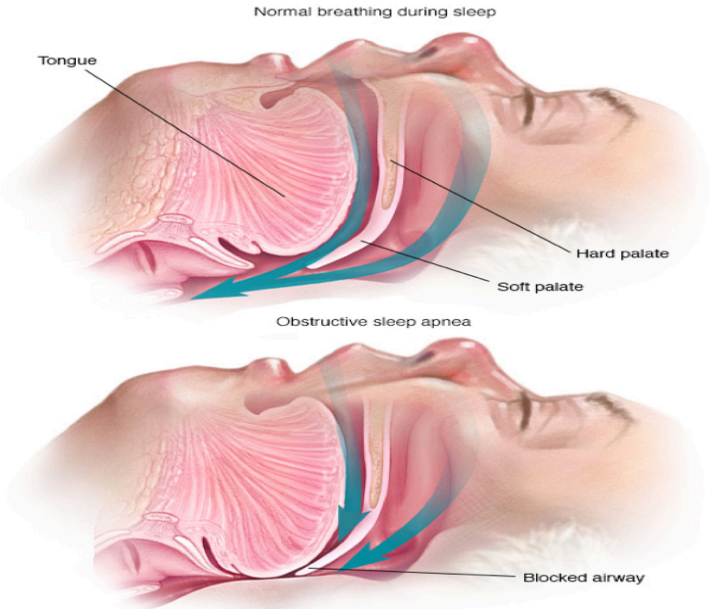

Figure 2.1.1-1 Picture showing a breath obstruction [10]

One characteristic of the OSA patients is that they have an anatomically small upper airway with enhanced pharyngeal dilator muscle maintaining airway patency awake [11]. Other aspects that can promote the development of OSA are obesity, alcohol and smoking.

OSA syndrome is a pathology affecting 100 million people worldwide, but it is suspected that many more cases exist without being diagnosed. A possible

justification is that a breath stop rarely triggers a full awakening. Since the medical examination is very expensive, this is another reason for the lack of diagnosed cases.

Then, there is a growing need for less invasive OSA detectors which should be planned to be used at ambulatory environment, comfortable and involving much less cost than the typical examination. These new devices would be suitable to be included in standard hospital beds, avoiding the use of special sleep disorders assessment units.

As an example in [12] a textile-based wearable system is described, associated with an apnea detection algorithm. This work proved the feasibility of a wearable system for early detection of OSA, alternative to the uncomfortable PSG systems.

Snoring

Snoring is the vibration of respiratory structure and the characteristic sound is due to the obstructed air movement during breathing while sleeping. When sleeping the throat muscle relaxes, the tongue falls backward turning the throat narrow and “floppy”. During the breath, the walls of the throat begin to vibrate, and these vibrations lead to the characteristic sound of snoring.

In some cases, the sound is smooth, but in most cases, it can be loud and unpleasant. It is a common problem among all ages and both genders, but people at most risk are the men and those who are overweight, presenting nasal problems or a narrow airway and alcohol drinkers. This problem becomes more serious as people age. It can cause disruptions, fragmented and un-refreshing sleep, leading to a poor daytime function and eventually heart diseases. About one-half of people who snore loudly have OSA [13]. Because of the sound, it is very easy to identify a person with this sleep disorder. But understanding the difference between snoring and breathing events is not so easy. In [14] the authors developed an algorithm which can distinguish between expiration, inspiration, snoring and breath.

Insomnia

The definition of insomnia consists in a difficulty of falling asleep or staying asleep, even when a person has the chance to do so. These unhealthy people feel dissatisfied with their sleep and the symptoms associated with this disease are: fatigue, low energy, mood disturbances, difficulty in concentrating and decreased performance at work or at school [15]. Figure 2.1.1-2 displays other complications of insomnia.

There are two types of insomnia: primary and secondary. We can label primary insomnia when sleep disorders happen without any relation to other health condition. The secondary type means that the patient has insomnia caused by other medical situation - asthma, depression, arthritis, cancer or heartburn - pain, medication prescribed by a doctor or self-medication or even substances that the patient is taking (drugs or alcohol). Insomnia has a wide range of apparitions, since it can vary in how long it lasts, how often it occurs, and the interval between each episode. It can be a short-term (acute insomnia) and it can last from one night to a few weeks or can be classified as long-term (chronic insomnia) when a person has three nights a week with insomnias for a month or longer.

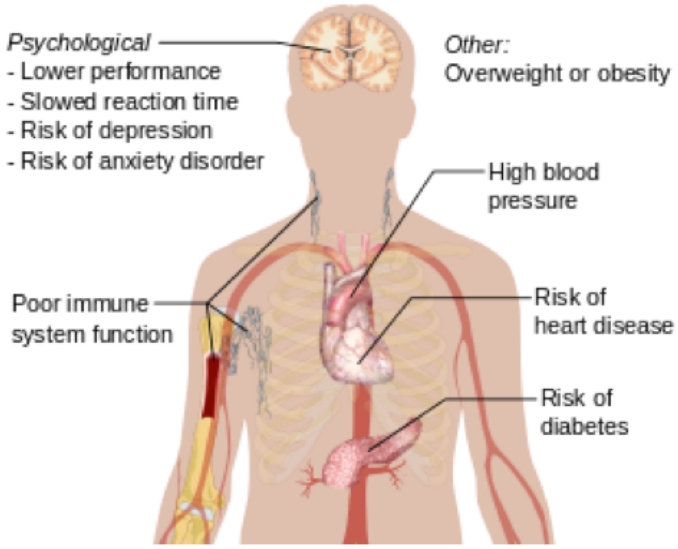

Figure 2.1.1-2. Complications of insomnia [16]

Studies were made as shown in [16] where the investigators used a combination of ECG and EEG to reveal the differences between a patient that had medication and other who received placebo. Some authors [17] analysed a single sleep stage instead of analysing a full night in order to diagnose and treat insomnia. In [5], an in-home monitoring system, had the ability to collect and send the required data to a smart system containing a sleep diary. This monitored the patient at his/her home without interfering with his/her sleeping habits, reducing the number of daily interviews carried out by the clinicians. An in-depth analysis of sleep stages and patterns in the vital signal is required to get an efficient insomnia diagnosis and treatment.

Parasomnias

The term Parasomnias refers to all the abnormal events that can happen to people while they sleep, apart from sleep apnea episodes. It is a category of sleep disorders which occur in any stage of the sleeping process. Most of them are dissociated sleep states that are partial arousals during the transitions between wakefulness and Non-REM (NREM) sleep, or vice versa.

The occurrence of parasomnia can be a heredity factor. Other causes are the abuse of alcohol, medications or stress. However, in most of the cases parasomnias are triggered by sleep deprivation caused by other sleep disorders like sleep apnea or sleep movement disorders.

We can divide parasomnias into two types: NREM and REM. The NREM parasomnias happen during the non-REM sleep. From this kind of parasomnias, the most usual include sleep-talking, sleep-walking, sleep-related eating disorder, night terrors, etc. The REM parasomnia occurs at REM stages of sleep and the most common type of this parasomnia are REM sleep behaviour disorder (RBD), catathrenia and sleep paralysis. In Figure 2.1.1-3 is presented a drawing of a children with sleep walking disorder.

Figure 2.1.1-3. Children with sleep walking disorder [19]

If a person has been suffering from this disease, he/she should seek treatment as soon as possible. It is not only the patient's health problem, but it subsists a considerable risk to injure another person, or even if the frequency is quite high or escalating, the possible injury problems increase.

As problematic as this disease seems to be, parasomnia is rarely linked with a psychiatric disorder. Furthermore, patients felt improvement in their symptoms simply by improving their sleep habits like having a good night sleep, managing stress and having a regular sleep schedule. In profounder cases drug therapies are also used to control symptoms [18].

Sleep Movement Disorders

This classification of sleep disorders refers to conditions that cause movement prior or during to sleep. It is difficult for people suffering from this conditions to fall asleep or to stay asleep. In this work It is mentioned Restless Legs Syndrome (RLS) and Periodic limb movement disorder (PLMD).

RLS is a neurologic sensorimotor disorder characterized by an overwhelming need to move the legs when people are at rest. The need to move is frequent, but not always accompanied by unpleasant sensations. It sometimes appears in different body locations like arms, face, torso and genital region, being more frequent in lower limbs. The symptoms occur during inactivity and a way to relieve them is by applying some pressure on the affected zone or trying to do some movement.

The symptoms are worst in the evening, and can affect the sleep of the patient and daily life. We have primary RLS (also called hereditary RLS) and secondary RLS. In the primary RLS, scientists have not found the causes yet, but in the secondary type, medical doctors believe that the cause is an underlying medical condition – kidney failure, low levels of iron, pregnancy, stress or use of some drugs.

This disorder is usually detected by one of the sensors in a body sensor network as demonstrated in [19]. Most of the times RLS is sensed by an accelerometer or an EMG detector. If the clinicians notice a strange recidivism behaviour coming from these sensors, this is probably an evidence of a pathology provoked by RLS.

PLMD is described as a set of simple and repetitive events of muscle movements. The patient cannot control those movements although it is not impeditive to keep the person from sleep. The movements tend to involve the tightening or flexing muscle, and can be very unpleasant for both ill person as for the person lying in the bed besides him. We can classify the movements according to the time they appear [20]:

- Periodic limb movements while the person sleeps (PLMS)
- Periodic limb movements while the person is awake (PLMW)

Of these two, PLMS occur more often. They occur through the night and generally, the patient is unaware of the movements. One typical movement is the extension of the big toe. Also can happen in the ankle, knee, hip or even in the

arms. The intensity of the movements changes from night to night. Each episode can last from just a few minutes to an hour. During that, movements tend to last from 20 to 40 seconds.

PLMS usually happens during the NREM sleep in the first half of the night. When episodes are more severe, they may also appear while the unhealthy person is awake (PLMW). This disorder can be a cause for some symptoms like depression, bad memory, short attention span and fatigue.

Polysomnography (PSG) is the only way to confirm that a person has PLMD since leg movements can be monitored while the patient sleeps in the clinical environment.

2.1.2 Sleep states

It is not general knowledge, but once a person falls asleep, the person progress through a series of stages, in which different brain wave patterns are displayed. These stages belong to the cycles of NREM and REM. The EEG has made possible the scientists to deepen the study in this matter.

The NREM means non-rapid eye movement and had four stages, but the scientist merged the stage 3 and 4 in 2008. During the NREM stages, the body heals himself, as it builds muscle and bones, regenerates tissues and strengthens the immune system. As a person ages, he/she sleeps more lightly and gets less deep sleep [21].

REM stands for rapid eye movement and usually happens 90 minutes after falling asleep. Dreams typically happen during this stage, because the brain is more active. The first phase of REM usually lasts about 10 minutes. Each of the rest of REM stages gets longer, and the final one may last up to one hour [21]. During this stage, the breathing and heart rate quicken.

The table below (Table 2.1.2-1) shows concisely the sleep states and their characterization.

Sleep state		Duration	Sleep cycle stage	Characterization
	AWAKE	16h to 18h		
CIRCADIAN RHYTHM: Transition between REM and NREM stages **every 1h30 to 2h (90-120min)**	**LIGHT SLEEP** (stage 1 & 2 merged)	**4h to 7h Non-REM Stage** (sleeping time of adults: stage 2=50% stages 1&3=30%)	**Stage 1**	• eyes move slowly and muscle activity is slow • many people present sudden muscle contractions.
			Stage 2	• eye movement stops and brain waves become slower with only one occasional burst of rapid brain waves • synaptic pruning
	DEEP SLEEP (stage 3 & 4 merged in 2008) OR **Slow-Wave-Sleep**		**Stage 3**	• extremely slow brain waves called delta waves are interspersed with smaller, faster waves • no eye movement or muscle activity
			Stage 4	• brain produces delta waves almost exclusively • no eye movement or muscle activity
	REM Stage	20% sleeping time of adults	**REM Stage**	• breathing becomes more rapid, irregular and shallow • eyes jerk rapidly and • limb muscles are temporarily paralyzed • Brain waves increase to levels experienced when a person is awake • heart rate increases, blood pressure rises • irregular body temperature

Table 2.1.2-1. Summary of sleep states and their characterization

Despite this reference table, we cannot use it indiscriminately for all patients, because the age influences the type and amount of sleep of each subject. Infants spend almost 50% of their time in REM sleep, while adults spend nearly 50% of sleep time in stage 2, about 20% in REM and the other 30% within other stages. Older adult spend progressively less time in REM sleep. The amount of REM sleep for elderly will decline roughly 10 minutes per night for every decade of life.

With regard to the circadian rhythm, it can be identified through the EEG, since it is easier to identify the sleep stages. Other biosignals that can help recognizing the circadian rhythm are the EMG, by distinguishing reduced muscle activity to differentiate between awake and asleep states, or REM, since follows a circadian rhythm and normally it takes ninety minutes for the first phase of REM sleep to appear. Also, galvanic skin response (GSR) can be useful to differentiate between awake and slept, it is not appropriate for identifying particular stages of sleep [22]. The ECG signal can also be used to differentiate between deep sleep and REM, checking if there is an increase of the heart rate variability; or even the chest movement, to analyse the respiratory rate.

2.2 Clinical instrumentation and respective signals for sleep disorders assessment

In order to diagnose a particular type of sleep disorder the acquired signals need to be suitable for sleep disorders' classification. As said before, PSG detects several signals, so to develop a minimally intrusive sleep disorder monitoring system, we need to reduce the number of signals processed in order to decrease the complexity of the proposed system.

The signals presented below are the ones who give a wider range of options to detect and process sleep disorders. The signals described in this sub-section are the electrocardiographic signal, the photoplethysmographic signal, the electromyography signal, the electroencephalography signal and the galvanic skin response.

2.2.1 Polysomnography

The golden standard procedure to detect any kind of sleep disorders is to submit the patient to a polysomnography test. The PSG is a complex system that makes use of a minimum of 22 thin electrodes and other sensors, which are pasted on specific body sites to provide readings during the patient's night sleep.

The PSG records the following signals:

- Electroencephalogram (EEG) signals, needing a minimum of three channels to record the brain wave activity;
- Electrooculogram (EOG) signals, using two electrodes to record the movement activity of the eyes;
- Electromyogram (EMG) requires the use of at least one sensor to record the body muscles activity;

- Electrocardiogram (ECG) requests a minimum of three sensors to monitor the heart rate and rhythm;
- Body movement detectors' signals to monitor shins and waist movement, usually it is required one electrode for each belt acting together with a body position sensor;
- Airflow through the nose and mouth signals, oxygen and carbon dioxide levels need one more channel.

Other additional parameters necessary to be known during a PSG evaluation are patient's age, patient health status, body position, body temperature, skin electric conductance and environmental temperature and humidity.

Because of the amount of measuring instruments involving a polysomnography examination, it is carried out by sleep disorders specialists. These tests are performed at the hospital or in a sleep centre under the surveillance of specialized clinicians. As shown in Figure 2.2.1-1, the PSG can be very unpleasant, and much more for people having sleeping problems.

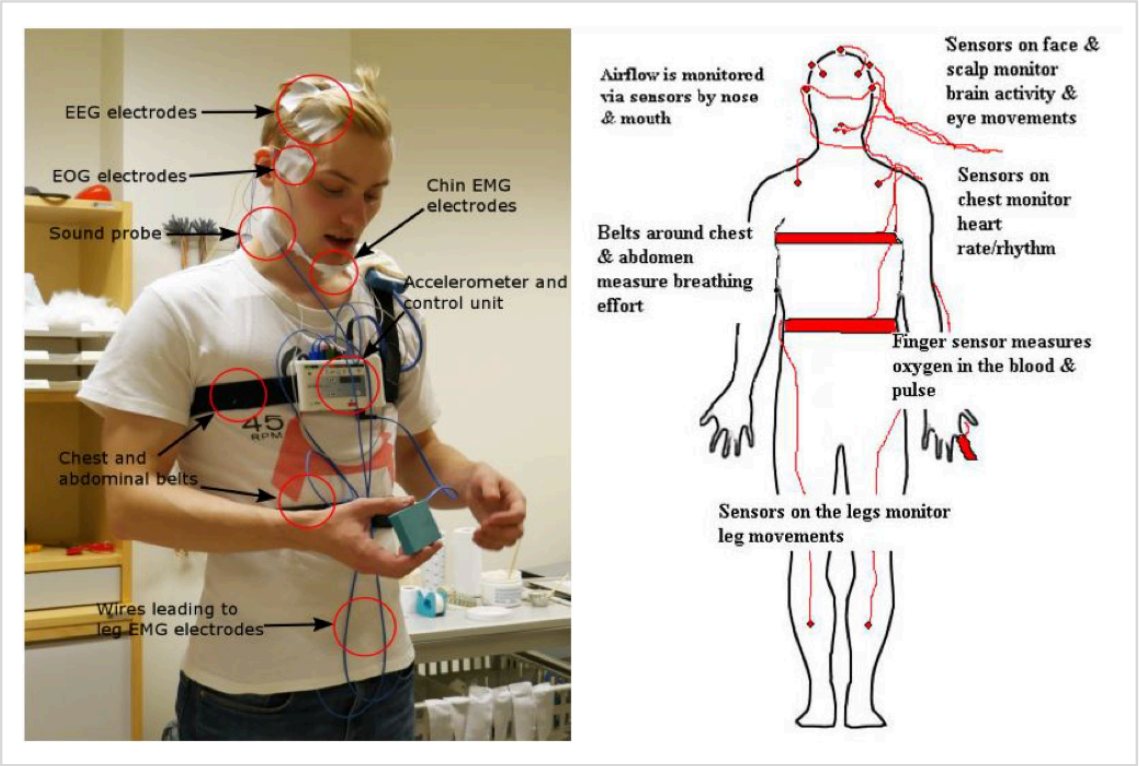

Figure 2.2.1-1. Patient being prepared for polysomnography [23] *and an example of how information is collected* [8]

In general, a medical doctor prescribes the PSG tests when the patient has some of the symptoms presented in the Table. 2.1-1. For the standard test, the patient goes early evening to the examination center when he/she starts to get wired up, to enable recording multiple channels of data. This phase takes 1-2 hours. In most clinics, the test is completed and the patient discharged home by 7 a.m. of the next day, unless the doctor decides to schedule a multiple sleep latency test to be done during the day to test the excessive daytime sleepiness.

After the procedure, the doctor will analyse the doctor will analyse the data in 30 seconds “epochs” and fill a form where he/she provides a score according to the following considerations:

- Sleep efficiency, where the number of minutes of sleep is divided by the number of minutes in bed. A normal ratio is approximately 85% to 90% or higher.

- Sleep onset latency, corresponds to the onset sleep from time the lights were turned off; usually takes less than 20 minutes.
- The Sleep Stages combined data from EEG, EOG and EMG. With this information a patient can be classified as awake or at one out of four sleep stages.
- Body position during sleep, where the patient will have a body position sensor around the waist together with a couple of electrodes placed on the muscles of the shins, recognizing the movement of the patient.
- Oxygen saturation during sleep, to measure the amount of oxygen in the blood using an oximeter placed on the earlobe or on a finger.
- Cardiac rhythm abnormalities. These irregularities are detected by 3 electrodes (Triangle of Einthoven) laid in the upper left part of the chest, which will save the ECG signal for further analysis.
- Arousals are the most evident sign of a sleep disorder. They are a sudden shift in brain wave activity. Example of arousals considered by the sleep expert can be breathing abnormalities (how often the patient stops breathing for at least 10 seconds or how many times the breathing is partly blocked for 10 seconds), muscle movements during the sleep and environmental noises. For an arousal to be counted the subject must be asleep for at least 10 seconds, also a minimum interval of 10 seconds between two arousals is required.

For a patient to be considered as presenting sleep disorders the number of arousals must be higher than 10 during one hour of recording. The physician interprets the recorded data in conjunction with the patient's medical history in order to provide a diagnosis. Table 2.2.1-1. shows a case study of a Polysomnogram result of a patient diagnosed with sleep apnea, where the abbreviations stand for: NREM – Non-rapid eye movement; REM – Rapid eye movement; RERA – Respiration effort related arousal; AHI – Apnea-Hypopnea Index; RDI – Respiratory Disturbance Index; HR – Heart Rate; BPM – Beats per minute; SaO_2 – Oxygenated Haemoglobin.

Time in Bed:	6.25 hours or 375 minutes
Total Sleep Time:	4.08 hours or 245 minutes
NREM Duration:	3.66 hours or 220 minutes
REM Duration:	0.26 hours or 15.7 minutes
Sleep Latency	22minutes
Wake after sleep onset:	68 minutes
Sleep Efficiency:	63.5%
Arousals/Awakenings	
Arousal (< 15sec)	59
Arousal (> 15sec)	20
Awakenings	31
Total Events:	31 REM = 0 NREM = 31 Supine=31 Non-Supine=0
Longest event (sec):	28.3 REM = 0 NREM = 28.3
Total Apneas:	11
Obstructive	2 REM = 0 NREM = 2
Central	9 REM = 0 NREM = 9
Mixed	0
Hypopneas	3 REM = 0 NREM = 3 Supine = 3 Non-supine = 0
RERAs	13 REM = 0 NREM = 13 Supine = 13 Non-supine = 0
AHI	3.2 REM = 0 NREM = 2.6 Supine = 3.2 Non-supine = 0
RDI	6.3 REM = 0 NREM = 5.4 Supine = 6.3 Non-supine = 0
Mean HR (REM) 56	(**NREM**) 49
Mean HR (BPM) 48	**(NREM)** 54
Max HR (BPM) 53	**(NREM)** 55
Mean SaO_2% (wake) 99%	**(REM)** 97% **(NREM)** 97% **(total)** 97%
Low SaO_2% (wake) n/a%	**(REM)** n/a **(NREM)** n/a **(total)** 93%

Table 2.2.1-1. Example of a Polysomnogram result from a Sleep Apnea Patient [7]

In this work, we will not analyse all the parameters shown in Table 2.2.1-1 since we are willing to produce a less intrusive sensing system than a typical Polysomnogram examination.

2.2.2 The Electroencephalogram

An electroencephalography instrument measures the electrical activity of the brain. The electroencephalogram (EEG) is the name given to the brain waves collected by the electroencephalography instrument and displayed in paper; sometimes EEG is used to mention the medical instrument also. The major parts of the brain are the brain stem (which includes the reticular formation, mid brain and pons medulla), the thalamus (between the hemispheres and the midbrain), cerebrum and the cerebellum [24]. Frequency (Hz) is a key characteristic used to define normal or abnormal EEG rhythms.

EEG is used in the diagnosis and management of seizures disorders, like epilepsy. Other applications involve the diagnosis of brain damage and disease (e.g., stroke, tumours, encephalitis), sleep disorders, mental retardation, mental disorders (e.g., alcoholism, schizophrenia, autism) and degenerative diseases such as Alzheimer's disease and Parkinson's disease [96].

EEG should be prescribed and interpreted by a trained medical professional. The expert place the electrodes on the scalp, after preparing the scalp area by light abrasion to reduce impedance. Other option is to use a nets or caps in which electrodes are embedded. Figure 2.2.2-1 shows an example of an EEG exam.

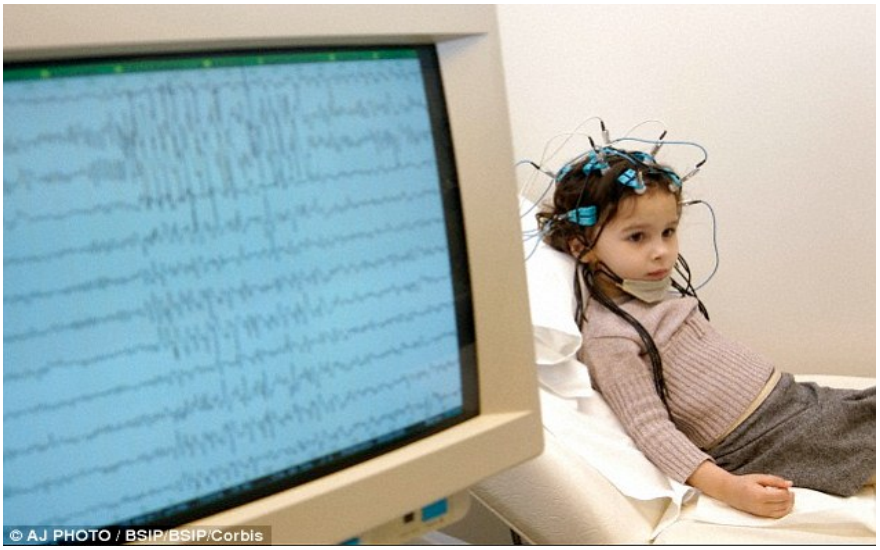

Figure 2.2.2-1. Example of an electroencephalogram exam [25]

Mental and physiological processes are associated with the EEG waveform, in which electroencephalography frequencies stands for different phenomenon in the EEG [24]. The EEG waveforms are classified according to their shape, frequency and amplitude. Another factor to influence the EEG signals is the site on the scalp at which the brain waves are recorded. The four best known EEG waveforms are alpha, beta, theta and delta. The waveforms are displayed in Figure 2.2.2-2.

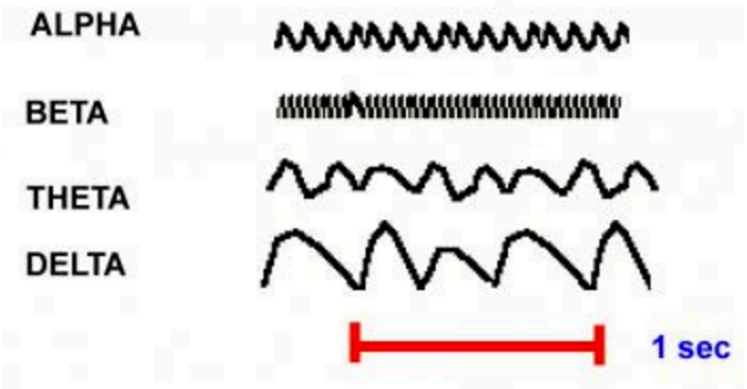

Figure 2.2.2-2. Examples of alpha, beta, theta and delta electroencephalography frequencies [25]

With the frequency and shape withdrawn from the EEG waveforms the clinician combines this information with the patient's age, his state of alertness or sleep to determine the information significance.

2.2.3 The Electrocardiogram

The electrocardiogram (ECG) is a very common instrument used to detect the electrical activity of the heart through time. Heart is covered by cell membranes each one containing a charge which will be depolarized during each heartbeat. Figure 2.2.3-1 shows the anatomy and the electrical system of the human heart.

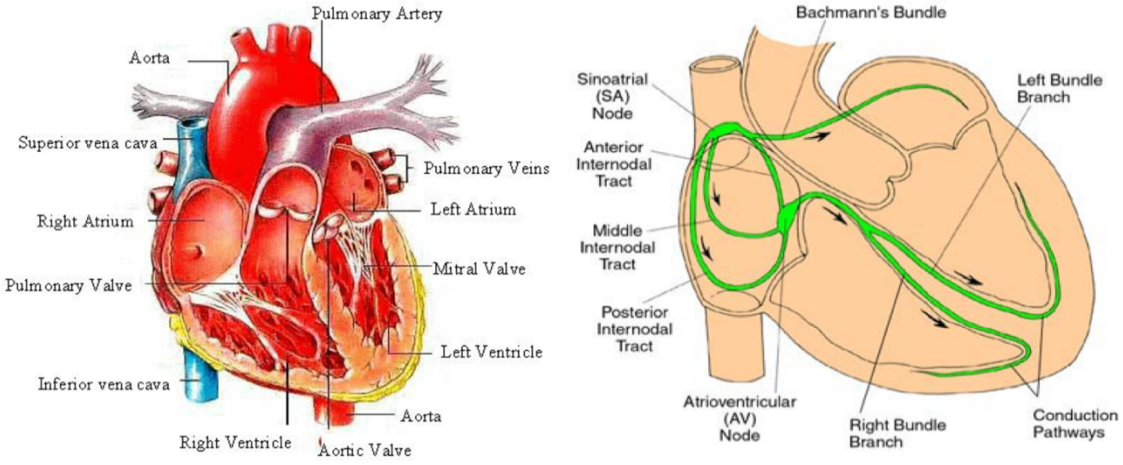

Figure 2.2.3-1. Left: the anatomy of a human heart [28] . Right: electrical system of the human heart [6]

The image 2.2.3-2 shows the ECG waveform. A cardiac cycle refers to a complete heartbeat from its beginning to the beginning of the next beat, and it has a series of waves labelled as P, QRS and T. It is possible to define each epoch in an ECG as:

- **P wave:** Represents atrial depolarization. When the valve between the atria and ventricles opens, 70% of the blood in atria is extracted by ventricles as they expand [26]. The contraction applied by the atria is needed for the final 30% and therefore the work done by the muscle is small. So only a small amount of voltage is needed.
- **PQ segment:** represents the stage before the beginning of the contraction where blood travels to the ventricles.
- **QRS wave:** Usually it corresponds to the most visually obvious part of the ECG tracing. This wave represents the depolarization of the

ventricles by contraction of ventricular muscles in a fast sequence from the apex upwards.

- **ST segment:** It connects the QRS wave and the T wave. It is flat and represents an isoelectric section. It represents the interval between ventricular depolarization and repolarization. When an irregularity exists, the main cause is infarction or myocardial ischemia.
- **T wave:** It relates to the last phase of the action potential of ventricular muscle cells, the process of relaxation potential. The same potential takes care of contraction and repolarization, but one is an upstroke and the other is a downstroke. For this reason, the T wave may be related to a non-specific event.

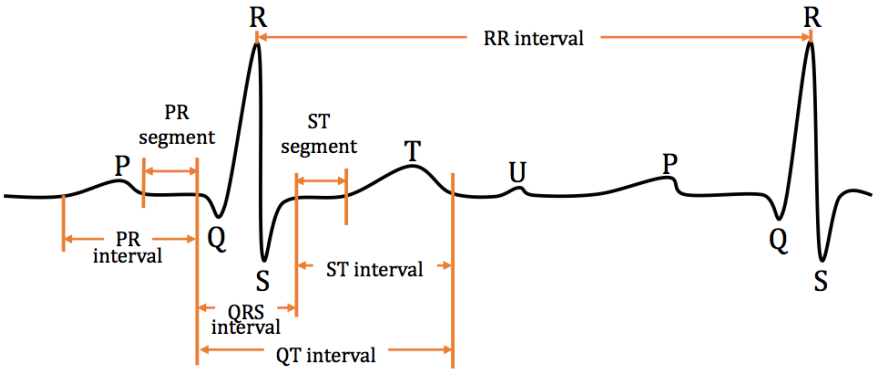

Figure 2.2.3-2. ECG peaks, waves and interval representations [27]

When recording the ECG signal, the frequency range interval for acquiring the main information goes from 200-500Hz. Since we do not want undesirable high frequencies, we use 256Hz to obtain the appropriate information. It is crucial to perform an accurate heartbeat detection. Quite often the signal is affected by artefacts, noise and interferences, and we have to pre-process the signal before performing ECG-based computations to obtain the information looked-for. The most common sources of noise in ECG signal are:

- ✓ **Power line interference:** Power line interference (PLI) is a significant source of noise during bio-potential measurements. The interference is coupled through the signal leads with a frequency of 50 to 60 Hz. It

degrades the signal quality and overwhelms tiny features that may be critical for clinical monitoring and diagnosis. The techniques that can be applied to solve this problem are, for instance, a Notch Filter or an Adaptive filtering [24].

- ✓ **EMG from the chest wall:** This noise is coming from the muscular activity near the electrodes. Sometimes the ECG signal is totally concealed by a muscular contraction. Because the muscle activation produces the increase of the energy at low frequency, the solution to remove this interference is to apply a low-pass filter with a cut-off frequency > 40 Hz or an Adaptive filter [28].
- ✓ **Baseline drift:** This effect produces a low frequency variation of the ECG baseline. A it happens at low frequency, we can remove it without losing important information from the ECG signal [28].
- ✓ **Electrode contact noise and Motion artifacts:** These effects are generally produced by a bad contact between the skin and the electrodes or small movements of the patient. The unconnected electrodes can act as antennas. These artefacts produce high frequency epochs, that can be misclassified with a R peak [24].

2.2.4 The Photoplethysmogram

Photoplethysmogram (PPG) is a simple and low-cost optical instrument used to detect blood volume changes in the microvascular bed of tissue to evaluate peripheral circulation. This non-invasive technique detects the oxygen saturation (SpO_2), and with this information it is possible to monitor if the oxygen is flowing properly.

The signal obtained has two components: heart pulse (AC) and venous pulse (DC). The AC component is attributable to variation in blood volume in the skin

and usually has fundamental frequency of 1 Hz. The component is synchronized with the heartbeat and is superimposed on a slow varying DC. This DC component of the signal is due to the bulk absorption of the skin tissue. Figure 2.2.4-1 presents a schematic display of the AC and DC components of the PPG signal.

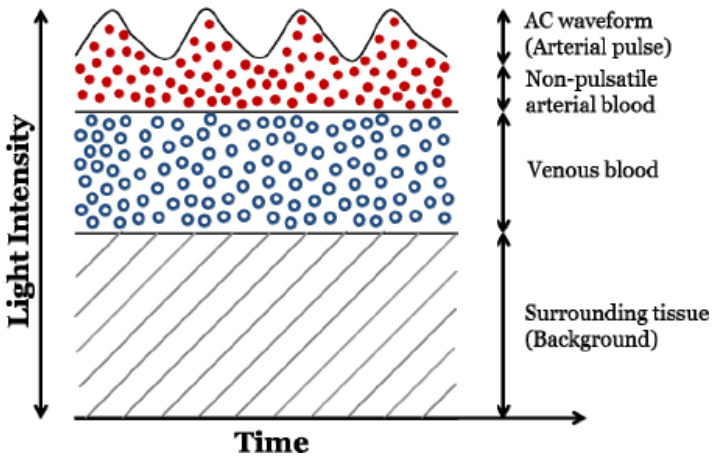

Figure. 2.2.4-1. Schematic of the PPG signal the AC and DC signals [32]

To obtain a PPG signal, we can use two types of sensors: transmission and reflectance. The most used in pulse oximeter detection is the transmission type. In this case, a LED illuminates an extremity of the body and the photo detector records from the opposite side. In reflectance type, source and detector are in the same plane. After detected the signal is amplified and filtered [16].

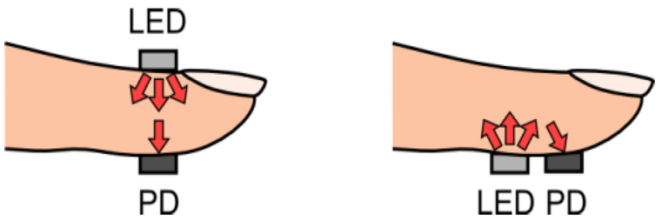

Figure 2.2.4-2. Left: Example of a transmission sensor. Right: Example of a reflectance sensor [33]

Some obstacles can appear when retrieving a PPG signal like a poorer blood perfusion and a lower compliance (stiffer arteries). In the case of elderly people, the reflectance and transmittance of light to the photo-detector is affected because of the wrinkled skin, that acts like a low-pass filter, preventing the current characterization of PPG pulse [29].

The Figure 2.2.4-3 compares the pulsatile (AC) component of the PPG signal and corresponding ECG. The AC component is overlaid by a DC component that relates to the average blood volume and with the tissue. It represents the increased light attenuation associated with the increase in microvascular blood volume with each heartbeat. In practice, the PPG waveform is often inverted [30], so that it goes in the same direction as the arterial pressure waveform.

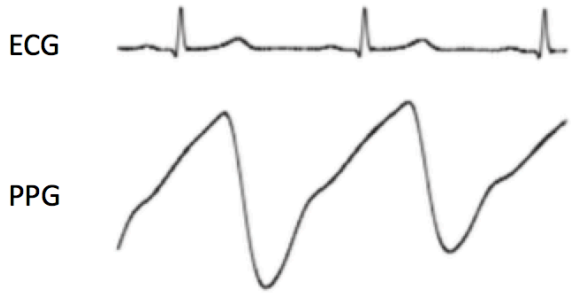

Figure 2.2.4-3. Comparison between corresponding ECG and the component AC of the PPG signal [35]

Although with a reflectance sensor it is possible to acquire a PPG signal from every local part of the body, the best places to obtain the best signals are ear lobe, fingers and forehead [31]. After the measurement, we have to apply some signal processing since the data contains low-frequency interferences, due to noise or motion artefacts [32].

2.2.5 The Electromyogram

The electromyogram (EMG) is a technique of electro diagnosis used in medicine, and it measures electrical currents produced in skeletal muscle, during the contraction of a muscle, which represents neuromuscular events.

The responsible for the control of muscle activity is the nervous system. The motor units (MU) are the constituents of the skeletal fibers. When stimulated by

a neuron signal, each MU contracts and produces an electrical signal retrieved by every cell. Their sum represents all the action potentials. This phenomenon it is known as Motor Unit Action Potential (MUAPS) and is what brings to life the interference pattern [33].

It is possible to measure EMG signals in two ways: surface and intramuscular. As the name indicates, the EMG surface detection corresponds to the recording of the muscles' activities at the skin on the surface of the muscle under analysis. In this way, it is impossible to retrieve data with only one electrode, because EMG recording displays the potential difference between two separated electrodes. The intramuscular EMG is an invasive method that uses a needle inserted in the muscle to collect the signals.

Figure 2.2.5-1 shows an example of intramuscular and surface EMG signals (iEMG and sEMG respectively). The MUAPS are visible in both images despite their different shapes due the different tissue filtering and detection modalities.

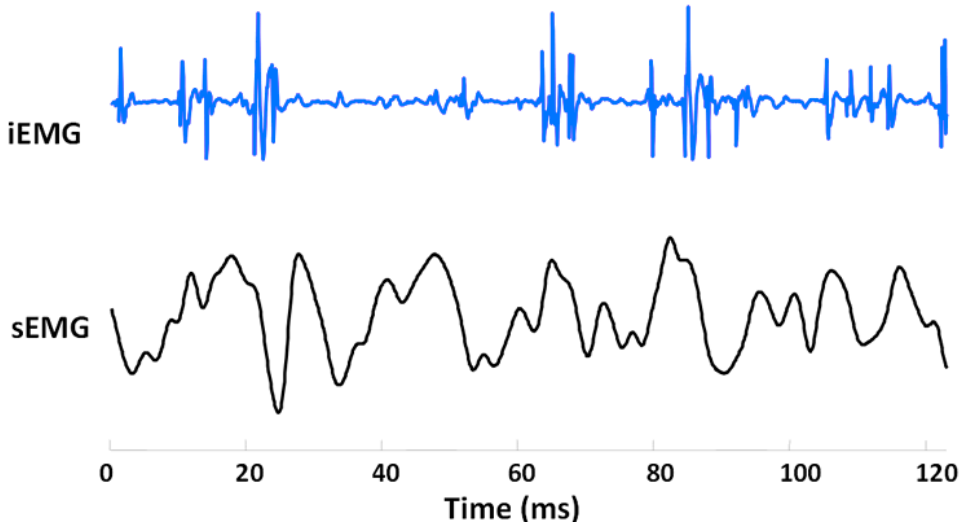

Figure 2.2.5-1. Blue signal: Intramuscular EMG signal (iEMG); Black signal: Surface EMG signal (sEMG) [39]

The figure that shows the iEMG signal is more reliable but it is very intrusive, while the sEMG lacks resolution. This can occur due to problems of excess of adipose tissue in the studied zone. Other reason for the lack of resolution is the muscle cross talk due to the EMG signal from one muscle is being affected the neighbour muscle.

Inevitably, the signal recorded is soiled with various artefacts and noise signals. Although the present technology is immune to some of these noises, baseline noise and movement artefact are still a problem for signal processing. In [34], the authors suggest a Butterworth filter to eliminate the baseline noise and movement artefact.

The analysis of the EMG can provide interested information for our work. In [35] it is stated that the mean power retrieved from the chin EMG is higher, one minute before and after waking up, on patients with obstructive sleep apnea. Also, at [36] is used the power spectral density to identify to compare the power before, during and after the incidents of different kinds of apnea.

2.2.6 Galvanic Skin Response

Human skin has electrical properties reflecting the sympathetic nervous system activity. Any arousal of the psychological or physiological state of the patient induces a variation on the blood flow and an increase of the sweet gland activity. Fright, anger, fear, anxiety, excitement, being startled or under mental stress are proved to induce hot flashes and sweating in many people. The more intense the epoch, the higher is the skin conductance variance.

The galvanic skin response (GSR) is an instrument used to measure the variation of the electrical conductance of the skin and can be charted and measured. This conductance is mainly affected by sweat, as salty water is an excellent conductor. The body parts with a larger amount of sweat glands are the hands and feet (200-600 sweat glands per cm^2). In other words, GSR measures how sweaty your palms are.

When measuring the GSR, it is possible to choose two different methods:

• **Active:** When the doctor applies a small current in the patient's body to measure the conductivity.

• **Passive:** Measures the current that is generated by the person's body itself.

The feedback from these measures will provide the GSR. A common usage of GSR is one of the measures used during a polygraph test. The GSR can detect a variation on the skin conductance, although it is not very reliable because it is impossible to know if the precise source of conductance variance is due to the stress of lying or being interrogated [45], or any other circumstance that can provoke sweating. Figure 2.2.6-1 shows an example of a person under a polygraph test.

Therefore, complementary physiologic measurements such as changes in perspiration, breathing and heartbeat, should be simultaneously analysed to differentiate the cause of GSR variations.

Figure 2.2.6-1. Example of a subject doing a polygraph test [42]

Different stimulus (mood, environment, medication and underlying conditions) will affect the people's autonomic activity in different ways. The skin conductance is captured by using skin electrodes, where the data is acquired with sampling rates between 1-10Hz. The time course of the signal is considered the result of two processes: a tonic base level driver and a phasic component. The tonic base level driver fluctuates very slowly (seconds to minutes), and the faster-varying phasic component fluctuates within seconds. The phasic component will show

the burst and distinctive peaks that are identified with our eyes, with a slow decline of the baseline level. These pikes are produced from stimulus such as fear, excitement, happiness or saddening.

2.3 Physiological parameters for sleep disorders assessment

In this section, is being analysed the physiological parameters that can be indicators of human health state and the techniques to register them. Physiological parameters are self-interdependent, and the diversity of them defines the human health.

One example of physiological parameters is the body temperature, which represents a balance between the heat produced by the body and the heat it loses. The blood pressure is also an important physiological parameter, representing the strength of the blood pushing against the sides of the blood vessels. Although it is not a physiological parameter, the body mass index (BMI) is an important parameter because obesity has implications in the sleep disorder study. IBM is defined as the body mass divided by the square of the body height.

Following the directions of medical investigations, the most vital parameters are those that specify the functioning of heart and respiratory system. In the next sub-sections heart rate variability, oxygen saturation and respiratory rate are described.

2.3.1 Heart Rate Variability

Heart rate variability (HRV) is the time variation between heartbeats. It is measured by the variation of the beat-to-beat interval and is controlled by the Autonomic Nervous System (ANS). These beats are produced by the sinus node in the heart. It generates electrical impulses and leads them throughout the muscle of the heart, stimulating the heart to pump blood. The firing rate of the

sinus atrial node is controlled by impulses from the autonomous and central nervous system.

HRV is directly related to the body's interdependent regulatory system, efficiency and health. Although generally the greater the HRV the better [37], it is better to have a small interval of values of HRV [80-65] instead of a larger one [100-60], because these kind of variability can lead to the suspicion of various health risk factors. Some examples are heart diseases, fetal distress, asthma, autonomic nervous system dysfunction and depression.

The HRV is also related to emotional arousal and reflects the moment-to-moment output of Central Autonomous Nervous and by association, an individual's capacity to generate regulated physiological responses in the context of emotional expression [38].

As Figure 2.3.1-1 shows, when the individual is frustrated, the HRV has a bigger interval of values and a larger amount of peaks, when comparing to a state when the individual feels appreciated and with a stable emotion.

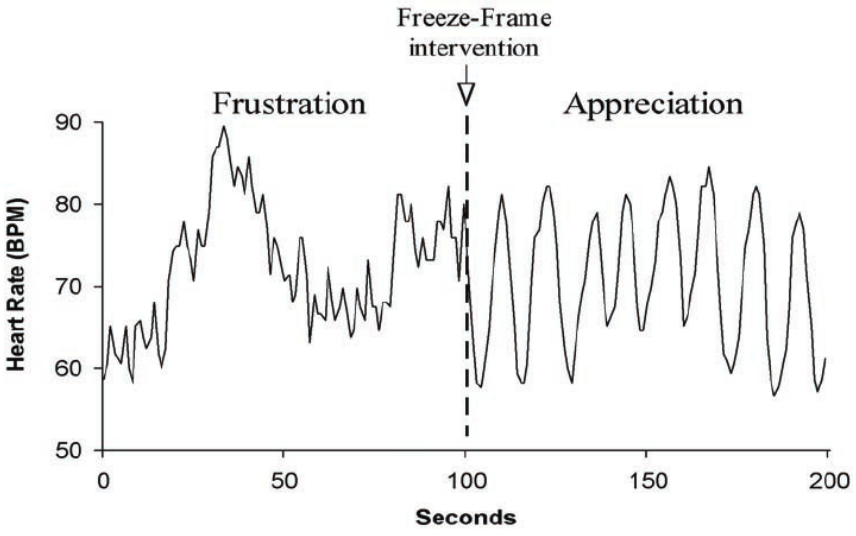

Figure 2.3.1-1. Difference in HRV between a state of frustration and appreciation [45]

The HRV signal can be analysed in different ways according to the application in study. Because of its clinical value, several studies have been made to retrieve features related to time, frequency and graphical representations.

The HRV can be measured with different protocols, and it can take from 1 to 10 minute tests. These measurements include:

- 1-minute-deep breathing test.
- Real time frequency spectrum indicating sympathetic and parasympathetic nervous system activity (Fast Fourier Transform).
- 10 minute supine/standing test [39].

The heart rate variability can be useful for the detection of sleep disorders, so is included in health monitoring and body sensor networks, as shown in [40] and [41].

2.3.2 Oxygen Saturation

Oxygen attaches to haemoglobin molecules to flow throw the blood current. Oxygen saturation indicates the level of haemoglobin contained in the red blood cells (erythrocytes) [42]. The two techniques most used to detect oxygen saturation are pulse oximetry and arterial blood gases (ABG).

The ABG measures the efficiency of the lungs carrying oxygen into the blood stream while removing carbon dioxide. It is usually measured from the wrist and it can be a painful method as shown in Figure 2.3.2-1. The critical oxygen blood level is 55-60mmHg (SaO_2). If the readings are below this level, they indicate that the person is under-oxygenated.

The pulse oximetry is defined by the SpO_2, measuring light absorption by blood. A SpO_2 of 90% (equivalent to SaO_2 of 55-60mmHg) is considered to be a critical level. When light passes through body tissues, it is absorbed in different amounts by body fluids, skin bones, vessels and venous or arterial blood. The light detector is applied to measure change in backscatter, which indicates change of absorption, which in turn indicates changes of flow volume. This way, the occurrence of blood pulse is non-invasively detected [42] by inserting a finger (can be used on the ear or on a toe as well) into the device – the oximeter where a red light calculates the redness of the blood pulsing through the finger, as indicated in Figure 2.3.2-1, the redder the blood the higher the oxygen saturation.

Figure 2.3.2-1. Left: Example of retrieving of ABG [53], Right: Example of recording Pulse Oximetry [50]

Some factors will affect the readings of the pulse oximeter:

- Nail polish.
- Poor circulation to the extremities.
- Dirty fingers.

As a conclusion, the pulse oximeter provides a quick and less intrusive indication of blood saturation levels, although the arterial blood gases will give the most accurate measure.

2.3.3 Respiratory Rate

The respiration rate is the number of breaths a person takes per minute. It is better to measure it when a person is at rest simply counting how many times the chest rises in one minute [43]. An optical breath rate sensor can be used for monitoring patients during a magnetic resonance imaging scan.

When a person has some fever or illness, the respiratory rate will change. Another aspect to considerer is to check if a person has any breathing problems. The normal number of breaths in a healthy person depends on the age. A normal range of breaths for an adult at rest varies from 12 to 16 breaths per minute.

As seen in [44] the respiratory rate is measured regularly with other vital signs to facilitate identification of change of physiology.

2.4 Types of sensors for sleep disorders assessment

Wearable sensors have been widely used in many applications such as medical, entertainment, security, and commercial fields. They are very beneficial when we wish to record data with a high accuracy and to get reliable information.

A body sensor network (BSN) is a set of wearable sensors for non-invasive real-time monitoring of vital parameters. This is a fast growing research area and represents an architecture of choice for distributed monitoring due to the easiness of deployment and configuration [19]. Their flexibility, low-cost, and uninterrupted operation make them suitable for a large variety of applications, such as telemedicine, health care (supervising of elderly patients, chronic diseases and enhanced diagnostic tools), e-fitness (monitoring of sport activities and physical performance) [45], etc. A example of a BSN is displayed s Figure 2.4-1.

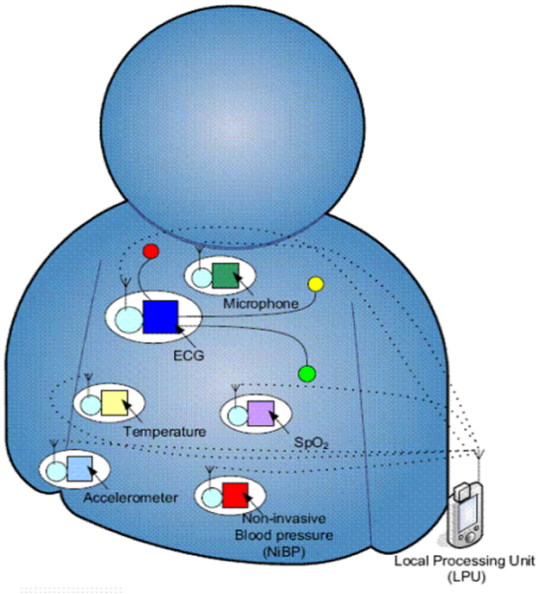

Figure 2.4-1. Example of a body sensor network [54]

These sensors are directly attached to the human body, and the information that they provide can be sent to a computer that is continuously running. When developing a BSN, some features have to be taken into account such as adaptive sampling, network performance, strong security, energy efficiency, adaptive communication strategies, etc. [45]

Developers in [46] compare pulses' transit times from different node and different parameters in BSN to compare measurements from arterial blood. As shown in [45], the investigators tried to design a BSN as less intrusive as possible and highly accurate. They inspect the lack of sleep deprivations by checking the skin temperature periodically with the objective of verifying whether mental activities affect the skin temperature. In [47] the researchers proposed both an activity monitoring and a BSN to recognize meaningful activities and keep control of the parameters related to health status.

Next subsection introduces a variety of sensors that can compose a body sensor network.

2.4.1 Body sensors

When designing body sensors networks, a sequence of procedures is required: firstly, we have to make the decision of what biological parameters to record, in order to choose the appropriate sensors; and secondly, commercial sensors are analysed to check if they match the body-monitoring goal and if their accuracy is sufficient for the purpose of the study. Only afterwards, the network can be implemented and data may start to be gathered.

Temperature sensor

A temperature sensor is the instrumentation equipment that is used to measure temperature or heat on a person or machine. Figure 2.4.1-1 presents an example of a skin sensor to monitor temperature.

Temperature sensing is performed by equipment called thermocouple. In activity monitoring, a temperature sensor installed in a home can be helpful, as it enables maintaining a steady temperature throughout the day. This is more important for the elderly people that suffer more with the temperature variations [48]. With regard to the sleep disorders, temperature issues in the two most common sleep disorders, insomnia and sleep apnea [49] cases, have been investigated aiming at the temperature regulation according to the individual comfort.

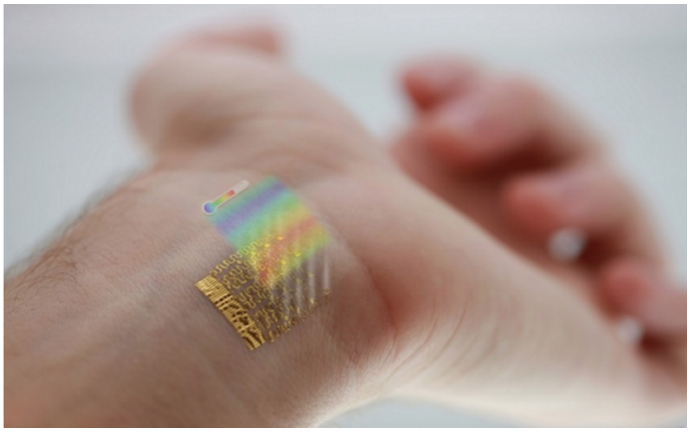

Figure 2.4.1-1. Example of a skin sensor to monitor temperature [59]

Pressure sensor

A pressure sensor provides information about the carried force per unit area of a surface. The electronic form of this sensor is displayed as an integrated circuit that acts as a transducer, that is, it replicates (in form of an electrical signal) the signal it receives as a function of the imposed pressure.

In [50] the researcher implemented a system imbued with pressure sensors, to identify the position of the patient. Chen et al [51] designed a system for recognizing complex living activities in a smart home, where, among others, they used a pressure sensor. In another example [52], authors developed a bed that can sense the patient body pressure and intelligently adjust to the benefit of the unhealthy subjects.

Also for the activity monitoring, if a bed has a pressure sensor - similar to the ones that cars have to inform if a person has fastened the seat belt or not - we could know when a person gets up from bed. This information can be helpful in case of sleep-walking.

2.4.2 Activity monitoring

As life expectancy is increasing, also is the number of elderly leading to an increase in healthcare costs. To avoid overcrowding the hospitals, it is being highly invested in sensing technologies, embedded systems, wireless communication technologies, nano-technologies, and miniaturizations that make possible the development of smart systems to monitor activities to detect any abnormal situation in the patient's house.

Activity monitoring is a real-time status of a person when deployed with sensors in a monitoring area. The preferred communication mode is wireless to form a self-organizing network system. This means that independently of the arming state of the sensors panel (activated, suspended, hibernation) we can set up the sensors in a way that, when they are triggered, a notification is sent to inform the user.

With activity monitoring, we can precise the type of activity the patient is carrying out. As seen in [53] , the proposed system is used to get the information regarding subjects' activity and posture. This system contains a position estimator, and can identify five types of physical activities, i.e. sitting, standing, walking, walking upstairs and walking downstairs, as seen in Figure 2.4.2-1.

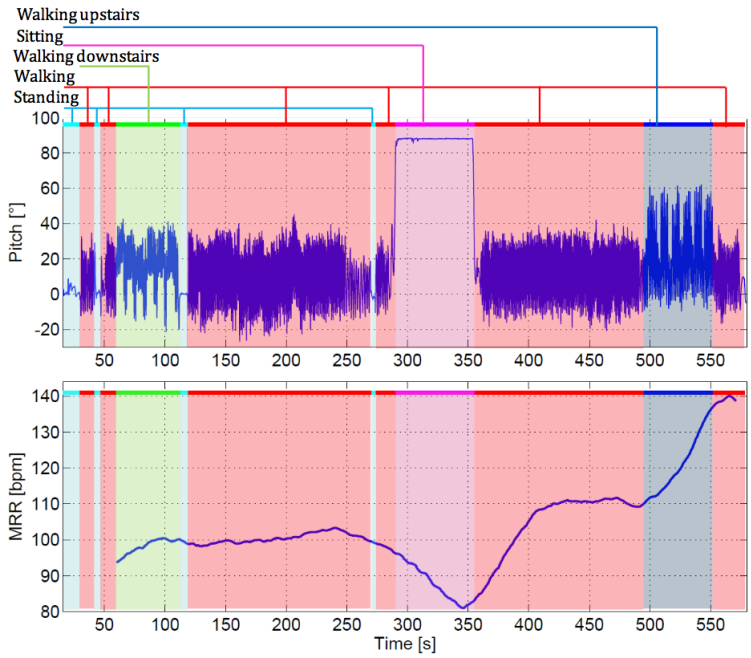

Figure 2.4.2-1. Example of activity monitoring where the upper subfigure shows the pitch angle estimation for a walk and where the lower figure shows the Mean RR signal, measured in beats per minute [30]

Activity monitoring has a large spectre of application in health-care. In this case, monitoring is being developed to increase the quality of life of the senior person as exemplified in [54], where a capacity sensing system can monitor the mobility of the person through sensing floor tiles. The author proposed a system that measures capacitance on an electrode from a charging/discharging cycle. The referred work is also capable of differentiating between a human and a house pet, by comparing threshold values, due to their different weights.

A problem that comes together with the monitoring, is the battery lifespan of the sensors, as the continuous usage of the sensor consumes huge amounts of energy. In [55] authors tried to lower energy consumption by implementing a duty cycling that minimizes the active time of the sensor. This improves the battery life of the sensor at the expense of information loss since it predicts the persons behaviour based on the activity history.

Chapter 3. Proposed Body Sensor Network

When designing a body sensor network in general, the physiological parameters to be analyzed should be defined in relation to the sensors to be used and how their relationship should work out algorithmically to accomplish the main objective. Considering this thesis, as mentioned in Chapter 2, it is required to keep in mind that each sleep disorder is characterized by different behaviors of physiological parameters

So, based on already published algorithms and/or signal processing algorithms developed within the research group, the combined action of all sensors' processed signals were gathered to be presented to the clinician through a real-time user friendly interface (to be described in this chapter). We also focus on the description of the particularities of the biomedical signals ECG, PPG, GSR and EMG.

From the ECG was generated the HRV signal, whose characteristics are analyzed to identify sleep disorders. The EMG is envisaged to be correlated with HRV, in order to detect the sleep disorders by measuring the chin movement, so it is possible to detect the arousals. With regard to the GSR and PPG, we do not go into great detail providing only an introduction, considering them for future work.

With respect to the movement signals, when detected from the chest, the accelerometer and gyroscope are used to try to correlate with HRV to identify sleep disorders and to identify the noise in the ECG recording. As we envisage a sleep disorder detector capable of being used at home, we propose to incorporate a model of activity monitoring, which can inform the clinician about

how the patient behaved during the night. This system is embedded in a device, and it is placed on the left thigh of the subject.

In this chapter we describe the composition of the proposed sensor network, the algorithms necessary to analyze the physiological parameters, the scheme to monitor the activity in a room and a Matlab™ interface to show the recorded signals.

3.1 Network Layout

With the main objectives of recording the maximum data as possible and in order to make this BSN as reliable as possible, was decided to use three sensors for this work. They record the biomedical and movement data, and all of them are based on wireless Shimmer™ platforms [56].

The Shimmer™ device is a wearable platform composed of a MSP430F5437A microprocessor and several internal sensors. Some of the peripherals are: a 3-axis low noise accelerometer array, a 3-axis wide range accelerometer array, a 3-axis gyroscope, 3-axis magnetic sensor, a relative pressure sensor and a temperature sensor as well as a bluetooth antenna and a micro SD card socket. In addition, there are several expansion boards for adding capabilities to the basic platform. For this research, two shimmer's ECG/EMG board [57] are used and also one shimmer GSR+ [58]. To retrieve the information from this instrument, we can send the data in real-time to our computer via its Bluetooth antenna, or it is also possible to save the data in a micro SD card.

A schematic example of how the sensors will bet displayed is depicted in Figure 3.1-1.

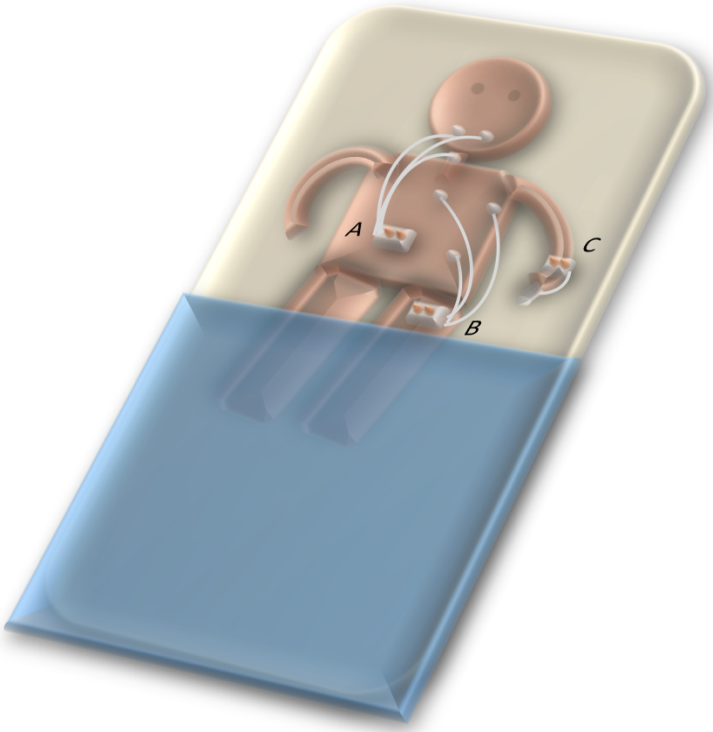

Figure 3.1-1. Arrangement of the proposed sensor network (A = Shimmer3 ECG/EMG; B = Shimmer3 ECG/EMG; C = Shimmer3 GSR)

As previously said, the proposed BSN is formed by 3 sensors, in this image defined by A, B and C, to facilitate the reader's understanding. The sensor A is one of the shimmer ECG/EMG board, and this sensor records not only the 3-lead EMG signal coming from the chin but also the data from the wide range accelerometer and the gyroscope, withdrawn from the diaphragm, since the shimmer is strap around the trunk.

The other Shimmer ECG/EMG board is the sensor B in Figure 3.1-1 and it is positioned in the left thigh, also insured by a strap. It records the information of the 3-lead ECG signal by using an Einthoven Triangle configuration [59], the gyroscope and also the wide range accelerometer.

Sensor C is the Shimmer GSR+, and his task is to record the PPG and GSR signal. It is placed on the left wrist.

Table 3.1-1 shows the task of each different sensor.

Sensors	Records
A Shimmer3 ECG/EMG	- EMG - Accelerometer and Gyroscope
B Shimmer3 ECG/EMG	- ECG - Accelerometer and Gyroscope
C Shimmer3 GSR+	- PPG - GSR

Table 3.1-1. Table showing the defined task of each sensor and figure of each (Left: Shimmer3 ECG/EMG; Middle: Shimmer3 GSR+; Right: Shimmer3 ECG/EMG)

The frequency sample to be used for all shimmers is 256 Hz that is high enough for the signals to be recorded, since it is permitted in [60]. The reason behind the same frequency for all sensors, is to facilitate the understanding and subsequent analysis of the signals.

Comparing to the PSG, our body sensor network may not give the same amount of information, but also is less intrusive than the standard PSG. Table 3.1-2 exhibits the relation between both approaches.

PSG Signals	Measure	To be included in BSN
EEG	brain wave activity (min 3 channels)	**NO**
ECG	heart rate and rhythm (min 3 sensors)	**YES**
EOG	Eye movement activity	**NO**
EMG	body muscles activity (min 1 sensor)	**YES**
Body Movement Detectors	shins and waist movement (min 3, 1 being reference)	**YES**
Airflow through the nose and mouth	Respiration rhythm	**NO**

Table 3.1-2. Comparison between the signals obtained by the PSG and the proposed body sensor network.

3.2 Signal Analysis

When collecting real data, it is difficult to conclude if the data corresponds to reality or not. The difficulty of biomedical signal analysis comes from the fact that the signals have low voltage (mV) amplitudes and they can be corrupted with noise, either from the instruments or from other body signals. Therefore, when acquiring a body signal, we are actually recording a set of biomedical signals and hence it is required a pre-processing.

Details about the processing of the raw data, both from the physiological parameters and activity monitoring, are explained in the next sub-chapters.

3.2.1 Physiological Parameters

After recording the data, we need to pre-process the signals according to their origin so that the next step, the sleep disorders decision stage, becomes as accurate as possible. It is important to keep in mind that filtering the signals may lead to the loss of information if the filter is not correctly tuned.

Analysis of Electrocardiogram

The objective when recording the ECG signal from the patient is to retrieve the R-peaks, to enable the calculation of the heart rate variability. This is an important step, since from the HRV we can withdraw features relevant for potential sleep disorders identification. The algorithm used was proposed by [27], corresponding to an improved version of the well-known algorithm Pan and Tompkins [61]. The author was able to reduce the computation complexity and improve the algorithm's performance. By applying an integration window, the computational

effort was reduced and the procedure to detect the position of the R peaks became dependent of only one threshold.

Figure 3.2.1-1 presents the block diagram of the algorithm proposed by [27].

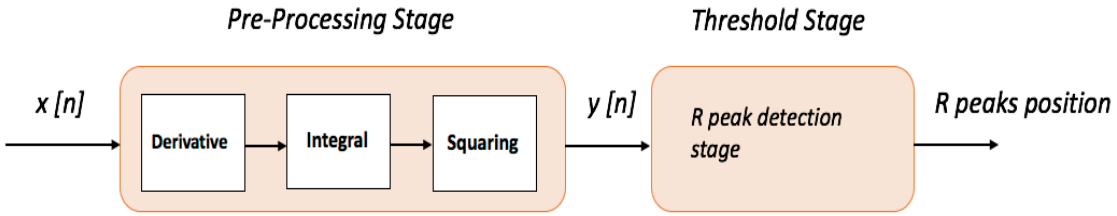

Figure 3.2.1-1. Block diagram of the proposed QRS complex detection algorithm [30]

The first pre-processing task is the derivation of the input ECG signal *x[n]*. The goal is to have a signal without wandering baseline effect, an effect caused by respiration. In the next step, we apply an integration to remove the high-frequency artefacts and it also acts as a low pass filter (Moving Average). To finish the pre-processing stage, the signal will be squared, in order to accentuate the R peaks.

During the threshold stage, the algorithm identifies the R peak position. The algorithm uses an adaptive threshold, which is very useful when the pre-processing stage cannot remove all the artefacts, or even for those signals presenting large T-waves, avoiding misclassifying them as R peaks. The threshold value is defined by a Finite State Machine (FSM), according to the following states:

- **State 1: Searching for a maximum peak.** The algorithm looks for the maximum peak of the signal during a time interval identical to the minimum feasible RR interval - RR_{min} - plus the standard duration of a QRS complex - QRS_{int} ;

- **State 2: Waiting state.** The period of this state depends on the position $R_{peak}Pos$ corresponding to the location where the R-peak was discovered in State 1. The FSM is waiting for a time equal to RR_{min} less the time between the position of the last R-peak and the end of State 1;

- **State 3: Threshold decreasing.** When State 2 finishes, the initial value of the threshold *th[n]* is computed as the mean value of all the previous spotted R-peaks. In this state, the threshold value *th[n]* is reduced with every new sample from the input ECG signal.

Figure 3.2.1-2 shows how the finite state machine works, and Figure 3.2.1-3 displays the correspondence between the states of the FSM and the phase of the ECG signal.

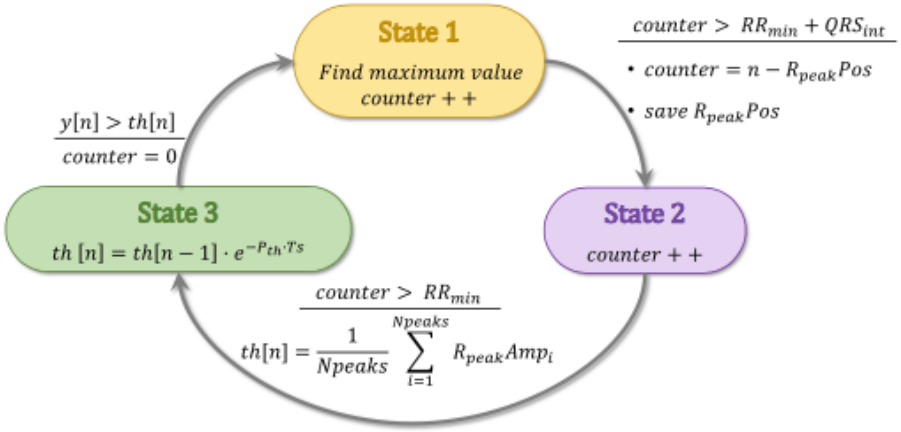

Figure 3.2.1-2. State machine diagram [30]

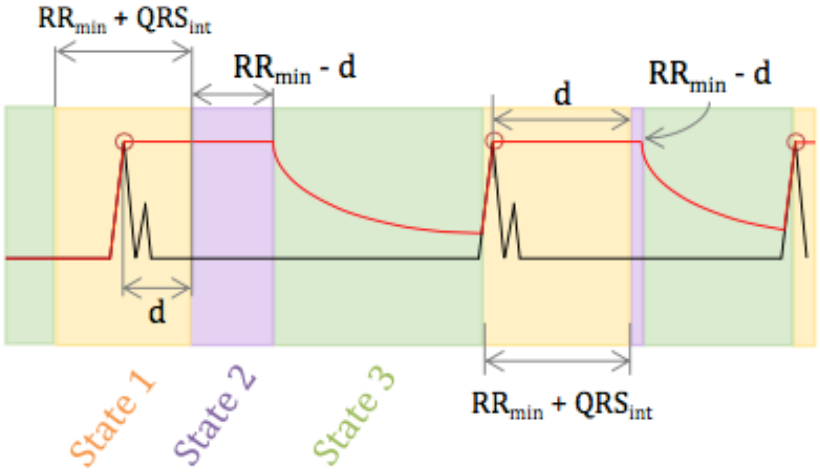

Figure 3.2.1-3. Correspondence between the FSM states and the ECG phase [30]

After identifying the R peaks position, it is possible to calculate the HRV, as the figure 3.2.1-4 shows.

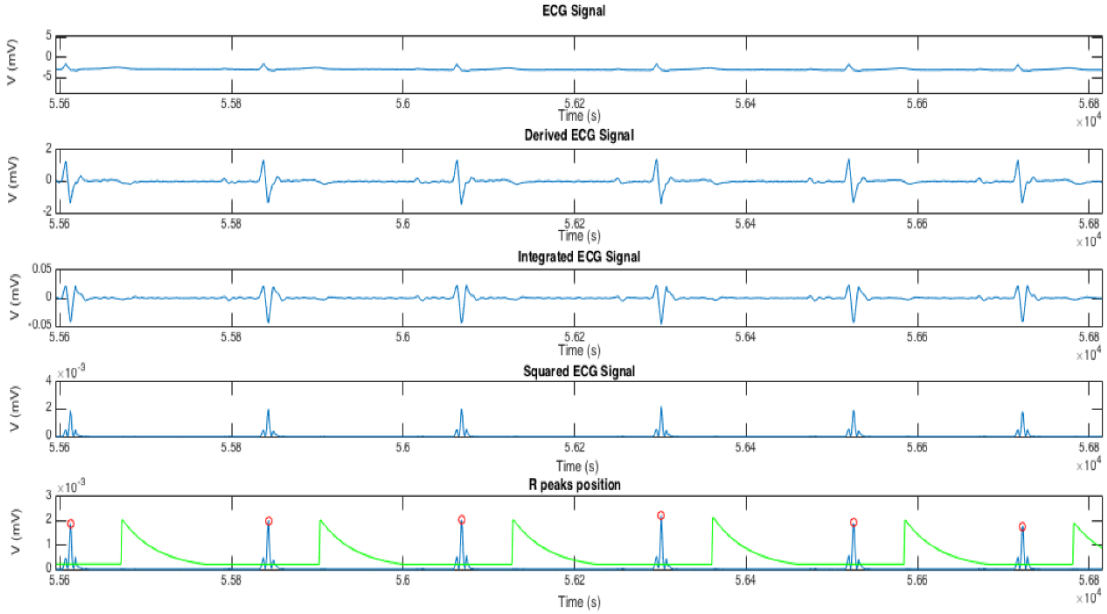

Figure 3.2.1-4. Proposed algorithm applied in the ECG signal

HRV Features

Here is the list of features obtained from the signal's HRV:

- **MRR:** Average HRV
- **STDNN:** Standard deviation of the RR intervals
- **CV:** Coefficient of Variance
- **RMSSD:** Root mean square of the RR intervals
- **NN50:** Number of successive pairs of RR intervals differing for more than 50 ms.
- **pNN50/pNN25:** Percentage of successive pairs of RR intervals that differ for more than 50/25 ms. of the RR intervals within the analyzed epoch.
- **STPP/STNN:** Number of RR intervals that are longer/shorter than the previous one.
- **CSI/CVI:** Cardio Sympathetic/Vagal Index
- **SD1/SD2:** Short/Long axis of the poincaré ellipsis
- **VLF/LF/HF:** Total power in the very low/low/high frequency bands
- **ratioLFHF or LFHF:** Ratio between LF and HF
- **Histo:** Histogram index

References [62] and [63] demonstrate that the above referred HRV's features can be used to compare patients suffering sleep apnea with healthy sleep patterns.

Analysis of Electromyogram

It was decided to record the EMG from the chin/genioglossus muscle by using surface electrodes. The aim is to search for distinct periods of movement that can correlate with the information provided by the ECG. The raw EMG signal is also targeted for pre-processing.

A notch filter was used with the objective to remove noise caused by power lines. Afterwards, a Butterworth filter was applied in order to cut-off undesired frequencies. Then, a moving average filter was applied to smooth the data.

Finally, the signal is rectified, by transforming the negative portion of the signal into positive values. Figure 3.2.1-2 shows the pre-processing applied on the EMG raw signal *x[n]*.

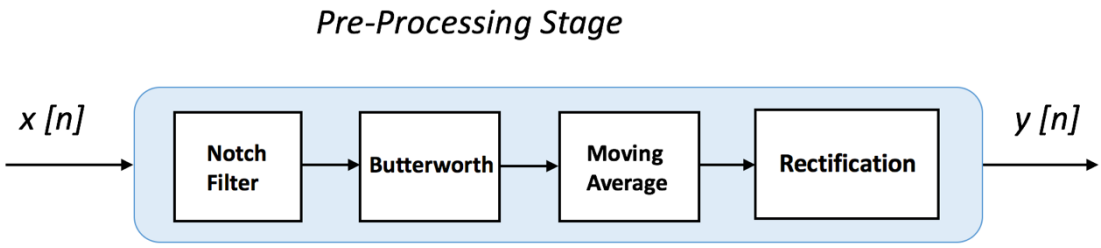

Figure 3.2.1-2. Block diagram of the pre-processing stage with the algorithm for the raw EMG

Each one of the referred operations is respectively implemented as follows:

- **Notch Filter** rejects a narrow frequency band and leaves the rest of the spectrum almost unchanged *(eq.3.2.1.1)*. The most common is having to remove 60Hz from power lines.

$$f_n = \frac{1}{2\pi R_0 C_0} \qquad (eq.3.2.1.1)$$

- **Butterworth Filter** works as band pass filter for noise cancelation of other sampling frequencies *(eq.3.2.1.2)*. The cut-off low frequency of 10 Hz is settled to get rid of the baseline wander, while the upper cut-off frequency of 100 Hz is established to avoid high frequency noises.

$$|H(\omega)|^2 = \frac{1}{1+\left(\frac{\omega}{\omega_c}\right)^{2N}} \qquad (eq.3.2.1.2)$$

- **Moving Average Filter** main purpose is to smooth the signal, a linear enveloped was created and the extreme parts of the signal were excluded (*eq.3.2.1.3*). The span used was five.

$$y[n] = \frac{1}{N-1}\sum_{k=0}^{N-1} z^{-k} \qquad \textit{(eq.3.2.1.3)}$$

- **Rectification** is implemented to rectify the signal, all negative values were transformed in positives one and added to the rest of the signal (*eq.3.2.1.4)*.

$$y(n) = y_1[n]^2 \qquad \textit{(eq.3.2.1.4)}$$

The features of this pre-processing stage are detailed in [64]. According to [63] a *root mean square* step was also recommended, but on present work this step was avoided because this action would influence the sample size, besides not being so relevant on this particular study.

Figure 3.2.1-3. shows the sequence of signals generated along the pre-processing stage. It can be seen how the different artefacts are removed, providing a clear output signal.

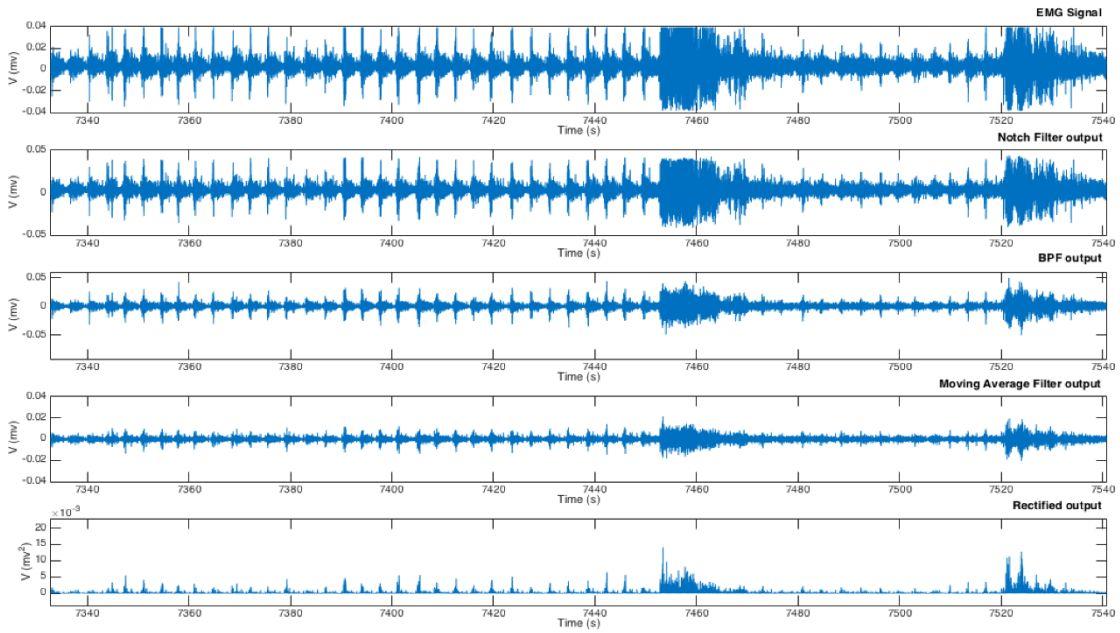

Figure 3.2.1-3. Signals generated during the pre-processing stage of the proposed algorithm.

Analysis of Photoplethysmogram

The photoplethysmogram signal is a valuable asset included in the proposed sensor network to provide the pulse rate variability (PRV). In the proposed BSN, the PPG can be detected either by using an optical pulse sensing probe that is inserted on the patient's finger, or by an optical ear pulse sensor, that has to be placed on the earlobe.

After acquiring the raw data, we have to filter the signal to reduce motion artefacts. The selected filter is the moving average. Figure 3.2.1-4 shows the difference between a raw PPG signal and the evolution the signal suffers, after being applied a Moving Average Filter.

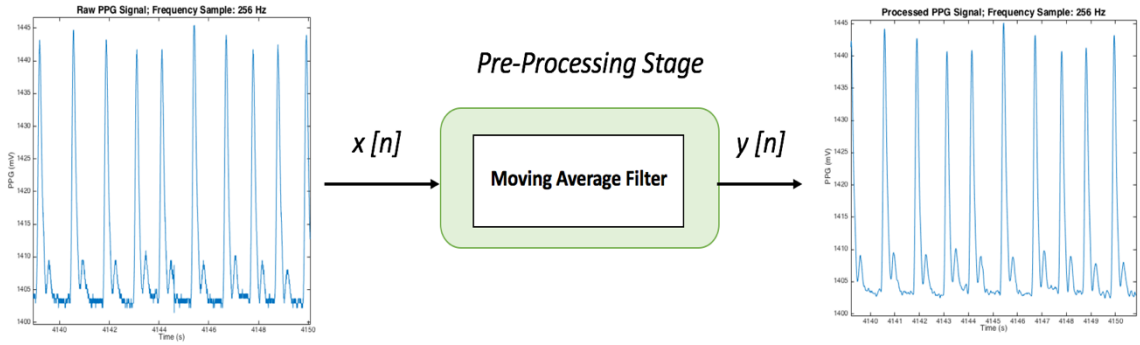

Figure 3.2.1-4. PPG signal before and after being pre-processed.

Although in this thesis, we do not go any further with the PPG signal, exist some methods to use this signal as an identifier of sleep disorders. As seen [29], the researchers obtained characteristics point positions, with the objective to extract the PRV features as surrogate for HRV indexes.

Analysis of Galvanic Skin Response

The galvanic skin response sensor is going to measure the electrical conductivity of the skin. The frequency sample that should be used to record this signal is between 1-5 Hz [58] . As explained before, all the signals will be recorded at 256Hz and since the GSR signal does not suffer corruption during the acquisition procedure at this sampling frequency, a low pass filter of 5 Hz was the only pre-processing done to the signal, as displayed in Figure 3.2.1-5.

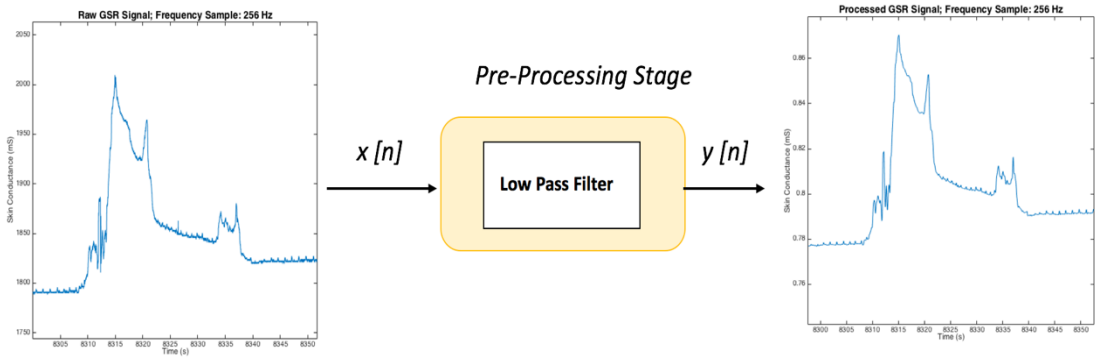

Figure 3.2.1-5. Block diagram of the processing stage for the raw GSR.

3.2.2 Analysis of the Activity Monitoring

One of the main drawbacks of PSG is the mandatory need to go to a health care center/hospital to undertake a sleep exam. Many studies are being developed to avoid this obligation. Then, instead of the patient goes to the site, the site comes to the patient, with the aim of improving the patient's comfort and reduce the cost related to hospitalization.

Therefore, in this proposal we provide sleep disorders' assessment at the patient's own home, with the possibility to be tested on their natural environment. However, at home the patient can move as he is no supervised by a nurse, being this a problem for recording the required signals. As we know from previous work

[53], some categories of movement have an effect on the HRV which can be misunderstood as being a peak of some kind of apnea.

We propose to include an activity monitoring system based on the so-called Pocket Navigation System.

Pocket Navigation System

The pocket navigation system was first developed in [53] and then used in [27] as personal navigator based on inertial sensors. It is usually bind to the leg with an elastic band or putted in the trousers or skirt pocket. The navigation is doable by the Shimmer [57], and contains a three mutually orthogonal accelerometers and gyroscopes.

This navigation registers the patient to walk along his/her house, while still being able to continue with the monitoring. This can be helpful if the patient is having an episode of sleepwalking, and we have means of differentiating normal movements from cardiac cycle movements when the patient is still. The pocket navigation system can identify five physical activities, i.e. walking, walking downstairs, standing and sitting [53]. These are the most common activities that a person can do at his own house.

These activities have an effect on the HRV, so we can misclassify them as an event of sleep apnea. For example, if the patient changes its posture from lying to seated, the action will be reflected on the HRV signal. These kind of events may also increase the number of false positives; therefore, we need to detect which HRV variations are provoked by which event.

It is also possible to measure the chest movement and correlate it with the increase in HRV. This means that for each unit of movement, the heart rate is increased by a fixed number of beats [27].

Figure 3.2.2-1 displays an example of a person using the Shimmer to monitor is activity.

Figure 3.2.2-1. Shimmer allocation for the pocket navigation system [30]

3.3 Decision Algorithm

The objective of the proposed algorithm is to detect OSA episodes based on parameters derived from ECG and EMG signals with a contribution from the motion signals, recorded from the accelerometer and gyroscope. The former provides the heart rate variability (HRV); and the latter, when retrieved from the chin, is a redundant signal, which is going to be used to confirm or discard possible OSA intervals from the ECG, as well as to confirm the OSA time period.

Starting with ECG, there are several ways of detecting OSA. The feature extraction can be performed in the time domain or in the frequency domain. An example of the first is the increase of mean HRV that occurs after an OSA interval, due to the effort made by the person to rapidly breathe and recover normal values of oxygen saturation. As for OSA, this behavior happens to be cyclic [65]. An example of the second is the presence of the characteristic peak shown in the high frequency range (in the 0,15-0,40 Hz band), due to the patient's normal breathing. This is due to the respiratory sinus arrhythmia (RSA), a physiological phenomenon defined as an increase in HRV when the person inhales, and a decrease in HRV when the person exhales [1] (see Figure 3.3-2).

Although our final goal is to use the ECG and EMG signals, in our first approach we are going to process only the ECG signal, as proposed in [65], in order to compare the results. Figure 3.3-1 shows the HRV of a patient when he/she is suffering an OSA episode (grey area). Notice the strong cyclic pattern that the HRV shows while OSA occurs compared to when it does not.

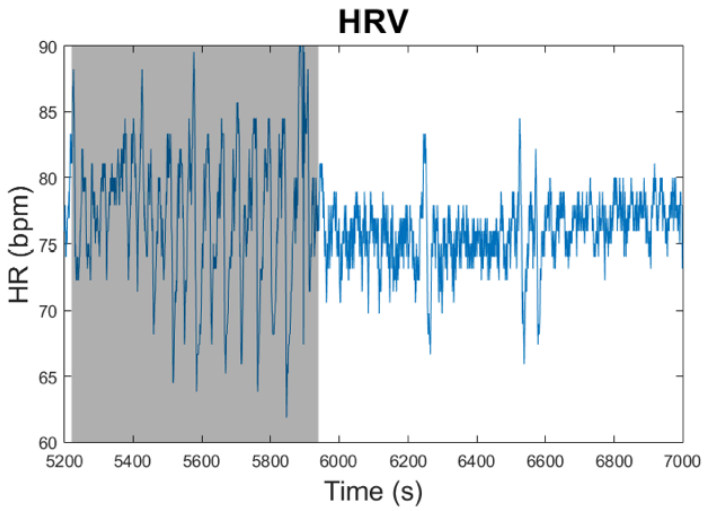

Figure 3.3-1. HRV for an OSA interval (gray background) and a normal sleep interval (white background)

Our proposal focuses on the frequency domain, as it better reveals the difference between OSA and normal sleep (NS) than time domain [1]. We perform power spectral density (PSD) of HRV through Lomb periodogram, which has been proven to be superior to FFT for these applications [66].

The monitored features are the variation of density of normalized power at different frequency ranges: 1) very low frequency (VLF), (0,003-0,04 Hz); and 2) high frequency (HF), larger than 0,15 Hz. These frequency bands have been proven to be the most powerful in order to classify OSA and NS [65]. Figure 3.3-2. shows the normalized PSD of HRV computed over 1-minute segments for the same patient when there are OSA (in red) and NS (in blue) episodes. The frequency bands (VLF, HF) that we are going to use for classifying these episodes are labelled in the figure. In order to improve OSA and NS classification, a novelty has been introduced so that the HF range is set automatically to be solely as wide as the RSA Gaussian shape for each individual, instead of being the full traditional range.

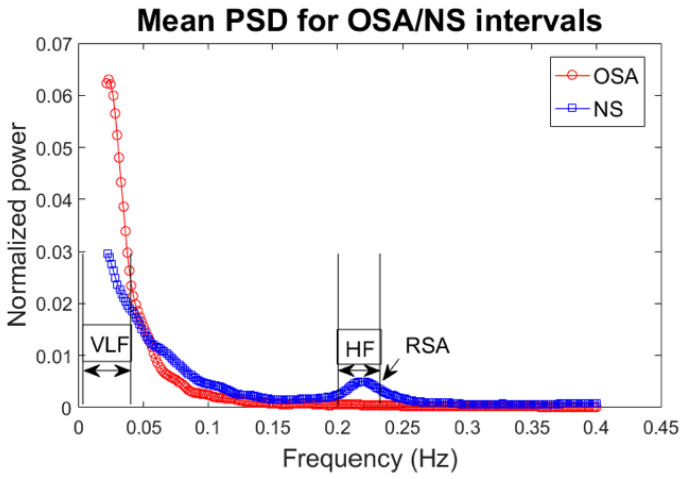

Figure 3.3-2. Mean PSD of HRV for OSA intervals (in red) and for NS intervals (in blue)

The frequency domain features, at VLF and HF, are monitored over time with a delay of 1 minute. A first-in first-out (FIFO) memory buffers the last minute recorded, and computes the normalized PSD of HRV (*PSDn*) with a moving window of width of 1 minute, and window displacement of 10 seconds. At this point the algorithm relies on a cumulative variable (*SPSDi*), *i* indicating the 10-second shift on the processed windows. For each window, the power of the VLF and HF regions is added as indicated in eq.3.1.1 and eq.3.1.2 (see Figure 3.3-2), obtaining the two classifying features. Note that the VLF frequency band is fixed [0.003-0.04], and the HF frequency limits [*flower -fupper*] depend on the position of the RSA at normal sleep (NS).

$$SPSD_{VLF_i} = \sum_{f=0.003}^{0.04} PSD_n(f) \qquad \textit{(eq. 3.3.1)}$$

$$SPSD_{HF_i} = \sum_{f_{lower}}^{f_{upper}} PSD_n(f) \qquad \textit{(eq. 3.3.2)}$$

For every sample *i*, the value of each feature to an empirically obtained threshold. This process can be clarified with the schematic diagram of the proposed algorithm shown in Figure 3.3-3. After computing the HRV and its PSD, the SPSD is calculated at each frequency range.

If $SPSD_{VLF_i} > SPSD_{VLF_{THR}}$ and $SPSD_{HF_i} < SPSD_{HF_{THR}}$, the algorithm then computes the mean value of each feature over the following minute eq. 3.3.3 and eq. 3.3.4 and if it also lies above or below the corresponding threshold, respectively, that minute is then classified as apneic (OSA).

$$\left(\frac{1}{N}\sum_i^N \boldsymbol{SPSD_{VLF_i}}\right) > \boldsymbol{SPSD_{VLF_{THR}}};\ \boldsymbol{N = i + 5} \qquad \textit{(eq. 3.3.3)}$$

$$\left(\frac{1}{N}\sum_i^N \boldsymbol{SPSD_{HF_i}}\right) < \boldsymbol{SPSD_{HF_{THR}}};\ \boldsymbol{N = i + 5} \qquad \textit{(eq.3.3.4)}$$

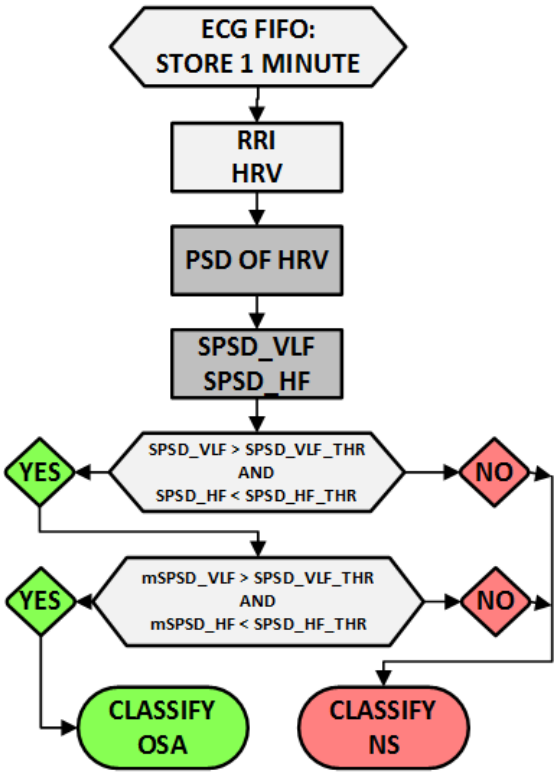

Figure 3.3-3. Schematic diagram of the proposed algorithm

With regard to the EMG signal, it is still a work in progress. An example of characteristic behavior of EMG signal after an OSA interval is the increase in mean muscular activity at the chin due to patient's jaw opening in order to intake a greater air volume. With this information, we tried to develop an algorithm, with a defined threshold. Each time the processed chin's EMG signal overcomes the threshold is marked as an epoch of apnea.

This first attempt was not successful. The main reason for the failure was because all three states during the sleep stage ('Normal Sleep', 'Sleep Apnea' and 'Movement Time') can vary their amplitude a lot. So even if we have a pre-defined mean for each state, a cluster of samples during "Normal Sleep" can be classified as 'Movement Time'. We also try variations of measures in amplitude, like histograms or measuring the standard deviation between peaks, but none of them provided the information desirable to elaborate an accurate algorithm.

The present approach was based on a study that did a comparison between neuropathic and Healthy EMG signal using PSD [2]. As there is a difference in the spectral analysis between normal and neuropathy signals, we tried to apply the same principal to detect the difference between "Normal Sleep" and "Obstructive Sleep Apnea". The Figure 3.3.4 shows the normalized PSD of EMG signal computed over 30 seconds segments for the same patient, when there are NS (in blue) or OSA (in red) episodes.

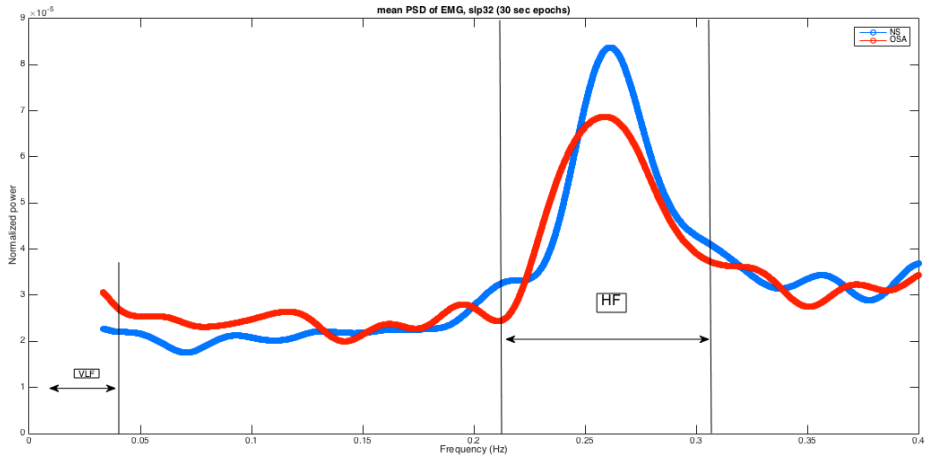

Figure 3.3-4. Mean PSD of EMG signal for OSA intervals (in red) and for NS intervals (in blue)

As is readily seen, the PSD of the normalized EMG signal in NS is quite similar to the one belonging to the ECG signal (Figure 3.3-2). The most noticeable feature in both signals is a high peak during the high frequency interval which derives from breathing. The second property involves the VLF. In the EMG signal, it is not so noticeable the disparity between the two states. The main reason for this setback is length of the apnea annotations intervals. In the previous ECG database, the apnea annotations are marked with one-minute apart intervals while the EMG database marks with 30 seconds apart.

This thirty seconds difference is important because the minimum frequency observable for each database varies with the interval of apnea annotations (i_{aa}), as shown in Equation 3.3.5.

$$f_{min} = \frac{1}{i_{aa}} \qquad \textit{(eq.3.3.5)}$$

$$f_{min_{ECG\_dat\_base}} = \frac{1}{60s} = 0.0166\ Hz \qquad f_{min_{EMG\_dat\_base}} = \frac{1}{30s} = 0.0333\ Hz$$

Since the VLF band is 0,003-0,04Hz, by using the ECG database we have a range from 0.0166 – 0.04Hz. On the other side, if we use the EMG database, we are only able to get from 0.0333 – 0.04 Hz.

This explains the difficulty of finding a major gap in VLF between OSA and NS for the database when the EMG signal retrieved from the chin is included. A way to overcome this problem is to find another data more suitable for our task.

Even though we have this problem with one of frequencies band, the algorithm will be applied on the EMG signal following the steps and procedures previously mentioned.

3.4 User Interface

In order to display the recorded signals in a friendly way, a Matlab™ GUIDE Interface was created. This interface provides the ability to not only see the documented signals but also to enable the application of the algorithms previously mentioned. Figure 3.4-1 is a schematic image showing the final aspect of the application. Furthermore, we can do certain adjustments and select the functions that we desire to implement (*callbacks)* in file signals.m.

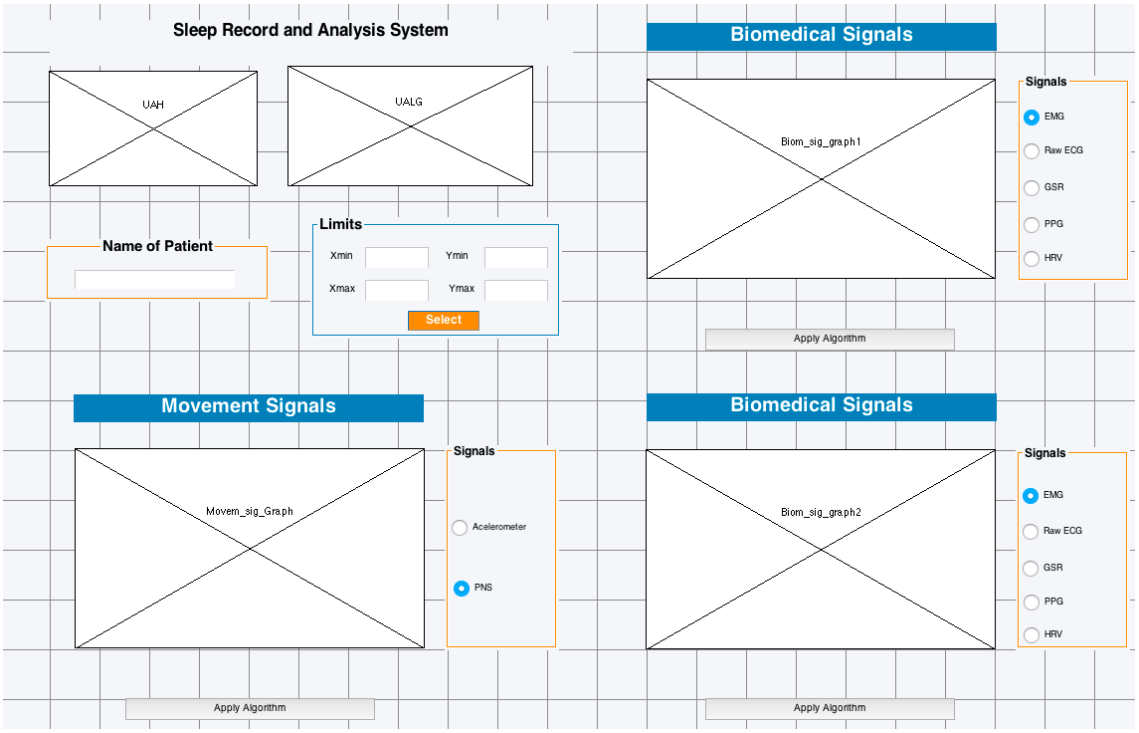

Figure 3.4-1. Schematic diagram of the proposed Matlab GUIDE Interface

One of the main features that was required was the easiness of use. So after the experiment, the user will be able to save the data from Shimmer in the same folder where the interface is stored. In order to identify the signals and the files, the user has to save it in txt format, providing an identifiable name (any name followed by the recorded signal, i.e. BeatrizECG.txt).

To access this file, it is only required to write the name of the patient and select the signal to be analysed. The different algorithms can be applied to each signal. Figure 3.4-2 presents an example of the proposed interface, displaying both biomedical and movement signals.

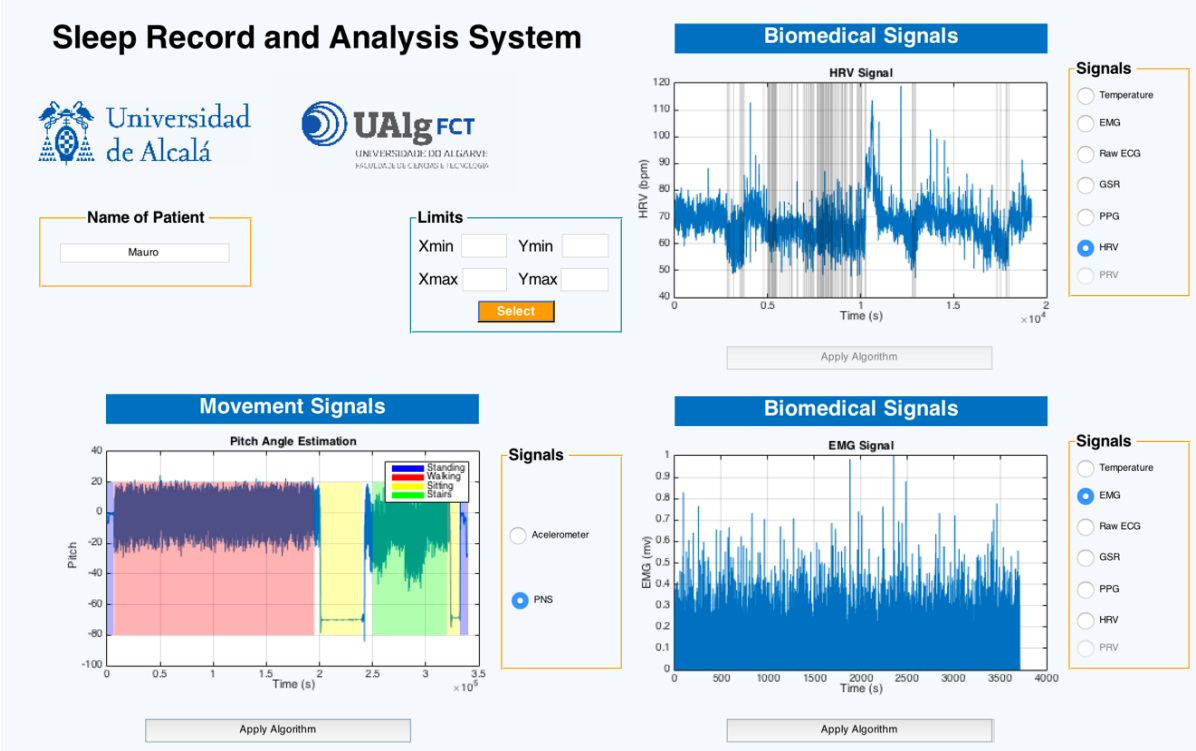

Figure 3.4-2. Display of the Matlab GUIDE Interface proposed in this Master Thesis

Chapter 4.
Experiments and Results

This chapter describes the experimental setup, and shows the obtained results with the available signals. In chapter 4, we started by explaining how the setup of the experiment is established and the test performed to validate the proposed BSN.

Since the data obtained in real experiments is more predisposed to have inaccuracies, we start testing the proposed algorithm in the PhysioNet database and then, in the data retrieved with the proposed body sensor network. We analyze the performed tests, the obtained results and the performance of the algorithms with different sources of data.

These strategies enable the comparison with other published results and allow differentiating what is due to algorithmic design against what is related to implementation issues.

4.1 Experimental Setup

Before seeing how the proposed algorithm works with different sources of data, it is required to know which the experimental setup is. This trial starts before the subject falls sleep, and it will end, when the person responsible for the experiment finishes it.

When the patient is a man, it is recommended to shave the beard, since it cause noise to the EMG recorded signal. In addition, to avoid discomfort for the male patient, is suggested to do the hair removal of the chest, as the electrodes, when removed, act as depilatory bands.

After taking care of all the hygiene issues, the electrodes are placed on the patient's skin and the Shimmers at the indicated body locations. As shown in Figure 3.1-1, one Shimmer is positioned on the diaphragm to measure the acceleration and signal from the gyroscope, and with three electrodes positioned at the chin, two below the lower lip [67], while one is putted below the jaw line, working as a reference. Other Shimmer is placed on the left leg, where it also measures the signal provided by the wide range accelerometer and gyroscope and the ECG signal, by using the Einthoven Triangle method. The last Shimmer is worn as a bracelet by the patient, and measures both PPG from ear or finger and the Galvanic Skin Response from finger.

After all the sensors are placed, we wait for the person to fall asleep and then we start recording data. We do not need to record 5 hours of sleep, but we need a minimum of 1 hour signals, to see how the signals develop. Since we have not enough time and resources to produce a sleeping test at a large scale, we decided to test the BSN system with volunteers. The first two cases were on healthy people, while in the third case, the patient had previously been diagnosed as a person with severe apnea.

4.2 Algorithm Test

To test the ECG algorithm, we decided to test it first with annotated signals from PhysioNet Databases. This database is used in various studies, where we can know almost every specification of the signal and the exact interval where an apnea epoch occurs.

In the second test, will be used the volunteers recorded data by the BSN with the Shimmer sensors. Below is explained how the records from PhysioNet are constituted and the process followed for acquiring data with the developed BSN, in order to test the algorithm.

4.2.1 Testing ECG

This section describes the process of selecting the ECG signal, and also the results after the application of the algorithm.

Data Selection

Despite the number of times that the information is checked, data selection can have a tremendous effect on the outcome of any work produced. A wrong choice can induce errors that will drive the user to a result completely different from the one imagined. This data selection involves both PhysioNet data and data recorded with the proposed body sensor network. This leads to different views, and with that, retrieve different interpretations for the same purpose.

I. PhysioNet database and their specifications

The database used in this work to test the algorithms developed for the ECG was extracted from the PhysioNet Website [68], more specifically from the Apnea-ECG Database [69]. The use of this database helps the comparison of our results with other that have been previously published.

Apnea-ECG Database consists of 70 records, divided into a learning set of 35 records and a test set of 35 records. The data records' length varies between 7 to 10 hours and the sampling frequency used was 100 Hz. The mean age from the group of subjects is 33 years (27-42 years).

II. Body Sensor Network Data

Two experiences of the same trial, when conducted by different people, will have different results. Then we decided to analyse the signals with the highest precision possible, defining an experimental plan, as the volunteers were not diagnosed with having apneas.

This plan was conceived with the objective of seeing the effect of the apnea on ECG signal. So to observe the effects, we decided to establish a 20 minutes' span to record the signals. For each volunteer we made two different recordings. The first recording is carried out when the volunteer is still, being the reference signal. On the second record we will simulate apnea at pre-set times with a pre-determine intervals. Those minutes were chosen because they had a wide period between them, so that the pretended apneas do not influence each other.

4.2.2 Results

The next subsection shows the results of our algorithm, when running on the above signals.

I. Data from PhysioNet

The first data to be tested corresponded to the patient *a19* from the PhysioNet Apnea-ECG database. Table 4.2.2-1 shows the main features characterizing this data.

The selection of this particular database is due to the fact that the apnea annotations are marked with one minute apart intervals and the proposed algorithm is optimized to operate with that interval size.

Record	Length	AHI	Age	Gender	Weight (Kg)
a19	8:40h	34	55	Male	92

Table 4.2.2-1. The characteristics of the first data record chosen to test the ECG algorithm. This subject, patient 19, belongs to Apnea-ECG Database [82].

This record was chosen among seventy, because it had ideal characteristics to test our algorithm, such as an AHI relatively low, for a person with severe apnea and also the apnea episodes had a good distribution, to make it easier to see the results of our algorithm.

Figure 4.2.2-1 shows the comparison between the Physionet's classification and the one obtained by the proposed algorithm with the described subject.

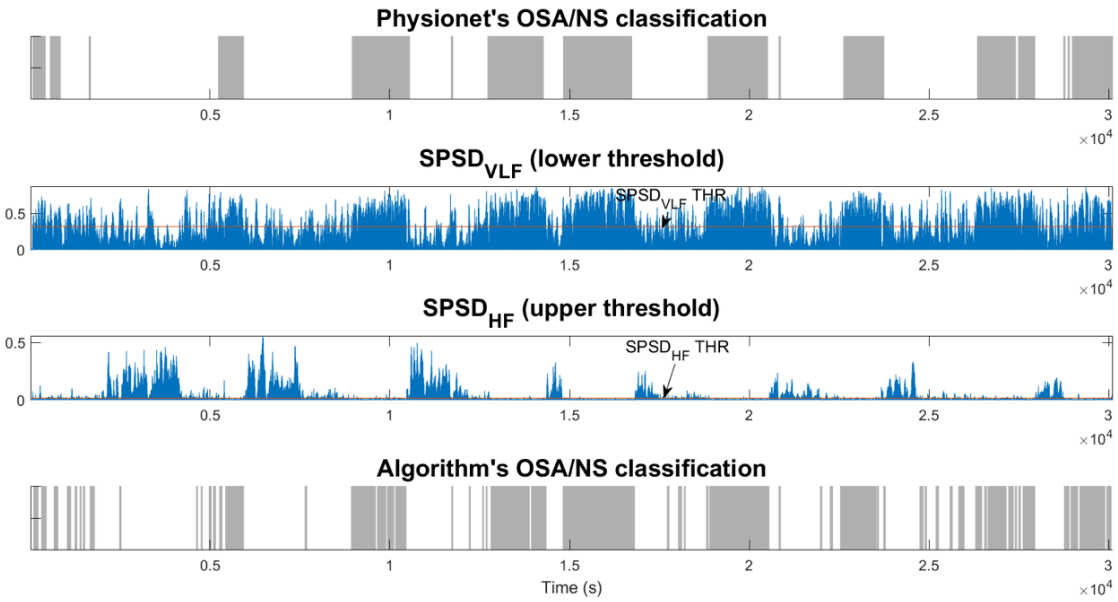

Figure 4.2.2-1. (from top to bottom) a) OSA classification by expert annotation on Physionet- grey area; b) SPSD_VLF sum of PSD on VLF range, and lower threshold used for classification; c) SPSD_VLF: sum of PSD on HF range, and upper threshold used for classification; d) Proposed algorithm's OSA classification – grey areas.

The algorithm has shown solid results with accuracy at 87,8%, specificity at 89,9% and sensitivity at 86,3%. And if we compare with Chen at [65], our outcome is very promising, since they also used single-lead electrocardiogram (accuracy of 82,1%, sensitivity of 83,2%, and specificity of 80,2%).

II. Body Sensor Network Data

Due to a lack of time, we only have carried out the analysis in the time domain, without using the described algorithm.

Incidents of apnea were simulated at 300, 600 and 900s and each one of these epochs lasted 30s. Table 4.2.2-2 shows the characteristics of the volunteer.

Record	Length	AHI	Age	Height (cm)	Gender	Weight (Kg)	IBM
Subject 1.	0:20h	?	24	187	Male	89	25.5

Table 4.2.2-2. Characteristics of the volunteer to contribute for the record

The apnea was simulated by inspiring the air with the mouth, and then, after the pre-set time, expelling it by the mouth. By comparing the two evidences, we can see how the apneas affect the signals. Figure 4.2.2-2 shows the results of this trial.

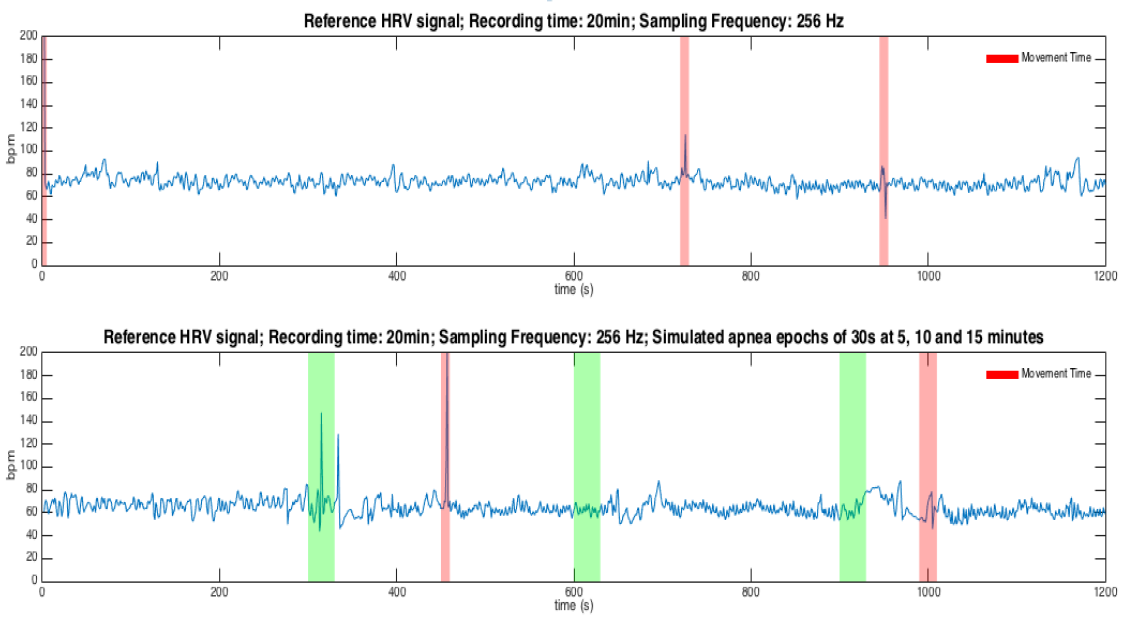

Figure 4.2.2-2. Graphics representing the body sensor network data acquired for Subject 1. The upper graph represents the reference HRV signal, and the below displays the signal with the simulated apneas.

The top graph shows the HRV reference signal, with some glitches probably provoked by a bad connection with the electrodes. The bottom graph represents the HRV signal when the apneas were simulated. In this case, each mock apnea had the size of 30s and they began at 5, 10 and 15 minutes. Analysing the data, the apnea periods are not so distinctive from others interval.

Instead of looking to the interval, we need to look from the point when the apnea ends to the next 30 seconds of each apnea. This interval displays a prominent variation, triggered by the apnea and because the lack of oxygen, causes the body to rule as well.

4.3 Testing the Body Sensor Network

The best way to check the feasibility of the proposed BSN is to use it with pre-diagnosed patients in a health center/hospital. This would help to know specifically what we were searching in each patient. Another advantage is that someone would be close to the subject during the full sleep test. Then, information about movement would be annotated, as this is the most difficult task is this work, to differentiate between the movement (defined as “Movement Time” in PhysioNet Database) and sleep disorders epochs, as the effect on the ECG is quite similar. Unfortunately, this has not been possible.

As our objective is to to prove that our proposal is able to detect sleep disorders with accuracy, we have used volunteers for recording their signals, and we have annotated the epochs we consider there are apneas according to the literature and the signals belonging to the PhysioNet database.

4.3.1 Body Sensor Network Data

Three volunteers collaborated in this trial. All those tests were different from each other for different reasons as it is explained below.

a) Subject 1.

The first test was carried out in a controlled environment, so if any problem happened it would be easy to solve it, and restart the session. As far as we know this subject was not diagnosed having sleep disorders. Table 4.3.1-1 shows the characteristics of the volunteer.

Record	Length	AHI	Age	Height (cm)	Gender	Weight (Kg)	IBM
Subject 1.	3:18h	?	24	187	Male	89	25.5

Table 4.3.1-1 Characteristics of the first volunteer to partake in the trial of the proposed Body Sensor Network

In this first trial, we tried the three Shimmers (2x Shimmer3 ECG/EMG and the Shimmer3 GSR+), and the sampling frequency was 256 Hz. Because we used more than one Shimmer, we needed to install the Consensys Pro software [70], that allow to connect multiple Shimmers at the same time. However, there was a problem with one of the Shimmer, and we only collected the information provided by two Shimmers:

- **Shimmer3 ECG/EMG -** (ECG + Accelerometer), allocated in the chest
- **Shimmer3 GSR+ -** (PPG + GSR), measured from the fingers, positioned in the wrist.

With this alteration, the data was fully recorded, and the signals were appropriate for the analysis.

b) Subject 2.

Although Subject 2 does not have any documented sleep disorder, he snores a lot, so he seemed a good candidate to test the BSN. Table 4.3.1-2 shows his relevant information for the test.

Record	Length	AHI	Age	Height (cm)	Gender	Weight (Kg)	IBM
Subject 2.	2:44h	?	23	181	Male	81	24.7

Table 4.3.1-2. Characteristics of the second volunteer to partake in the trial of the proposed Body Sensor Network

In this specific trial, we used the three Shimmers, and for avoiding the problem that happened with the first trial we only recorded the first hour after the volunteer fell asleep. With this option, we got all the proposed movement and biomedical signals, except for the gyroscope ones belonging to the chest.

c) Subject 3.

The last test was performed in a subject that has sleep disorders, in a severe state. So severe, that he needs to sleep with a support machine, allocated at is face, and every time he as an incident of apnea, the machine will conduct air through his respiratory system, to re-establish the healthy state. Table 4.3.1-3 shows the characteristics of the unhealthy volunteer.

Record	Length	AHI	Age	Height (cm)	Gender	Weight (Kg)	IBM
Subject 3.	5:03h	?	36	180	Male	100	30.9

Table 4.3.1-3. Characteristics of the third volunteer to partake in the trial of the proposed Body Sensor Network

For this test, we only used two Shimmers, since the subject did not desire such a high level of discomfort. So based in our published work [71], that correlates both EMG and ECG signal in order to detect obstructive sleep apneas:

- **Shimmer3 ECG/EMG -** (ECG + Accelerometer + Gyroscope), allocated in the chest
- **Shimmer3 ECG/EMG - (**EMG + Accelerometer + Gyroscope), positioned in the left thigh

In order to avoid the problems of the two previous tests, we decided to pre-program the Shimmers in order that when the button in the side is switched (see Figure 4.3.1-1), each Shimmer starts recording directly to the SD Card. With this approach, every Shimmer is independent, so each one will record autonomously.

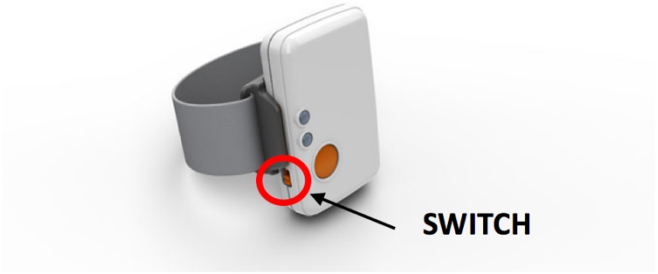

Figure 4.3.1-1. Image showing the position of the switch in Shimmer3

Although we avoided the problems with Shimmer connections, we also lost the synchronization provided from the ConsensysPRO software. In order to minimize this problem, it is recommended to turn on the Shimmers at the same time.

In the Appendix there is a description of the instructions to carry out this process. Subject 3 was provided with this information as he did himself the recordings at home.

4.3.2 Results

This subsection will show the output signals retrieved from the body sensor network, in all of the trials with the volunteers. In this results, we search for events in the signals, that when appearing, they probably indicate an incident of apnea. At this stage we cannot guarantee that this events are real apneas as we do not have a doctor's confirmation, and on top of that, we have the interference of the movement.

In order to distinguish between these two different states, we relied on the literature previously read, reference signals previously recorded and the algorithms formerly explained. The proposed algorithm for OSA detection was applied in each trial, aimed at HRV signal in order to check if it works properly using the data retrieved from the sensors.

a) Subject 1.

As has been previously mentioned, in this first trial we recorded the signals ECG, GSR, PPG and the accelerometer measured from the chest. Figure 4.3.2-1 shows a segment of the recorded signals.

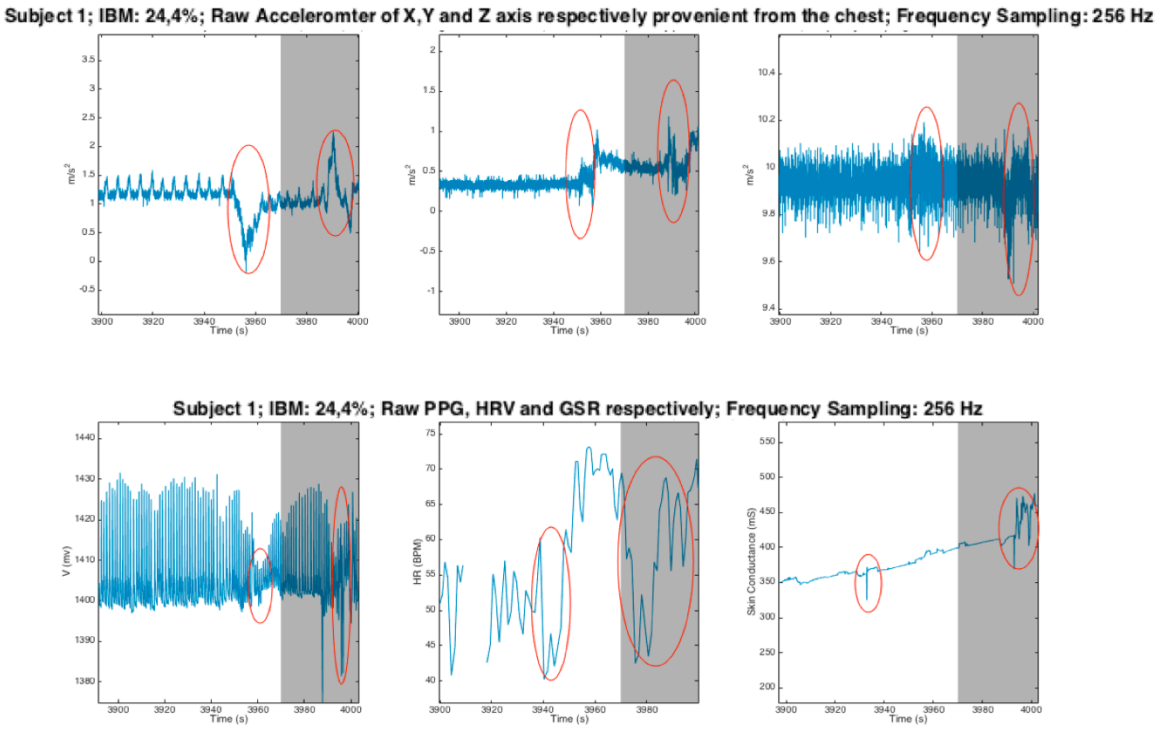

Figure 4.3.2-1. Accelerometer, HRV, PPG and GSR retrieved from the trial.1. The grey parts are the classification made by the proposed algorithm for OSA detection. (Note: All intervals displayed are taken when the subject is sleeping)

This test shows two incidents (at seconds 3950 and 3990) that can be classified as apnea. In the entire accelerometer axis, it shows clearly two peaks. These two events show a change of the state of the patient, indicating a blockage of an air flow in the lungs, and posterior effort to return to a normal state. The PPG signal shows a clear decrease of the amplitude near the peaks marked in the accelerometer signal. This evidence is often used in works as [72] [29], to detect sleep breathing disorders. HRV also proves our point explained in Subchapter 4.2.1, by existing a high variation signal after the epoch displayed at 955s. Another indication that we are facing with an apnea is the variation in the signal GSR, representing a stress indicator.

After running the algorithm, we can see that the result displayed goes according to our assumptions, that is, an incident of apnea affects several signals either movement or biomedical.

b) Subject 2.

In this trial, all biomedical and movement signal (except Gyroscope from chest) proposed in the body sensor network were recorded. This trial provides the biggest amount of information, since almost every signal proposed in the body sensor network is recorded. This gives the opportunity to accomplish one of the objective for this Master Thesis, and that is, gathering the maximum number of signals as possible in order to identify sleep disorders.

Figures 4.3.2-2 and 4.3.2-3 show the obtained results.

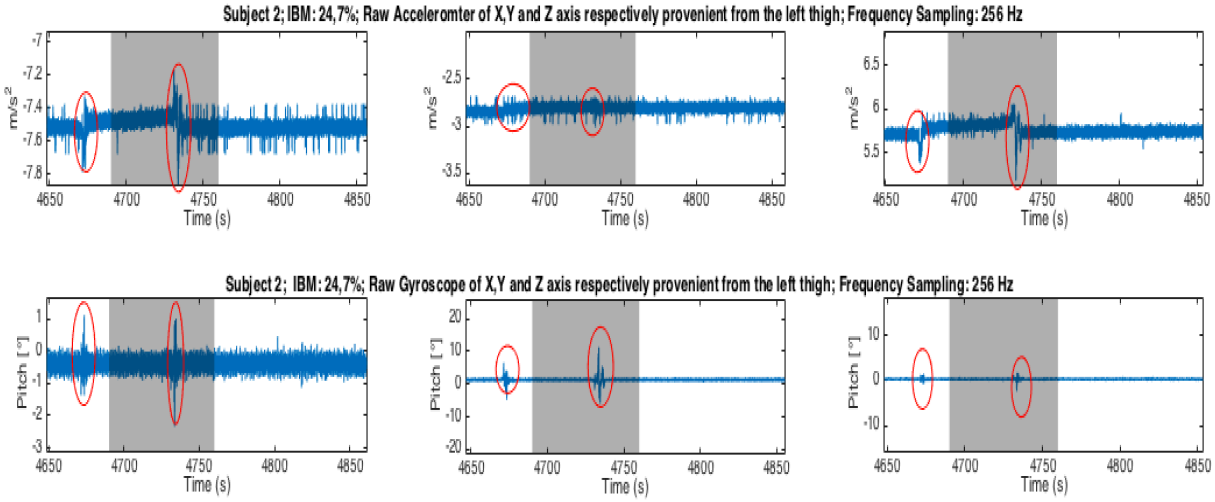

Figure 4.3.2-2. Accelerometer and gyroscope signals retrieved from the left thigh trial (Note: All intervals displayed are taken when the subject is sleeping)

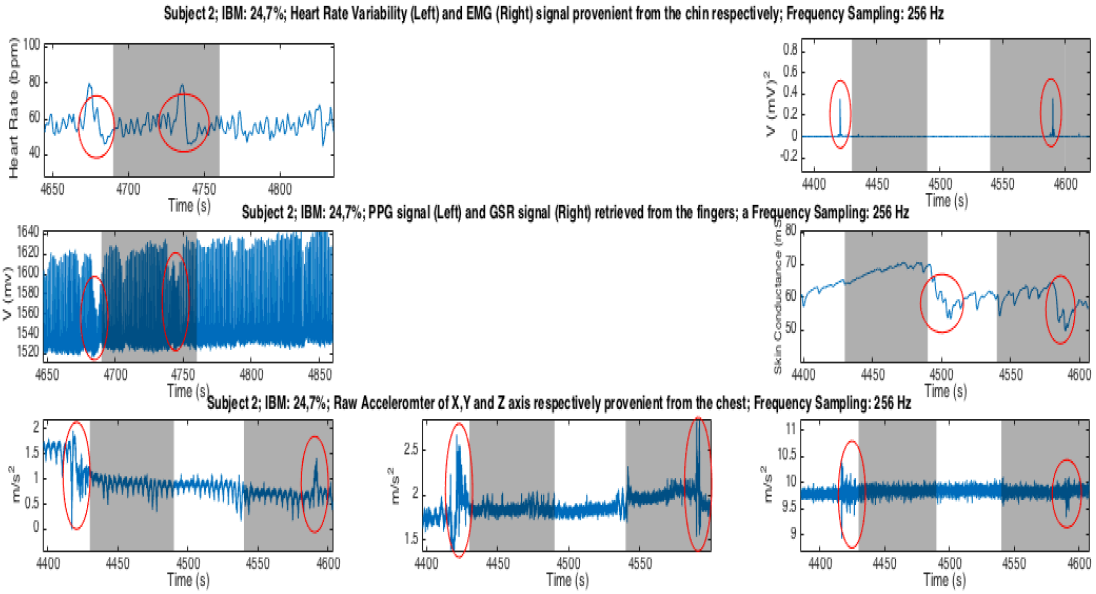

Figure 4.3.2-3. HRV, EMG, GSR, PPG and accelerometer signals (Note: All intervals displayed are taken when the subject is sleeping)

In the interval presented (from 4650s to 4850s), we can see two incidents that can suggest an epoch of some kind sleep apnea. We see a correlation between the movement signals retrieved from the left thigh and also the HRV and PPG signal at 4680 and 4750s. The signals EMG, GSR and the accelerometer are synchronized, maybe indicating that before an apnea starts, an arousal occurs, characterised here by these signals.

When the algorithm is applied, it is observable that the effects shown on PPG and HRV signal are synchronized with the period referred as apnea, showing again the utility of recording the maximum number of signals as possible.

c) Subject 3.

The last trial was performed on a patient pre-diagnosed with sleep related breathing disorders. Since we had an opportunity to test the BSN in a real patient, we decided to use the sensors necessary to prove the algorithm presented in [71]. Figures 4.3.2-4 and 4.3.2-5 show the obtained results.

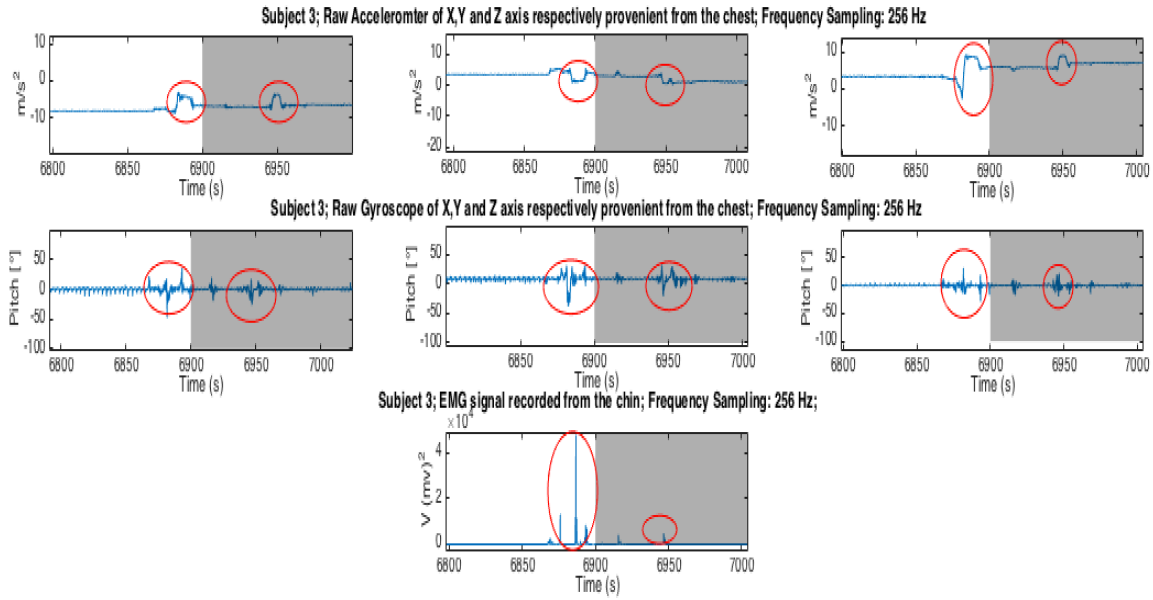

Figure 4.3.2-4. EMG, gyroscope and accelerometer signals obtained from subject 3, when shimmer was positioned in the chest. The grey parts are the classification made by the proposed algorithm for OSA detection. (Note: All intervals displayed are taken when the subject is sleeping)

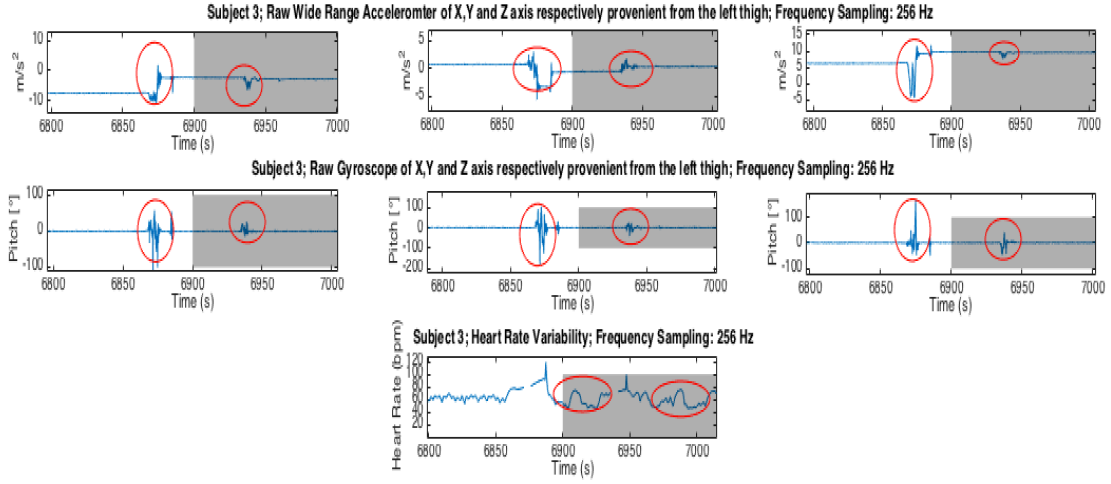

Figure 4.3.2-5. HRV, gyroscope and accelerometer signals acquired from subject.3. The grey parts are the classification made by the proposed algorithm for OSA detection. (Note: All intervals displayed are taken when the subject is sleeping)

The interval from 6800 to 7000 seconds shows signs of sleep related illnesses. In both marked intervals, HRV together with the EMG, accelerometers and gyroscope, show clear signals of a possible apnea. This conclusion is due to the presence of high variability in small intervals in both accelerometers and

gyroscopes positioned throughout the body and also the shape curve recorded in the HRV signal, that suggest a cycle of obstructive sleep apneas [65].

A special reference for the axis X and Z of the wide range accelerometer located on the chest in Figure 4.3.2-4, since it shows a signal similar to the one recorded during previous experiments plans. The comparison between them is shown in Figure 4.3.2-6.

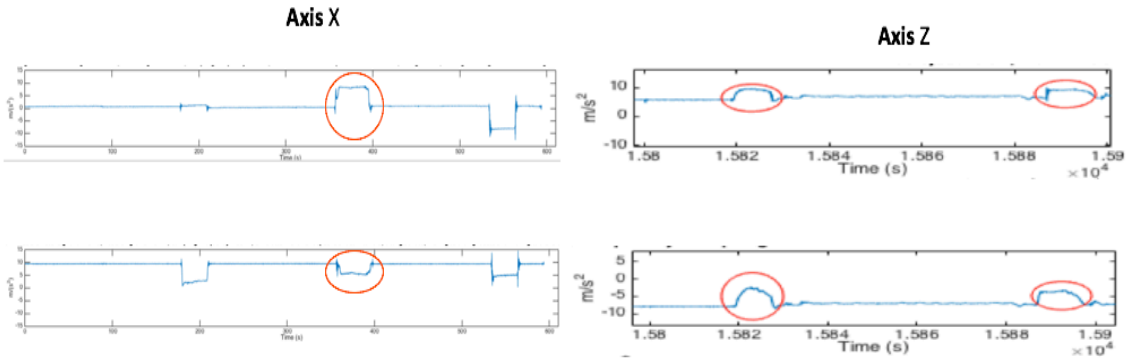

Figure 4.3.2-6. Comparison between: (Left) An accelerometer signal acquired from the experimental plan developed in the lab, when simulating a apnea; (Right) The accelerometer signal retrieved from trial.3. (Note: All intervals displayed are taken when the subject is sleeping)

Once again, we confirm our suspicion, since the algorithm indicates that the subject is having apneas in the interval where the cyclic epochs appear in the HRV signal. Despite the EMG signal is not so synchronized with the ECG, we also need to consider the fact that first will appear the EMG peak - due the interruption of normal air flow -, and only after that, it will be shown on the HRV features.

4.4 Work in Progress

Similar to the Subchapter 4.2.2, this section explains the procedure of picking the finest EMG signal with the purpose of testing the adapted algorithm. Not only we analysed the simulated data, but also the EMG signals retrieved from the trials, in order to see if we can proceed with the idea of using the same algorithm for both biomedical signals.

a) Data Selection

I. PhysioNet database and their specifications

For the development of this work, the EMG signal was also retrieved from the PhysioNet Website [68], particularly from MIT-BIH Polysomnographic Database [73].

To test the EMG algorithm, MIT-BIH Polysomnographic Database contains 16 PSG recordings, each one with different lengths, all using a sampling rate of (F_s) 250 Hz. In this database, all 16 subjects were male, aged from 32 to 56 years old (average age 43 years old), with weights ranging from 89 to 152 kg (average weight 119kg).

For the purpose of this work, it is only possible to analyse 5 out of the 16 cases since not all patients include EMG record signal, while ECG signals were recorded for all of them. Therefore, for testing the EMG algorithm, the database has 5 suitable cases: slp32, slp37, slp41, slp45, slp48. The summary of the available records is presented in Table 4.4-1.

Record	Length	AHI	Age	Gender	Weight (Kg)
Slp32	5:20h	22.1	54	Male	92
Slp37	5:50h	100.8	39	Male	125
Slp41	6:30h	60 [1]	45	Male	145
Slp45	6:20h	5 [1]	42	Male	133
Slp48	6:20h	46.8	56	Male	[2]

[1] Estimated from visual review; apnea annotations unavailable.

[2] Information not available.

Table 4.4-1. The database records of the patients to whom the EMG signals were recorded [75]

For testing the algorithm that relates ECG and EMG, the records used were Slp37, Slp48 and Slp32. Both Slp41 and Slp45 do not have the apnea annotations, so we cannot use them to check the accuracy of the results.

II. Body Sensor Network Data

To see how the EMG signal works when a subject has apnea, we decided to record some interval of 20 minutes of the EMG signal retrieved from the chin.

A. Simulated Apnea Data

As mentioned above for the ECG signal, we made two different records. The first one was the reference signal, and with the second one we simulated apneas to see the differences.

The apnea was simulated by inspiring the air with the mouth, and then, after the pre-set time, expelling it by the mouth. By comparing the two evidences, we can see how the apneas affect the signals. Figure 4.4-1 shows the results.

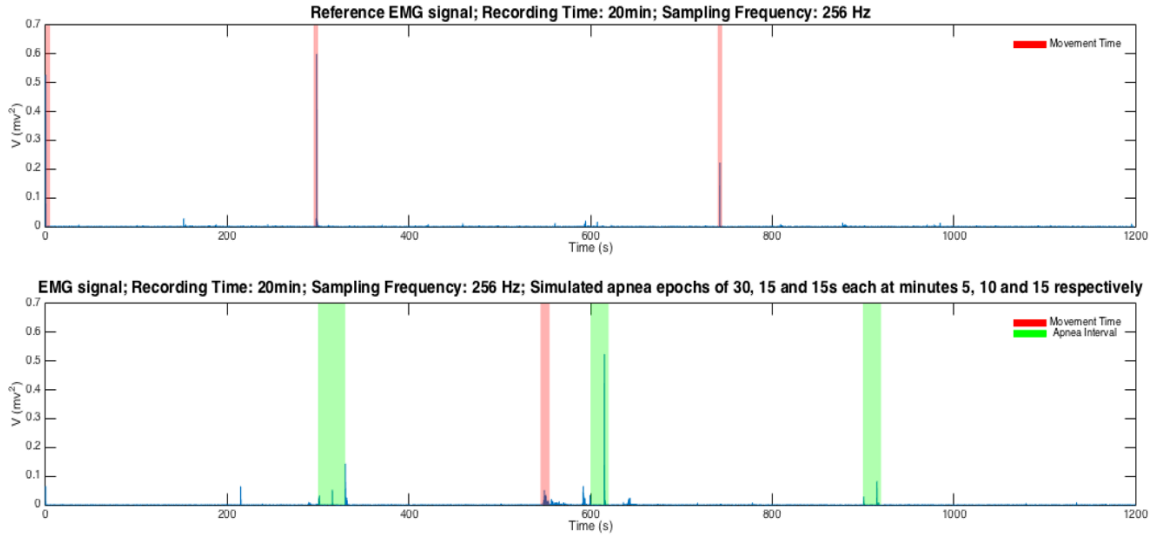

Figure 4.4-1. Graphics representing the body sensor network data acquired on EMG from chin. The upper graph represents the reference EMG signal, and the below displays the signal with the simulated apneas.

The upper graph, in Figure 4.4-1, shows the EMG reference signal. The three peaks on the chart are defined as movement-time, as they were not supposed to appear in a reference signal, but sudden movements were made and created such irregularities.

The second graph displays the EMG signal, with the simulated apnea intervals, identified by the green colour. These intervals were originated at 5, 10 and 15 minutes. At 5 minutes, the subject hold on the respiration for 30 seconds. In both 10 and 15, it was held for 15 seconds. The change of time in simulated apnea was necessary to see if any difference exist between the two different times. Nothing important of mention was found, so we decided to specify 30s for holding breath in all future mock apneas.

Those minutes were chosen because they had a wide period between them, so that the mock apneas do not influence each other. The signal generated clearly shows three intervals, corresponding to the previously identified intervals. This result demonstrates that there is a variation of the EMG signal upon inspiration and subsequent expiration, which we can be used to help identifying the beginning and the end of the apnea.

B. Trial Data

Now we retrieved the EMG signal recorded throughout the trials and we it was check if there is some evidence that can be considered an apnea incident. In Figure 4.4-2, it shows an example when our algorithm outlined an apnea, and we see some effects on the EMG signal on Subject 3

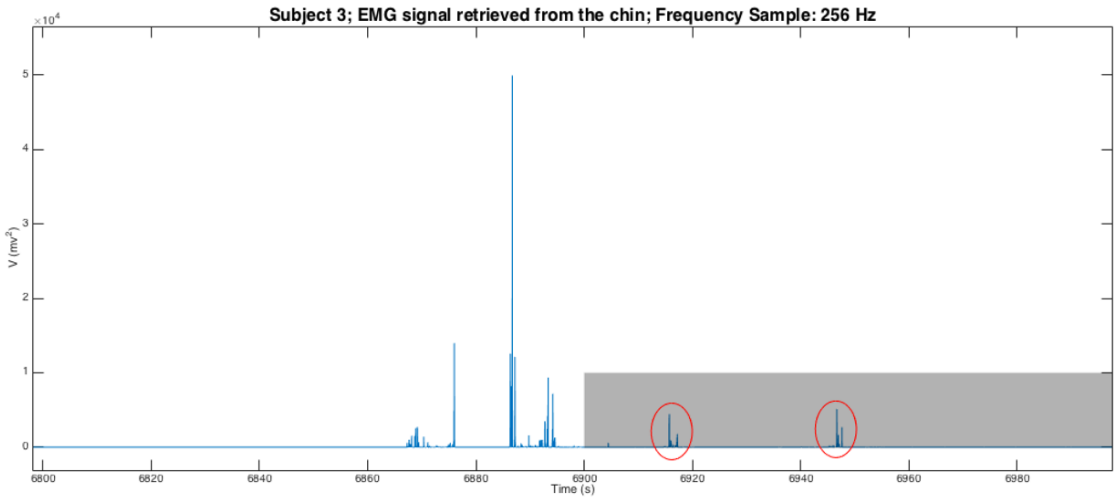

Figure 4.4-2. Example of the EMG signal when the exchange takes place from Normal Sleep to Sleep Apnea from Subject 3 signal.

In this example is shown a peak of movement at 6890 seconds. But when we enter at sleep apnea state, we see two peaks at 6920 and 6945 second, that may indicate the opening of the mouth, trying to restore the healthy state and the second one, is the signal that appears when the apnea ends, and the subject starts to breathing normal.

Now looking at Subject 2, the signal in Figure 4.4-3, we also see variance in the signal, suggesting a potential apnea epoch.

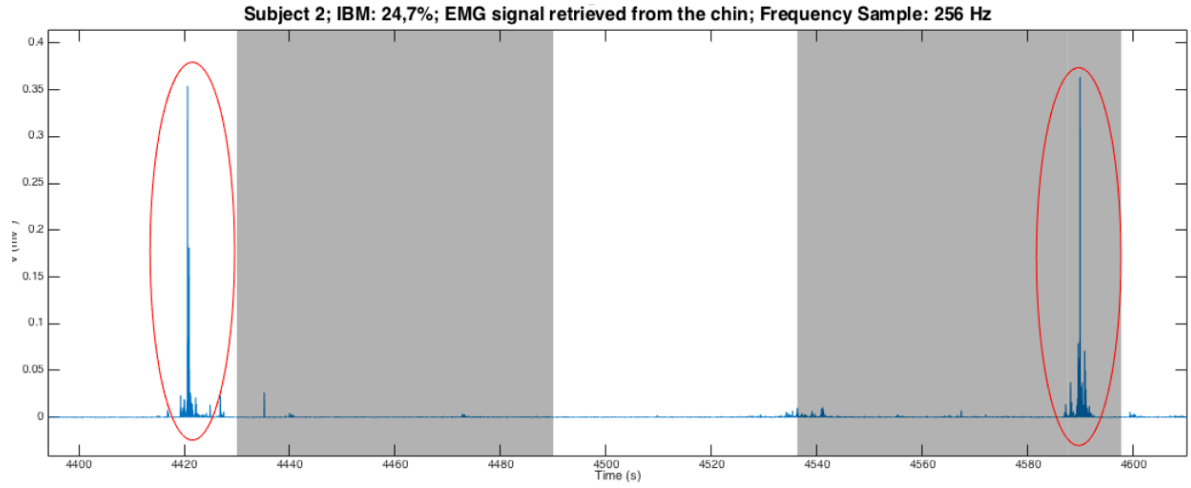

Figure 4.4-3. Example of the EMG signal when the exchange takes place from Normal Sleep to Sleep Apnea from Subject 2 (Trial.2).

These two examples show that the EMG signal can be taken into account for improving our algorithm to detect sleep disorders.

4.5 Conclusions

In this chapter, we have explained how the experimental setup of the body sensor network is defined, and how this help us detecting sleep related disorders, since every sensor of the proposed BSN should have a reason to be included. Then the ECG algorithm is tested. The results have shown a high precision comparatively with previous developed algorithms. So with this information, we applied the algorithm to all the volunteers, and we searched for patterns that could indicate epochs of apnea.

Since the data recorded from the body sensor network is not clinically annotated, we changed to the time domain analysis, to search for event that can justify the onset of apnea. Although the algorithm has been designed for detecting episodes of obstructive sleep apnea, it can also detect other kinds of apnea. After analysing some OSA intervals, we can recognize repetitions previously read in literature, that suggest episodes of apnea, as seen in HRV in the figure 4.3.2-5.

With regard to the work in progress, the EMG appears to be a reliable signal that can be included in order to improve the precision of the proposed algorithm.

Chapter 5. Conclusions and future work

This chapter summarizes the key contributions of this Master Thesis. Firstly, the conclusions extracted from this work are analysed; secondly some future research lines are suggested; and finally the publication derived from this work is included.

5.1 General Conclusions

In order to help the diagnosis of sleep disorders in the elderly, this work proposed the development of two sensor networks (BSN and HSN), by relating biomedical and movement signals.

In this work we developed a body sensor network to record all the required signals for analysing the sleep disorders at home. Although we recorded a big amount of signals, we decided to focus on the relationship between ECG and EMG signals, when developing an algorithm for sleep disorder detection.

We spotted an increase of the mean activity of the EMG signal from the chin, when an incident of apnea occurs, followed by a high variation of the HRV signal coming from the ECG signal. Using an algorithm that compares the Power Spectral Density from both “Sleep Apnea” and “Normal Sleep”, we were able to check for differences at the VLF and HF frequency bands.

Since the algorithm using EMG is a working progress, in this thesis we were able to automatically classify OSA episodes only based on the frequency domain analysis of the ECG. The preliminary results are very promising with sensitivities

around 85%, although we desire to increase the accuracy of the algorithm, by correlating with the set of signals provided by the rest of the BSN (EMG and Accelerometer).

It also has been programmed a user interface that helps to check the recorded signals, and to evaluate the proposed algorithm. It was programmed in a Matlab based User Interface.

5.2 Future Work

In this Thesis, a comprehensive study regarding the development of a non-invasive Body Sensor Network to detect sleep disorders has been carried out. As it has been shown throughout this work, this is such a large research area that just some points will be mentioned below to improve and progress this work:

- **Increase of the database for the EMG signal:** As felt from the beginning of this work, the lack of signals to test the methodologies is a major constraint in research. The PhysioNet Database only had 5(!) subjects where the evaluation of sleep disorders could be assessed through the analysis of signals from EMG recorded from the chin. To add up, only three of the five had clinical annotations. This amount of data is clearly insufficient to establish any kind of pattern affecting the development of the EMG algorithm.

- **Create a PPG algorithm for the detection of Obstructive Sleep Apnea incidents:** After the development of the ECG and EMG algorithm, the next signal to be processed should be the PPG. Since we can obtain the Pulse Rate Variability from it, this will allow us the possibility to compare results with the ECG algorithm and maybe increase the accuracy of the results. The reasoning for this proposal is that sleep disorders profoundly affect the PPG amplitude thus, combining those two properties, may allow increasing the performance of the algorithm by comparison of redundant information. In addition, the laboratory just bought a Shimmer3 GSR+ therefore no economic effort would come from this proposal.

- **Add an online mode to the Matlab GUI Interface:** For practical application of the proposed system, the real-time implementation of both processing algorithms and GUI interface is required. Due to timing issues, this task was not developed during the present Master Thesis.

- **Expanding the Body Sensor Network:** Another future research guide-line is the expansion of the BSN to allow collecting different sets of data. To be mentioned that EEG signals are recommended for differentiation of sleep states. However, as mentioned previously, EEG sensors are uncomfortable during sleep, so, as an alternative, a respiration sensor could be introduced in the system to allow measurement of breathing flow, or at least, by introducing a pulse oximetry sensor, the amount of oxygen in the patient could be assessed.

- **Reduce the intrusiveness:** Another long-term objective of this research is to reduce the intrusiveness of the BSN, in order to improve the comfort of the patient. Since doctors will be able to diagnose patients after monitoring them while they sleep at home, our proposal will result in a more suitable patient education and more appropriate treatment, avoiding harmful and unnecessary medications.

- **Initiate a clinical trial:** The objective of the trial, is to validate the proposed sensor networks and algorithm. By using data recorded in patients previously diagnosed with different kinds of sleep disorders, will grant us the opportunity to identify specific illnesses.

5.3 Publications Derived from the Thesis

5.3.1 International Conferences

M.C.Alberto, M.A. Herrero, M. Graça Ruano, Ana Jiménez, J.J. García, Edel Díaz, “Sensory System for the Sleep Disorders Detection in the Geriatric Population”, in 2017 4th Experiment International Conference EXP.AT’17 ,2017

References

[1] D. H. Park *et al.*, “Correlation between the severity of obstructive sleep apnea and heart rate variability indices,” *J. Korean Med. Sci.*, vol. 23, no. 2, pp. 226–231, 2008.

[2] A. K. Bhoi, K. S. Sherpa, and P. K. Mallick, “A comparative analysis of neuropathic and healthy EMG signal using PSD,” *Int. Conf. Commun. Signal Process. ICCSP 2014 - Proc.*, no. November, pp. 1375–1379, 2014.

[3] “The Internet Classics Archive | On Sleep and Sleeplessness by Aristotle.” [Online]. Available: http://classics.mit.edu/Aristotle/sleep.html. [Accessed: 23-Oct-2016].

[4] L. Samy, P. M. Macey, and M. Sarrafzadeh, “A gender-aware framework for the daytime detection of obstructive sleep apnea,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2015–Novem, pp. 7683–7687, 2015.

[5] S. T. Ben Hamida and B. Ahmed, “A remote deep sleep monitoring system based on a single channel for in-home insomnia diagnosis,” *2015 7th Int. Conf. New Technol. Mobil. Secur. - Proc. NTMS 2015 Conf. Work.*, 2015.

[6] S. Shafiee, F. Kamangar, L. S. H. Ghandehari, and K. Behbehani, “A multi-feature classification approach to detect sleep apnea in an ultrasonic upper airway occlusion detector system,” *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2014, pp. 254–257, 2014.

[7] “A guide to heart rhythms for first aiders – First aid for free.” [Online]. Available: http://www.firstaidforfree.com/a-guide-to-heart-rhythms-for-first-aiders/. [Accessed: 15-Nov-2016].

[8] “The Polysomnogram Test for Sleep Apnea.” [Online]. Available: http://www.sleep-apnea-guide.com/polysomnogram.html. [Accessed: 16-Nov-2016].

[9] C. Weng, J. Chen, and C. Huang, “A FPGA-based Wearable Ultrasound Device for Monitoring Obstructive Sleep Apnea Syndrome,” *IEEE Ultrason. Symp. Proc.*, pp. 2–5, 2015.

[10] “Health Consequences | Sleep Apnea.” [Online]. Available: http://healthysleep.med.harvard.edu/sleep-apnea/living-with-osa/health-consequences. [Accessed: 26-Oct-2016].

[11] D. P. White, “Pathogenesis of obstructive and central sleep apnea,” *Am. J. Respir. Crit.*

Care Med., vol. 172, no. 11, pp. 1363–1370, 2005.

[12] R. Crupi, T. Faetti, and R. Paradiso, “Preliminary evaluation of Wearable Wellness System for Obstructive Sleep Apnea detection,” *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS*, vol. 2015–Novem, pp. 4142–4145, 2015.

[13] M. S. Member, S. Saha, S. Member, P. Hadi, F. Rudzicz, and A. Yadollahi, “Snoring Sound Classification from Respiratory Signal,” pp. 3215–3218, 2016.

[14] X. Dang and R. Wei, “Snoring and breathing detection based on Empirical Mode Decomposition *,” pp. 79–82, 2015.

[15] “Insomnia (Chronic and Acute Insomnia) Causes and Symptoms.” [Online]. Available: http://www.webmd.com/sleep-disorders/guide/insomnia-symptoms-and-causes#1. [Accessed: 25-Oct-2016].

[16] I. Chouvarda, C. Papadelis, N. Domis, L. Staner, and N. Maglaveras, “Insomnia treatment assessment based on physiological data analysis,” *Annu. Int. Conf. IEEE Eng. Med. Biol. - Proc.*, pp. 6694–6696, 2007.

[17] S. T. Hamida, M. Glos, T. Penzel, and B. Ahmed, “How Many Sleep Stages Do We Need for An Efficient Automatic Insomnia Diagnosis ?*,” pp. 2431–2434, 2016.

[18] “Parasomnia & Sleep: Causes & Treatment - National Sleep Foundation.” [Online]. Available: https://sleepfoundation.org/ask-the-expert/sleep-and-parasomnias. [Accessed: 25-Oct-2016].

[19] P. Madhushri, B. Ahmed, T. Penzel, and E. Jovanov, “Periodic leg movement (PLM) monitoring using a distributed body sensor network,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2015, vol. 2015–Novem, pp. 1837–1840.

[20] “Periodic Limb Movements - Overview and Facts.” [Online]. Available: http://www.sleepeducation.org/sleep-disorders-by-category/sleep-movement-disorders/periodic-limb-movements/overview-facts/. [Accessed: 04-Dec-2017].

[21] “Stages of Sleep: REM and Non-REM Sleep Cycles.” [Online]. Available: http://www.webmd.com/sleep-disorders/guide/sleep-101. [Accessed: 20-Apr-2017].

[22] L. E. Lajos, “The relation between electrodermal activity in sleep, negative affect, and stress in patients referred for nocturnal polysomnography.,” *Diss. Abstr. Int. Sect. B Sci. Eng.*, vol. 65, no. 5–B, p. 2633, 2004.

[23] “XeThru sensor provides quality data comparable to Polysomnography medical sleep monitoring study - Xethru Blog.” [Online]. Available: https://www.xethru.com/blog/posts/xethru-monitoring-study. [Accessed: 04-Nov-2016].

[24] Rangaraj M. Rangayyan, “Biomedical Signal Analysis,” pp. 1–2, 2002.

[25] “Normal EEG Waveforms: Overview, Frequency, Morphology.” [Online]. Available: http://emedicine.medscape.com/article/1139332-overview. [Accessed: 31-Jan-2017].

[26] “The P Wave - Sinus Rhythm - Normal Function of the Heart - Cardiology Teaching Package - Practice Learning - Division of Nursing - The University of Nottingham.” [Online]. Available:

http://www.nottingham.ac.uk/nursing/practice/resources/cardiology/function/p_wave.php. [Accessed: 18-Nov-2016].

[27] R. G. Rivas, “National University of Ireland , Cork Real-Time Early Detection of Allergic Reactions based on Heart Rate Variability,” 2016.

[28] Willem Einthoven’s, “ECG Filtering.”

[29] N. Pinheiro *et al.*, “Can PPG be used for HRV analysis ?,” *Ieee Embc 16*, pp. 2945–2949, 2016.

[30] J. Allen, “Photoplethysmography and its application in clinical physiological measurement.,” *Physiol. Meas.*, vol. 28, no. 3, pp. R1–R39, 2007.

[31] Y. Mendelson and C. Pujary, “Measurement site and photodetector size considerations in optimizing power consumption of a wearable reflectance pulse oximeter,” *Proc. 25th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (IEEE Cat. No.03CH37439)*, vol. 4, pp. 3016–3019, 2003.

[32] T. Tamura, Y. Maeda, M. Sekine, and M. Yoshida, “Wearable Photoplethysmographic Sensors—Past and Present,” *Electronics*, vol. 3, no. 2, pp. 282–302, 2014.

[33] M. B. I. Reaz and M. S. Hussain, “Techniques of EMG signal analysis : detection , processing , classification and applications,” vol. 8, no. 1, pp. 11–35, 2006.

[34] C. J. De Luca, L. Donald Gilmore, M. Kuznetsov, and S. H. Roy, “Filtering the surface EMG signal: Movement artifact and baseline noise contamination,” *J. Biomech.*, vol. 43, no. 8, pp. 1573–1579, 2010.

[35] H. A.-A. King, “Evaluation of Chin EMG Activity at Sleep Onset and Termination in Obstructive Sleep Apnea Syndrome,” pp. 677–679, 2008.

[36] M. R. Azim, S. A. Haque, M. S. Amin, and T. Latif, “Analysis of EEG and EMG signals for detection of sleep disordered breathing events,” *ICECE 2010 - 6th Int. Conf. Electr. Comput. Eng.*, no. December, pp. 646–649, 2010.

[37] “Interpreting HRV Trends in Athletes: High Isn’t Always Good and Low Isn’t Always Bad - SimpliFaster Blog.” [Online]. Available: https://simplifaster.com/articles/interpreting-hrv-trends-athletes/. [Accessed: 06-Jul-2017].

[38] J. F. Thayer and R. D. Lane, “A model of neurovisceral integration in emotion regulation and dysregulation,” *J. Affect. Disord.*, vol. 61, no. 3, pp. 201–216, 2000.

[39] “Electrocardiogram (ECG) and Heart Rate Variability (HRV) | Mega Electronics Ltd.” [Online]. Available: http://www.megaemg.com/knowledge/heart-rate-variability-hrv/. [Accessed: 03-Dec-2016].

[40] S. Eyal, Y. Dagan, and A. Baharav, “Sleep in the Cloud: On How to Use Available Heart Rate Monitors to Track Sleep and Improve Quality of Life,” *Comput. Cardiol.*, pp. 329–332, 2012.

[41] A. Sivanantham, “Measurement of heartbeat, respiration and movements detection using Smart Bed,” in *2015 IEEE Recent Advances in Intelligent Computational Systems (RAICS)*, 2015, no. December, pp. 105–109.

[42] “Oxygen Saturation levels and what do they mean? | Easy Oxygen.” [Online]. Available:

http://www.easyoxygen.com.au/oxygen-saturation-levels-and-what-do-they-mean/. [Accessed: 05-Dec-2017].

[43] "Vital Signs (Body Temperature, Pulse Rate, Respiration Rate, Blood Pressure) | Johns Hopkins Medicine Health Library." [Online]. Available: http://www.hopkinsmedicine.org/healthlibrary/conditions/cardiovascular_diseases/vital_signs_body_temperature_pulse_rate_respiration_rate_blood_pressure_85,P00866/. [Accessed: 04-Dec-2016].

[44] S. Dabiri and M. A. M. Shirazi, "Estimation of respiratory rate from photoplethysmogram signal of sleep apnea patients: A comparative study of different methods," *2015 38th Int. Conf. Telecommun. Signal Process.*, pp. 440–443, 2015.

[45] C. A. Boano *et al.*, "Accurate Temperature Measurements for Medical Research Using Body Sensor Networks," *Object/Component/Service-Oriented Real-Time Distrib. Comput. Work. (ISORCW), 2011 14th IEEE Int. Symp.*, pp. 189–198, 2011.

[46] X. Ding, W. Dai, N. Luo, J. Liu, N. Zhao, and Y. Zhang, "A flexible tonoarteriography-based body sensor network for cuffless measurement of arterial blood pressure," *2015 IEEE 12th Int. Conf. Wearable Implant. Body Sens. Networks*, pp. 1–4, 2015.

[47] Y. H. Chen, M. J. Tsai, L. C. Fu, C. H. Chen, C. L. Wu, and Y. C. Zeng, "Monitoring Elder's Living Activity Using Ambient and Body Sensor Network in Smart Home," *Proc. - 2015 IEEE Int. Conf. Syst. Man, Cybern. SMC 2015*, pp. 2962–2967, 2016.

[48] K. Komai, M. Fujimoto, Y. Arakawa, H. Suwa, Y. Kashimoto, and K. Yasumoto, "Beacon-based multi-person activity monitoring system for day care center," *2016 IEEE Int. Conf. Pervasive Comput. Commun. Work. PerCom Work. 2016*, 2016.

[49] "Temperature Issues and Sleep Disorders | Sleep Dynamic Therapy." [Online]. Available: http://www.sleepdynamictherapy.com/index.php/temperature-issues-and-sleep-disorders/. [Accessed: 03-Feb-2017].

[50] T. L. M. Van Kasteren, G. Englebienne, and B. J. A. Kröse, "An activity monitoring system for elderly care using generative and discriminative models," *Pers. Ubiquitous Comput.*, vol. 14, no. 6, pp. 489–498, 2010.

[51] L. Chen, C. D. Nugent, and H. Wang, "A Knowledge-Driven Approach to Activity Recognition in Smart Homes," *IEEE Trans. Knowl. Data Eng.*, vol. 24, no. 6, pp. 961–974, 2012.

[52] "Smart Bed." [Online]. Available: http://www.boditrak.com/products/smartbed.php. [Accessed: 03-Feb-2017].

[53] E. M. Díaz, "Inertial Pocket Navigation System for Pedestrians," Universidad de Alcalá, 2014.

[54] A. Arshad *et al.*, "An activity monitoring system for senior citizens living independently using capacitive sensing technique," *Conf. Rec. - IEEE Instrum. Meas. Technol. Conf.*, vol. 2016–July, 2016.

[55] H. Park, S. Hwang, M. Won, and T. Park, "Activity-aware Sensor Cycling for Human Activity Monitoring in Smart Homes," *IEEE Commun. Lett.*, vol. 7798, no. c, pp. 1–1, 2016.

[56] “Wearable Sensor Technology | Shimmer | Wearable Wireless Sensing Technology and Solutions.” [Online]. Available: http://www.shimmersensing.com/. [Accessed: 13-Feb-2017].

[57] “Shimmer. Shimmer ECG & EMG Module Retrieved from http:// www.shimmersensing.com/images/uploads/docs/Shimmer3_ECG_EMG_Specification_ Sheet_Revision_1.7.pdf.”

[58] “Wearable GSR Sensor | Shimmer Galvanic Skin Response Sensor | EDA sensor.” [Online]. Available: http://www.shimmersensing.com/products/shimmer3-wireless-gsr-sensor. [Accessed: 23-Apr-2017].

[59] F. N. Wilson, R. Johnston, and C. E. Kossmann, “The substitution of a tetrahedron for the Einthoven triangle.,” *Am. Heart J.*, vol. 33, no. 5, pp. 594–603, 1947.

[60] S. P. Patil, “What every clinician should know about polysomnography.,” *Respir. Care*, vol. 55, no. 9, pp. 1179–1195, 2010.

[61] J. Pan and W. J. Tompkins, “A Real-Time QRS Detection Algorithm,” *IEEE Trans. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, 1985.

[62] C. Nakayama, K. Fujiwara, M. Matsuo, M. Kano, and H. Kadotani, “Development of sleep apnea syndrome screening algorithm by using heart rate variability analysis and support vector machine,” *37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 8165–8168, 2015.

[63] P. C. N. Pinheiro, R. Couceiro, J. Henriques, J. Muehlsteff, I. Quintal, L. Gonçalves, “Can PPG be used for HRV analysis?,” pp. 2945–2949, 2016.

[64] L. R. Altimari, J. L. Dantas, and M. Bigliassi, “World ’ s largest Science , Technology & Medicine Open Access book publisher Influence of Different Strategies of Treatment Muscle Contraction and Relaxation Phases on EMG Signal Processing and Analysis During Cyclic Exercise.”

[65] L. Chen, X. Zhang, and H. Wang, “An obstructive sleep apnea detection approach using kernel density classification based on single-lead electrocardiogram,” *J. Med. Syst.*, vol. 39, no. 5, p. 47, 2015.

[66] G. D. Clifford and S. C. College, “Signal Processing Methods for Heart Rate Variability,” *St Cross Coll.*, 2002.

[67] N. Butkov and T. L. Lee-Chiong, *Fundamentals of Sleep Technology*. Lippincott Williams & Wilkins,US; 1 edition, 2007.

[68] H. E. S. Ary L. Goldberger, Luis A. N. Amaral, Leon Glass, Jeffrey M. Hausdorff, Plamen Ch. Ivanov, Roger G. Mark, Joseph E. Mietus, George B. Moody, Chung-Kang Peng, “Physiobank, PhysioToolKit and Physionet: Components of a New Research Resource for Complex Physiologic Signals,” 2000.

[69] T. Penzel, G. B. Moody, R. G. Mark, A. L. Goldberger, and J. H. Peter, “Apnea-ECG Database,” Jan. 2000.

[70] “ConsensysPRO Software | Collect and analyze biometric and motion data from Shimmer sensors.” [Online]. Available: http://www.shimmersensing.com/products/consensys. [Accessed: 28-May-2017].

[71] M. C. Alberto and M. G. Ruano, “Sensory System for the Sleep Disorders Detection in the Geriatric Population Sensory System for the Sleep Disorders Detection in the Geriatric Population,” no. June, 2017.

[72] H. K. Lee, I. Heo, S. Yang, and K. J. Lee, “Discrete wavelet transform-based method for automatic evaluation of sleep-disordered breathing using photoplethysmography,” *Proc. - Int. Conf. Intell. Syst. Model. Simulation, ISMS*, vol. 2015–Septe, pp. 206–208, 2015.

[73] “MIT-BIH Polysomnographic Database.” [Online]. Available: https://www.physionet.org/physiobank/database/slpdb/. [Accessed: 23-Feb-2017].

Appendix

User guide to perform a ECG/EMG test at home

Inventory:

- 6x 1-meter-long leads
- 2x Shimmer3 ECG/EMG
- 2x adhesive tapes
- 12x electrodes (6 large for the heart and 6 for the chin)
- 2x elastic holding straps.

Instructions:

1) The elastic straps are used to place SHIMMER devices attached to the body. One is placed on the center of the chest (the one that measures the chin) and another is placed on the left thigh, at the height of a pocket (the one that measures the heart). Figure A-1 exemplifies the position of the straps.

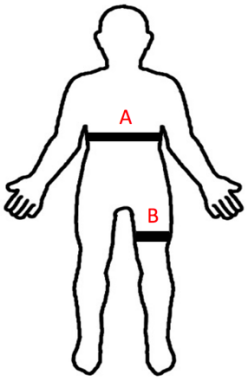

Figure A-1. Position of the straps: A allocated in the chest and B in the left thigh.

2) The electrodes should be connected properly as indicated in Figure A.2

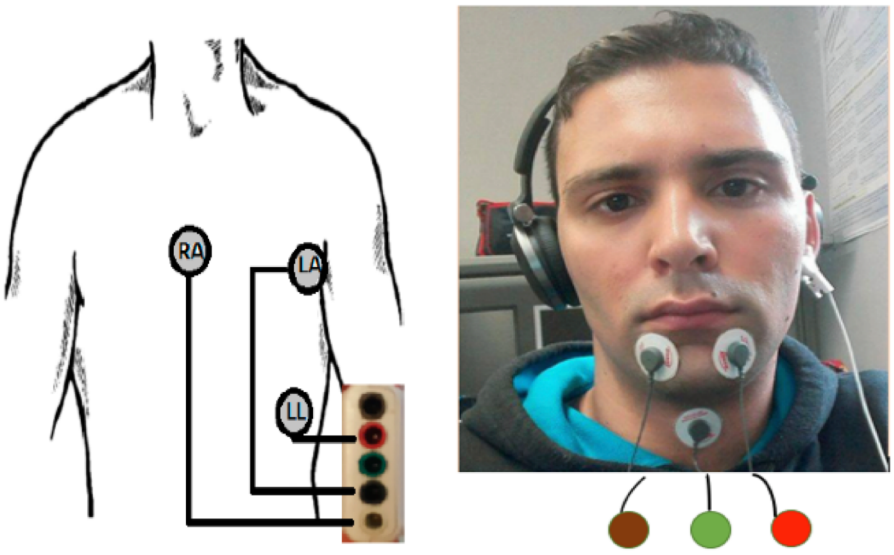

Figure A-2. Example on how positioning the electrodes in the right position. LEFT: Shimmer **B**; RIGHT: Shimmer **A.**

For small electrodes it is necessary to use a little bit of adhesive tape to fix them. It is recommended to follow the recommendations of Figure A.3.

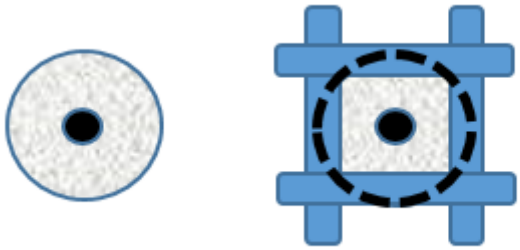

Figure A-3. Example of how to put adhesive tape around the electrodes.

3) When the electrodes are attached, the SHIMMER device can be switched on with the switch (NOT THE ROUND BUTTON). The switch is located on one side. Green and blue lights will turn on and within seconds, only a green light will blink. The device will automatically start taking measurements. Figure A.4 shows the correct switch.

Figure A.4. Image showing the position of the switch in Shimmer3

IMPORTANT

If both SHIMMERS have to be used at the same time (FACE AND HEART), turn on the two devices at the same time so that the measurements are as synchronized as possible.