



Universidade Nova de Lisboa

Faculdade de Ciências e Tecnologia

Departamento de Engenharia Electrotécnica

# **Automatic Sleep Apnea Detection and Sleep Classification using the ECG and the SpO2 Signals**

Dissertation for a Masters Degree in  
Computer and Electronic Engineering

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**You may not have thought about it, but people sure sleep a lot. Imagine...if on the average, people sleep 8 hours a day, they are sleeping away 1/3 of their life. How much is that? Well, 8 hours of sleep every day is the same as 233,600 hours of sleep by the time you are 80 years old. That's the same as sleeping 26.67 years!!! We also dream about 4-5 times a night: that is the same as 116,800 to 146,000 dreams by the time you are 80 years old!!!**

**Dreaming permits each of and every one of us to be quietly and safely insane every night of our lives**

**William C. Dement, sleep researcher**

# Agradecimentos

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## **ABSTRACT**

The present work describes the aspects to implement a system that can be used as a swift and accessible screening tool in patients whose complaints are compatible with OSAS (Obstructive Sleep Apnea Syndrome). This system only uses two signals, electrocardiogram (ECG) and the saturation of oxygen in arterial blood flow (SPO<sub>2</sub>). This system would be applied for the ambulatory automatic screening of OSAS, which currently are done in a Hospital environment, with a substantial waiting list. The system also would overcome the time consuming visual sleep scoring that contributes for the mentioned waiting list. We have developed a system that automatically detects OSAS based on the ECG and SpO<sub>2</sub>. However this system has to be paired up with another that detects the awake/sleep/REM periods (also based on the ECG), which is also part of this work. This last component has proved to produce results that are complex to classify, for which there is still a lack of research work. However we have described the necessary algorithms, and have used state-of-the-art signal processing tools, such as wavelets.





# 1 Introduction

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## 1.1 Introduction of the theme and Justifications

Obstructive sleep apnea syndrome (OSAS) is a clinical condition deemed by international statistics to affect 4% of middle-aged men and 2% of middle-aged women<sup>1,2,3</sup>. OSAS is presently a serious public health concern, one which is under-diagnosed. It is believed that around 93% of women and 82% of men suffering from OSAS are undiagnosed<sup>4</sup>. The definitive diagnosis is established in patients with a suggestive clinical report and confirmed by polysomnography (PSG), demonstrating the apneas associated with the physiological disorders. However, PSG is performed in a Sleep Laboratory, being very expensive, and demanding considerable human and technical recourses, not being readily available<sup>2,3</sup>. Therefore, it is necessary to find other diagnose methods for OSAS, which are simpler and available sooner to patients – and that is the goal of this work. The purpose is to develop a system that can help diagnose OSAS with very few signals (two: ECG and SPO2), that are easily obtained; a system where the patients do not have to leave their homes and that is less expensive.

## 1.2 Specified Questions

- Which signals to use?
- How can we diagnose OSAS with the less signals possible?
- Which tools will we use to withdraw as much information as possible from the two signals used?
- Can we obtain a Hypnogram from the ECG signal?
- Can we obtain a signal corresponding to the respiration signal from the complex QRS (complex QRS is a structure on the ECG that corresponds to the depolarization of the ventricles) of the ECG?

### 1.3 The Purposes of the Research

#### 1.3.1 Main Purpose

The purpose of this work is to be able to diagnose OSAS, in a simple and inexpensive way. The system developed must be able to diagnose OSAS with only two signals (ECG e SPO2).

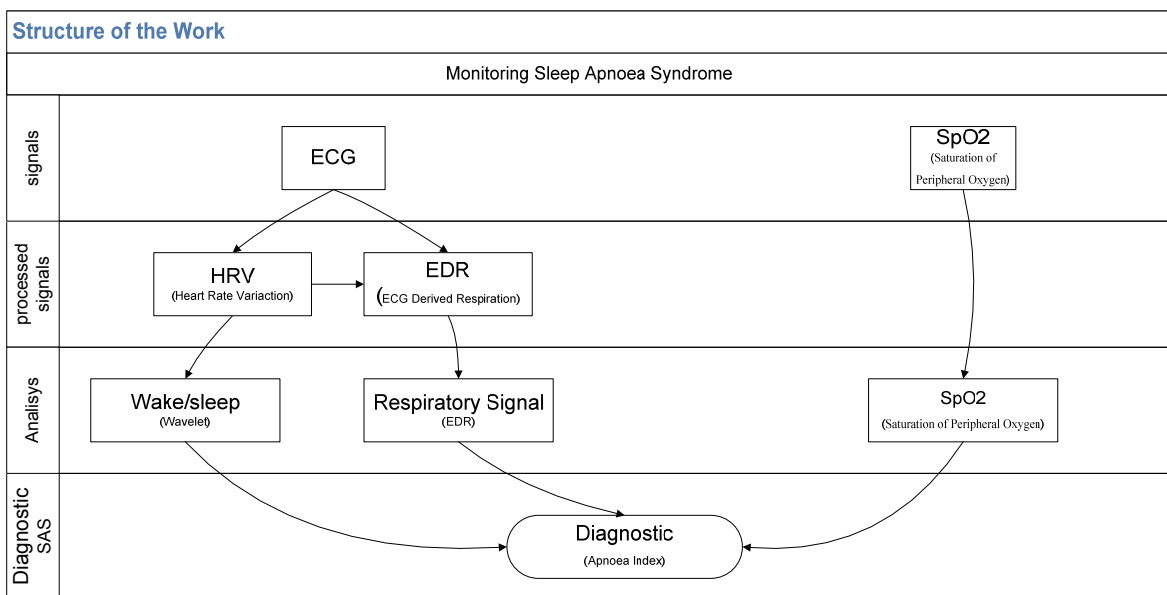
#### 1.3.2 Specific Purposes

The specific purposes are:

- To eliminate the noise of the ECG;
- To use the wavelet's tool, producing the Hyponogram from the ECG signal;
- To use the ECG-derived respiration (EDR) technique to detect apnea and hypopnea
- To determine the indexes of oxygen saturation in the arterial blood stream.

Table 1.3.1 sums up the purposes of the work developed and every technique used herein.

**Table 1.3.1** – Summary of the purposes of this work and techniques used



#### **1.4 Organization of the Thesis**

The outline of this thesis is as follows.

Chapter 1 provides a general overview of the present work, preliminary aspects, relevance of the theme and its structure. Chapter 2 gives a brief description of sleep definitions and their structure, as well as the apnea classification, and oxygen desaturation. The typical representation of the ECG signal is also discussed. Chapter 3 briefly describes the theory concepts of wavelet analysis and EDR. Chapter 4 introduces the algorithm design, explaining all functions that compose this algorithm, while in Chapter 5 the flowchart of each function representing that algorithm is presented. Chapter 6 contains a small manual for software user interface. Chapter 7 provides the results of our modeling. The conclusions and guidelines for future work are presented in Chapter 8.



# 2 Basic Medicine Notions

---

## 2.1 Sleep and its Structure

### 2.1.1 Sleep

Sleep is a natural state of bodily rest observed throughout the animal kingdom. It is common to all mammals and birds, and it is also seen in many reptiles, amphibians and fish, birds, ants and fruit-flies. Regular sleep is essential for survival.<sup>5</sup> However, its purposes are only partly clear and are subject of intense research.<sup>6</sup>

### 2.1.2 Stages of Sleep

In mammals and birds the measurement of eye movement during sleep is used to divide sleep into the two broad types of Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM) sleep. Each type has a distinct set of associated physiological, neuronal and psychological features.

Sleep proceeds in cycles of REM and the four stages of NREM, the order normally being:

*Stages 1 -> 2 -> 3 -> 4 -> 3 -> 2 -> REM*

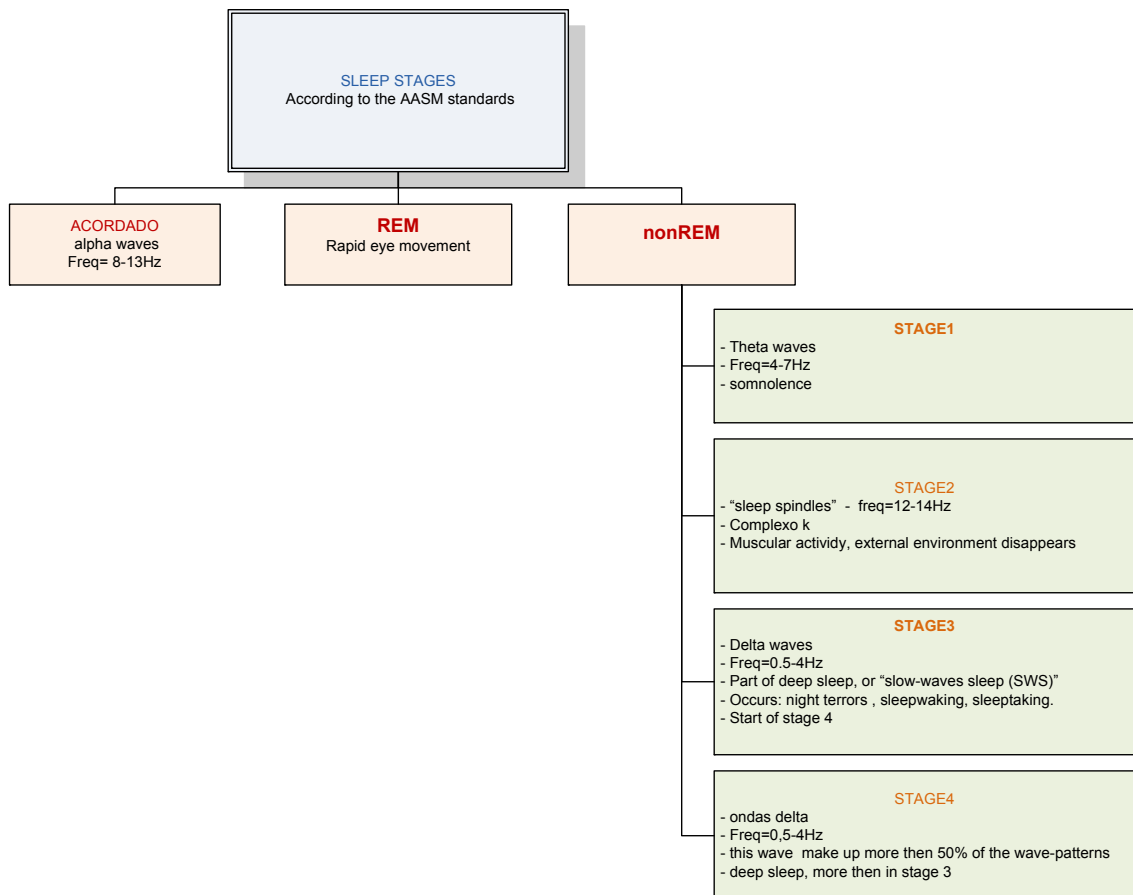
In humans, this cycle lasts, on the average, 90 to 110 minutes<sup>7</sup>, with a greater amount of stages, where stage 4 presents itself early in the night and more REM stages later in the night. Each phase may have a distinct physiological function.

Allan Rechtschaffen and Anthony Kales originally outlined the criteria for indentifying the stages of sleep in 1968. The American Academy of Sleep Medicine (AASM) updated the staging rules in 2007.

The criteria for REM sleep include not only rapid eye movements but also a rapid low voltage EEG. In mammals, at least, low muscle tone is also a sign. Most memorable dreaming occurs in this NREM stage, which accounts for 75-80% of the total sleep time in normal human adults. There is relatively little dreaming during the NREM sleep stage. NREM encompasses four stages; stages 1 and 2 are considered 'light sleep' and 3 and 4 'deep sleep' or slow-wave sleep, SWS. They can only be differentiated by using

an EEG, unlike REM sleep which is characterized by rapid eye movements and relative absence of muscle tone. In NREM sleep there are often limb movements, and parasomnias, such as sleepwalking, may occur.

NREM consists of four stages, according to the 2007 AASM standards:

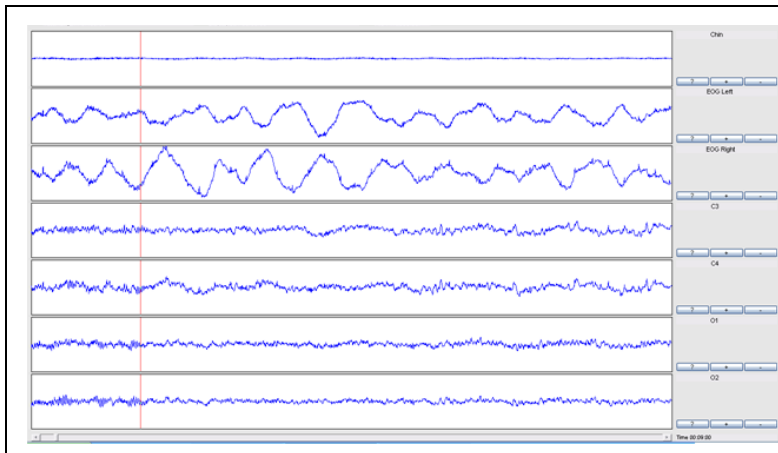


**Table 2.1.1** – NREM and its four stages, according to the 2007 AASM standards

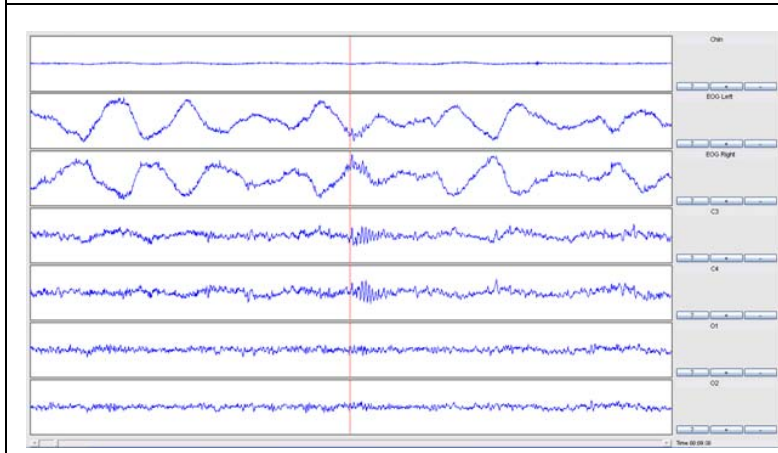
The method used to detect these stages is the Polysomnography, or PSG. This is a multi-parametric test applied to the study of sleep; the test result is called a polysomnogram. The PSG monitors many body functions including brain activity (EEG), eye movements (EOG), muscle activity or skeletal muscle activation (EMG), heart rhythm (ECG), and the breathing function or respiratory effort during sleep.

Here are some examples of different sleep states: awake, asleep, complex k, and spindles.

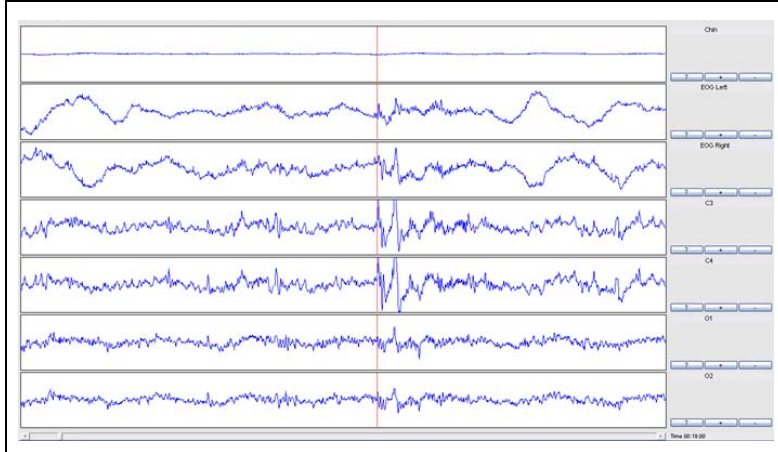
**Table 2.1.2** – Examples of different sleep states: awake, asleep, complex k, and spindles.



Passing stage *awake* to  
stage *asleep*



Spindles (rapid wave),  
sleeping stage 2



Complex k, stage 2  
appear in C3 and C4





### 2.2.2 Oxygen Desaturation

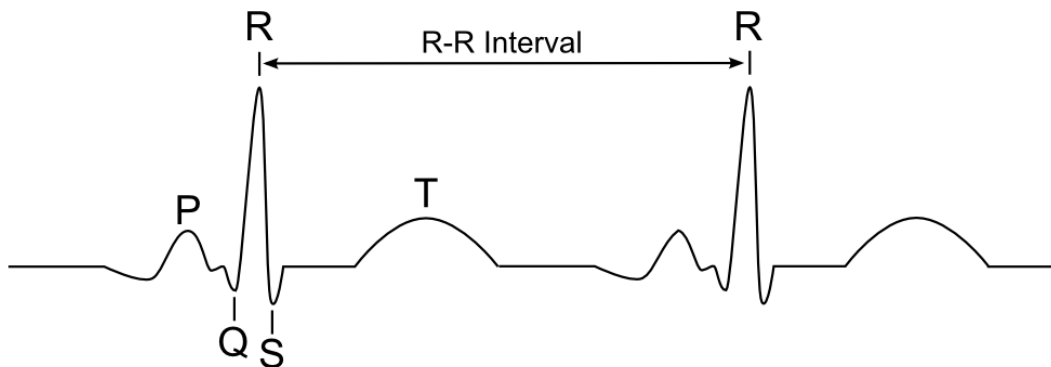
To detect a desaturation there has to be a  $\geq 4\%$  desaturation from pre-event baseline.

## 2.3 The ECG Signal

In order to use this signal it is important to be aware of the typical representation of the ECG signal, so that it is possible to understand all techniques and further techniques that can be applied to an ECG signal.

### 2.3.1 Typical Representation of the ECG

In figure 2.3.1 it's possible to understand the representation of a typical ECG signal.



**Figure 2.3.1** – A typical representation of an ECG signal.

All these waves are very important for the studies undergone in this present work.

### 2.3.2 The QRS Complex

The QRS complex is a structure on the ECG that corresponds to the depolarization of the ventricles. Because the ventricles contain more muscle mass than

the atria, the QRS complex is larger than the P wave. A normal QRS complex has a duration of 0.08 to 0.12 sec (80 to 120 ms). Figure 2.3.2 represents the QRS complex.



**Figure 2.3.2** –A QRS Complex.

# 3 Theoretical Concepts

---

## 3.1 The wavelets

A wavelet is a mathematical function used to divide a given function or continuous time signal into different frequency components and to study each component with a resolution that matches its scale. A wave transform is the representation of a function by wavelets. The wavelets are scaled and translated copies of a finite-length or fast-decaying oscillating waveform. Wavelet transforms have advantages over traditional Fourier transforms for representing functions that have discontinuities and sharp peaks, and for accurately deconstructing and reconstructing finite, non periodic and non-stationary signals.

**The Fundamental idea behind wavelets is to analyze to scale.** The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet function), data operation can be performed using just the corresponding wavelet coefficients. And if one further choose the best wavelets adapter to the data, the coefficient below a threshold, the data is sparsely represented. This sparse coding makes wavelets an excellent tool in the field of data compression.

### 3.1.1 Wavelet versus Fourier Transform

The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) are both linear operations that generate a data structure that contains  $\log_2 n$  segments of various lengths, usually filling and transforming it into a different data vector of length  $2^n$ .

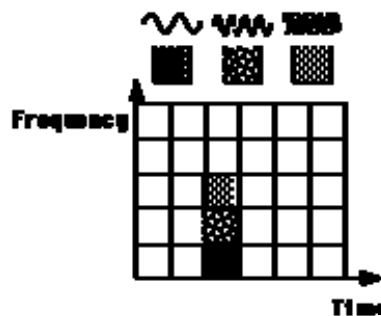
The mathematical properties of the matrices involved in the transforms are similar as well. The inverse transform matrix for both the FFT and the DWT is the transpose of the original. As a result, both transforms can be viewed as a rotation in

function space to a different domain. For the FFT, this new domain contains basis functions that are sines and cosines. For the wavelet transform, this new domain contains more complicated basis functions called wavelets, mother wavelets, or analyzing wavelets.

There is another similarity between both transforms. The basis functions are localized in frequency, making mathematical tools such as power spectra (how much power is contained in a frequency interval) and scalograms (to be defined later) useful at picking out frequencies and calculating power distributions.<sup>8</sup>

The most interesting dissimilarity between these two kinds of transforms is that individual wavelet functions are localized in space. Fourier sine and cosine functions are not.

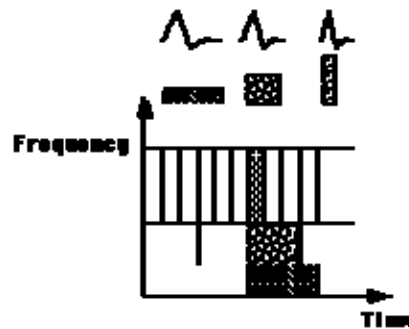
One way to see the time-frequency resolution differences between the Fourier transform and the wavelet transform is to look at the basis function coverage of the time-frequency plane.<sup>9</sup> Figure 3.1 shows a windowed Fourier transform, where the window is simply a square wave. The square wave window truncates the sine or cosine function to fit a window of a particular width. Because a single window is used for all frequencies in the WFT, the resolution of the analysis is the same at all locations in the time-frequency plane.



**Figure 3.1.1** -Fourier basis functions, time-frequency tiles, and coverage of the time-frequency plane.

An advantage of wavelet transforms is that the windows *vary*. In order to isolate signal discontinuities, one would like to have some very short basis functions. At the same time, in order to obtain detailed frequency analysis, one would like to have some very long basis functions. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones. This is exactly what we get with wavelet

transforms. Figure 3.1.2 shows the coverage in the time-frequency plane with one wavelet function.



**Figure 3.1.2-** Wavelet basis functions, time-frequency tiles, and coverage of the time-frequency plane.

One thing to remember is that wavelet transforms do not have a single set of basic functions like the Fourier transform, which utilizes just the sine and cosine functions. Instead, wavelet transforms have an infinite set of possible basis functions. Thus wavelet analysis provides immediate access to information that can be obscured by other time-frequency methods such as Fourier analysis.

### **3.2 The EDR method**

Knowledge of respiratory patterns would be clinically useful in many situations in which the ECG, but not respiration, is routinely monitored. We describe a signal-processing technique which derives respiratory waveforms from ordinary ECGs, permitting reliable detection of respiratory efforts. Central and mixed apnea, hypopnea, and tachypnea may be identified with confidence. In many cases, obstructive apnea and changes in tidal volume are also clearly visible in the ECG-derived respiratory signal (EDR).

This algorithm extracts approximate respiration signal from a single-lead ECG using measurements across a fixed window. The window defines the QRS complex and by default extends from -40ms to +40ms (relative to each R-wave). If the sample rate of the ECG data is low (e.g. 100Hz) then one may wish to use the T-wave as the basis for the EDR signal (since this part of the ECG is more slowly-changing than the QRS complex).

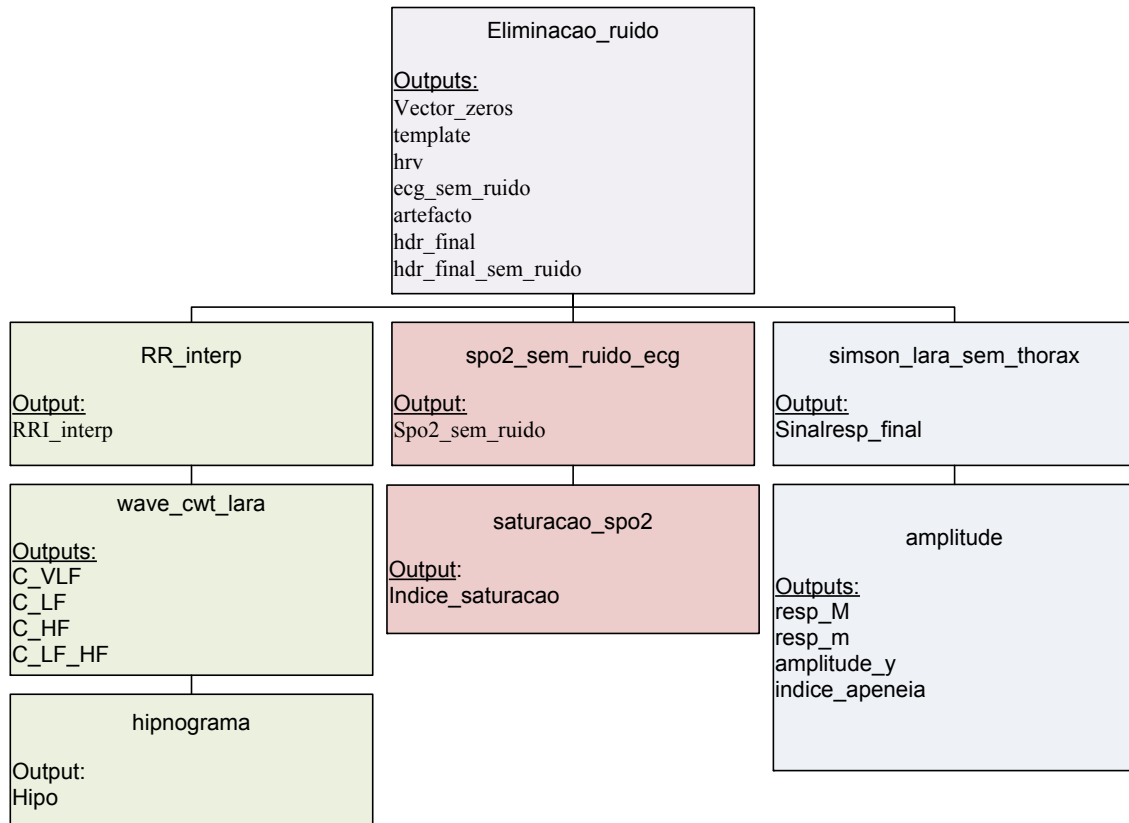


# 4 Functions Description and Interpretation

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## 4.1 Function Architecture

The present work was organized, as shown in figure 4.1, where the titles stand for the Matlab function names.



**Figure 4.1.1-** Work Organization.

There is a main function that eliminates all noise from the ECG signal, and constructs an ECG signal without artifact beats. When the ECG is noise free, there are three main purposes to be achieved by this work:

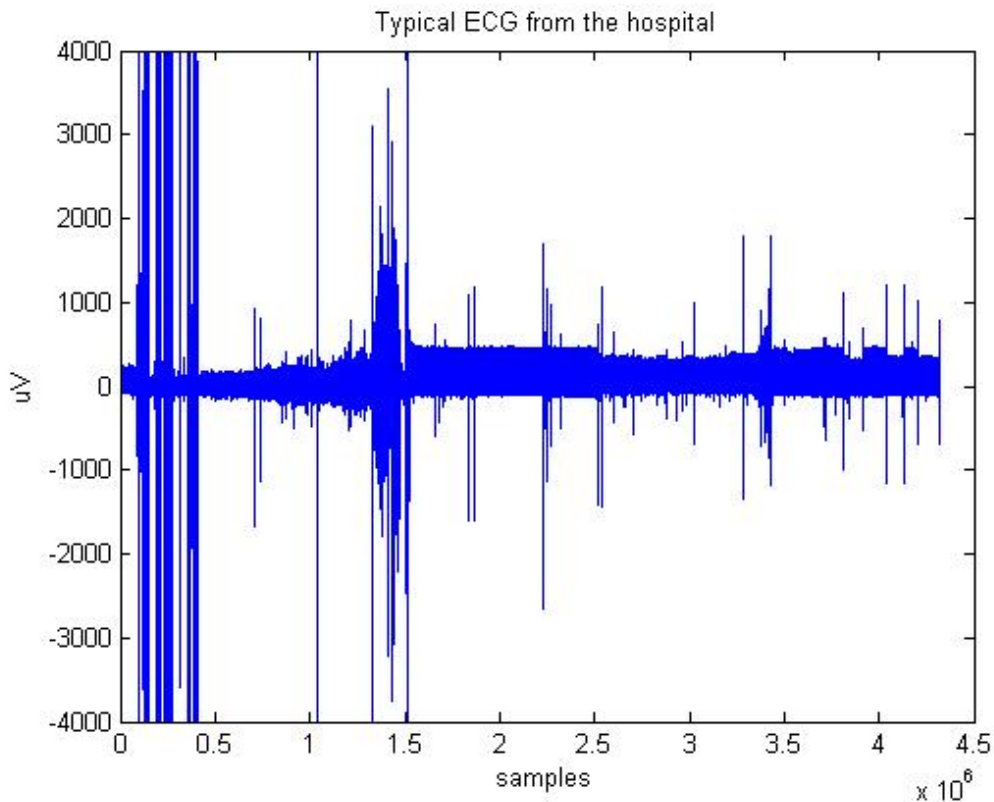
1. To produce a respiration signal using EDR technique, and detect if there is any apnea;
2. To elaborate a Hypnogram, using the ECG signal;

3. And to compute the Oxygen Desaturation Indices (ODI).

#### 4.2 Eliminating the EGC noise

Our data is obtained from patients that underwent an all night recording session. In this context, continuous data is acquired. This data is prone to be contaminated with the artifacts that arise from sources such as unmanageable patient movements and electrode displacement. This is one of the hardest tasks in this kind of work. There is very little information on how to clear a signal from all types of noise, and many sorts of noise can be found in a signal. Therefore, it is of the utmost importance to eliminate the artifact contaminated beats from the signal in order to initiate all the further computing that is required, without the noise that would bring several errors to the aforementioned processing.

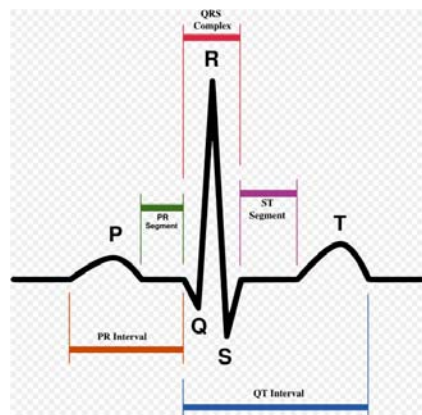
Figure 4.2.1 represents a typical ECG signal from a patient for a night session. It is possible to observe various types of noise that need to be eliminated, in order to carry out all the further processing.



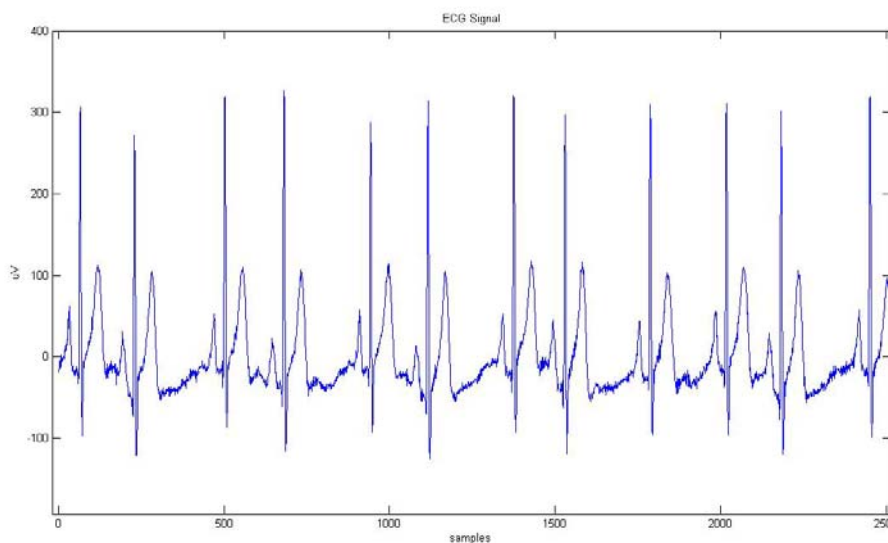
**Figure 4.2.1-** Typical ECG signal of a patient under study, for an all night session



The ECG signal is a cardiac cycle coordinated by a series of electrical impulses produced by specialized heart cells found within the sino-atrial and the atrioventricular nodes. Therefore, the ECG signal is a cycle of heart beats, as observed in figure 4.2.2 and figure 4.2.3.



**Figure 4.2.2-** Schematic representation of a Normal ECG

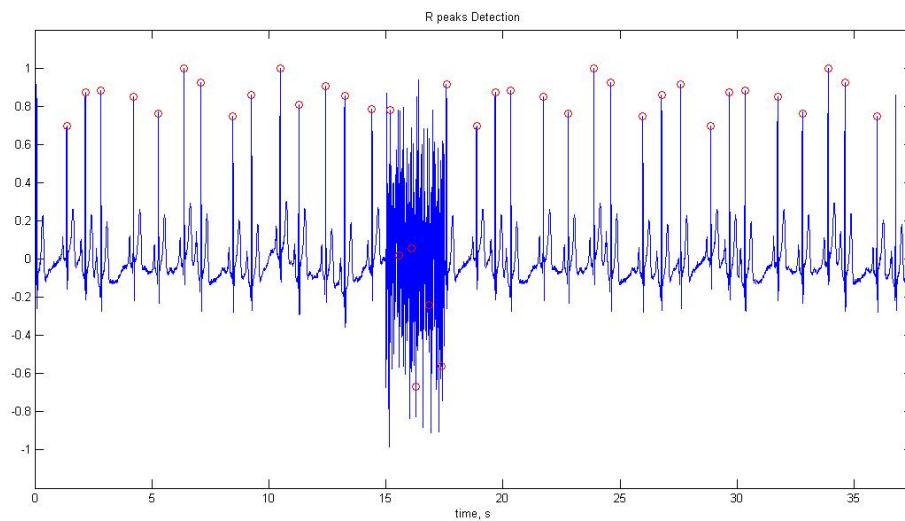


**Figure 4.2.3-** Patient ECG signal

The elimination of the ECG noise starts by eliminating the various parts of the signal that differ from the typical representation of the ECG, so the first computing performed is to detect all R picks in the signal. To detect those R picks an existing function `qrsdetect` was applied. The results can be found in figure 4.2.4. This function was obtained from the *The BioSig Project* (<http://biosig.sourceforge.net/>), an

open source code repository. Under test the function revealed to be stable and accurate enough for our purposes.

As observed, this function works the best when the signal has no noise, since noise causes the function to detect several types of wrong peaks, detrimental to the results of the computing process.



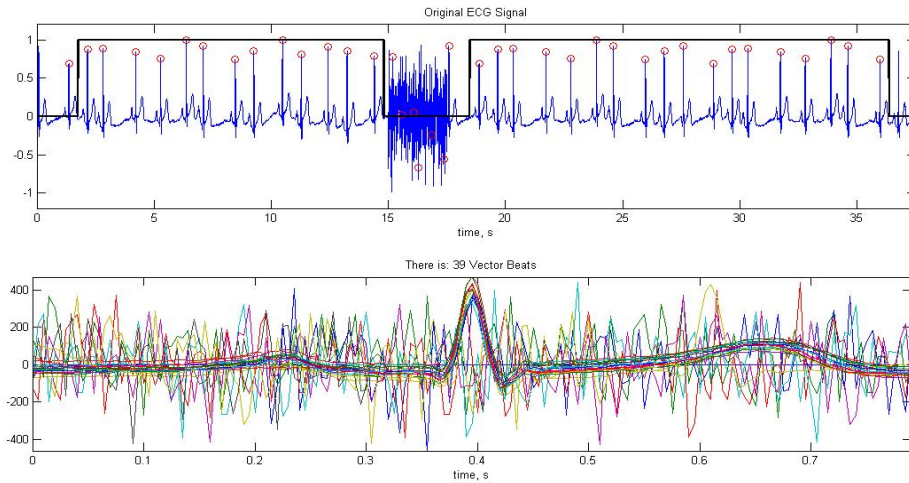
**Figure4.2.4-** Detection of R peaks

One of the purposes of this function is to make a distinction between the good and the bad peaks detected. After getting the vector that contains all peaks, there has to be a way to identify and eliminate the bad ones, so that the signal can be freed from this interference.

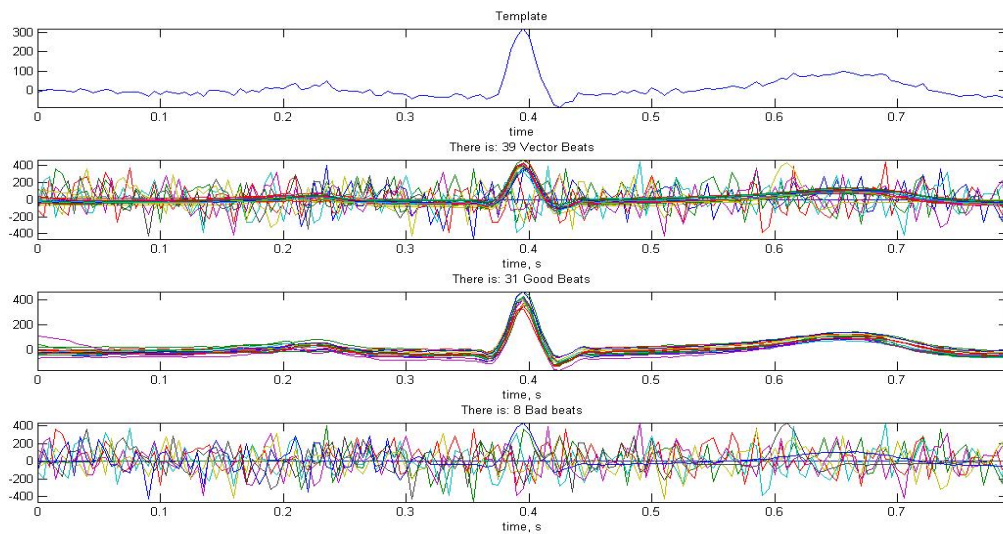
The algorithm that identifies and eliminates this type of noise works as follows:

1. Get a vector with all the R peaks invoking an existing function *qrsdetect*, (figure 4.2.5 top)
2. Get a vector with the difference between R peaks, that is, get the Heart Rate Variability (HRV);
3. Distinguish the good HRV from the bad one, which can be done since the R-R intervals have a human limit;

- The purpose is achieved when the signal is split into pieces, which should represent one cardiac cycle (figure 4.2.2). Figure 4.2.5 bottom represents a split signal. The vector that contains the split signal is a vector herein called *beat* (figure 4.2.5 bottom )



**Figure 4.2.5-** The ECG signal with artifact beats. Graphic 1 – ECG signal (blue), R-peaks (red) and vector that is zero when the artifacts occur (black); Graphic 2 – The splitted ECG signal

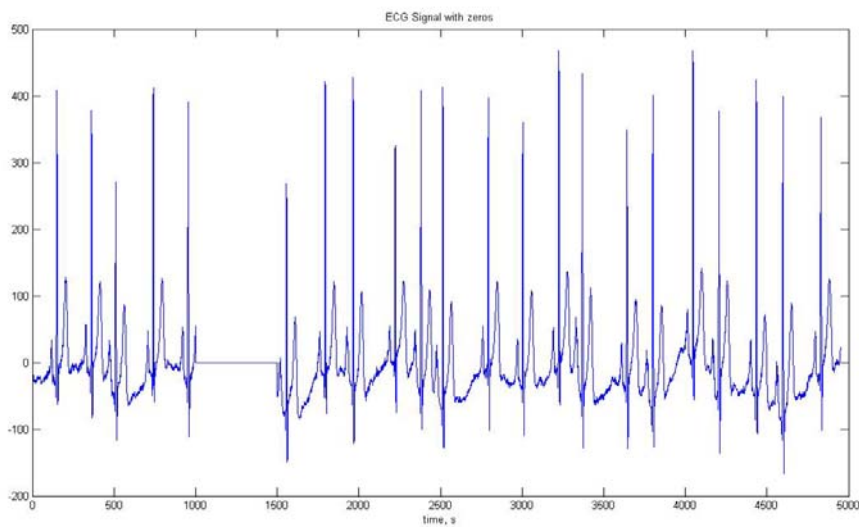


**Figure 4.2.6-** Correlation Algorithm. Graphic 1: the obtained template; Graphic 2: All the separated beats, including the noisy ones; Graphic 3: Good beats only; Graphic 4: Bad beats only

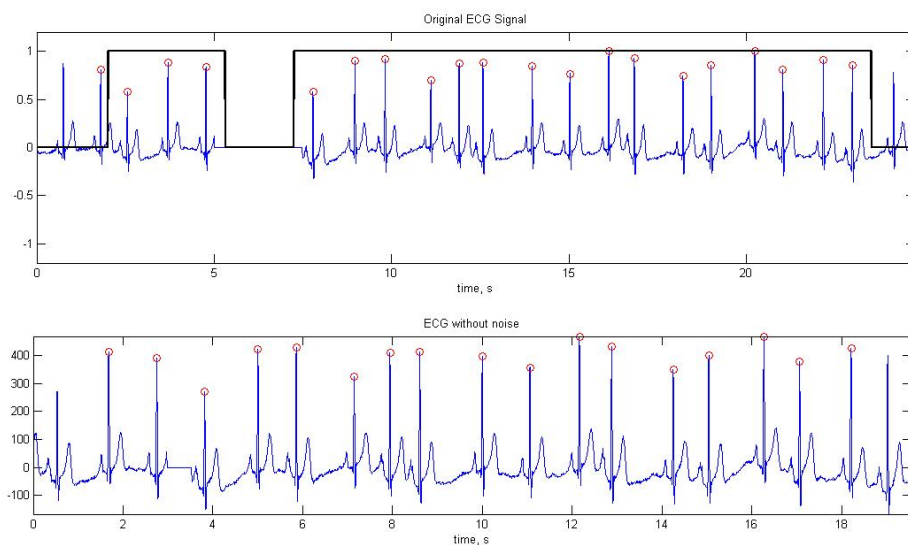
- Once, the signal is all split, by getting the mean of the vector beat, it is obtained the template that will serve to compare with the entire beat vector (figure 4.2.6 – graphic 1)

6. Correlation has the biggest computational load. This takes a long time processing. Therefore, it is very difficult to process an entire night sleep with *standard pc's*. The result can be seen in figure 4.2.6.
7. After getting a vector with only good beats, all the good ones are connected and the signal is freed from the artifact beats (figure 4.2.6 – graphic 3 good beats, graphic 4 bad beats)

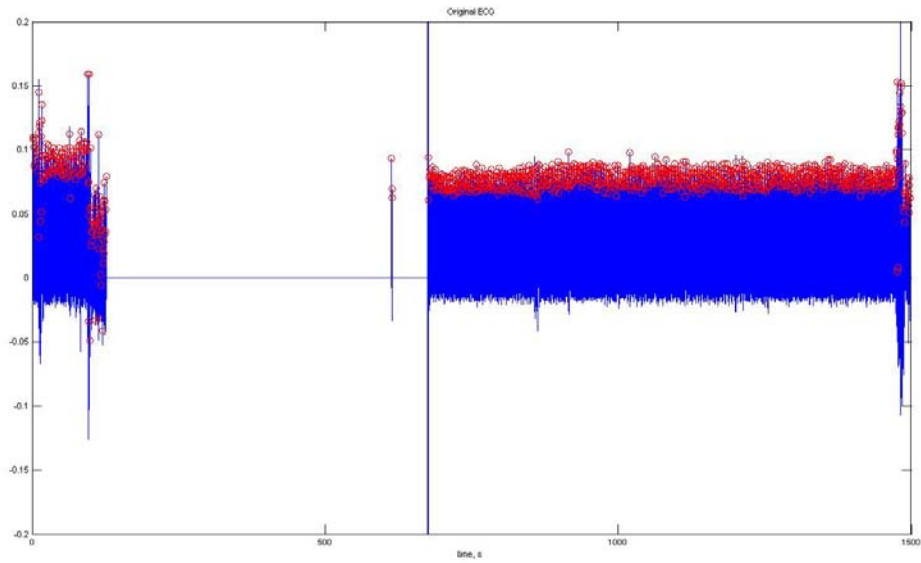
However, another type of noise can occur, as seen in figure 4.2.7. It happens when the electrode comes off, for some reason, during a night sleep, making the signal flat in the respective interval.



**Figure 4.2.7-** Another type of Noise – zeros



**Figure 4.2.8-** Graphic 1 – ECG signal (blue) and selection function (black); Graphic 2- ECG Signal where the artifact beats where eliminated and removed.

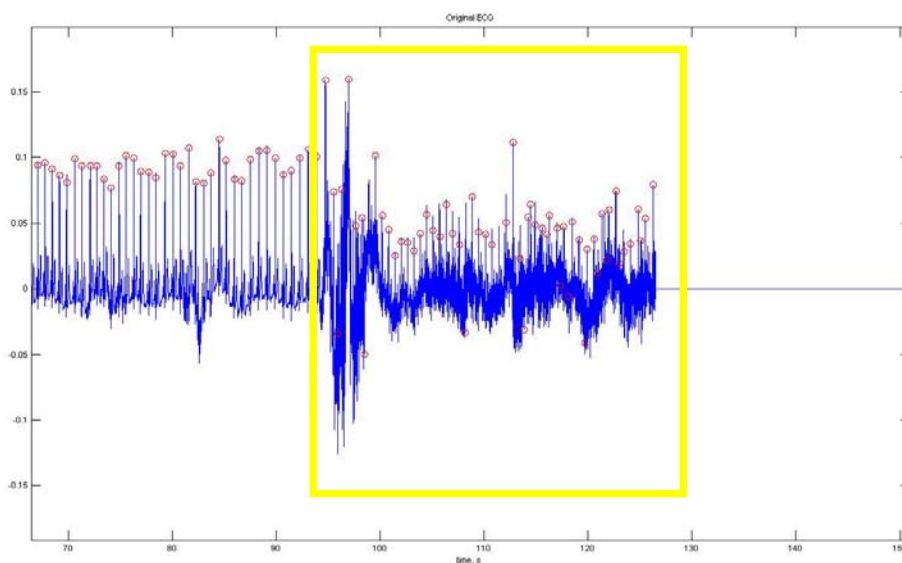


**Figure 4.2.9-** Original ECG with Noise

This is another type of noise that has to be eliminated. Figure 4.2.8 (bottom) shows how the algorithm results: the flat zone was eliminated and the bears put together.

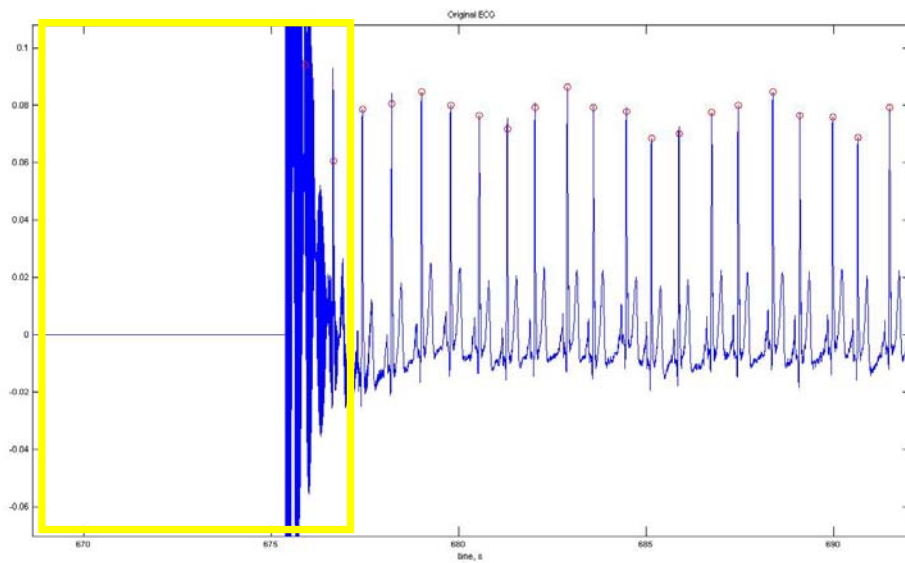
Figure 4.2.9 represents an original ECG signal with some noise and zeros, the red dots represent the R waves location.

Figure 4.2.10 zooms in on figure 4.2.9, where R peaks, representing noise (yellow rectangle) can be seen.



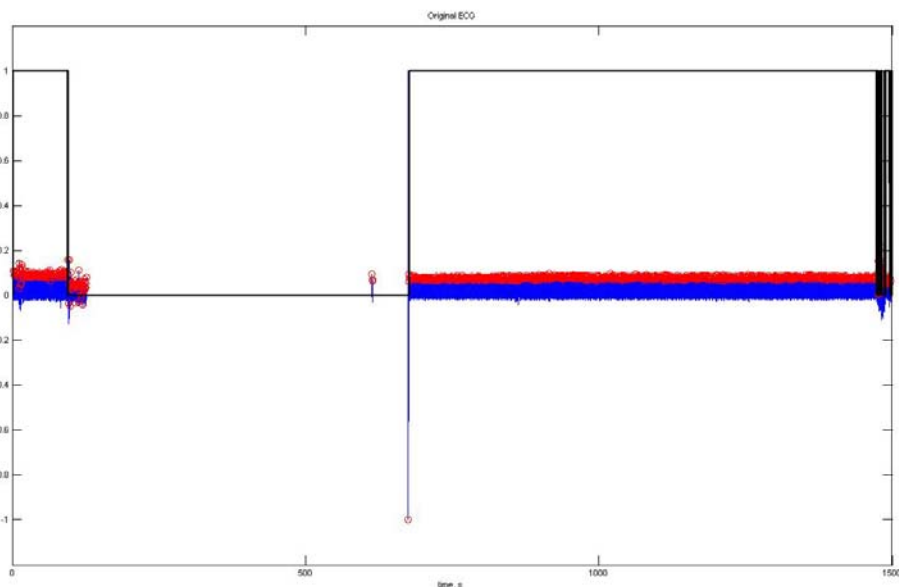
**Figure 4.2.10-** Zoom of figure 4.2.9, yellow rectangle represents bad R peaks detected

Figure 4.2.11 also zooms in on figure 4.2.9 – One can see some noise in this part of the signal; zeros represent noise as well (yellow rectangle).



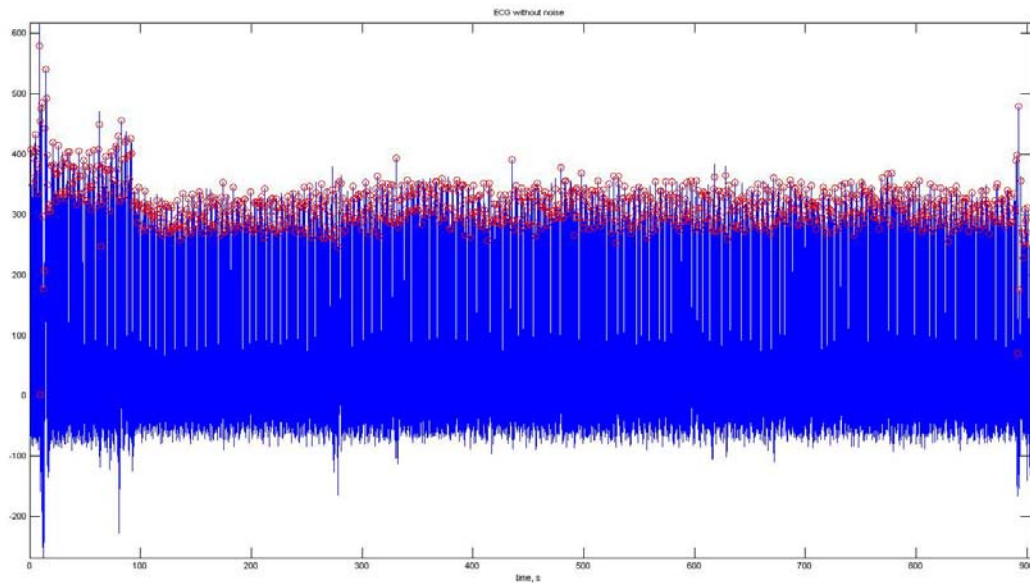
**Figure 4.2.11-** Zoom of figure 4.2.9, yellow rectangle represents different types of noise.

Finally, it is possible to see the algorithm at work in figure 4.2.12. When the rectangular signal (black signal) is 1, it represents a good signal; when it is 0 (zero) it represents noise.



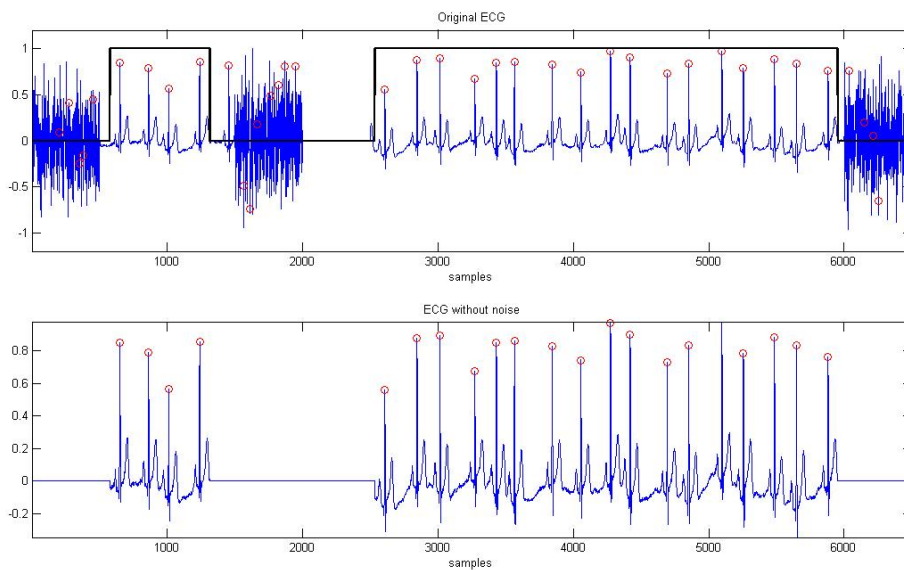
**Figure 4.2.12-** Elimination of the ECG noise. When the rectangular signal (black signal) is 1, it represents a good signal; when it is 0 (zero) it represents noise.

Eventually, an ECG signal with reduced noise level is obtained; ready to be used in further processing, as seen in Figure 4.2.13.



**Figure 4.2.13-** Result after elimination of the ECG noise.

It is important to mention that the noise was removed from the ECG signal, and the parts with no noise placed together. This decision was taken because the intervals needed for further processing are the R-R ones. Therefore, the difference between the peaks will be the object of further computing. Initially, zeros were placed where artifacts was detected, figure 4.2.14.



**Figure 4.2.14-** Removing the artifacts, Graphic 2 – zeros were placed where the artifacts were detected.



But this decision was quickly reversed, because the R-R intervals would be affected. This is why the good parts of the ECG signal were attached. This function would work better if, instead of using the template obtained from ALL beats, it used the template with only the good beats. This creates a problem for the computing process, because in order to obtain a template with only the good beats the function would have to be processed twice. It would have to get a template with the mean of all the beats, by correlation, get a vector only with the good beats and get a new template with the mean of the good beats and finally, by correlation once more, remove the artifacts beats of the ECG signal. Figure 4.2.15 shows what happens when an ECG has too much noise.

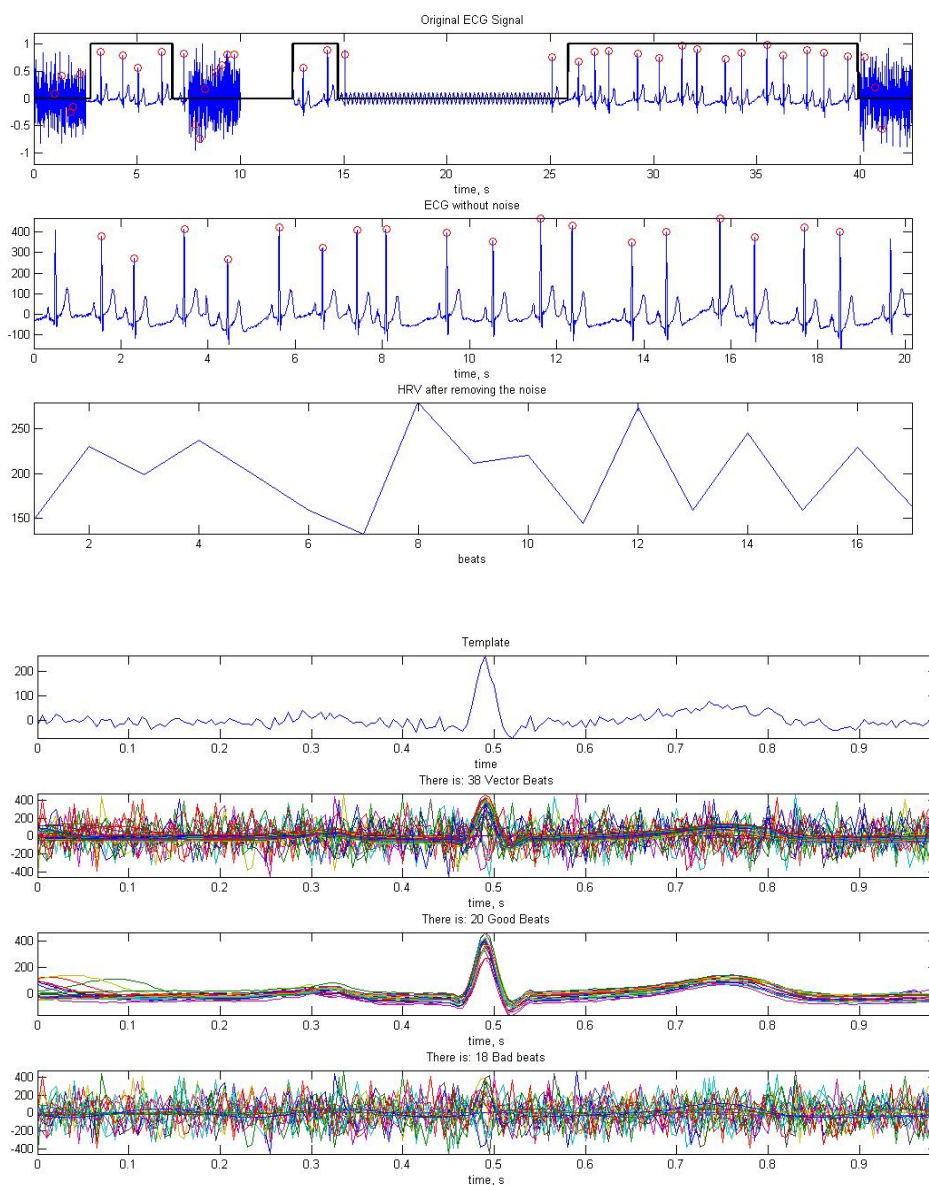


Figure 4.2.15- Algorithm steps. See text,



In figure 4.2.15 (graphic 4) it can be seen what can happen if the ECG is contaminated with severe noise, the template that is obtained by the mean of all beats, it not the best.

Graphic 1 – ECG signal (blue) and selection function (black);

Graphic 2- ECG Signal where the artifact beats where eliminated and removed;

Graphic 3- Represents the HRV signal;

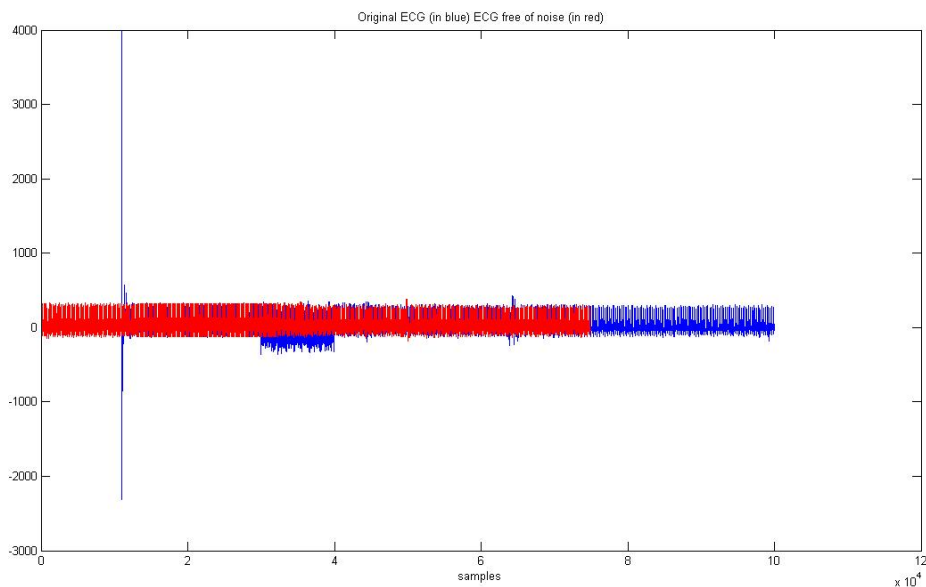
Graphic 4-The template obtained;

Graphic 5-The vector containing all the beats;

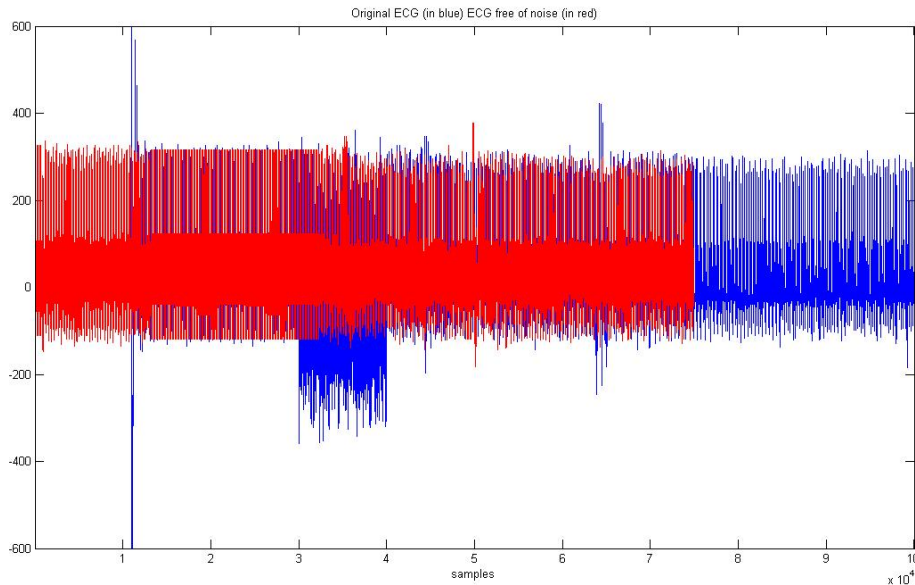
Graphic 6-The vector with the good beats:

Graphic 7-The vector with the bad beats only.

The ECG signal without noise then becomes out of phase with the original ECG, and with less samples. This will most likely bring about problems in the future when comparing these results with the hospital results, since the noisy epochs in the visual scoring done by the Hospital Cardiopneumologists are replaced by the previous ones, thus maintaining the signal length, which is not the case of our algorithm. Figure 4.2.16 shows the difference between the original data set and the one after removing the noisy heart beats. . Figure 4.2.17 is zoomed version.



**Figure 4.2.16-** portraits the original ECG signal (blue), and the ECG signal after applying the aforementioned algorithm (red).



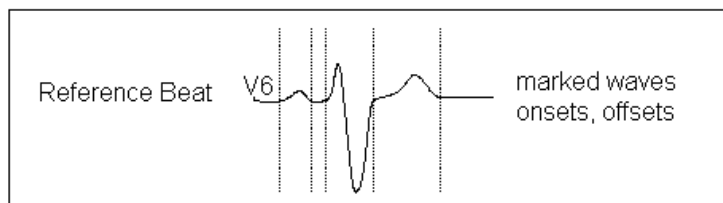
**Figure 4.2.17-** Zoom over Figure 4.10 (ylim([-600 600]))

### 4.3 Calculation of the Respiration Signal

It was our desire, in an early stage, to get the respiration signal by using wavelets. But the signals obtained at the hospital were filtered in the band where the respiration signal is present. We have demonstrated, after some testing, this result. Even though this tool could not be used with these signals, another one could, the EDR. The EDR used in this project has already been explained in chapter 3.2.

#### 4.3.1 The EDR

To use this technique (EDR - *Copyright Ben Raymond, March 2000 This file is free software*); several elements are required: R-R intervals, an ECG signal free from different types of noise (achieved by previous function described in chapter 4.2), the QRS onset and offset, and the ECG frequency. Figure 4.3.1 represents the onset and offset waves in an ECG beat reference.

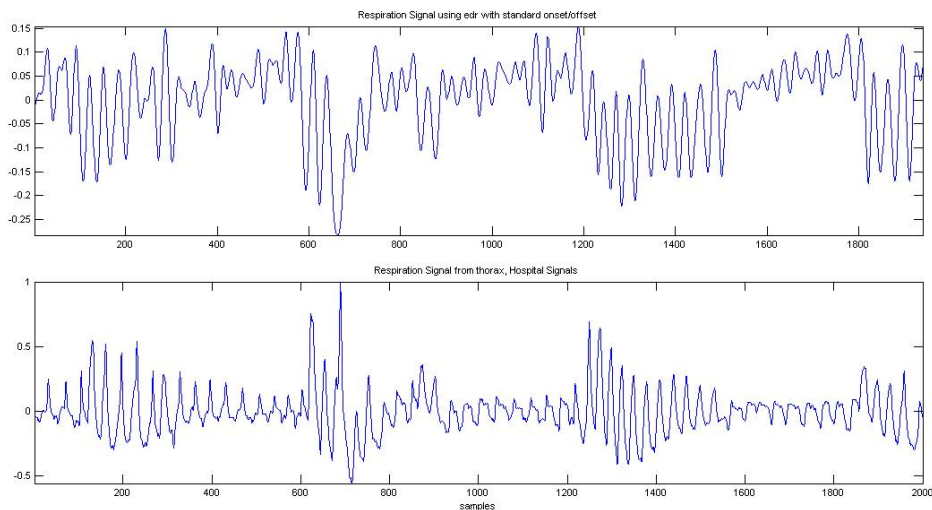


**Figure 4.3.1-** Marked waves onset, offset

A standard function can be used to detect the onset and offset of the QRS:

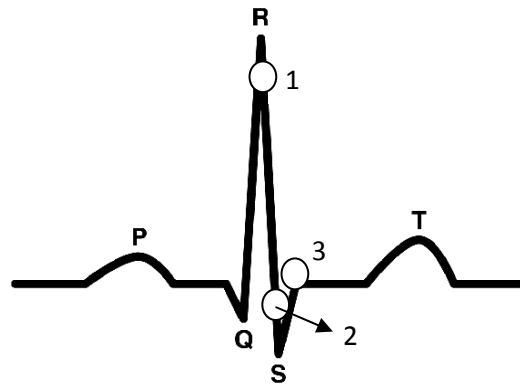
```
sinalresp_final_1=edr(hdr_final',ecg_sem_ruido,[-40 40],fa);
```

Figure 4.13 shows the respiration signal obtained from the EDR with the onset, offset of the QRS standard, and the respiration signal from the thorax (signal obtained by plethysmography sensor) of a patient. When observing figure 4.3.2 one has to take into account the fact that the respiration signal obtained by the EDR is out of phase with the thorax signal, due to the missed ECG beats, eliminated due noise. There is a good accordance between the plots.



**Figure 4.3.2-** The EDR versus the Thorax signal.

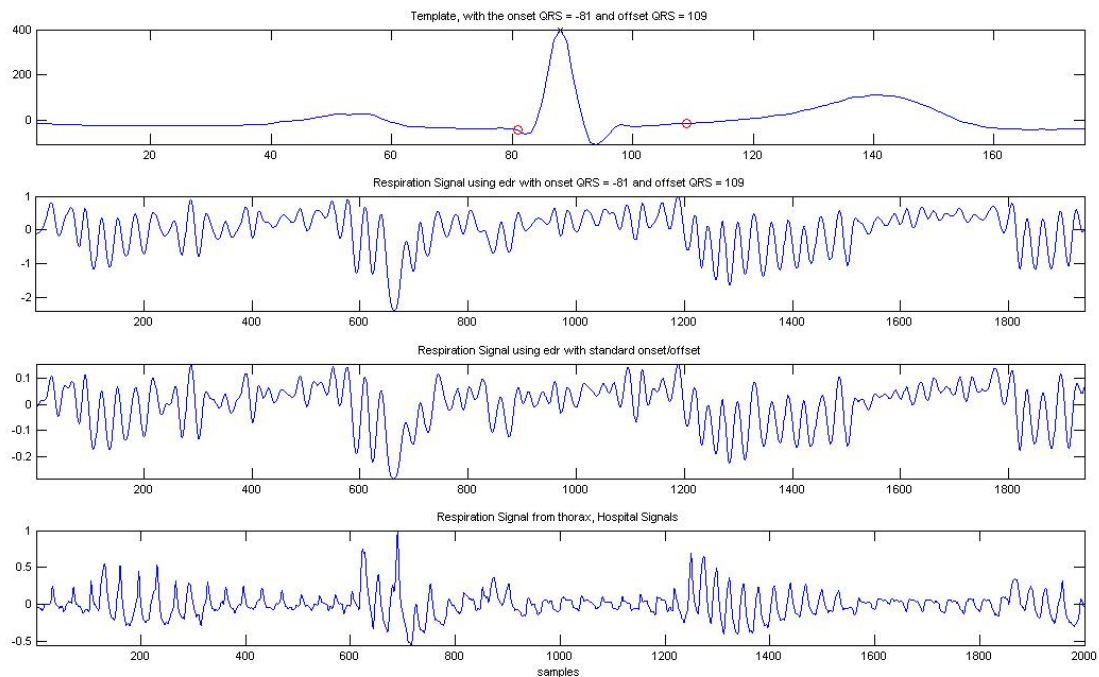
To improve these results, the onset and offset must not be standard, but linear. The onset and the offset must be calculated according to each template. To make that calculation, an algorithm developed by Carlos Mendes (a colleague of mine studying high resolution ECG in the same department) was used. This algorithm consists of (see figure 4.3.3):



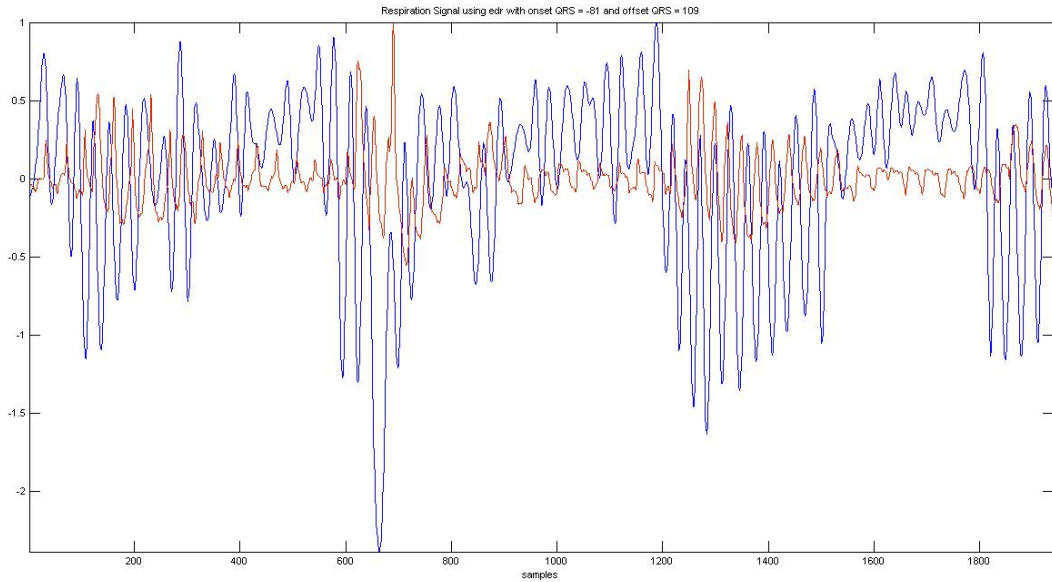
**Figure 4.3.3-** The normal ECG's timing and shape.

1. Detects R peak;
2. Detects the maximum slope between point 1 and point 2;
3. Detects S peak;
4. From S peak, when the slope is smaller than it is the offset - in this case point 3;
5. To find the onset, the same algorithm is used, but symmetrically, between R peak and Q peak.

The results, as seen, for one beat, in figure 4.3.4, are much better when using this algorithm. The apnea is already visible in graphic 2, and one must keep in mind that graphic 2 is out of phase with graphic 4.



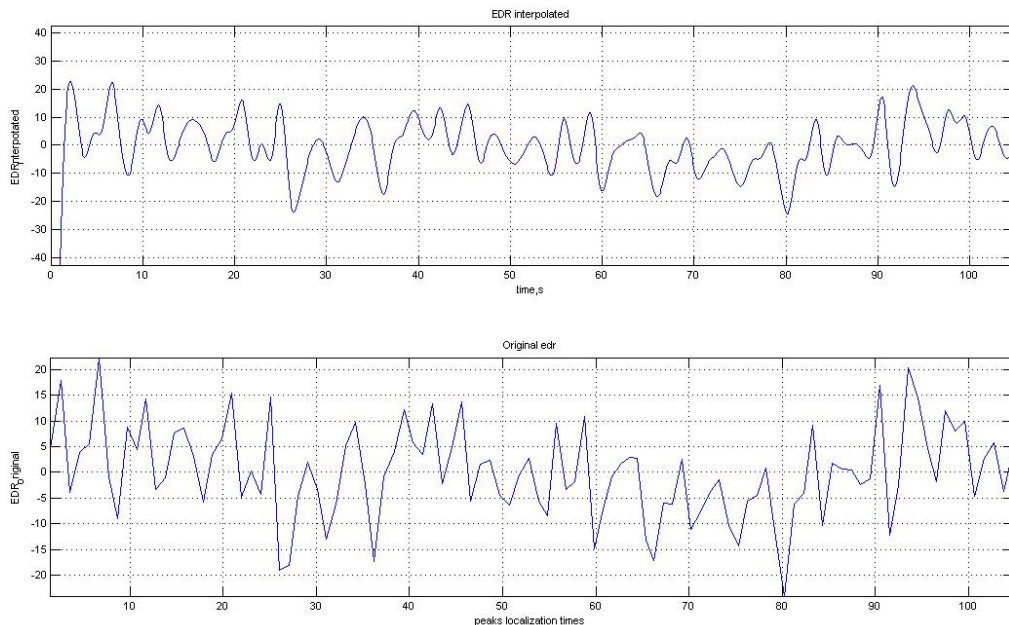
**Figure 4.3.4-** The EDR with standard and non standard onset and offset. Graphic 1 – Template (blue) and the onset and offset detected in (red); Graphic 2 – EDR signal with a non standard onset and offset; Graphic 3 – EDR signal with a standard onset and offset; Graphic 4 – Thorax signal



**Figure 4.3.5-** Red: Plethysmography respiration signal. Blue: EDR signal with linear onset/offset detection.

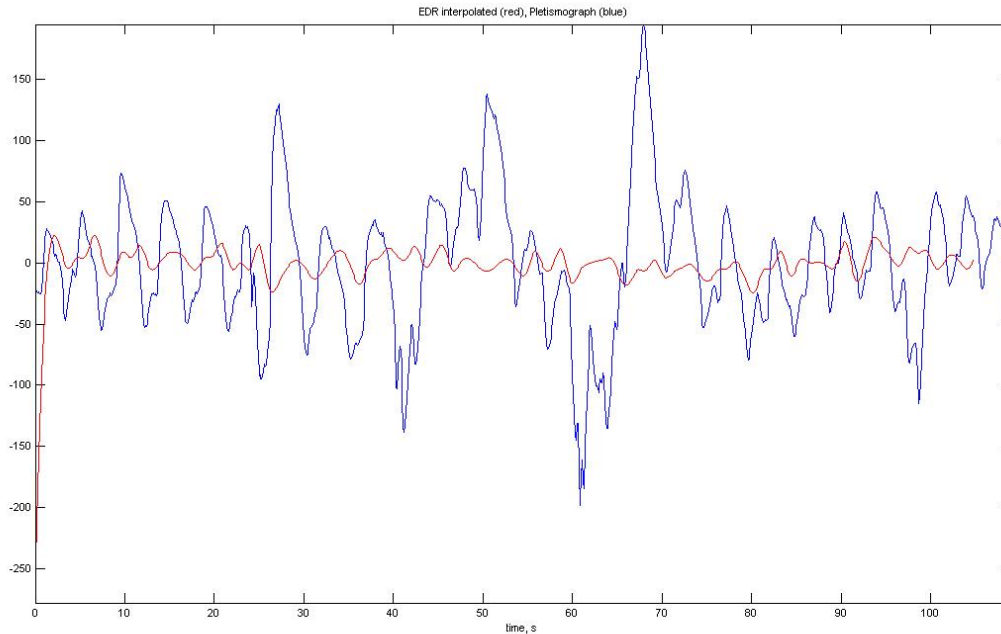
Figure 4.3.5 shows in red the Plethysmography respiration signal, and in blue the EDR signal with linear onset/offset detection. Despite not being clear in Figure 4.3.4, this EDR version produces a respiration signal that better follows the original signal.

Since the EDR signal represents one sample for each heart beat this un-homogeneous sample rate is much lower than the plethysmography signal (100Hz). We have therefore to interpolate the signal to the same sampling rate of the plethysmography signal to be able to compare both. Figure 3.3.6 shows on the top the interpolated signal and on the bottom the original signal.



**Figure 4.3.6-** Graphic 1- EDR Interpolated and Graphic 2 - Original EDR.

.Figure 4.3.7 shows the interpolated signal red along with the original Plethysmography signal. We can see that the respiratory signal that the interpolated signal detects all the respiratory cycles.



**Figure 4.3.7**-EDR Interpolated (red) and Plethysmography (blue).

Finally, we proceed to develop a function to detect apnea.

#### 4.3.2 Number of Apnea

The purpose of this function is to detect the type of apnea. As it was described in chapter 2.2.1, to score an apnea there has to be a drop in the peak thermal sensor excursion by  $\geq 90\%$  and the event has to last at least 10 seconds. To achieve this goal, the known function was used:

```
res = nbmaxima(t, f, position)
```

This function was developed by Jeremie Bigot, from the University Paul Sabatier, in France. There are three principles in this function:

1. A point is maximum in a strict sense if the points that are immediately on its left and right sides are smaller than it.

Example:  $x_0, x_1, x_2, \dots, x_{(j-1)}, x_{(j+1)}, \dots, x_n$

$X_j$  is maximum in a strict sense if  $x_{(j-1)} < x_j$  and  $x_{(j+1)} < x_j$

2. A point is a left maximum if it is bigger than the point on its left side and equal to the point on his right side.

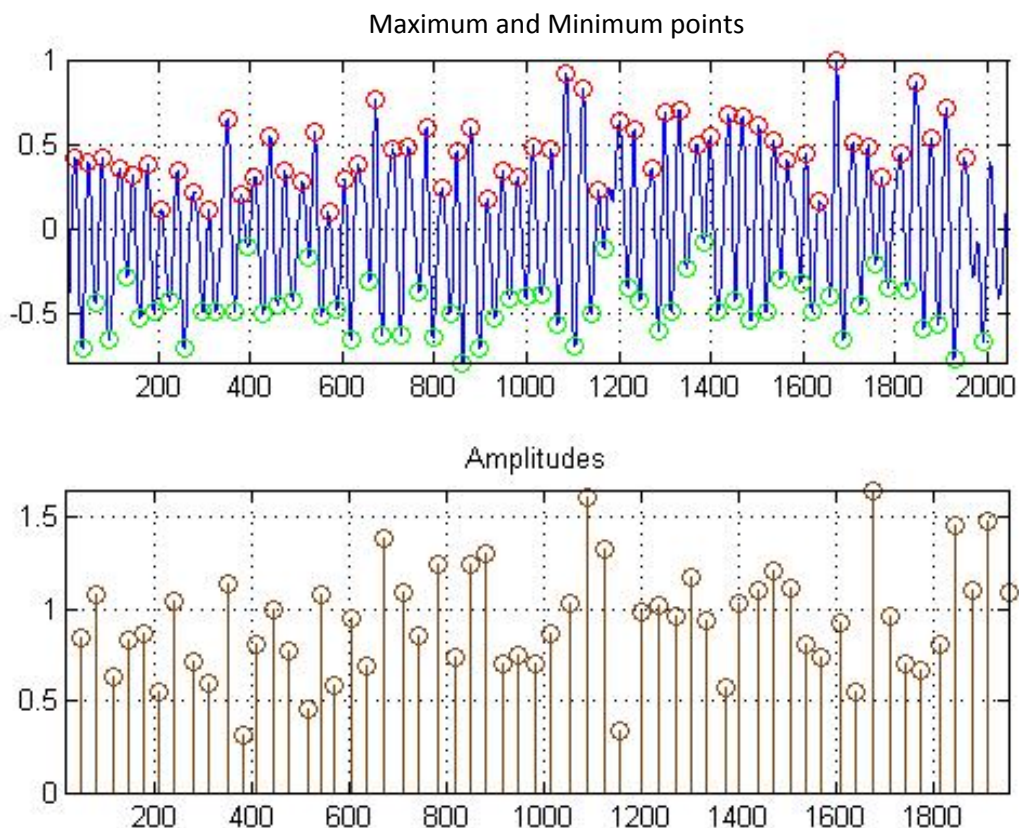
Example:  $X_j$  is left maximum if  $x_{(j-1)} < x_j$  and  $x_{(j+1)} = x_j$

3. A point is a right maximum if it is bigger than the point on its right side and equal to the point on its left side.

Example:  $X_j$  is left maximum if  $x_{(j-1)} = x_j$  and  $x_{(j+1)} < x_j$

The function was developed to calculate the respiration amplitudes. Figure 4.3.8, graphic 1 represents the respiration's signal with its maximum and minimum detected, and graphic 2 represents the correspondent respiration amplitudes.

These respiration amplitudes will be used to detect apnea events.



**Figure 4.3.8-** The Respiration Signal and the correspondent respiration amplitudes.



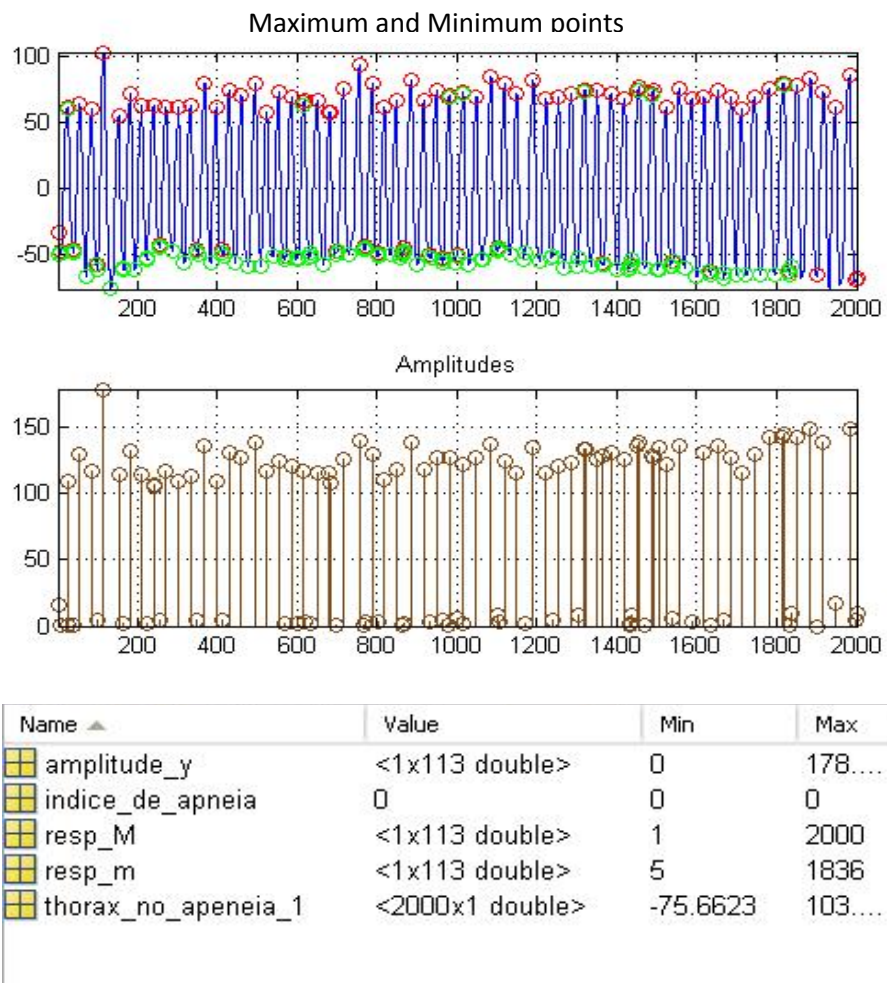
When the amplitude vector is obtained, it is possible to detect apnea events. The algorithm used to detect the apnea consists of:

1. Initially, the amplitude vector contains all amplitudes;
2. Using the “find” function (Matlab function) it returns all the indices whose amplitude is lower than 90% when compared to the baseline. It is rather difficult to define a baseline; normally it is done manually, by an expert. In this case, the baseline is obtained by calculating the average of the first ten samples. This can cause some problems, if the scoring starts with an apnea event;
3. Finally, by applying the “diff” function (Matlab function) to the vector and dividing it by the sample frequency, a vector is obtained, containing all the times the amplitude is lower than 90% when compared to the baseline. All those bigger than 10 seconds correspond to an apnea event.

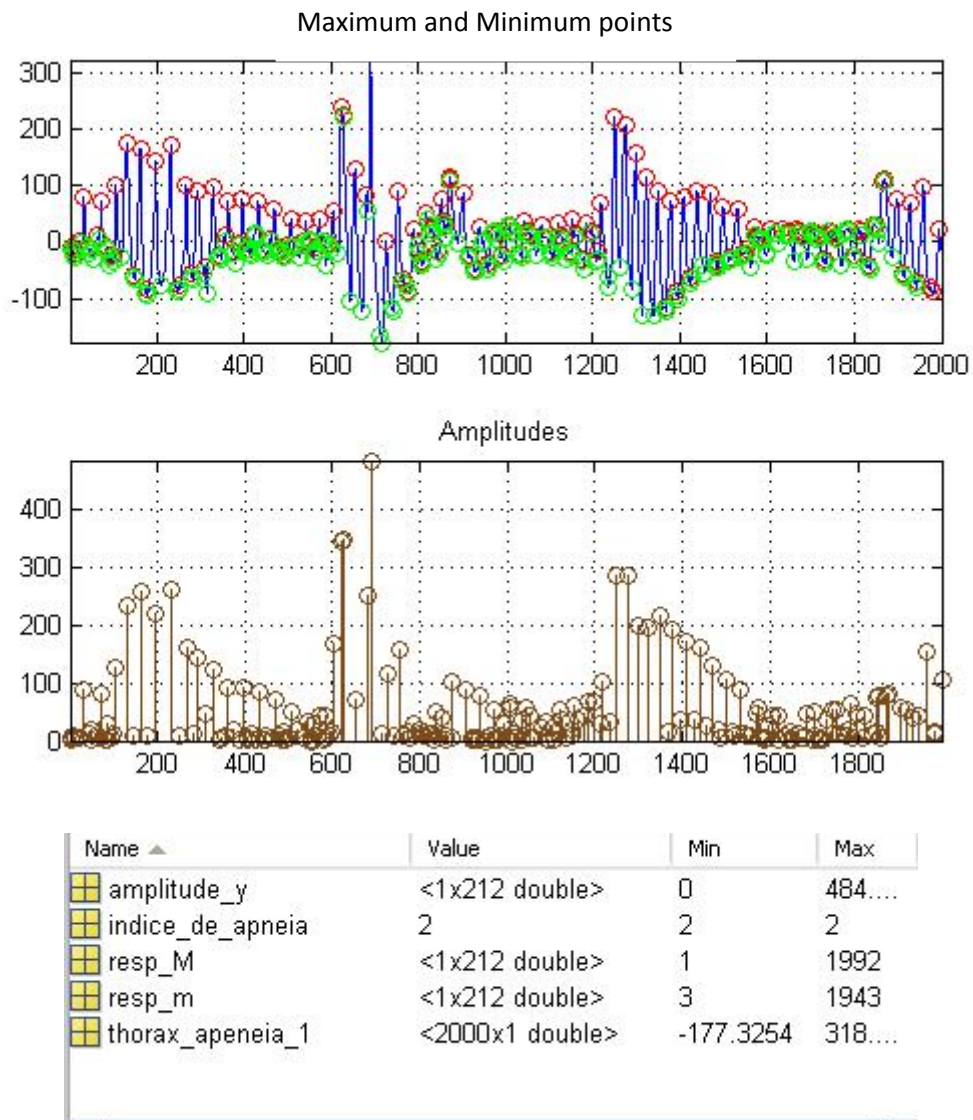
Figure 4.3.9 shows the algorithm running. The output variable ‘indice\_apeneia’ is zero. No apnea events can be seen. In graphic 1 the EDR interpolated signal is showed with the maxima (red) and minima (green) of the respiratory signals, graphic represents the respiratory cycles, graphic 3 shows the apnea index.

Figure 4.2.10 represents the same situation with a signal with two apnea events the output variable ‘indice\_apeneia’ is two. As described before, an apnea event is characterized by a 90% amplitude decrease that lasts at least 10 seconds



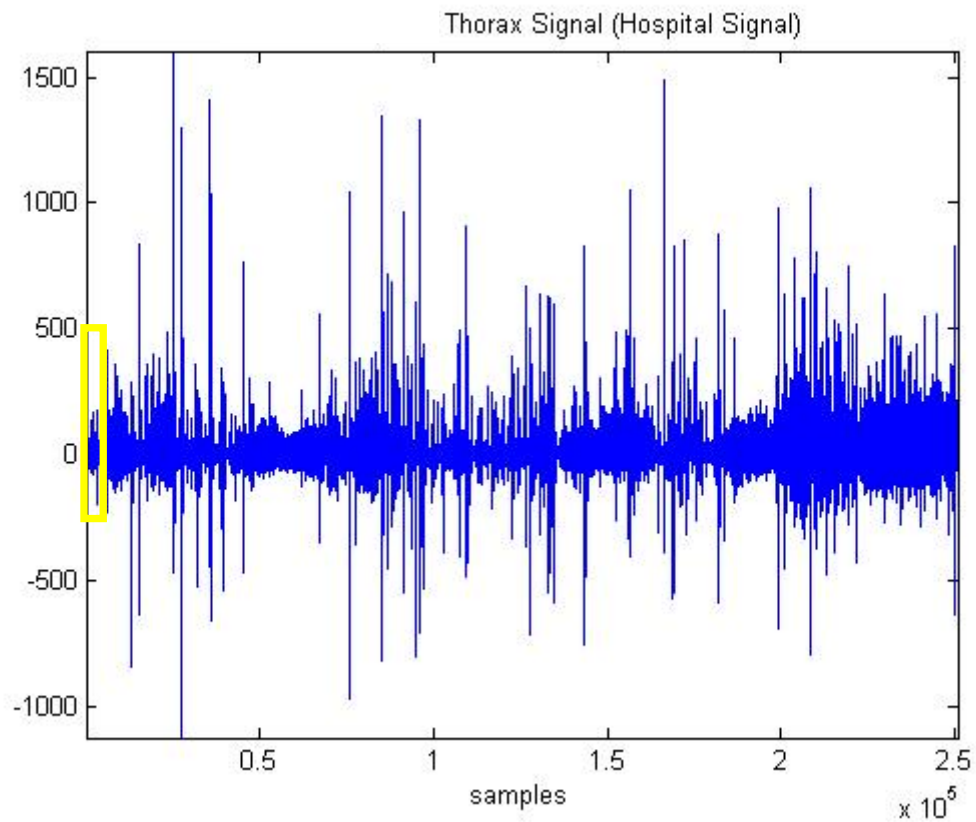


**Figure 4.3.9-** The Respiration Signal with no apnea events (see text).

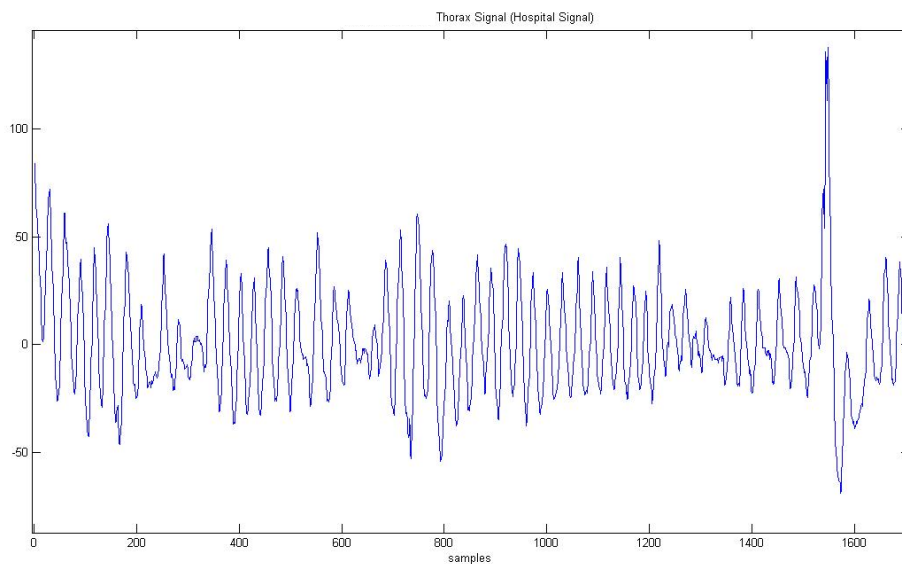


**Figure 4.3.10-** The Respiration Signal with two apnea events (see text).

Lastly, using a plethysmography signal (Hospital Signal) as an input signal for the function developed to calculate the respiration amplitudes, it is possible to observe that the algorithm works correctly. Figure 4.3.11 represents the thorax signal and figure 4.3.12 represents a zoom out from figure 4.3.12, being possible so observe the respiration signal and its constitution.



**Figure 4.3.11-** The thorax Signal. The yellow rectangle is zoomed in the figure 4.3.12.



**Figure 4.3.12-** Zoom of figure 4.3.11, representing the yellow rectangle in figure 4.3.11.

For the above patient, it is possible to check in table 4.3.1 that the results are rather satisfactory and acceptable.

Output from matlab	<table border="1"> <thead> <tr> <th>Name ▲</th> <th>Value</th> <th>Min</th> <th>Max</th> </tr> </thead> <tbody> <tr> <td>amplitude_y</td> <td>&lt;1x29926 double&gt;</td> <td>0</td> <td>1.79...</td> </tr> <tr> <td>indice_de_apneia</td> <td>132</td> <td>132</td> <td>132</td> </tr> <tr> <td>resp_M</td> <td>&lt;1x29926 double&gt;</td> <td>1</td> <td>249798</td> </tr> <tr> <td>resp_m</td> <td>&lt;1x29926 double&gt;</td> <td>17</td> <td>250712</td> </tr> <tr> <td>thorax_antonio_sequeira</td> <td>&lt;1x250800 double&gt;</td> <td>-1.1263e...</td> <td>1.59...</td> </tr> </tbody> </table>			Name ▲	Value	Min	Max	amplitude_y	<1x29926 double>	0	1.79...	indice_de_apneia	132	132	132	resp_M	<1x29926 double>	1	249798	resp_m	<1x29926 double>	17	250712	thorax_antonio_sequeira	<1x250800 double>	-1.1263e...	1.59...
Name ▲	Value	Min	Max																								
amplitude_y	<1x29926 double>	0	1.79...																								
indice_de_apneia	132	132	132																								
resp_M	<1x29926 double>	1	249798																								
resp_m	<1x29926 double>	17	250712																								
thorax_antonio_sequeira	<1x250800 double>	-1.1263e...	1.59...																								
Polysomnography Report (hospital)	Obstructive Apnea:	138	41,6 / h																								

**Table 4.3.1** - Comparison of the results.

#### 4.4 Calculating the Hypnogram

In recent studies<sup>11</sup> the electrocardiogram (ECG) has been used to classify sleep into different states: Wake, REM and Sleep. These studies are recent and information concerning autonomic changes is scarce when trying to classify sleep stages.

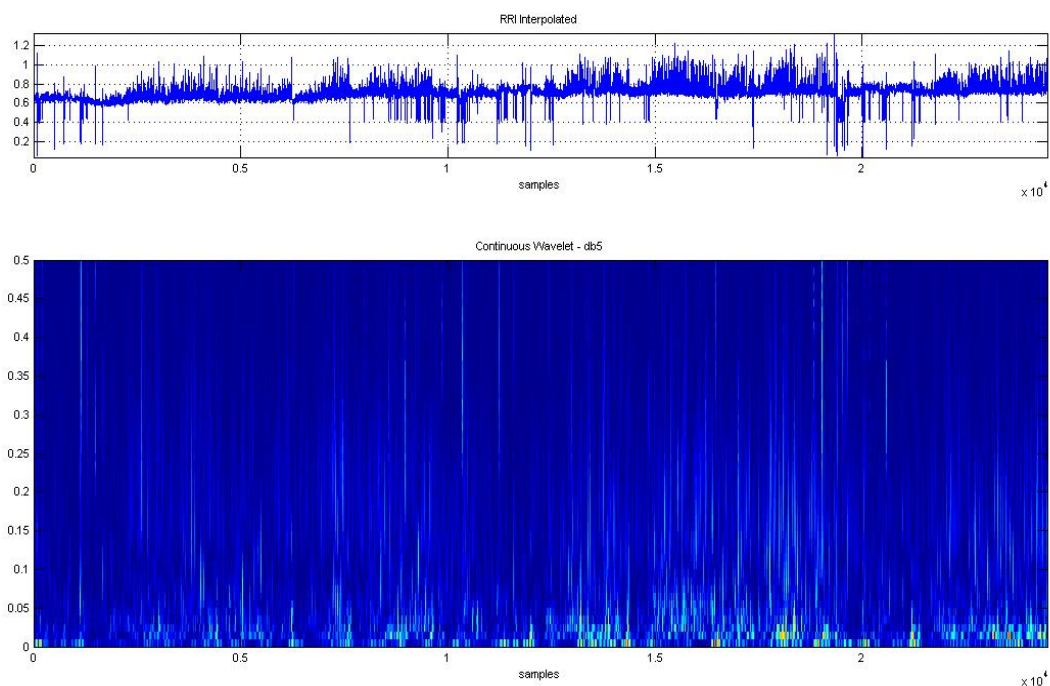
After extensive research, the purpose of this part of the work is to study the ECG and be able to classify the three sleep stages (Wake, REM and Sleep). This autonomic function was based on time-frequency analysis of the RR-Interval series, using the power components in very-low-frequency range (0,005-0.04Hz), low-frequency (0.04-0.15 Hz), and high-frequency (0.15-0.5 Hz).

##### 4.4.1 The RR-Interval Series

The R waves were automatically detected at the ECG, chapter 4.2, and their occurrences as a function of time composed the RR interval series (RRI). RRI was interpolated by equally spaced samples, and its time-frequency decomposition was performed by a continuous wavelet algorithm. The power was calculated in 3 standard frequency bands according to<sup>11</sup>:

1. VLF - very-low-frequency range (0.005-0.04Hz),
2. LF - low-frequency (0.04-0.15 Hz),
3. HF - high-frequency (0.15-0.5 Hz).

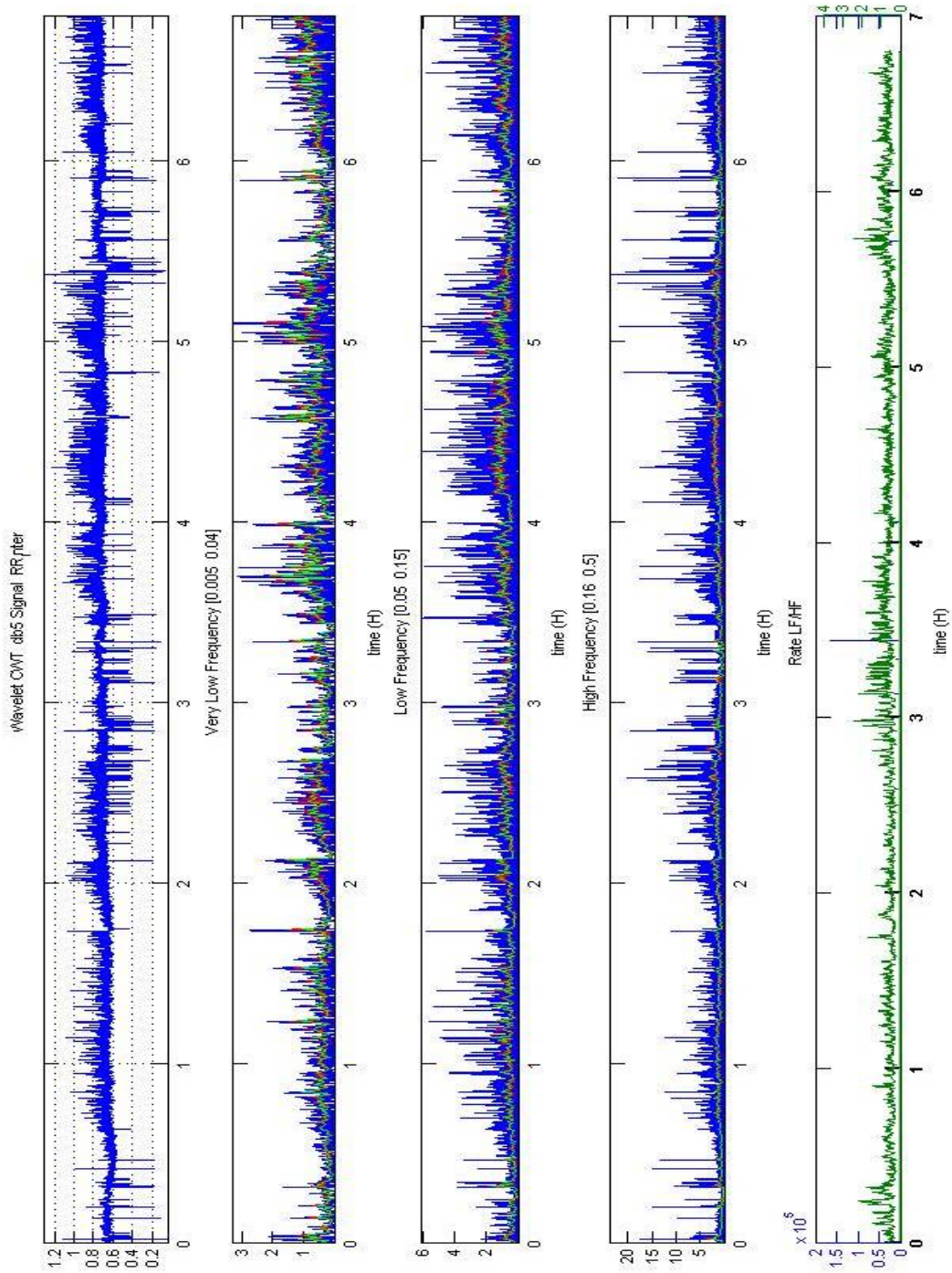
In figure 4.4.1, it is possible to observe the RRI Interpolated (graphic 1) and the continuous wavelet used db5 (graphic 2). This is a reference plot only, and the wavelet scalogram reveals no particular information, since it refers to an all night RRI and all the frequency bands. The RRI was interpolated to 4 Hz and the interest band limited to 0.5 Hz.



**Figure 4.4.1-** RRI Interpolated (graphic 1) and the continuous wavelet (graphic 2), for an all night session.

The frequency bands were extracted from the EEG signal via continuous wavelet transform with DB5. Figure 4.4.2, graphic 1 represents the RRI interpolated and graphic 2, 3 and 4 represent the power in the 3 standard frequency bands. For further studies, if necessary, the blue signal in graphic 2, 3 and 4 is the wavelet power, the red signal is the wavelet power using a 30 second sliding window, and in each window the average is calculated. And finally, the green signal is the power frequency using a window every 30 seconds with no overlap.





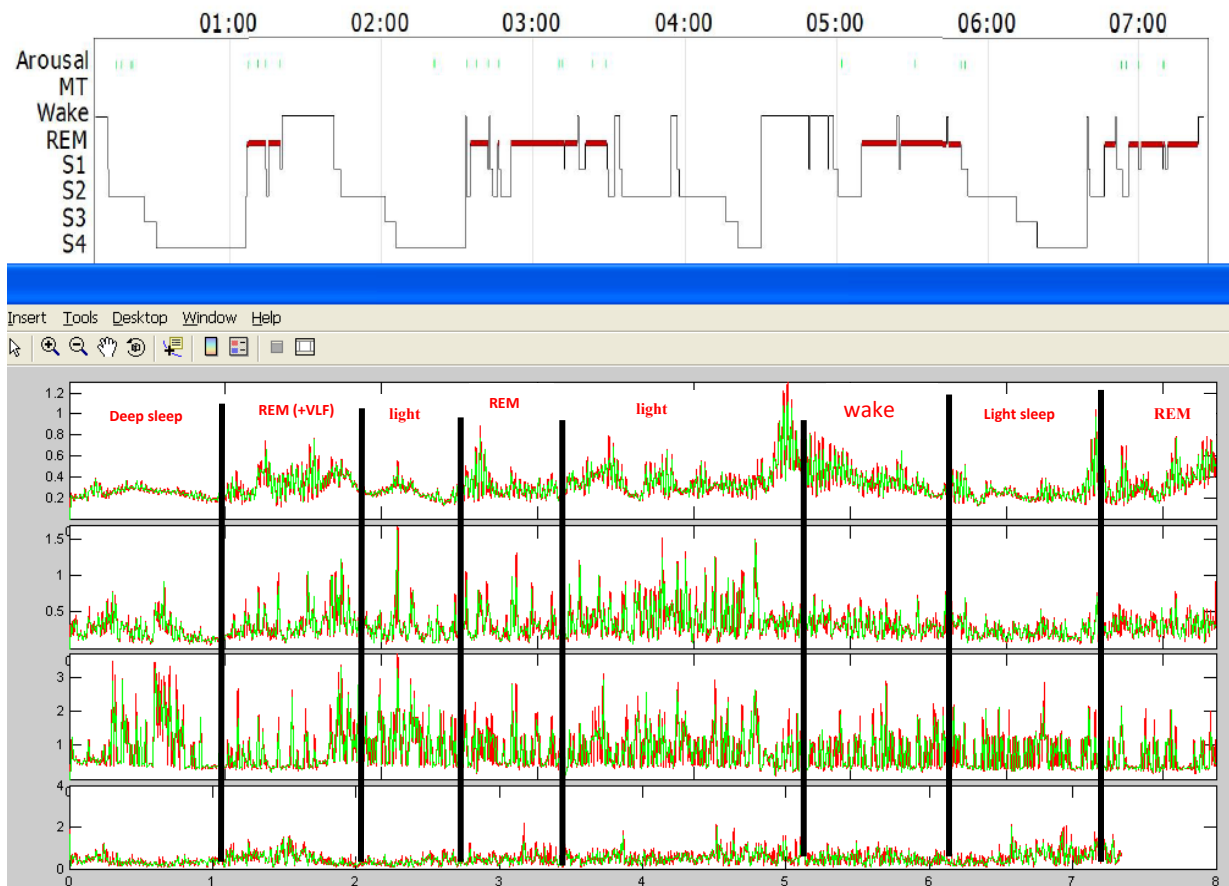
**Figure 4.4.2-** Graphic 1 – RRI interpolated, Graphic 2 – wavelet power frequency band (0.005-0.04) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds with no overlap. Graphic - 3 power frequency band (0.05-0.15) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds with no overlap. Graphic - 4 power frequency band (0.16-0.5) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds with no overlap. Graphic - 5 LF/HF ratio.

Subsequently, it is possible to analyze the frequency bands to create rules for the elaboration of the Hypnogram

#### *4.4.2 The Hypnogram*

The final goal of this chapter is to create a Hypnogram using the three frequency bands (VLF, LF, HF) and the LF/HF ratio described in chapter 4.4.1. There are no standard values for these parameters values in the wake, sleep and REM stages. The purpose of this chapter is to make a contribution in this area, still in need of extensive research. After studying various papers and documentation <sup>11</sup>, it was verified that the parasympathetic nervous system activity increases progressively and the sympathetic nervous system activity decreases after falling asleep. In order to obtain a Hypnogram a set of rules has to be created according to the alteration in frequency bands during changes in wake, sleep and REM stages. It is known, that the high frequency band is close to the respiration frequency, and represents the parasympathetic activity. The low frequency includes information of the parasympathetic and sympathetic activity. The sympathetic balance is defined by the quotient of the low frequency and the high frequency. Lastly, very high frequency is defined as the mental and physical activity.

At first, after studying several papers on this subject, it was necessary to visually observe the wavelet frequency bands and the respective curves of the VLF, LF, HF and the LF/HF. It is possible to observe in figure 4.4.3 what happens to frequency bands in each stage of sleep, and take the necessary conclusions, so that rules can be created.



**Figure 4.4.3-** Manual Monitoring: graphic 1- VLF, graphic 2 - LF, graphic 3 – HL and graphic 4 – LF/HF

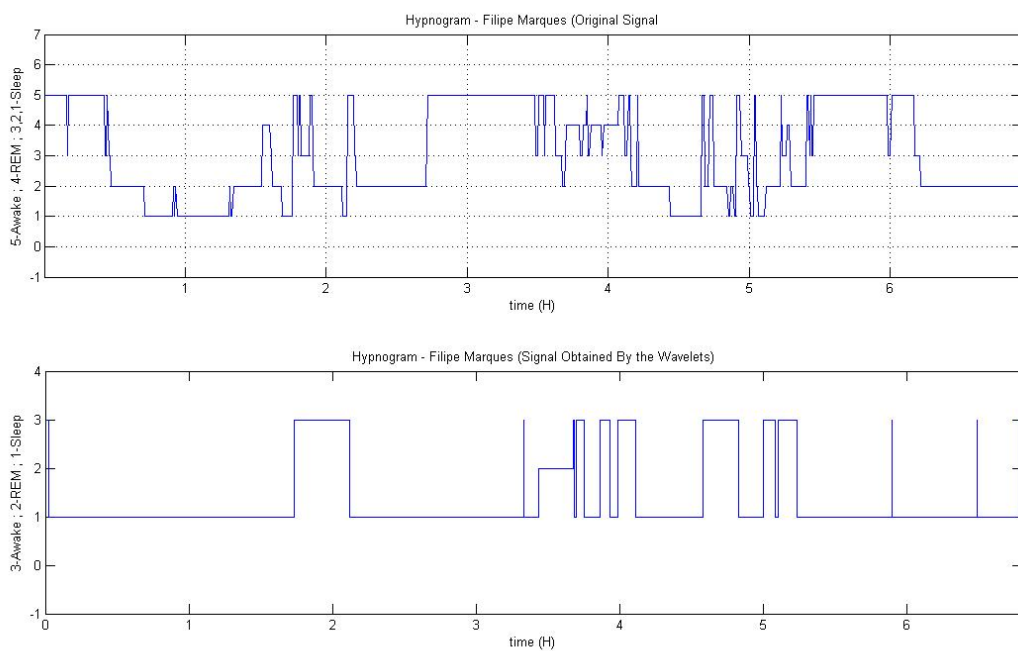
Initially, when the visual scoring was done, there were 4 states: awake, REM, light sleep and deep sleep. But since the three main states for sleep apnea are the awake, REM and sleep ones, those were the ones defined. Rules had to be created to distinguish between each state.

1. During the awoken state, the mental and physical activity is very high; this corresponds to the VLF band; the parasympathetic activity (HF band) and the LF band are very low. VLF is high and HF and LF are very low.
2. During the REM state, the mental and physical activity is high (lower then while awake), and the sympathetic balance is high. VLF is high (but lower then awake) and LF/HF is high.
3. During the sleep state, mental and physical activities (VLF band) are low, and so is the sympathetic balance (LF\HF band). The parasympathetic activity (HF band) is high. VLF is low, LF\HF is low and HF is high.



The energy in each band and for each epoch was divided in four steps: Very High, Low and Very Low. This scoring was applied to each of the frequency bands.

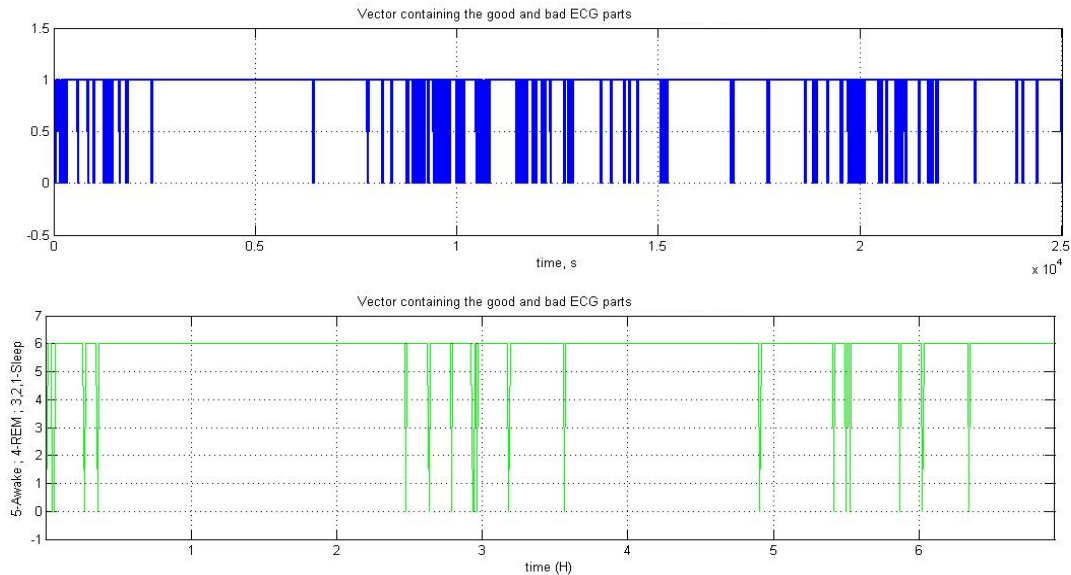
All these states were computed so that it is possible to generate an automatic hypnogram using the ECG signal. A major problem arose; *how can the Hypnogram signals be compared?* Initially (chapter 4.2) were the algorithm detected noise in the ECG signal, those parts were deleted from the ECG signal and the ‘good’ parts were placed together, so there is missing data. On the other hand, the Hospital hypnograms do not have missing data, since all the artifact epochs were replaced by previous ones. If a hypnogram is obtained from the ECG signal, the two graphics cannot be compared if artifact data has been removed. Figure 4.4.4 shows the reference Hypnogram and our version. The results are obviously not good for reasons we proceed to explain.



**Figure 4.4.4-** The two Hypnograms; graphic 1 - hypnogram signal of a patient under study, graphic 2 – hypnogram obtained from the ECG signal

In chapter 4.2 the artifact beats were eliminated and removed. There is a vector, stored in the memory, containing all information of the eliminated beats. That vector has a 200 Hz sampling frequency. In figure 4.4.5 it is possible to observe the vector

with a 200Hz sampling frequency. But our Hypnogram has a 4 Hz sampling frequency so it is necessary to apply a down sample to the graphic (200Hz to 4Hz)

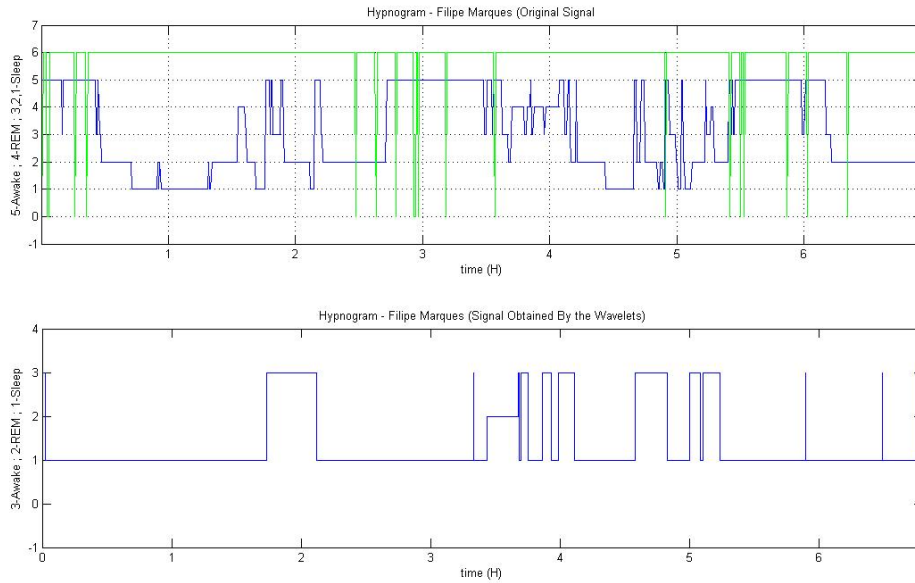


**Figure 4.4.5-** artifact beats were eliminated and removed; graphic 1 – vector containing the eliminated beats (when the vector is zero valued), graphic 2 – down sample of graphic 1 (200Hz to 4Hz)

Figure 4.4.5 shows that many information is lost by down sampling the vector. This lost information is important to compare the two graphics. There are two solutions for future studies - either the artifacts beats are not eliminated and instead replaced by good beats, or the professional sleep technicians performing the visual scoring only in the intervals classified as having good ECG beats. This last option seems rather unlikely since the visual scoring is time-consuming.

Another important issue is that the Hypnogram signal that serves as a comparison has more sleep states (awake, REM, S4, S3, S2 and S1) than the one obtained by the ECG signal (awake, REM and sleep). To be able to compare those states, S4, S3, S2 and S1 must be analyzed as corresponding to the sleep state in our work.

In figure 4.4.6 it is possible to view the two hypnograms.



**Figure 4.4.6-** Hypnograms. Graphic 1 – Represents the original Hypnogram (blue signal). The green signal is the vector containing the removed artifacts and a down sample is applied; graphic 2 – represents the hypnogram obtained by the ECG signal using wavelet (describe chapter 4.4.1)

There are some correspondences in the two graphics, although this part of the algorithm requires further studies. The wavelet used to obtain frequency bands (VLF, LF and HF) still has to be studied, which one can offer more results. The one used in this work is the continuous wavelet 'db5':

```
[C_VLF C_LF C_HF C_LF_HF C_VLF_filtro1 C_LF_filtro1 C_HF_filtro1
C_LF_HF_filtro1] = wave_cwt_laral(RRI_interp,'db5',4,'RR_inter',0.01);
```

It is also important, for further work, to have a hypnogram corresponding to the hypnogram obtained from the ECG signal, since the comparison achieved in this study was not the one desired.

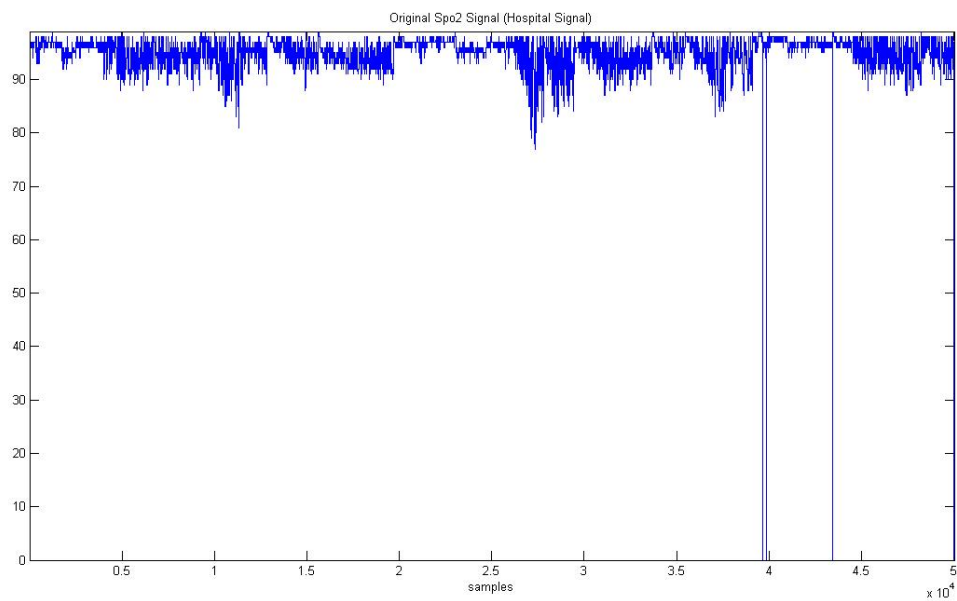
Although this part of the work still needs further research, it has been proved here that it is possible to obtain a hypnogram from an ECG signal. This technique can be very useful to track sleep disorders, since the ECG signal is easily obtained it is much less expensive and would allow for ambulatory recordings.

## 4.5 Computing the Oxygen Desaturation Indices

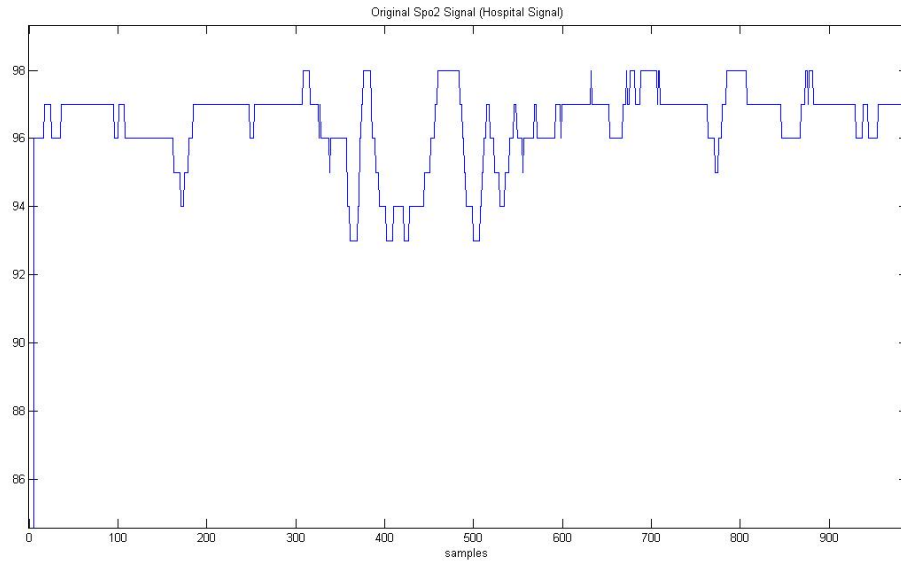
### 4.5.1 Removing noise from the SpO<sub>2</sub>

This signal is very basic; figure 4.5.1 represents an original SpO<sub>2</sub> Signal from the hospital, and figure 4.5.2 zooms in on figure 4.5.1, so it is possible to observe the signal structure.

In this signal the only noise that exists is when the signal equals zero (due to the sensor falling off), and it is not necessary to eliminate that part of the signal, it is just not considered as an oxygen desaturation event at all.

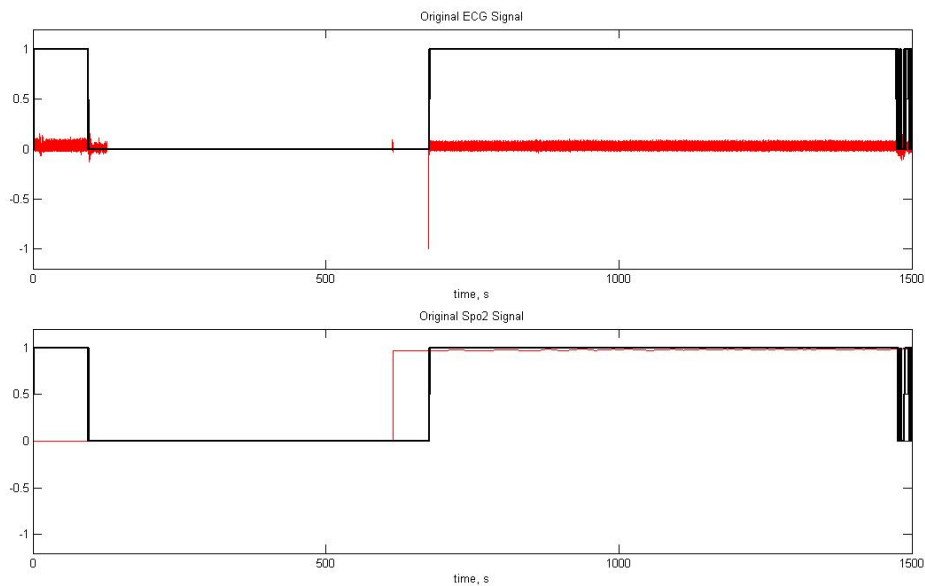


**Figure 4.5.1-**An Original SpO<sub>2</sub> Signal.

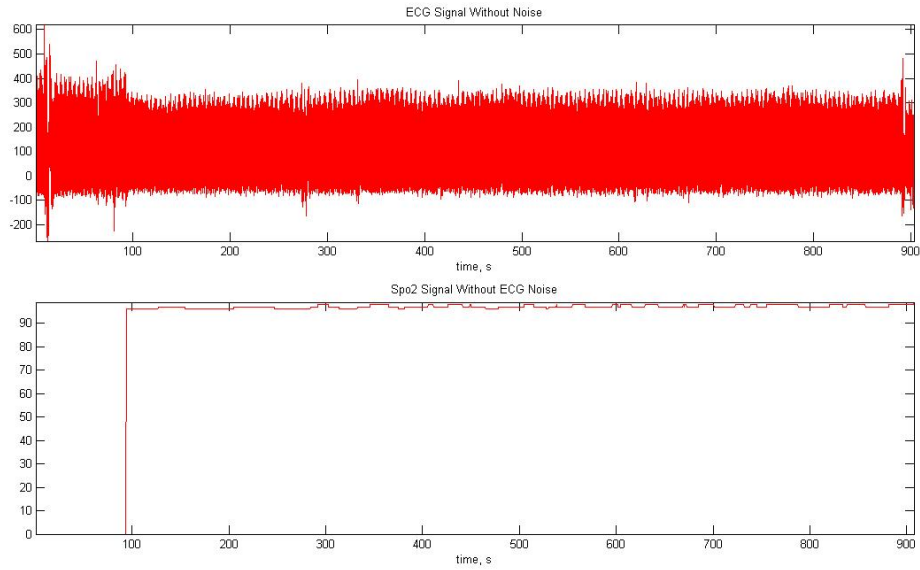


**Figure 4.5.2**-Zoom of figure 4.5.2.

Even though there is some noise to be removed from this signal, it is necessary to remove first, from the signal, the parts taken from the ECG signal, so that they have the same length. It is possible to view the signals in figure 4.5.3 and in figure 4.5.4.



**Figure 4.5.3**-Grafic 1-Original ECG (red), and the Rectangle Signal (black) - is one it is a good signal, zero represents noise. Grafic 2-Original Spo2 (red), and the Rectangle Signal (black) is the same as in graphic 1.



**Figure 4.5.4**-The two signals with the same length.

#### 4.5.2 Computing indices of SpO2

To compute the indices of SpO2, as described in chapter 2.2.2, there has to be a  $\geq 4\%$  desaturation from pre-event baseline and zeros do not count. It is a very simple algorithm. It is possible to compare in table 4.5.1 the results of the algorithm and the hospital results.

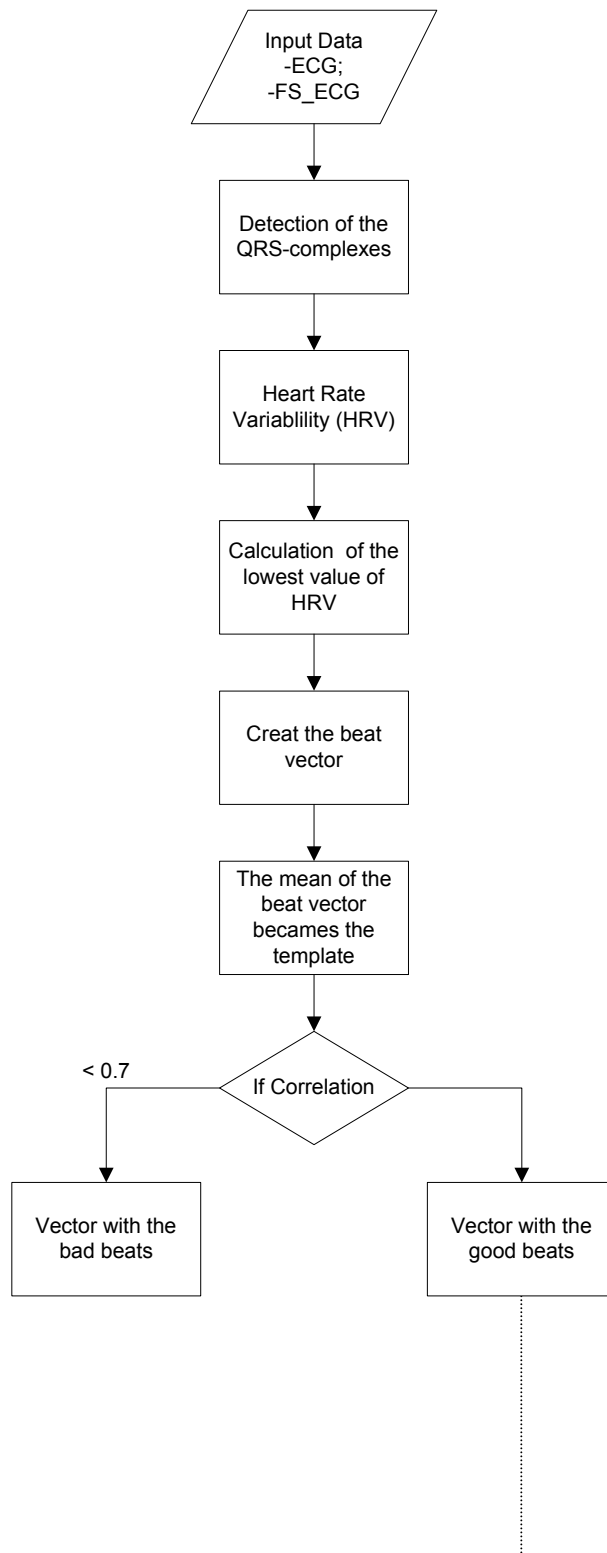
**Table 4.5.1**- Comparing results.

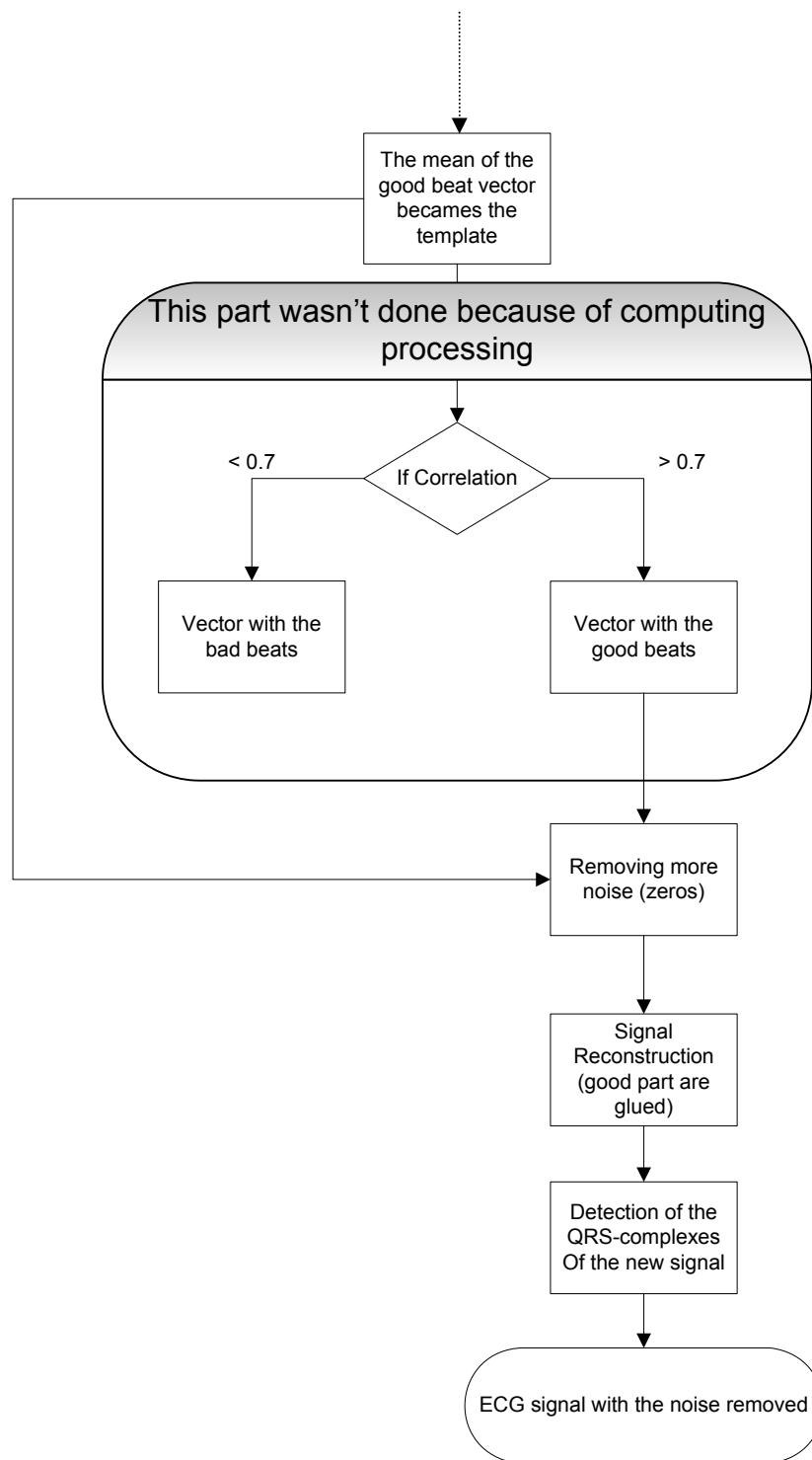
Output from matlab (using the developed software tool)	<div style="background-color: #e6f2ff; padding: 10px; display: inline-block;"> <b>Saturation of SPO2: 268</b> </div>
Polysomnography Report (hospital)	<p style="text-align: center;">Oxygen Desaturation Events (OD): <span style="float: right;">275</span></p>

# 5 Flowchart of the Functions

---

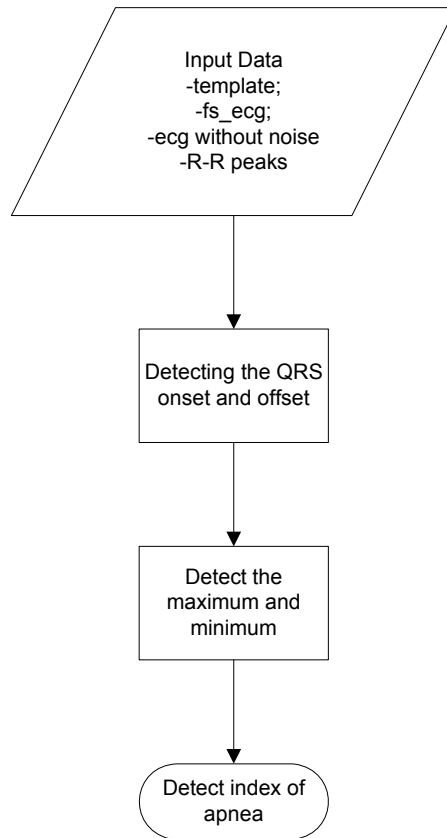
The first flowchart represents the function that removes the noise from the ECG, as described in chapter 4.2.



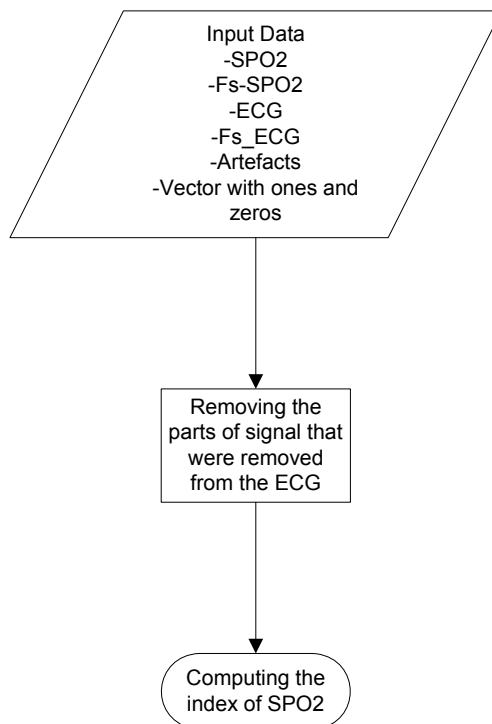


The second flowchart represents the function that produces the respiration signal and gives the index of apnea, as described in chapter 4.3.

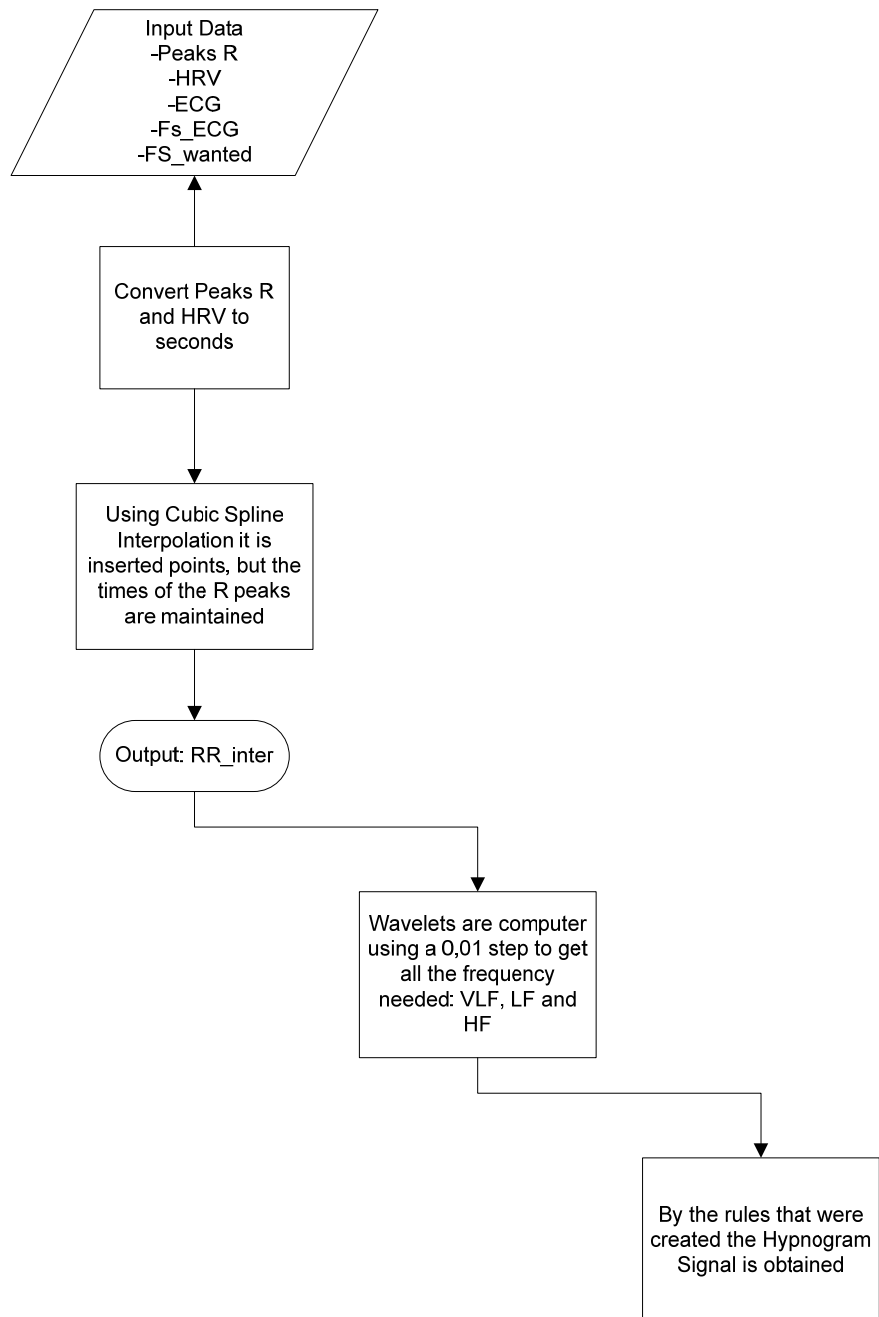




The third flowchart represents the function that Computes the Oxygen Desaturation Indices and gives the index of apnea, as described in chapter 4.5.



And the fourth flowchart represents the function that Computes the Hypnogram graphic, as described in chapter 4.4.



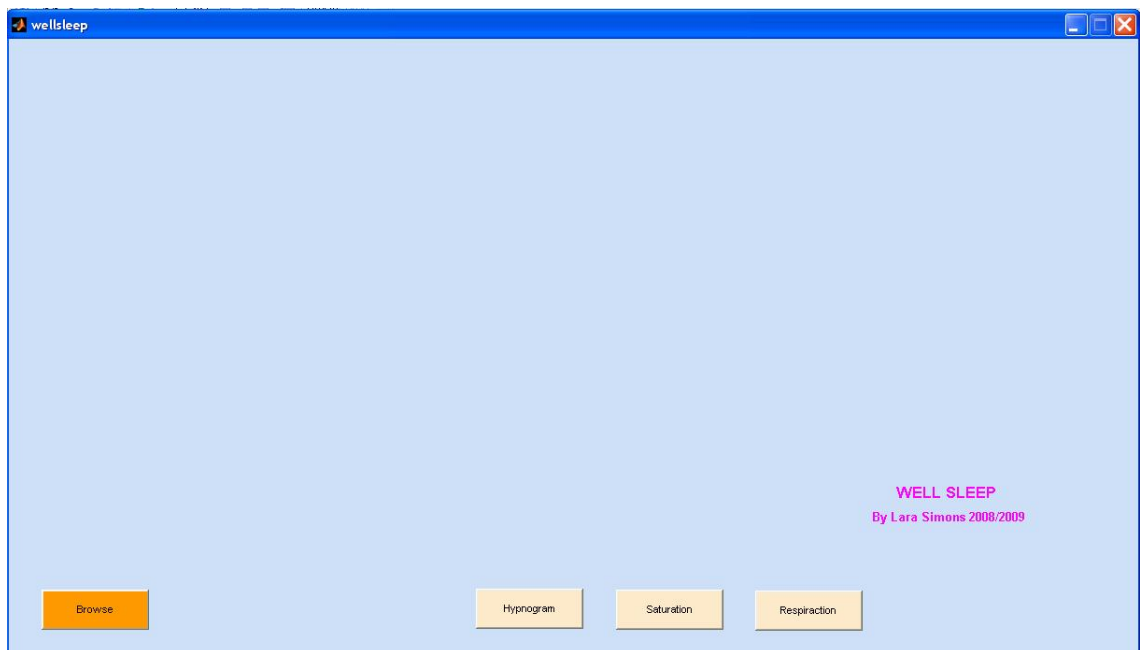
# 6 Graphical User Interface

---

A Graphical User Interface is needed to make it easier to run the algorithm. As it was explained previously in chapter 4, most functions depend on other functions, thus, it is rather difficult to run the algorithm without an interface.

This Graphical User Interface has to be user-friendly. It has been designed for professionals in the medical area and it is a working tool. The easier the Interface is, the faster the tool can be used to help diagnose Obstructive sleep apnea syndrome.

The Interface will open with the following window, figure 5.1



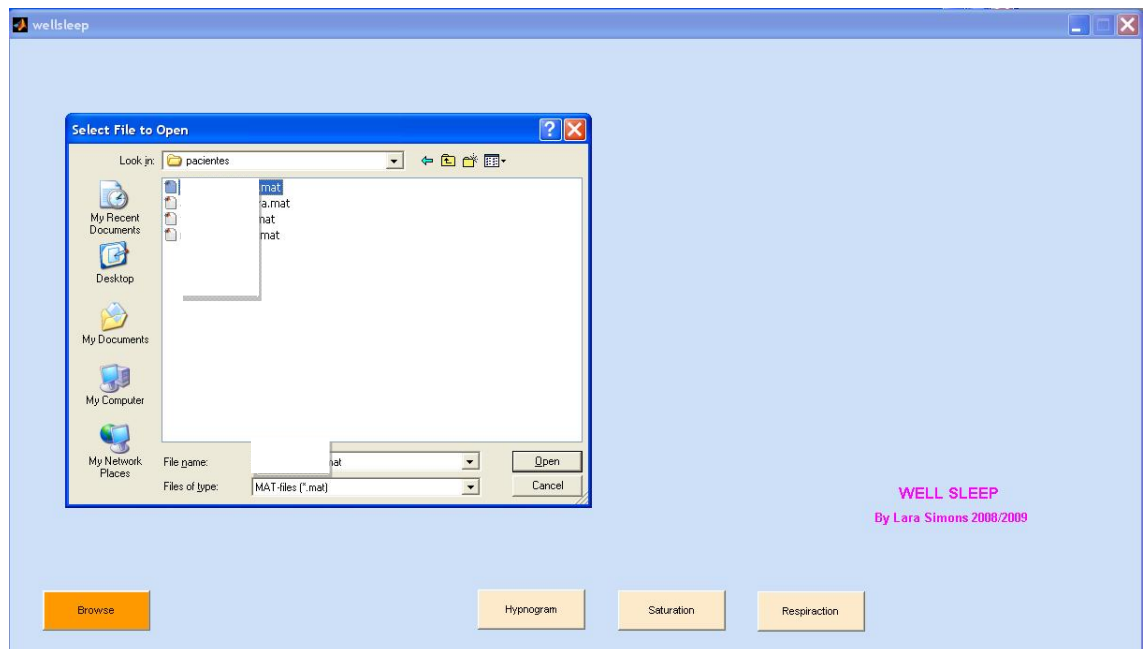
**Figure 5.1-** First Interface window.

There are four rectangular buttons. The first one is the browse Button, to get the patient's data to be examined. It is important to notice that the patient's data has to be in a certain Matlab format:

dados =

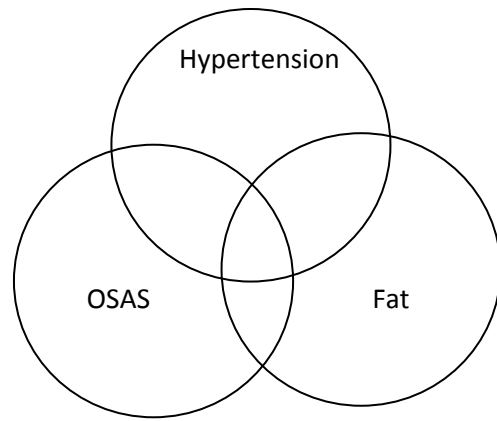
```
nome: 'Manuel Farinha'  
idade: '55'  
morada: 'Rua das Cravos'  
peso: 78  
pressao: '13'  
ecg: [1x5334000 double]  
spo2: [1x53340 double]  
telemovel: '924536543'
```

Figure 5.2 shows the patient's data already in the proper Matlab format, it is then possible to browse a patient's data and run the algorithm.



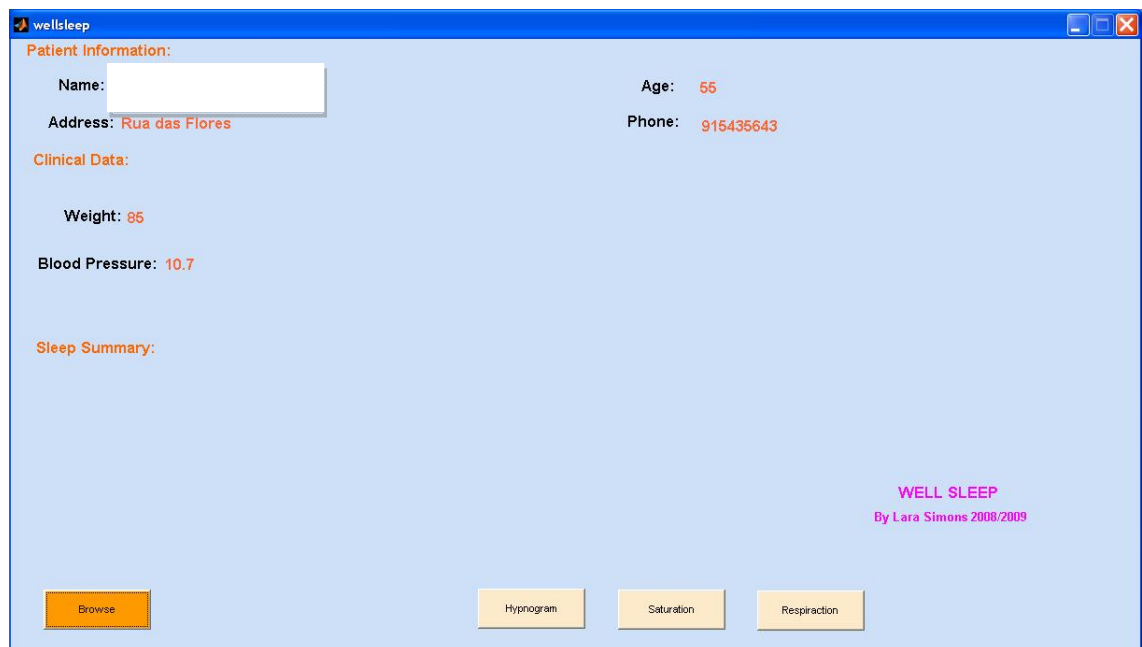
**Figure 5.2-** Browse window.

In the following window it is possible to observe the Patient Information, so it is possible to contact the patient if necessary. It is also possible to view the patient's clinical data – this information is very important because Obstructive Sleep Apnea Syndrome (OSAS), hypertension and obesity are all connected, making it very important to the medical professionals to have access to this information.



**Figure 5.3-** Figure based on a medical class I attended (Prof. Cristina Barbara).

In Figure 5.4 it is possible to see the patient's information window.



**Figure 5.4-** Patients Information window.

By clicking the browse button, the patient's information shows up, and it is possible to see three graphics that represent the ECG signal, with the noise removed and the SPO2.

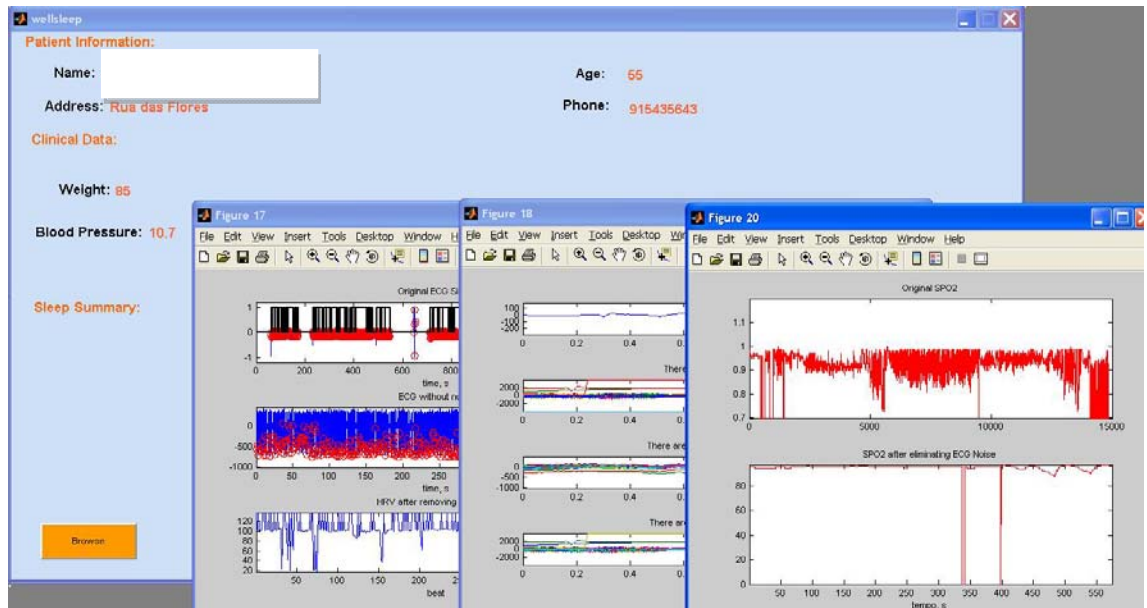


Figure 5.5- ECG and SPO2 signal windows, with the noise removed.

After having all the patient's information, three buttons can be loaded:

1. Hypnogram Button
2. Saturation Button
3. Respiration Button

These buttons will show information that is important for the Medical Professionals to diagnose OSAS.

When click the Hypnogram Button four graphics appear. The first one shows the RRI interpolated, and the Continues Wavelet. The second and third ones show the RRI interpolated, and the power components: very-low-frequency range (0,005-0.04Hz), low-frequency (0.04-0.15 Hz), and high-frequency (0.15-0.5 Hz). And the fourth graphic shows the Hypnogram.

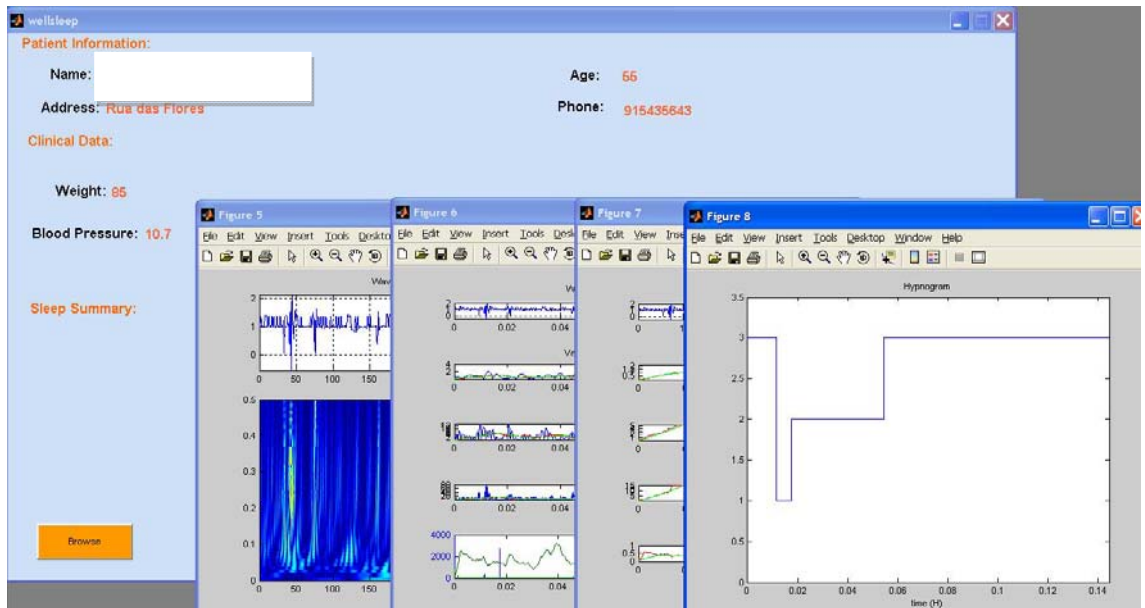


Figure 5.6- Hypnogram window.

If on clicks on the Saturation Button the Desaturation events pop up.

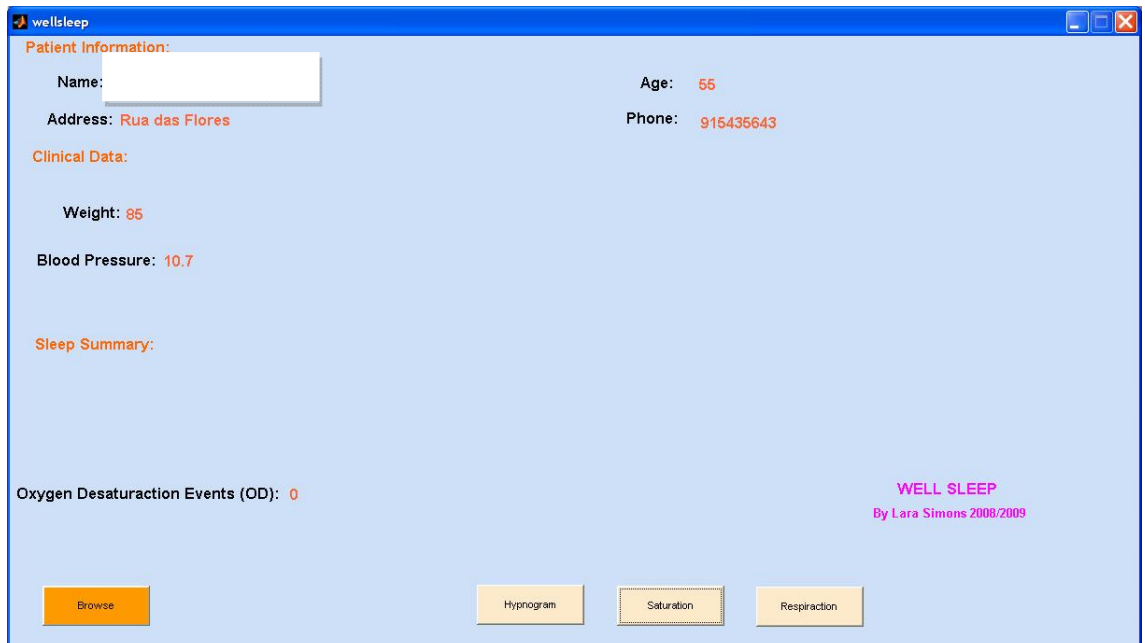


Figure 5.7- Saturation window.

Finally, by clicking the Respiration Button two graphics show up. The first one shows the template, the respiration signal with the automatic onset and offset QRS, and the respiration signal with the standard onset and offset QRS. The second graphic shows the detection of the maximum and minimum points and the amplitudes. Lastly, the apnea events show up in the interface window.



Figure 5.8- Respiration window.

Eventually, in the interface window behind the patients' information, it might be possible to observe the sleep summary (Apnea events and Desaturation Events).

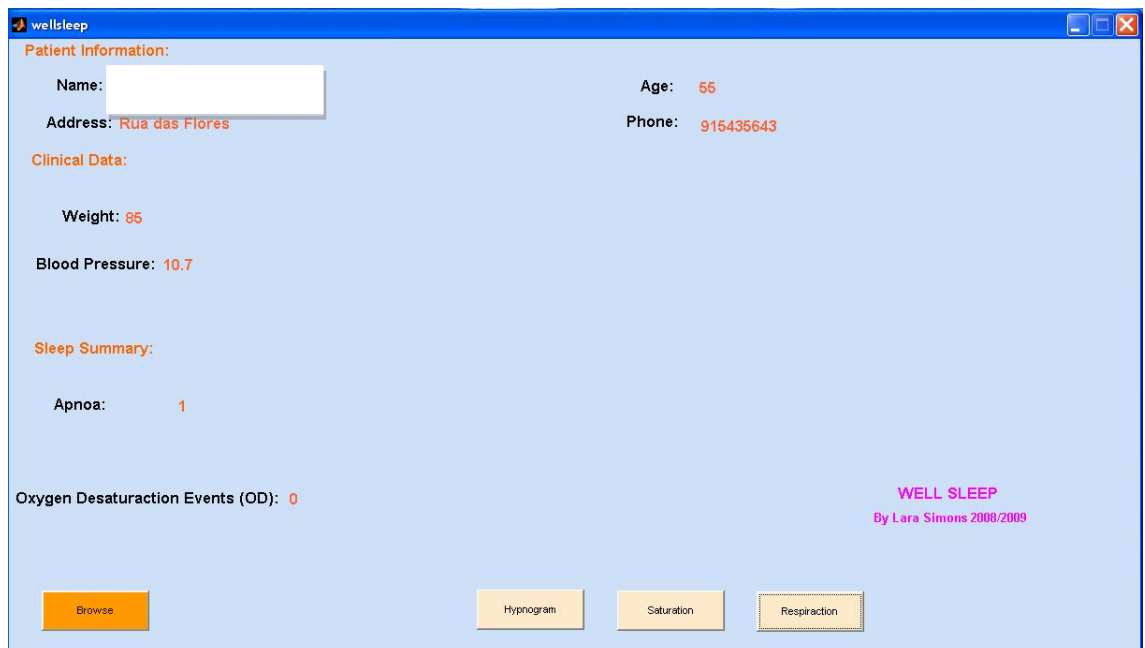


Figure 5.9- Sleep Summary window.



# 7 Final Results

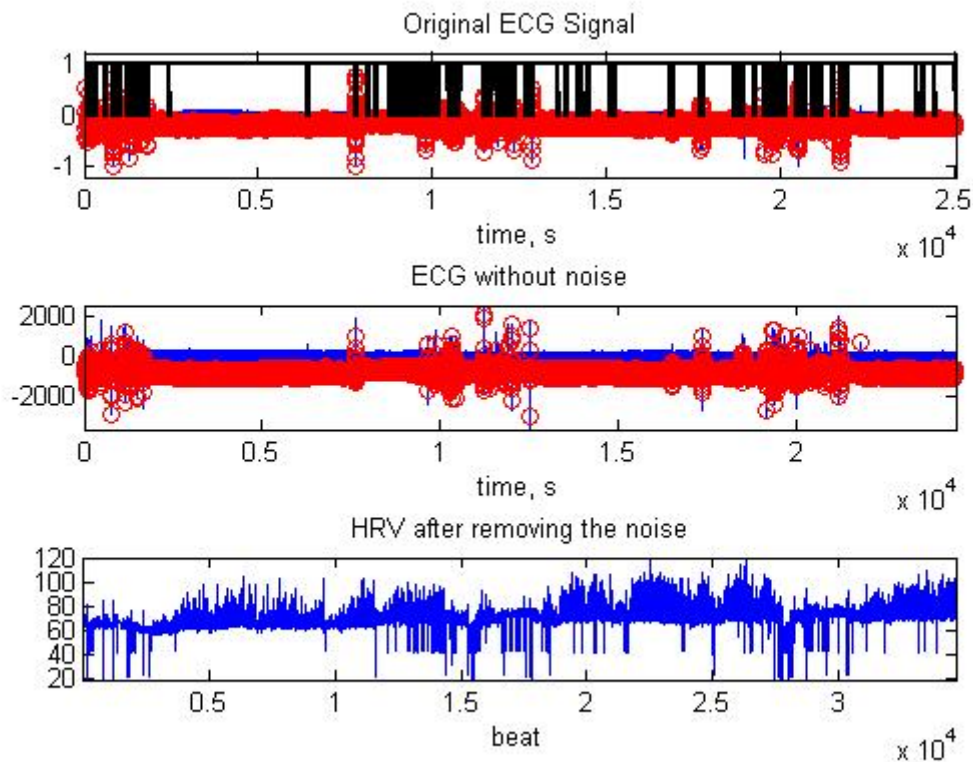
---

Finally, since the entire algorithm has already been presented, it is possible to observe in this chapter the results of applying the said algorithm, to the two signals (ECG and SPO2).

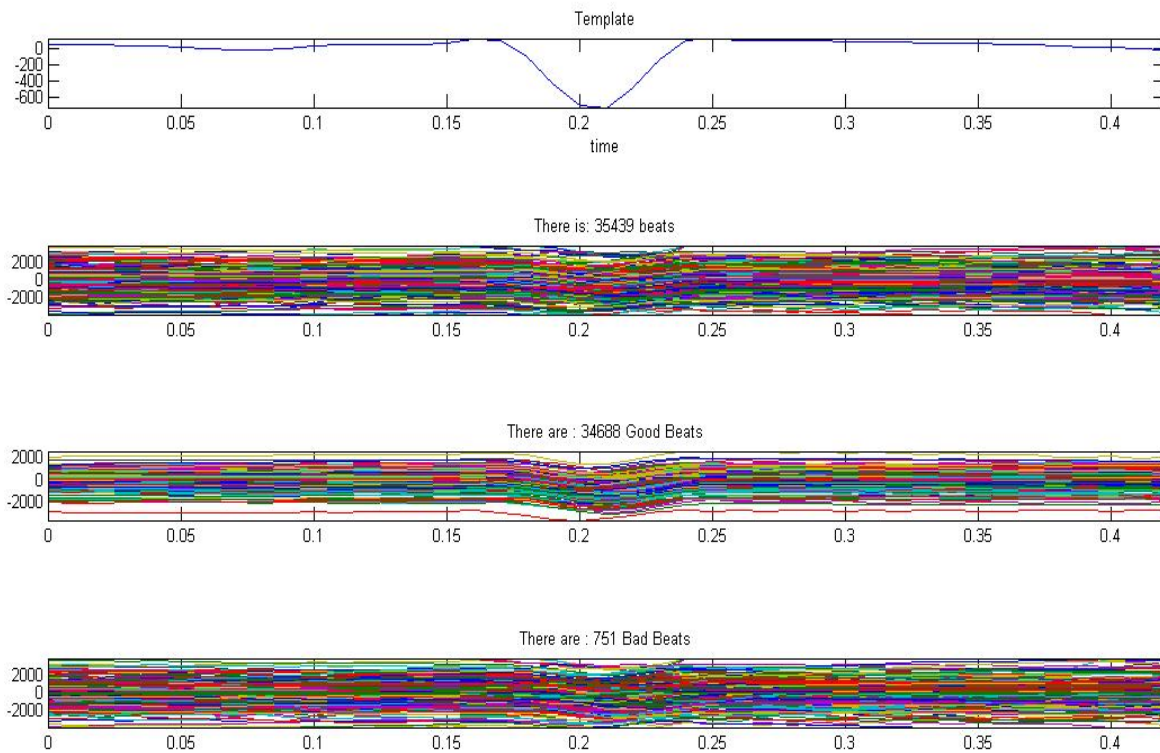
Three major results will be present. The comparison point will be the reports that the hospital gave. In the previous chapters each part of the work was tested separately (removing the artifacts' beats from the ECG signal, detecting the apnea and oxygen desaturation events and the creation of the hypnogram). In this chapter all parts of the work will be tested together. Graphics for each result will be shown, as well as the sleep summary.

## The first result – Patient 1

These first two graphics are describe in chapter 4.2



**Figure 7.1** - Removing the artifacts' beats from the ECG signal.

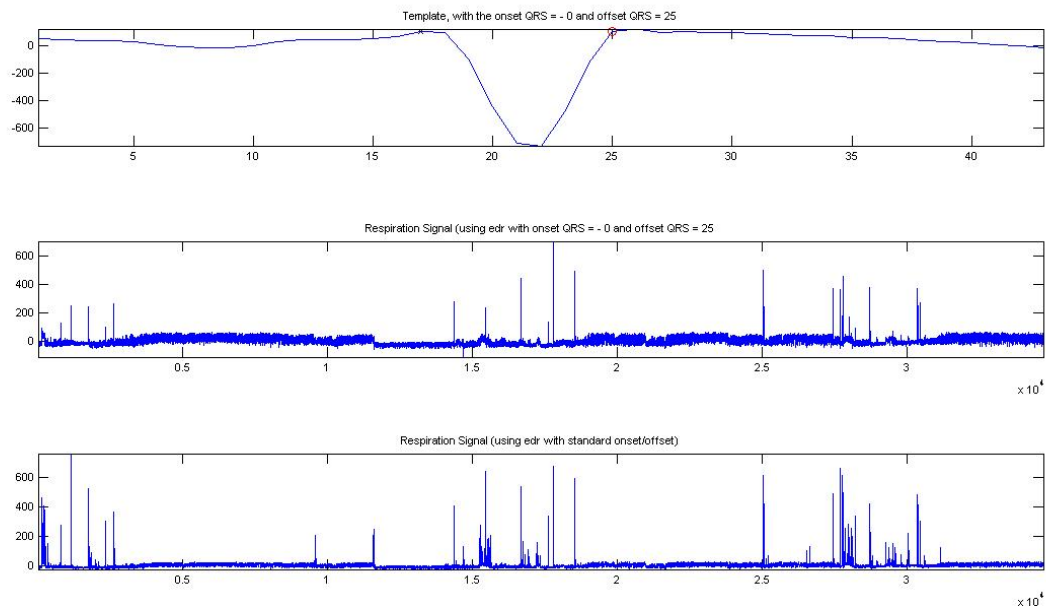


**Figure 7.2-** Graphic 1 –Template, Graphic 2 – Total beats (35439 beats), Graphic 3 – Good beats and Graphic 4 – Bad beats, the ones that will be removed.

In figure 7.1, it is possible to observe that this ECG signal has less artifact beats. Graphic 1 shows the template obtained by the mean of all beat vector, that is, 35439 beats. It has been explained in a previous chapter (Chapter 4.2) that this function would work better if, instead of using the template obtained from ALL beats, it used the template with only the good beats. This creates a problem - Computing Process. In this particular case the ECG signal does not have various artifacts, so the algorithm works well. Another important issue to observe is that there were 751 beat eliminated from the ECG signal. Since each beat corresponds to more or less (+/-) 1 second, there were more or less (+/-) 751 seconds eliminated from the ECG signal, this which will bring problems in further comparisons.

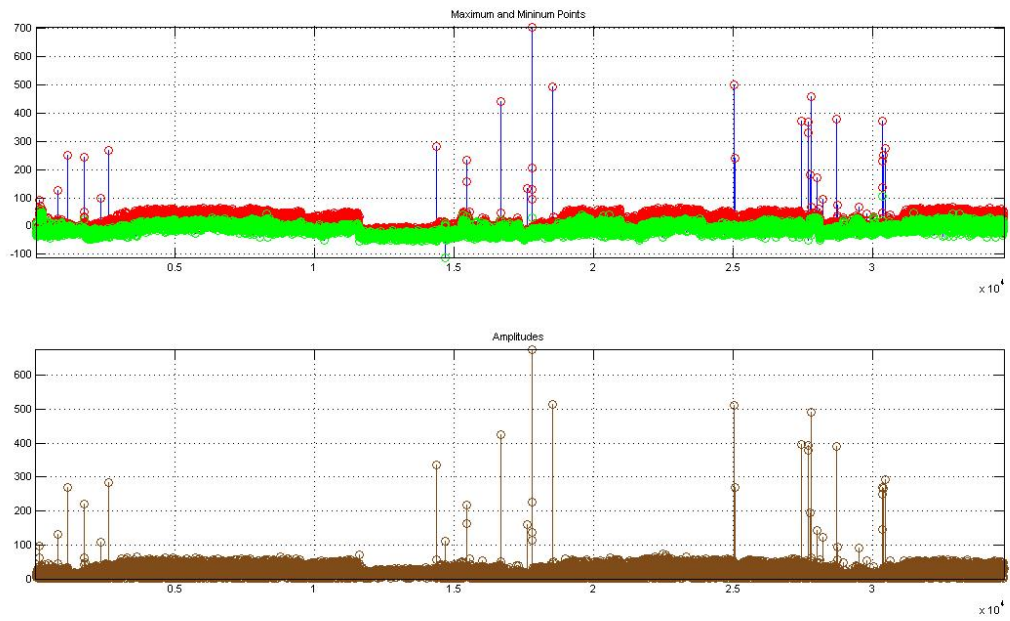
In figure 7.1, graphic 2, an ECG signal is obtained without the artifacts' beats. With this signal, the R-R peaks are detected using the mean of the good beats vector and the template is finally obtained using the algorithm designed by Carlos Mendes, obtaining the onset and offset. It is then possible to achieve the respiration signal using the EDR technique.

```
sinalresp_final_1=edr(hdr_final',ecg_sem_ruido,[-40 40],fa);
```



**Figure 7.3-** Graphic 1 –Template (mean of the good beats), Graphic 2 – Respiration Signal with non standard onset and offset, Graphic 3 – Respiration Signal with standard onset and offset

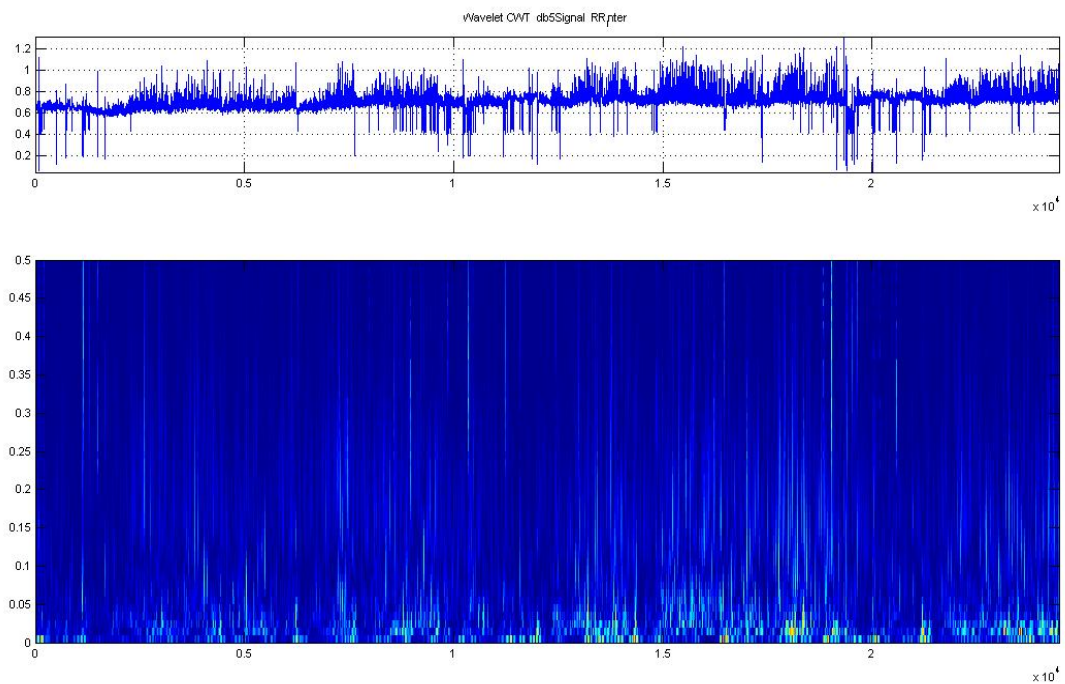
Using the respiration signal and by detecting the maximum and minimum points, it is possible to obtain the respiration amplitudes. With the respiration amplitudes, it is possible to detect apnea events. The algorithm used to detect the apnea events has been described in chapter 4.3.2. The number of apnea will be present afterwards, in the user interface - sleep summary (figure 7.10).



**Figure 7.4-** Graphic 1 – The Respiration Signal (EDR) with the maximum (red) and minimum (green) points detected, Graphic 2 – Respiration Amplitudes

Graphic 7.3 and 7.4 are explained in chapter 4.3.

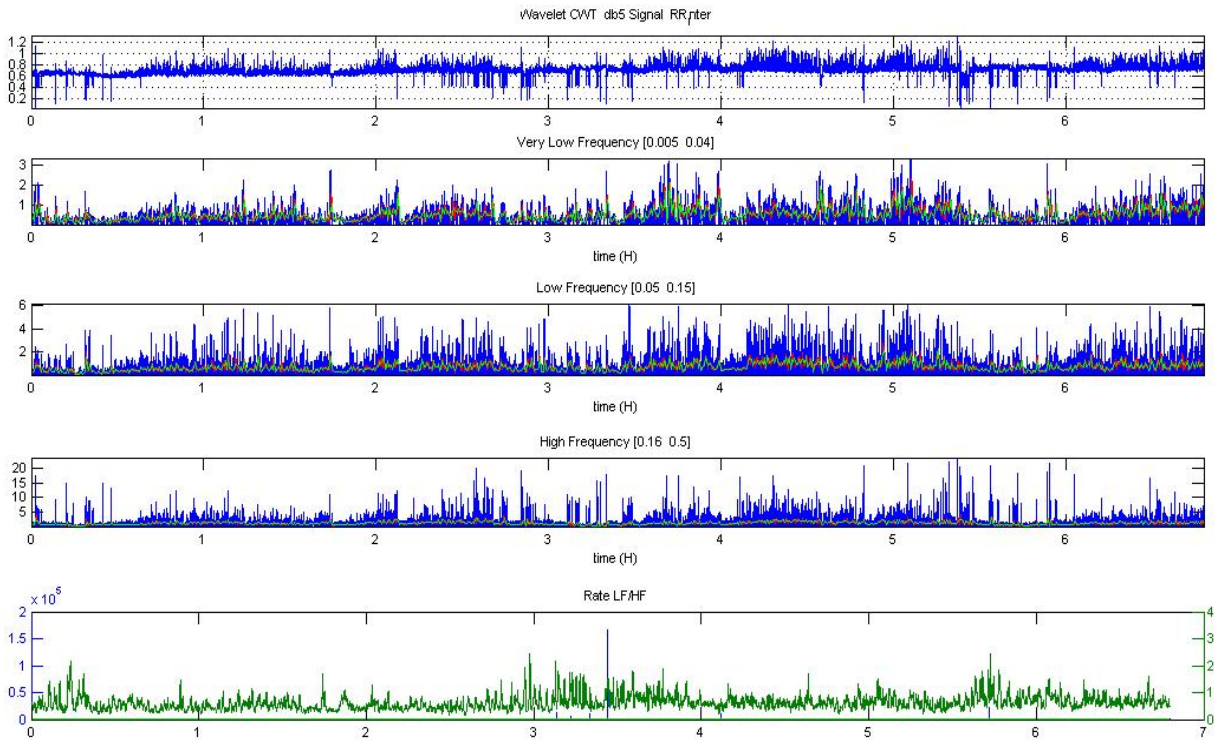
From the ECG signal RR interval series (RRI) are obtained. RRI was interpolated and a continuous wavelet applied.



**Figure 7.5 –** Graphic 1 – RRI interpolated, Graphic 2 – Continuous Wavelet

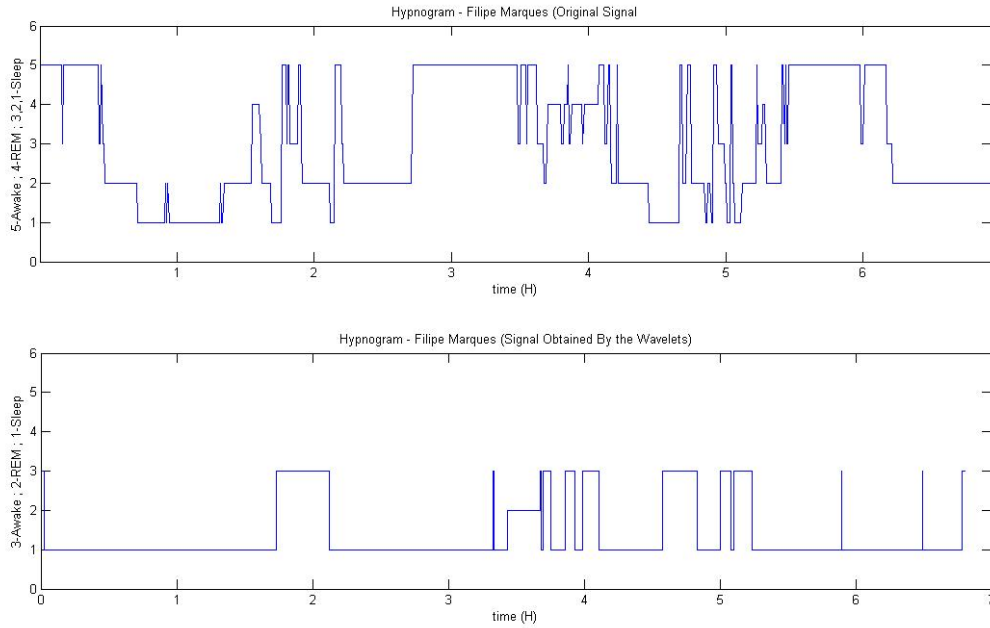
The frequency bands were extracted from the EEG signal. Those bands correspond to very low frequency (VLF [0.005 0.04]), low frequency (VF [0.05 0.15]) and high frequency (HF [0.16 0.5]).

Figure 7.5 and figure 7.6 are described in chapter 4.4.1



**Figure 7.6-** Graphic 1 – RRI interpolated, Graphic 2 - power frequency band (0.005-0.04) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 3 power frequency band (0.05-0.15) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 4 power frequency band (0.16-0.5) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 5 LF/HF ratio

Finally, after applying the rules that were described in chapter 4.4.2, the Hynogram was created.



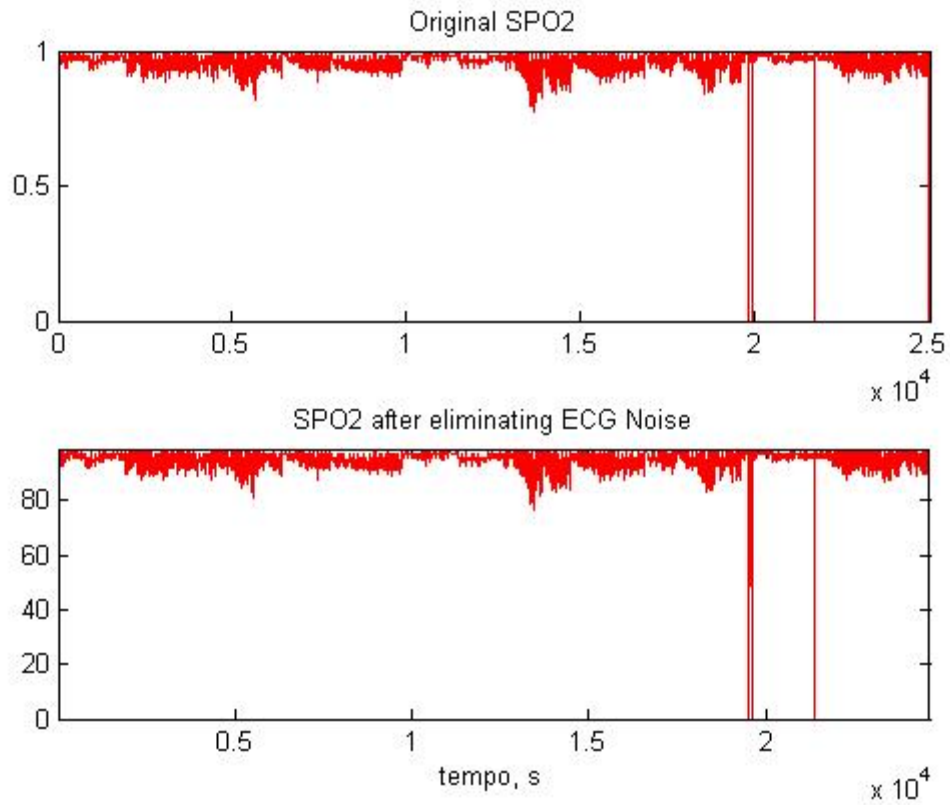
**Figure 7.7-** Hypnogram. Graphic 1 – Original Signal, graphic 2 – Signal obtained by the wavelets

Figure 7.7 is very difficult to compare for the aforementioned reasons (chapter 4.4). The main purpose is to prove that with more studies this algorithm is can be used and will bring a good advance in detecting apnea.

Further studies can focus on which continuous wavelet has to be used to extract frequency bands from the EEG signal. Is there differences in the results if the frequency bands uses a sliding window of 30 seconds, or the signal uses a window of 30 seconds or simply if it uses the power frequency band. And finally, more information about each frequency band creates better rules for better results.

Figure 7.8 showed below correspond to the Oxygen Desaturation. This figure simply shows that the artifacts' beat eliminated in the ECG signal have also been eliminated in the SPO2 signal.



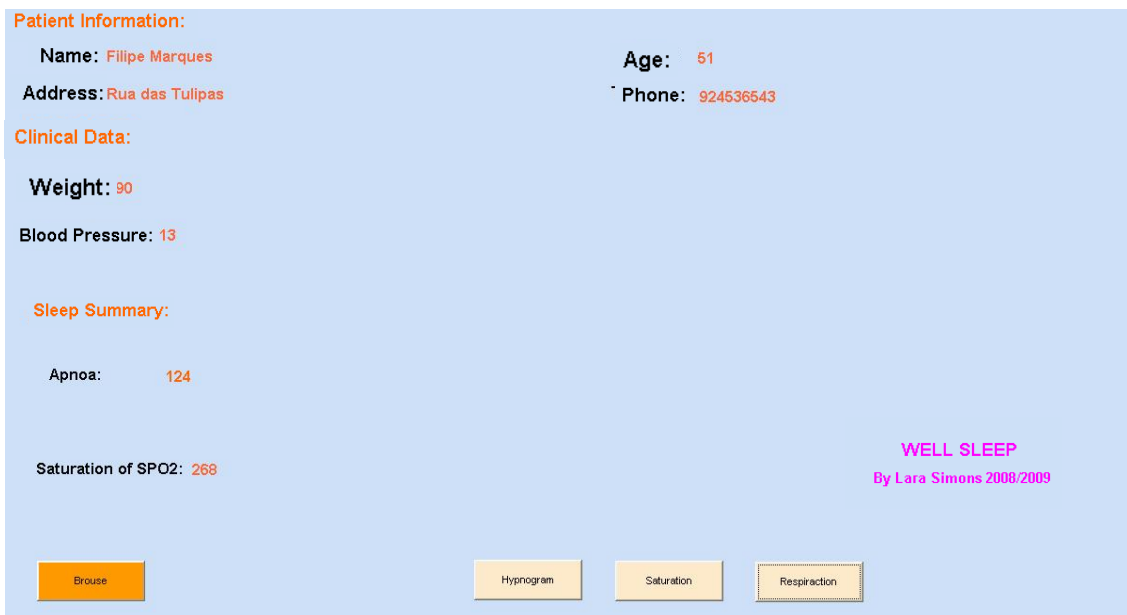


**Figure 7.8-** Oxygen Desaturation. Graphic 1 – The Original SPO1 and graphic 2 – SPO2 after removing the artifact beats removed in the ECG signal

Finally, the user interface gives the sleep summary. This sleep summary is to be compared with the hospital report.





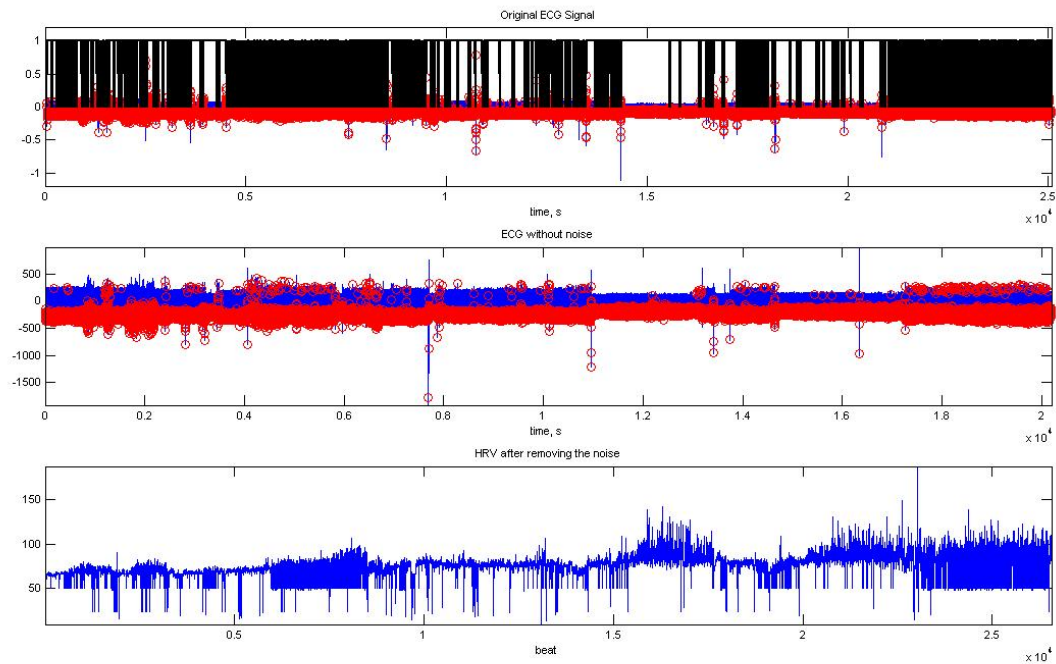


**Figure 7.10** - Sleep Summary – Note: the Patient Information and Clinical Data are fictitious

The results are fairly satisfactory for patient 1 - regarding apnea events the algorithm counted 124 events and the hospital report 174. It must be taken into consideration that the respiration signal was obtained by the ECG signal, which, in turn, had the artifact beats removed. As for the Saturation of SPO2 / Oxygen Desaturation (OD) the algorithm counted 268 and the hospital report 275. Taking into account that the ECG artifacts were also removed from the SPO2 and that the baseline is normally detected manually, and in this case, it is the mean of the first ten points, the results are very satisfactory. The difference between the number of apnea events is 50, while the Oxygen Desaturation (OD) the difference is only 7.

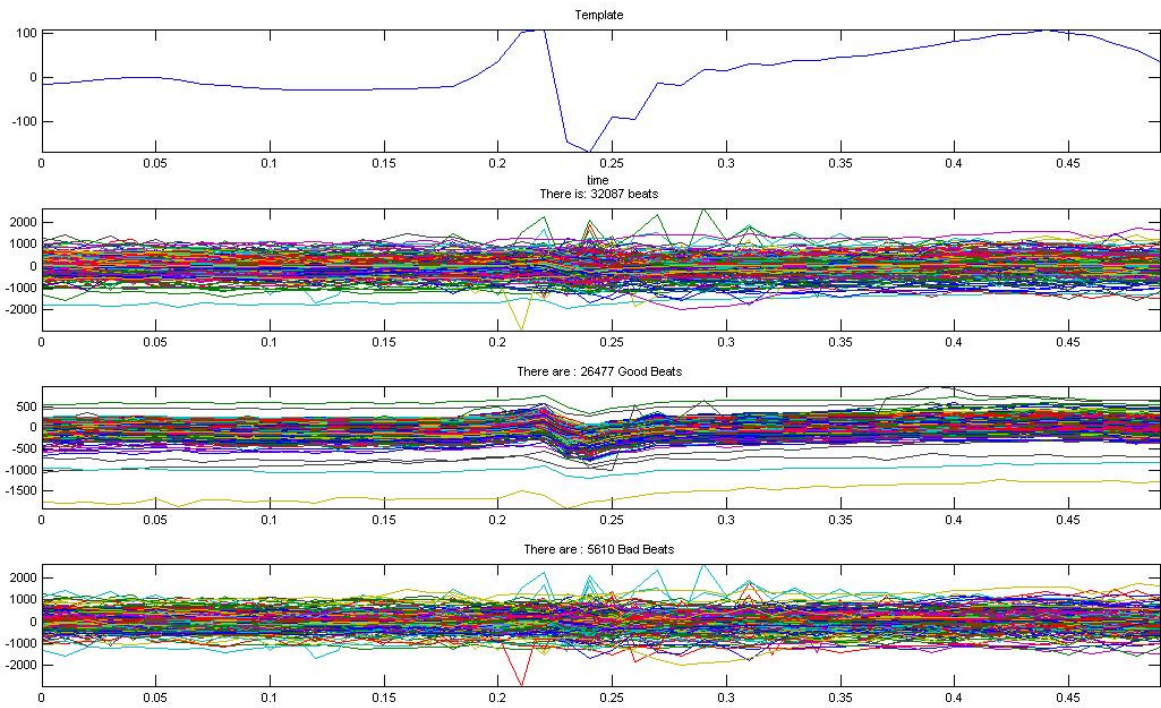
## The second result – Patient 2

All graphic will be present, just like for the first patient. The first figure, figure 7.11, represents several artifacts elimination from the ECG signal.



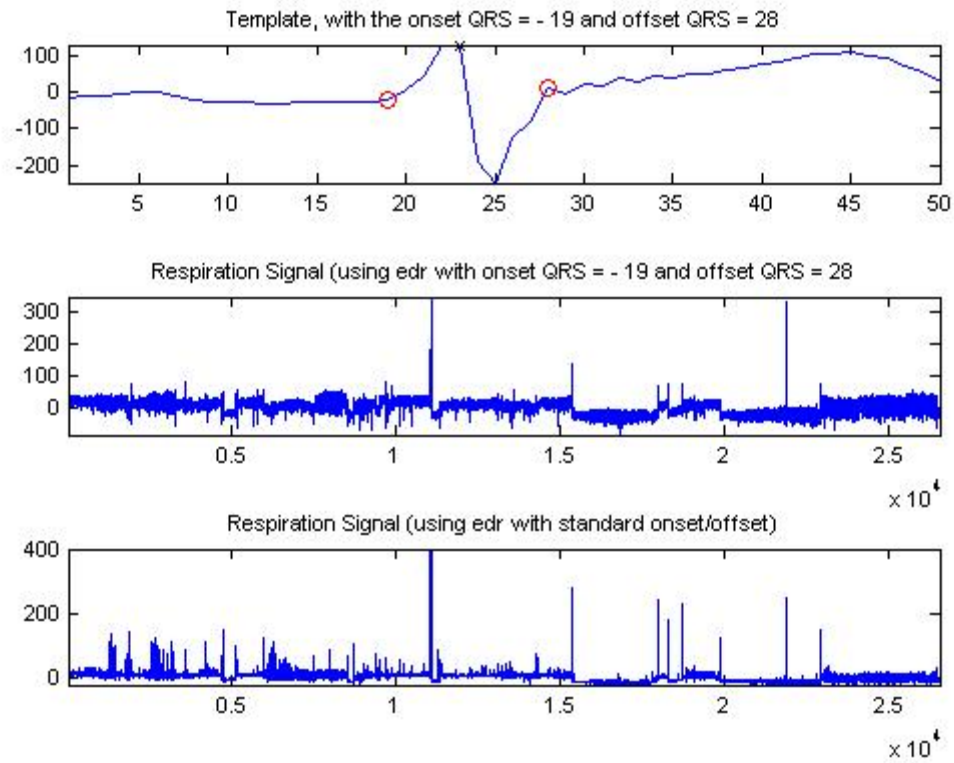
**Figure 7.11** - Removing the artifacts beats from the ECG signal.

In this case, the template obtained by the mean of all the beats (32087 beats), was not the best. This ECG signal has various artifacts beats. In figure 7.12, graphic 4, it can be seen that there were 5610 eliminated beats. In this case the algorithm should be run twice through the ECG signal for better results.



**Figure 7.12-** Graphic 1 – The Template, Graphic 2 – Total of beats (32087 beats), Graphic 3 – Good beats and Graphic 4 – Bad beats, the ones that will be removed.

In figure 7.13, graphic 1 the template obtained is the mean of the good beats. Has it can be observed this template is quiet better comparing with the template of figure 7.12, graphic 1 (mean of all beats). The offset and onset is detected by Carlos Mendes algorithm, and using EDR technique it is obtained the respiration signal (figure 7.13, graphic 2). In Figure 7.13, graphic 3, the onset and offset are standard, and the respiration signal is also obtained by the EDR technique.



**Figure 7.13-** Graphic 1 –Template (mean of the good beats), Graphic 2 – Respiration Signal with non standard onset and offset, Graphic 3 – Respiration Signal with standard onset and offset

Figure 7.14 shows the maximum and minimum points detected in the respiration signal (figure 7.14, graphic 1) and the respective amplitudes. With these amplitudes the apnea events will be counted and showed in the user interface. Graphic 7.13 and 7.14 are explained in chapter 4.3.

RR interval series (RRI) are obtained from the ECG signal. RRI was interpolated and a continuous wavelet applied. In figure 4.15, graphic 1 shows the RRI, and in figure 4.15, graphic 2 represents the continuous wavelet.

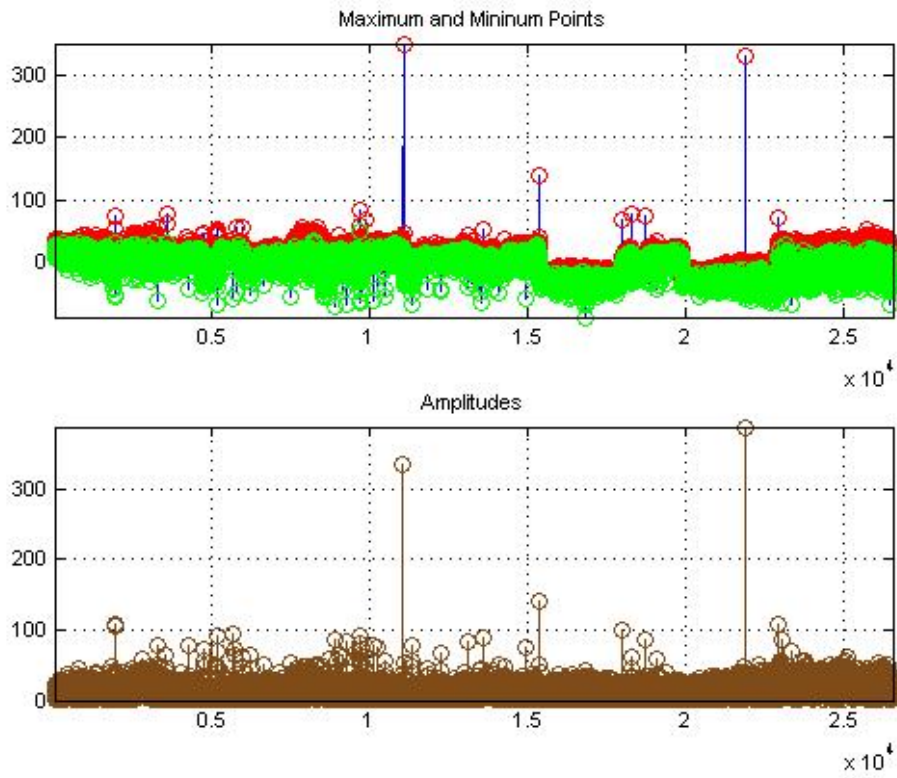


Figure 7.14- Graphic 1 –Template (mean of the good beats), Graphic 2 – Respiration Signal with non standard onset and offset, Graphic 3 – Respiration Signal with standard onset and offset

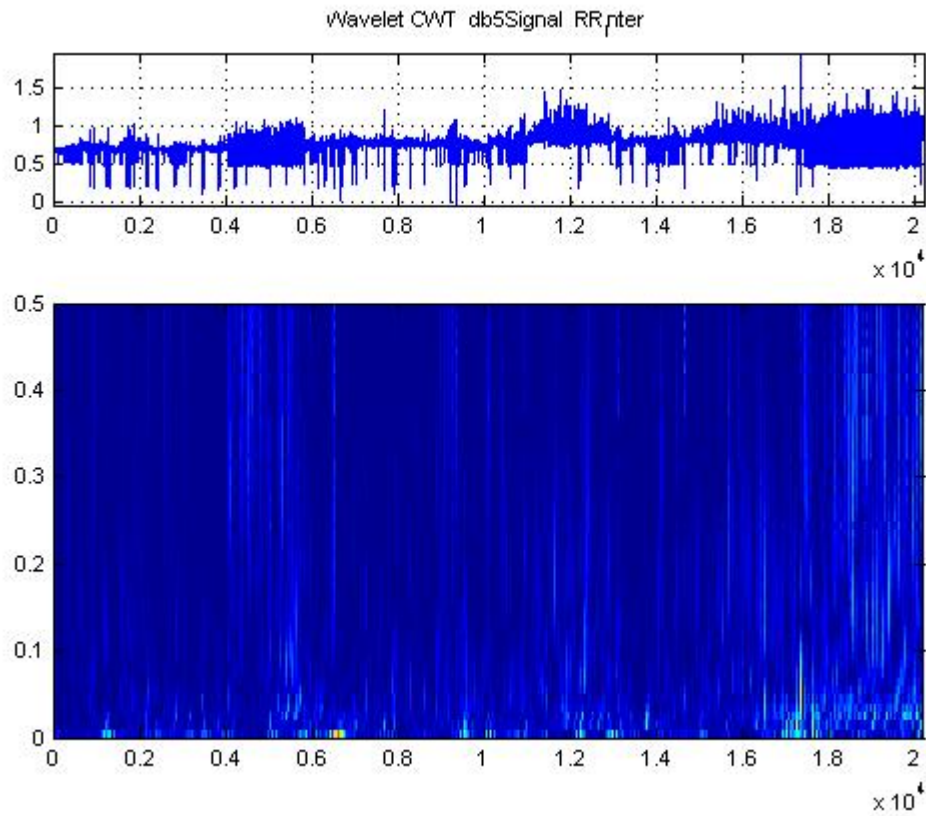
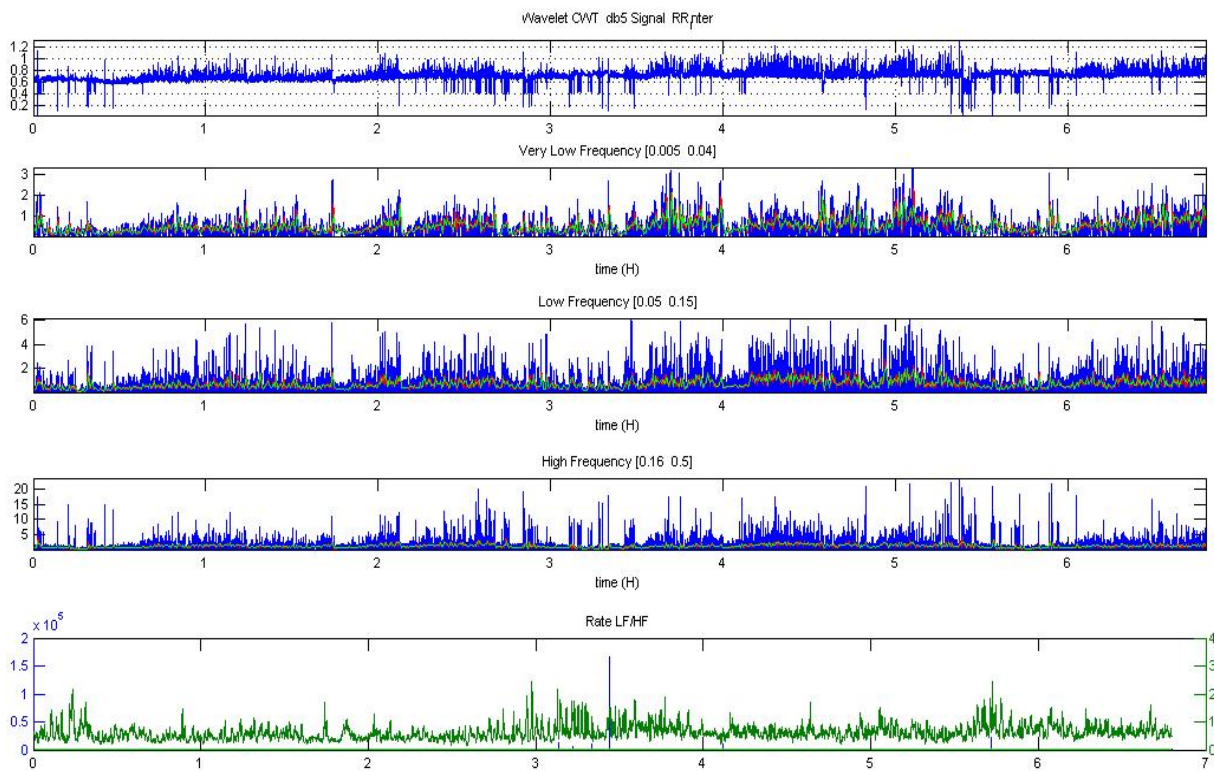


Figure 7.15 – Graphic 1 – RRI interpolated, Graphic 2 – Continuous Wavelet

The frequency bands were extracted from the EEG signal. Those bands correspond to the very low frequency (VLF [0.005 0.04]), low frequency (VF [0.05 0.15]) and high frequency (HF [0.16 0.5]).

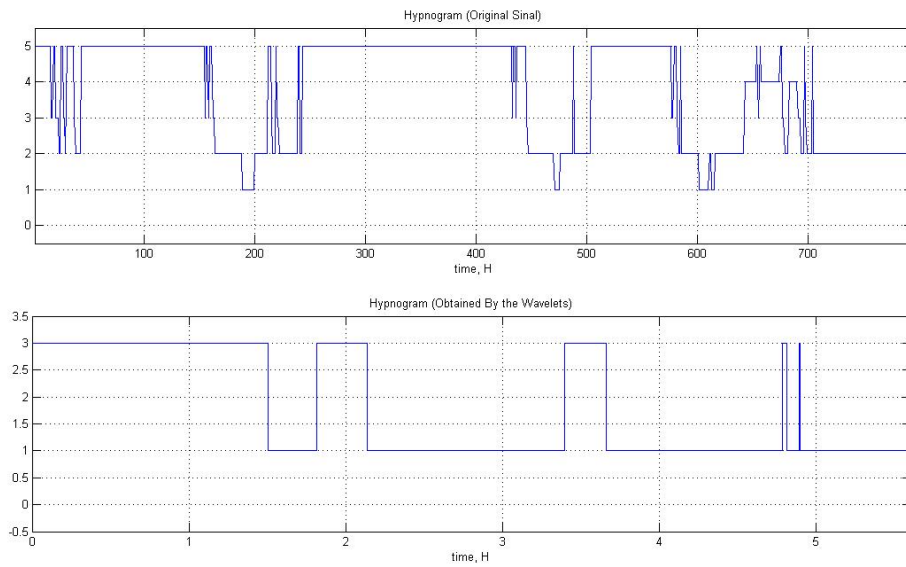
Figure 7.15 and figure 7.16 are describe in chapter 4.4.1



**Figure 7.16-** Graphic 1 – RRI interpolated, Graphic 2 - power frequency band (0.005-0.04) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 3 power frequency band (0.05-0.15) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 4 power frequency band (0.16-0.5) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 5 LF/HF ratio

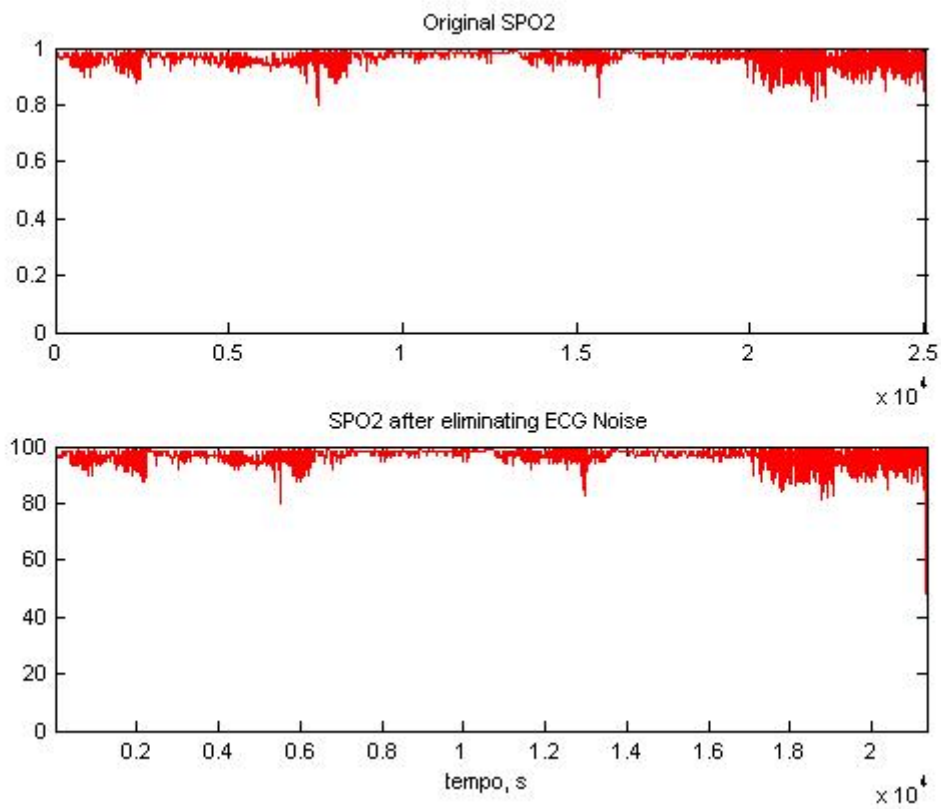
Applying the rules describe in a previous chapter (chapter 4.4.2) the Hypnogram is created. It is almost impossible to compare this graphic (figure 7.17). Once again, the purpose of this part of the work is to demonstrate that **this is possible**; still various studies are required to achieve the goal.





**Figure 7.17-** Hypnogram. Graphic 1 – Original Signal, graphic 2 – Signal obtained by the wavelets

The next figure 7.18 corresponds to the Oxygen Desaturation. Figure 7.19 is the hospital report, which will serve as a comparison for the algorithms results.



**Figure 7.18-** Oxygen Desaturation. Graphic 1 – The Original SPO1 and graphic 2 – SPO2 after removing the artifact beats removed in the ECG signal

# Polysomnography Report



**Centro Hospitalar Lisboa Norte - HPV**  
 Alameda das Linhas de Torres, 117  
 1769-001 Lisboa

Analyzed Time: 6 hours 58 minutes ( 418 minutes )  
 Analysis Start Time: 04-01-2007 23:55  
 Analysis Stop Time: 05-01-2007 6:53

## Patient Information

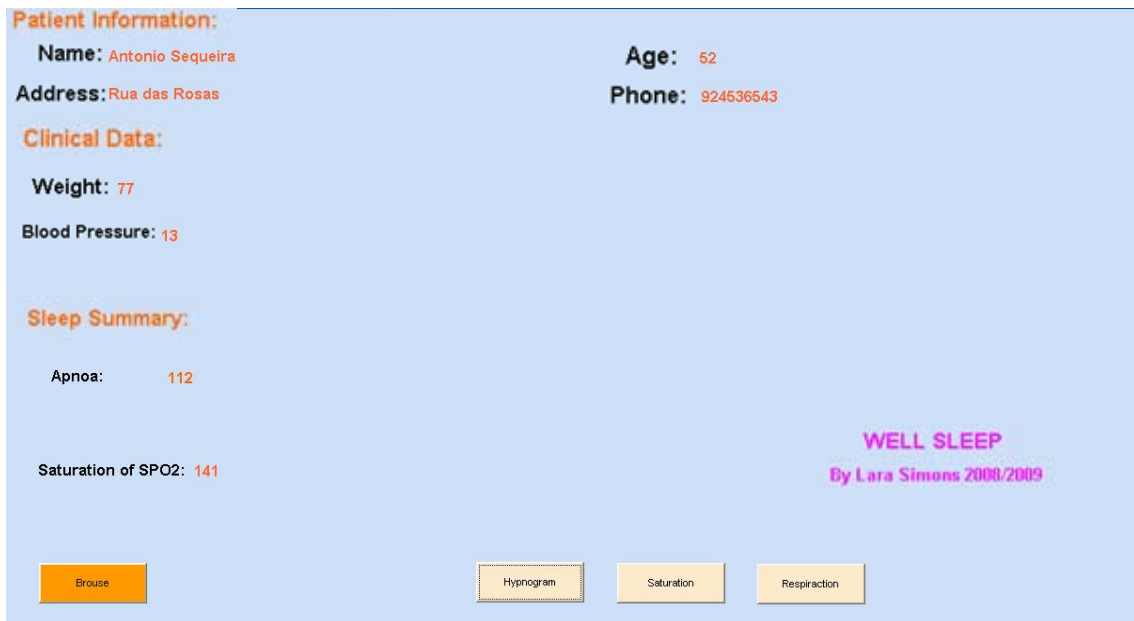
Name:	[REDACTED]	Date of Birth:	N/A
ID:	[REDACTED]	Age:	-
Address:	[REDACTED]	Gender:	Male
City:	[REDACTED]	Height:	N/A m
Zip Code:	[REDACTED]	Weight:	N/A kg
e-Mail:	[REDACTED]	BMI:	N/A
Phone:	[REDACTED]		

## Sleep Summary

Total Time Analyzed:	418,1 minutes	
Sleep Period:	409,6 minutes	
Wake Time During Sleep Period:	210,1 minutes	
Total Sleep Time:	199,5 minutes	
Sleep Onset:	8,5 minutes	
Sleep Efficiency:	48,7 %	
Number of Awakenings:	14	
Number of Movement Time Epochs:	0	
Sleep Latency to S1:	8,5 minutes	
Sleep Latency to S2:	12,0 minutes	
Sleep Latency to SWS (S3 or S4):	95,0 minutes	
REM Latency from Sleep Onset:	333,5 minutes	
Apnea + Hypopnea (A+H):	196	59,1 / h
Obstructive Apnea:	138	41,6 / h
Central Apnea:	0	0,0 / h
Mixed Apnea:	0	0,0 / h
Hypopnea:	58	17,5 / h
Oxygen Desaturation Events (OD):	177	53,3 / h
Snore Time:	4,2 minutes	2,1 %
Limb Movement:	30	
PLM Sequences:	0	

**Figure 7.19** - Hospital Report. Important Information: Obstructive Apnea and Oxygen Desaturation Events (OD)



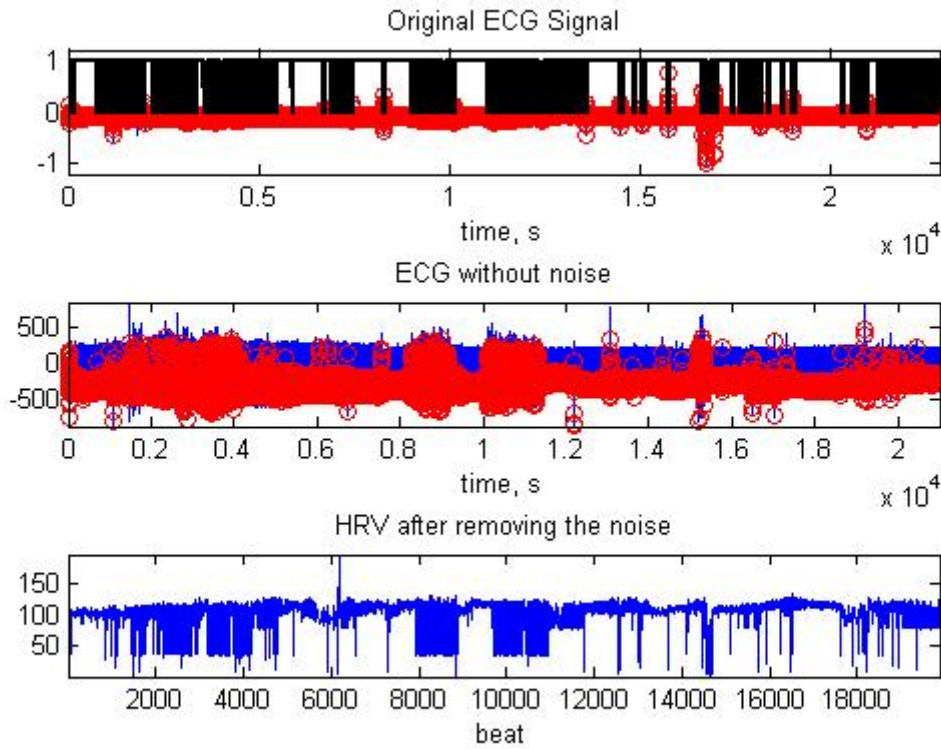


**Figure 7.20** - Sleep Summary – Note the Patient Information and Clinical Data are fictitious

The results are also quite satisfactory for patient number 2 - regarding apnea events the algorithm counted 112 events while the hospital report counted 138. It must be taken into consideration that the respiration signal was obtained by the ECG signal which, in turn, had the artifact beats removed and that, in this case, the algorithm had various artifacts. As for the Saturation of SPO2 and Oxygen Desaturation (OD) the algorithm counted 141 and the hospital report 177. Taking into account that the ECG artifacts were also removed from the SPO2, that the baseline is normally detected manually, and in this case, it is the mean of the first ten points, the results are very satisfactory. The difference between the number of apnea events is 50, while the Oxygen Desaturation (OD) the difference is only 36.

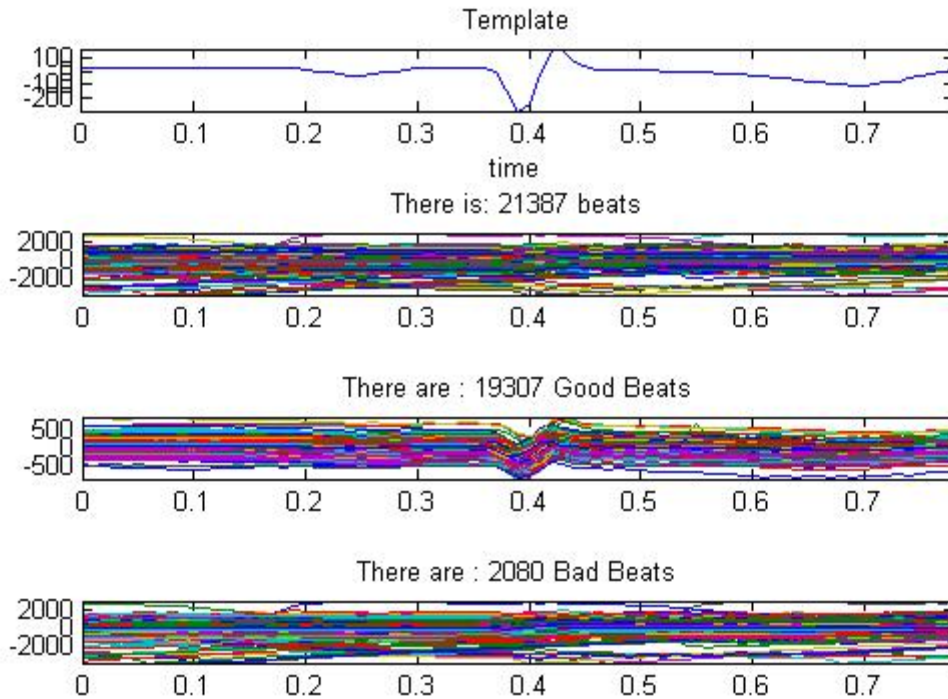
### Third result – Patient 3

All graphic will be present for patient 3, as well. The first figure, figure 7.21, represents several artifacts elimination from the ECG signal.



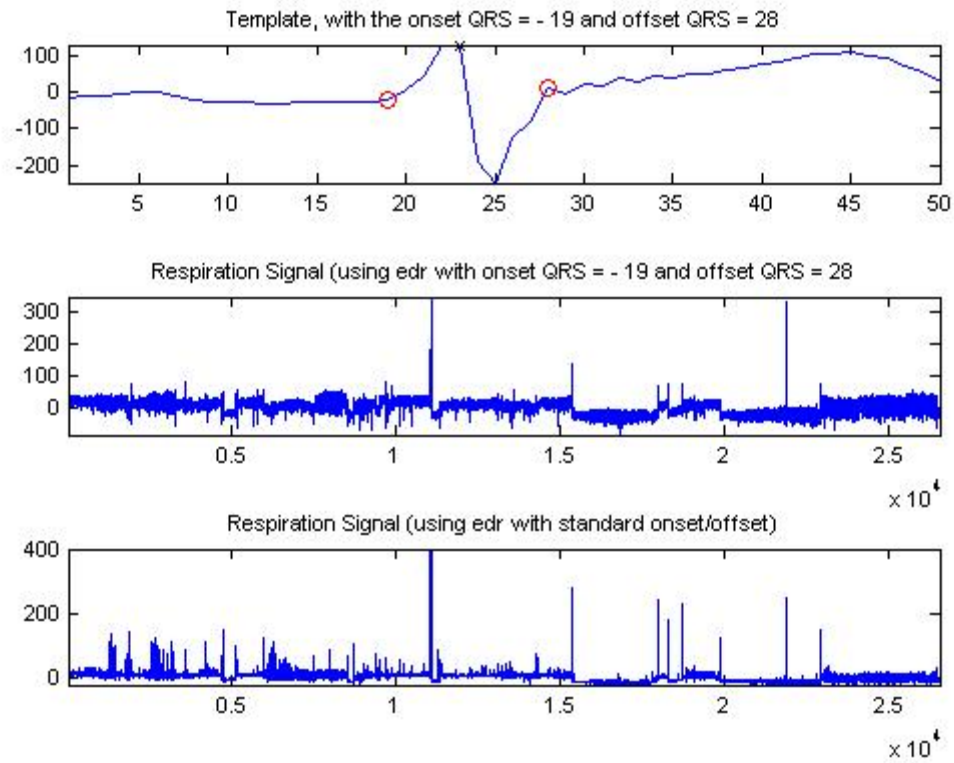
**Figure 7.21** - Removing the artifacts beats from the ECG signal.

As for patient 1, the template obtained by the mean of all the beats (21387 beats), was satisfactory. This ECG signal did not have various artifacts beats. In figure 7.22, graphic 4, it can be seen that there were 2080 eliminated beats. In this case the algorithm worked fine, using the mean of all beats. In the future, it will be important to examine if it is relevant, to go over the algorithm twice, taking into account the results versus the time to process it.



**Figure 7.22-** Graphic 1 –Template, Graphic 2 – Total of beats (32087 beats), Graphic 3 – Good beats and Graphic 4 – Bad beats, the ones that will be removed.

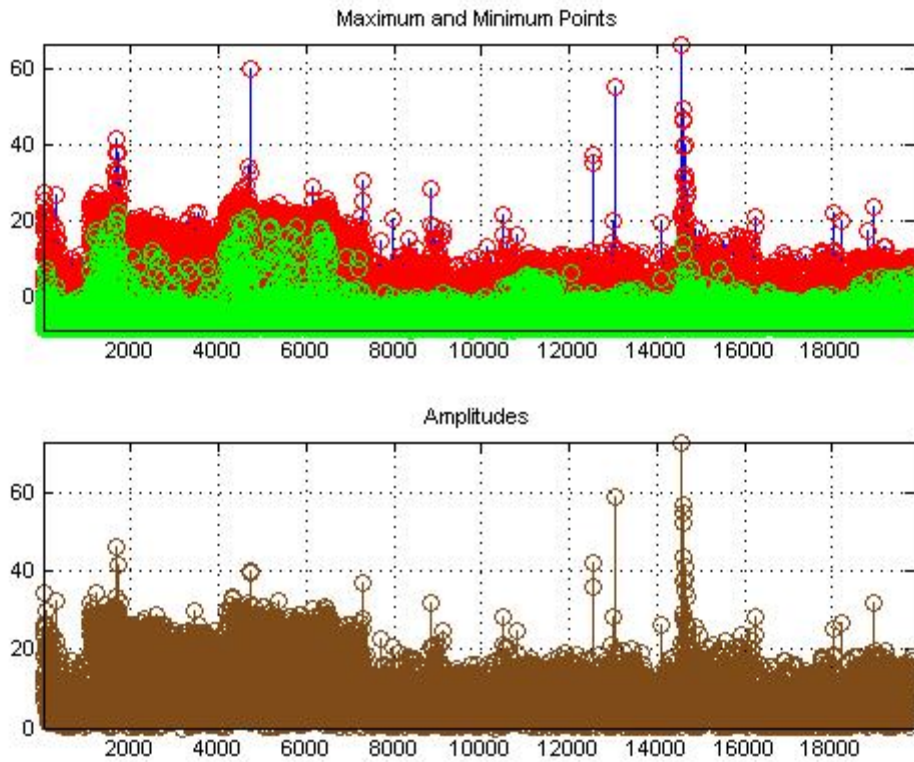
In figure 7.23, graphic 1, the template obtained is the mean of the good beats. The offset and onset is detected by Carlos Mendes algorithm, and using EDR technique it is obtained the respiration signal (figure 7.23, graphic 2). In Figure 7.23, graphic 3, the onset and offset are standard, and the respiration signal is also obtained by the EDR technique.



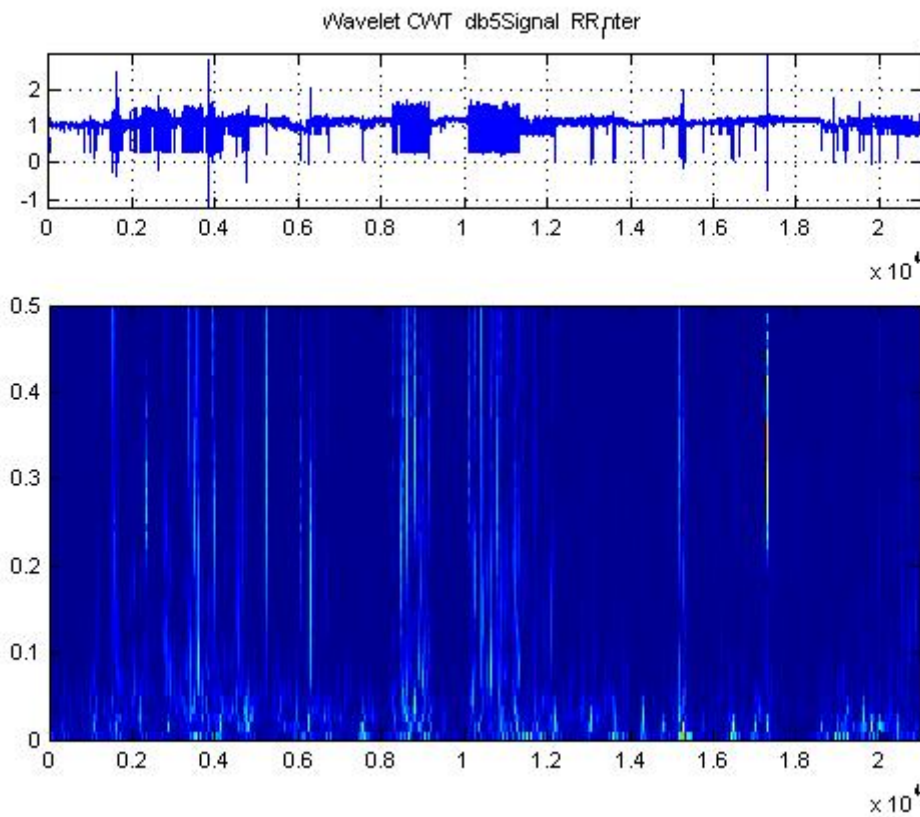
**Figure 7.23-** Graphic 1 –Template (mean of the good beats), Graphic 2 – Respiration Signal with non standard onset and offset, Graphic 3 – Respiration Signal with standard onset and offset

Figure 7.24 below represents the maximum and minimum points detected in the respiration signal (figure 7.24, graphic 1) and the respective amplitudes. With these amplitudes the apnea events will be counted and showed in the user interface. Graphic 7.23 and 7.24 are explained in chapter 4.3.

RR interval series (RRI) are obtained from the ECG signal. RRI was interpolated and it a continuous wavelet applied. In figure 4.25, graphic 1 shows the RRI, and in figure 4.25, graphic 2 represents the continuous wavelet.



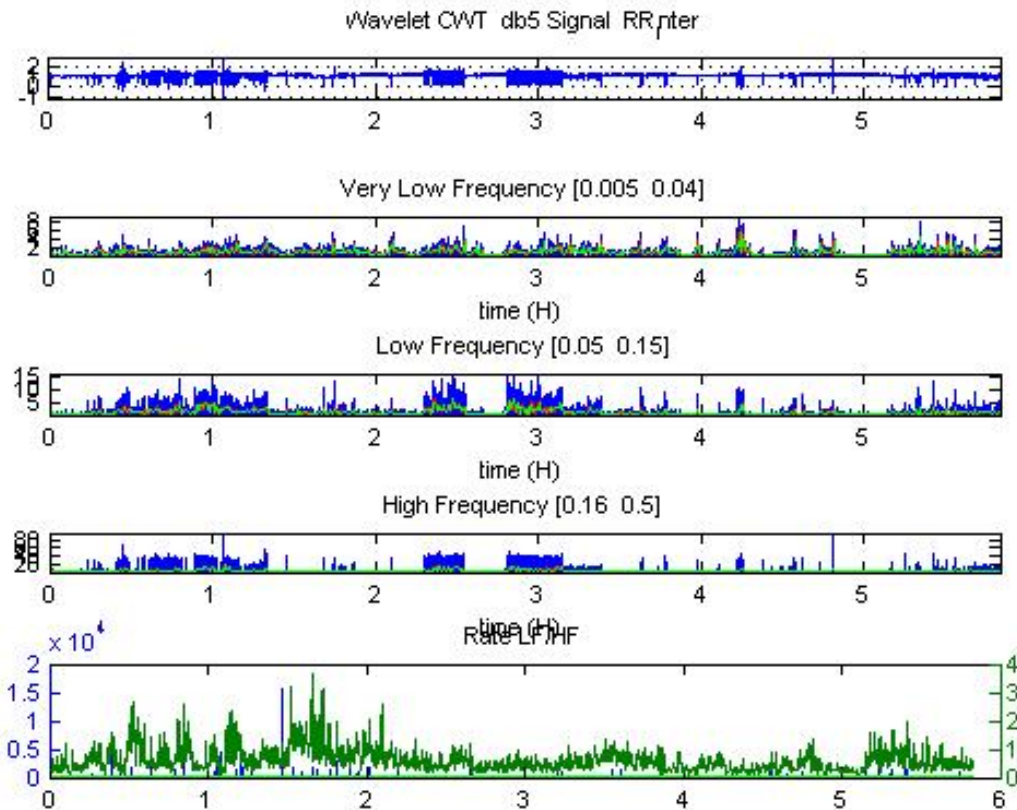
**Figure 7.24-** Graphic 1 –Template (mean of the good beats), Graphic 2 – Respiration Signal with onset non standard and offset, Graphic 3 – Respiration Signal with standard onset and offset



**Figure 7.25 –** Graphic 1 – RRI interpolated, Graphic 2 – Continuous Wavelet

The frequency bands were extracted from the EEG signal. Those bands correspond to the very low frequency (VLF [0.005 0.04]), low frequency (VF [0.05 0.15]) and high frequency (HF [0.16 0.5]).

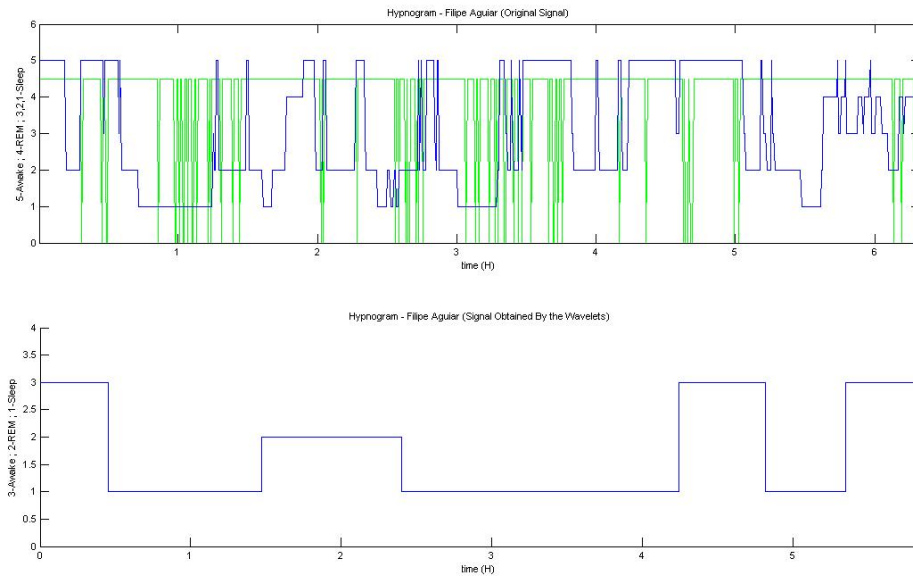
Figure 7.25 and figure 7.26 are describe in chapter 4.4.1



**Figure 7.26-** Graphic 1 – RRI interpolated, Graphic 2 - power frequency band (0.005-0.04) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 3 power frequency band (0.05-0.15) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 4 power frequency band (0.16-0.5) blue signal power frequency band, red signal using a sliding window of 30 seconds and green signal using a window of 30 seconds. Graphic - 5 LF/HF ratio

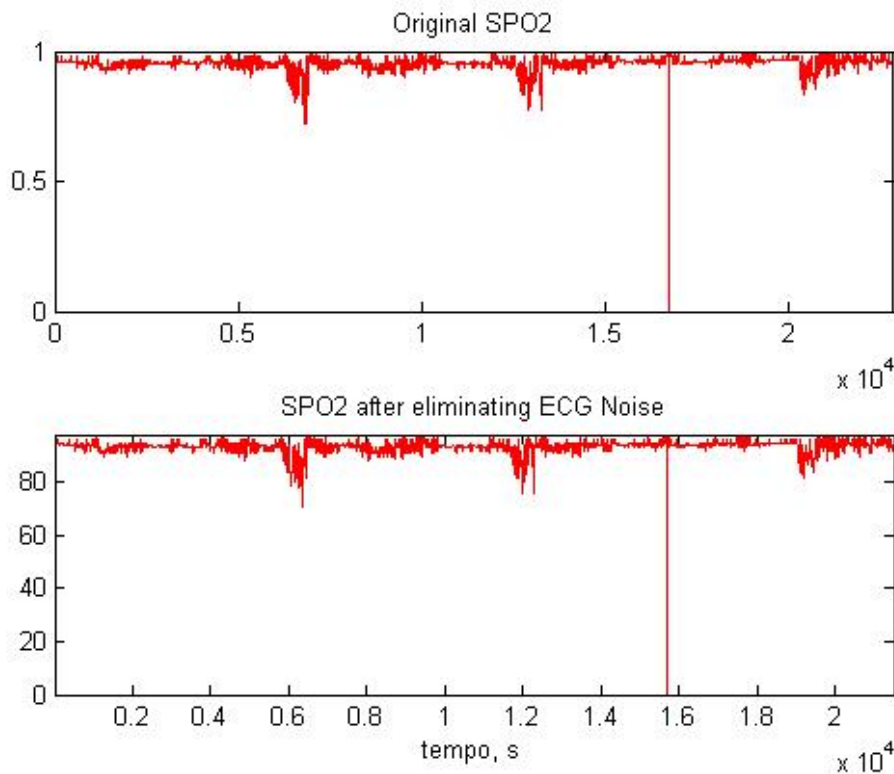
Applying the rules describe in a previous chapter (chapter 4.4.2) the Hypnogram is created. It is almost impossible to compare this graphic (figure 7.17). Once again the purpose of this part of the work is to demonstrate that **this is possible**, still various studies are required to achieve the goal. Figure 7.27 demonstrates that a considerable amount of information is lost by down sampling the vector (figure 7.21, graphic 1, black signal). This lost information is important to properly compare the two graphics.





**Figure 7.27-** Hypnogram. Graphic 1 – the blue signal is the Original Signal and the green signal is the vector containing the removed artifacts and applied a down sample, graphic 2 – Signal obtained by the wavelets

Figure 7.28 corresponds to the Oxygen Desaturation. Figure 7.29 is the hospital report, which will serve as a comparison for the algorithms results.



**Figure 7.28-** Oxygen Desaturation. Graphic 1 – The Original SPO1 and graphic 2 – SPO2 after removing the artifact beats from the ECG signal

# Polysomnography Report



## Centro Hospitalar Lisboa Norte - HPV

Alameda das Linhas de Torres, 117  
1769-001 Lisboa

Analyzed Time: 6 hours 21 minutes ( 381 minutes )

Analysis Start Time: 03-05-2006 0:12

Analysis Stop Time: 03-05-2006 6:32

### Patient Information

Name: ██████████	Date of Birth: █-█-████
ID: █████ - █████	Age: █
Address: ██████████	Gender: ███
City: ██████████	Height: █0,00 m
Zip Code: ██████████	Weight: █3,0 kg
e-Mail: ██████████	BMI: 0,0
Phone: ██████████	

### Sleep Summary

Total Time Analyzed:	380,7 minutes	
Sleep Period:	368,2 minutes	
Wake Time During Sleep Period:	112,5 minutes	
Total Sleep Time:	255,7 minutes	
Sleep Onset:	12,5 minutes	
Sleep Efficiency:	69,4 %	
Number of Awakenings:	16	
Number of Movement Time Epochs:	0	
Sleep Latency to S1:	202,0 minutes	
Sleep Latency to S2:	13,0 minutes	
Sleep Latency to SWS (S3 or S4):	44,0 minutes	
REM Latency from Sleep Onset:	95,0 minutes	
Apnea + Hypopnea (A+H):	115	27,0 / h
Obstructive Apnea:	45	10,6 / h
Central Apnea:	0	0,0 / h
Mixed Apnea:	0	0,0 / h
Hypopnea:	70	16,4 / h
Oxygen Desaturation Events (OD):	78	18,3 / h
Snore Time:	184,8 minutes	72,3 %
Limb Movement:	201	
PLM Sequences:	7	

Figure 7.29 - Hospital Report. Important Information: Obstructive Apnea and Oxygen Desaturation Events (OD)





**Figure 7.30** - Sleep Summary – Note the Patient Information and Clinical Data are fictitious

The results are also quite satisfactory for apnea events - the algorithm counted 96 events while the hospital report counted 45. It must be taken into consideration that the respiration signal was obtained by the ECG signal, which, in turn, had the artifact beats removed. As for the Saturation of SPO2 and Oxygen Desaturation (OD) the algorithm counted 53 and the hospital report counted 78. Taking into account that the ECG artifacts were also removed from the SPO2, that the baseline is normally detected manually, and in this case, is the mean of the first ten points, the results are very satisfactory. The difference between the number of apnea events is 51, while the Oxygen Desaturation (OD) the difference is only 25.



# 8 Conclusions and Further Work

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The purpose of this dissertation was to create an algorithm that could diagnose OSAS in a simple and inexpensive way. The algorithm should be able to extract the maximum information possible with only two signals (ECG and SPO2).

This aim was achieved - the algorithm proposed detects apnea events, Oxygen Desaturation (OD) events and it has been demonstrated that it is possible to extract the Hypnogram from the ECG signal using wavelets.

Beyond the scientific and technical achievement, the idea behind the entire algorithm and structure (table 1.3.1) has been deeply studied; in what way could the 2 signals bring the most information possible. This part of the work was the one that gave me more pleasure. My desire was to elaborate something new, not only technically but as a whole new structure. This aim was also achieved - the algorithm designed covers all requirements.

Further work is necessary to put the algorithm into practice within the medical context. The main study is to review the wavelet used and the rules applied for the creation of the Hypnogram (chapter 4.4) - this thesis has proven that such is possible but also demonstrated that once the VLF, LF, HF and LF/HF are calculated the way they are used to score the sleep is very much open to debate. It should also be considered if the best solution is to remove the artifacts or to replace the artifacts using good beats obtained from other parts and is if it is worth to run the algorithm twice (chapter 4.2). Chapter 4.4 and chapter 4.5 work quiet well, after the revision on chapter 4.4 and 4.2 the algorithm is ready for medical tests.

*My final wish is that this thesis contributes to health benefits. That helps improving the hospital's waiting lists and that a larger number of people can have access to quick diagnosis methods within the shortest period of time.*



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