Signal Processing Techniques in Spectral Analysis for sleep stage study of Physiological Signals

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Abstract— Objective: The goal of this report is to study differences in the stages of sleep (wakefulness, phases I, II, III and REM phase) and events (apneas, hypopneas, and arousals) through the changes that occur in the energy and spectral characteristics of electrocardiographic (ECG), electroencephalographic (EEG) and respiratory (Resp) signals, recorded during a Polysomnographic (PSG) sleep study.

The report presents a signal processing approach that uses various spectral analysis techniques to extract relevant features from ECG, Respiratory and EEG signals.

Conclusion: **In conclusion,**

Index Terms – Heart rate variability, Cardiac frequency, Respiratory frequency, EEG waves, Signal processing.

I. Introduction

The study of sleep is a crucial aspect of understanding human physiology. Sleep is a complex process that is characterized by the cyclic alternation of different stages, each of which is associated with specific physiological changes. One of the most widely used methods for studying sleep is polysomnography, which involves the simultaneous recording of various physiological signals, including the electrocardiographic (ECG), electroencephalographic (EEG), and respiratory (Resp) signals. The goal of this report is to analyse these signals from a polysomnographic study in order to identify and quantify the different stages of sleep and sleep-related events, such as apnoea's, hypopneas, and arousals. To accomplish this, we will focus on the changes that occur in the energy and spectral characteristics of these signals. We will also investigate the usefulness of different signal processing techniques for analysing these signals and determining the presence of sleep-related events. [1][2][3]

II. Material and Methods

The following material was used for the realization of this report.

A. Data

The data used was the sample tr03-0083 from the 2018 Computers in Cardiology Challenge database on physionet. This database includes data from 1985 subjects who were monitored during a polysomnographic (PSG) study at a sleep laboratory for the diagnosis of sleep disorders. The sleep stages of the subjects were manually scored by clinical staff. The following six sleep stages were annotated in 30 second contiguous intervals: wakefulness, stage 1, stage 2, stage 3, rapid eye movement (REM), and undefined.

B. Signals

Several biomedical signals were acquired during the PSG study, following the American Academy of Sleep Medicine (AASM) standards. These were 13 biomedical signals: 6 electroencephalographic (EEG) channels (F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, and O2-M1, based on the International 10/20 System), an electromyographic (EMG) channel measured at the chin, one electrocardiographic (ECG) channel recorded below the right clavicle near the sternum and over the left lateral chest wall, 2 respiration channels from the abdomen and chest. From these 13 signals the 6 EEG derivations, the ECG and one of the respiratory signals (the abdominal one) were used.

C. Matlab functions

The functions used for the signal processing were provided by WFDB toolbox, TFRtoolbox and from Biomedical Signal Analysis Toolbox by Abel Torres from IBEC-ESAII-UPC.[5][6]

D. Segment chosen of the whole signal

For the selection of the signal section the annotations provided by physionet are used. The selcted section is the hour from 1:40 to 2:40, as it shows several sleep stages and obstructive apnoeas which we want to correlate with our results (see appendix figure 16).

E. Cardiac frequency

First, a spectral analysis is carried out to pre-process the signal. To do this, the *perdiodogram* function is used to calculate the power spectral density (PSD). The PSD showed that the signal contains high frequency noise around 60 Hz, so a bandpass filter is applied with the frequency band 58-62 Hz (Figure 1A). In addition, the power of the signal is mainly below 30 Hz, therefore a second low-pass filtering step is performed with a frequency cut at 40 Hz.

The comparison of the PSD visualized using the *findpeaks* function of a 10 second section of both signals is shown in figure 2. The last peak is excluded in the analysis, as it is most probably noise. As a 4 Hz lowpass filtering was applied, the algorithm excludes every peak that lays above 4 Hz.

To determine the heart rate in the frequency domain, we can use the PSD peaks, as the fundamental frequency of the filtered ECG signal is the heart rate. To avoid aliasing, the signal is filtered again with a 4Hz low-pass filter. The signal is then decimated to a sampling frequency of 2 Hz. The main reason for this is to improve the resolution of the signal processing. Decreasing the sample rate of a signal increases the effective frequency resolution, which can make it easier to resolve closely spaced frequency components.

For the calculation of the PSD for the whole signal the periodogram function is selected. As an ECG signal can be stationary it might perform just as good as for instance the burg algorithm for the PSD calculation. The Burg method adapts to changes in the signal and is therefore suitable for stationary and non-stationary signals. Whereas the periodogram only performs well for stationary signals.

The Burg method might have higher resolution and better noise reduction, but as our signal is stationary and filtered using a Hamming window as weighting function, the resolution of the periodogram estimate is increased.

F. Heart Rate Variability

The HRV is a non-invasive method to evaluate the regulation of the autonomic nervous system (ANS). Heart rate variability (HRV) is a measure of the variation in time between consecutive heartbeats. It reflects the activity of the ANS, which controls heart rate. The ANS has two branches: the sympathetic nervous system (SNS), which increases heart rate and prepares the body for a "fight-or-flight" response, and the parasympathetic nervous system (PNS), which controls heart rate and "rest and rest." lowers rest." Answer "promotes digestion".[7]

To obtain the RR plot we first use the Pan-Tompkins method, which is an algorithm that detects the presence of QRS complexes. The algorithm is based on the computation of several signal features, such as the slope, width, and amplitude of the QRS complex, which are then used to determine whether a QRS complex is present or not (see figure 5).

From the detected R marks, the RR series can be obtained by differentiating between R points. To correct possible artefacts in the RR signal and failures in the detector, it is recommended to apply a filter to the RR signal. To allow a better frequency analysis of the RR signal it needs to be sampled at a constant frequency. A signal resampled at a low frequency can be used for low-frequency signal analysis, which is our case as the VLF (0.003 - 0.04), LF (0.04 0.15), HF (0.15 - 0.4) frequency bands of the RR signal are very low values. Therefore, the RR signal is resampled at 2 Hz instead of 200Hz. For this, the Spline Interpolation is used, which is a method of constructing a smooth curve that passes through a given set of data points. [8] The idea behind spline interpolation is to approximate a smooth function that is well-behaved and easy to evaluate while closely matching the input data.[9]

For the analysis of the HRV time-frequency the function powerband is used. Which calculates the mean power for a certain frequency band from the PSD of the signal. For this, the PSD of the resampled RR signal was calculated for 30 second sections and then fed into the powerband function to obtain the time spectra shown in figure 7.

G. Respiratory frequency

Regarding the methodology used to obtain the respiratory frequency, in order to analyse it the abdominal signal was used, cropped to the same hour as before for further comparation. No pre-processing was done on the abdominal signal, as its periodogram showed that it had no apparent noise, and that all the frequencies seemed of normal energy and inside the physiological range of frequencies (0 to 1 Hz).

The same principle as in cardiac frequency detection was used to detect the respiratory frequency. The spectral peaks of samples of 10 seconds from the signal were analysed to find the differences between peak, which correspond to the frequency at which the patient breathes. A periodogram with a *hamming window* and the function *findpeaks* were used to find these peaks between 0 to 10Hz in the PSD. Later this information was restructured to deliver a boxplot of how many breathes per minute the patient showed in blocks of 10 minutes (over the 60 of the cropped signal).

H. EEG energy study

In order to study the energy and frequencies of the EEG a special approach had to be developed, as compared to the previous cases, the information came from six different signals or leads instead of only from one.

To study the energy and frequency properties of the EEG, the energy of its characteristic waves was studied: delta (δ, 0.5–4 Hz), theta (θ, 4–8 Hz), alpha (α, 8–12 Hz) . sigma (σ, 12-16 Hz) and beta (β, 16-40 Hz). The actual approach has been to perform a welch periodogram to estimate the PSD of each lead in windows of 10 seconds with 50% overlap, and compute the relative energy of the given wave respect to the total lead for each of the windows.

It was estimated to be necessary to filter each EEG lead signal prior to the wave energy estimation, because even though the 60Hz noise present in the signal was of low power and out of the range of the frequencies of study, the relative energy used to quantify the presence or absence of each EEG is affected by the total energy of the EEG signal in the denominator, therefore modifying the final relative energy results. The filtering was done at 58-62Hz Butterworth stopband of order 2.

After this analysis, the evolution of the relative energy of each of the EEG waves over time was obtained, and the mean performed across the different leads as there was no significative difference in their tendency. In this way the evolution of the different EEG waves relative energy over the sleep time was accomplished.

I. Signal and Sleep stages Relations

In this sections the data from the stages has been used to compute boxplots of the different parameters extracted from the signals across the five different sleep stages. Actually, what has been done is to use the logical vectors available for each of the stages that have a 1 if the patient is in the stage and a 0 if it is not (e.g. a 1 if the patient is awake and a 0 if it is in any other stage of sleep). In this way it has been possible to extract the mean and standard deviation of the beats per minute, breathes per minute and relative energy (divided by EEG waves) and build boxplots to deliver the information.

In order to perform this resampling has been performed over some of the parameters, as instead of 7200000 samples (3600 seconds and 200 sampling frequency) most of our parameters had 360 samples (as the value had been computed from windows of 10s). Through resampling it has been possible to harmonise the dimensions of the parameters in order to correctly deliver the information.

III. Results

The results are divided into 4 sections, ECG, respiratory signal, EEG signal and the relation between the different signals and the sleep stages as well as the apnoea's.

A. ECG Signal – Cardiac Frequency

The ECG signal and its corresponding PSD is shown in figure 1A and the filtered signal is shown in figure 1B.

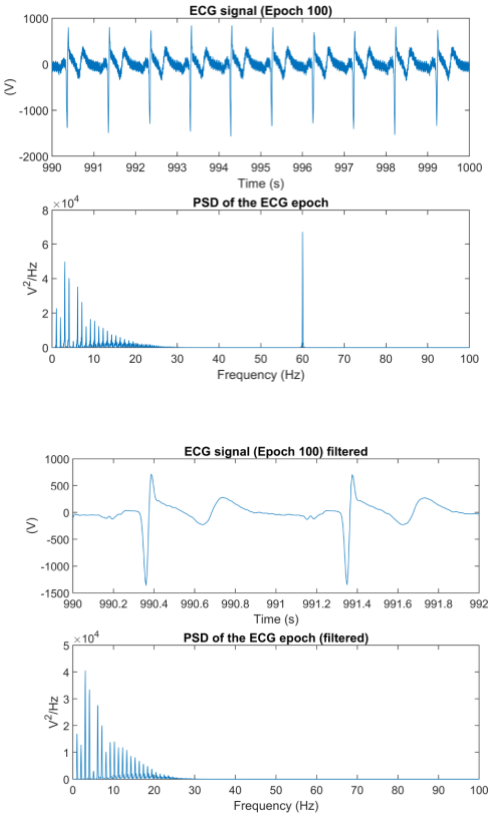

Figure 1: Signal and PSD for original (A) and filtered signal (B) respectively.

The applied filters effectively removed the 60 Hz artefacts and also big parts of the high frequency aliasing noise in the lower frequency sections.

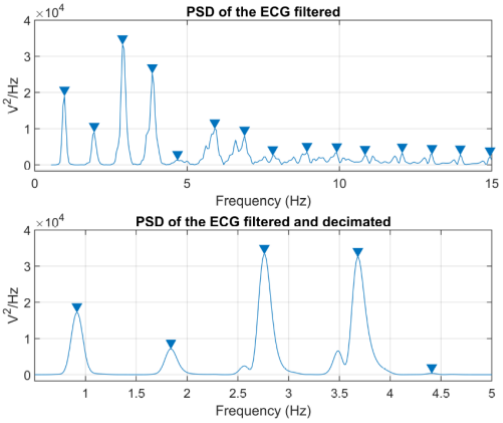

Figure 2: PSD of filtered signal (above) and resampled filtered signal (below).

Both the PSD of the decimated and undecimated signal look clean. There is an artefact around the frequencies 2.5Hz and 3.5Hz. It is visible that the distance between the first four peaks of the PSD of the filtered and decimated ECG is constant.

The results of the calculated cardiac frequency are shown in Figure 3.

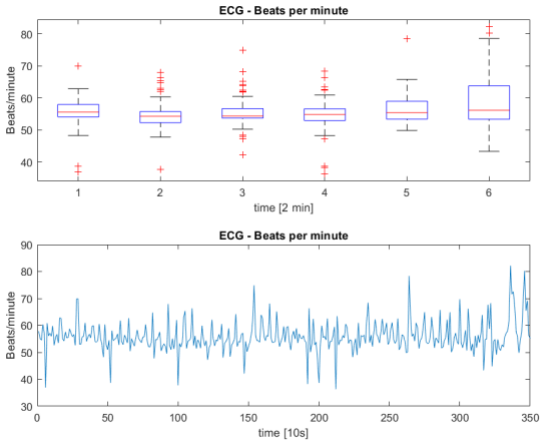

Figure 3: BPM for 10-minute sections as boxplot (above), BPM for 10s sections as xy plot (below).

The CF suddenly decreases at some time instances, this could be because *findpeaks* found peaks that were noise or an apnoea event. During an apnoea event, heart rate could decrease due to the lack of oxygen reaching the body. This lack of oxygen can cause the heart rate to slow, leading to cardiac arrest.[5][10] But as apnoea is a complex pathology, the heart rate may also increase due to the body's response to the lack of oxygenase the body's attempt to increase breathing and oxygenation. [10]

The average CF over 10 minutes has similar value throughout the recording but showed different variances. The highest variance in the last 10-minute part of the signal, which cannot be explained by the annotations provided by physionet and is therefore most likely due to misread peaks (see figure 4).

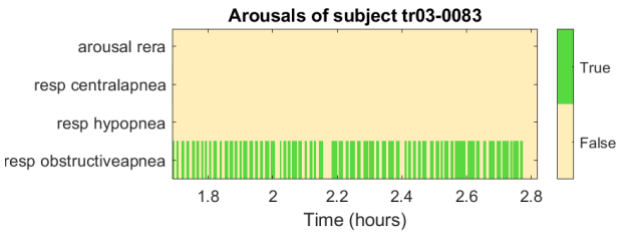

Figure 4: Arousals of the subject, for the observed section.

To analyse the evolution of the frequencies and the PSD obtained in the previous section, a 3D plot can provide insight (Figure 5). It shows that the fundamental frequency stays in the range around the 1 Hz frequency throughout the recording and stays at a power of about 2 V^2/Hz until the ~40 minutes starts to decrease. The components around 2.8 and 3.8 Hz show the greatest power variability. This could be because as the frequency increases, so does the aliasing noise.

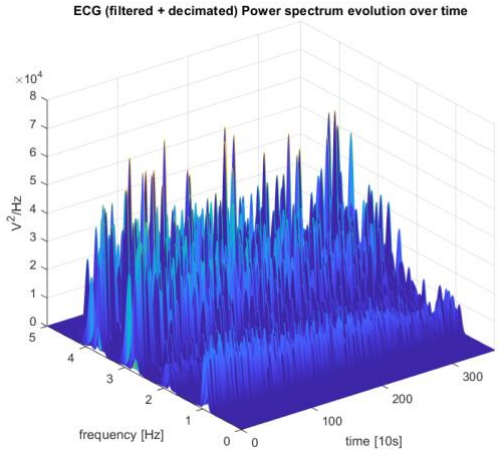

Figure 5: PSD evolution over time of the filtered and resampled ECG signal.

B. ECG Signal – Heart Rate Variability

The pan Tompkins detection algorithm successfully identified QRS complexes of an example 10 second section of the signal (see figure 6). In figure 7 the RR signal calculated using the same method is shown.

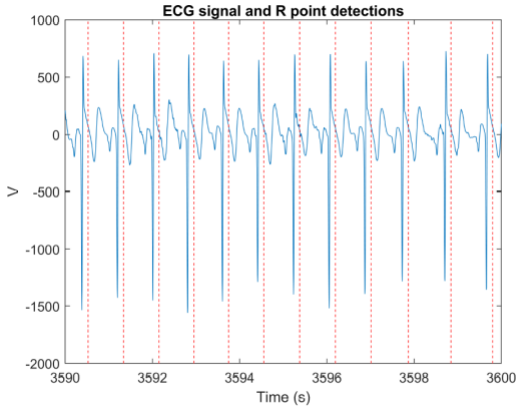

Figure 6: Filtered ECG signal (blue) with QRS detection annotations (red)

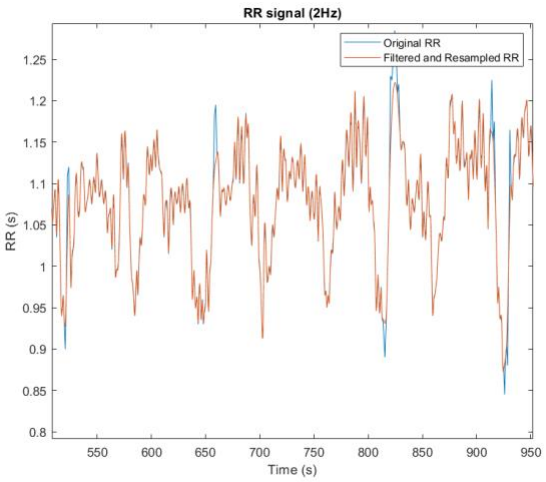

Figure 7: Original RR signal (blue) and filtered and resampled RR signal (red).

The filtering and resampling of the RR signal did not change the signal much. For the results from the powerband functions for the different frequency band are shown in figure 8.

The VLF signal components have either been neglected by the algorithm or show no variability, while the LF and HF have the same trajectory but different energies. The HF components have more energy and are narrowed in the plot compared to the LF components.

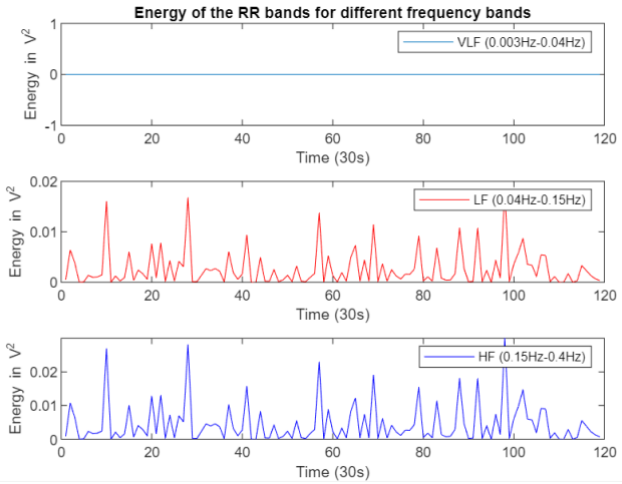

Figure 8: PSD of the VLF (top), LF (middle) and HF (bottom) components of the filtered and resampled RR signal.

The suddenly increasing energy along the recording could be related to an increase of the heart rate and to the apnoea's present annotated. But as mentioned before, is an increase in heartrate not necessarily indicating the presence of apnoea.

A low HRV can indicate that the ANS is not regulating heart rate effectively, which can be a sign of poor cardiovascular health or an increased risk of future health problems.[4] As the very low frequency (VLF) band of heart rate variability (HRV) is believed to be primarily affected by PNS activity, a lack of variability in this band could indicate that the PNS is not functioning properly. It is important to note that these results may have been caused by a lack of sensitivity in the algorithm.[7]

C. Respiratory Signal

The respiratory signal was tailored to the same hour as for the other parts of the work: from second 3600 (or minute 10) to second 9600 (or minute 70).

Respiratory analysis of the PSG was performed using the abdomen signal, which provides information about the movement of the abdomen when the patient breathes and therefore contains information about the respiratory cycle. This signal alone appeared to be enough for respiratory frequency estimation, so the other respiratory signal (chest) was not necessary to be used.

It was assumed that the abdominal signal needed no pre-processing filter since there was no noise of 50-60 Hz or any other frequency except those within the physiological range of 0-1 Hz, as shown in Figure 9.

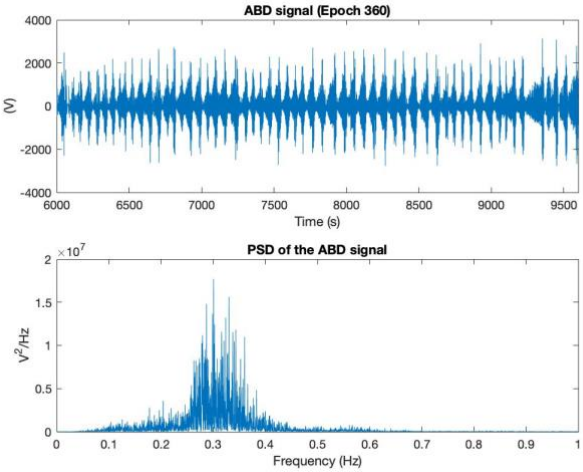

Figure 9

The result of the first spectral analysis is shown above, it would be interesting to see how the spectral properties of the signal change over the different sleep stages of the patient shown in Figure 10.

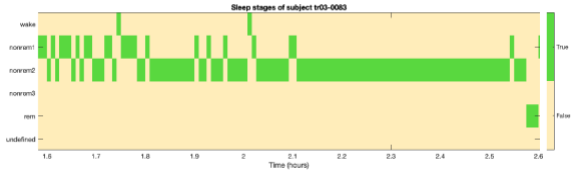

Figure 10

The first spectral analysis performed in Figure 9 is not useful for this purpose, since it performs the periodogram of the whole hour of our signal and thus “averages” the spectral properties of the different times of the signal in just one PDS plot. On the other hand, this first spectral approach already informs us that the frequencies between 0.2 and 0.4 Hz are strongest, so the respiratory rate could probably fall in these values.

To achieve our goal of obtaining the patient's respiratory rate, a spectral analysis in 10-second epochs was performed on the 60-minute signal mentioned above, and the results were combined in 10-minute epochs to form a boxplot with statistical values to provide the information shown in Figure 11. A periodogram with a Hamming window of size L = 10 s*200 Hz and an NFFT of 4096 was used to calculate the periodogram of each epoch and the difference in frequency of the higher peaks was taken as the respiratory rate. The results are shown below.

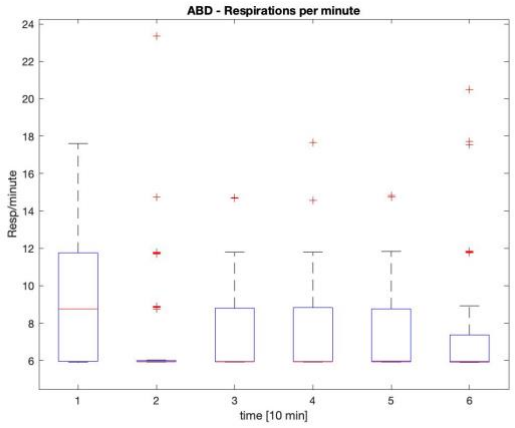

Figure 11

Alternative visualisation:

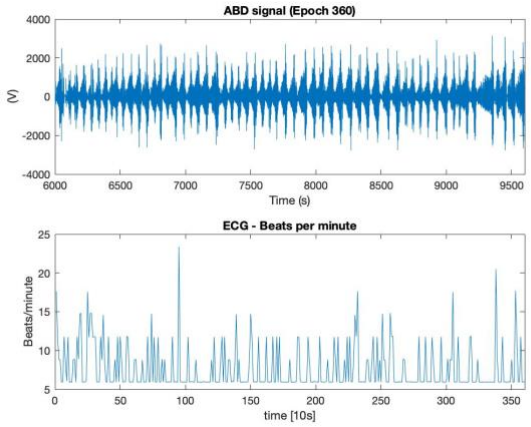

Figure 12

When performing the mean of the respiratory frequency and translating it into breathes per minute we get a result of 7.64 breathes per minute, which is a completely coherent and physiological value for a person in rest.

D. EEG Signal

This section uses 6 electroencephalographic (EEG) channels (F3-M2, F4-M1, C3-M2, C4-M1, O1-M2 and O2-M1, based on the international 10/20 system) in which EEG Signals are recorded at various locations on the patient's scalp.

To study the energy and frequency properties of the EEG, the energy of its characteristic waves are studied: delta (δ, 0.5–4 Hz), theta (θ, 4–8 Hz), alpha (α, 8–12 Hz) . sigma (σ, 12-16 Hz) and beta (β, 16-40 Hz).

The energy of the different waves is compared to the energy of the entire EEG signal. Therefore, it is important to first filter the EEG signal with a night filter around 60 Hz, where the signal has a small energy peak.

Once this is done, 3 different spectral methods are compared at the first EEG derivation, concluding that the Welsh periodogram with a 60 second window and 50% overlap gives the better performance for the power band analysis to be performed.

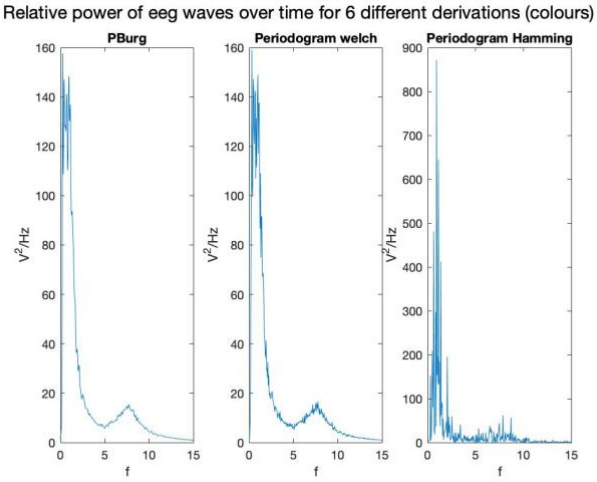

Figure 13

Using the welsh periodogram with the mentioned characteristics, the PSD function for each epoch of 10 seconds was estimated, so that the relative energy of each of the EEG waves could be computed for each epoch.

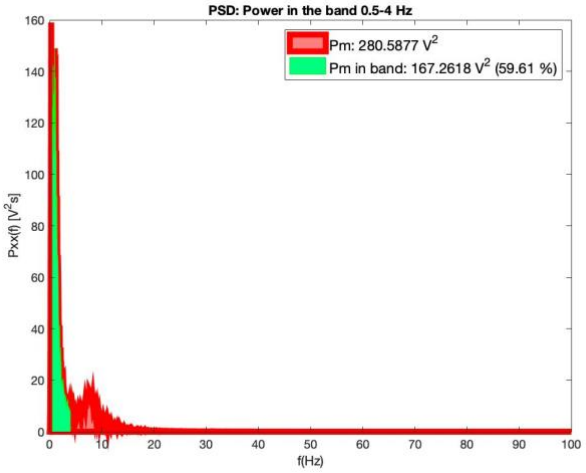

Figure 14

The figure above shows an example plot of the relative energy of the delta wave (0.5-4 Hz) in the F3-M2 EEG lead over the entire section, which is 0.59. At this point, a function was created that inputs the entire section of the EEG of a lead and uses the Welsh periodogram to return the relative energy of the given lead in 10 second windows as a function of time. In this way, the change in each relative energy of each EEG lead was

calculated and plotted over 10 s gaps as shown in Figure 15, offering an overview of the energy of the waves across time.

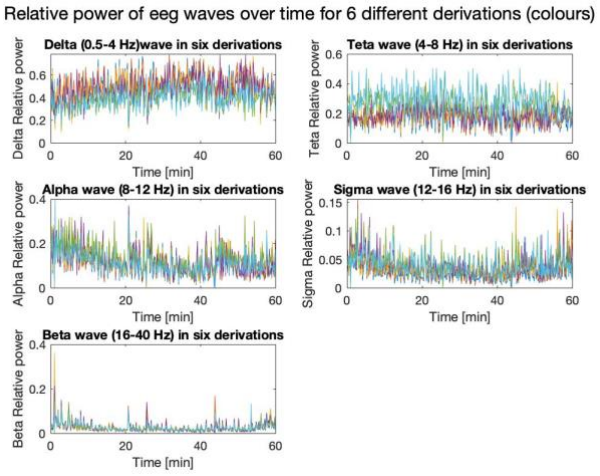

Figure 15

After noticing that the trend is similar in the six leads, meaning that even though the six must not have the same value they do have the same behaviour, the mean between the six leads was calculated and shown in Figure 16.

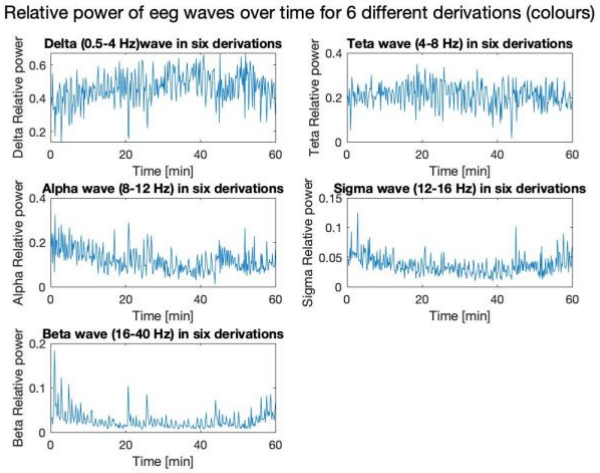

Figure 16

As it is visible in the plot above, a visualisation of how each EEG wave energy changes over the sleep was achieved.

In this way, energy and frequency characterization was performed and the data obtained can be further used to relate brain wave energy levels to the patient's sleep stages.

E. Signal and Sleep stages Relations

In this section the relationship between the behaviour of the studied signals and the stage of sleep is analysed.

As mentioned in the methodology section, the three main extracted parameters have been used to evaluate if the signals contain information about which is the stage of sleep the patient is in. The results are shown in figure 12, 18 and 19.

In our analysis only Wake, nonrem1, nonrem2 and REM have been studied, as the part of the signal we chose did not have a nonrem3 stage.

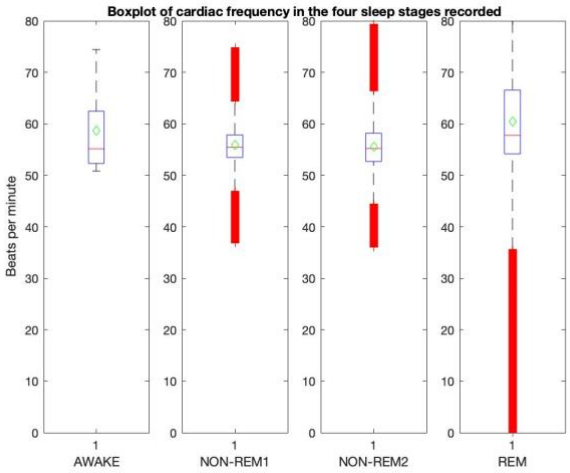

Figure 17: Cardiac frequency

At first sight there is no significative difference in neither the mean nor the median of the cardiac frequency through the stages of sleep. On the other hand, the peak values of cardiac frequency seem to decrease as the sleep deepens, making highest and lowest cardiac frequency values decrease as the patient approaches REM stage.

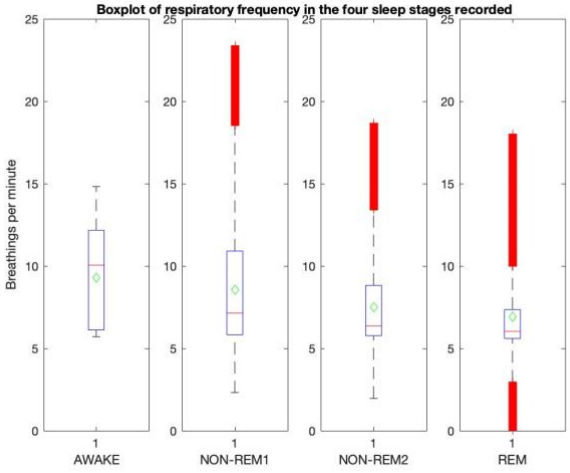

Figure 18: Respiratory Frequency

The reparatory frequency consistently decreases from awake into REM, being so coherent with what typically happens and even more considering there are a considerable number of apneas in this section of the signal, meaning that the breathing per minute also decrease.

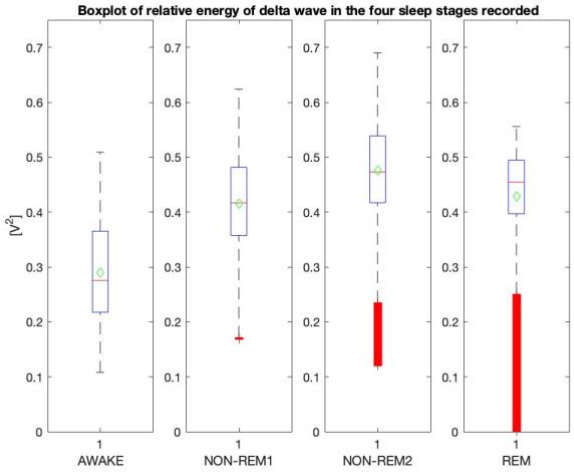

Figure 19 Delta wave

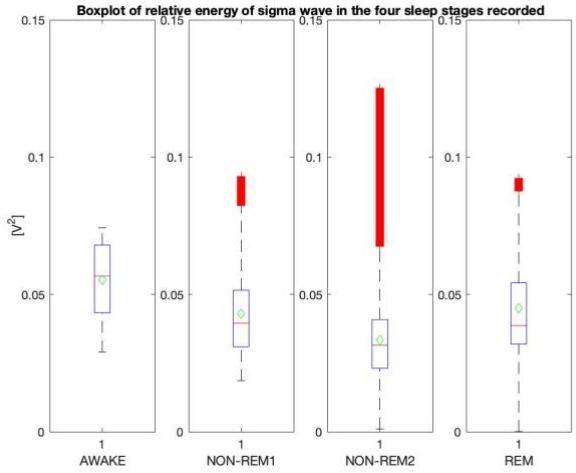

Figure 22: Sigma wave

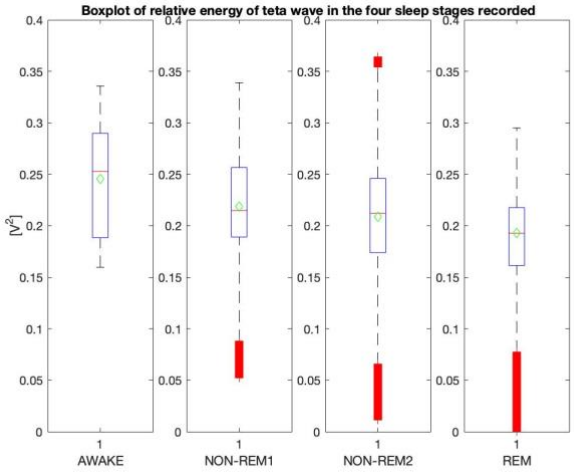

Figure 20: Teta wave

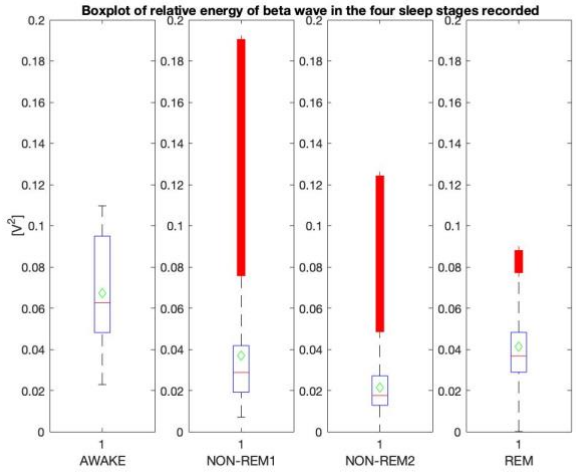

Figure 23: Beta wave

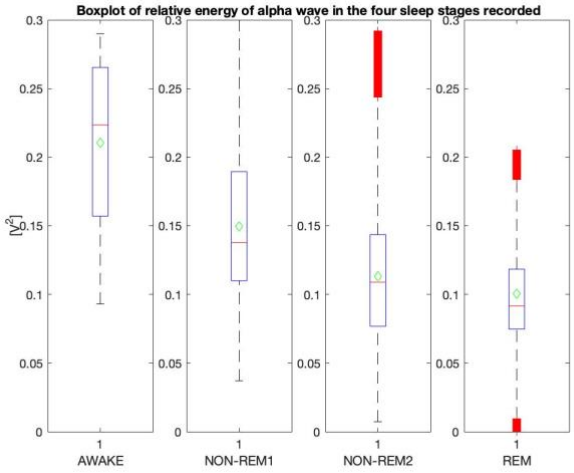

Figure 21: Alpha wave

In general, the EEG waves decrease when the sleep deepens, with some increase of the wave energy when achieving the REM stage for sigma and beta waves. The only wave that consistently increases is the delta wave, which also is consistent because the delta wave is the lowest frequency EEG wave, and low frequency EEG are typically enhanced when people sleep. Also, an increase does not mean that the cerebral activity in the frequencies of delta wave increase, but that the relative energy of the delta wave with respect to that of the total EEG increases.

IV. Conclusion

To sum up, the determined cardiac frequencies were similar in the mean but had different variance, making them of difficult interpretation. To increase algorithm reliability it would be useful to add a statistical analysis of the obtained results. As it can't be said for sure that changes were either present due to the signal's properties or because of missing or over- sensitivity of the algorithm.

Regarding the sudden changes maybe the Burg method to calculate the PSD would have resulted in a better performance as it is adapting to changes of the signal.

Same applies to the HRV algorithm. The HRV was determined using the RR intervals of the signal. The variability of 0 of the VLF could indicate either pathological PNS or that the algorithm is not working properly. The latest might also explain why the trajectory of the LF, and HF are qualitative the same. An analysis via a scalo- or spectrogram might be more suitable for this kind of signal as it allows the detection of pattern in the signal's frequency and power characteristics over time.

The results were not directly related to the apnoea annotations and only left for speculative relations. Therefore, the analysis of CF and HRV alone is considered not to be enough to differentiate between sleep stages or apnoea's.

Regarding the respiratory frequency estimation, the results were coherent both with healthy physiology and with the one we could expect from an apnoeic event. Therefore, even though the result seems the most significative one it probably is not useful for stage or apnoea determination alone.

Finally, the results obtained from the relative energy of the EEG waves were the most coherent ones, showing a relative decrease of all the EEG waves only in benefit of the one of lowest frequency, as was expected. These results are probably significative for sleep stage study, but not for apnoea study, as it has not been properly compared. In order to further study the effect of sleep stages in the parameters analysed, longer interval of PSG should be studied along with statistical significance of the results.

V. Appendix

Figure 24: Annotations of arousals and sleep stages for the time period used for the ecg signal.

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