MICA Project

TS114 - Digital Signal Treatment

Fares Boudjaoui - Joumana Benguenna - Saad Bengrain

fboudjaoui@bordeaux-inp.fr - jbenguenna@bordeaux-inp.fr - sbengrain@bordeaux-inp.fr

Supervised by Romain Tajan - Malek Ellouze - Rémi Buisson
rtajan@bordeaux-inp.fr - mellouze@bordeaux-inp.fr - rbuissonjar@bordeaux-inp.fr

And by Cécile Malet-Dagréou
cecile.malet-dagreou@enseirb-matmeca.fr

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1 Introduction

The MICA project was a first year Telecom project about how, with signal treatment, it is possible to help cardiologists to detect a patient's heart problems with an application that detects a patient's pathology.

Firstly, a spectrogram can be used to detect heart pathology. It is a tool to visualize a signal with frequency and time. Spectrograms can be used to detect ventricular fibrillation. Indeed, ventricular fibrillation is a type of abnormal heart rhythm. During ventricular fibrillation, disorganized heart signals cause the lower heart chambers (ventricles) to twitch uselessly [1]. Thanks to the spectrogram, we can detect the change of frequency and when it happens, we have both pieces of information on one graph.
The yellower is the color, the higher this frequency appears in the spectrum of frequency.

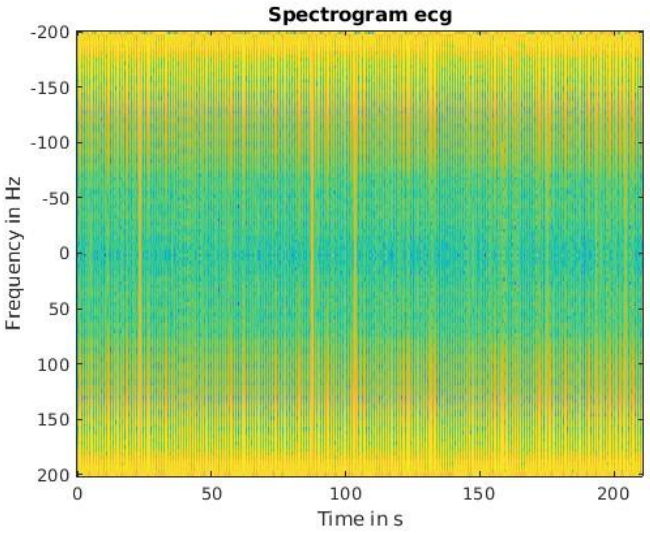


Figure 1

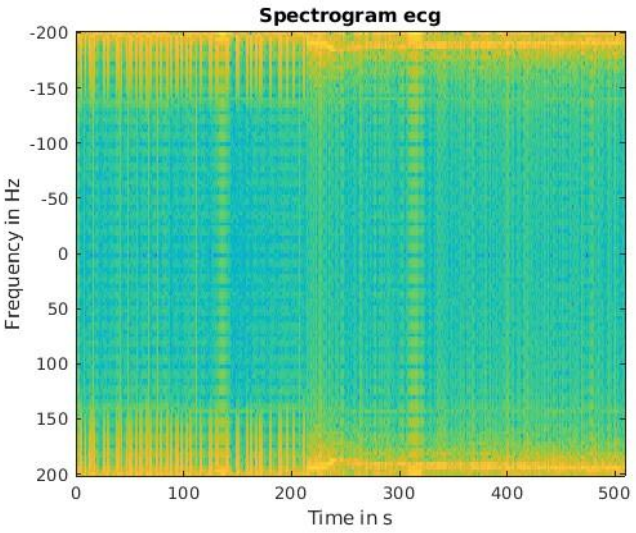


Figure 2

On Figure 1, there is a normal heart ECG. It means that there are 2 big yellow "bands" around 200 Hz and -200Hz and frequency changes, as time changes. There are multiple frequencies on the signal because of the way the heart beats, which is not a sinus: it is a PQRST signal (cf. Part.5); there are harmonics.

On Figure 2, at the beginning, the heart beats like a normal one (the yellow band is smaller than in figure 1, that's means there are fewer frequencies in the spectrum) but at 214 seconds, we can see a change, there is only one frequency in the spectrum equal to 200 Hz. It beats like a sinusoidal movement, not a PQRST. This patient has a heart condition. The fact that his heart beat changes into a "sinus" (it's not a pure sinus) shows that he suffers from ventricular fibrillation.

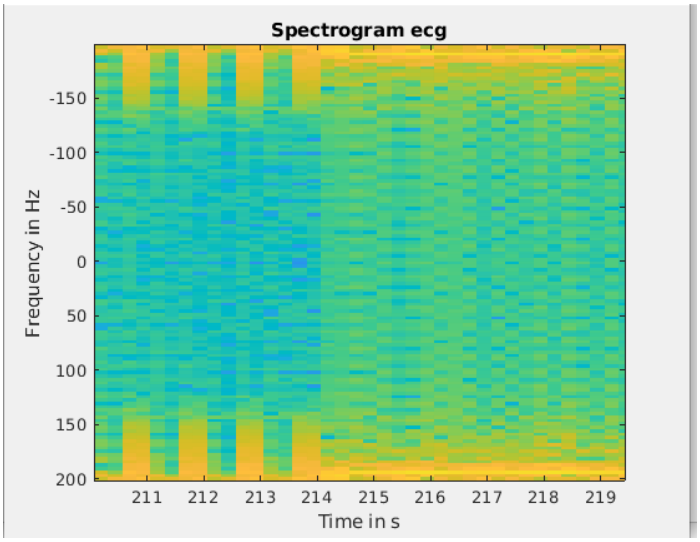


Figure 3

The signal from Figure 2 is zoom and we can see the heart's BPM irregularity. It is changing immediately at 214 seconds.

To make the story short, spectrograms are useful to detect frequency changes over time like, for example, arrhythmia (ventricular fibrillation, tachycardia, brachycardia…) or malformation [3]

2 Detection of the QRS Complex

To determine pathologies, the electrocardiogram was used to locate the PQRST complex (Figure 4). As a first step, the three heartbeat peaks named Q, R and S were located by using the Pan and Tompkins algorithm.

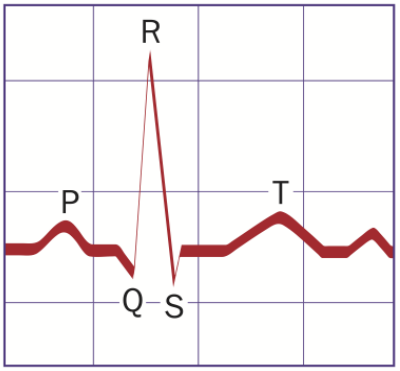


Figure 4 : PQRST complex [4]

2.1 The Pan and Tompkins Algorithm

This algorithm goes through several steps. The electrocardiogram was firstly filtered with a band pass filter which is the combination of a low pass filter and a high pass one. This was done in order to avoid noise as much as possible. Then, the signal was filtered once again with a derivative filter to bring out information about the QRS complex slope. After squaring these pieces of information, the peaks were enhanced. Thus, moving-window integration calculated the mean of the QRS complex to make the three extremes closer and consequently easier to extract with the thresholding. Indeed, this step used a threshold to determine the values of the signal which formed part of a QRS complex. In particular, all the points above this threshold were included in a complex and consequently, the QRS peaks were among them.
Finally, considering the group delay of all the filters, the R maximum was detected from the electrocardiogram generated after the band pass filter. This identification was possible because the location of the QRS complex values in the thresholded signal was the same in the filtered signal.

2.2 Filters Implementation

As the Pan and Tompkins algorithm suggested, the electrocardiogram was filtered to make it more useful. The signal was convolved with three filters and that had an impact on the signal's frequencies but also on its shape.

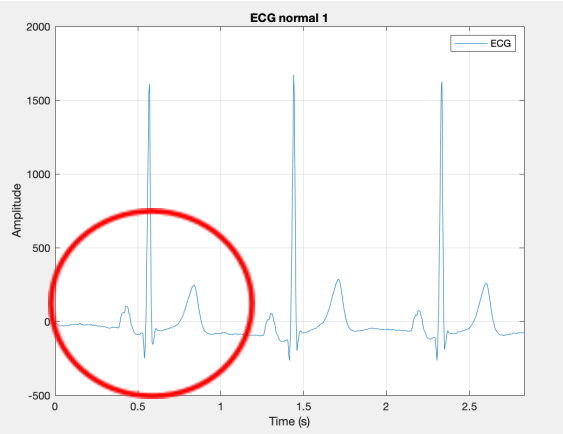


Figure 5 : Electrocardiogram before filters

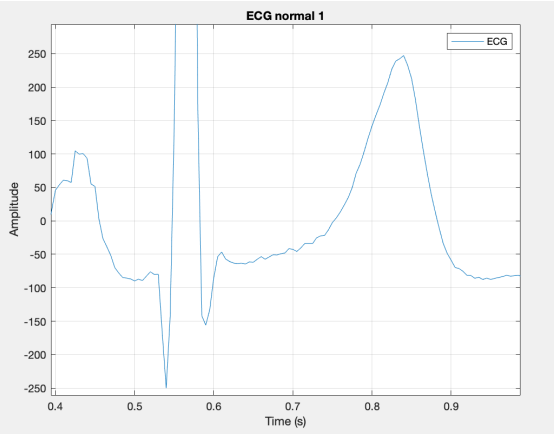


Figure 6 : Zoom of Figure 2

Figure 5 represents the electrocardiogram before any work. They are three distinct QRS complexes and the third figure shows it more precisely.

- **Low-Pass Filter**

The first filter used was a low-pass filter. Its goal was to prevent high frequencies which impact the signal. Figure 7 represents the signal after this filter.

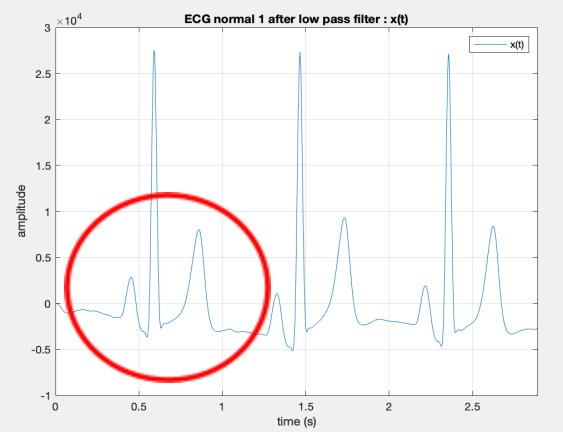


Figure 7 : Signal after low-pass filter

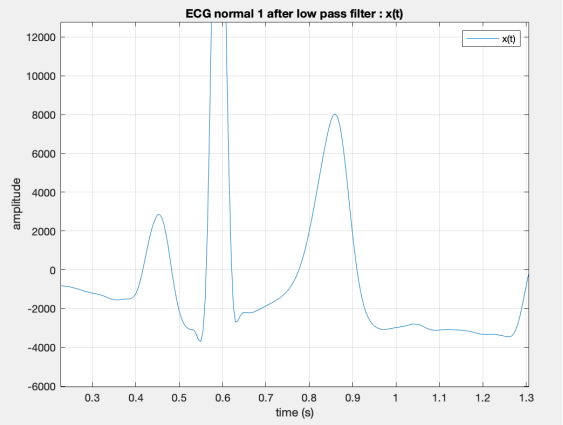


Figure 8 : Zoom of Figure 4

On Figure 8, the signal has less noise represented by little and numerous variations. This low-pass filter is causal and has a finite impulse response. Its group delay[1] is equal to 5.

[1] All group delays were found with the matlab grpdelay() function except for moving-window integration.

- **High-Pass Filter**

The second filter used was a high-pass one which eliminated the signal's low frequencies. The aim was to keep only frequencies which were around a heart frequency.

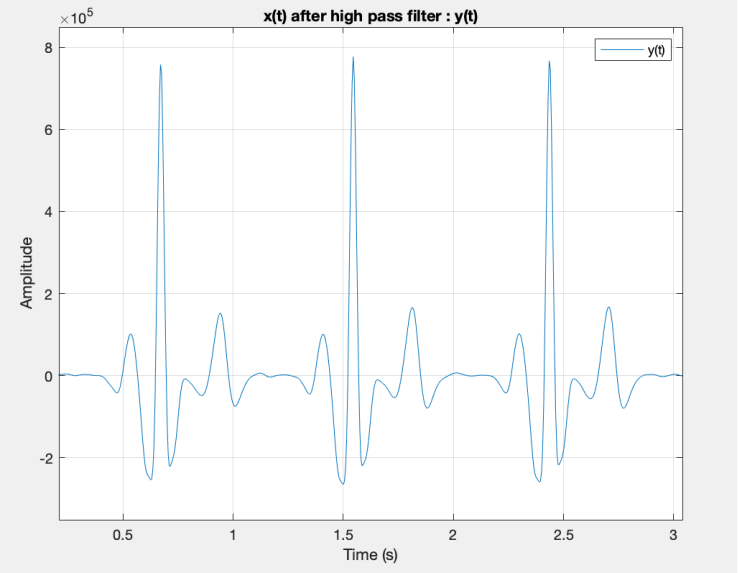


Figure 9 : Electrocardiogram after high-pass filter

The general shape was restored (Figure 9) but without undesirable variations. This filter is also causal, has a finite impulse response and its group delay is 16. Combining this one with the-low pass filter, it created a band-pass filter.

- **Derivative Filter**

The third and final filter used was a derivative filter.

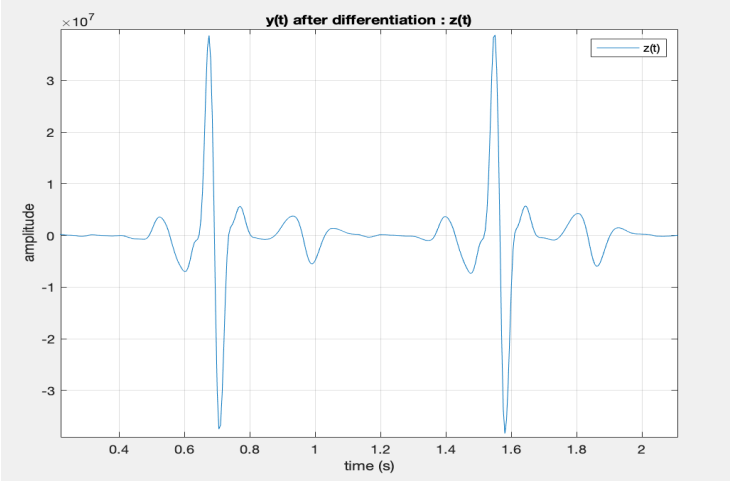


Figure 10 : Signal after derivative filter

Its non-causality divided its implementation into two steps. The first one was the implementation of a causal filter with a group delay of 2. The second step consisted in filtering the signal with a filter which created only a group delay of 2 but did nothing else to the electrocardiogram.

2.3 R Detection

After the filters, the signal is squared to enhance the QRS peaks.

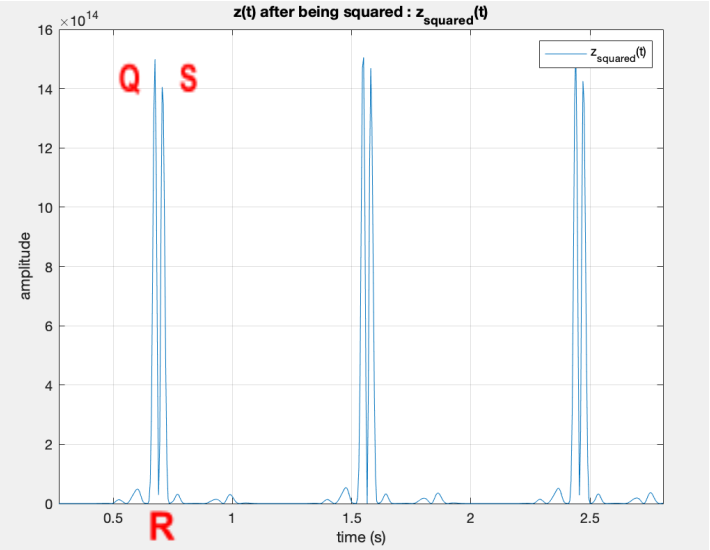


Figure 11 : Signal after being squared

As Figure 11 shows, Q and S points are closer but R is still too far from them. Thus, it was impossible to locate a QRS complex in one phase. To solve this problem, moving-window integration was used but with a group delay of 12. Indeed, its expression was actually a convolution with a constant function equal to 1.

$$s_{MWI}(n) = \frac{1}{N} \sum_{i=0}^{N-1} s_{sq}(n-i)$$

Knowing this, the group delay was calculated by using the z-transform. Figures 12 and 13 represent the location of a QRS complex after the moving-window integration was applied where the three peaks are very close.

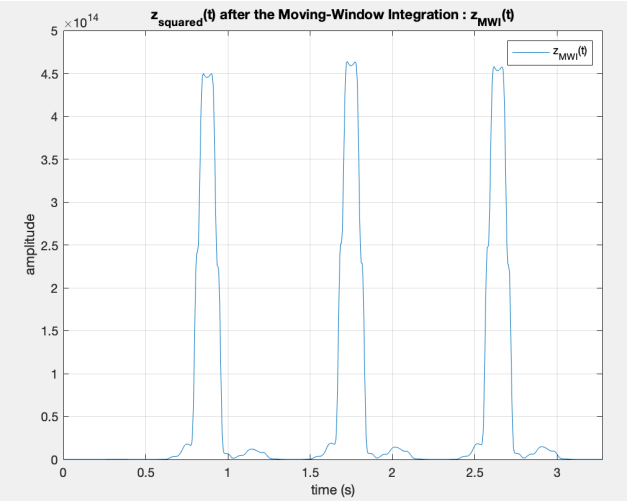


Figure 12 : Signal after MWI

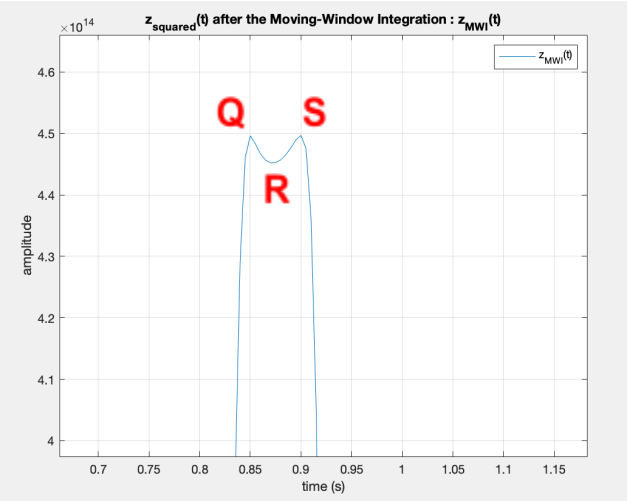


Figure 13 : Zoom of Figure 12

Finally, thresholding extracted the signal's values which were part of a QRS complex. The mean of the signal after moving-window integration was calculated and the threshold was chosen as 90% of this value.
The QRS complex locations in the signal after moving-window integration were the same in the filtered signal (Figure 9). Therefore, the R peaks were located simply by finding the maximum of each QRS complex.

2.4 Q and S Detection

The first minimum before an R peak is a Q and S is the first minimum after R. Knowing that, an algorithm found their indexes in the electrocardiogram from the filtered signal (Figure 9) which passed through a fenestration.

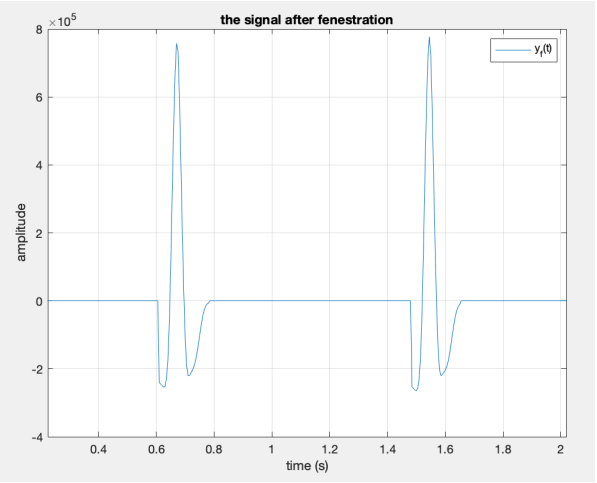


Figure 14 : Signal fenestration

Figure 14 represents the signal after a fenestration where all the values which are not part of a QRS complex are set to zero.

2.5 P and T Detection

P and T are detected more simply using RR intervals and a three-step filtering process. Starting with a differentiator with the following transfer function:

$$H_1(z) = 1 - z^{-6}$$

Then a low-pass filter with the following transfer function:

$$H_2(z) = \frac{1 - z^{-8}}{1 - z^{-1}}$$

Finally, the T wave is detected by considering it as the highest peak between R and 0.7 of the RR interval, and the P wave is the highest peak in the remaining section of the RR interval.

3 Identification of Cardiac Pathologies

3.1 Tachycardia/Bradycardia

The detection of these arrhythmic pathologies can be easily achieved by calculating cardiac rhythm. This calculation consists in averaging R-R interval durations. Which means if Δn is the n-th occurrence of the RR interval, and N is the number of R peaks contained in the ECG signal, the average heart beat per minute is then computed thanks to the following formula :

$$\Delta = \frac{1}{N}\sum_{n=0}^{N} \Delta_n$$

The table below is used to identify tachycardia and bradycardia based on the assessment of the cardiac rhythm:

BPM	Pathology
≥100	Tachycardia
≤60	Bradycardia

4 ECG Denoising

The ECG signal can be contaminated by noise such as baseline wander, power line interference or muscle activities. Thus, the filtering of the ECG signal is paramount to get the best clinical value out of the signal.

4.1 Butterworth Filter

The following low-pass filter was designed to cut the power line interference off:

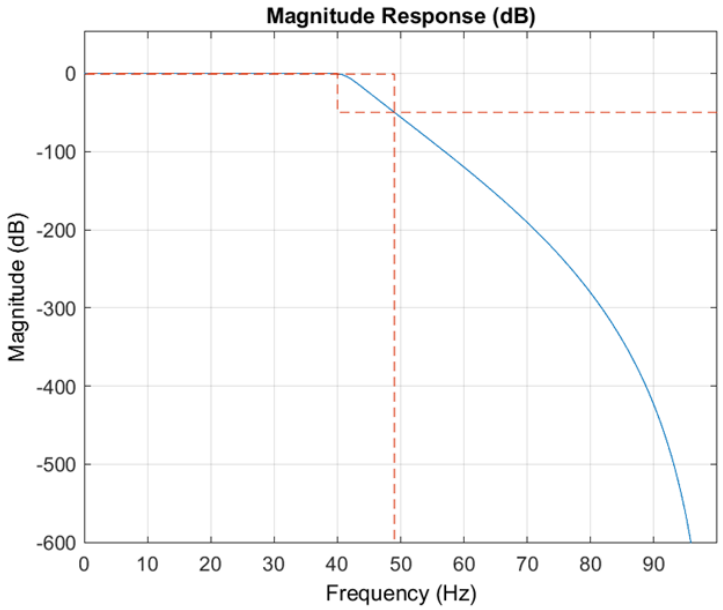


Figure 15 : Magnitude of the designed Butterworth filter

Figure 15 shows a low-pass IIR Butterworth filter designed with minimum level to cut the power line interference off, with 50 Hz cut off frequency.

Considering the time evolution and the power spectrum of the following ECG signal:

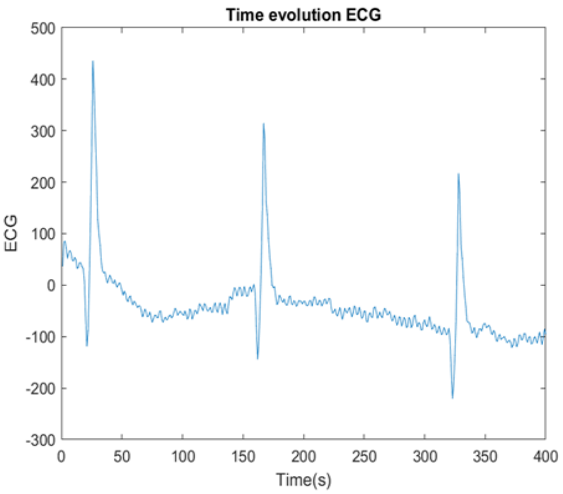


Figure 16 : Time evolution of noisy signal

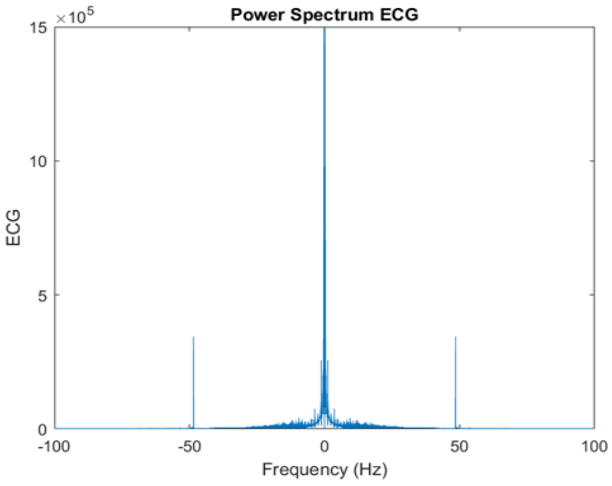


Figure 17 : Power spectrum of noisy signal

Figure 16 does not give a clear idea about the noise, but Figure 17 shows the noise at 50 Hz frequency. Figure 18 represents the power spectrum after applying the Butterworth filter:

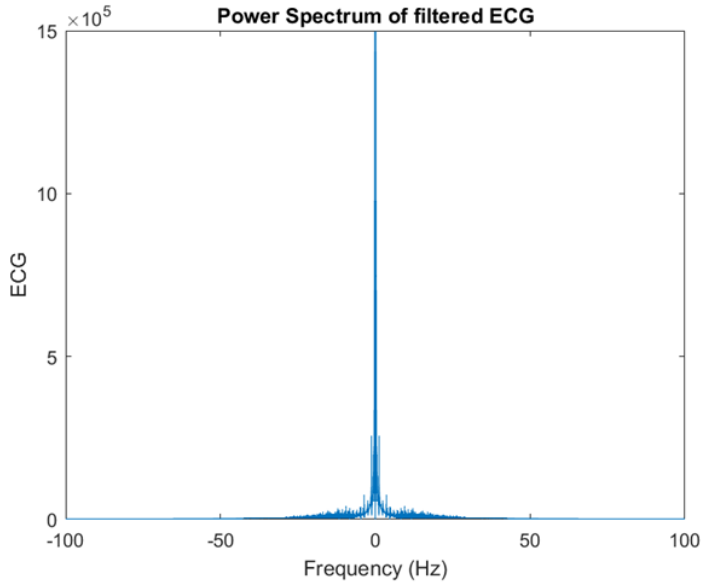


Figure 18 : Power spectrum of the filtered signal

As Figure 18 shows, the peaks at 50 Hz disappear after applying the filter and the frequencies that are higher than 50 Hz are also attenuated, which means that the designed low-pass filter is cutting the power line interference off.

4.2 Chebyshev Filter

The following high-pass filter was designed to remove the baseline interference:

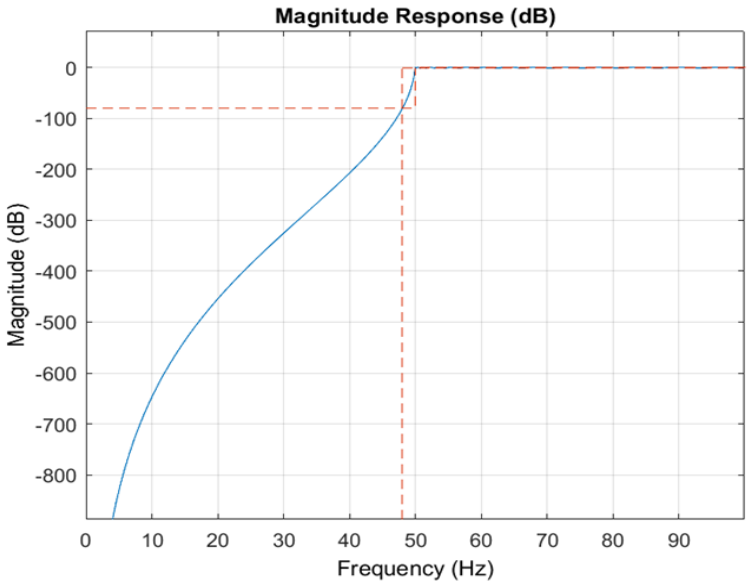
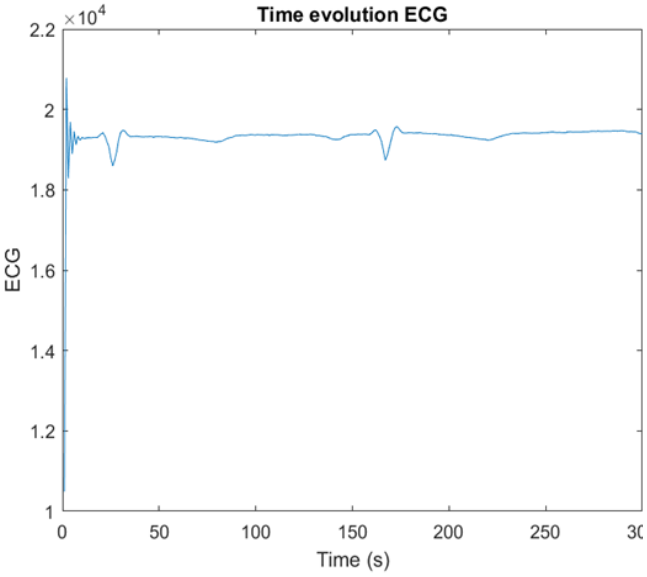


Figure 19 : Magnitude of the designed Chebyshev filter

Figure 19 shows a high-pass Chebyshev filter designed to remove the baseline interference, with 50 Hz cut off frequency.

Considering the time evolution and the power spectrum of the following ECG signal:



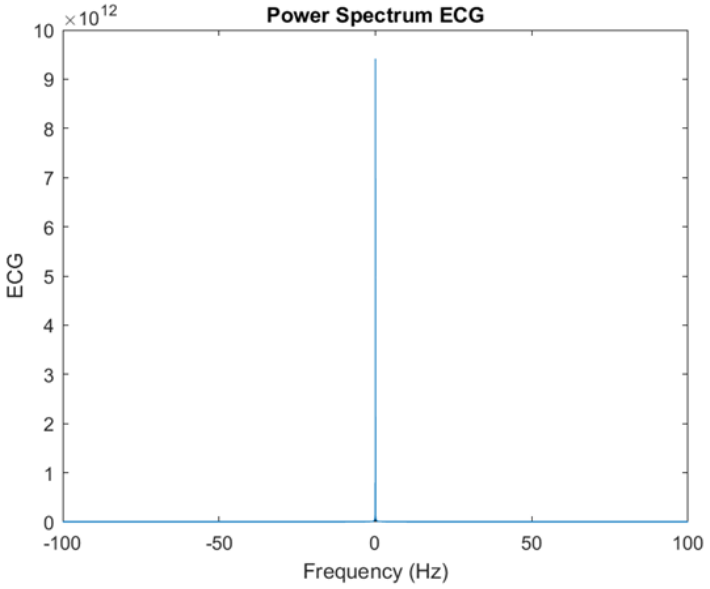


Figure 20 : Time evolution of noisy signal

Figure 21 : Power spectrum of noisy signal

Figure 20 does not give us a clear idea about the noise, but Figure 21 shows that the noise is located in the frequencies under 50 Hz. Figure 7 represents the power spectrum after applying the Chebyshev filter :

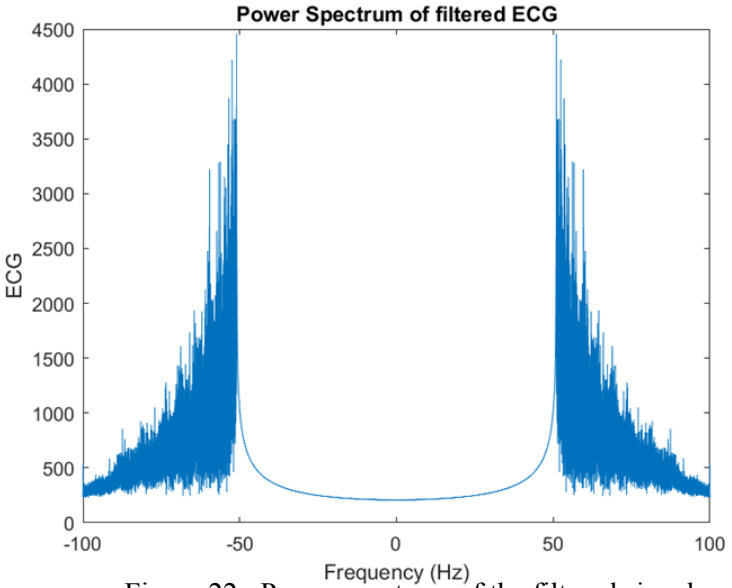


Figure 22 : Power spectrum of the filtered signal

As Figure 22 shows, the peaks at 50 Hz disappear after applying the filter and the frequencies that are lower than 50 Hz are also attenuated, which means that the designed high-pass filter is removing the baseline interference.

5 Conclusion

In this project, an algorithm was introduced for the detection of two pathologies. The proposed algorithm analyzes ECG signals, the duration and shape of each waveform and the distances between different peaks to diagnose heart diseases. In addition, due to many noise sources, this signal has to be denoised and presented in a clear waveform. Noise sources may consist of power line interference, external electromagnetic fields, random body movements or breathing. For those reasons, two important denoising methods were presented and applied on real ECG signals contaminated with different noise levels.

References

[1]Ventricular fibrillation - Symptoms and causes - Mayo Clinic

[2]https://www.nhs.uk/conditions/arrhythmia/

[3]https://fr.mathworks.com/help/signal/ref/spectrogram.html

[4] https://www.healio.com/cardiology/learn-the-heart/ecg-review/ecg-interpretation-tutorial/qrs-complex