TS114 Signal processing

Semestre 6

Project report

Telecommunication - ENSEIRB-MATMECA

Conducted by :

Amine KARTIT
Hicham FELLAH

Contents

1 Introduction

1.1 Presentation of the project

Electrocardiogram **ECG** which is an electrical recording of the heart movements is used in the investigation of certain heart pathologies. In this project the **Matlab** environment is used to analyse the ECG.

The aim of this project is to perform an algorithm that studies the heart state. The use of the **DSP** method (especially the **Short Term Fourier Transform**) is necessary in order to detect the **PQRST** complex as it can be seen in **figure 1**.

The ECG signal is used to obtain all the parameters needed for the detection of the five characteristic wave-forms, called respectively P, Q, R, S and T. This information is then submitted to the Matlab program to acquire the heart's cardiac results: *premature atrial contraction, premature ventricular contraction and the atrial or the ventricular fibrillation.*

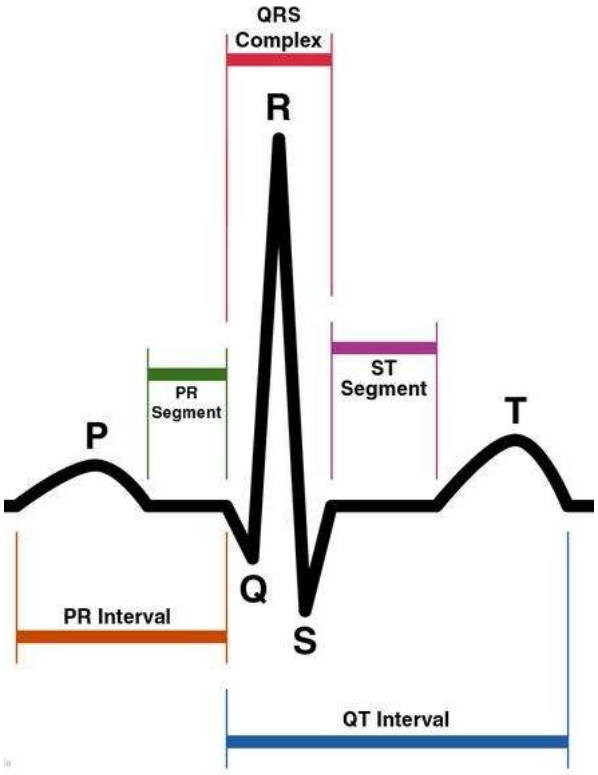
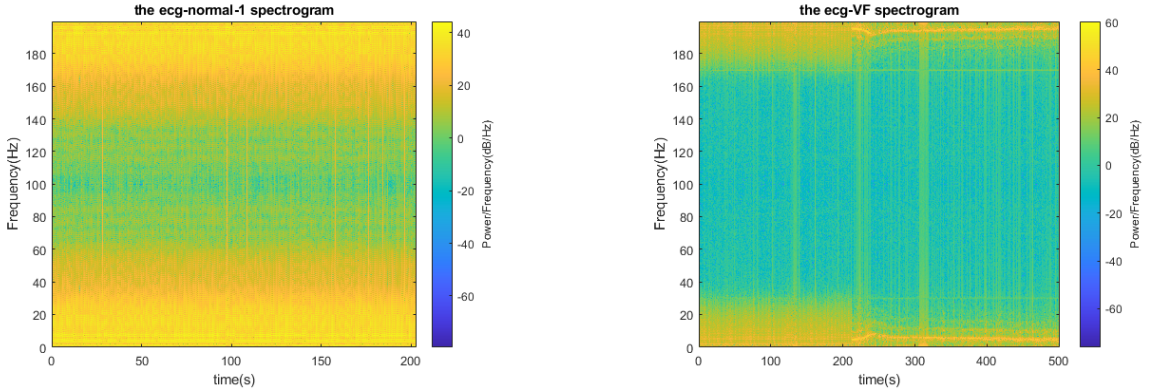


Figure 1: example of an ECG wave-form *[1]*

Initially the heart rate varies over time, which makes it hard to distinguish the difference between some pathologies and basic efforts. The Fourier transform helped to solve this issue. The process is called **Short Term Fourier Transform**.

1.2 Data visualization



(a) Spectogram applied to ecg_normal_1 (b) Spectogram applied to *ecg_ VF*

Figure 2: spectograms with the Hamming window method

1.3 Comments

The figures above illustrate the *ecg_ VF* and *ecg_ normal_ 1* spectogram using an 8-second Hamming window. On the one hand, the spectogram obtained have two large yellow areas where the power spectral is intense due to P, Q, R, S and T waves presence as it can be seen in **figure a**; And it remained stable during the whole simulation, therefore it represents a normal ECG signal.

On the other hand, **figure b** illustrates a spectogram with less important yellow areas for a 215-second simulation, then a remarkable two yellow lines obtained for the rest of the simulation.

Thus, **figure b** represents a ventricular fibrillation ECG signal because of it similarity to a pure sine after 215 seconds.

2 Technical Part : PQRST detection

2.1 Pan and Tompkins algorithm

2.1.1 Algorithm presentation

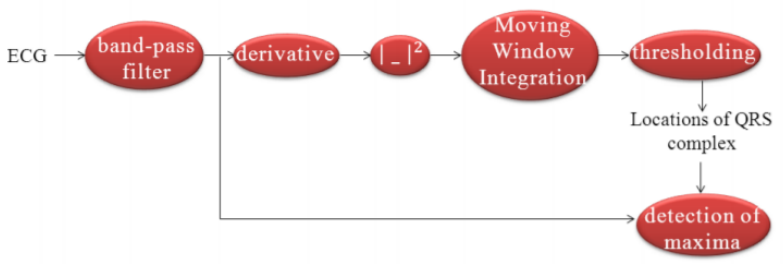


Figure 3: Pan and Tompkins block diagram process *[2]*

2.1.2 The Pan and Tompkins explanation

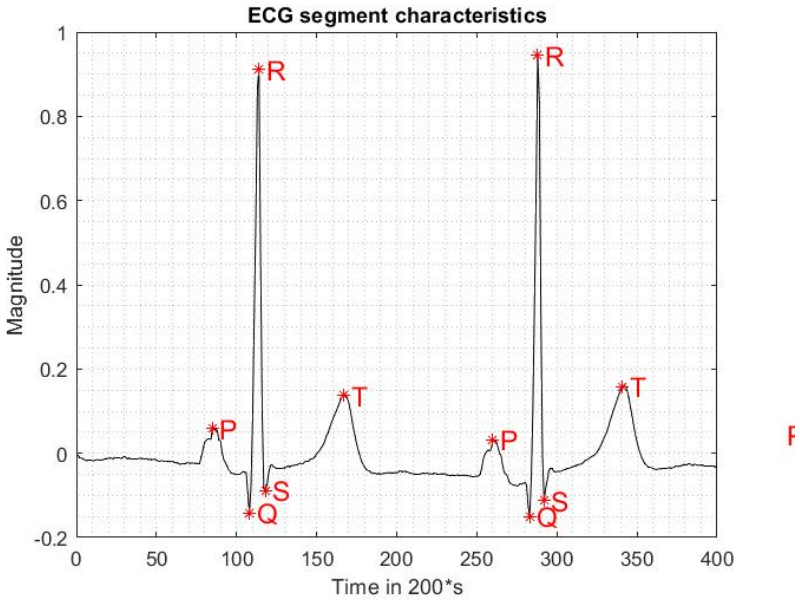


Figure 4: ECG PQRST auto-detection applied to *ecg_normal_1* : 2 seconds duration

The Pan & Tompkins algorithm is used to detect the QRS complex in the ECG by detecting the main spike as seen in **figure 4**, the QRS complex is also composed of three main deflections: the first is a downward deflection called Q wave followed by an upward one which is called R wave and finally the S wave.

The Pan & Tompkins algorithm is represented in **figure 3 in page 4**, it consists of a series of filters used to point up the frequency content of the heart depolarization and to eliminate the system's noises. The signal is then squared to highlight the QRS complex in the ECG, and the moving-window makes it easy to spot the major peaks by applying an adaptive threshold that provide a boolean vector "*tresh*" with value of one if the R wave is possibly in.

The R wave position is then located precisely by the use of an algorithm that consists on finding the first step where the previous step has a lower value (With a loop "*while*" where the "*tresh(i)*" = 1) **without forgetting to shift "*tresh*" by the equivalent group delay**. The result is a vector "*Max*" with the same length of the ECG signal containing zeros except in the R peaks positions.

Then the Q waves are located by browsing the vector "*Max*" using a loop "*while*" that progresses backwards and stops in the first step where the step after is higher. Otherwise, the S waves are located with the same technique but the loop "*while*" progresses frontwards.

The P and T waves detection uses the R-R interval to be detected. Since the T wave is the maximum of the first 0,7 of the R-R interval (Starting from the S wave location), In order to be able to identify the maximums a **differentiator** as well as a **Low pass filter** are required, then finding exactly where the filtered function equal zero in the corresponding interval provides different locations, but the maximum of the corresponding values of these locations in the ECG signal is the exact T location. In the remaining 0.3 R-R interval (ending at Q wave location) the maximum obtained using the same method and it matches the P location. The figure down bellow explains how the R-R interval is divided.

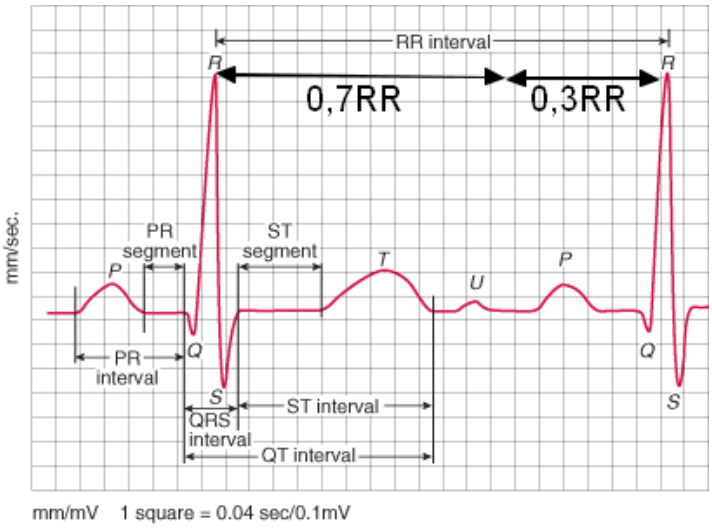


Figure 5: R-R intervals division [7]

2.2 Implementation

The first step is applying a combination of a Low-Pass and a High-Pass filters to the ECG signal to increase the signal intensity compared to the noise (*signal/noise ratio*).

The low-pass filter :

$$H_1(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2} = \frac{N(z)}{D(z)}$$

$>D(z) \neq 1 \Rightarrow$ an IIR filter
$>Y(z)(1-z^{-1})^2 = X(z)(1-z^{-6})^2 \Rightarrow y(n) - 2y(n-1) + y(n-2) = x(n) - 2x(n-6) + x(n-12) \Rightarrow$ Causal filter
>the filter has a 3dB cut-off frequency of about 0.23dB obtained using the *powerbw.m*
>a group delay of 5 samples and has a non-linear phase as observable using the function *fvtool.m*.

The high-pass filter :

$$H_2(z) = \frac{(1+32z^{-16}-32z^{-17}+z^{-32})}{(1-z^{-1})} = \frac{N(z)}{D(z)}$$

$>D(z) \neq 1 \Rightarrow$ an IIR filter
$>Y(z)(1-z^{-1}) = X(z)(1+32z^{-16}-32z^{-17}+z^{-32})$
$\Rightarrow y(n) - y(n-1) = x(n) + 32x(n-16) - 32x(n-16) + z(n-32) \Rightarrow$ Causal filter
>the filter has a 3dB cut-off frequency of about 2.87dB
>a group delay of 15 samples and the phase is non-linear.

The derivative filter :

$$H_3(z) = \frac{1}{8T_s}(-z^{-2} - 2z^{-1} + 2z^1 + z^2) = \frac{N(z)}{D(z)}$$

$>D(z) = 1 \Rightarrow$ an IIR filter
$>Y(z) = \frac{1}{8T_s}X(z)(-z^{-2} - 2z^{-1} + 2z^1 + z^2)$
$\Rightarrow y(n) = \frac{1}{8T_s}(-x(n-2) - 2x(n-1) + 2x(n+1) + x(n+2)) \Rightarrow$an acausal filter and as a consequence the peaks are simple to detect and there was less group delay.
> a group delay of 2 samples and a 3dB cut-off frequency of about 0,18dB. The filter has a non-linear phase.

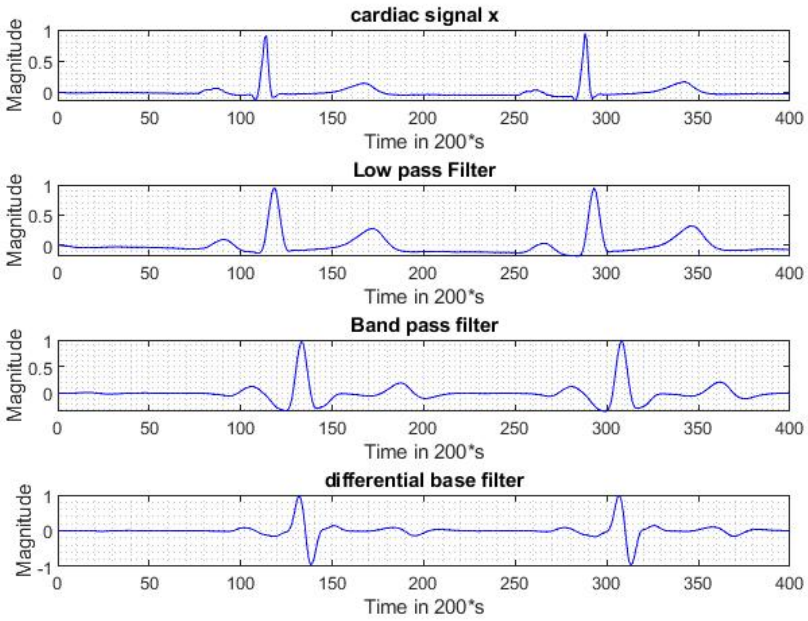


Figure 6: Illustration of the Pan & Tompkins algorithm filters

As seen in **figure 6**, the filters have a direct influence on the cardiac signal. The ECG was filtered and the resulting signal is then used in the rest of the steps as seen above in **figure 3**.

Only **figure 4** is important, in fact this figure is the only one used to determine whether a patient has a heart illness.

To detect the P and T waves, two other filters were introduced :
>The derivative filter :

$$G_1(z) = 1 - z^{-6}$$

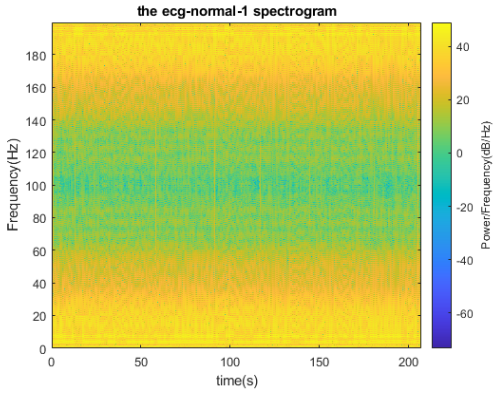
The first filter is causal, IIR and a non-linear phase differentiator whose function is to simplify the detection of the local maximums and minimums in the ECG, the filter has a group delay of 3 samples and a 3dB cut-off frequency of about 0,7dB.
>The low-pass filter :

$$G_2(z) = \frac{1-z^{-8}}{1-z^{-1}}$$

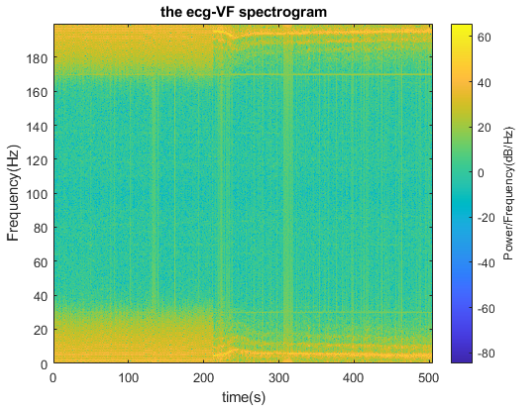
The second one is a low-pass causal and FIR filter, the group delay of this filter is nearly 4 samples and the 3dB cut-off frequency is 0,18dB.

3 Automatic identification of cardiac pathologies

3.1 Spectrogram analysis



(a) Spectogram applied to ecg_normal_1.mat



(b) Spectogram applied to *ecg_ VF.mat*

Figure 7: spectograms with Hamming window (4 seconds)

3.1.1 Comments

As was previously explained in **page 3 Section 1.2.2**, **figure a** represents a normal ECG signal, and **figure b** represents a ventricular fibrillation ECG signal. In this case a 4-second Hamming window is used to provide more details about the transition before and after 200 seconds in **figure b** to obtain an intense yellow line.

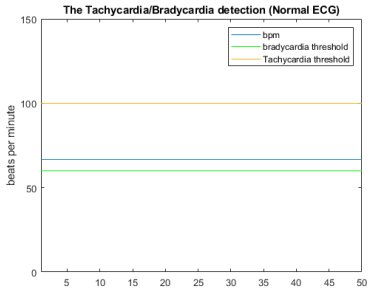
3.2 Tachycardia/Bradycardia

Tachycardia and **Bradycardia** are basic *arrhythmia pathologies* detected using the heart cardiac rhythm. If it's under 60 bpm it is called **Bradycardia**, else if the cardiac rhythm is above 100 bpm it is called **Tachycardia**.

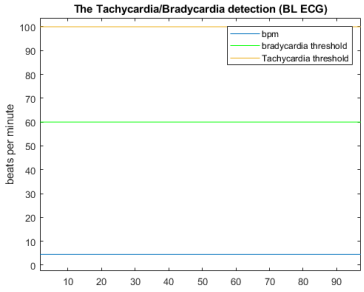
To estimate the cardiac rhythm of an N number of R peaks at times $t_0 < .. < t_N$, the n-th occurrence of the R_R interval is defined as $\Delta_n = t_{n+1} - t_n$. The mean of all occurrences R-R intervals is computed :

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

Then the bpm is computed as : $bpm = \frac{60 * F_s}{\bar{\Delta}}$



(a) Bpm of a normal ECG



(b) Bpm of a noise-BL ECG "Bradycardia case"

Figure 8: Tachycardia and Bradycardia detection

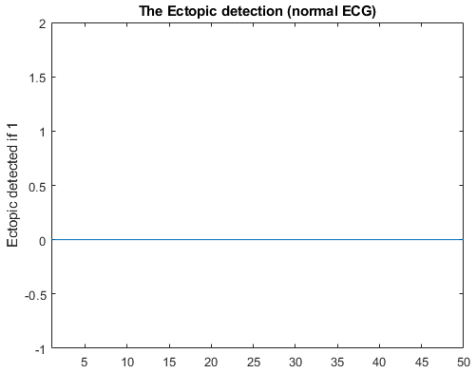
3.2.1 Comments

As expected, the bpm of a **normal** ECG is between 60 and 100. While the *noise-BL ECG* has a low bpm value (under 60 bpm) therefore, it is a **Bradycardia** case.

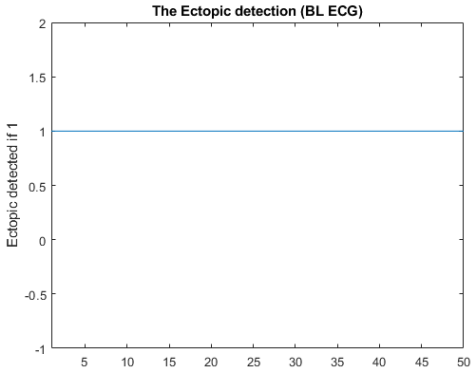
3.3 Ectopic beat

The **Ectopic detection** is based on comparing the difference of duration between two R-R intervals respectively to a certain threshold ε to detect an early R wave followed by a prolonged R-R interval.

With the n-th R peak an **Ectopic beat** is detected if : $|\Delta_n - \Delta_{n-1}| \geq \varepsilon$



(a) Ectopic beat of a normal ECG



(b) Ectopic beat of a noise-BL ECG

Figure 9: Ectopic beat detection

In **figure a** there was no **Ectopic beat** detection. Thus the patient has a normal ECG activity.

In **figure b** there is as seen an **Ectopic beat** detected so it is clear that the patient does not have a normal ECG activity.

3.4 Atrial Fibrillation (AF)

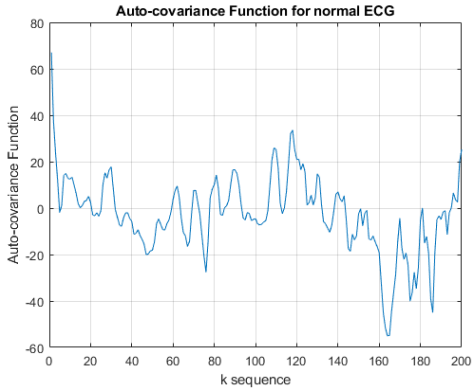
Atrial fibrillation is an irregular and often rapid heart rate that can increase the risk of strokes, heart failure and other heart-related complications.

During **Atrial fibrillation**, the heart's two upper chambers (the Atria) beat chaotically and irregularly — out of coordination with the two lower chambers (the Ventricles) of the heart [3].

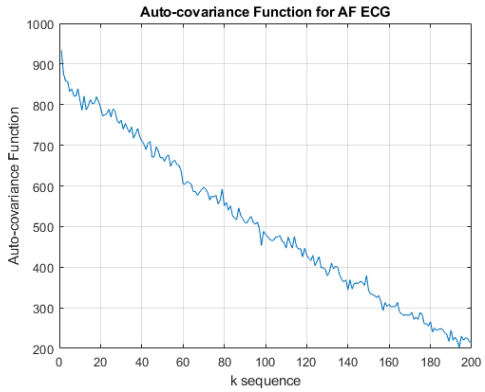
Thus, the process $(\Delta_n)_{n\geq 0}$ that represent the R-R intervals is considered as a *white noise*. It **auto-covariance** function is defined as :

$$\tilde{\gamma_k} = \frac{1}{N-k-1} \sum_{n=0}^{N-k-1} (\Delta_{n+k} - \bar{\Delta})(\Delta_n - \bar{\Delta})$$

3.4.1 Results



(a) Auto-covariance function of normal ECG



(b) Auto-covariance function of AF ECG

Figure 10: Atrial Fibrillation

In **figure a** the auto-covariance function fluctuate around the value of 0 and the fluctuation is mainly stable, which means that the patient has a normal ECG.

Although, **figure b** is different due to the fact that the patient suffers from *Atrial fibrillation* as it can be seen in this figure, the auto-covariance seems to decrease *rapidly* toward the value 0.

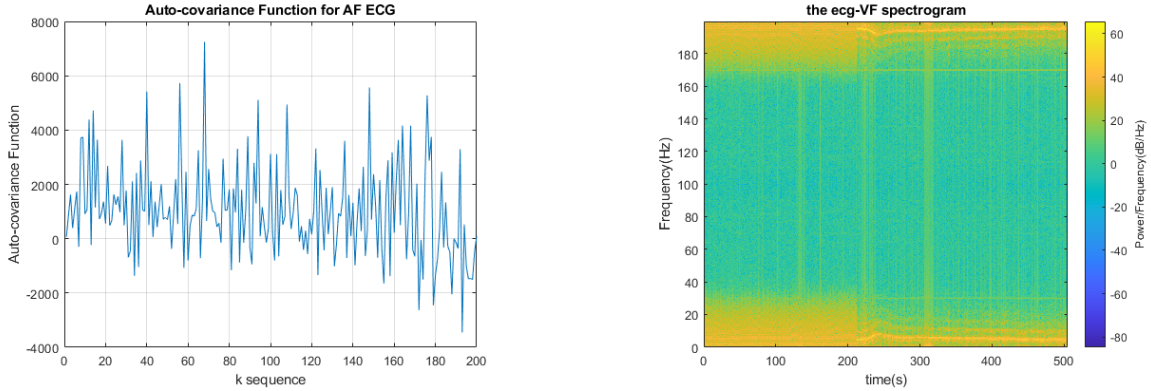
3.4.2 Comments

During a normal cardiac rhythm, the covariance coefficients γ_k are statistically significant, even at sequence 200, while during AF the auto-covariance function is only significant in γ_0 compared to the others [4]. Hence, the R-R intervals during AF are highly uncorrelated.

3.5 Ventricular fibrillation

Ventricular fibrillation is an abnormal heart rhythm in which the ventricles of the heart quiver instead of pumping normally. This phenomena is due to a disorganized heart-electrical activity.

3.5.1 Results



(a) Auto-covariance function of VF ECG (b) Spectogram of AF ECG

Figure 11: Ventricular Fibrillation

3.5.2 Comments

Studies have found that the auto-covariance function (**ACF**) can indeed display some unique modes of VF signals, such as a-periodicity and random amplitude. According to the auto-correlation regression test of **S.Chen & N.V.Thakor** [5] based on ECG, for quasi-periodic signals, such as SR and Tachycardia. **ACF** usually showed a regular peak value and a linear decreasing trend in most cases. While for VF: it showed scattered distribution [6] and the only auto-covariance that has a value of 0 for the first sample.

4 Bonus part

The idea behind the conception of this part of the project is to create a function that does the detection of the PQRST complex and implement it in the *MICA project* to obtain an interface that provides an easiest way to read and understand a patient pathology.

5 Conclusion

5.1 Summary

On the basis of the findings, several conclusions concerning the detection of various heart problems (*as seen above in section 3*). The findings of this project were able to help us to make it easy identify these pathologies.

Indeed, the algorithm based on Pan & Tompkins and proposed earlier is useful when it comes to detecting the characteristic PQRST complex and analysing the heart-cardiac signal making the identification of illnesses possible. Still it is not a faithful solution since the user is not able to control the values of the threshold neither the type of window.

Although, **section 4 page 12** explains the aim and the utility behind the development of an application to detect the PQRST complex and give the pathologies without having a basic signal processing knowledge. Unfortunately, the algorithm was not completely finished due to a lack of time.

5.2 References

[1] Wikipedia from: en.wikipedia.org/wiki/Pan%E2%80%93Tompkins_algorithm#/media/File:SinusRhythmLabels.svg

[2] Projet TS114 rtajan.github.io/assets/cours/TS114

[3] Atrial fibrillation mayoclinic.org/diseases-conditions/atrial-fibrillation/symptoms-causes/syc-20350624#:~:text=and%20chaotic%20heartbeat.-,Atrial%20fibrillation%20is%20an%20irregular%20and%20often%20rapid%20heart%20rate,to%20175%20beats%20a%20minute.

[4]Sandberg, Frida; Time-frequency analysis of atrial fibrillation portal.research.lu.se/portal/en/publications/timefrequency-analysis-of-atrial-fibrillation(a18494ac-4a43-.html

[5] Chen, S.; Thakor, N.V.; Mower, M.M. Ventricular fibrillation detection by a regression test on the autocorrelation function. Med. Biol. Eng. Comput. 1987, 25, 241–249 link.springer.com/article/10.1007%2FBF02447420

[6]Juan Pablo Martínez; Detection of Ventricular Fibrillation Based on Ballistocardiography by Constructing an Effective Feature Set mdpi.com/1424-8220/21/10/3524

[7] PQRSTU complex psychology.stackexchange.com/questions/16076/what-is-the-difference-