ENSEIRB-MATMECA

Telecommunications Semester 5

Digital Signal Processing : MICA Project

MICA Project

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Summary

1 About MICA

It is very unlikely that one happens to be both a cardiologist and a signal processing specialist. As a doctor, one needs proper tools to be able to analyse the data they receive which, in the context of this project, consists of electrocardiogram signals.

The MICA Project aims at being the tool one would use to analyse said signals, and thus detect potential cardiac pathologies of a patient. The main purpose consists in a user friendly interface, allowing to dial in all the settings one would need for a proper analysis. Once the application has been set up, it will compute the interest values (like heart rate of example) and display the results in a sensible way for the doctor to make conclusions. An example spectrogram can be found in figure 1.1.

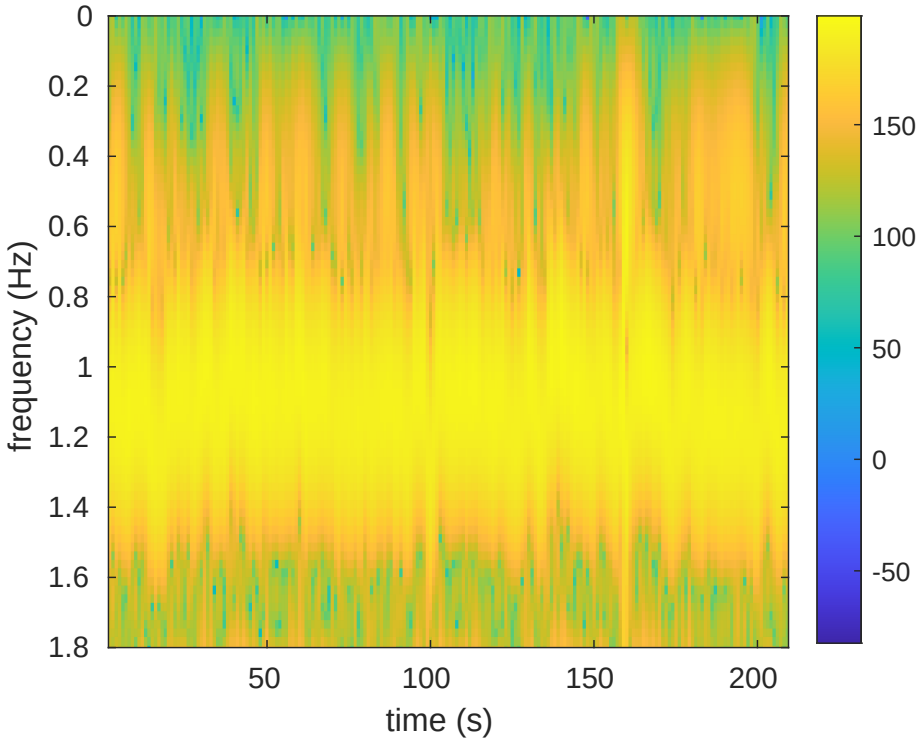


FIGURE 1.1 – A spectrogram generated from a supposedly normal ECG signal

It is important to note that the previously mentioned software has been entirely developed using Matlab and a template interface provided from the start.

2 Pan and Tompkins algorithm

2.1 Global presentation

In order to be able to analyse the signal properly, a few interest points need to be identified. They correspond to the different waves of a typical cardiac contraction cycle. This step first requires the signal to be processed to remove useless information. Only then can the PQRST points corresponding to said waves be detected properly (see figure 2.1).

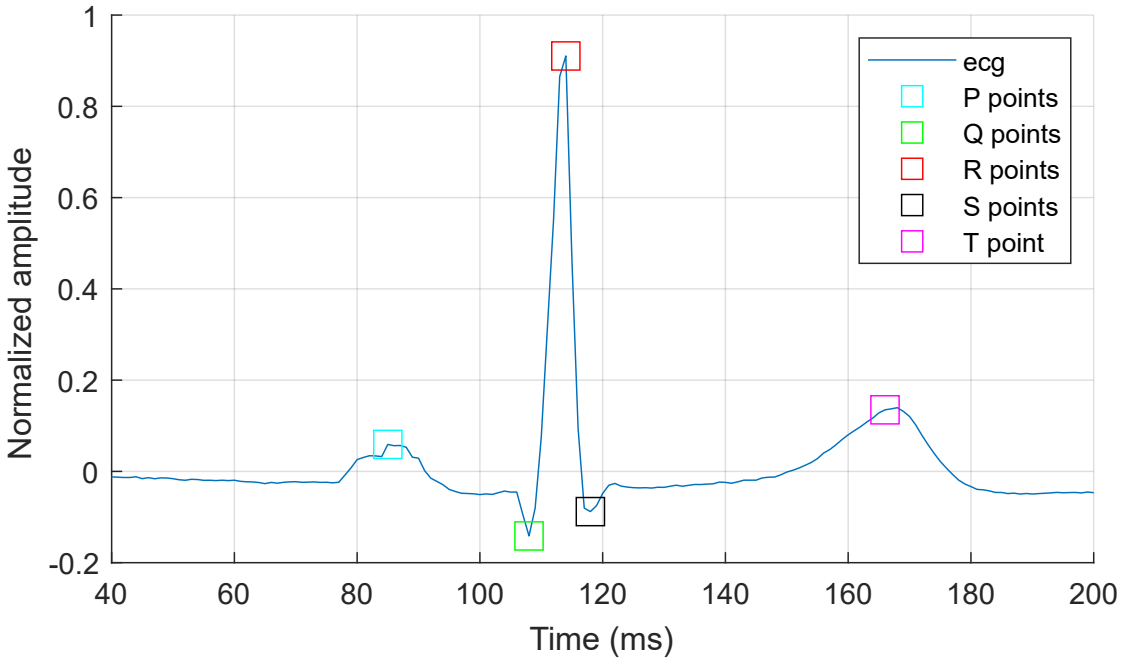


FIGURE 2.1 – P, Q, R, S and T points for a normal ECG signal

2.2 Band pass filter

In order to eliminate the useless frequencies, a band pass filter is applied to the signal. This filter is actually composed of two separate filters : a low pass, and a high pass which have the following transfer functions respectively :

$$H_{lp}(z) = \left(\frac{1 - z^{-6}}{1 - z^{-1}}\right)^2$$

$$H_{hp}(z) = \frac{-1 + 32z^{-16} - 32z^{-17} + z^{-32}}{1 - z^{-1}}$$

In other terms, here is how the output y of each filter is computed from the input x :

$$y_{lp}(n) = x(n) - 2x(n-6) + x(n-12) + 2y(n-1) - y(n-2)$$

$$y_{hp}(n) = -x(n) + 32x(n-16) - 32x(n-17) + x(n-32) + y(n-1)$$

Both are causal, IIR (Infinite Impulse Reponse) filters. The low pass filter has a group delay of 5 samples, while the high pass has a group delay of approximately 15 (although this value isn't exactly constant because the filter doesn't have a linear phase response).

2.3 Differential filter

The signal now has to differentiated, which allows for easier maxima detection later on. The differential is computed by applying the following filter :

$$y(n) = \frac{1}{8T_s}(-x(n-2) - 2x(n-1) + 2x(n+1) + x(n+2))$$

with T_s the sampling period.

Note that this filter is non causal. This issue is addressed by adding a delay to the system. The filter therefore becomes :

$$y(n) = \frac{1}{8T_s}(-x(n-4) - 2x(n-3) + 2x(n-1) + x(n))$$

Unlike the previous band pass filter, the differential filter has a finite impulse response and a group delay of 1.5 samples.

2.4 Moving window integration

A moving average consists of calculating the average over a set of data which changes across iterations. For example, if at step k, the signal is averaged from n_1 to n_2, then at step $k+1$, it is averaged between n_1+1 and n_2+1 : the oldest value is replaced by a brand new one.

This operation removes transitions interfering with the analysis in order to obtain a relevant scale. Here, this scale is N : the size of a QRS complex. The figure 2.2 illustrates it : unusable transitions are in blue and the result of this filtering is in orange. A delay of $\frac{N}{2}+1$ samples can also be observed.

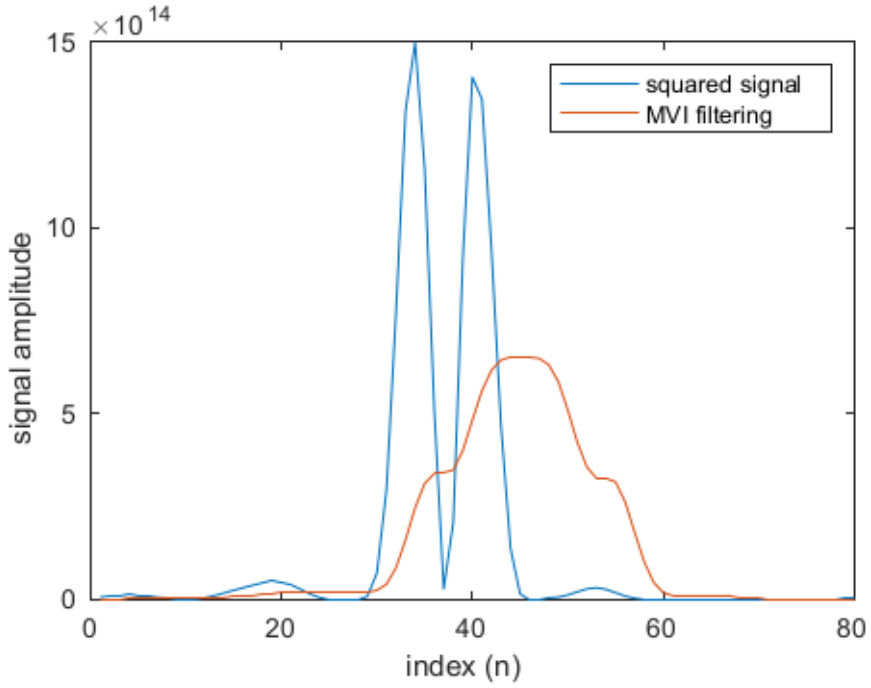


FIGURE 2.2 – Moving Window Integration effect

2.5 Thresholding

The previous operation windows the signal from the beginning to the end of a QRS complex. Those windows are detected thanks to a threshold based on statistical parameters such as the mean and standard deviation of the filtered signal. How exactly the threshold is defined will be discussed in the Q, R and S wave detection section.

2.6 Maxima detection

Both R peak and middle of window share the same position once delays considered. Then, we studied both right and left side of the windowed ecg. The local minimum in the left corresponds to the Q point and the right one to the S one. An illustration is given by 3.1.

3 Applications and results

3.1 PQRST detection

3.1.1 Q, R and S wave detection

The threshold used to detect the orange window is : $\overline{MWI} + \sigma_{MWI}$. It corresponds to the black horizontal line in 3.1. Assuming the signal follows a normal distribution, this threshold is the value under which $\approx 60\%$ of the signal is located.

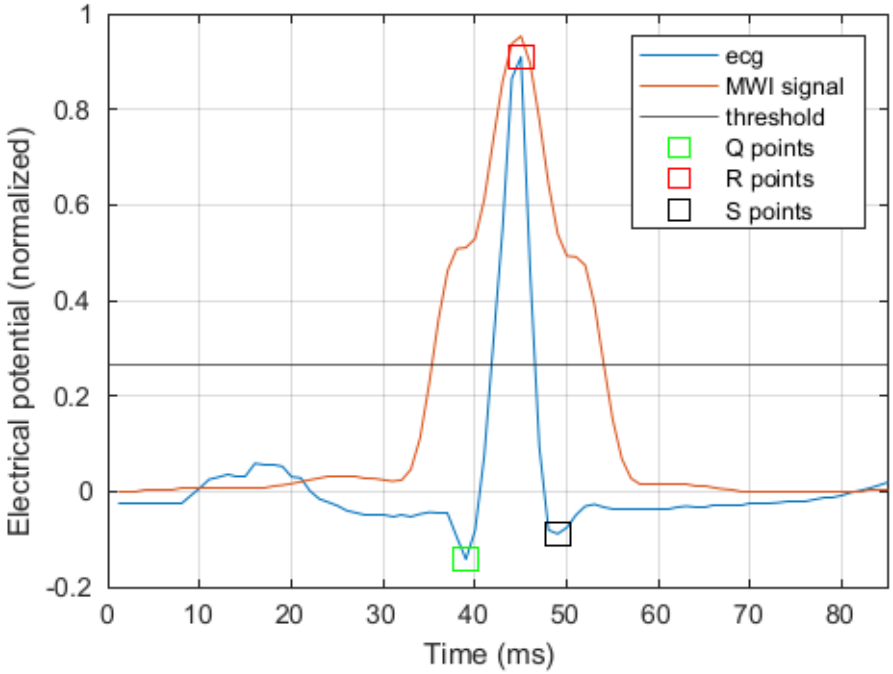


FIGURE 3.1 – QRS detection

3.1.2 P and T wave detection

Lastly, the P and T points of the cycle are detected using a derivated version ECG signal, which is calculated by the following filter :

$$y_1(n) = x(n) - x(n-6)$$

Let $x_d(n)$ be said signal. x_d is filtered using a low pass :

$$y_2(n) = x_d(n) - x_d(n-8) + y_2(n-1)$$

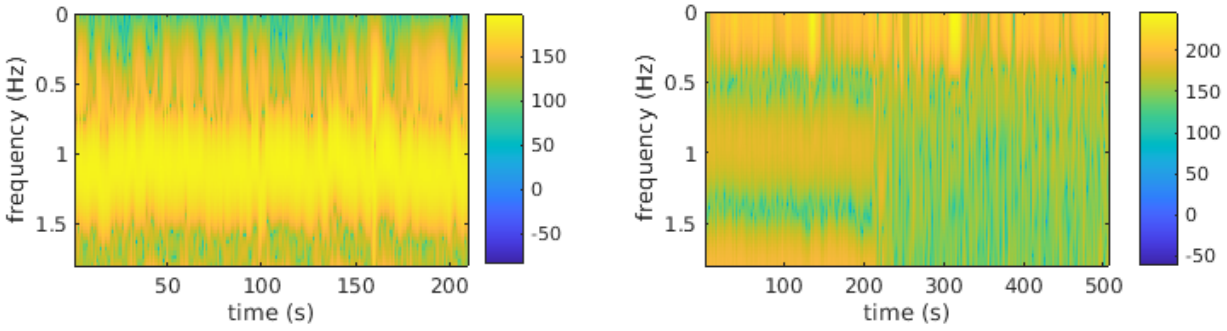
The P and T points being the local maxima on both sides of the QRS complex, they are located where x_d crosses 0 while decreasing, which is to say where the second derivative of x reaches local minima. It was decided that since x_d crosses 0 on multiple spots, it would be easier to search for the minima of the second derivative of x. Therefore the RR interval was split in two parts to ensure P and T wouldn't be detected in the wrong order, and the second derivative was then used to determine their exact locations.

3.2 Cardiac pathologies identification

3.2.1 Spectrogram analysis

A spectrogram displays frequency evolution along time. It gives a first overview on an ecg based on a color bar. The brighter the color, the more relevant the frequency is.

In 3.2a, frequency is around 1.2 Hz during the whole examination. It corresponds to 70 bpm : a regular resting value. The same situation occurs in 3.2b until 200s. After, the main frequency disappears because the heart rate becomes random. This point will be explained in the section about Atrial fibrilation.



(a) Normal ecg

(b) Abnormal ecg

FIGURE 3.2 – Ecg spectrograms

3.2.2 Tachycardia and Bradycardia

Tachicardia and Bradycardia are pathologies which manifest themselves through an abnormally high (respectively low) heart rate. A simple approach to detect these is to compute said heart rate using an averaging of the RR interval duration. Let (Δ_n) be the set of the RR interval durations (in samples) within the signal, the average heart rate in beats per minute is then computed via the following formula :

$$bpm = \frac{60F_s}{\overline{\Delta_n}} = 60F_s \left(\frac{1}{N} \sum_{n=0}^{N-1} \Delta_n \right)^{-1}$$

Although it is useful to know the average heart rate, it is much more relevant to see how it evolves over time, which is possible by computing the average rate on a moving window. The window size can be changed in order to compute more or fewer values, like on figure 3.3 :

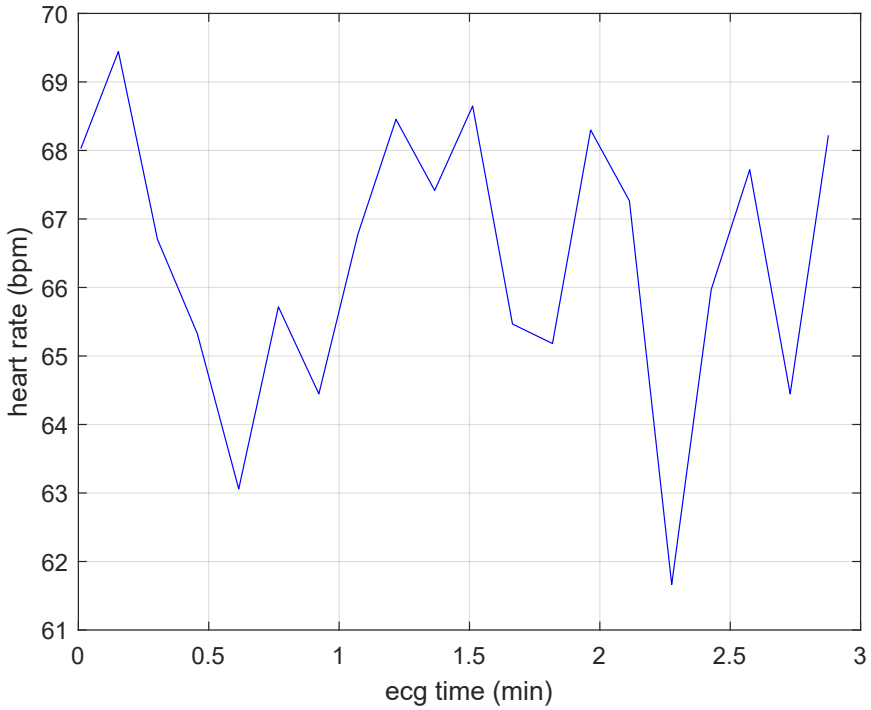


FIGURE 3.3 – Heart rate variations for a normal ECG signal

3.2.3 Ectopic beat

The ectopic beat anomaly consists of abnormal variations of the heart rate. It can be identified by observing the difference between each Δ_n value and the previous one : $|\Delta_n - \Delta_{n-1}| \geq \epsilon$ with ϵ a threshold which is determined statically. Under the assumption that $\delta_n = \Delta_n - \Delta_{n-1}$ has a normal distribution, the threshold is

defined as $\epsilon = \overline{\delta_n} + \alpha \times \sigma_{\delta_n}$, with α a parameter that can be changed depending on the context.

Whenever $|\delta_n| > \epsilon$ is where the heart is having an ectopic beat, as clearly shown by figure 3.4

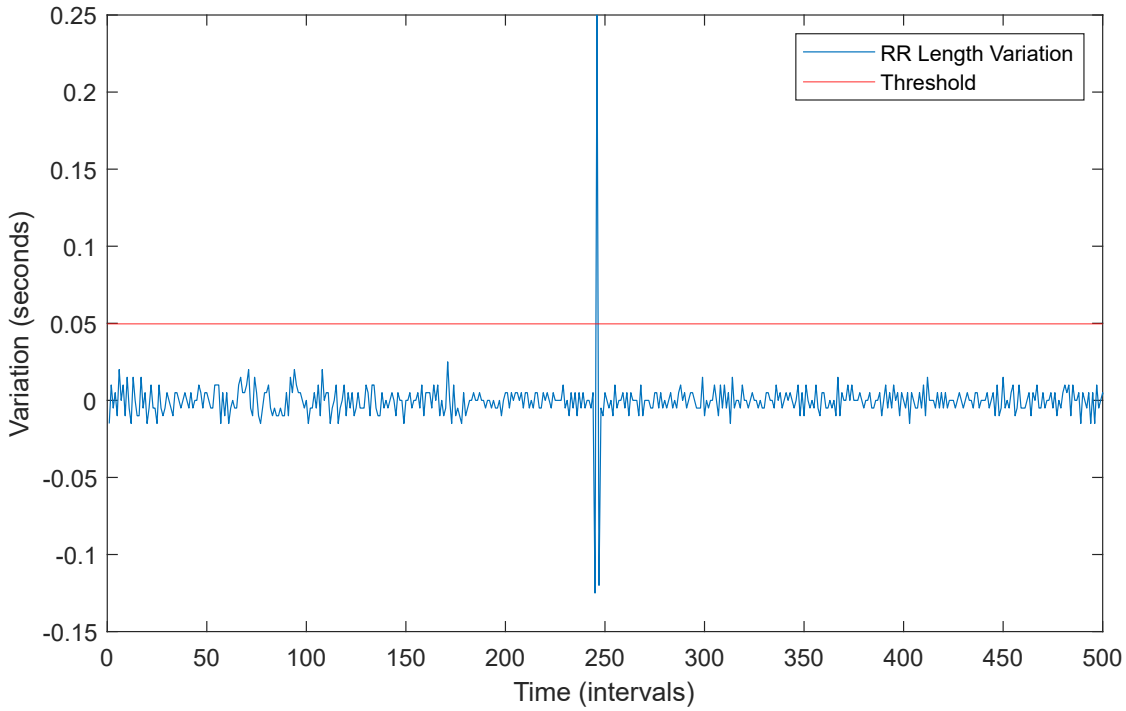
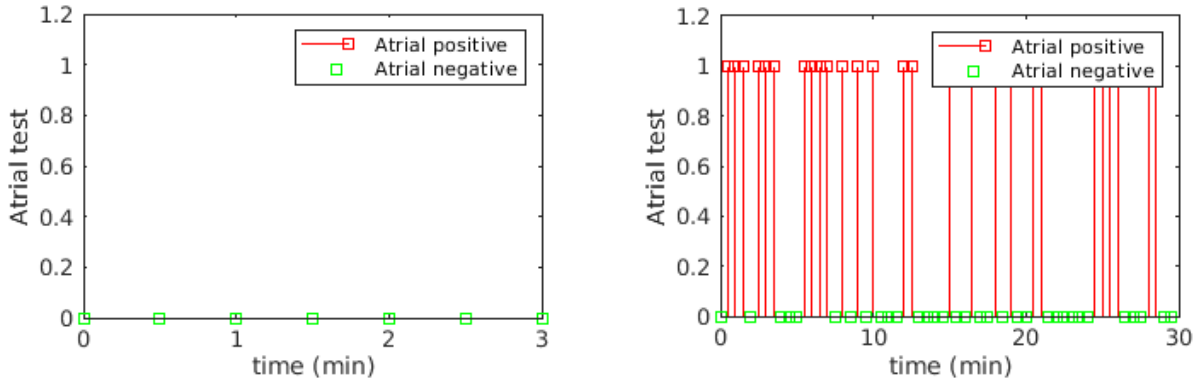


FIGURE 3.4 – ECG signal which presents signs of ectopic beat

3.2.4 Atrial fibrillation

During atrial fibrillation, the heartbeat is random. So, to detect this disease, it can be assumed that the time difference between two peaks R behaves like a white Gaussian noise.

Therefore on one hand, during atrial fibrillation, the auto-correlation function of these deviations must be characterized by a null function at all points, except at 0 where the value of $\mu^2 + \sigma^2$ is reached. On the other hand,for a healthy patient, this same function must be globally constant. Consequently, the variance σ^2 of the values taken by the auto-correlation function is greater in presence of atrial fibrillation. It is therefore easy to detect this peak by setting a threshold just below $\mu^2 + \sigma^2$. Here the chosen threshold was $0.9(\sigma^2 + \mu^2)$, to ensure that the peak would indeed be detected when needed, while a normal ECG would have its auto-correlation function sitting way below. The result obtained for the ecg used in the figure 3.2b clearly shows that Atrial fibrillation is responsible for the disappearance of a dominant heart rate.



(a) Normal ecg (b) Abnormal ecg

FIGURE 3.5 – Atrial fibrillation tests

3.2.5 Ventricular fibrillation

A ventricular fibrillation is characterized by sine waves with a frequency going from 4 to 10 Hz. So, to detect ventricular fibrillation, the spectrogram is observed within the mentioned frequency band. Horizontal lines should be visible, and their absence is a sign of ventricular fibrillation as we can see on figure 3.6, starting from 200s :

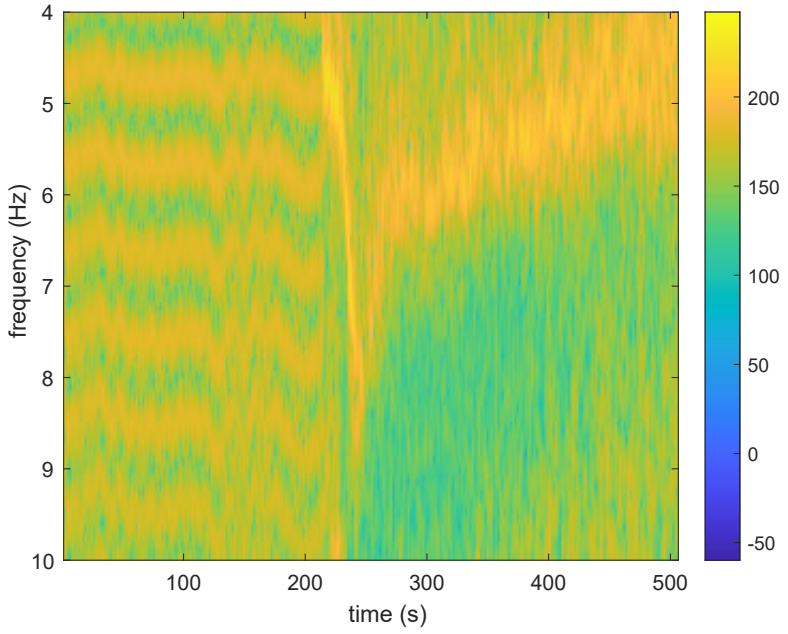


FIGURE 3.6 – Spectrogram of an ECG which presents signs of ventricular fibrillation

3.3 GUI interface

3.3.1 Implementation

The interface can be installed by using the *MICA.mlappinstall* package or by running the *MICA.mlapp* script. Both are located in the project root directory. Also, some data files can be load from the *data* directory.

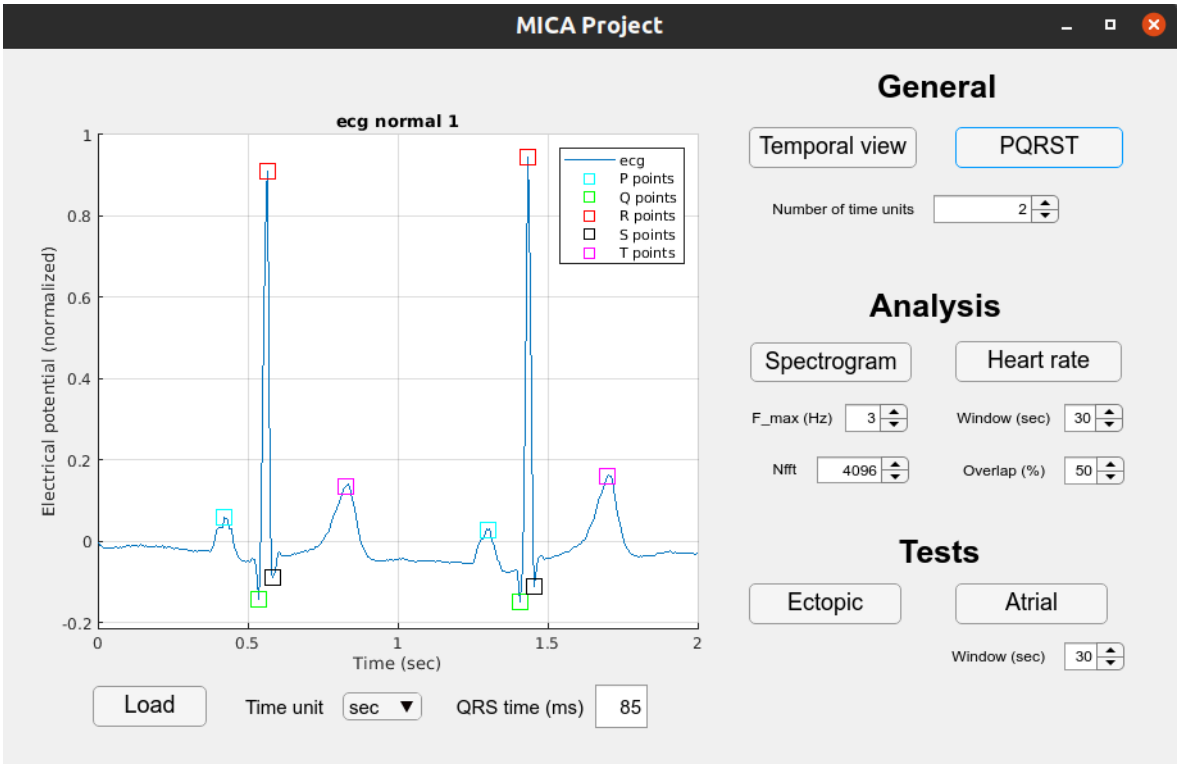


FIGURE 3.7 – screenshot of the GUI interface

3.3.2 Usage

A *.mat* file containing a $(1 \times N)$ chart (the ecg) and an integer (the sampling rate) is required. It must be loaded with the button in the bottom left corner before using any other option. Then, the QRS time can be changed using the corresponding field of the "Temporal view" panel. The default value (85 ms) corresponds to a normal QRS time, which is not relevant for some diseases...

Observe that even if the "overlap (%)" value is not under the spectrogram button, it still impacts the display.

4 Conclusion

Any ECG analysis starts with PQRST points detection, using the Pan and Tompkins algorithm. It mainly consists in filtering, averaging and differentation. When this step is done, Tachycardia and Bradycardia can be detected by looking at the RR interval durations. Ectopic beat anomaly is recognized by measuring the variations in said durations. Atrial fibrillation manifests itself by a random (gaussian) repartition of the RR durations. Lastly, Ventricular Fibrillation causes the apparition of bands between 4Hz and 10Hz which can be observed on a spectrogram.

All the settings (thresholds, window sizes etc) can be adjusted at any time using the application graphical interface, for ease of use. Default values are suggested for relevant results. This entire project therefore reaches the goals described in the introduction of the present report. Although, there are a few things that could be improved. Namely, the P, Q, S and T points could probably be exploited for a better detection the pathologies mentioned above, or even a few others.