MSc Biomedical Engineering

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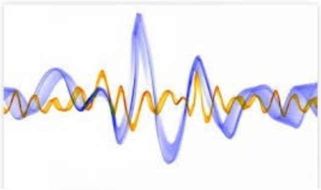
Biomedical Signal Processing (Project)

ECG Processing



Patras 2018

Project 1: Two channels ECG - Remove artifacts and Noise

Theory

ECG Signal

Electrocardiogram (ECG) is the graphical representation of heart functionality. The ECG finds its importance in the detection of cardiac abnormalities [1]**.**

Electrical activity which is caused due to the muscle contraction gets reflected in the ECG signal which is typically analyzed in the time domain. One normal sinus cycle of the ECG corresponds to a single heartbeat. An ECG signal is typically labeled with the letters P, Q, R, S and T which signifies its critical points as illustrated in *Figure 1*.

The frequency ranges from 0.67 to 120 Hz, and 0.67 Hz is the frequency (minimum) which is observed when the pulse rate is 40 beats/min. Low frequency components consist of the P and T waves (5–9 Hz) while the QRS complex resides at higher frequency.

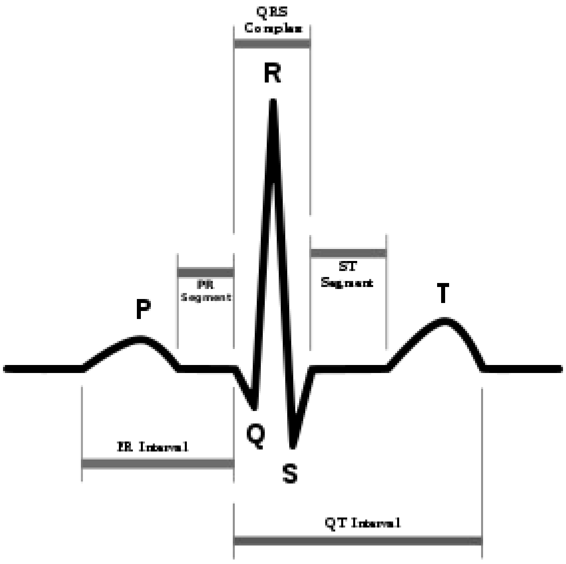


Figure 1: ECG

The origins of these waves are:

1. P wave: sequential activation (depolarization) of the right and left atria
2. QRS complex: right and left ventricular depolarization
3. T wave: ventricular repolarisation
4. U wave: repolarisation of the papillary muscles, rarely seen

Noise and artifacts in ECG signals

Table 1: Types of ECG artifacts

Types of ECG artifact	Cause
Baseline Wandering	Baseline wander is a low-frequency component present in the ECG system. This is due to offset voltages in the electrodes, respiration, and body movement. Baseline wander have frequency greater than 1Hz.
Motion artifact	Occurs when the skin is stretched, resulting in a change to the skin voltage at the stratum lucidum, the second layer down in the skin.
Muscle artifact (known as an Electromyography (EMG) Noise)	Generated by skeletal muscles. This noise occurs at the time of muscle activity during an ECG recording especially in a stress test. This artifact consist of maximum frequency of 10 Khz.
Electrostatic artifact	When an electrostatically charged person moves near the patient or ECG device, currents flow through the high resistance of the stratum corneum (top skin layer) and generate a voltage.
Poor contact artifact	Caused by dried gel, excessive hair, poor adhesion or when breaks in connectivity occur anywhere between the electrode and the monitor.
Electromagnetic Interference (EMI)	Generated by items like power lines, cell phones or radios; relatively uncommon.
Implanted stimulators	Artifact is greatest in leads parallel to the stimulus lead; pacemakers are common but other stimulators are rare.

Biosignals are usually contaminated with artifacts from limb movements, muscular contraction or electrical interference.

The identification of a representative ECG signal may be affected or even compromised by the presence of noise and artifacts. Anything that doesn't belong to the electrical activity generated by the heart is described as interfering signal.

The sources of these artifacts can be physiological, such as muscle activity or skin movements, or non-physiological as a result of neighboring electrical devices or incorrect use of the equipment [2].

Kinds of noise which are common in ECG signal are presented in the below pictures in *Figure 2.*

Both *Figure 2a* and *1b* are usually a result of movements of the subject.

Figure 2a represents motion artifact (MA), which appears to be more related with random limb movement.

Figure 2b represents Wandering Baseline (WB) which is a systematic modulation that represents periodic movements, such as respiratory activity.

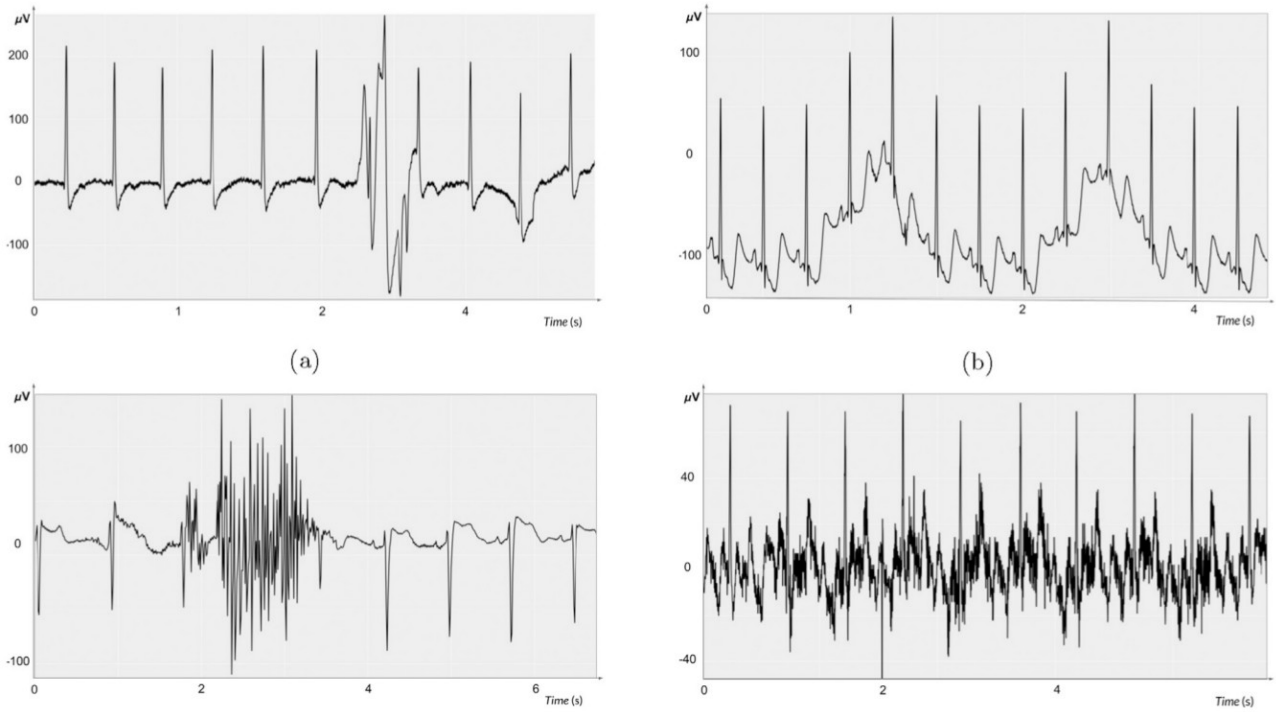


Figure 2: Common Kinds of Noise in ECG Signal

Figure 2c represents Muscular Activation Interference (MI), that means that the ECG is contaminated with muscular contraction artifacts.

Figure 2d represents AC Interference (ACI) and it shows the presence of the baseline noise, possibly due to the electromagnetic noise induction of the equipment and surrounding electronic devices [2].

Table 2: ECG Noise Frequencies

Minimizing motion artifacts:
Respiration: is used to characterized by low frequency 0.4-2Hz. Patient Movement: 1-3 Hz Transport: Medium frequency 3-15 Hz
Minimizing muscle artifact
Muscle tension: high frequency 20-150 Hz (Reducing the upper cutoff frequency filter from 150 to 40 Hz reduces muscle artifact)
Muscle Tremor: High frequency (20-150 Hz) and/or medium frequency (3-5 Hz)
Minimizing electromagnetic interference
Power line: usually 50-60 Hz Cell Phone or Other Equipment: High frequency

Denoising Techniques

There are many techniques to remove ECG signal noise and artifacts. In the below scheme are displayed

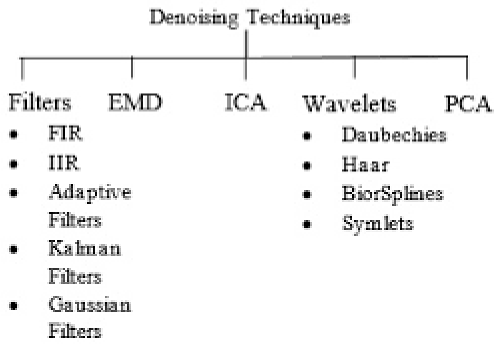


Figure 3: Denoising Techniques

We will present mainely wavelet transform and filters, as was our choice to solve the "Project 1".

Wavelet Transform:

The time-frequency representation of DWT is performed by repeated filtering of the input signal with a pair of filters namely, low pass filter (LPF) and high pass filter (HPF), and its cutoff frequency is the middle of input signal frequency. The coefficient corresponding to the low pass filter is called as Approximation Coefficients and similarly, high pass filtered coefficients are called as Detailed Coefficients. The approximation coefficient is consequently divided into new approximation and detailed coefficients. This decomposition process is carried out until the required frequency response is achieved from the given input signal. This multi-resolution analysis enables us to analyze the signal in different frequency bands; therefore, we could observe any transient in time domain as well as in frequency domain. The choice of mother wavelet can be selected based on correlation between the signal of interest and the wavelet-denoised signal. Discrete Wavelet (DWT) based wavelet denoising have incorporated using Transform different thresholding techniques to remove power line interference from ECG signal. Thresholding methods are used to denoise the ECG signals. For example, a wavelet decomposition until level 3, is represented in *Figure 4.*

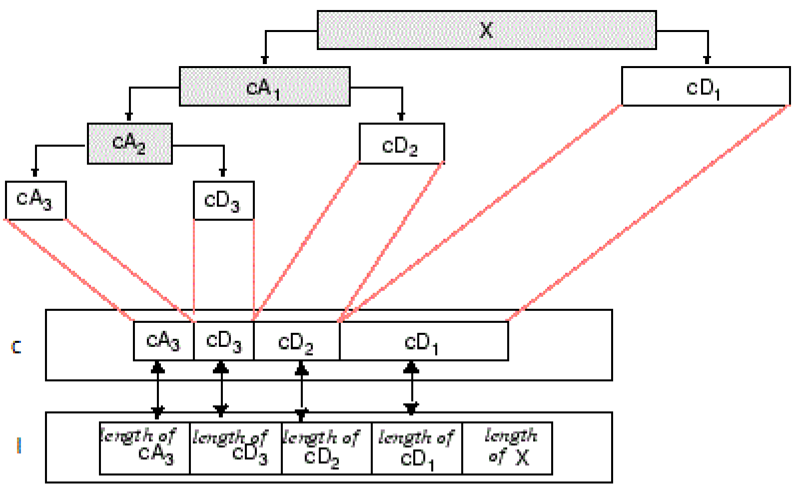


Figure 4: Wavelet Decomposition of Level 3

Thresholding algorithms. The algorithms proposed by Donoho and Johnston can reduce the noise by shrinking or scaling the detail coefficients smaller than threshold.

Two kind of threshold are used

1. Hard threshold

$$\widetilde{D}_j = \begin{cases} D_j & if\ |D_j| > \lambda \\ 0, & if\ |D_j| \leq \lambda \end{cases}$$

2. Soft threshold

$$\widetilde{D}_j = \begin{cases} sign(D_j)(D_j - \lambda) & if\ |D_j| > \lambda \\ 0, & if\ |D_j| \leq \lambda \end{cases}$$

where $D_j = \sigma \sqrt{2 \log \|d_j\|}$ and $\sigma = median\, d / 0.6745$

Wavelet Implementation Combining IIR Filter

The first approach was with wavelet technique. We read many algorithms such as [3], [4], [5], however the main idea is almost the same. Combining *Table 1* and *Table 2* we will use the below algorithm in order to remove same noises and artifacts in our ECG.

Algorithm Implemented

1. In time domain, an IIR notch filter is used in order to remove powerline noise (result is displayed in *Figure 5).*
2. Decomposing of the noisy signal using wavelet transform. Using the discrete wavelet transform by selecting mother wavelet (sym5 or sym8, db4, db6 etc), the noisy signal is decomposed, at the decomposition level of 10. As a result approximate coefficients and detail coefficients are obtained.

Table 3: 10 level Coefficients for Fs=360Hz

Coefficients	**Fs=360Hz**
cD1	180-360
cD2	90-180
cD3	45-90
cD4	22.5-45
cD5	11.25-22.5
cD6	5.6-11.25
cD7	2.8-5.6
cD8	1.4-2.8
cD9	0.7-1.4
cD10	0.35-0.7
cA10	0.17-0.35

3. Removing Basline Wander. Baseline wander is a low frequency component, so is removed by setting to zero cD10 and cA10 coefficients (results are displayed in *Figure 6).*
4. Reduction of EMG noise. Cumulative density function is calculated in order to apply a thresholding window for the cD3 and cD4 coefficient. (results are displayed in *Figure 7)*
5. Apply soft thresholing to the coefficients cD8 and cD9 in order to reduce motion artifacts. The result is displayed in the final signal.
6. Removing high frequencies. Frequencies higher than 100Hz in a ECG has no useful information. So coefficients cD1 and cD2 are set to zero. The result here again is displayed in the final signal.
7. Reconstruct the wavelet using modified coefficients and same mother wavelet and same level. Final results of all the above steps are shown in final signal displayed in *Figure 8*.

The results received from this implementation are appeared following.

Figure 1 displays the signal of channel 1 before and after the IIR Notch filter. The IIR Notch filter was applied in both channels, however for comfortable reasons of view only the channel 1 is displayed, in a random period of time.

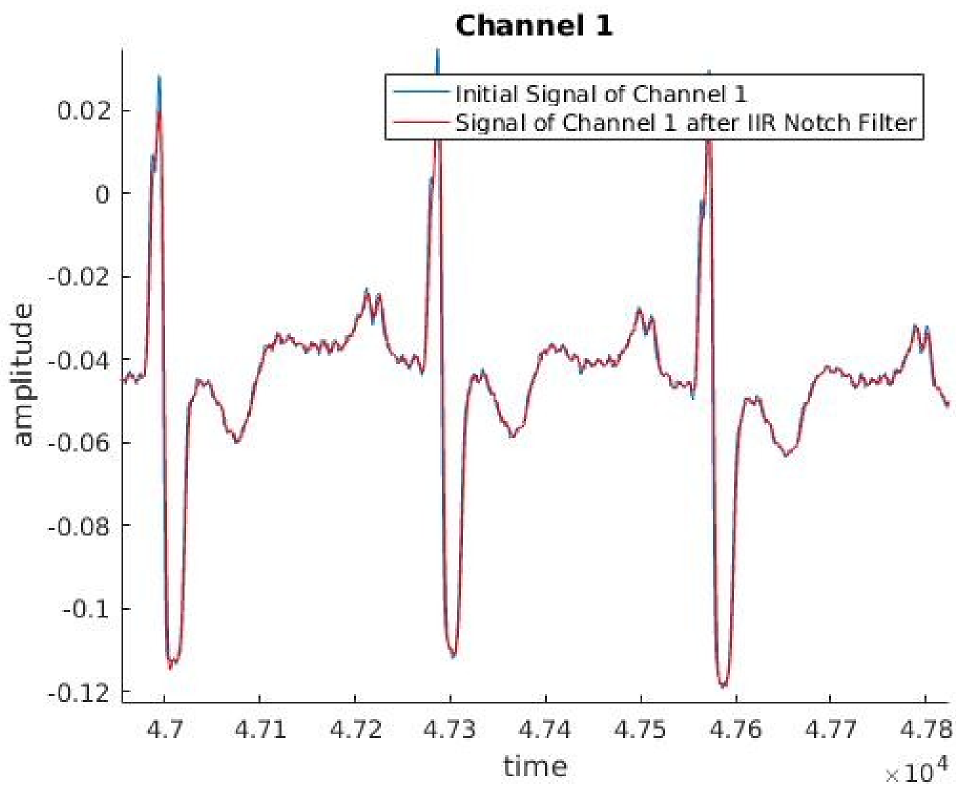


Figure 5: Signal of Channel 1 before and after IIR Notch Filter

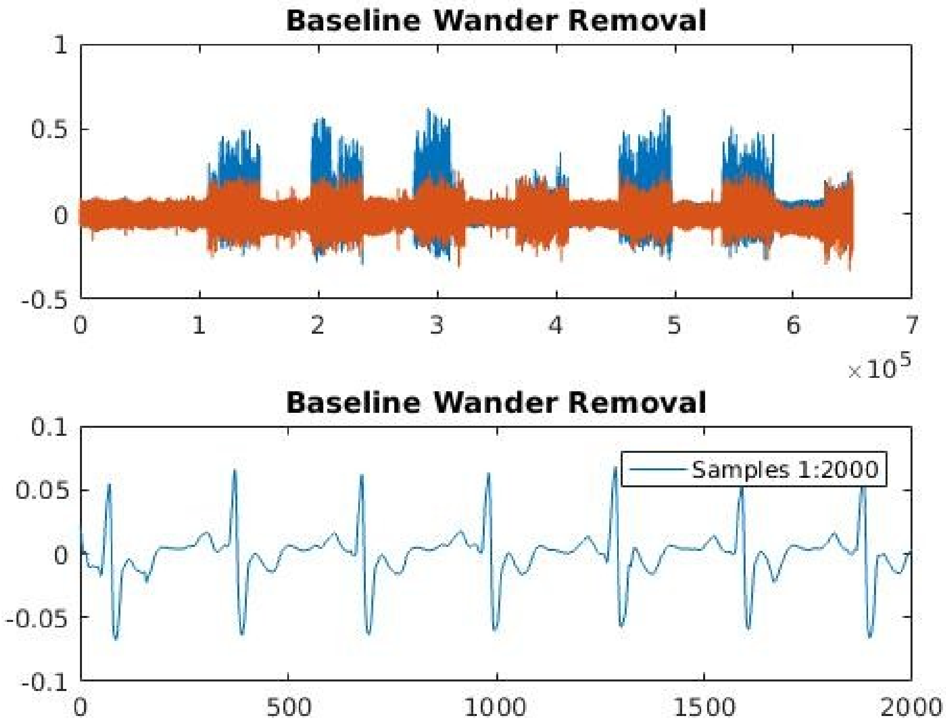


Figure 6: Baseline Wander Removal

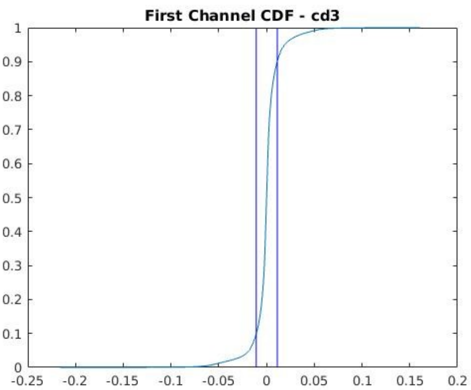
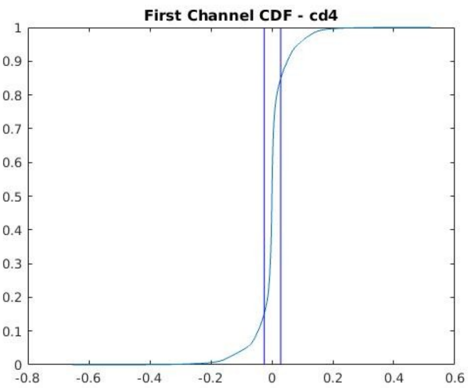
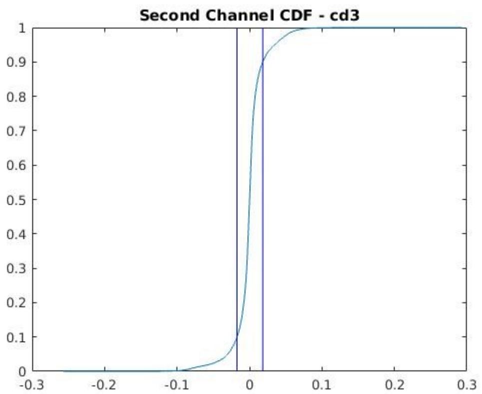
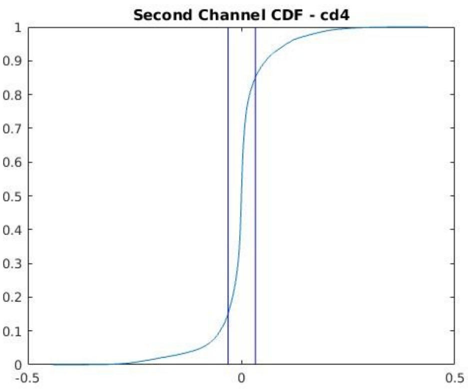
Channel	cD3	cD4
1		
2		

Figure 7: Cumulative Density Functions with the Respective Thresholding Windows.

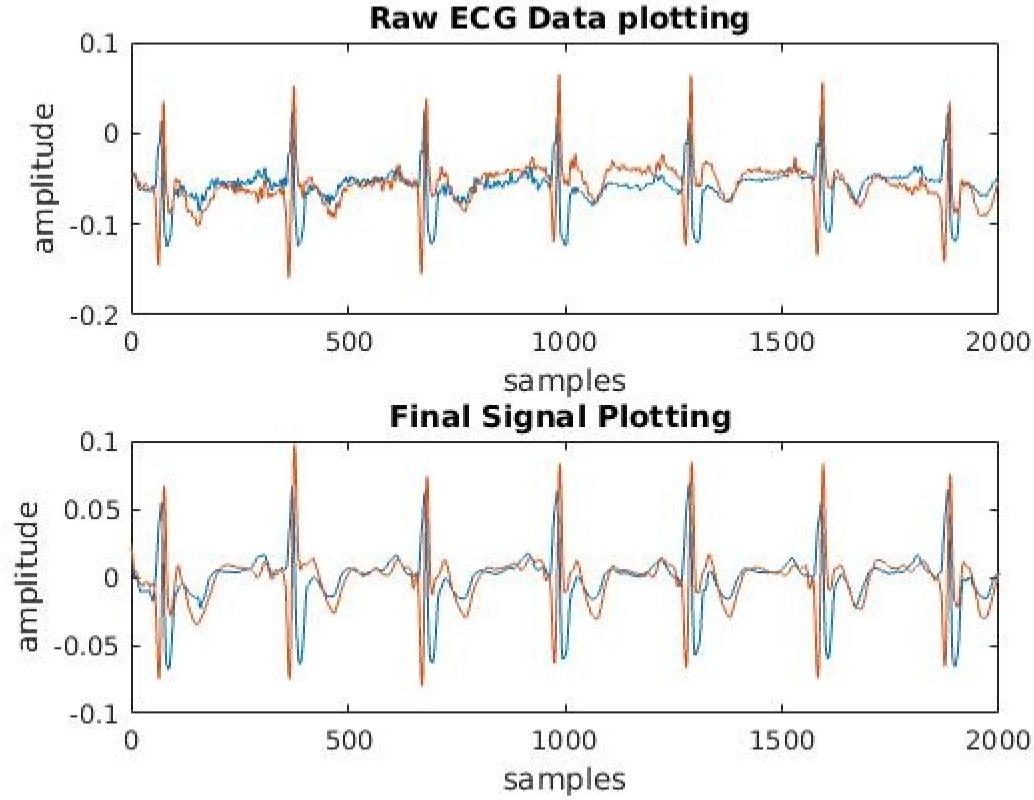


Figure 8: Final Filtered Signal after IIR Notch Filter and Wavelet Transform

As shown in *Figure 8*, for a random sample of values (1:2000) has been zoom in. Comparing to the initial signal, the final signal is seems to be much more clean and denoised for both channel 1 and 2. The analytical implementation can be found on the code progr_1.m.

Project 2: Two channels ECG - Eliminate noise and Estimate mean heard rate (every 0.5 secs)

In “project 2” almost the same technique with “project 1” was used. The only new is the function that was written for R peaks location and for the calculation of mean heart rate per 30seconds.

Running the code (progr_2.m) with the new signal imported, we plot the same things like in “project 1”. However on report here, we plot only the initial and final filtered signal as shown in *Figure 9.*

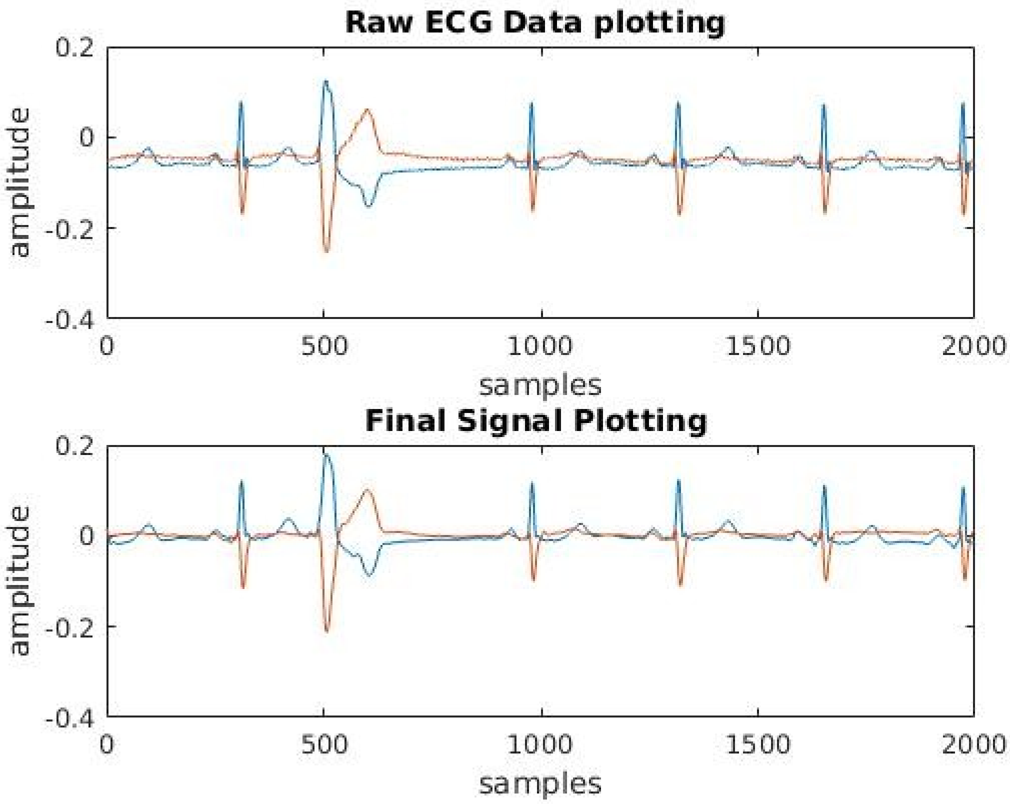


Figure 9: Initial and Final Filtered Signal For the New ECG Signal

As in “project 1”, we have again same satisfactory results. However it is observed that channel 2 probably has negative polarity. At step of heart peak and mean heart beat calculation, only the one channel is used. For this reason, we avoided to inverse the second channel.

Before running the new function, an average filter was used to the final signal in order to remove glitches and to increase in this way the performance of peak detection.

Algorithm for R peak detection and mean heart rate calculation

This algorithm is implemented in the function *Rpeakfinder*. It takes three parameters, one the signal, one the minimum distance between R peaks and finally the minimun height is excpected the R peak to be.

1. This function stores R peaks locations and time that were occurred.
2. The algorithm works inspecting every value of signal to be higher than the previous and the next one.

3. Next, from the previous values that it found, it compares which values are higher than the threshold (minpeakh→ minimum peak height).
4. Finally, the values that were smaller than threshold (minpeakh→ minimum peak height) are removed.
5. From values that remained from the previous step, the differentiation between every value which it's next was extracted. If this value satisfies minimum peak distance then it consider to be an R peak.
6. Finally the matrix with locations of R peaks and the amplitude of signal for that location (i.e. R peak), are returned.

The mean heart rate per minute results from the formula:

$$\frac{60}{RR\,internal\,(seconds)}$$

In our task is requires mean heart rate for half minute, the above formula implies to be:

$$\frac{30 * fs * Total\,Number\,of\,Peaks}{Total\,Number\,of\,Samples}$$

The final results from algorithm implemented is displayed in following figure

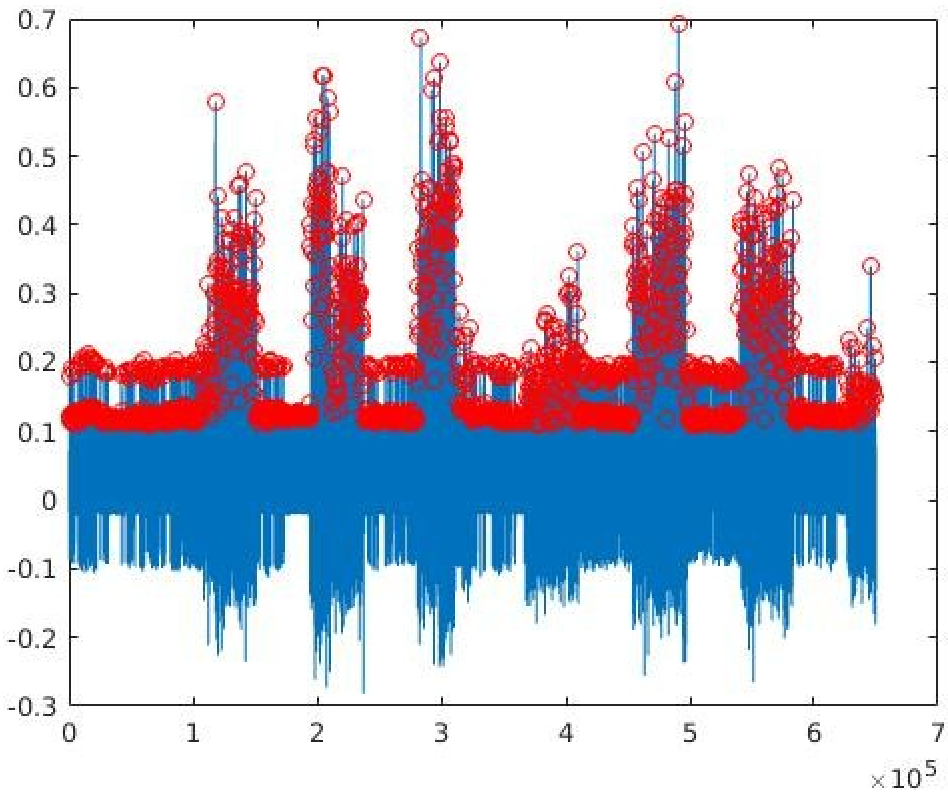


Figure 10: R Peaks Locations

Zooming in randomly in *Figure 10, R peaks are shown in a better way.*

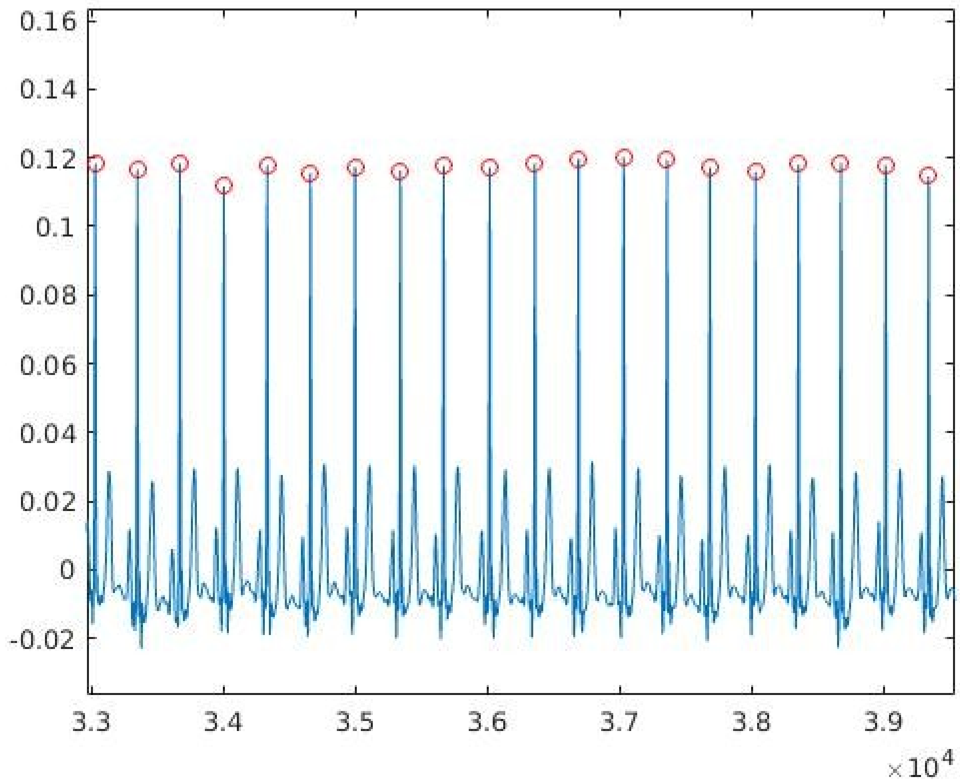


Figure 11: R Peaks in a Random Part of ECG Signal

The mean heart rate was found to be 30.42 beats per 30 seconds, otherwise almost 61 beats per minute. This number is normal rate for a normal person.

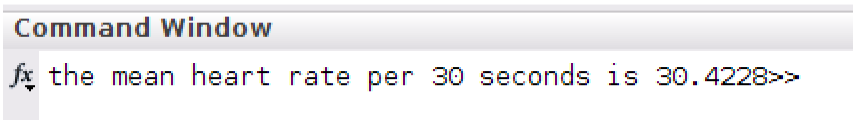


Figure 12: Mean Heart Rate per 30 Seconds

Project 3: One channel ECG - Eliminate artificial noise

In this project we tried lot of approaches as we have a very noisy signal:

1. The first approach was to resample the signal with a sampling frequency of 250Hz, using the command in matlab:

```
[p,q] = rat(250/44100);
resampled_signal = resample(Original_signal, p, q);
```

After resampling the signal, the next step was to design a notch filter removing powerline frequency. Finally designing filters for removing low and high frequencies. However the result was not so satisfactory.

2. The second approach was to remove the DC in time domain. After that to find the FFT of the new signal. So in the frequency domain to cut-off low frequencies and high frequencies. Finilly calculating the IFFT and ploting the final signal. Or we could do the same in time domain designing some low pass and high pass filters. In both cases however, again the result was not so satisfactory.

3. However, we preferred this approach just for the simplicity of implementation and the almost clear result. The approach here was to remove first the DC component and after that designing an IIR notch filter for removing power line in time domain (we preferred removing 30Hz instead of 50Hz). In the final step we used the MATLAB built-in wavelet automatic 1-D denoising function:

```
xd = wden(ecg_notch,'sqtwolog','s','mln',100,'sym5');
```

In this way with an extremely short code implementation we had better results than the other two approaches.

Instead of sym5, we had good results with other wavelet families as ‘sym8’, ‘db4’, ‘db6’, but we preferred (almost randomly ‘sym5’) and “100” for level decomposition after some experiments trying different levels. Following, we display the initial signal and the final filtered signal *Figure 12*.

The result it is like we have an contaminated PRQRST with an other (second) ECG signal (see the zoom in part at samples 570000 to 650000. It sensible the information to be on the second signal. So possibly, it would be a good approach in some way to remove big PQRST which is beyond $1\,x\,10^6$ and $1.3\,x\,10^6$

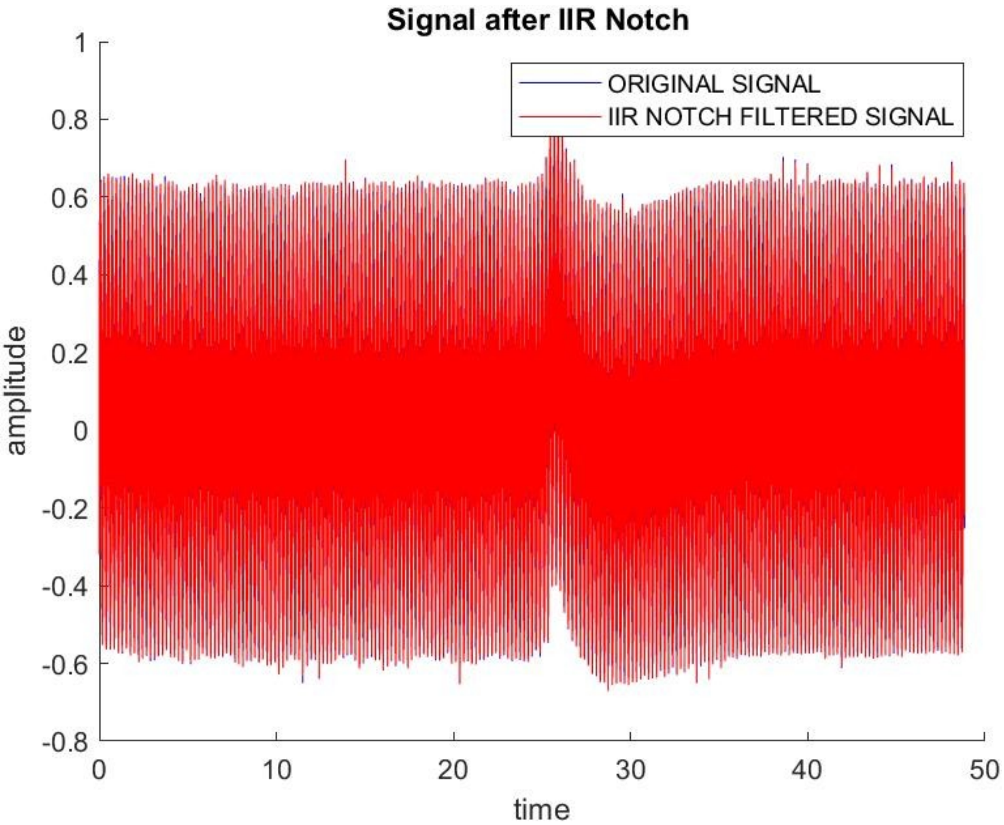


Figure 13: Initial Signal and Signal after IIR Notch filter

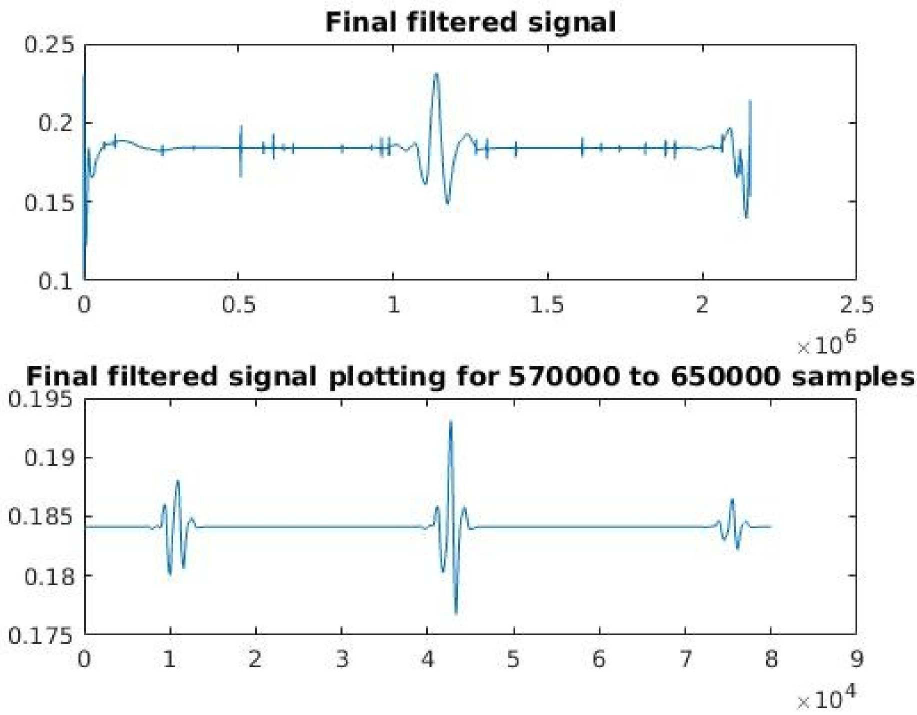


Figure 14: Final Filtered Signal

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