



**ΠΑΝΕΠΙΣΤΗΜΙΟ
ΠΑΤΡΩΝ**
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MSc in Biomedical Engineering

Biomedical signal processing

Project

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MATERIALS & METHODS

ECG signals

Electrocardiogram (ECG) is a non-linear non-stationary quasi periodic time series. It is a wide-spread tool to examine the electrical and muscular functions of the heart. It is a time-varying bio-signal reflecting the ionic current flow, which causes contractions and subsequent relaxations in the cardiac fibres and provide indirect insight into the blood flow to the heart muscle. It gives information about heart rate, rhythm, and electrical activity. The information contained within ECG is both physiological and pathological, which are integral to the diagnosis of heart diseases. ECG monitoring and subsequent analyses find a lot of applications in the medical domain. However, ECG is susceptible to different types of noises, which might distort the morphological features and the interval aspects of the ECG leading to a false diagnosis and improper treatment of patients. Therefore, the development of denoising methods is a necessity. ECG is recorded by measuring the potential difference between two electrodes placed on the patient's skin.

Figure 1 shows the form of an ECG signal. The ECG signal belongs to the weak physiological signal with amplitudes ranging from $10\mu\text{V}$ to 5mV and frequencies from 0.05 to 100 Hz, however the most useful information distributes in the range of 0.5-45 Hz. An ECG signal consists of the following components, which are symbolized by the letters P, Q, R, S, T and U. But the U wave is usually not consistent and invisible among 70% of the people as a result it is not that much of importance as other waves clinically. P wave indicates the atrial depolarization and contraction, which represents the activation of the upper heart chambers. While the QRS complex and T wave represent the ventricle excitation of the lower heart chamber. PR interval measures the time during which a depolarization wave travels from the atrial to the ventricles. ST segment measures the time between ventricular depolarization and beginning of repolarization and QT interval represents total ventricular activity.

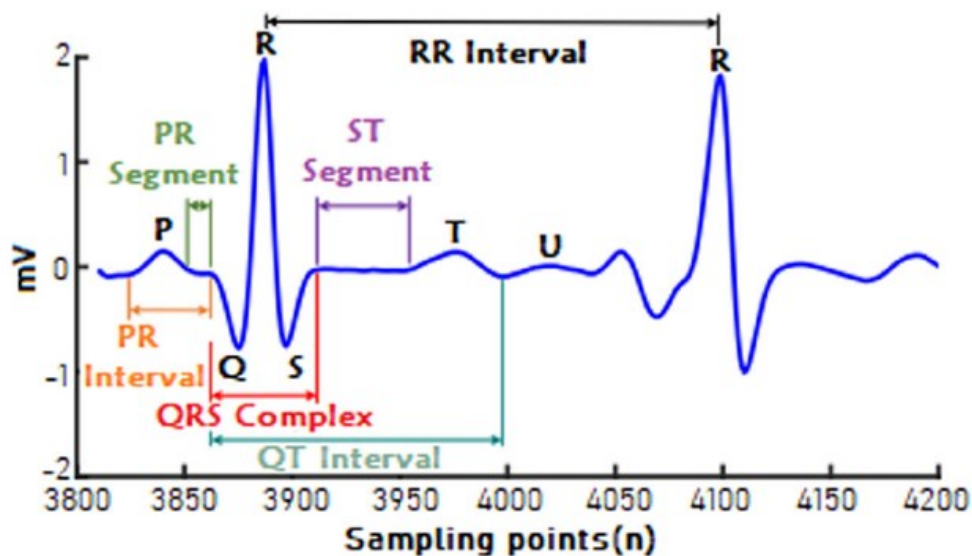


Figure 1: A typical ECG waveform.

Noises in ECG signals

ECG signals have a wide variety of applications in the medical domain such as cardiorespiratory monitoring, seizure detection and monitoring, ECG-based biometrics authentication, real-time analysis of electrocardiographic rhythm, heart-rate variability analysis using smart electrocardiography patch, and study of cardiac ischemia. ECG signals are susceptible to various kinds of predominant noises and miscellaneous noises.

Predominant noises and artefacts lie within the spectral range of interest and manifest themselves pre-dominantly as morphological features similar to the inherent aspects of the ECG or similar to any disease specific aspects. A brief description of predominant noises in ECG is given below:

- **Base-line wander.** BW is a low-frequency (LF) artefact caused mainly by respiration, body movements, bad electrode contact, and skin-electrode impedance. The amplitude and duration of the wander depends on electrode properties, electrolyte properties, skin impedance, and body movements. This drift in the baseline is of magnitudes as high as around 15% of full-scale deflection (FSD), the peak-to-peak ECG amplitude over a frequency range of 0.15–0.3 Hz. Abnormal breathing rate and electrode movement alter the ECG by increasing the wandering frequency and causing motion artefacts, respectively. BWs distort the ST-segment and other LF components of the ECG signal causing the wrong diagnosis of myocardial infarction, Brugada syndrome, and other ST-segment related abnormalities.
- **Power-line interference.** PLI noises are caused by inductive and capacitive couplings of $50/60 \pm 0.2$ Hz power lines during ECG signal acquisition. It is narrowband with a bandwidth of <1 Hz and with an amplitude of up to 50% FSD [15, 16]. The intermixing of the PLI contents with the ECG distorts morphology of the signals. This leads to P-wave distortions, leading to the wrong diagnosis of atrial arrhythmias like atrial enlargement and fibrillation.
- **Muscle artefacts or electromyogram (EMG) noise.** MA or EMG noise is caused by electrical activities in muscles, which arise from eye and muscle movements and heartbeat. Typical sources of MA are muscle movements near the head region, like neck movements, swallowing, and so on. The electrical activities due to muscle contractions last for a duration of around 50 ms between DC and 10,000 Hz, the amplitude being around 10% FSD. EMG leads to distortion of local waves of the ECG signals due to a frequency match in the range of 0.01–100 Hz. This makes it challenging to denoise the signals for proper recognition of various ECG arrhythmias.
- **Channel noise.** Channel noise is induced in ECG signals when they are transmitted through a channel with poor channel conditions.

Miscellaneous noises are difficult noises to handle because they make challenging to determine disease-specific morphological anomalies in the ECG signals. Some types of miscellaneous noises are the following:

- composite noise (CN).
- random noise.
- electrode motion artefacts (EM).
- instrumentation noise.

Butterworth filter

Signal denoising is an important issue in signal processing, therefore several techniques are developed in order to reduce noise. Some of these techniques are low-pass/high-pass Butterworth filter, IIR and FIR filters, Wavelet transform, EMD-based models, deep-learning based autoencoder models (DAEs), sparsity-based models, Bayesian filter-based model and hybrid models. Buterworth filter and EMD method is used in order to reduce the noise in this project.

Low-pass and high-pass Butterworth are two effective methods to remove signal noises. As for ECG signal, Butterworth high-pass filter will result in more distortion. a Butterworth filter is designed using $[B, A] = \text{butter}(n, W_n)$. Where n is the order of the filter and W_n is cut-off frequency. B (numerator) and A (denominator) are the filter coefficients with the length of $n + 1$. In this project a bandpass filter is designed in order to cutoff both low and high frequency noise.

EMD-based models for ECG signal denoising

In general, EMD is an adaptive iterative algorithm through which a signal is decomposed into a series of its oscillatory segments, known as intrinsic mode functions (IMFs). With this iterative decomposition of signals, EMD separates the full signal into ordered elements with frequencies ranged from higher to lower frequencies in each IMF level. The decomposition of the EMD procedure is based on the local time characteristics of the signal, thus it applies to nonlinear and non-stationary processes, such as ECG signals. EMD relies on an entirely data-driven mechanism that does not require any a priori known basis, as opposed to data analysis methods like Fourier transform.

The steps, which describe the denoising algorithm of EMD-based denoiser, are the following:

1. Noisy ECG $x(n)$ is given to the denoiser as an input.
2. Sifting processes.

First, all the maxima of the noisy input are joined using cubic spline interpolation, giving $e_u(n)$ as the upper envelope. Similarly, the minima are connected to get the lower envelope $e_l(n)$. The next step is to obtain the mean of the envelopes, as shown below:

$$m(n) = \frac{e_u(n) - e_l(n)}{2}$$

This mean is subtracted from the signal to obtain the first proto-IMF:

$$h_1(n) = x(n) - m(n)$$

This procedure is called sifting process.

3. Repetitive application of the sifting process on proto-IMF $h_k(n)$ until the stopping criterion (SD) gives the first IMF $c_1(n)$

An IMF holds two characteristics: (i) the number of zero-crossings and extrema differ by at most one, (ii) the IMF waveform is symmetric concerning the local mean.

Therefore, if $h_1(n)$ does not satisfy the characteristics, all the steps from interpolation to subtracting the mean from the signal are repeated until $h_k(n)$ becomes an IMF, where k is the iteration variable. To stop the iteration, a certain terminating criterion is required. More than seven different stopping criteria have been proposed after the development of the EMD algorithm. One stopping criterion is accomplished by limiting the size of the standard difference (SD) calculated from the two consecutive sifting results

$$SD = \sum_{n=0}^{N-1} \frac{|h_{k-1}(n) - h_k(n)|^2}{h_k^2(n)}$$

A typical value for SD can be set between 0.2 and 0.3. Hence, repetitive application of the sifting process on protoIMF $h_k(n)$ until the stopping criterion gives the first IMF $c_1(n)$. It reveals that the lower order IMFs show the fast and high frequency oscillations and upper order IMFs correspond to slow or low frequency oscillations.

4. Calculation of the residue

Residue is obtained by subtracting the IMF from the noisy input, as it is described below:

$$r_1(n) = x(n) - c_1(n)$$

Obviously, $c_1(n)$ represents the finest scale mode of oscillation, and $r_1(n)$ still contains useful information about longer time scale components. Therefore, the residue is treated as a new signal, and repeated sifting processes are conducted to obtain:

$$r_2(n) = r_1(n) - c_2(n), \dots, r_l(n) = r_{l-1}(n) - c_l(n)$$

The whole process can be stopped for two reasons. Firstly, when $c_n(n)$ or $r_n(n)$ is less than a predetermined threshold, or secondly $r_n(n)$ becomes a constant or monotonic function.

5. Obtain the decomposition result.

Combining the above information, we finally get the following decomposition result:

$$X(n) = \sum_{l=1}^L c_l(n) + r_L(n)$$

Thus, $x(n)$ has L IMFs as the algorithm terminates at the L th iteration.

6. Output: $X(n)$: denoised ECG signal.

Calculation of heart rate

There are several ways to calculate heart rate from ECG. It is important to understand what a heartbeat looks like on an ECG. A heartbeat is represented by a series of waves that show how the heart muscle contracts and relaxes over time. The largest deflection on an ECG is often the R wave, this represents the main muscle of the heart contracting. By identifying the R wave in each beat, we can measure the time taken between one heartbeat and the next. In this project, I calculated heartbeat based on the following method: I count the number of R waves over a 10 second period and multiply that number by 6.

Rate= number of R waves over a 10 second period*6

Overall, a normal heart rate for adults ranges from 60 to 100 bpm.

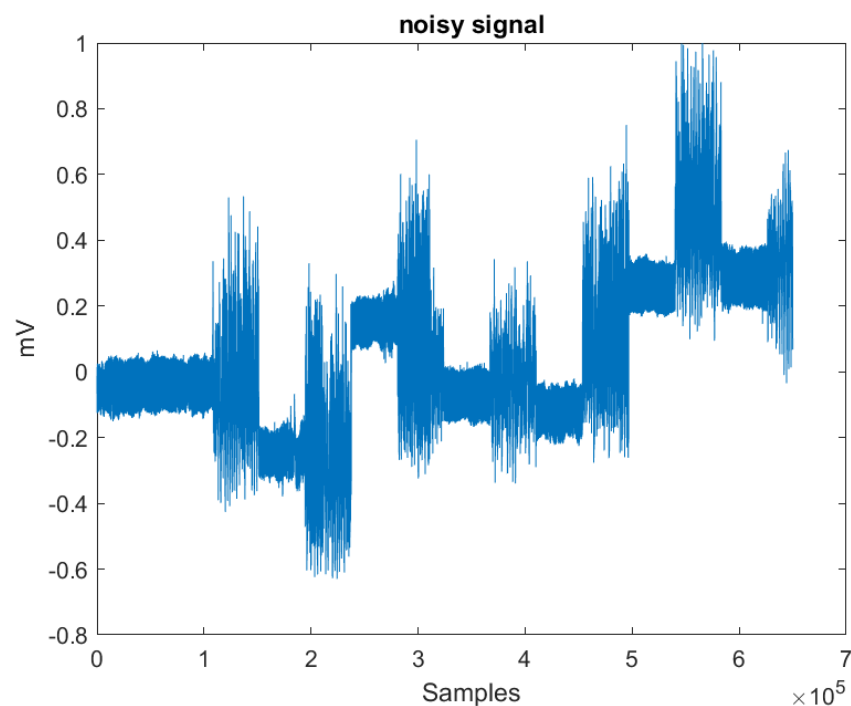
Project 1

The aim of this project is to remove noise and artifacts from an ECG signal. This signal consists of 2 channels. All ECGs pick up heart signals through electrodes connected externally to specific locations on the body. The specific locations of the electrodes allow the heart's electrical activity to be viewed from different angles, each of which is displayed as a channel on the ECG printout. Each channel represents the differential voltage between two of the electrodes, or the differential voltage between one electrode and the average voltage from several electrodes. The different combinations of electrodes allow more channels to be displayed than there are electrodes. The channels are commonly referred to as "leads," so a 12-lead ECG device has 12 separate channels displayed graphically. The number of leads varies from 1 to 12 depending on the application.

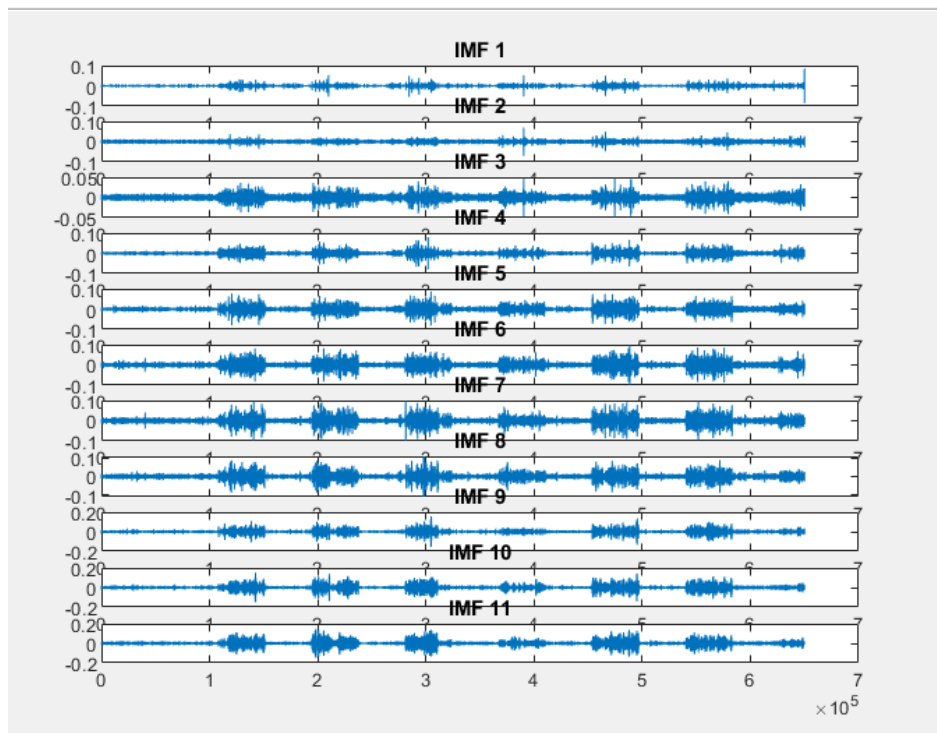
The ECG signal contains 650.000 samples and has sampling frequency 360Hz.

For signal denoising, an EMD-based model is used. The steps of this algorithm are explained above. The results of the first channel are introduced below.

The noisy signal of channel 1 is the following.

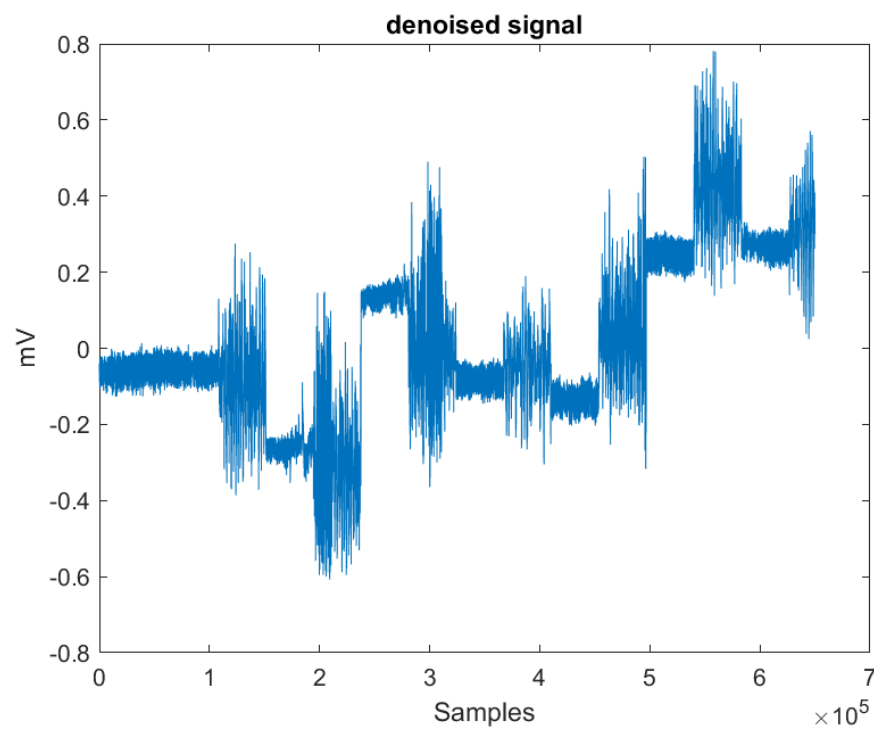


The IMFS, which occur, are the following:

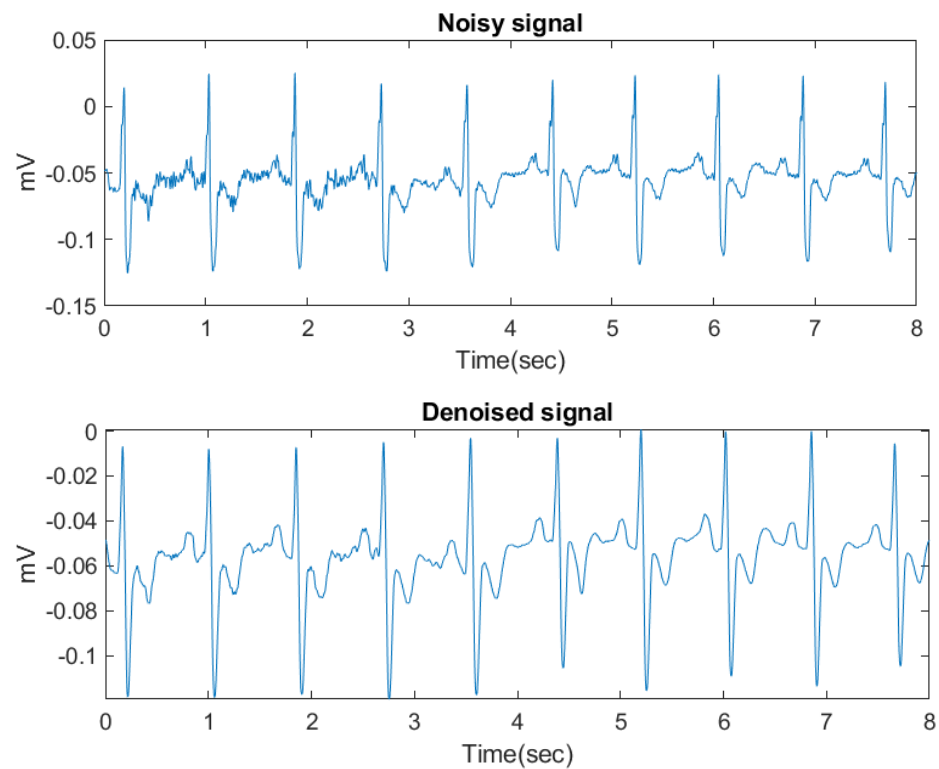


As it is explained before the lower order IMFs show the fast and high frequency oscillations whereas upper order IMFs correspond to slow or low frequency oscillations.

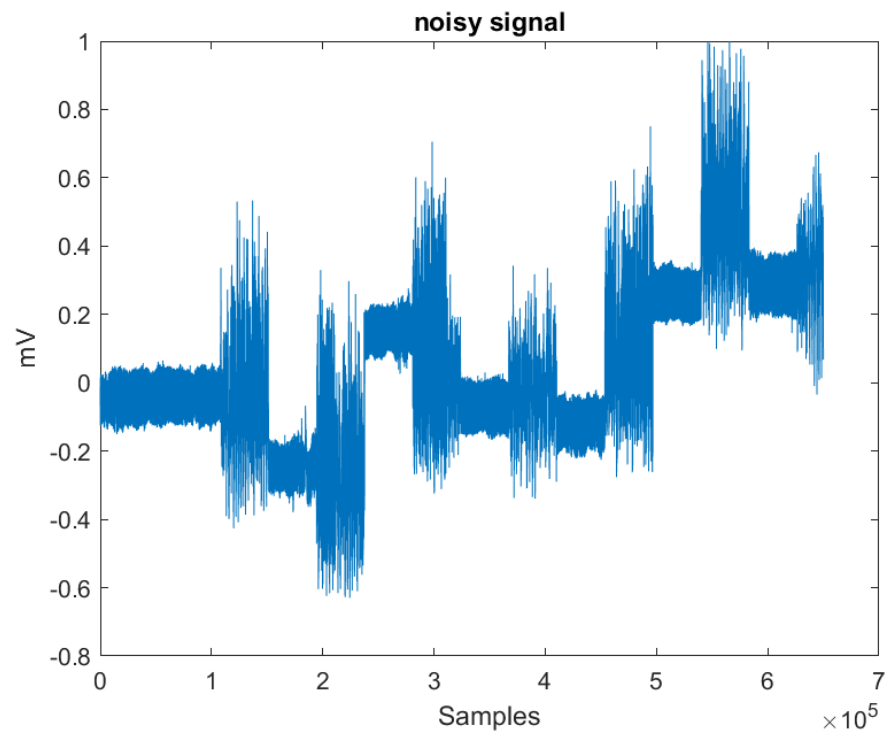
The signal after reducing the noise is the following.



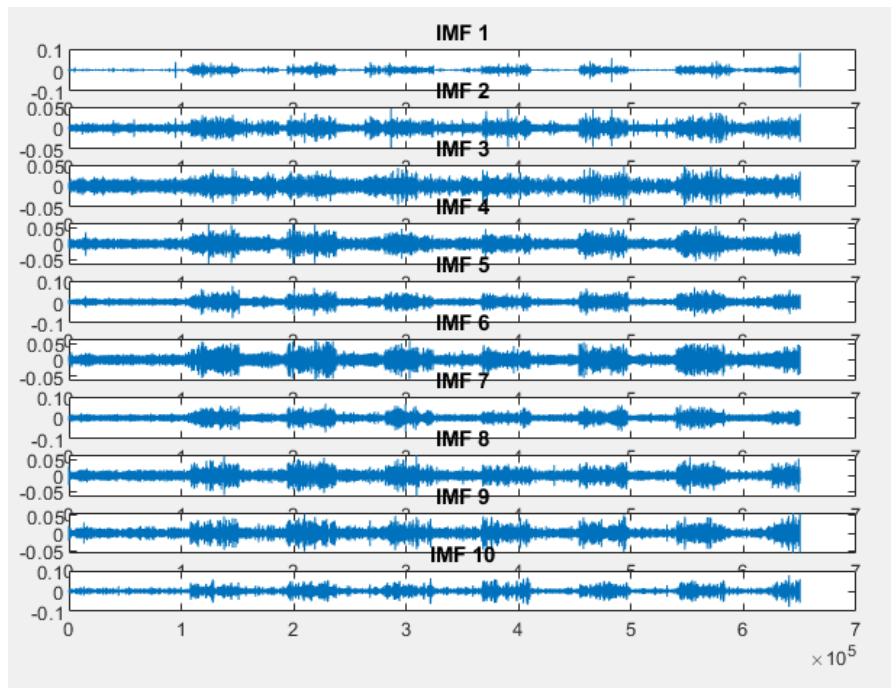
We can observe that noise has been reduce significantly. In order to observe that better, we can take a part of that signal. The results are the following.



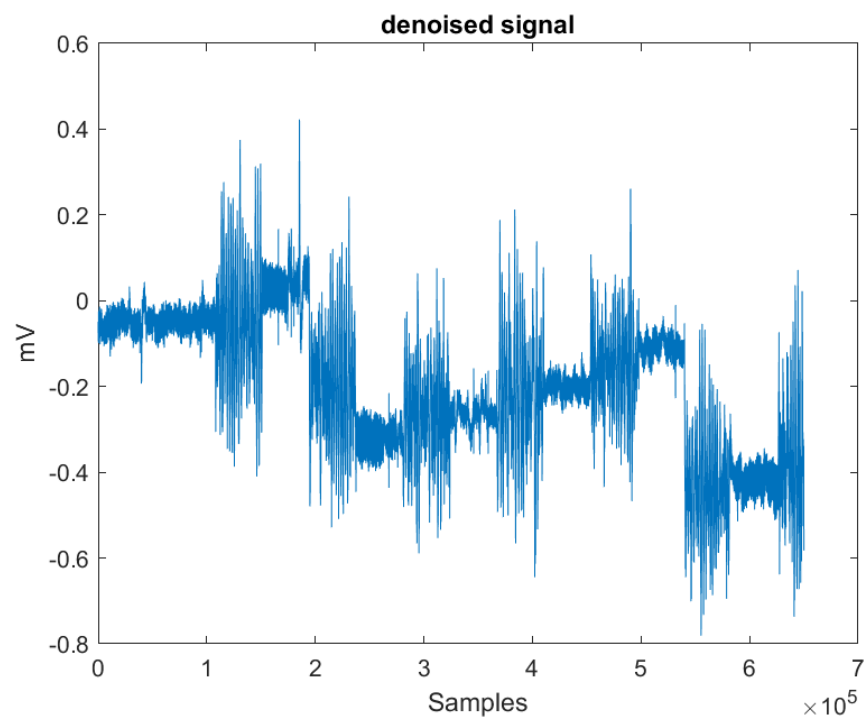
I followed the same procedure for channel 2. The noisy signal of channel 2 is the following.



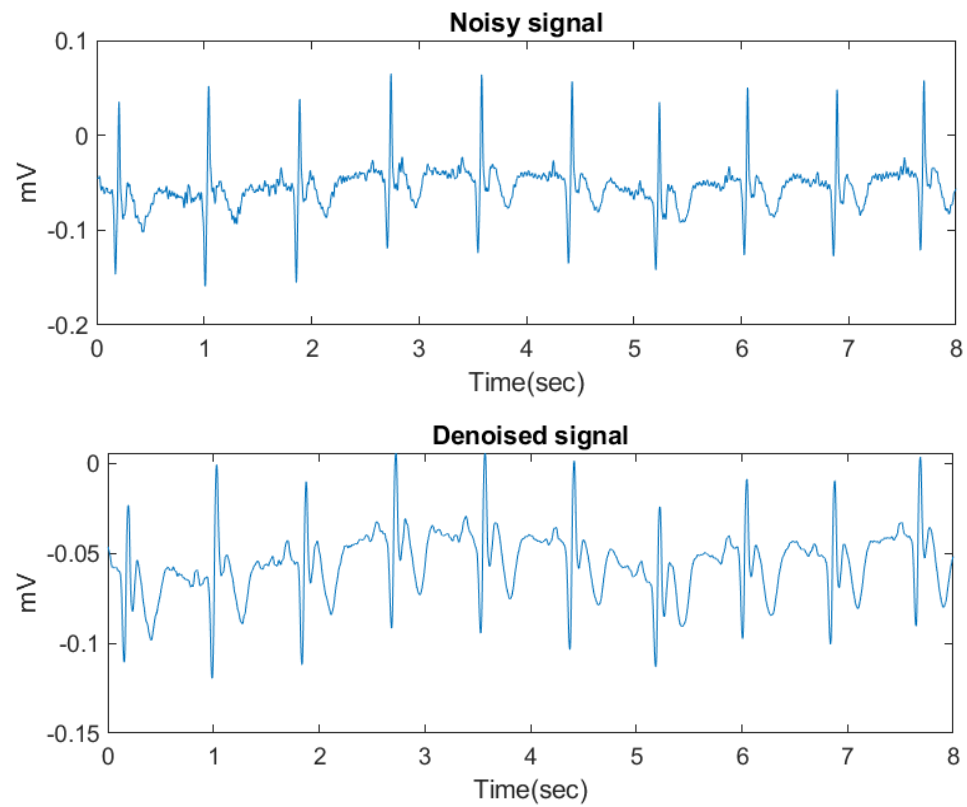
The IMFS, which occur, are the following:



The signal after reducing the noise is the following.



We can observe that noise has been reduce significantly. In order to observe that better, we can take a part of that signal. The results are the following.



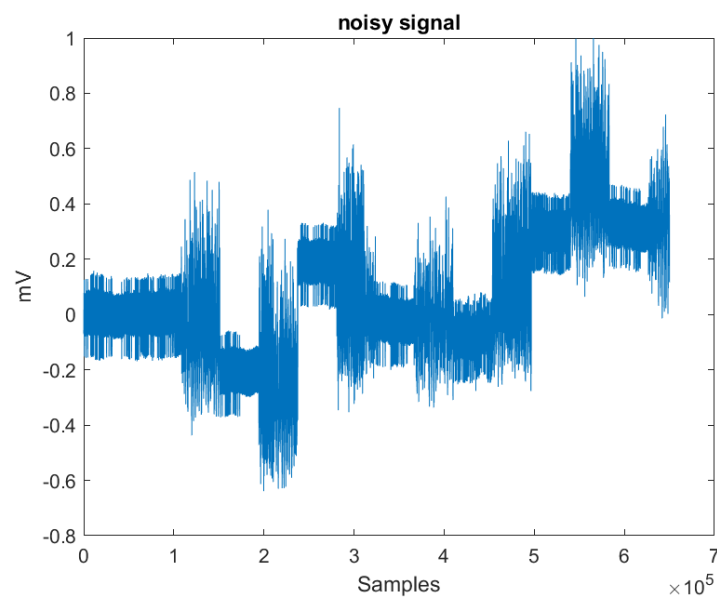
Project 2

The aim of this project is to eliminate noise and estimate heart rate from an ECG signal. The signal contains two channels, so I process each channel separately.

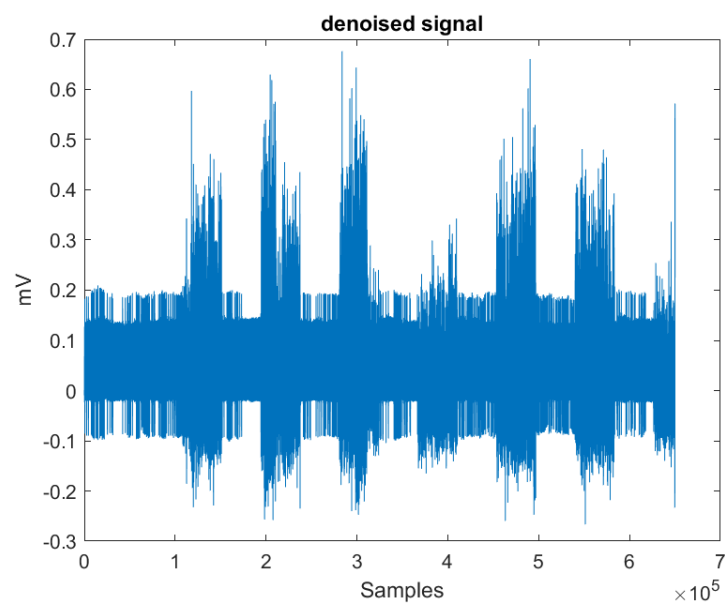
The ECG signal contains 650.000 samples and has sampling frequency 360Hz.

For signal denoising, a band-pass butterworth filter, which is explained before, is used.

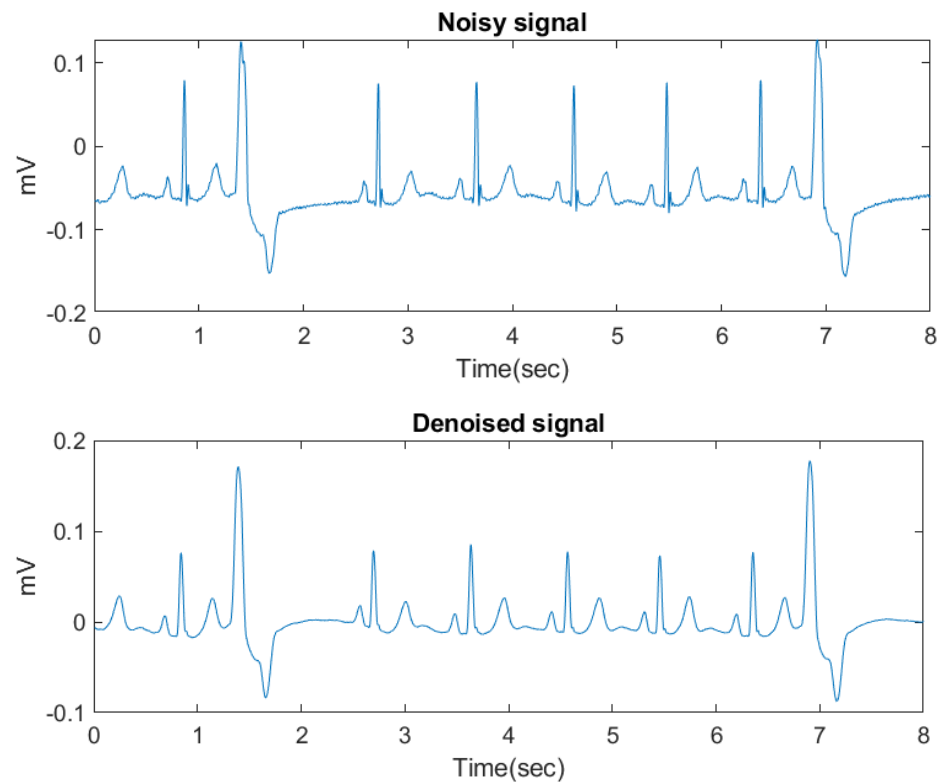
The noisy signal of channel 1 is the following.



The signal after reducing the noise is the following.



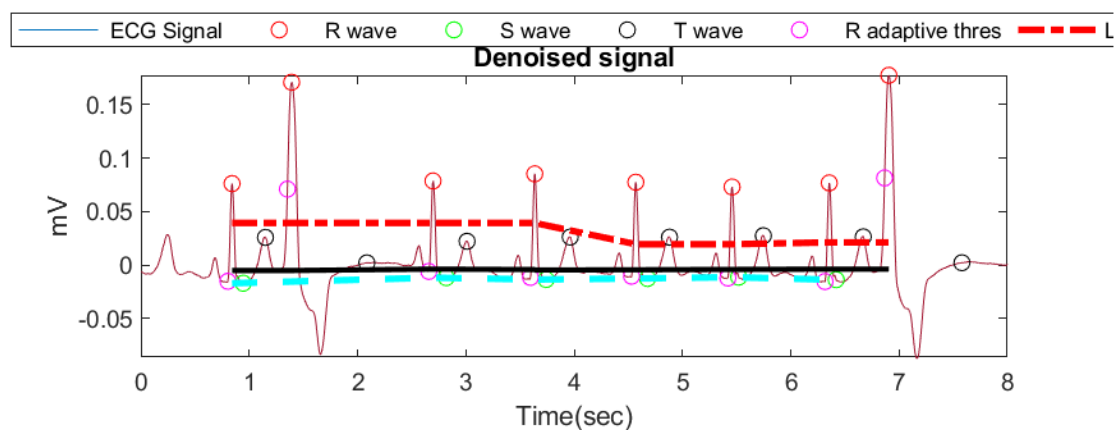
We can observe that noise has been reduced significantly. In order to observe that better, we can take a part of that signal. The results are the following.



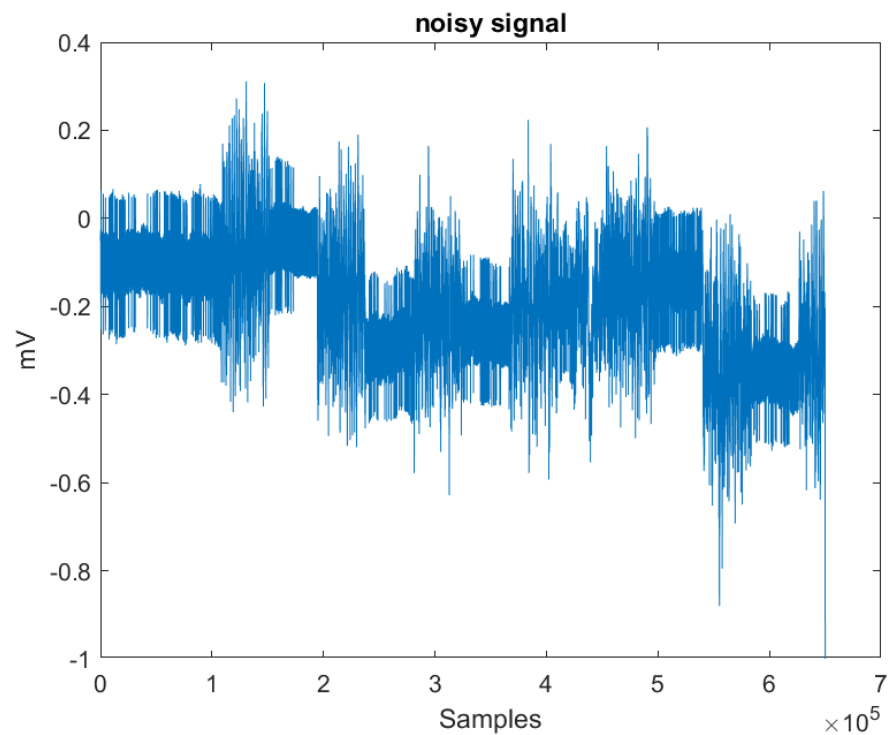
The heart rate for this signal is depicted in the command window and its value is near 68bpm, which is a logical value for a heartbeat.

```
Heart rate is 68.0234 beats per minute
```

The following picture depicts a part of the ECG signal, which shows the principal parts of it.

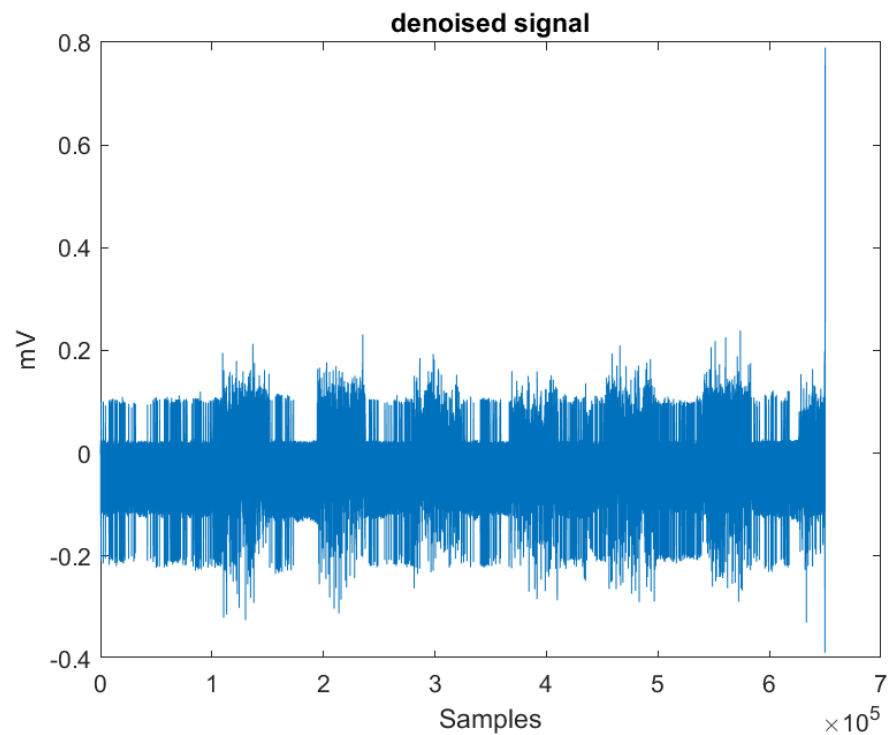


I followed the same procedure for channel 2. The noisy signal of channel 2 is the following.

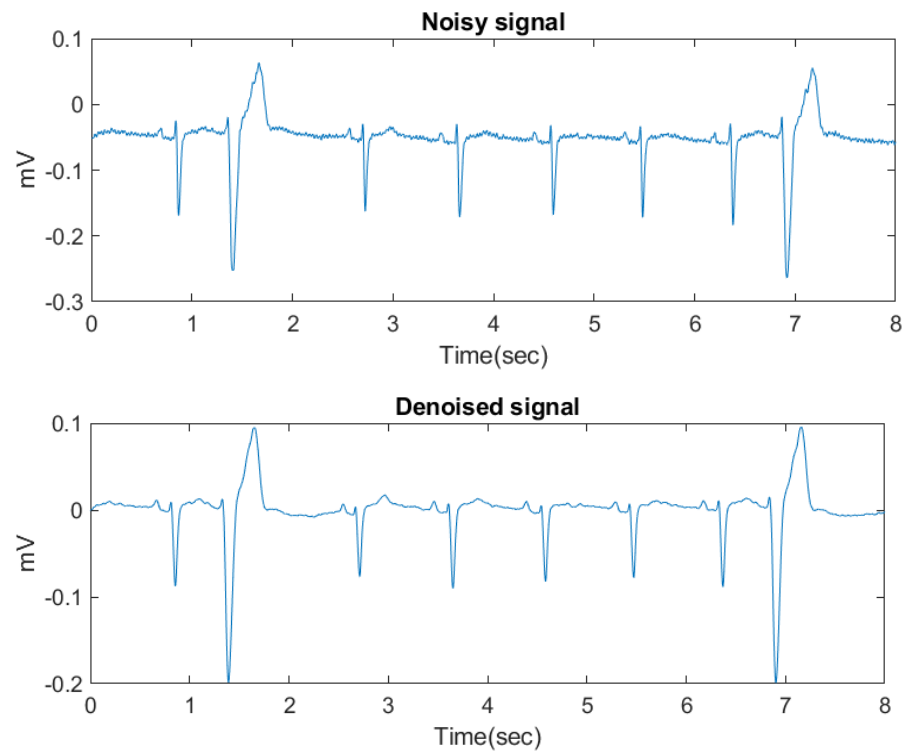


For signal denoising, a band-pass butterworth filter, which is explained before, is used.

The signal after reducing the noise is the following.



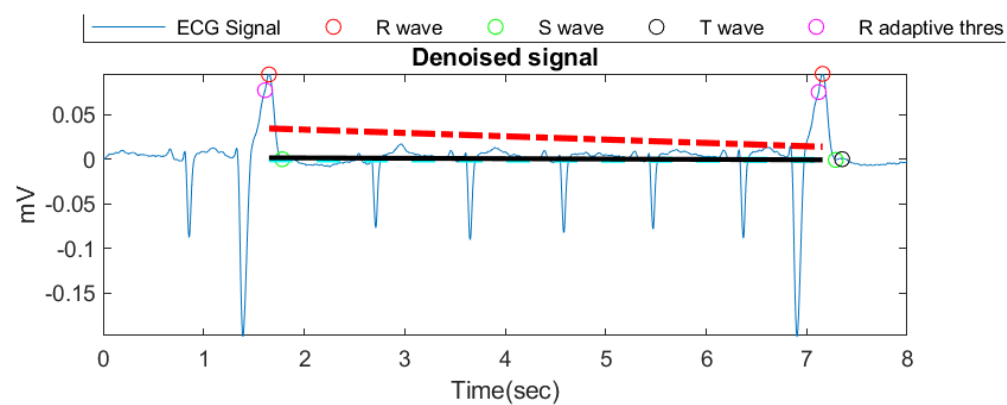
We can observe that noise has been reduced significantly. In order to observe that better, we can take a part of that signal. The results are the following.



The heart rate for this signal is depicted in the command window and its value is near 53bpm, which is a logical value for a heartbeat.

```
Heart rate is 53.4351 beats per minute
>>
```

The following picture depicts a part of the ECG signal, which shows the principal parts of it.



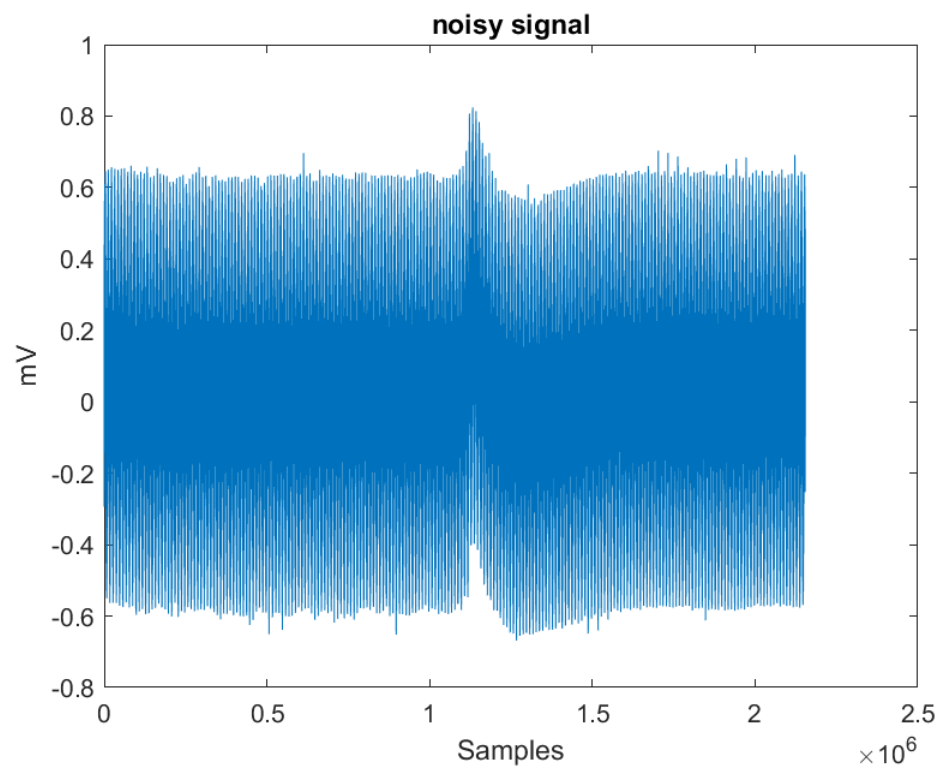
Project 3

The aim of this project is to remove artificial noise from an ECG signal. This signal consists of 1 channel.

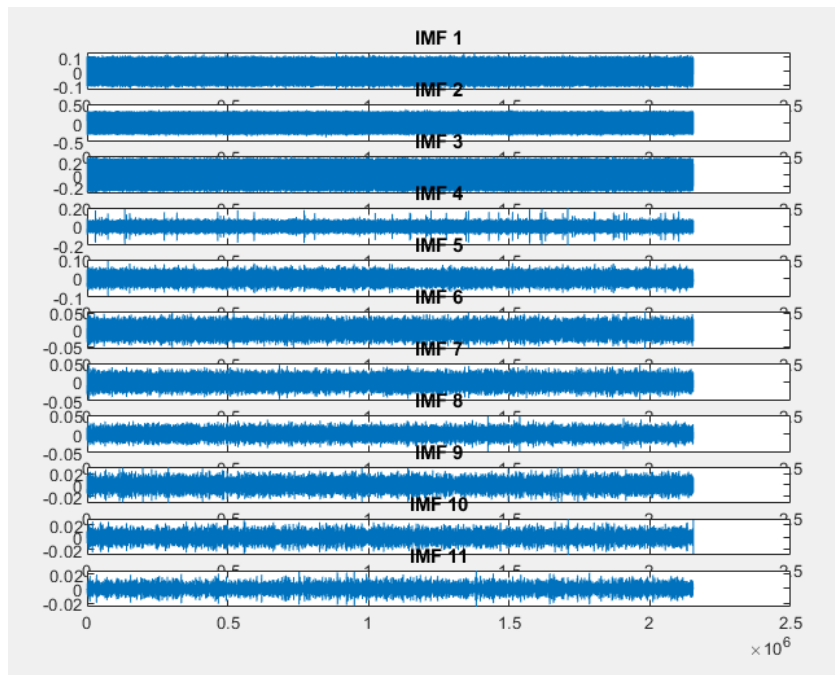
The ECG signal contains 2.154.163 samples and has sampling frequency 44100Hz.

For signal denoising, an EMD-based model is used. The steps of this algorithm are explained above. The results of the process are introduced below.

The noisy signal of channel 1 is the following.

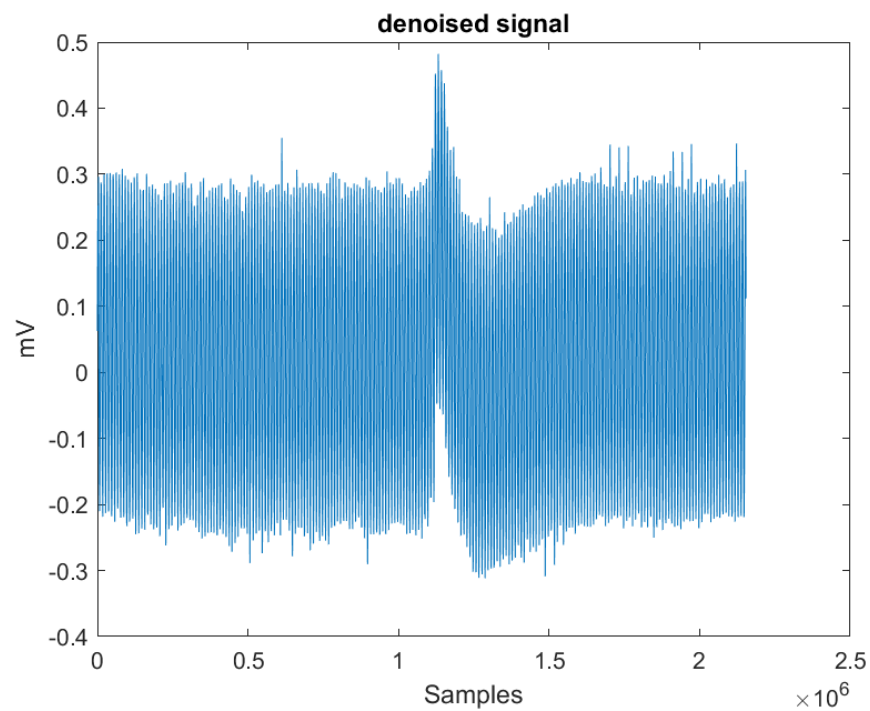


The IMFS, which occur, are the following

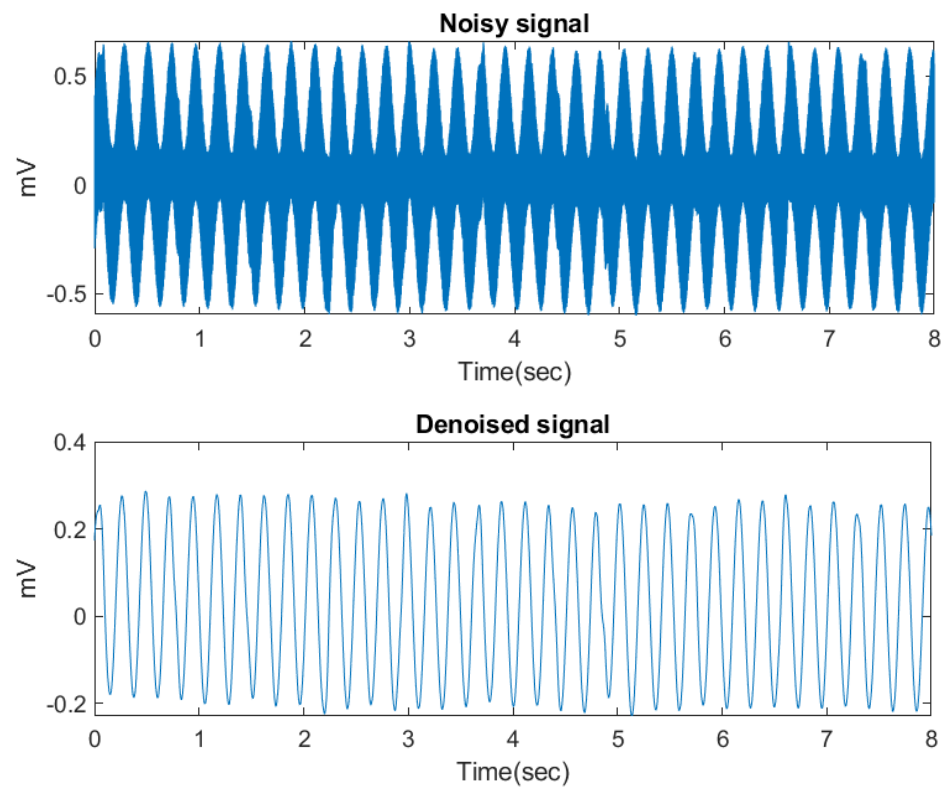


As it is explained before the lower order IMFs show the fast and high frequency oscillations whereas upper order IMFs correspond to slow or low frequency oscillations.

The signal after reducing the noise is the following.



We can observe that noise has been reduced significantly. In order to observe that better, we can take a part of that signal. The results are the following.



What can I observe from the pictures is that the noise has been reduced. However, I am concerned because the signal does not have the typical form of an ECG signal.

References

- <https://ch.mathworks.com/matlabcentral/fileexchange/45404-an-online-algorithm-for-r-s-and-t-wave-detection?fbclid=IwAR1LebZRd8qYVyVJphrxjvnsR09FyUxajxFYIqOvTE4KhKNzXC47cDsAaqw>.
- <https://ch.mathworks.com/matlabcentral/fileexchange/52502-denoising-signals-using-empirical-mode-decomposition-and-hurst-analysis>.
- <https://seermedical.com/blog/calculate-heart-rate-ecg>.
- G. Han, 1. B. (2017, March 10). Electrocardiogram signal denoising based on empirical mode decomposition technique: an overview.
- Shubhojeet Chatterjee, R. S. (2020, July). Review of noise removal techniques in ECG.
- Yan Lu, J. Y. (X.X.). Model-based ECG Denoising Using Empirical Mode Decomposition.