Report of Sample Project-Signal processing

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Fall 2022

Abstract

The electrocardiogram (ECG) is a commonly used tool to examine the electrical and muscle activity of the heart when the morphological and interval features of the recorded ECG signal need to be precisely assessed. ECG recordings frequently contain various types of noise and artifacts. In order to identify the fiduciary points (P, Q, R, S, and T) as features, the preprocessing procedure aims to reduce noise and artifacts. In this study, we describe ECG and its components, After that we evaluate the ECG noises and methods of noise removal and Remove noises of sample data and extract the features.

Keywords:

electrocardiogram (ECG), Noise, Features, fiduciary points

Table of Contents

List of Figures

List of Tables

Chapter One: Introduction

Electrocardiogram (ECG)

The electrocardiogram (ECG) is a non-linear non-stationary quasi-periodic time series [1]. It is a widely used instrument to look at how the heart's electrical and muscular processes work. It is a time-varying bio-signal that reflects the ionic current flow that drives cardiac fiber contractions and relaxations, giving indirect information about blood flow to the heart muscle [2].The ECG technique was created in the early 1900s by Willem Einthoven. The depolarization and repolarization stages of the heart's muscle fibers can be generally separated out in the ECG [3]. The trace of each heartbeat consists of three complexes: P, R, and T. In Fig. 1, the components of the ECG complex are depicted [4].

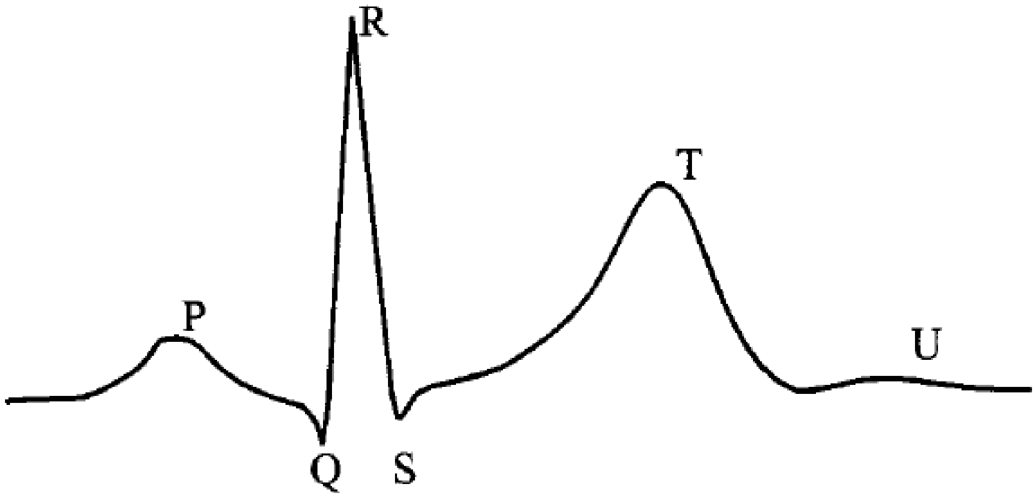

Fig. 1. Elements of the ECG-complex [5].

ECG Components

The physical contraction of the heart muscle known as a heartbeat is brought on by chemical and potential changes in the cells that make up the heart, known as myocytes. The interior of the myocytes is negatively charged. The Sinoatrial (SA) node fires first, triggering the heartbeat. The primary pacemaker of the heart is the SA node (Fig. 2). As the electrical signal spreads, sodium (NA+) ion migration causes the myocytes to depolarize and compress quickly. The ECG trace's P wave represents this. When the signal reaches the atrio-ventricular (AV) node, where the chemical signal transforms into relatively slow moving calcium (CA+) ions, the depolarization rate slows down significantly. The difference between the P and R complexes represents the change in contraction. The signal reaches the cells lining the ventricles after passing the AV node. The R complex is created as a result of the ventricles' fast contraction. Due to the chemical agents and the delay between the end of the electrical impulse and the physical displacement, repolarization does not completely replicate polarization [6].

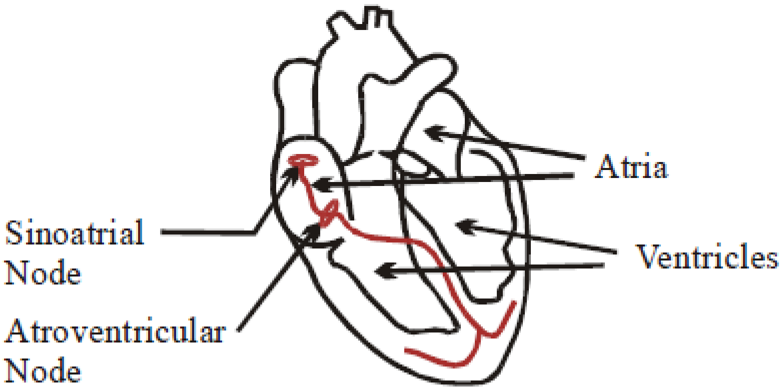

Fig. 2. The heart and its pacemakers [7].

Ten electrodes are positioned on certain areas of the surface of the human body to measure the ECG. Four electrodes are put on the extremities, and six electrodes are put on the chest. The electrical potential fluctuations across the ten electrodes in 12 different directions are monitored for routine ECG recordings. Leads are the typical name for these 12 various electrical perspectives of the heart's activity. Three bipolar and nine monopolar leads make up the 12 leads. The electrical potentials between the right and left arms (lead I), the right arm and left foot (lead II), and the left arm and left foot make up the three bipolar leads (lead III). Four separate artificial reference points are built for the monopolar leads. The signals observed at two or more electrodes were averaged to provide these reference points. These reference points are used to calculate the potentials on the left arm (aVL), right arm (aVR), left foot (aVF), and six electrodes on the chest (V1-V6). Normally, the right foot is only utilized for grounding [5]. The Electrode placement in 12 lead system is shown in Fig. 3.

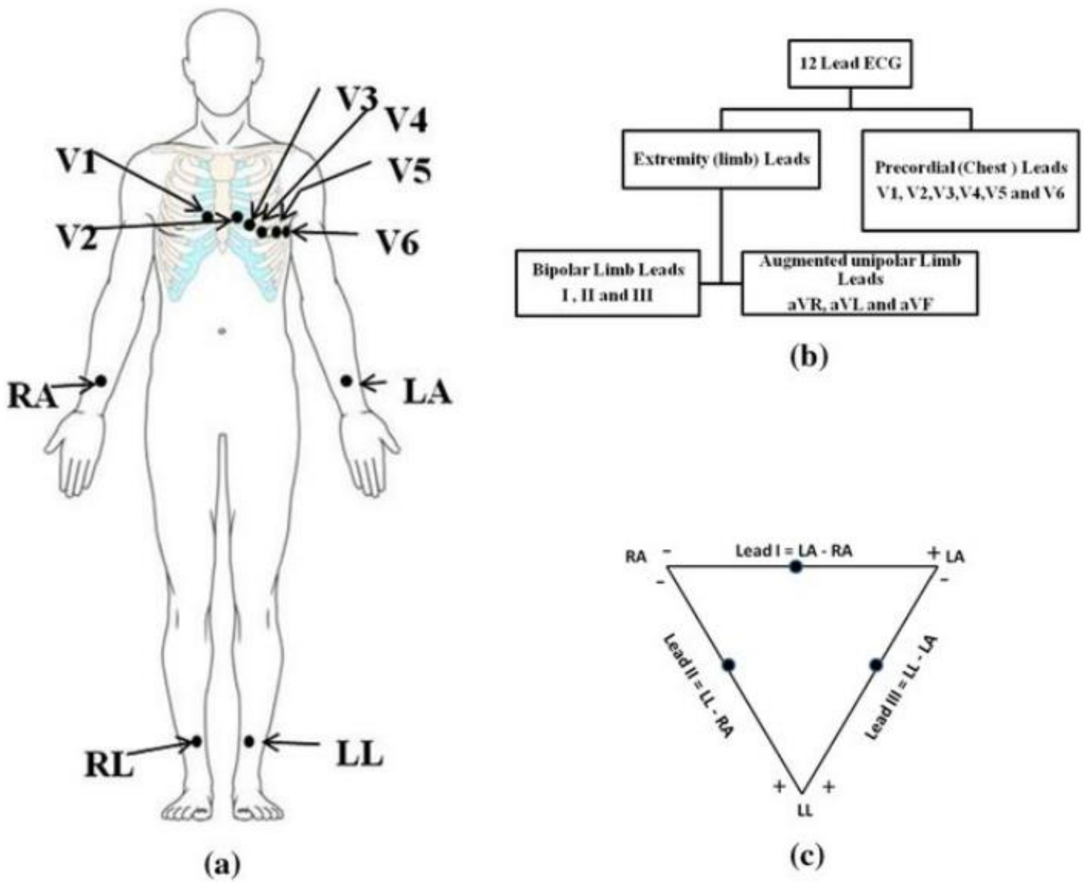

Fig. 3. a Electrode placement in 12 lead system, b 12 Lead ECG, c Einthoven's triangle describing lead I, II, and III [8].

Doctors can determine whether a patient's heart condition is normal or not by examining the ECG's characteristics. They may also determine what problems the heart is currently experiencing. However, it is problematic and even impossible for doctors to deal with vast amounts of ECG data in the short period due to the limitations of the human eye as well as the complex variations of ECG data [9].

As a result, research interest in computer-aided diagnostic systems has grown to this point. Such technologies can assist physicians in improving the accuracy of their diagnoses and decreasing the rate of misdiagnosis by automatically analyzing ECG data. Signal de-noising, singularity detection, and arrhythmia classification are the key components of ECG analysis [4].

Report Structure

This report consists of four chapters. In the second chapter, after dealing with the general concepts and introducing ECG signal noise and checking some of its characteristics, we will deal with noise removal methods and their codes. Then, in the third chapter, the results obtained from the implementation of the methods reviewed in the second chapter are reported on the research data. Finally, in the fourth chapter as the last chapter, after the brief description of the processing steps and general summary of the obtained results, a comparison will be made between the results and normal amounts.

Chapter Two: Methods

ECG Noises

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 are just a few of the many medical applications for ECG signals [10-12]. For these applications, the recorded ECG signal's morphological and interval characteristics must be accurately determined. ECG recordings are frequently tainted by various noise and artifact kinds. The preprocessing step's objectives are to lessen noise and artifacts so that the fiduciary points (P, Q, R, S, and T) can be identified, as well as to prevent amplitude and offset effects when comparing signals from various patients. The following categories are used to group common noise kinds [9, 13, 14]:

1) Baseline wander (BW): a low-frequency noise that ranges from 0.15 to 0.3 Hz. The noise that the patient inhales causes forces an adjustment in the baseline of the ECG readings.

2) Power line interference (PLI): a signal with a bandwidth of less than 1 Hz and a frequency of 50 or 60 Hz

3) Electrode contact noise: noise that develops when the electrode and skin are not sufficiently contiguous, effectively cutting the measurement system off from the subject.

4) Electrode motion artifacts: These artifacts are caused by changes in the electrode-skin impedance that happen when an electrode moves.

5) Muscle contraction noise (Electromyography noise): This noise is produced when muscles other than the heart contract.

6) Instrumentation noise: This is the sound that the electronic tools used to measure the ECG make.

Denoising

The preprocessing stage uses a filtering block to delete artifact signals from an ECG signal (Fig. 4).

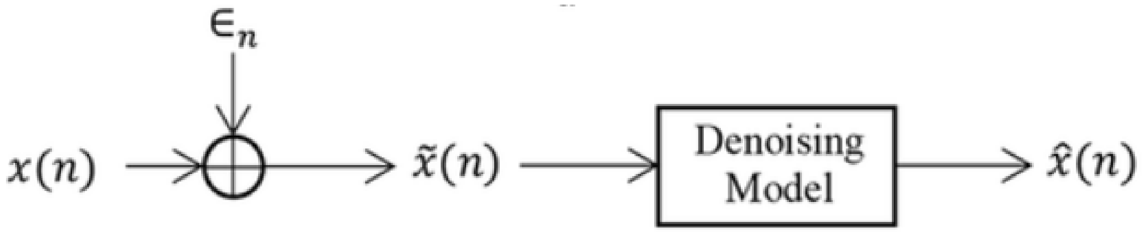

Fig. 4. Estimation of clean ECG using the denoising model to get xˆ(n) [15].

Before analysis, an ECG signal is typically first bandpass filtered using various frequency ranges. In order to reduce ADC saturation and address antialiasing, bandpass filtering is frequently used to remove muscle noise, baseline wander, power line interference, and low- and high-frequency noise components. The frequency range of 0.1–100 Hz for the bandpass filtering is most often used [9]. The QRS complex, epsilon, and J-waves are noticeably altered by analog low-pass filtering, but the repolarization signals are unaffected. A decent low-pass filter can remove the noise while leaving a lot of data behind for additional processing. Analog high-pass filters do not significantly reduce the signal, in contrast to low-pass filters. However, analog high-pass filters suffer from phase shifts that affect the first 5–10 harmonics of the signal. In ECG work, a high-pass filter is primarily used to eliminate the DC offset, which is primarily brought on by the electrode/gel/body interface [16]. In addition, The purpose of a notch filter is to reduce some single frequencies while maintaining others. High-pass and low-pass filters are combined to create a narrow frequency range that needs to be removed with notch filters. Software can be used to produce high-quality notch filters that only work at 50 or 60 Hz (In Iran 50 HZ) [9].

In this project, Based on [9], The goal of filtering is to remove the signal above 100 Hz and below 0.1 Hz and remove the signal at 50 Hz. We can filter with 2 methods:

1) Filter signal between 0.1 and 40 Hz.

2) Filter signal between 0.1 and 100 Hz and use a notch filter for 50 Hz.

You can see the filters in Fig. 5 and Fig. 6. We used the scipy library in python for designing filters and for exerting Fast Fourier Transform (FFT) .

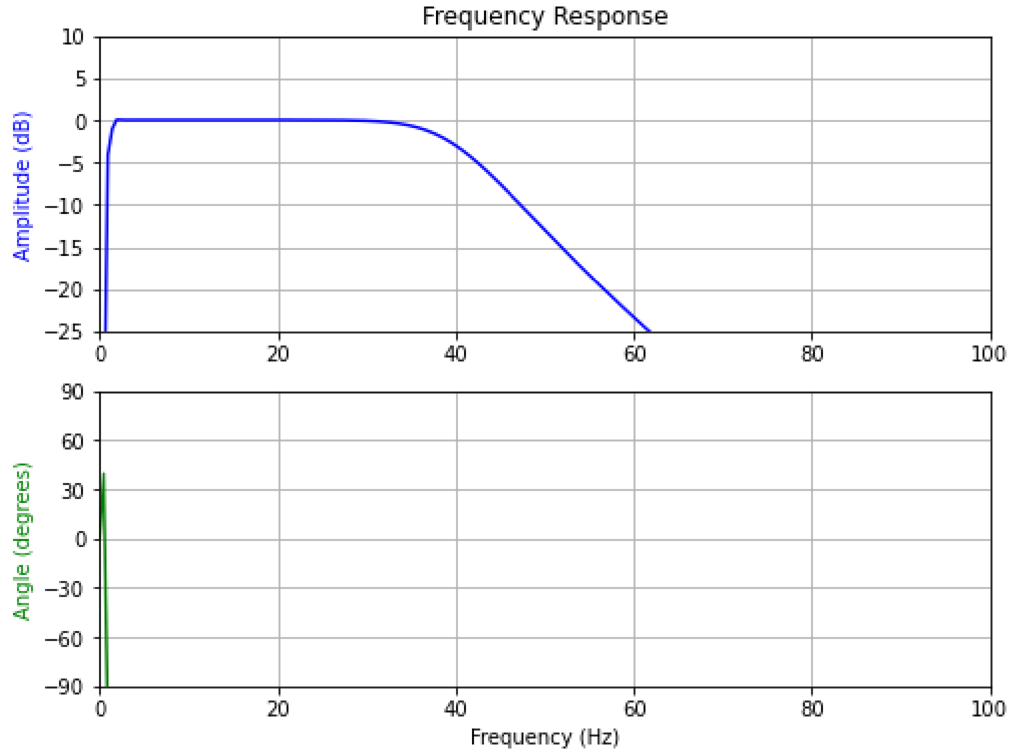

Fig. 5. Bandpass filter for filter signal between 0.1 and 40 Hz.

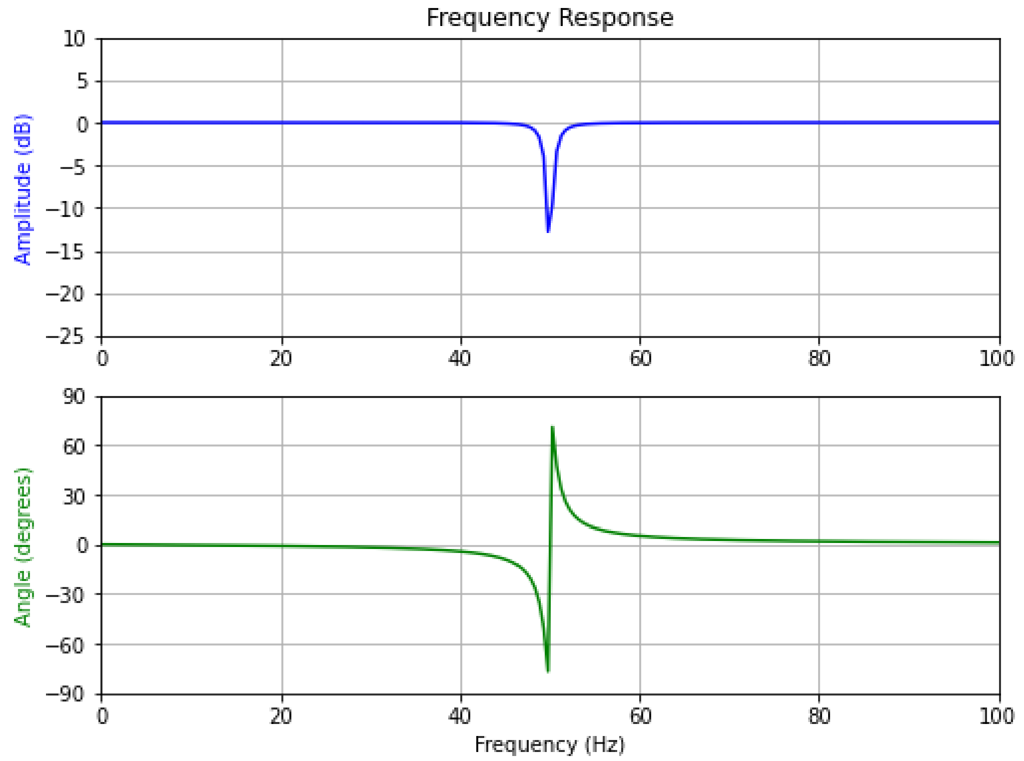

Fig. 6. Notch filter for remove the 50 Hz signal.

We don't know that the signal belong to Iran or not. Hence, the first method is better. We use 40 Hz as the high bandstop of our filter, Because our filter is not Ideal and if we use higher frequency as bandstop, The 50 Hz signal will be remaining. We used 6^{th} degree butterworth filter with filtfilt function for not changing phase in Python. In Matlab we used In addition, We use IIR filter for notch, because The FIR filter effects on phase of the signal. You can access the codes on Github.

Locate Peaks of ECG signal

Once the non-signal components were removed from the ECG data stream, the ECGtrace fiducial positions were located. The standard medical fiducial labels do not fully characterize the entire heartbeat trace. From pattern recognition science, additional feature attributes are rarely completely correlated or independent. However, additional subject attributes generally improve the scalability to larger populations at the cost of reducing the tolerance intra-subject variability. For human identification, attributes were extracted from the P, R, and T complexes. The slope of the R wave is a popular signal feature used to locate the QRS complex in many QRS detectors [17]. We used the scipy library in python for locating the R wave in signal and will show you on results. In addition, We calculated the Average Heart Beat, Number of peak, mean and standard deviation of R to R intervals in the signal.

Chapter Three: Results

This chapter presents the results of each of the steps described in the previous chapter, along with images and tables. It should be noted that all steps on Sample_data are implemented. As mentioned in the previous chapter, the results were obtained in Python using the Scipy library and will be mentioned in order.

Filtering

The time diagram and frequency spectrum of signal before and after filtering are shown in Fig. 7 and Fig. 8. As can be seen, the noise is almost eliminated.

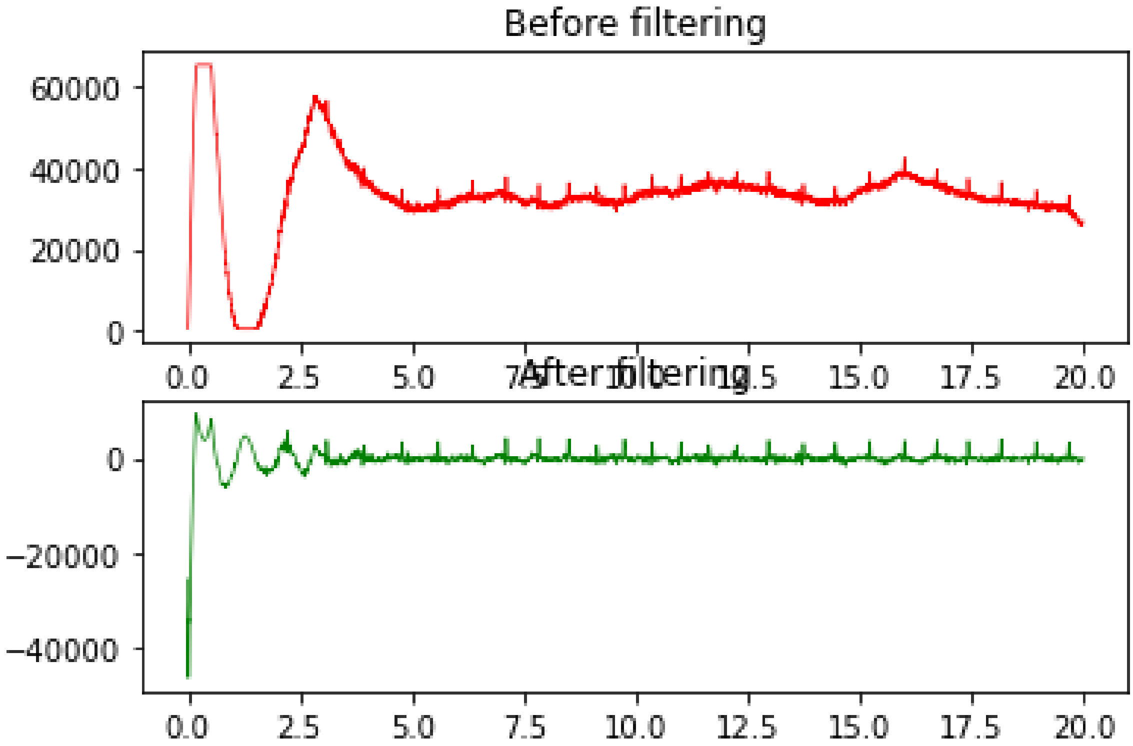

Fig. 7. Signal time diagram before and after filtering.

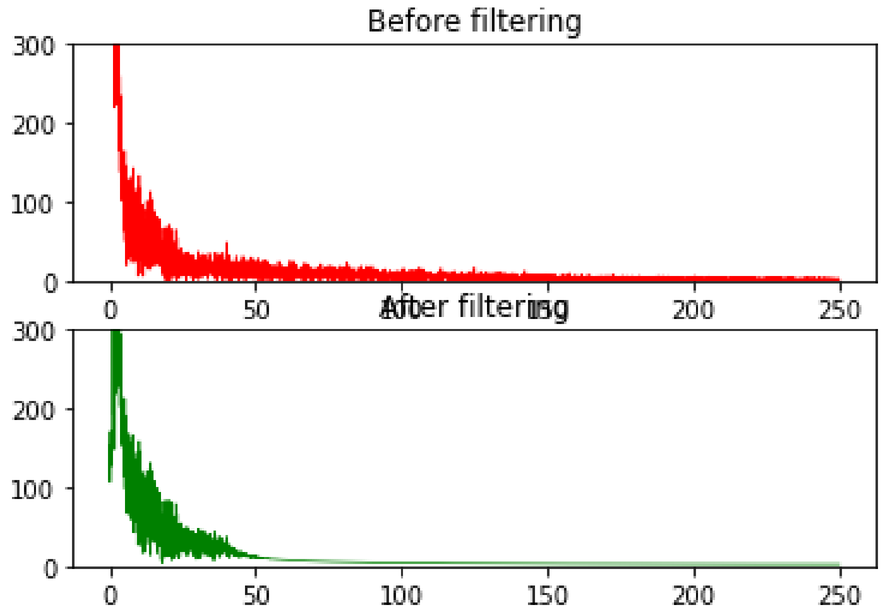

Fig. 8. frequency spectrum of signal before and after filtering.

Feature Extraction

You can show the R-R intervals and peak of signal in Fig. 9. In Table 1, the Average Heart Beat, Number of peak, mean and standard deviation of R to R intervals in the signal are shown as features of signal.

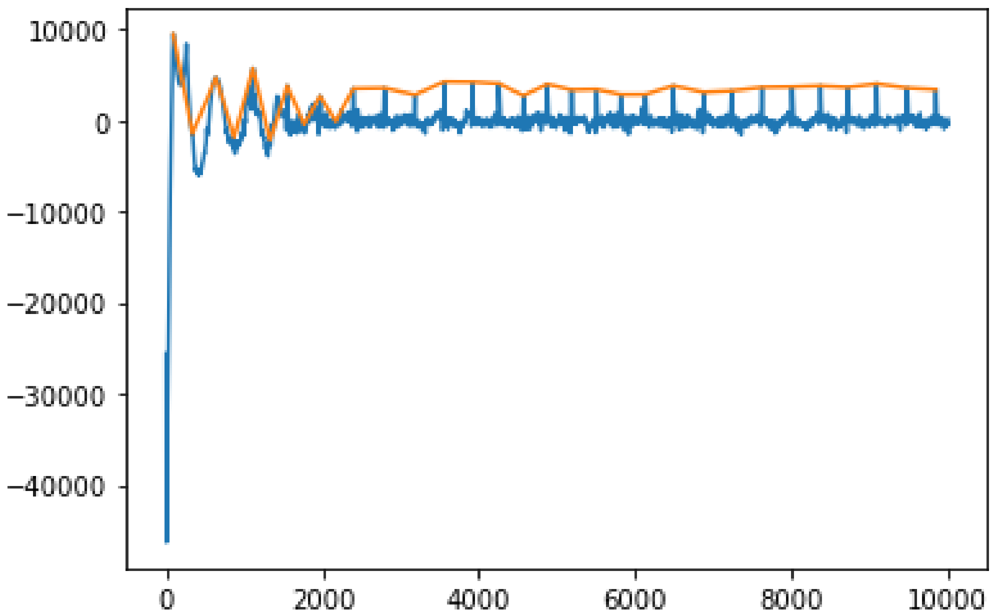

Fig. 9. R-R intervals and peak of signal.

Table 1. features of signal.

Feature	Results
Average Heart Beat	95.4
Number of peak	32
Mean deviation of R to R intervals	629.1
Standard deviation of R to R intervals	131.1

Chapter Four: Conclusion & Discussion

We Calculated the Average Heart Beat, Number of peak, mean and standard deviation of R to R intervals in the signal are shown as features of signal and you showed the amounts in Table 1. But, Are Results Correct?

The normal heartbeat for a young human is 80-120. That shows our result in the normal area. mean of R to R intervals in the signal is in the nomal area too. But in first samples, we have bad data, we could remove this samples and improve results. After that we use 6^{th} degree butterworth (based on [18]). We can also use other filter degree and improve our results.

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Attachments: Results in MATLAB

The time diagram of signal after filtering are shown in Fig. 10.

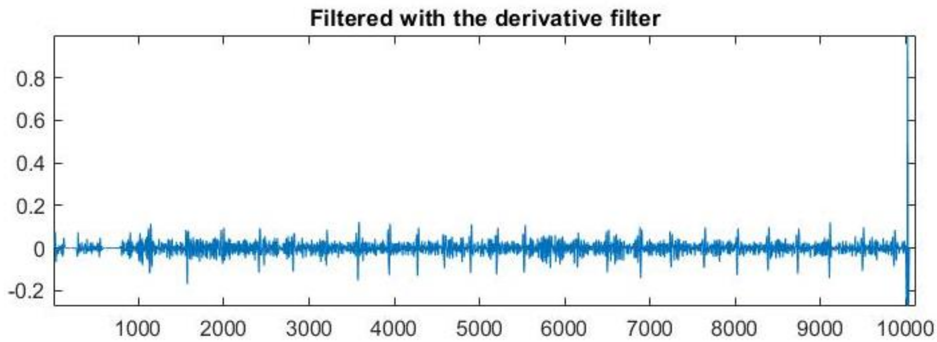

Fig. 10. Signal time diagram after filtering.

You can show the R-R intervals and peak of signal in Fig. 11.

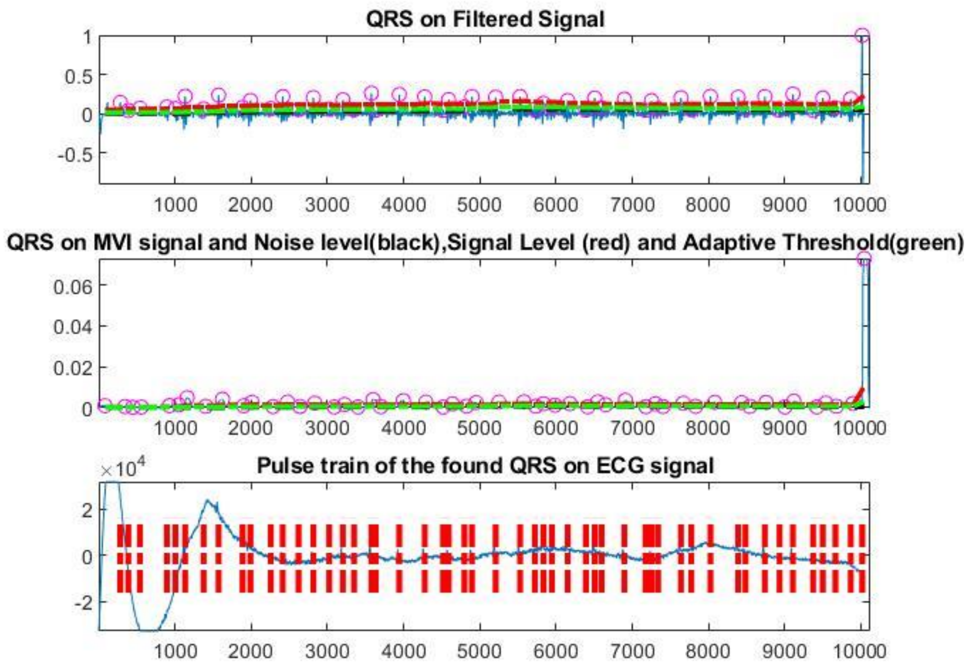

Fig. 11. R-R intervals and peak of signal.