Application of Adaptive System to ECG Analysis: Noise Attenuation and ECG Detection

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ABSTRACT

ECG or electrocardiogram is a tool used to monitor the electrical activity of a heartbeat. However, the detectable signal is incredibly small, and an electrical noise could be relatively large. This means it is necessary to design a filter for better attenuating the noise below and beyond a certain frequency. Moreover, the abnormal ECG results from abnormal heart rate is the best notification for any potential heart diseases and should get notice as soon as possible. Therefore, this project focus on designing a system for both solving noise attenuation and ECG detection issues.

1.Introduction

1.1 ECG Signals

ECG measurements are taken analysing the flow of electricity from every beat of the heart, and especially this occurs with an oscillation frequency of 1.3 Hertz, which is equivalent to 80 beats per minute. In addition, ECG measurements are taken by attaching leads to the skin of a patient cause of the physical constraints of monitoring the heart rate through the surface of the skin (Deergha Rao & Swamy 2018, pp. 35-57). Before choosing the effect processing techniques for the designed filter, it is essential to understand the waveform of the ECG waveform. As Figure 1 shows, electrical activity of tracing results from the propagation of five events. In a normal heart, each beat starts in the right atrium with an action potential signal from the sinoatrial node. The signal spreads across both atria, causing muscles cells to depolarise and contract to induce a phase known as atrial systole (P wave), while ventricular repolarisation is shown by the T wave (Saritha 2008, pp. 68-77). As a result, the signal should go into a linear system that is sinusoidal fidelity to make the output signal shares the same frequency as the input signal for better detecting both the P wave and the T wave (Saritha 2008, pp. 68-77). Moreover, the transform function bases on the mathematical technology of decomposition should be the general consideration for choosing the filters and effects within the system.

In addition, PR-Segment on the ECG, a flat line following the P wave when the signal leaves the atria, depicts the period of operation that follows atrial systole and proceeds the contraction of the ventricles, while the ST-Segment depicts the period when the ventricles are depolarised. Most importantly, as the signal spreads through the ventricles, the QRS Complex represents rapid ventricular depolarisation (Saritha 2008, pp. 68-77). The FIR filters or the IIR filters bases on the DFT fits the function for detecting specific frequency component from each period of the ECG very well. Besides, one of the two filters forms the input signal of ECG along with the impulse response from the PR-Segment, P wave, T wave, ST-

Segment, and the QRS Complex into the output signal in the frequency domain to describe the heart rate (Deergha Rao & Swamy 2018, pp. 35-57).

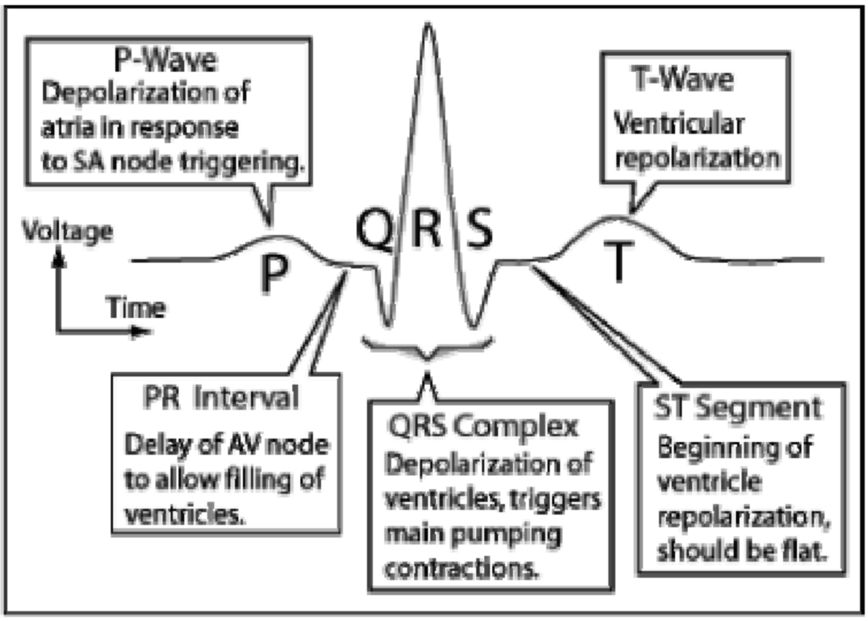


Figure 1. The normal ECG waveform (Saritha 2008)

1.2 ECG Signals and the Filters

1.2.1 FIR Filter and IIR Filter

The difference between the FIR filter and the IIR filter is the limitation of the impulse response. The FIR filters do not have the past outputs fed forward to the current outputs, which means it has no feedback to keep the impulse response duration finite. On the other hand, the IIR filters have both the past input signals and the past output signals.

Compared to the IIR filters, it is hard to use FIR filters to implement the frequency response design for the ECG signals. Detecting the specific frequency of the QRS complex according to different people and filtering a range of undesired noise requires a band-pass filter or the combination of high-pass filters and low-pass filters to achieve the same effect. However, a simple band-pass or combinative FIR filter usually needs more coefficients than an IIR filter did. For example, the moving average filter is one of the classic FIR filters that hold finite past input signals in a buffer and sums them with each new input signals to produce an output signal, while a simple IIR filter can replace it with fewer coefficients. Apart from this, the filter needs to be less effective to get more precise ECG signals. The FIR filter's roll-off sharpness is significant, and the stopband attenuation is larger than the IIR filter's (Smith 1999). Therefore, the IIR filter is the choice for the ECG signals with gently fluctuating and less attenuation compared to the original input ECG signals.

1.2.2 Butterworth Filter and Chebyshev Filters

Two classic IIR filters from which one of them is the Butterworth filter and the other one is the Chebyshev 2 filter. Based on the choice of the IIR filters for less effective on purpose, the two filters are especially useful for separating one band frequency from another. The Chebyshev filter uses the Chebyshev response for achieving a faster roll-off by allowing ripple in the frequency response. As the ripple increases, the roll-off gets sharper, and the Chebyshev response means the two parameters share an optimal trade-off relation from which type 1 has the ripple in the passband while type 2 has the ripple in the stopband.

Furthermore, the Butterworth filter also depends on the two parameters of ripple and roll-off, but the ripple of it is set to 0% (Smith 1999, pp. 333-342). The low pass Chebyshev filters of type 2 are part of the designed filters for moving the unwanted noise of the ECG signals. As illustrated in figure 2, the low-pass Chebyshev filter achieves a faster roll-off than the

Butterworth filter with the 0% ripper. To move the noise from the ECG signals and maintain the precision of it at the same time, I choose to use the low-pass Chebyshev filter of type 2. It can achieve a slower roll-off than the type 1 low-pass Chebyshev filter but faster roll-off than the Butterworth filter by allowing ripper in the stopband. To centre the shape of the output signals from the type 2 Chebyshev filter, I choose to use the high-pass Butterworth filter with slower roll-off. The combination of them as a designed filter is in figure 3.

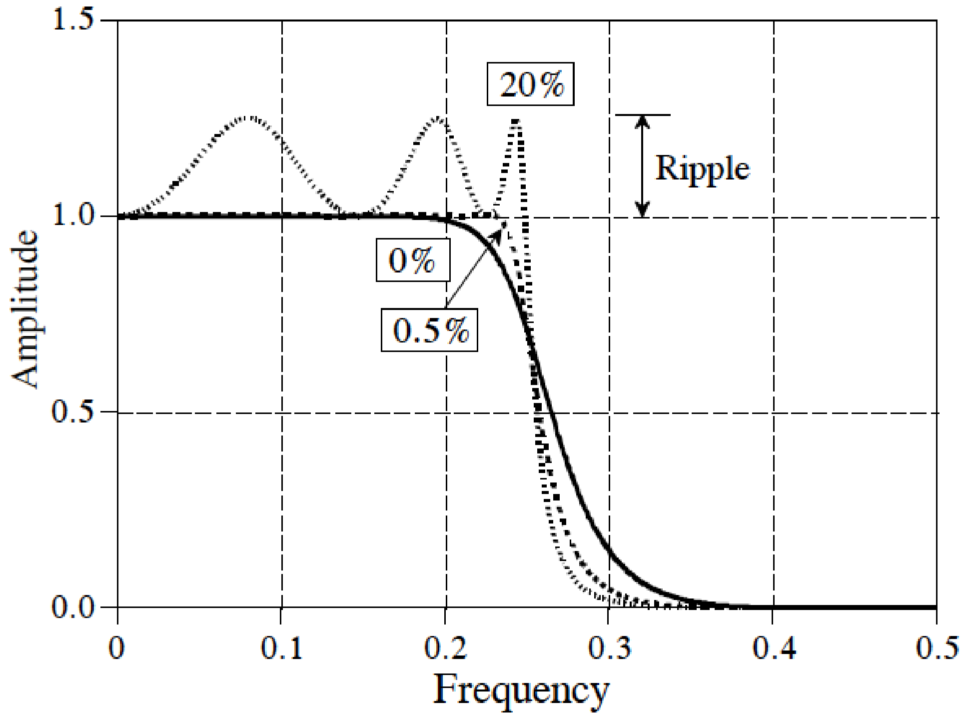


Figure 2. The low-pass Chebyshev filter and Butterworth filter (Smith 1999, p. 334)

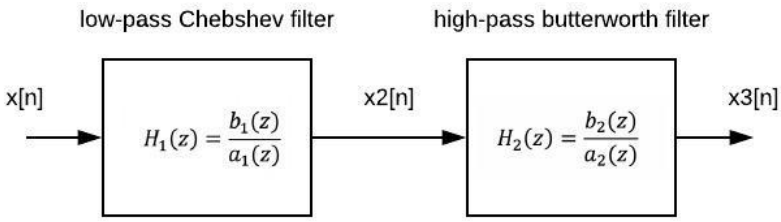


Figure 3. The designed filter

1.3 Combining the system

1.3.1 Time-variant Effect Processing

Two main types of abnormal ECG signals are detectable for the system. One of them is Ventricular Tachyarrhythmias, and the other is Arrhythmia. Ventricular Tachyarrhythmias appear in people who have structural heart problems (Ramli & Ahmad 2003, p. 232). If the delay of the original ECG signals continuously varied with a low frequency such as 1 Hz, the low-frequency oscillator (depth) of the vibrato effect triggered to reflect the original ECG signal is too low that the individual is under risk of the Ventricular Tachyarrhythmias (Zölzer 2011, p. 76). Moreover, Arrhythmia is a change in the rhythm of the heart rate. The tachycardia happens when the heart beats too fast, and the bradycardia happens when the heart beats too slow (Thakor & Zhu 1991). If the pitch variation of the frequency of the original ECG signals is significant, the delay-line (width) of the vibrato effect will reflect into the delayed signals.

1.3.2 Settings of Effect Processing Techniques

Vibrato effect use modulation of a simple delay on the ECG signal basing on rate and depth. The pitch effect of vibrato applied to one-channel with the delay line. According to the standard ECG signal from table 2, the QRS duration of all abnormal ECG signals is below 0.01 seconds. Nevertheless, the QRS duration of normal ECG signals is over 0.01 seconds. Besides, the Ventricular Tachyarrhythmias happen when the frequency of the QRS is lower than the 0.2V (Islam et al., 2012, p. 9770). Therefore, the vibrato effect would be triggered when the low-frequency (depth) is lower than 0.2V, or when the delay-line (width) is less than 0.01s.

Signal	RR interval (seconds)	Heart rate (beats/min)	QRS duration (seconds)	Condition
Normal signal	0.791	75.84	0.094	STANDARD
Signal A	0.877	68.41	0.093	NORMAL
Signal B	0.911	65.83	0.088	NORMAL
Signal C	1.059	56.65	0.238	ABNORMAL
Signal D	0.80	75.00	0.080	NORMAL
Signal E	0.516	116.07	0.197	ABNORMAL
Signal F	0.78	76.90	0.083	NORMAL
Signal G	0.45	133.33	0.162	ABNORMAL

Table 1. data of the normal and abnormal ECG signals

2. Lab Report

2.1 Analysing ECG signal

In table 2, there is a summary of four types of ECG signals that got from the PhysioNet. The database includes three half-hour recordings of noise, especially in ambulatory ECG recorders and 12 half-hour ECG recordings（Goldberge et al., 2000). After finding and selecting, four types of ECG signals are chosen as the samples of the designed filter. According to different characteristics, the best sampling frequency for each signal depends on their size for maintaining the signal structure. The sampling results in Figure 4 include a normal ECG signal with noise, the Arrhythmia signal that the heartbeat is very slow (bradycardia), one of the Ventricular Tachyarrhythmias signals that the heartbeat drops instantly (type 1), and the other that the heartbeat increases instantly (type 2). The sampling process is skipped in the Matlab for keeping simple of the script file.

Types of ECG Signals (Filename)	Sampling Frequency	Size	Detail
Normal (ECG1)	1000 Hz	1 x 10000 double	Noise is within the signal
Arrhythmia-bradycardia (ECG2)	200 Hz	1 x 2000 double	The heart beats very slow
Ventricular Tachyarrhythmias Type1 (ECG3)	50 Hz	1 x 500 double	The heart attack makes the heartbeat drops instantly
Ventricular Tachyarrhythmias Type2 (ECG4)	10 Hz	1 x 100 double	The heart attack makes the heartbeat increases instantly

Table 2. the summary of four types of ECG signal

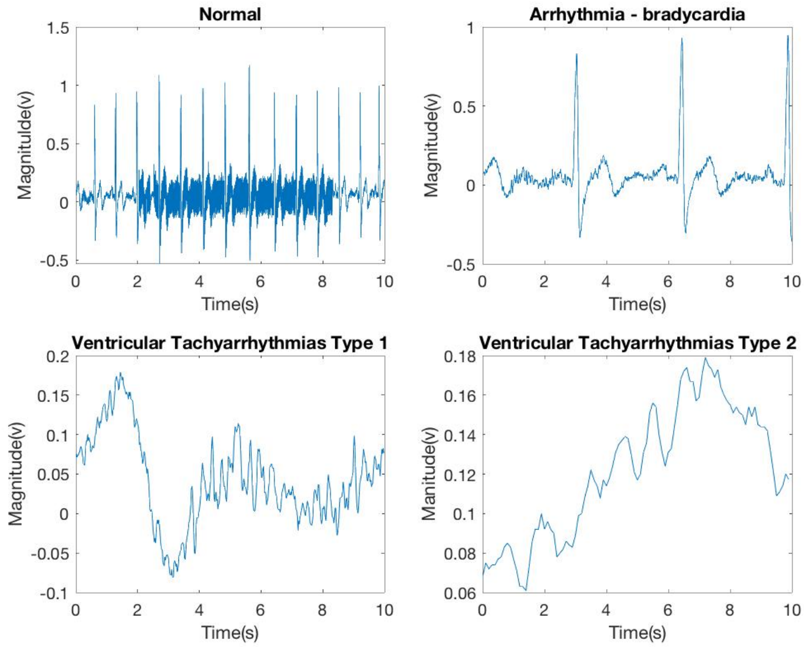


Figure 4. the normal ECG signal and abnormal ECG signals

After using the FFT function to find the specific frequency component within the normal ECG signal, it can be seen in figure 5 that the noise is around 50 Hz.

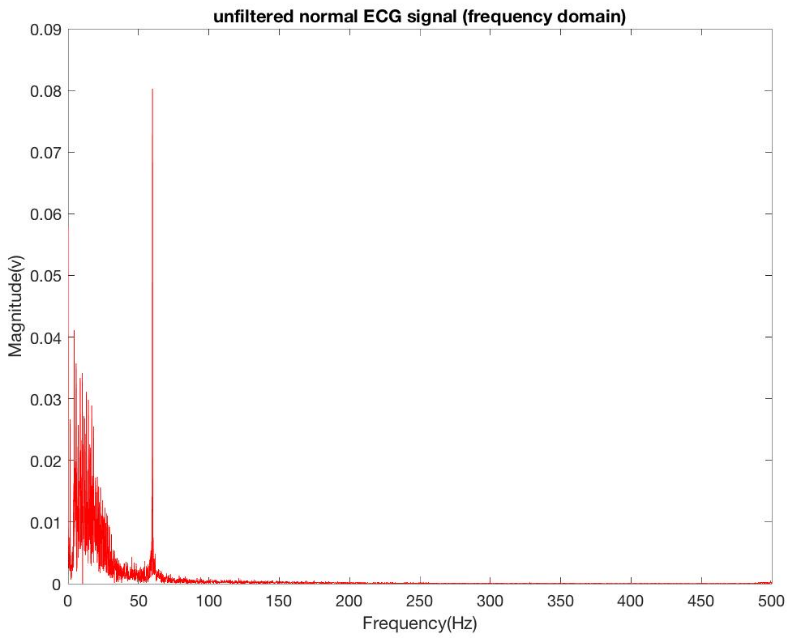


Figure 5. the unfiltered normal ECG signal in frequency domain

Moreover, I designed a DTFT function to analyse both the magnitude and phase response of the 50 Hz noise. As Smith (1999) said, the phase is not important in most frequency domain applications because it is relatively easy to design filters with a perfect phase response. As a result, we only look at the frequency response in figure 6, and we can find both the noise frequency of 0.1π (50 Hz) and sampling frequency of 2π (1000 Hz) in it as a natural frequency between 0 and 2π.

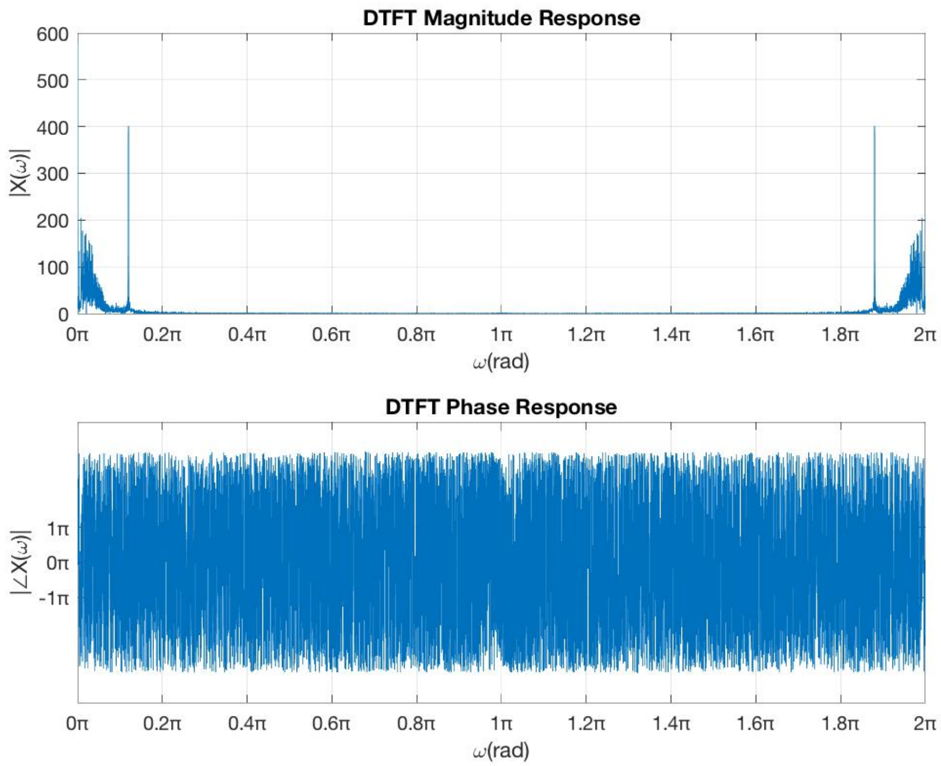
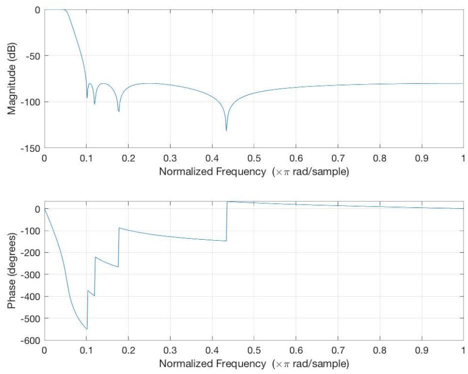


Figure 6. the DTFT magnitude and phase response of the normal ECG signal

2.2 Designing the filter

The designed filter is a combination of a low pass Chebyshev filter, and a high pass Butterworth filter with the relative transfer function as figure 8 showed. Because the designed filter consists of two IIR filters, so the denominator (poles) of the transfer function is zero. At the same time, the a_1, a_2 and b_1, b_2 are the feedback coefficients and feedforward coefficients for the numerator (zeros), and the Cheby2 function and Butter function would calculate the result automatically. Moreover, the details of filter order, low and high cut frequency is in the practical component of the project.



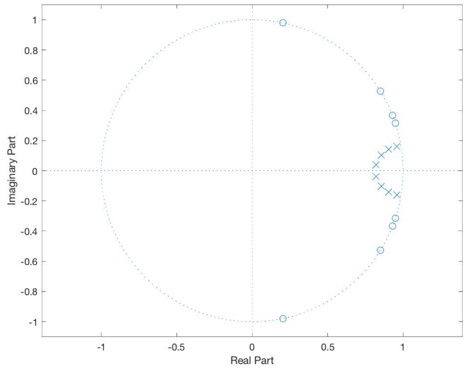
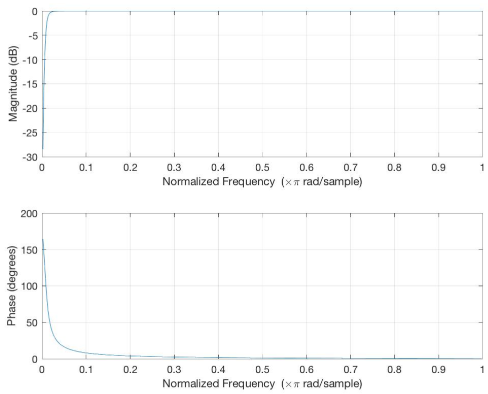


Figure 7. z-plane of the magnitude and phase response final filtering

Figure 8. poles and zeros before final filtering before

In the simple pole-zero model, figure 7 and figure 8 represent the magnitude response and pole-zero location of the x_2 signal, which is the output signal of the low-pass Chebyshev filter. Besides, figure 9 and figure 10 represent the magnitude response and pole-zero location of the x_3 signal, which is the output signal of the high-pass Butterworth filter. As we can see from them, the ripple of the magnitude response changes from the range of pi to the range below 0.1 pi, while the pole-zero location changes from the right side to 0. Furthermore, the comparison among the normal signal in figure 4, the x_2 output signal in figure 11, and the x_3 output signal in figure 12 show the graduate attenuation of the noise by the designed filter. Finally, the comparison of figure 5 and figure 13 also demonstrates the efficiency of the designed filter that the 50 Hz noise disappeared.



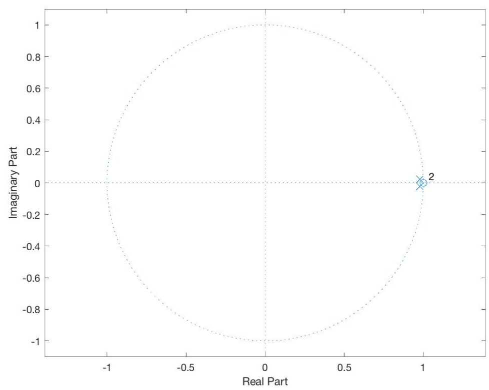


Figure 9. z-plane of magnitude response and phase response after final filtering.

Figure 10. poles and zeros before final filtering

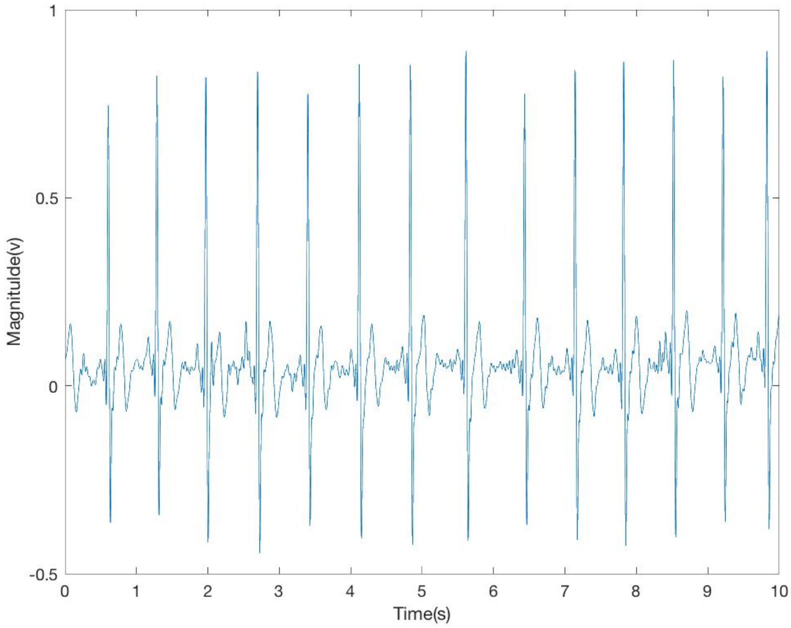


Figure 11. The frequency of the normal ECG before final filtering

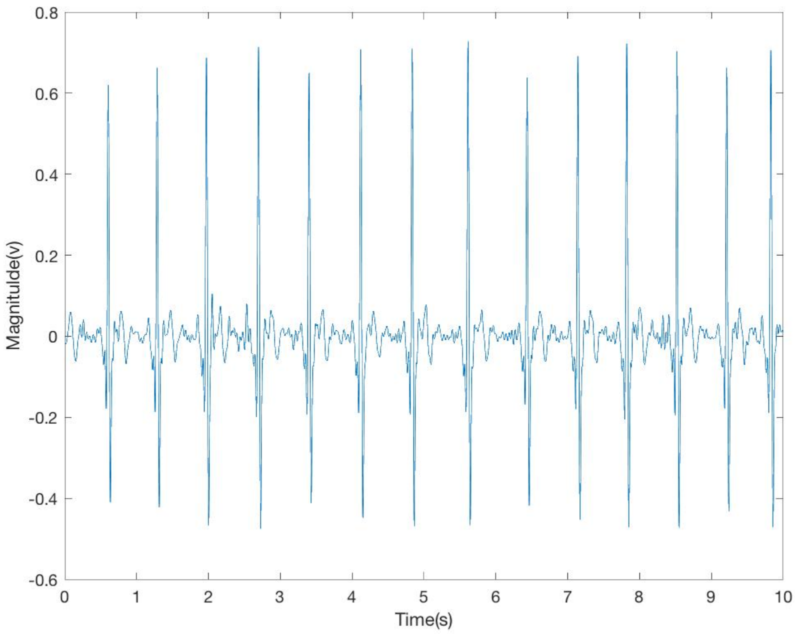


Figure 12. The frequency of the normal ECG after final filtering

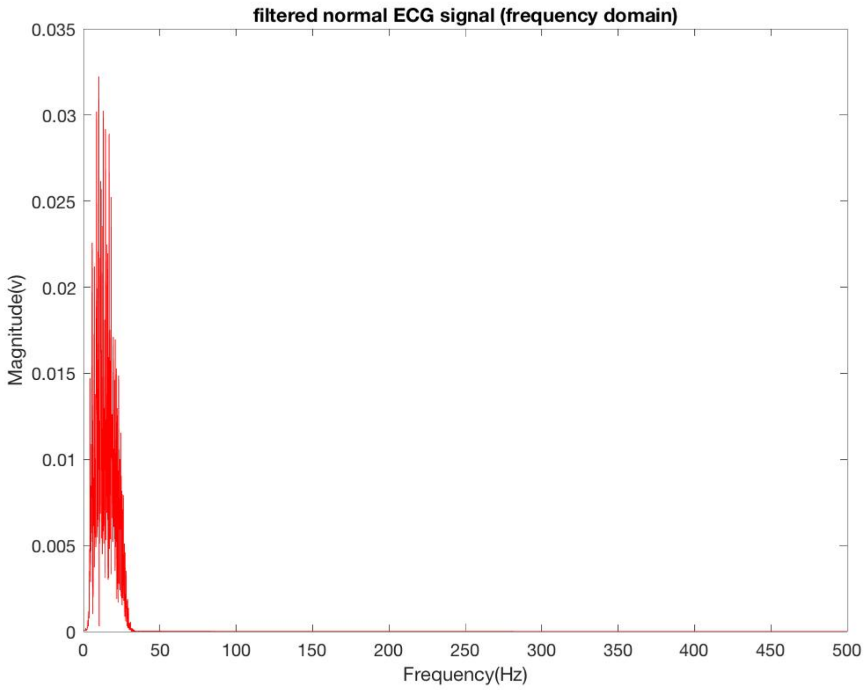


Figure 13. The filtered ECG signal in frequency domain

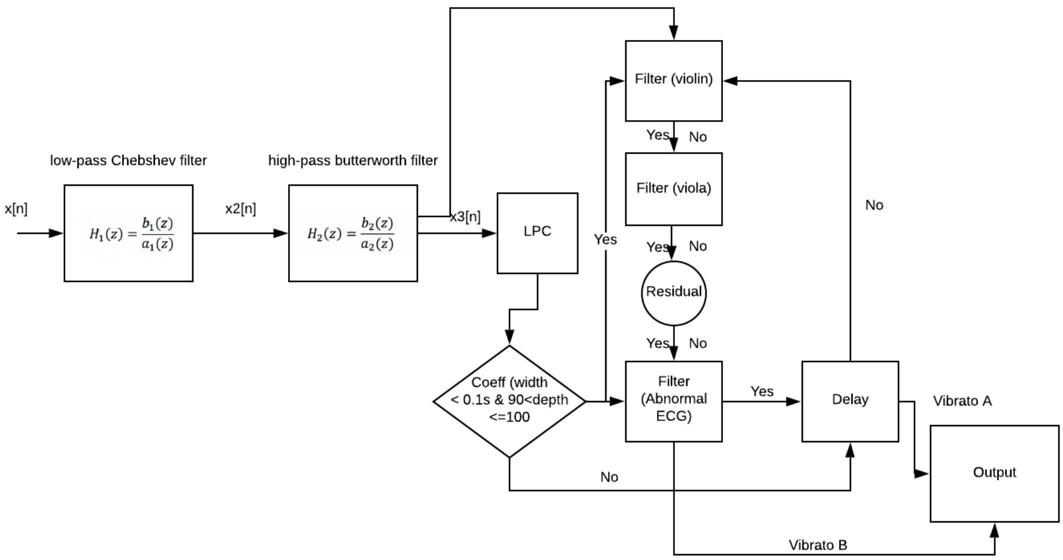


Figure 14. The final adaptive filter for the ECG signals

3. Discussion

The residuals of the violin or the viola will be filtered with the cross-synthesis LPC coefficients of the two types of abnormal ECG signals with the vibrato function. The two settings of the low-frequency oscillator (depth) and the delay-line (width) are supposed to connect with the designed filter with 0.01s and 100 Hz respectively as their critical points. However, two types of abnormal ECG signals in figure 4 as Arrhythmia of bradycardia and type 1 and type 2 of Ventricular Tachyarrhythmias are beyond the range of the detecting system. The 100 Hz seems too over for the recommended range of 1 to 8 Hz, and the vibrato effect cannot apply to the ECG signal very well that the cross-synthesis between the residuals and the vibrato effect does not successfully create an audio file.

As a result, the detection system manually imitates the process of judging whether an ECG signal is abnormal or not, and mainly focus on cancellation of the noise. The ECG signal filtered firstly, and then is classified as the bradycardia or Ventricular Tachyarrhythmias by the residuals of violin, or the residuals of viola respectively. Moreover, vibrato A and vibrato B are in favor to judge the type1 and type2 of the Ventricular Tachyarrhythmias. The vibrato A refers to the type 1 of Ventricular Tachyarrhythmias when the width is less than 0.1s and the depth is more than 90 Hz , while the vibrato B refers to the type 2 of Ventricular Tachyarrhythmias when width is less than 0.1s and depth is less than or equal to 90Hz (figure 14). In the future, the alternative effects and the corresponding parameters to the relevant frequency and time interval of the abnormal ECG should fits the detecting system for giving a better performance.

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