

Performance of Digital filters for noise removal from ECG signals in Time domain

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Abstract: Electrocardiogram (ECG) is the cheapest and noninvasive method of depicting the heart activity and abnormalities. It provides valuable information about the functional aspects of the heart and cardiovascular system. It is the record of variation of bioelectric potential with respect to time as the human heart beats. The classification of ECG signals is an important application since the early detection of heart diseases/abnormalities can prolong life and enhance the quality of living through appropriate treatment. Since the ECG signals, while recording are contaminated by several noises it is necessary to preprocess the signals prior to classification. The ECG signal can be processed in time domain as well as in frequency domain. Digital filters are used to remove noise from the signal. The present paper shows the performance of removal of noise like baseline wander and power line interference from the signal using Band Pass filter and Notch filter. The performance is tested on the Arrhythmia signals from MIT-BIH and Myocardial infarction signals from PTB Diagnostic database.

Keywords: ECG, Band pass filter, Notch filter, SNR

I. INTRODUCTION

The ECG is a recording of the electric potential generated by the electric activity of the heart. The ECG thus represents the extracellular electric behaviour of the cardiac muscle tissue [4]. It describes different electrical phases of a cardiac cycle and represents a summation in time and space of the action potentials generated by millions of cardiac cells. The state of the cardiac health is generally reflected in the shape of ECG waveform and the heart rate. The variability of the human heart beat is unexpected. ECG signal preprocessing is the first step for the classification of heart diseases. The noise reduction is the important factor since the signal should be accurately represented for further analysis. The classification of heart diseases depends on P, QRS, ST waves or their combination. The decision to choose the type of filter for denoising depends on various factors like the extraction of type of waves, time required for preprocessing, complexity involved, reconstruction of signal (if converted to different transform e.g. Wavelet). A signal can be analysed and processed in two domains, time and frequency. ECG signal is one of the human body signals which can be analysed and worked in these two domains.

II. ECG SIGNAL IN THE TIME DOMAIN AND FREQUENCY DOMAIN

In the Time domain the ECG signal is identified by different waves viz., P, Q, R, S, T and U. The letters P, Q, R, S, and T were selected in the early days of ECG history and were chosen arbitrarily. The ECG waveform is as shown in fig.1.1. The P wave represents atrial depolarization. The Q, R & S waves together make up a complex, QRS complex, which represents ventricular depolarization and T wave corresponding to the period of ventricular repolarisation. The interval between S wave

and the beginning of T wave is called the ST segment. In some ECGs an extra wave can be seen on the end of the T-wave, called as U wave. Its origin is uncertain, though it may represent repolarisation of the papillary muscles. If a U wave follows a normally shaped T wave it can be assumed to be normal. If it follows a flattened T-wave it may be pathological.

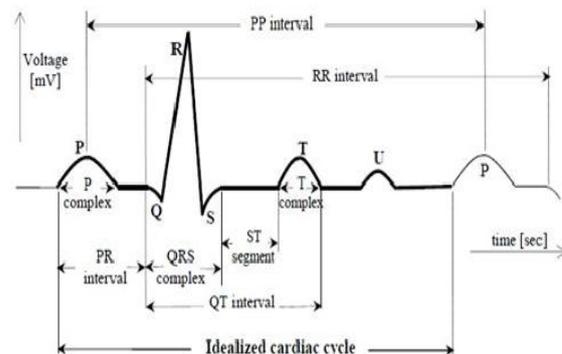


Fig.1.1 ECG wave in Time Domain

The frequency of ECG signal varies from 0.05 Hz to 100Hz whereas the associated amplitude values vary from 0.02 mV to 5 mV. The amplitude values of human body bioelectrical signals are measured in micro volts (mV). The amplitude values of these signals are small voltage values and are being measured using traditional electronic devices. There are different sources of noise at the moment of getting a human body signal. The frequency domain helps us to know of how additional sources affect the important signal in the time domain.

A. Different types of ECG contaminants

There are different sources for ECG signal distortions. Few of the ECG contaminants are as given below[2]

Electrode contact noise: Improper contact of the electrodes interrupts for a short period the connection between patient and measuring system creating electrode contact noise. The duration of noise signal is 1 sec and amplitude is maximum recorded output with frequency of 60Hz.

Motion artifact: The cause of motion artifact is assumed to be vibrations or movements of the subject. The duration of this kind of noise signal is 100-500ms with amplitude of 500% peak to peak ECG amplitude.

Muscle Contractions: This type of noise generates my level artifactual potentials. The standard deviation of this kind of noise is 10% of peak to peak ECG amplitude with duration of 50ms and the frequency content being dc to 10 KHz.

Baseline Wander: Low frequency wander can be caused by respiration or patient movement. This kind of noise causes problems in the detection of peaks. Due to wander T peak would be higher than R peak and it might be detected as R peak instead. Amplitude variation is 15% of peak to peak ECG amplitude and baseline variation is 15% of ECG amplitude at 0.15 to 0.3Hz.

Power line Interference: Power line interference consists of 60/50 Hz pickup and harmonics that can be modeled as sinusoids and combination of sinusoids. The frequency content of this kind of noise is 60/50 Hz with harmonics and the amplitude is 50% of peak-to-peak ECG amplitude.

III. ECG SIGNAL FILTERING

The extraction of high-resolution cardiac signals from a noisy electrocardiogram (ECG) remains an important problem for the biomedical engineering community. The numerous noncardiac ECG contaminants, such as electromyography noise, overlap with the cardiac components in the frequency domain, particularly in the 0.01 Hz to 100 Hz range.

Band Pass Filter:

Pan and Tompkins [1] developed a real time algorithm for the detection of QRS complex. The algorithm identifies QRS complexes depending on analysis of the slope, amplitude, and width of the QRS. The various stages of the algorithm are Band pass filter, Differentiator, squaring operation and moving window integrator. The band pass filter formed using low pass and high pass filters reduce the noise in the signal.

The transfer function of the second –order low pass filter is given by,

$$H(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-2})^2}$$

The design of the high-pass filter is based on subtracting the output of a first-order low pass filter from an all-pass

filter (i.e., the samples in the original signal). The transfer function for such a high pass filter is

$$H(z) = \frac{(-1 + 32z^{-16} + z^{-32})}{(1 + z^{-1})}$$

Notch Filter :

In many Signal processing applications it is desired to remove the distortions or noise leaving the original signal unchanged. Applications like communications, biomedical engineering etc. are major areas of using the Notch filters. The frequency response of the digital notch filter satisfies the following constraints.

$$H(e^{j\omega})_{\omega=0,\pi} = 1 \text{ and } H(e^{j\omega})_{\omega=\omega_0} = 0$$

A second order IIR notch filter is used for removing the powerline interference in the ECG signal. The given signal is contaminated with noise at 50 Hz and also with the baseline wander. The notch filter is designed to remove the 50 Hz powerline interference and the low pass filter is used to remove the baseline wander.

IV. PERFORMANCE ANALYSIS

The Data is collected from Physionet. It is considered as the research resource for complex physiologic signals. It is a unique web based resource funded by NIH intended to support current research and stimulate new investigations in the study of complex biomedical and physiologic signals. The collected ECGs are from MIT-BIH Arrhythmia Database which is a set of over 4000 long-term Holter recordings that were obtained by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. The database contains 23 records (numbered from 100 to 124 inclusive with some numbers missing) chosen at random from this set, and 25 records (numbered from 200 to 234 inclusive, with some numbers missing) selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small random sample of Holter recordings. The data is sampled with sampling frequency of 360 Hz. The signals available on the website are raw signals. In order to use them in any analysis it is suggested to subtract base from the signal and divide by gain . The base given for MIT-BIH database is 200 and the gain is 1024. In these signals since the original individual sources are not available, following formula is used to determine the SNR of the signal.

$$SNR_{dB} = 10 \log_{10} \frac{\sum_{i=1}^n [s(i)]^2}{\sum_{i=1}^n [s(i) - x(i)]^2}$$

In the above equation, $s(i)$ is the recorded or noisy signal and $x(i)$ is the denoised counterpart. The length of the signal is denoted by n . [20]

Method:

First the ECG signal is considered lead wise i.e one lead signal at a time. Then powerline interference of 50 Hz is added to the signal followed by adding the baseline wander. This contaminated signal is then filtered using two filtering methods viz Bandpass filter and Notch filter. The results are given as below.

Table 1.1 Results for MIT BIH Arrhythmia Signals

Sr No.	MIT_BIH (1 min) SIGNAL	SNR Using Notch	SNR Using BPF
1	101m	1.061	0.8309
2	102m	1.0424	0.5485
3	103m	2.529	1.7442
4	104m	2.1068	0.741
5	105m	3.2343	1.5212
6	106m	3.0099	1.5359
7	107m	7.4924	0.9669
8	108m	0.9691	0.3738
9	109m	3.5076	1.3867
10	111m	1.6884	0.9356
11	113m	3.3282	1.1886
12	116m	1.0947	0.4848

ECGs are also collected from PTB (Physikalisch-Technische Bundesanstalt), the National Metrology Institute of Germany. The ECGs in this database were collected from healthy volunteers and patients with different heart. The database contains 549 records from 290 subjects out of which 148 were suffering from Myocardial Infarction. Each record includes 15 simultaneously measured signals: the conventional 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs. Each signal is digitized at 1000 samples per second, with 16 bit resolution. The base is 0 and the gain of the signal is given as 2000.

Table 1.2 Results for Myocardial Infarction Signals from PTB Diagnostic Database

Sr No.	PTB SIGNAL	SNR using NOTCH	SNR using BPF
1	s0016lrem	1.716	0.4251
2	s0015lrem	0.2566	-0.8153
3	s0039lrem	1.3357	0.4633
4	s0043lrem	0.8954	-0.0848
5	s0045lrem	1.0373	0.6175
6	s0047lrem	1.4307	0.6369
7	s0052lrem	1.9809	0.3949
8	s0053lrem	1.9528	1.4668
9	s0062lrem	1.4237	-0.6176
10	s0066lrem	1.1082	-0.7539
11	s0080lrem	1.2755	0.4483
12	s0087lrem	0.3162	-1.6346

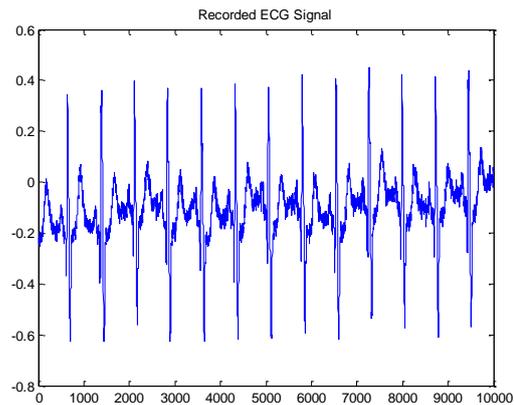


fig . 1.2 Recorded ECG signal lead 1 from PTB

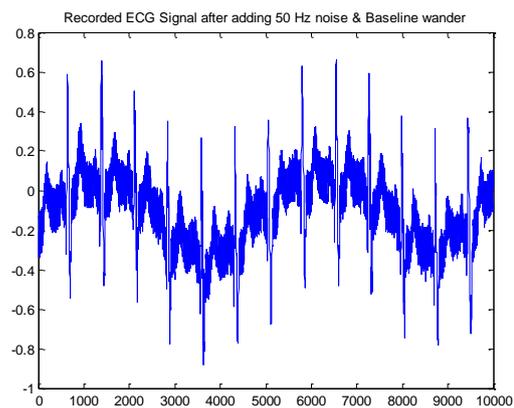


fig . 1.3 ECG signal after adding PLI and Baseline Wander

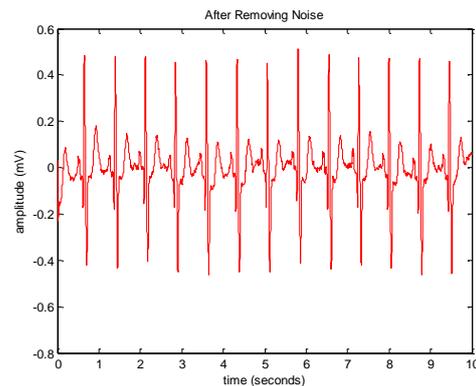


fig . 1.4 ECG signal lead 1 after Notch filter

V. CONCLUSION

Two filtering methods are applied on 12 different ECG signals from MIT BIH database and PTB database from Physionet. The first filtering method, Band pass filter gives SNR in the range of 0.4 to 1.7 dB for the signals in MIT BIH database and range of -1.6 to 1.4dB for signals in PTB database. The SNR using second method with the Notch filter for MIT BIH database is in the range of 0.4 to 1.7dB and for the PTB database is 0.2 to 1.9dB. SNR values of both methods are compared and analyzed. The Notch filter gives better results as compared to Band pass Filter.

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BIOGRAPHY



Smita Kasar received the B.E. degree in Computers from Mumbai University in the year 2000 and joined as a Lecturer in Jawaharlal Nehru Engineering College, Aurangabad. Later completed M.E (Computer Science and Engineering) from Government Engineering College Aurangabad. Presently pursuing Research under the guidance of Dr. Madhuri Joshi. Her area of interests includes Biomedical Signal processing, Artificial Neural Networks, Evolutionary Algorithms.