

Low Frequency Noise Remove from EEG Signal

Awnish Kumar, Rahul Tiwari, Abhilash Gaur



Abstract: The electrical activity of the brain recorded by EEG which used to detect different types of diseases and disorders of the human brain. There is contained a large amount of random noise present during EEG recording, such as artifacts and baseline changes. These noises affect the low-frequency range of the EEG signal. These artifacts hiding some valuable information during analyzing of the EEG signal. In this paper we used the FIR filter for removing low-frequency noise (<1Hz) from the EEG signal. The performance is measured by calculating the SNR and the RMSE. We obtained RMSE average value from the test is 0.08 and the SNR value at frequency (<1Hz) is 0.0190.

Index Term : EEG data , Artifact , noise, RMSE, SNR

I. INTRODUCTION

Any change in the activity of the brain can be determined using EEG that further can be useful diagnosing disorder of the brain mainly epilepsy or another seizure disorder. EEG also useful in testing different disorder [11]:

- Brain tumor
- Stroke
- Sleep disorders
- Brain damage from head injury

Two types of techniques for EEG recording which is the first one invasive and second non-invasive. The electrode is placed under the skull through surgery is called invasive. The electrode placed scalp of the head is called non-invasive [2]. A measuring head placing electrode by 10-20 international method. In this project we use a data set of non-invasive EEG recording techniques.

EEG rhythm divide into five different sub-bands [3]:

- a) Delta (0.5 - 4 Hz)
- b) Theta (4-8Hz)
- c) Alpha (8 - 14 Hz)
- d) Beta (14 - 30 Hz)
- e) Gamma (above 30Hz)

We know from these EEG frequency bands various appearance mental conditions of the human brain and this deviation of normal EEG activity is useful for doctors to detect mental diseases in patients.

Sometimes it is difficult when artifacts are present in the EEG signal, we do not know which disease is available in the mental. Two types of artifacts are available during EEG recording psychological artifact and system artifact [12].

Four types of psychological artifacts are available during EEG recordings such as EMG (electromyography), EOG (electrooculographic), artifacts, and sweat pulse artifacts. EMG activity (due to muscle contraction in the vicinity of EEG recording site), EOG activity (due to eye blink or movement), and pulse artifacts (due to pulsation of blood vessels). system artifact is also present different types of artifact which is power line interference (50/60Hz), electrode impedance fluctuations, dry scalp-electrode contact, movement of electrode and low battery of acquisition [10]. This artifact disturbance at the low-frequency range component of EEG. EMG disturbs the frequency range of EEG signal from 20Hz to a few hundred hertz and EOG disturb the EEG signal frequency range up to 10Hz. The key role of noise cancellation or artifact removal for finding disease and disorder in the human brain.

Many technique has been available to remove noise from EEG signal, for example, ICA, Empirical Mode Decomposition (EMD) [2], Kalman filter [6], Wavelet Thresholding [3], Multivariate EMD and CCA [4], Grey Wolf Optimizer [7], etc.

Some research has been done to remove the artifacts or noise from the EEG signal. Sugondo use Empirical Mode Decomposition to remove noise from Mild Cognitive Impairment EEG recording [2]. Mahipal Singh Choudhry use to remove noise from EEG recording using different Discrete Wavelet Transforms and Thresholding Techniques [3]. Laxmi Shaw uses the Kalman filter for EEG signal denoising [6]. Martin J. McKeown combined Multivariate EMD and CCA for Denoising EMG Artifacts from EEG Recordings [4]. Rachana Nagal uses the Grey Wolf Optimizer technique to remove white Gaussian from EEG recording [7].

In this research paper, we use the FIR filter to remove low-frequency noise from the EEG signal. Section II explained the data set to use in the research, Wavelet transform, FIR filter, and Butterworth band-pass filter. Section III explained the flow chart of the EEG signal de-noising. Section IV explained the methodology of the project. Section V provides result by FIR filter and compare the result of Butterworth band-pass filter. Finally Section VI describes the conclusion.

II. MATERIAL AND METHOD

A. Dataset

In this project we used a public database that is taken data from CHB and MIT created and contributed this database to PhysioNet [12].

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This database is recorded in pediatric subjects with intractable seizures. This database is collected from 22 subjects, in which 5 males and 17 females, where the age of males from 3 to 22 years old and female aged from 1.5 to 19 years old.

Placed the position of electrode using the international 10-20 method. Sampling rate of data 256 sampled per second. The recording process completed in 1hr[12].

B. Wavelet Transform

Small waves are located at different times by wavelet transform. It is obtained by scaling and translation of scaling function. Where WT is in both time and frequency domain. It is suitable for feature extraction of EEG raw data into the time-frequency domain because of EEG signal is non-stationary [8].

Furthermore, Wavelet transform only involve multiscale structure and to a single scale. It is in continuation of the basic Fourier transform. If we talk about the WT method, secured and simple building blocks represent the EEG which is known as wavelet. These wavelets are risen by mother wavelet which are derived function by translation and dilation, which are shifting and stretching operation along the time axis.

Wavelet transform divided into two categories, which is the first one continuous WT and second is discrete WT. In this project we used a continuous wavelet transform method for feature extraction of EEG raw data into the time-frequency domain[8].

CWT defined as:

$$CWT(a, b) = \int_{-\infty}^{\infty} x(t) \psi_{a,b}^*(t) dt \quad (1)$$

Where

$x(t)$ = Uncompressed EEG

a = Dilation

b = Translation factor

$\psi_{a,b}^*$ = complex conjugate

Complex conjugate calculated by

$$\psi_{a,b}^*(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right)$$

C. Finite Impulse Response (FIR) Filter

The characteristic of the FIR filter is that is used only the delay version of the input signal $x(t)$ to filter the input to output. This filter does not use the previous output value. A part of that feedback is missing in the structure. Linear phase-frequency can be guaranteed by FIR. The sequence of output values for discrete causal of N times order is a weighted sum of recent input values. The output signal for an input signal of the N th order is explained with Eqn2 [2]. Where impulse response value is defined with b_i

$$y[n] = \sum_{i=0}^N b_i \cdot x[n - i] \quad (2)$$

D. Butterworth Band-pass Filter

Signal processing design to have a frequency response as flat as possible as band-pass is known as Butterworth filter. A Band-pass filter passes any certain frequencies and it rejects all the frequencies which outside of this band [9]. So just cascading the high pass and low pass filter we can

designed this band-pass filter. We design the 5th order Butterworth band-pass filter for removing a low-frequency noise from EEG, which is obtained by high power DC wave.

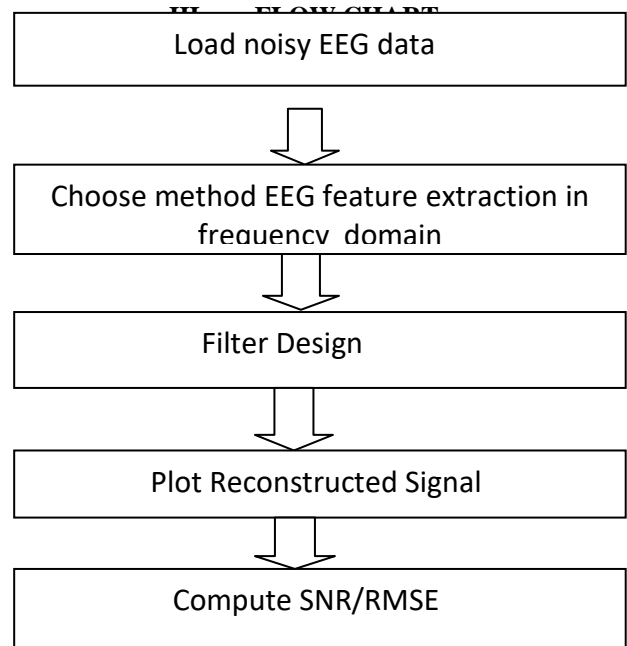


Figure1. Flow chart of EEG de-noising

IV. METHODOLOGY

Step1: load EEG data

We loaded EEG noisy data having a frequency less than 1Hz.

Step2: chose the method EEG signal feature extraction in Frequency domain

In this project we use the 1d decomposition level of the Wavelet transform.

Step3: Filter design

In this project we designed the FIR stop-band filter and Butterworth band-pass filter for removing noise from the EEG signal.

Step4: Plot filter signal

Step5: Compare the average SNR value

Compare average value SNR of EEG signal before and after filter by FIR stop-band and Butterworth band-pass filter.

V. RESULT AND DISCUSSION

Successfully remove low-frequency noise from the EEG signal by FIR filter, low-frequency noise was obtained from a high power DC wave. While already filter high-frequency noise by EEG recording devices. fig2 shows EEG noisy signal(<1Hz), amplitude spectrum of EEG noisy signal shown in fig3, and fig4.shown de-noising EEG signal. Table I shows the RMSE value of 10 raw data with the length of each 1200 samples and Table II shows SNR value comparison between Noisy EEG signal, reconstructed EEG signal from FIR stop-band filter, and reconstructed EEG signal from Butterworth band-pass filter.

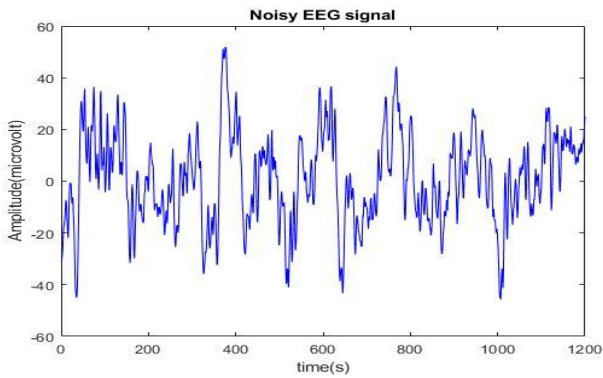


Figure2. EEG signal with low noise

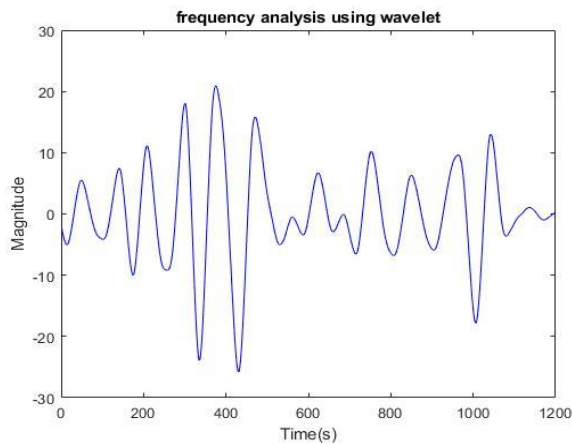


Figure3. Time-frequency domain analysis

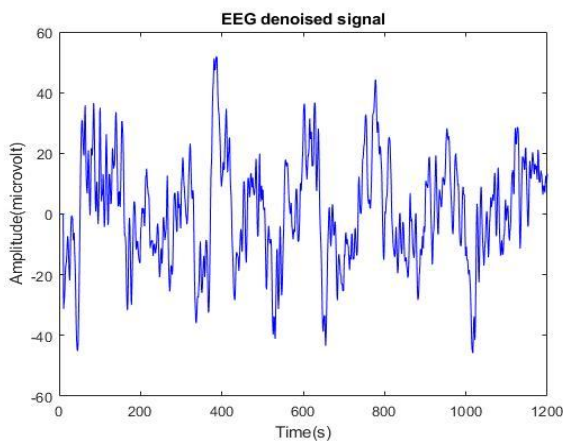


Figure4. Butterworth Filter

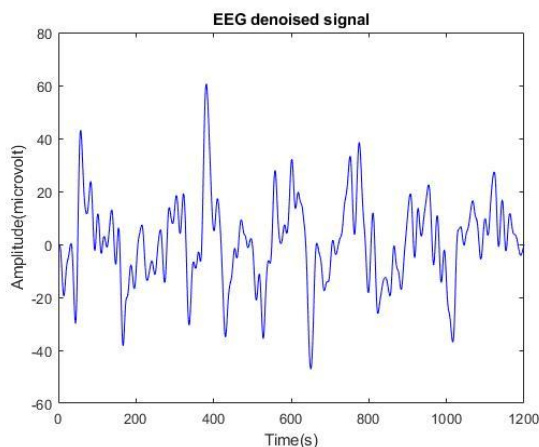


Figure5. FIR filter

Table 1 RMS Result for 10 data

EEG Data	RMSE
1	0.0942i
2	0.0145i
3	0.1062i
4	0.0491i
5	0.0439i
6	0.0524i
7	0.0802i
8	0.0398i
9	0.0361i
10	0.0395i
Mean = 0.088	

Table2 SNR calculation for frequency under 1Hz

EEG Data	Raw	FIR filter	Butterworth Filter
1	0.6209	0.0029	0.3940
2	1.7640	0.0254	0.1602
3	0.2742	0.0098	0.0367
4	0.5311	0.0239	0.0660
5	0.9422	0.0215	0.6940
6	1.6989	0.0047	0.1826
7	0.8537	0.0004	0.0529
8	2.7575	0.0047	0.6435
9	2.8869	0.0464	0.3140
10	0.5390	0.0038	0.0334
Mean	1.2892	0.01901	0.28321

VI. CONCLUSION

This study was successful in removing low-frequency noise from the EEG signal by applying the FIR filter. The FIR filter performance measurement was done by calculating RMSE and SNR. For comparison, the Butterworth filter applied in the signal de-noising process. RMSE average value of the FIR filter is 0.08, which means the resulting error is very small or zero. The Mean SNR value of the FIR filter is 0.01901 and the Butterworth filter is 0.28321, which means the FIR filter is better than the Butterworth Band-pass filter.

FUTURE WORK

We will work to remove high-frequency noise that can be present in the EEG signal. High-frequency noise may be present as artifacts and baseline changes.

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