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Comparison of Different Linear Filter Design Methods for Handling Ocular Artifacts in Brain Computer Interface System

Sahar Seifzadeh[a], Karim Faez[b*], Mahmood Amiri[c]

[a]*Faculty of Computer and Information Technology Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran*

[b]*Electrical Engineering Department, AmirKabir University of Technology Tehran, Iran*

[c]*Medical Biology Research Centre, Kermanshah University of Medical Sciences, Kermanshah, Iran*

Abstract

Brain-computer interfaces (BCI) record brain signals, analyze and translate them into control commands which are relayed to output devices that carry out desired actions. These systems do not use normal neuromuscular output pathways. Actually, the principal goal of BCI systems is to provide better life style for physically-challenged people which are suffered from cerebral palsy, amyotrophic lateral sclerosis, stroke, or spinal cord injury. One of the focal points in Brain-Computer Interface (BCI) systems is physiological artifacts handling. Physiological artifacts such as Electrooculography (EOG) and Electrooculography (EMG) are considered among the most important sources of physiological artifacts in BCI systems. Pre-processing is considerable step by means of next steps such as feature extraction and classification that we need clean signals without undesirable artifacts to have better classification rate. Using a linear filter to remove these artifacts is like a dime a dozen due to their acceptable results in recent BCI pre-processing researches. Although this method has different options, Forasmuch as the mu (8–13 Hz) and beta (16–25 Hz) frequency bands play a key role in classification of motor imagery we have decided to design two band pass filters with Elliptic and Butterworth Infinite impulse response designing methods in 8 to 40 Hz frequencies. Our results in Graz 2a dataset in BCI Competition IV indicates that, Elliptic band-pass filter has better performance for EOG removing in this specific dataset.

Keywords: Brain computer interface, Band pass filter, EEG, EOG.

1. Introduction

Brain-computer interface (BCI) is collaboration between a brain and an external device that enables signals from the brain to direct some external activity, like control of a wheel chairs or a prosthetic limb or arm. In fact, BCI is a way to interact with the environment, without the use of peripheral nerves and muscle interfaces. The interface enables a direct communications pathway between the brain and the object to be controlled. This interface also referred to as a brain machine interface (BMI), a mind machine interface (MMI) have become a central part of neuroscience systems [1]. In the case of cursor control, for example, the signal is transmitted directly from the brain to the mechanism directing the cursor,

* Corresponding author. Email: kfaez@aut.ac.ir

rather than taking the normal route through the body's neuromuscular system from the brain to the finger on a mouse. This could be so beneficial for paralyzed people who have suffered spinal cord injury, or in diseases such as stroke [2] amyotrophic lateral sclerosis (ALS) [3].

Current brain-interface devices require deliberate conscious thought, some future applications, such as prosthetic control, are likely to work effortlessly. One of the biggest challenges in developing BCI technology has been the development of electrode devices and/or surgical methods that are minimally invasive. In the traditional BCI model, the brain accepts an implanted mechanical device and controls the device as a natural part of its representation of the body. Much current research is focused on the potential on non-invasive ones, because invasive ones are harmful for human. The Graz BCI with Pfurtscheller leadership, they use Mu and Beta rhythm of sensory cortex for training and control, one of their substantial approaches is non functional arm grasping for paralyzed people by functional electrical stimulation (FES) that controlled by EEG signals. Some of their works have been reported in references [4-7].A BCI can recognize a certain set of patterns in brain signals following five Sequential steps: signal acquisition, pre-processing or signal enhancement, feature extraction, classification, and the control interface[8] figure 1.

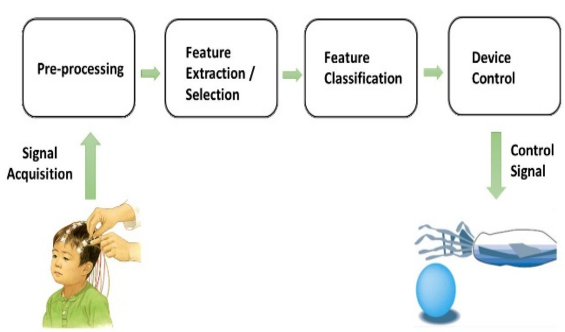

Fig. 1. A representation of a conventional BCI.

1.1.Electrooculography

Electrooculography is a technique for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye. The resulting signal is called the electrooculogram (EOG). This signal consider as artifact for a BCI that should be remove in pre-processing step. These artifacts are contained of two phenomena: 1) Eye blink; they are low frequency signal (< 4 Hz) which could be noticeable in amplitude. It is asymmetrical activity mainly located on front electrodes (Fp1, Fp2) with a low propagation. 2) Eye movement; it is illustrated by a low frequency signal (< 4 Hz) too, but with a higher propagation [9-10].

1.2.Preprocessing

Artifacts are undesired signals which divided into two major categories: non-physiological or physiological sources: Non-physiological like changes in electrode impedances, 50/60 Hz power-line noise, electrode impedance and etc. physiological artifacts like potential created by the eye or body movement like heart beats, respiration, skin responses. Physiological artifacts, especially those generated by body or eye movements, remain a challengeable issue in BCI systems. In this paper, we only considered “Artifact removal” approach that can be mentioned in the following:

1.2.1. Artifact removal

Artifact removal is the process of identifying and eliminating artifacts from brain signals. An artifact-removal approach should be able to remove the artifacts as well as keeping the related neurological phenomenon intact. This method consists of common approaches that you can refer to [11] but in this paper we use the linear filter one.

1.2.1.1. Linear filtering

This method is one of the most common methods for the sake of simplicity of implementation. These filters are appropriate when artifacts are in particular frequency bands and not overlap with the original signal. For instance, for instance, to remove EMG artifacts, the low - pass filter is suitable and a high-pass filter can be used for EOG artifacts. This method can be efficient for BCI systems which use a neurological phenomenon with high-frequency bands (like Beta or Mu rhythms).

2. Experimental Results

In this paper we use Graz 2a data set that we have downloaded from BCI Competition IV. This data set recorded from 9 subjects, which sitting in a comfortable armchair in front of a computer screen. Twenty-two Ag/AgCl electrodes (with 10-20 system) with 3 monopolar EOG were used to record the EEG from subjects, the montage is shown in Figure 2. The EOG channels are provided for application of artifact processing methods and should not be used for classification. For more details please refer to [12].

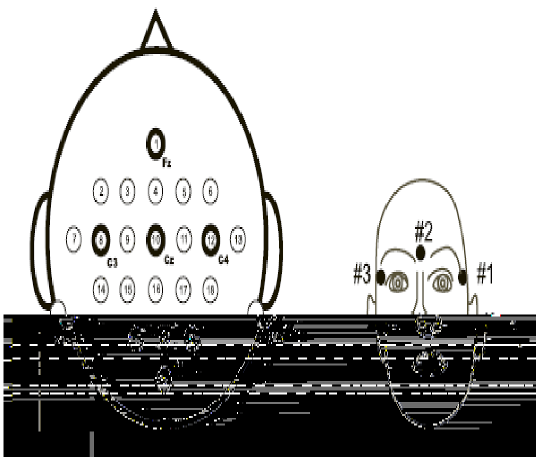

Fig. 2. Left: Electrode montage corresponding to the international 10-20

System. Right: Electrode montage of the three monopolar EOG channels

First of all, we have downloaded dataset Graz 2a from BCI Competition IV. This dataset consists of 18 .mat fileswhich divided into two categories, test and train ones (table 1).

Each .mat file consists of 1*9 cellular array, which has eight structures itself (figure 3). At the beginning of each session, approximately 5 minutes was recorded to estimate the EOG influence and calibration.

First third structures are due to this. Because of that, first of all we should eliminate these third structures.

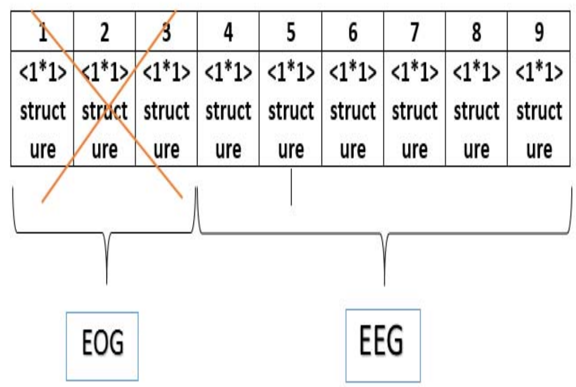

Fig. 3. The consistency of each .mat file

Forasmuch as the mu (8–13 Hz) and beta (16–25 Hz) frequency bands play a key role in classification of motor imagery tasks [13], we have designed two band pass filters with 8 to 40 Hz bands with these specific properties that demonstrates in table2. Figure 4 and 5 shows the schema of our band pass filers. The original signal of 25th channel illustrates in figure6.The results of band pass filter on this channel with Butterworth design method indicates in figure 7 and Elliptic the ones in figure 8[14].

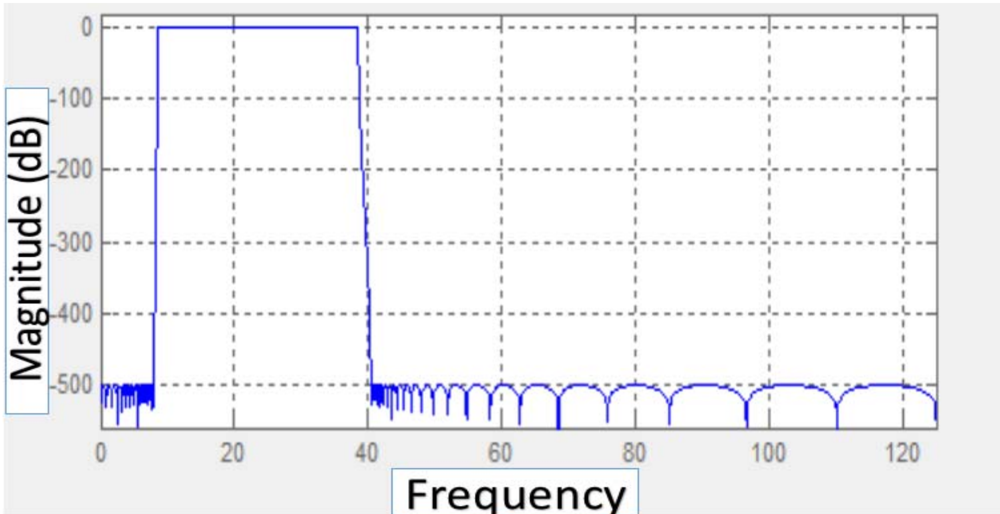

Fig. 4. The schema of our designed band pass filter with Elliptic design method

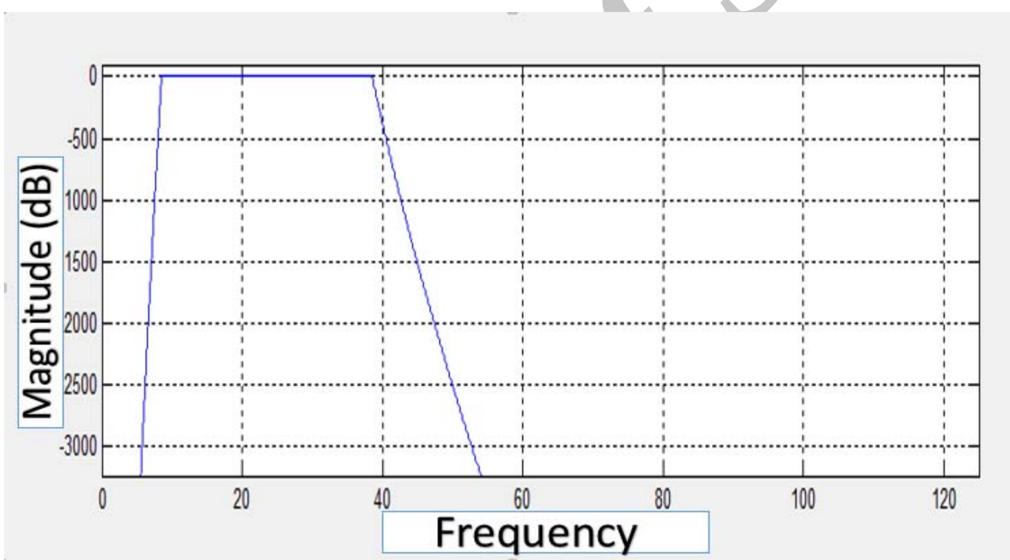

Fig. 5. The schema of our designed band pass filter with Butter worth design method

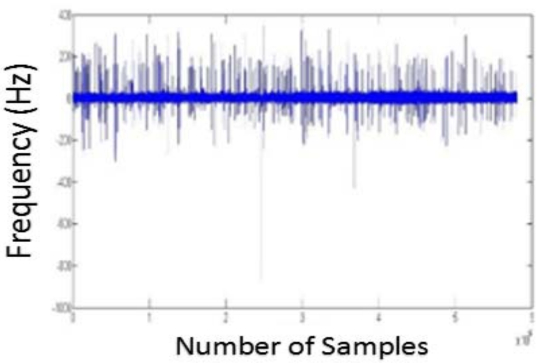

Fig. 6. The original signal of 25th channel

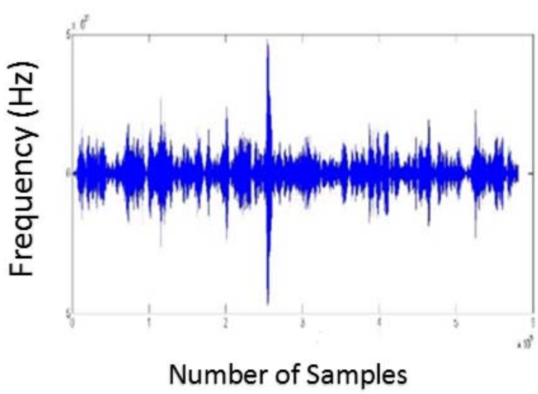

Fig. 7. The result of band pass filter with Butter Worth design method

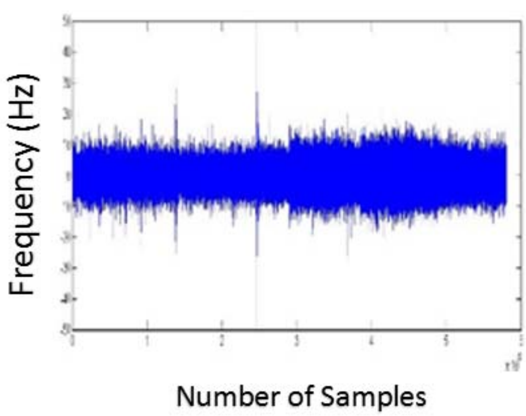

Fig. 8. The result of band pass filter with Elliptic design method

Table 1

18 .mat fileswhich divided into two categories

ID	Training	Test
1	A01T.mat	A01E.mat
2	A02T.mat	A02E.mat
3	A03T.mat	A03E.mat
4	A04T.mat	A04E.mat
5	A05T.mat	A05E.mat
6	A06T.mat	A06E.mat
7	A07T.mat	A07E.mat
8	A08T.mat	A08E.mat
9	A09T.mat	A09E.mat

Table 2

The properties of our designed band pass filters

<table>
<tr><td>Fstop1</td><td colspan="2">7.5</td></tr>
<tr><td>Fpass1</td><td colspan="2">8.5</td></tr>
<tr><td>Fstop2</td><td colspan="2">38.5</td></tr>
<tr><td>Fpass2</td><td colspan="2">40.5</td></tr>
<tr><td rowspan="3">Magnitude Specifications</td><td>Astop1</td><td>500</td></tr>
<tr><td>Apass</td><td>1</td></tr>
<tr><td>Astop2</td><td>500</td></tr>
<tr><td>Order</td><td colspan="2">100</td></tr>
</table>

3. Conclusion

As we know, physiological artifact removal like EOG removal in the preprocessing step plays as a key role for next steps. To the best of our knowledge, there is no publication in BCI researches with Elliptic band-pass filter which we could compare with our proposed work, and this is first time usage of Elliptic band-pass for the purpose of eliminating EOG artifacts. By means of this, in this paper we compare two different design method of band pass filter between 8 to 40 Hz (regarding Mu and Beta bands) in one specific EOG channel in Graz 2a dataset. Our experiments shows that, Elliptic design method in 25th channel with same properties is really more efficient than Butterworth one in this specific dataset provided by Graz lab, as you can see in figures, the amplitude of it is noticeably lower and it is highly smoother.

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