AN EFFICIENT APPROACH FOR REMOVAL OF OCULAR ARTIFACTS IN EEG-BRAIN COMPUTER INTERFACE

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Abstract:- **Electroencephalogram (EEG) signals have a long history of use as a noninvasive approach to measure brain function. Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain. It is an important testing method which enables the capture [using electrode positioned on the scalp] of very useful information relating to the different physiological states of the brain. . Unfortunately, EEG signals are highly contaminated with various artifacts, one of the artifacts that occur due to the eye-blinks and movement of the eyeballs produce electrical signals that are collectively known as Ocular Artifacts (OA).The main objective of the project is to reduce or eliminate ocular artifacts without damaging that part of the signal which is related to brain activity. The method is to develop an efficient and effective method to remove ocular artifacts using Discrete Wavelet Transform (DWT) and Adaptive Noise Cancellation (ANC). Then the result can be simulated in Lab VIEW.**

1. INTRODUCTION

The study of human brain function can benefit both engineering and medicine. Clinical neural monitoring is critical in diagnosing and treating many neurological disorders such as epilepsy. Brain–computer interfaces (BCIs) present the possibility of creating a direct link between humans and their environment, allowing the use of brain-controlled devices to assist people with disabilities. One problem in neural signal processing is the presence of noise and artifacts in neural recordings. Major artifacts can come from a variety of sources, including eye movement, muscle movement, cardiac rhythm, outside sources, and even neural processes other than the one of interest. Artifacts produced by eye movement and blinks, which are commonly referred to as ocular artifacts (OA).

Epilepsy is a neurological disorder that presumably results from abnormally synchronized electrical activity in groups of neurons in the brain and affects about 1% of the world's population. Epileptic seizures produce characteristic changes in the EEG that can be used in its diagnosis and treatment. However, electrical field changes due to normal eyeblink activity can distort this activity and make effective analysis difficult if not impossible .

The EEG records the electrical activity of the brain through surface electrodes that are placed onto the scalp of a patient. EEG is frequently used because it is non-invasive and is capable of detecting rapid changes in electrical activity, although several other recording methods exist such as magneto encephalography (MEG), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET). Analysis of these recordings has been a major resource in the efforts related to the attempt to gain some insight about the onset and activity associated with the development of seizure activity. Unfortunately, EEG data is commonly contaminated by ocular artifacts which makes the analysis of neuronal data very difficult. The focus of this thesis is the development of a novel technique that can automatically detect and remove eyeblink artifacts in order to facilitate analysis of EEG recordings.

2. EEG and Ocular Artifact

An EEG waveform has many variations in terms of shape, frequency, and amplitude. Waveforms such as rhythmical spikes, spindles, and complexes can be present. The frequency of EEG is divided into four sub-bands: delta – under 4 Hz, theta – 4 to 8 Hz, alpha – 8 to 13 Hz, and beta – above 13 Hz. Typically amplitudes under 20 μV are considered low, 20 – 50 μV are medium, and over 50 μV are high. Several other descriptors such as distribution and phase, can be used in describe the waveform of an EEG signal. [9]As the human eye moves or blinks, it creates an electric field that can be two orders of magnitude larger than the desired brain wave activity [10]. As the electric field propagates across the scalp it can mask and distort signals originating from the brain.

Originally, the eye was modeled as a dipole because the cornea is about 100 mV positive with respect to the retina [9], [11]. It was believed that when the eye moved, the rotation of the eye created an electromagnetic field due to the movement of this dipole [11].Recently it has been found that this corneo-retinal dipole was not necessarily the only factor responsible for causing the artifact. The eyelids moving across the eyeball act as sliding electrodes that produce the same artifact on the EEG [12], [13]. Low amplitude movement artifacts have been recorded even when the eye was removed, suggesting that the orbital tissue could be the cause of ocular artifacts [9].

An eyeblink can last up to 400 ms and can be 10 times larger in amplitude than electrical signals originating from cerebral cortex [13]. Movement artifacts are thought to be caused by the inherent dipole of the eye while blink artifact is thought to be a combination of the eyelid and dipole movement. During an eyeblink the lids move to close the eye and the eyeballs move up and away from the center of the face. The recorded electrical activity associated with the movement of the eyes is known as the electrooculogram (EOG).

The shape of EOG waveforms depends on the origin of the generator and direction of eye movement. Human eyeblinks can produce 500 μV spikes at the eye that can last up to 400 ms while rapid eye movements, or saccades, produce square shaped EOG waveforms. Figure 1.1 demonstrates the clear morphological difference between an eyeblink and a saccade, with eyeblink spikes over 100 μV in amplitude [15], [16].

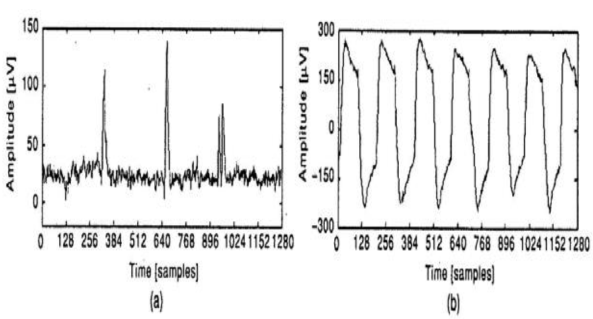

Figure : (a) EEG contaminated with Eyeblink Artifact (b) EEG contaminated with Eye Movement Artifacts [15]

The placement of the EEG electrodes on the scalp is standardized by the international 10-20 system shown in Figure 1.2. The electric field intensity of the EOG decreases with distance from the eyes when observing individual channels of the EEG from the frontal,central, and the parietal regions of the scalp.

A variety of methods have been used at this agency to cor- rect OA in EEG signals based on diverse assumptions about the relationship between the EEG signals and the artifacts [2]–[5]. However, most of these methods are offline. In order to ac- commodate online applications, much research has focused ex- tensively on nonlinear filtering and eye tracking methods such as nonlinear filtering (which includes adaptive filters), statis- tical models (e.g., ARMAX) and Artificial Neural Networks (ANNs).

An example of adaptive filtering for online OA removal has been documented in He *et al.* [6]. The method applied separately recorded vertical EOG and horizontal EOG signals as two ref- erence inputs and was implemented by a recursive least squares algorithm to track the non-stationary portion of the EOG signals. Noureddin *et al.* in [7] describes an approach using a high-speed eye tracking with a novel online algorithm [to remove both eye movement and blink artifacts] to enable the extraction of the "time-course" of a blink from eye tracker images. However, the two methods are dependent on having access to one or more regressing (EOG) channels.

3. MODELS AND METHODOLOGY

The preceding section has considered the background and re- lated research with an overview of our proposed approach. In this section we present a detailed discussion of the model(s) and methodology. Recorded EEG signals are contaminated by the OA. The eye and brain activities have physiologically separate sources; therefore this contamination is considered to be an additive noise within the EEG signal [12]. A general model for EOG contamination can be described by

$$y(n) = x(n) + F(r); \quad \textbf{(1)}$$

where: $y(n)$ and $x(n)$ are the samples of the recorded (noisy) and true EEG, r respectively, represents the source EOG, and F is an unknown transfer function.

Model Based on DWT and ANC

Wavelet Transform (WT) is an important frequency-based tool for extracting both time and frequency domain information of non-stationary signals such as EEG [14]–[16]. WT can pro- vide flexible control over the resolution with which events are localized in time, space and scale. OA are mainly concentrated on the low frequency band, therefore DWT is used to construct the OA in the frequency domain. DWT is given by

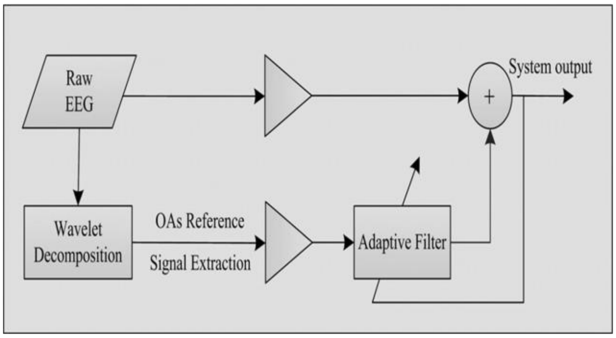

Fig. 2. Block diagram of DWT and ANC.

where I and j are integers; is the "mother" wavelet function which generates the set of expansion functions with integer indices the scales and positions . Depending on the choice of mother wavelet function [which may resemble the noise component] larger coefficients will be generated corresponding to the OA affected zones and smaller coefficients will be generated in the areas corresponding to the actual EEG. The block diagram of the model DWT and ANC is shown in Fig. 2, including two main steps:

• Initially, the reference signal is constructed. Wavelet decomposition is applied to expand the contaminated EEG signal and obtain the wavelet coefficients. Thereare several possible mother wavelet functions. Because the *Daubechies* (dbN) family has greater similarity morphologically to the OA we select the db7 wavelet as the mother wavelet function to decompose the contaminated EEG signal into seven layers. Following the construction of the reference signal we apply a soft threshold [13] to the three lowest level coefficients to obtain the new coefficients for those three levels. The new coefficients are used to reconstruct OA reference signals.

Then we removal the OA from the recorded EEG signal by applying the ANC based on a recursive *Least Squares* (RLS) algorithm. The reconstructed reference signals are used as the reference input of the ANC. Space restricts a detailed discussion on the topic however a full exposition can be found.

4. Experiment on Simulated Data Set

In Lab VIEW, the raw signal which is collected from the patient given as input signal that is converted into array and it is given as input to Adaptive filter and DWT .Then Adaptive update coefficient is used to improve the accuracy of noise removal, and destroy adaptive filter is used to check the error and it is given to channel denoised and it will the recover of true EEG signals. The implementation is executed with in the while loop and structure.

INPUT SIGNAL FOR ANC AND DWT

The below Figure describes about the raw input signal which was collected from the patient. This raw signal is given as input to adaptive filter and discrete wavelet transform.

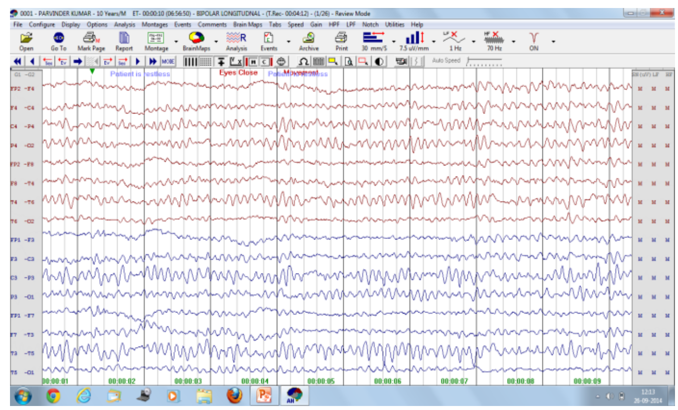

Figure Input signal

BLOCK DIAGRAM IMPLEMENTATION OF ANC AND DWT

The below Figure describes about the block diagram of ANC and DWT. In this input signal is converted into array ,then array input is given to Adaptive filter and DWT and ocular artifacts can be removed.

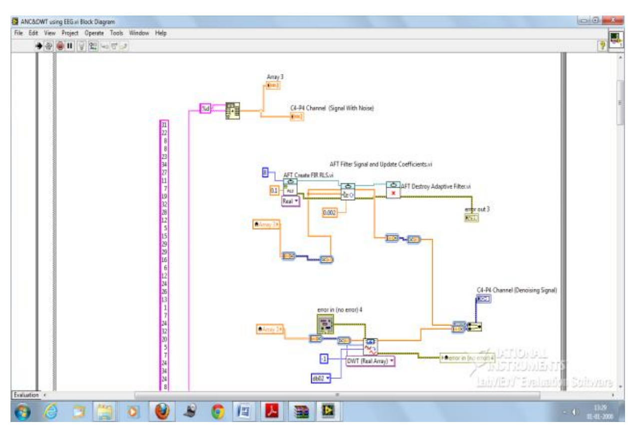

Figure 10.2 Block diagram of ANC and DWT.

RESULT

OUTPUT OF ANC and DWT

The below Figure describes about the overview of the simulated output in Lab VIEW.

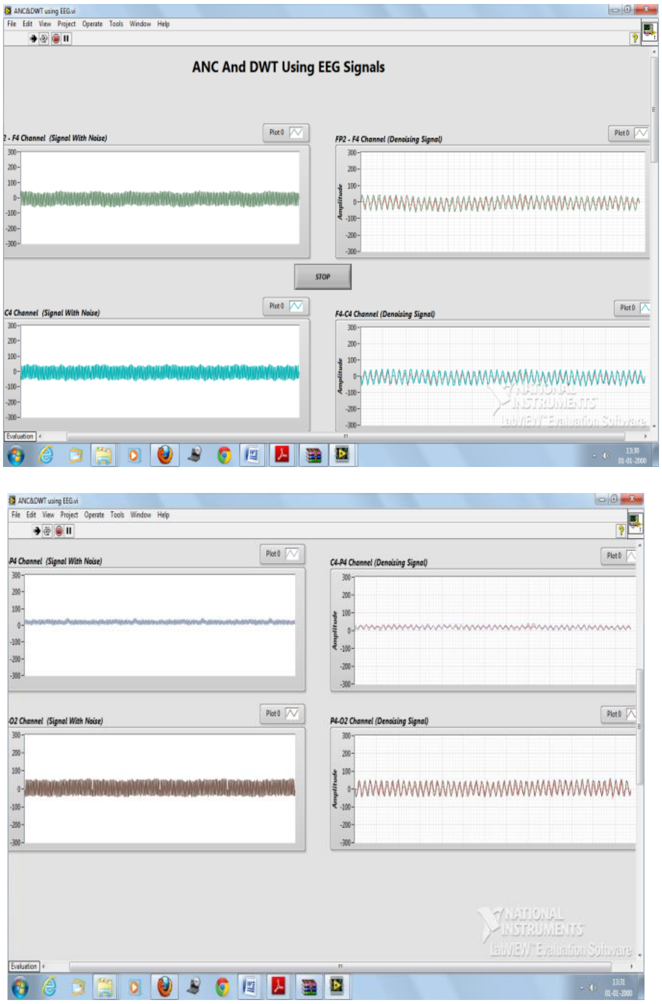

Figure 10.3 Output of ANC and DWT.

6. FUTURE WORK

In considering the research presented in this paper while our approach has shown some promising results, there are several features that require further investigation:

• EEG signals have very complicated pseudo-random nature. Many linear and nonlinear prediction techniques can be used to predict the EEG signal in the short-term. However, the duration of prediction needs to be increased to improve efficiency. Efforts should be directed towards addressing long-term EEG signals.

• In spite of AAR modeling having been successfully used by many investigators for EEG signal analysis, a parametric method is only efficient within relatively restricted parameter ranges. With consideration to online de-noising problems such as the extremely low signal-to-noise ratio and limited number of channels; obtaining reliable EEG signals remains a hot topic.

• In future studies, we will use additional statistical methods to prove our model with respect to efficiency and real time constraints.

7. CONCLUSION

In this project the ocular artifacts is removed by using by Adaptive filter and Discrete wavelet transform. .A key technique in approach of the utilization of Adaptive Filter techniques to recover true EEG by predicting EEG signal amplitudes in OA zones..These methods have an advantage that they can effectively remove OA without using an EOG reference channel. It lies in the fact that it allows the description of a signal by means of model coefficients and parameters characterizing the basic rhythms. Moreover, it can automatically adjust parameters with respect to the changes of signal input to achieve the optimal filter performance.

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