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A PERFORMANCE COMPARISON AND IMPROVEMENT FOR REMOVAL OF OCULAR ARTIFACTS IN EEG-BCI

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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 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. It is used to develop an efficient and effective method to remove ocular artifacts using two method. First method is Discrete Wavelet Transform (DWT) and Adaptive Noise Cancellation (ANC) and second method by using LMS algorithm.comparison result can be shown Then the result can be simulated in Lab VIEW.**

I. 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.

II. 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. 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. 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. 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].

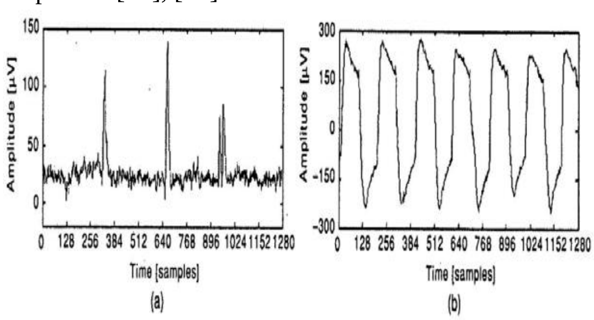

Figure.1 : (a) EEG contaminated with Eyeblink Artifact

(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. [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.

III. MODELS AND METHODOLOGY

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

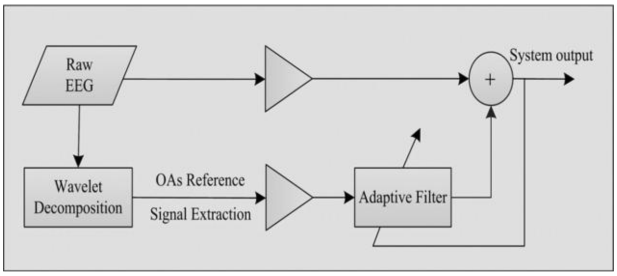

Fig. 2. Block diagram of DWT and ANC.

where iand j are integers; is the "mother" waveletfunction 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 willbe 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:

Model Based on LMS algorithm

One of the most used algorithm for adaptive filtering is the LMS algorithm. LMS adjusts the adaptive filter taps and modifying them by an amount proportional to the instantaneous estimateof the gradient of the error surface [7]. It neither requires correlation function calculation normatrix inversions, which makes it simple and easier when compared to other algorithms. The
Minimization of mean square error is achieved due to the iterative procedure incorporated in it to make successive corrections in the direction of negative of the gradient vector it is represented in following equations.

Y (n) = F (n). U (n)…………………(i)
E (n) = G (n) – Y (n)………..........(ii)
F (n + 1) = F (n) + µ. U (n). E (n)…..(iii)
Where, Y(n) = filter output, X(n) = input signal, E(n) = error signal, G(n) = other observed signal.

BLOCKDIAGRAM OF LMS ALGORITHM

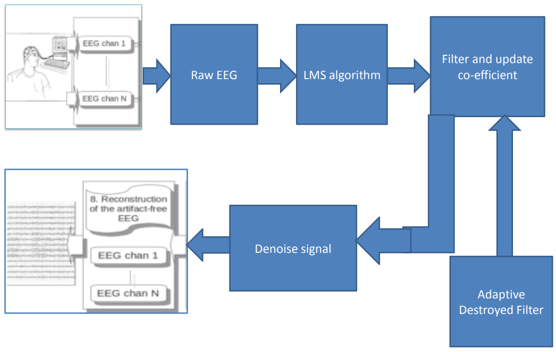

Fig.3. Block diagram of LMS algorithm.

IV. EXPERIMENT ON SIMULATED DATA SET

In Lab VIEW,Signal can be taken from one of the channel in EEG ,the raw signal which is collected from the patient is 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.

V. RESULT

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 signal to adaptive filter and discrete wavelet transform and also for LMS algorithm.

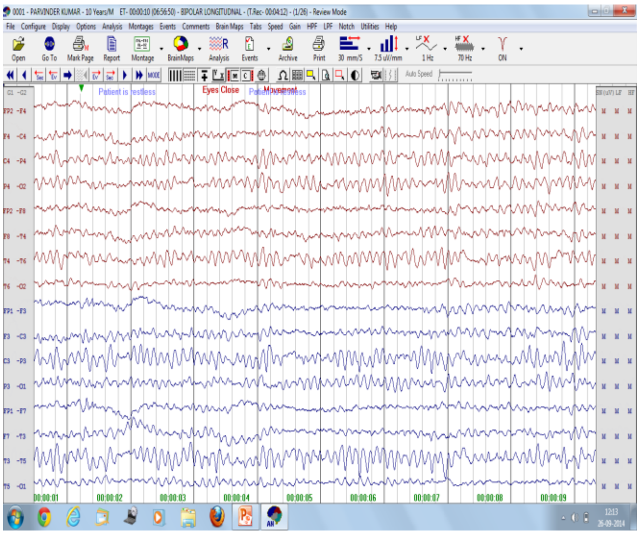

Figure.4: Input signal

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.this implementation can be executed within the while loop and structure.In Adaptive filter coefficient the output is given is 50.If it extent above 50 the error will occur,then it can be overcome.

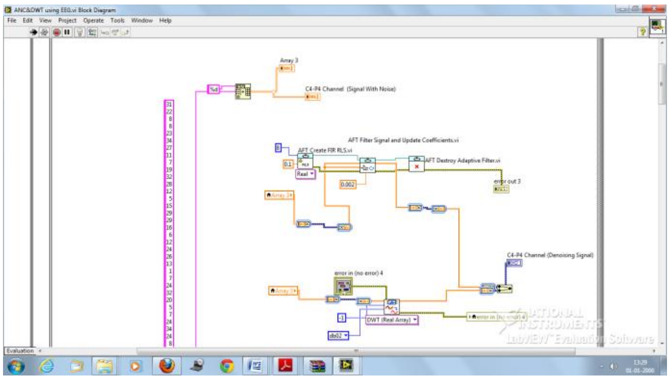

Figure.5 : Block diagram of ANC and DWT.

RESULT

OUTPUT OF ANC and DWT

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

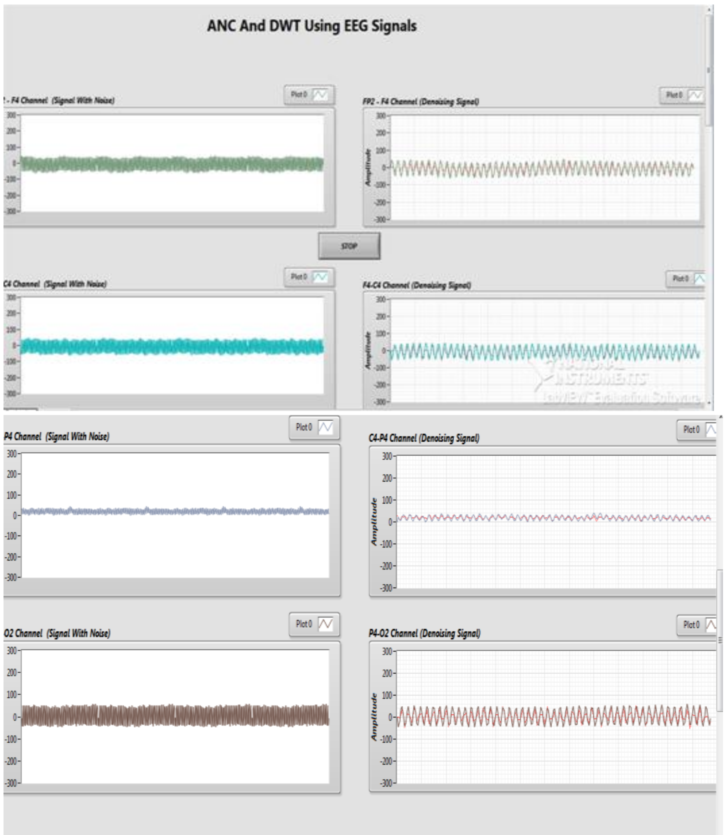

Figure.6 : Output of ANC and DWT.

Implementation of LMS algorithm.

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 LMS and ocular artifacts can be removed.

Block Diagarm of LMS

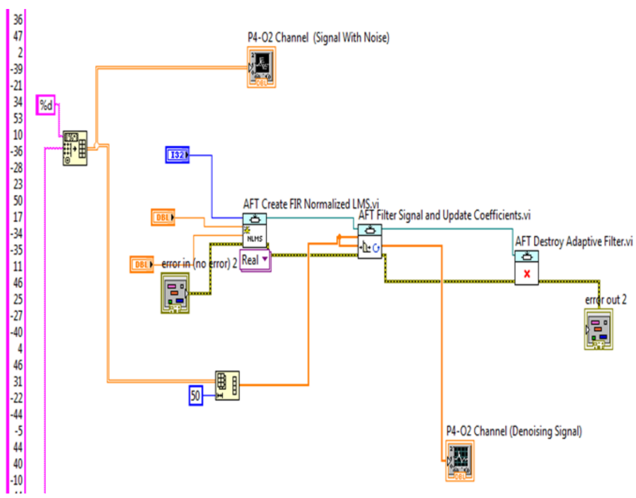

FIG.7: Block diagram of LMS

OUTPUT of LMS

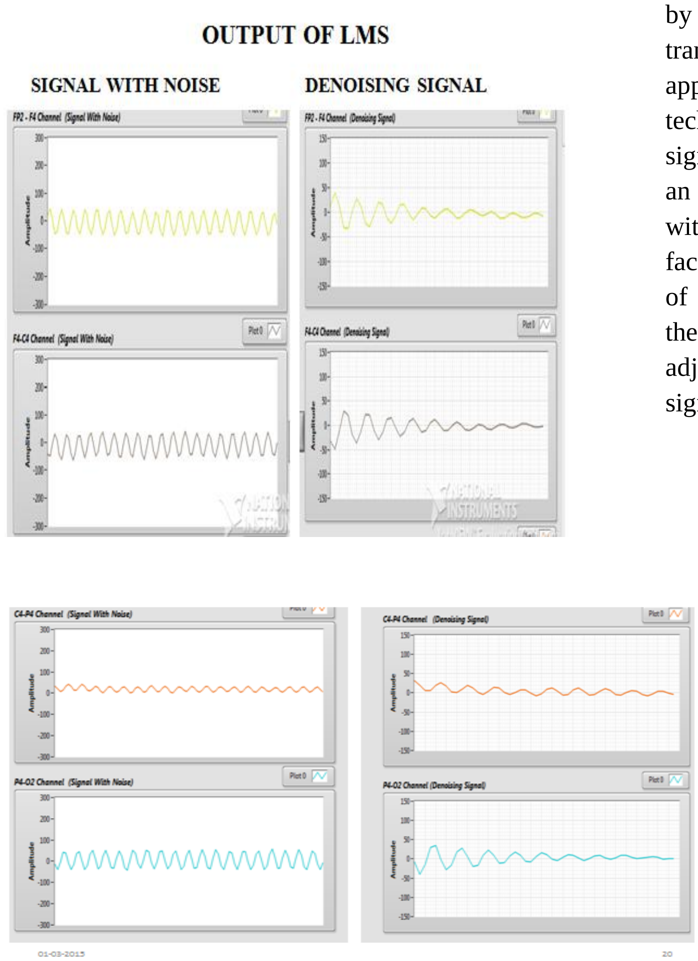

FIG.8: Output of LMS

VI. COMPARISON RESULT

		ANC	LMS
	Time samples	Amplitude	Amplitude
S.NO	1090305	44	39.6
2.	1090306	17	12.8152
3.	1090310	40	27.0589
4.	1090320	37	14.7608
5.	1090326	40	7.61502
6.	1090330	25	5.79986
7.	1090336	43	4.3451
8.	1090337	18	3.38853
9.	1090341	38	1.06139

FIG.9 :comparison of ANC and LMS

VII. CONCLUSION

In this project the ocular artifacts is removed by using by Adaptive filter and Discrete wavelet transform and LMS algorithm. .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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