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Artificial Neural Networks (ANNs) for EEG Purging using Wavelet Analysis

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Abstract

The Electroencephalogram (EEG) is a biological signal that represents the electrical activity of the brain. Artifacts in EEG signals are caused by various factors, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram). The removal of artifact from scalp EEGs is of considerable importance for analysis of underlying brainwave activity. The presence of artifacts such as muscle activity, eye blinks, pulse signals and line noise in electroencephalographic (EEG) recordings obscures the underlying processes. These artifacts sources increase the difficulty in analyzing the EEG. For this reason, it is necessary to design a procedure to decrease such artifacts in EEG. A commonly encountered problem in artifact removal is the 'blanking' of the EEG signal due to blinking of the patient's eyes. In biomedical analysis, EEG signal consists of artifacts. The fundamental basis of the paper here is to address the elimination of ocular artifact called Electroculogram (EOG) from Electroencephalogram (EEG) signal using wavelet method. An algorithm using wavelet analysis is implemented to eliminate the eye blink artifact without compromising the integrity of the primary EEG data.

Keywords: Ocular artifact, haar wavelet, EEG, Discreet Wavelet Transform, EOG

Introduction

Normal EEG signals are usually registered from electrodes placed on the scalp and are often very small in amplitude of order 20 μV. The electroencephalogram (EEG) contains useful diagnostic information on a variety of neurological disorders. It is a non- invasive method used to measure the electrical activity of human brain. The EEG like all biomedical signals is very susceptible to a variety of large signal contamination or artifacts (signals of other than brain activity) which reduce its usefulness [1]. Blinking or moving eyes produces large electrical potentials around the eyes called the electro-oculogram (EOG). The EOG spreads across the scalp to contaminate the EEG, when it is referred to as an ocular artifact (OA). For example, In Figure 1, the effects of blinks and eye movements on an EEG and an EOG are illustrated. The upper two plots illustrate EEG and EOG during which no significant eye movements or blinks occur. The middle two plots show the effect of two brief eye movements. The change in amplitude that is caused by the movement is more prominent in the right plot because the EOG is recorded closer to the eyes. The lower two plots illustrate the effect of a blink

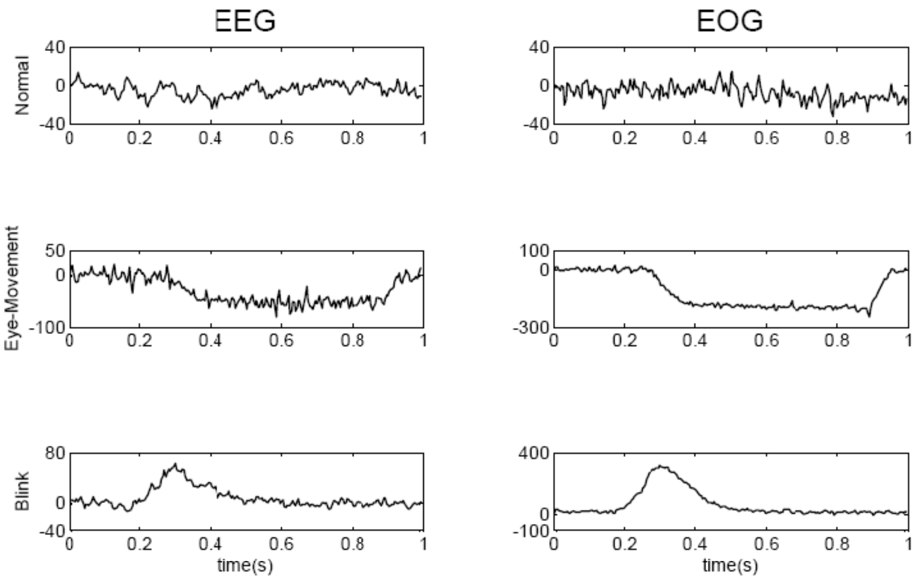

Figure 1: Illustration of the effects of eye movements and blinks in the EEG and in the EOG.

LabVIEW is graphical programming environment. Programs in IDE are called Virtual Instruments (VIs), consists of a Block Diagram (BD) and a Front Panel (FP). A BD provides a graphical code development environment whereas a FP allows the user to interact with a VI. It provides an efficient and easy-to-use environment for code development especially when the user needs to interact with the program and visualize the results. Unlike text-based programming languages like C which follow a control flow execution model, the environment of programming follows a dataflow execution model.

Ocular Artifact Removal Methods

To eliminate artifacts is prevent them from occurring in the first place. Of course prohibiting subjects from blinking or moving their eyes is uncomfortable for the patient, and nearly impossible to achieve. To have a person in such a controlled or constrained state could affect the EEG output and even introduce new artifacts. Fixation of the eye is inadequate because it does not eliminate involuntary eye movement and cannot be used when performing a task requiring eye movement [2]. The effectiveness of this method is highly questionable, especially in children and patients suffering from neurological pathology [3].

The least elegant method of removal is to have trained technicians manually detect and remove epochs of corrupted data based on artifact characteristics such as amplitude, signal variance, frequency content, or slope that exceed a certain threshold [4], [3].This extremely arduous and very subjective task leads to a significant amount of data loss, especially when there is a limited amount of data or a high frequency of blinking and saccades [2].

Linear Filtering

When presented with the problem of artifact removal, one potential solution is to analyze frequency characteristics of the signal and artifact and filter out the artifact. The reason that EOG cannot be simply filtered out is because of the spectral overlap between the EOG and the EEG [5]. In [7] an eye blink waveform model was created by averaging over 500 normalized blinks that were visually detected and the spectral content was obtained via the use of the Fourier transform as shown in Figure 2.1. The frequency spectrum of EEG data is generally from close to DC up to 75 Hz [6] which clearly has a huge overlap in the spectrum seen in Figure 2.1.

Advanced Regression Techniques

A major improvement on the analogue techniques was the use of the 'least squares' regression function introduced by Quilter and co-workers. The regression function calculates *B*, the proportion of one variable that is explained by another, and in terms of EOG correction, an estimate of the amount of EOG that is present in a particular EEG channel. Formally this is given in Eqn. 1, where Xi represents the EOG and Yi the EEG voltage at time *i*. A separate *B* is calculated for each subject and electrode site. The equivalent formula of Eq. 2 is perhaps more intuitive. Here we have rxy the correlation between the EOG and EEG channels, and it has been scaled by the standard deviations of the two channels to yield the same result.

$$B=\sum (\overline{X}i-X)(\overline{Y}_i-Y_i)/\sum (Xi-X)^2 \qquad (1)$$

$$B = r_{xy} . sd_y / sd_x \qquad (2)$$

This is referred to as the time domain approach (TDA) because it compares voltages from EOG and EEG channels at each time point, irrespective of fre-quency. Correction then takes place as per Eq. 3, where at a particular scalp site, estTEEG is the esti-mated true neural potential and MEEGi the measured EEG at time *i, B* is the propagation coefficient de-scribed in Eq. 1 and 2, and C is the y-intercept of the regression equation. The subtraction of C is to remove the EOG baseline effect from the EEG, and its calculation is described in Eq. 4, where X and Y are as defined in Eq. 1.

$$estTEEG_i = MEEG_i - (B.\ EOG_i) - C \qquad (3)$$

$$C = \bar{X}_i - (\bar{Y}_i\ .\ B) \qquad (4)$$

The obvious extension of this procedure is to use two EOG channels, generally VEOG and HEOG, but it can be extended to include any number of channels. The principle is the same, but the formulae are a little more complex. *B* is calculated for each EOG channel using Eq. 5, where *BYX..Z* is the propagation value from EOG channel X to EEG channel Y, after taking into account the influence of EOG channel Z, sd is standard deviation and *r* the Pearson's product-moment coefficient. *B* is calculated separately for each EOG channel. We then correct with Eq. 6, differing only from Eq. 3 in so far as it subtracts a portion of each EOG channel.

$$B_{yx\,.\,z} = ([\,r_{yx} - r_{yz}\ .\ r_{zx}]/1 - r^2_{xz}).\ Sd_y/sd_x \qquad (5)$$

$$estTEEG_i = MEEG_i - (B_{yx\,.\,z} * EOG_{xi}) - (B_{yz\,.\,x} * EOG_{zi}) - C \qquad (6)$$

Some of other ocular removal techniques are listed in below table with their limitations.

Table 2.1: Techniques for ocular artifacts removal.

Techniques	Limitations
Experimental Control	Controlling patients blinking is unrealistic, difficult to accomplish , and nearly impossible
Rejection	Rejection of ocular artifacts results in significant information loss which is impractical for clinical data
Linear Filtering	Information loss or insufficient ocular artifact removal result due to a large spectrum overlaps between ocular artifacts and brain activity.
Regression Analysis	Highly dependent on a clean EOG channel, varies from one ocular artifact to another, and does not account for EEG propagating onto EOG electrodes.

Wavelet Analysis

Orthonormal Wavelet Bases

Wavelets are families of basis functions able to accurately describe other functions in a parsimonious way [8].

In L2 (R), for example, a Daubechies wavelet basis is obtained as translations and dilations of two basis functions, with a scaling function and a mother wavelet. The wavelet collection is obtained by translations and dilations as:

$$\Psi_{j.n}(t)=2^{j/2}\Psi(2^{-j}t\text{-}k). \quad (1)$$

$$\varphi_{j.n}(t)=2^{-j/2}\varphi(2^{-j}t\text{-}k) \quad (2)$$

With *j*, *k*, *Z* and the family of wavelets {Ψj.k(t), j,k,z} forms an orthonormal basis in *L*2 (*R*) [8]. Interesting recursive relationships hold between the detail coefficients dj.kand the scaling coefficients aj.k. Using (1), coefficients at a scale j can be obtained from scaling coefficients at the finer scale j + 1 as:

$$a_{j.k}=\sum_{l} h[l\text{-}2n]a_{j+1,l} \quad (3)$$

$$d_{j,k}=\sum_{l} g[l\text{-}2n]a_{j+1,l} \quad (4)$$

Where, *h* and *g* are the filter coefficients.

Wavelet Analysis for Detecting Patterns in EEG

The application of wavelet-based analysis to neuronal waveforms such as EEG has been demonstrated to offer advantages in signal detection, component separation, and computational speed over traditional time and frequency techniques [9]. A wavelet representation improves time resolution as the length of the neuronal event decreases, allowing improved resolution in the detection of the time of its occurrence. The use of wavelet packets introduces precise control of frequency selectivity which results in accurate component detection even if they overlap in time and frequency. Because “wavelets sweep through a signal at different scales” to identify a pattern similar to itself, matching the wavelet shape to the artifact desired, specifically targets the artifact for detection and feature extraction [10]. Thus, a pattern recognition scheme is possible that can be used for artifact detection in EEG that is not sensitive to physiological variations [9].

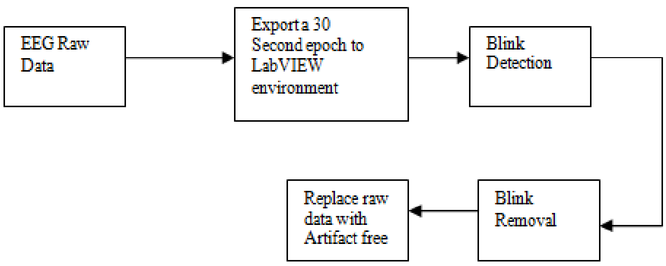

Figure 3.1: Flow Chart.

EEG of Healthy Patient, (Eyes Open) using Virtual Instrumentation

The EEG are contaminated by EOG signal. The EOG signal is a non-cortical activity. The eye and brain activities have physiologically separate sources, so the EEG is a superposition of the true EEG and some portion of the EOG signal [11]. It can be represented as

$$EEGrec(t)=EEGtrue(t)+k.EOG(t) \tag{1}$$

Where, *EEGrec(t)* - contaminated EEG,
EEGtrue(t) - EEG due to the cortical activity (i.e., Brain activity)
k.EOG(t) - Propagated ocular artifact from eye

The Algorithm involves the following steps:

i. Apply Discrete Wavelet Transform to the contaminated EEG with Haar wavelet as the basis function to detect the OA zone [12].
ii. Apply Wavelet Transform with Coif 3 as the basis function to the contaminated EEG with OA zones identified for removing Ocular Artifacts then reconstruct the EEG signal.

Figure 4.1shows front panel of EEG healthy patient eye open, EEG in upper waveform graph and lower waveform graph represent removal of artifact from EEG data. EEG data in upper waveform graph does not immediately convey useful information. Applying discrete wavelet transform to EEG signal is able to extract the useful information from the noise and present it in a form, more comprehensible than the original data. Figure 4.2 show block diagram of EEG healthy patient eye open.

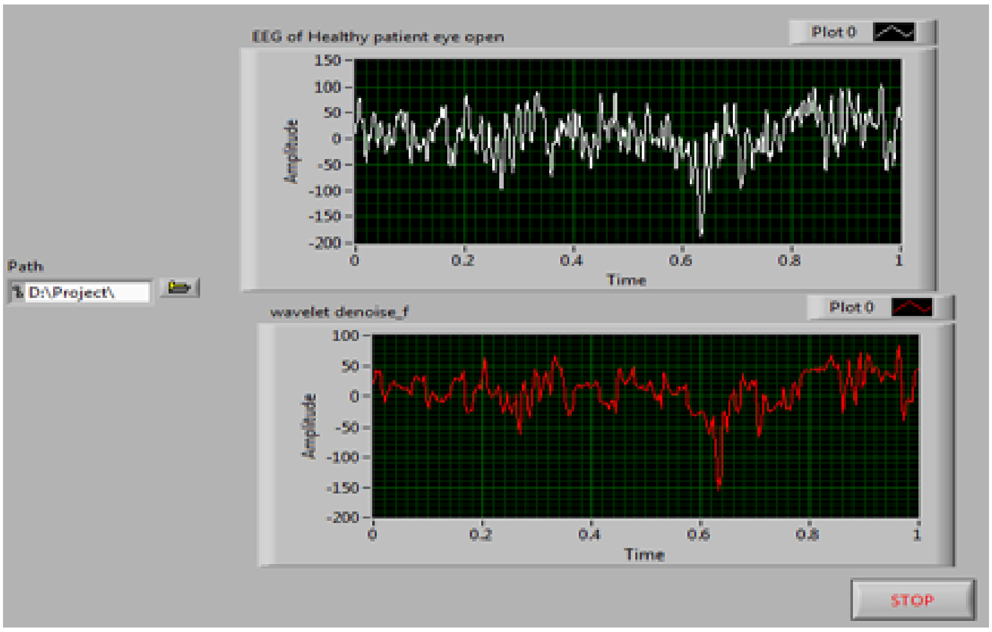

Figure 4.1: Front Panel of EEG Healthy Patient Eye Open.

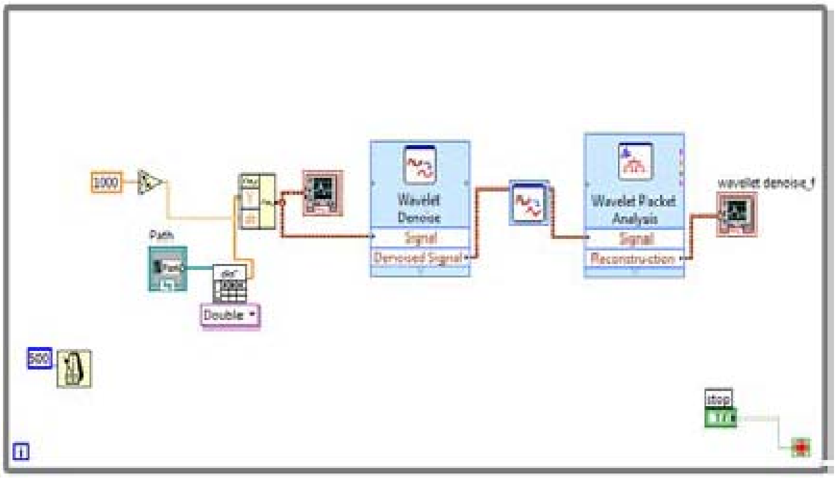

Figure 4.2: Block Diagram of EEG Healthy Patient Eye Open.

Haar wavelet is used to decompose the EEG Signal to detect the exact moment when the state of the eye changes. Decomposition of the EEG with the Haar wavelet results in a step function with a falling edge for a change in the state of the eyes from open to close and a step function with a rising edge for a change in state of the eyes from close to open. Here the EOG contaminated EEG is decomposed up to 6 levels using Haar wavelet is shown in figure 4.3.

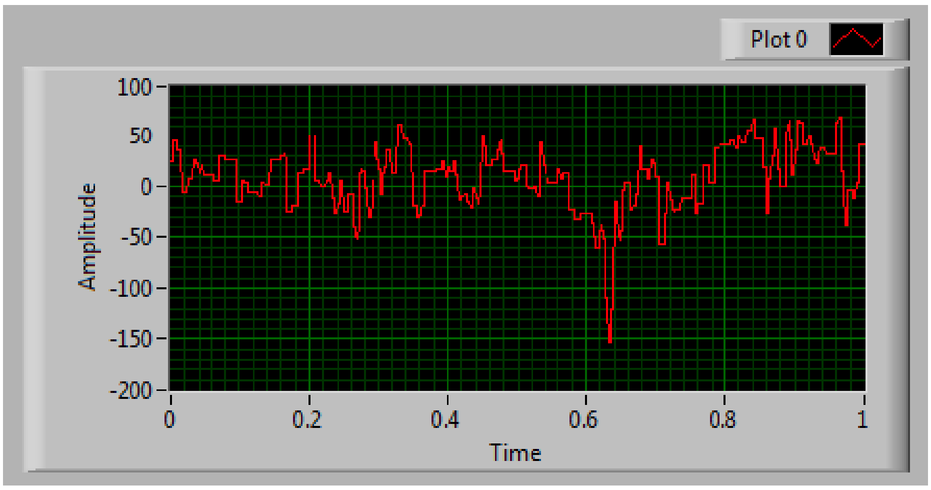

Figure 4.3: Haar wavelet.

Conclusion

The use of wavelet analysis was successfully used in the detection and removal of eye movement and eye blink artifacts, in EEG.

Future Developments

This paper has outlined a pathway toward effective ways for EEG purging using Artificial Neural Networks. In future it made as the Real Time Application like EEG signals control targeting equipments such as Home Appliance etc.

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