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Artifact Removal from EEG Signals

A.GuruvaReddy, HOD, Ph.D
Department of Electronics & Communication
DVR & Dr.HS MIC College of Technology,
Kanchikacharla, Krishna District, India.

Srilatha Narava
M.Tech, Digital Electronics & Communication Systems
DVR & Dr.HS MIC College of Technology
Kanchikacherla, Krishna District, India.

ABSTRACT
Electroencephalographic (EEG) recordings are often contaminated with several artifacts.Powerline interference and baseline noise is always present in EEG response of every patient. A number of strategies are available to deal with noise effectively both at the time of EEG recording as well as during preprocessing of recorded data. The aim of the paper is to give an overview of the most common sources of noise and review methods for prevention and removal of noise in EEG recording ,including elimination of noise sources.

Keywords
Artifact, Electroencephalogram, Line interference.

1. INTRODUCTION
Electroencephalography (EEG) is one of the key tools for observing brain activity. While it cannot match the precision and resolution of spatial localization of brain activity of many other brain imaging methods, its main advantages are low costs, relative ease of use and excellent time resolution. For these reasons, EEG is widely used in many areas of clinical work and research. One of the biggest challenges in using EEG is the very small signal-to-noise ratio of the brain signals that we are trying to observe, coupled by the wide variety of noise sources.

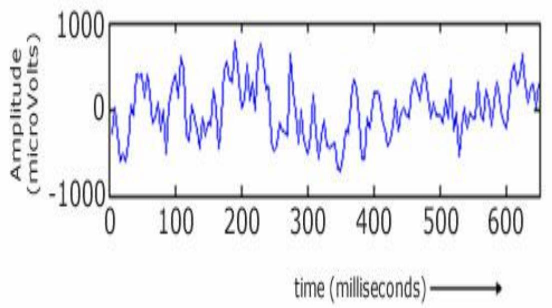

Fig 1: Normal EEG Waveform

2. COMMON ARTIFACTS
By artifacts it is understood all signals that appear in the EEG record which don't come from the brain. The most common artifacts in the EEG signal appear during the acquisition due to different causes, like as bad electrodes location, not clean hairy leather, electrodes impedance, etc. There is also a finding of physiological artifacts, that is, bioelectrical signals from other parts of the body (heart and muscle activity, eye blink and eyeball movement) that are registered in the EEG.

2.1 Powerline Noise
Biological records, especially EEG signals, are often contaminated with the 50 or 60 Hz line frequency interference from wires, light fluorescents and other equipments which are captured by the electrodes and acquisition system. The ignition of light of fluorescents usually causes artificial spikes in the EEG. They are distributed in several channels of EEG and can made a mistake in the analysis of the record.[1]

2.2 Baseline Noise
Poor contact of the electrodes and perspiration of the patient under the electrodes may affect the electrode impedance which causes low frequency artifacts. Baseline drift may sometimes be caused by variations in temperature and bias in the instrumentation and amplifiers as well. This type of noise is undesired and needs to be removed before any further signal processing, for proper analysis and display of the EEG signal.

2.3 Occurrence Of Noises
It is recorded from surface electrodes that are not tightly in contact with the scalp. It results in low frequency baseline wander.EEG signals are often contaminated with 50 or 60 Hz line interference results in power line interference.Here Removal of the baseline wanders and power line interference by Preserving the low frequency EEG clinical information is done by using Adaptive filtering technique.

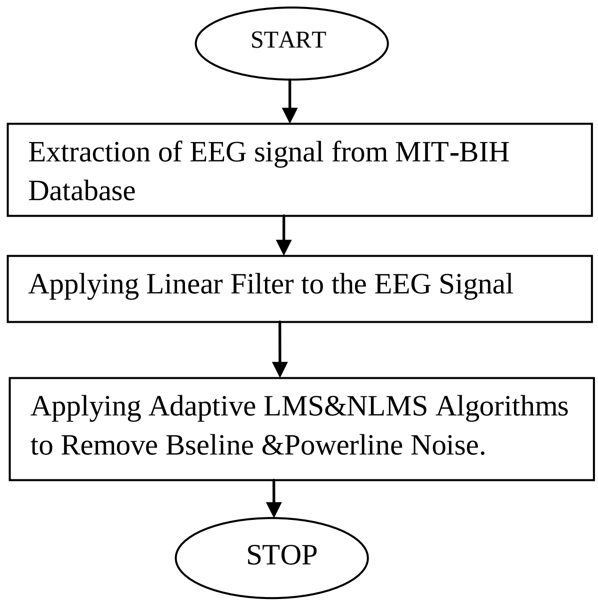

Fig 2: Flowgraph for Noise Removal

3. METHODOLOGY
Here in, we propose the use of adaptive filters to remove artifacts from EEG signal acquired in PSG studies. Usually, biological signals (ECG, EOG and others) have overlapped spectra with the EEG signal. For that, conventional filtering (band-pass, lower-pass or high-pass filters) cannot be applied to eliminate or attenuate the artifacts without losing

significant frequency components of EEG signal.Due to this reason, it is necessary to design specific filters to attenuate artifacts of EEG signals in PSG studies.[6] The adaptive interference cancellation scheme is a very efficient method to solve the problem when signals and interferences have overlapping spectra.

3.1 Adaptive Filter

Adaptive filters are based on the optimization theory and they have the capability of modifying their properties according to selected features of the signals being analyzed fig2 illustrates the structure of an adaptive filter. There is a primary signal *d(n)* and a secondary signal *x(n)*. The linear filter *H(z)* produces an output *y(n)*, which is subtracted from *d(n)* to compute an error *e(n)*.[8]

The objective of an adaptive filter is to change (adapt) the coefficients of the linear filter, and hence its frequency response, to generate a signal similar to the noise present in the signal to be filtered. The adaptive process involves minimization of a cost function, which is used to determine the filter coefficients. Initially, the adaptive filter adjusts its coefficients to minimize the squared error between its output and a primary signal. In stationary conditions, the filter should converge to the Wiener solution. Conversely, in non-stationary circumstances, the coefficients will change with time, according to the signal variation, thus converging to an optimum filter.[3]

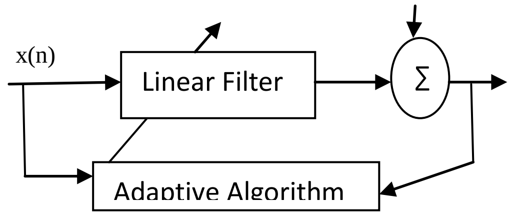

Fig 3: Structure of an Adaptive Filter

In an adaptive filter, there are basically two processes:

1. A filtering process, in which an output signal is the response of a digital filter. Usually, FIR filters are used in this process because they are linear, simple and stable.

2. An adaptive process, in which the transfer function *H(z)* is adjusted according to an optimizing algorithm. The adaptation is directed by the error signal between the primary signal and the filter output..

The structure of the FIR can be represented as,

3.2 LMS Algorithm

$y(n) = \sum k = 0Lwkx(n-k)$…….(1)

where L is the order of the filter, *x(n)* is the secondary input signal, w_k are the filter coefficients and *y(n)* is the filter output.[7]

The error signal *e(n)* is defined as the difference between the primary signal *d(n)* and the filter output *y(n)*, that is,

$$e(n) = d(n) - y(n)$$

where,

$$e(n) = d(n) - \sum k = 0Lwkx(n-k)$$

Since *d(n)* and *x(n)* are independent with respect to w_k, then,

$$wk(n+1) = wk(n) - 2\mu e(n)x(n-k) \dots \dots \dots . . (2)$$

where μ is a coefficient that controls the rate of adaptation.[4]

Equation (2) *is* the final description of the algorithm to compute the filter coefficients as function of the signal error *e(n)* and the reference input signal *x(n)*. The coefficient μ is a constant that must be chosen for quick adaptation without losing stability. The filter is stable if μ satisfies the following condition,

$$0 < \mu < 1(10.L.Pxx)/; Pxx \approx 1M + 1\sum n = 0M - 1x2(n)$$

where L is the filter order and P_{xx} is the total power of the input sig nal.[3]

3.3 NLMS Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration.This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable. Even if we assume the only signal to be input to the adaptive echo cancellation system is speech, there are still many factors such as signal input power and amplitude which will affect its performance.The normalised least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by calculating maximum step size value. Equation (3) is the final description of the algorithm Step size value is calculated by using the following formula.
Step size=1/dot product (input vector, input vector)

$$wk(n+1) = wk(n) - \mu e(n)x(n-k) \dots \dots \dots . . (3)$$

4. EXPERIMENTAL RESULTS

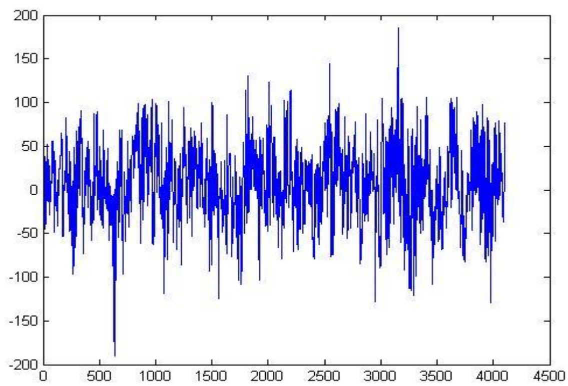

Fig 4: Acquired Signal Contaminated with Noise

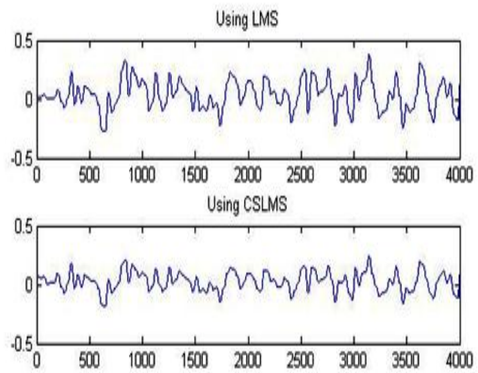

Fig 5: Removal of Baseline Noise

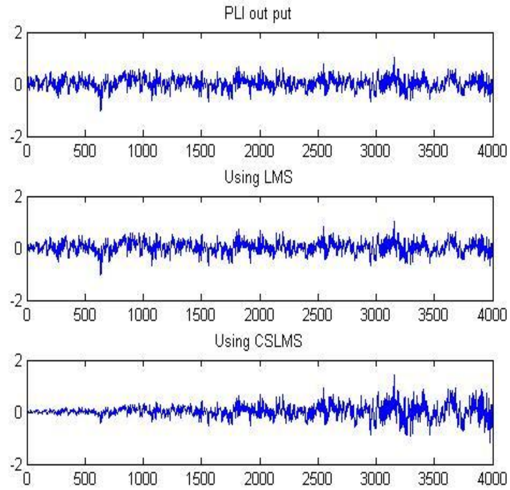

Fig 6: Removal of Powerline Noise

5. CONCLUSION

Noise can present a significant challenge in analysis and interpretation of EEG data, necessitating efficient strategies for noise prevention and removal. A large amount of noise can be avoided by taking care of the appropriate recording environment and carefull planning of experiments and recording sessions. Additionally, a number of methods and algorithms can be employed to reject noisy data, remove noise signal and improve signal-to-noise ratio of the data. In order to effectively choose and use methods of dealing with noise, their advantages and challenges need to be considered in relation to the properties of the data and the analytical questions being asked.

6. REFERENCES

[1] M. Ferdjallah and R. E. Barr "Adaptive Digital Notch Filter Design on the Unit Circle for the Removal of Powerline Noise from Biomedical Signals", *IEEE Trans. on Biomedical Engineering*

[2] M. V. Dragosevic, and S. S. Stankovic "An Adaptive Notch Filter with Improved Tracking Properties", *IEEE Trans. Signal Processing*, vol. 43, no. 9, pp. 2068–2078.

[3] He P, Wilson G, Russel C: Removal of artifacts from electro-encephalogram by adaptive filtering. Medical & biological engineering & computing 2004; 42(3): 407-12.

[4] R. H. Kwong, and E. W. Johnston "A Variable Step Size LMS Algorithm", *IEEE Trans. Signal Processing*, vol. 40, no. 7, pp. 1633–1642, 1992.

[5] Haykin, Simon, 2001, "Adaptive Filter Theory", ISBN-10: 0130901261, Prentice-Hall, pp. 231-38, 320-24.

[6] MIT-BIH arrhythmia database, Http://www.physionet.org/phsiobank/database/mitdb/

[7] Haykin, Simon, 2003, "Least-Mean-Square Adaptive Filters", ISBN 0-471-21570-8 Wiley, pp. 315.

[8] Honing. M.,Messerschmitt. D, 1984, "Adaptive Filters: Structures, Algorithmsand Applications", ISBN-13: 978-0898381634, Kluwer Academic Publishers,