International Journal of Electronics Signals and Systems

Volume 1 | Issue 1 Article 10

January 2011

Removal of ocular artifacts from EEG signals using adaptive threshold PCA and Wavelet transforms

P. Ashok Babu
Narsimha Reddy Engineering College, Hyderabad, ashokbabup2@gmail.com

K. V.S.V.R. Prasad
D.M.S.S.V.H.college of Engineering, Machilipatnam, A.P.(state), INDIA, kvsvr@yahoo.com

Available online at www.interscience.in

Removal of ocular artifacts from EEG signals using adaptive threshold PCA and Wavelet transforms

P. Ashok Babu[1], K.V.S.V.R.Prasad[2]

[1]Narsimha Reddy Engineering College, Hyderabad,
[2]D.M.S.S.V.H.college of Engineering, Machilipatnam, A.P.(state), INDIA
Email: ashokbabup2@gmail.com[1], kvsvr@yahoo.com[2]

Abstract - It becomes more difficult to identify and analyze the Electroencephalogram (EEG) signals when it is corrupted by eye movements and eye blinks. This paper gives the different methods how to remove the artifacts in EEG signals. In this paper we proposed wavelet based threshold method and Principal Component Analysis (PCA) based adaptive threshold method to remove the ocular artifacts. Compared to the wavelet threshold method PCA based adaptive threshold method will gives the better PSNR value and it will decreases the elapsed time.

Keywords— Electroencephalogram (EEG), Principal Component Analysis (PCA), Stationary Wavelet Transform (SWT), Discrete Wavelet Transform (DWT), PCA based Adaptive threshold algorithm.

I. INTRODUCTION

EEG is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. In clinical contexts, EEG refers to the recording of the spontaneous electrical activity over a short period of time. In neurology the main diagnostic application of EEG is in the case of Epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study i.e., eye movements and eye blinks mostly disturb the EEG signals. EEG activity shows oscillations at a variety of frequencies, shapes and amplitudes. Several of these oscillations have characteristic frequency ranges, spatial distributions and are associated with different states of brain functioning. The EEG signal is considered to be in low state when the amplitude of EEG signal is below 20µV, if it ranges between 20µV to 50µV it is considered as medium and if amplitude is above 50µV it is considered as high. An electric field is conjured which is two order of magnitude

Greater than the desired electrical activity when the human eye blinks or moves. “An eye blink can last up to 400ms and can be 10 times larger in amplitude than electrical signals originating from cerebral cortex.” EOG is defined as the electrical activity associated with the eye movement [1].

This paper is mainly focused to detect the artifacts and remove them in order to have a clear and clean study of EEG. There were several methods which were introduced and brought up by several authors in order to remove the ocular artifacts from EEG. G.Wilson introduced a method of adaptive filtering using RLS algorithm in order to eliminate artifacts which are embedded in the EEG signals [2]. Rebeca Romo-Vazquez applied a method which was a combination of independent component analysis (ICA) and wavelet de noising in order to remove the ocular artifacts from EEG[3].V.Krishnaveni proposed wavelet transform to automatically identify and remove ocular artifacts from EEG[4]. P.Senthil Kumar combined adaptive technique using Recursive Least Square algorithm and wavelet transform to get correct the ocular artifacts without removing the underlying EEG information [5].

II. WAVELET TRANSFORMS

The EEG signals are analyzed techniques named wavelet transforms. The characteristics of the signal are analyzed by the wavelet transforms by transforming the signal into time and frequency localizations i.e., wavelet can keep track of time and frequency.

In numerical analysis and functional analysis a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. The main advantage is it captures both frequency and location information. Wavelets are defined by the wavelet function Ψ(t) i.e., the mother wavelet, we are choosing the scales i and positions j of the mother wavelet.

$\Psi_{i,j}(t) = 2^{i/2}\,\Psi(2^i t - k)$ where i ,k are integers

Scales and positions chosen based on powers of two are named as dyadic scales and positions. “A wavelet can be built for any function by dilating a function Ψ(t). With a coefficient 2^i and translating the resulting function on a grid whose interval whose interval is proportional to 2^{-i}. The dilated i.e., the stretched versions of the wavelet match the low frequency components and the contracted i.e., the compressed versions match the high frequency components. The signal is split into "detail" and "approximation" using the multi resolution decomposition algorithm [4].

The Stationary wavelet transform (SWT) is a wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of 2^i in the i^{th} level of the algorithm [9]. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input. So for a decomposition of N levels there are a redundancy of N in the wavelet coefficients.

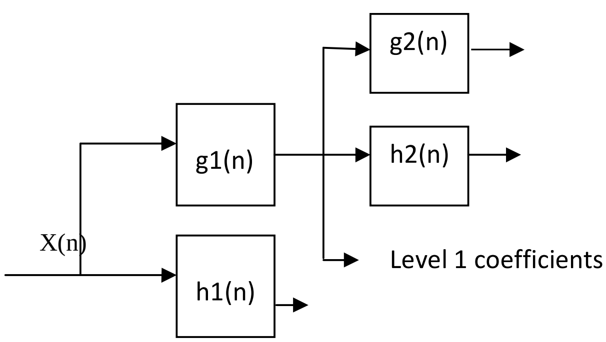


Fig.1. Stationary wavelet transform

III. METHODOLOGY

1) Stationary wavelet transform (SWT) is applied to the contaminated EEG signal (EEG with eye artifacts) with Symlet wavelet of order 3 being used and the EEG signal is decomposed into eight levels.
2) The eye blink artifacts should be identified.
3) Setup a threshold value and a threshold function for the ocular artifacts.
4) To reconstruct the EEG signal, apply wavelet reconstruction procedure.

Threshold value was selected based on rig sure which is based on stein's unbiased estimate of risk "One gets an estimate of the risk for a particular threshold value t. minimizing the risks in t gives a selection of the threshold value".

The threshold function used in Hard is as follows:

If wavelet coefficient value > threshold value

Then new wavelet coefficient value = (-0.7) ×(wavelet Coefficient value) else new wavelet coefficient value = (old) wavelet coefficient value.

A. Wavelet Modified Threshold Algorithm

1). Read the EEG signal, EOG signal and get noisy EEG signal

2). For each wavelet decomposition level perform low pass and high pass filtering on original signal or approximate signal , dilate low pass and high pass filters.

3). For each wavelet decomposition level (only the bands whose frequency range corresponds to EOG signals, i.e. from 1 to 50 Hz), if the wavelet coefficient > threshold then new wavelet coefficient = (-0.7) * wavelet coefficient.

4). Perform reconstruction using filtered wavelet coefficients.

5). Calculate MSE and PSNR for noisy and filtered EEG signals.

B. Principal Component Analysis

Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. Principal components are guaranteed to be independent only if the data set is jointly normally distributed. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

The mathematical technique used in PCA is called Eigen analysis: we solve for the Eigen values and eigenvectors of a square symmetric matrix with sums of squares and cross products. The eigenvector associated with the largest Eigen value has the same direction as the first principal component. The eigenvector associated with the second largest Eigen value determines the direction of the second principal component. The sum of the Eigen values equals the trace of the square matrix and the maximum number of eigenvectors equals the number of rows (or columns) of this matrix.

PCA is the simplest of the true eigenvector-based multivariate analyses. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its (in some sense) most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced.

PCA is sensitive to the scaling of the variables. If we have two variables and they have the same sample variables and are positively correlated, then the PCA will tend to rotate by 45^0 and the loadings for the two variables with respect to the principal components will be equal.PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

IV. ADAPTIVE THRESHOLD PCA METHOD

In this method, Eigen values are not used for selection, only those vectors with significant low frequency energy are used. The adaptive thresholding mechanism for the signal is below:"Static threshold may not be suitable for all cases. So threshold value is adopted based on low frequency band energies of Eigen vectors encountered so far. Here an exponentially decaying mechanism is used to have maximum effect of most recent Eigen vectors. Thus we can choose significant Eigen vectors in each cluster (due to adaptive thresholding) and thus vectors discarded may correspond to artifact related. However the factors for adaptive thresholding are chosen based on experiments"

A. PCA Algorithm:

1). Read the EEG signal, EOG signal and get noisy EEG signal

2). Split the EEG data into vectors of length 100 and covariance matrix of the vectors.

3). Perform Eigen values and Eigen vectors of the above data based on covariance matrix.

4). For each Eigen vector perform low pass filtering using a filter of cut off frequency 50 Hz and calculate the energy of filtered data.

5). If the energy calculated corresponding to Eigen value is greater than a threshold, mark these for reconstruction else discard the vector.

6). Perform reconstruction only on these Eigen vectors which are marked for reconstruction.

7). Calculate MSE and PSNR for noisy and filtered EEG signals.

B. Adaptive Threshold PCA Algorithm

1). Read the EEG signal, EOG signal and get noisy EEG signal

2). Split the EEG data into vectors of length 100 and covariance matrix of the vectors.

3). Perform Eigen values and Eigen vectors of the above data based on covariance matrix.

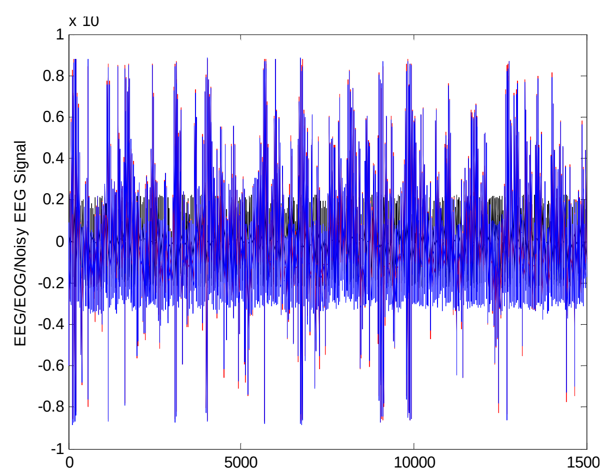
4). For each Eigen vector perform low pass filtering using a filter of cut off frequency 50 Hz and calculate the energy of filtered data.

5). Calculate the Threshold value by using the formula, Current low frequency energy/2 + A (Previous threshold value).

6). Perform reconstruction only on these Eigen vectors which are marked for reconstruction.

7). Calculate MSE and PSNR for noisy and filtered EEG signals.

In the wavelet threshold method we used the technique of hard thresholding. It has one disadvantage that it is independent of Eigen vectors. To avoid the disadvantage we can use adaptive threshold PCA method. For equivalent or filter response consider the low frequency components. In adaptive threshold method for first lowest frequency assume threshold value as ‘x’ and second threshold value can calculated as current low frequency energy/2 + A (Previous value). In this way we can calculate the remaining threshold values, where ‘A’ is the adaptive threshold value. For each Eigen vector if Eigen value is significant, pick the Eigen vector with considerable energy in low frequency range. By initializing the threshold value find out the filtered data and calculate the energy.



No.of samples
Fig.2(a)

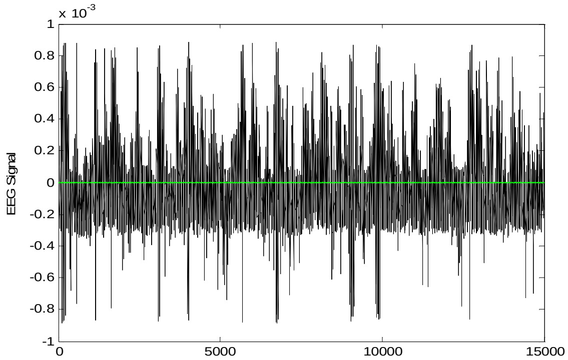


Fig.2.(b)

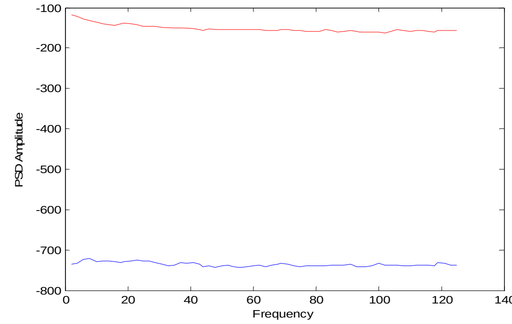


Fig.2. (c)

Fig.2. Results for Adaptive threshold PCA method: (a) is the EEG/EOG/Noisy EEG signal, (b) is the estimated EEG signal, (c) is the power spectral density curve.

Table 1: Comparison of Wavelet threshold and PCA adaptive threshold methods

Parameter	Noisy MSE	Filtered MSE	Noisy PSNR	Filtered PSNR	Elapsed time
EEG Wavelet Threshold method	6.0351e-008	1.4217e-008	0.9342	13.4916	3.638039sec
EEG Wavelet Modified Threshold method	6.0351e-008	4.4251e-008	0.9342	3.6292	1.405553 sec
PCA Denoise method	6.0351e-008	7.8260e-009	0.9342	18.6770	1.440508sec
PCA Adaptive Threshold denoise method	6.0351e-008	7.4452e-009	0.9342	19.1103	1.602615sec

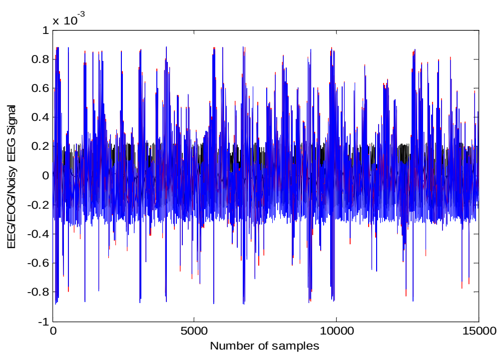


Fig 3(a)

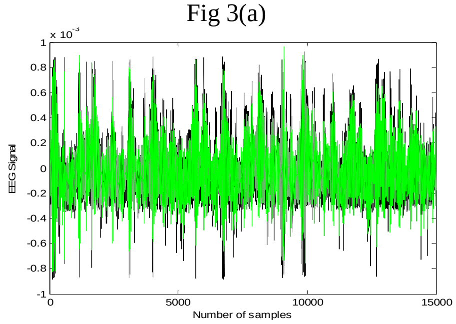


fig 3(b)

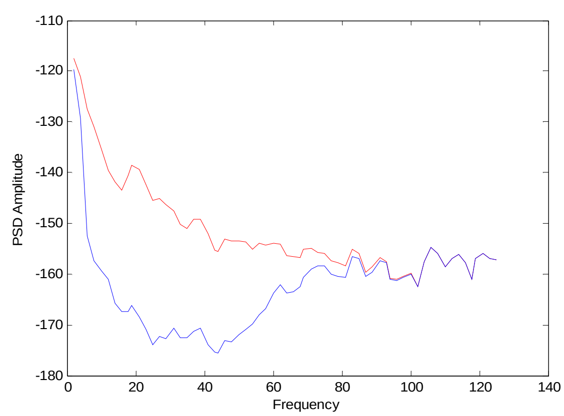


fig3(c)

Fig.3.Results for Wavelet modified threshold method: (a) is the EEG/EOG/Noisy EEG signal, (b) is the estimated EEG signal, (c) is the power spectral density curve.

V. RESULTS AND DISCUSSION

From the above results we can observe that fig 2(a) is the combination of EEG, EOG, and with some noise. The black colored signal is the EEG signal, red colored signal is the EOG signal and blue colored signal is the noisy signal. Fig 2(b) is the estimated EEG signal. Where black colored signal is the noisy EEG data and green colored signal is the estimated EEG signal by using adaptive threshold PCA method. Fig 2(c) is the comparison of power spectral densities. Where red colored signal is the noisy PSD and blue colored signal is the filtered PSD signal.

Fig 3(a) is the combination of EEG, EOG, and with some noise. The black colored signal is the EEG signal, red colored signal is the EOG signal and blue colored signal is the noisy signal. Fig 3(b) is the estimated EEG signal. Where black

Colored signal is the noisy EEG data and green colored signal is the estimated EEG signal by using wavelet modified threshold method. Fig 3(c) is the comparison of power spectral densities. Where red colored signal is the noisy PSD and blue colored signal is the filtered PSD signal.

From the table we can observe that comparison of MSE, PSNR, and Elapsed times. PCA adaptive threshold method will gives the best PSNR value compares to other algorithms but the elapsed time will be slightly higher than PCA method due to adaptive threshold. In adaptive threshold method for each low frequency it will adopt a threshold value. So the elapsed time will be slightly greater than PCA method. In EEG modified threshold method the PSNR value is very low compared to other methods. This is because of inter band interference between different low frequency bands. Because mixing of low frequency band with other frequency band the PSNR value decreases when reconstructing the signal.

V. CONCLUSION

The performance of two methods mainly PCA adaptive threshold and wavelet threshold methods are discussed in this paper. In PCA adaptive threshold method the elapsed time is slightly less than the other methods. To improve the elapsed time we can use the more efficient

REFERENCES

[1]. Jimy Psein, “Detection and removal of eye blink artifacts from EEG using wavelet analysis and independent component analysis”, Thesis, RIT, New York, 2007.

[2]. P.He, G.Wilson, C.Russell, “Removal of ocular artifacts from EEG by adaptive filtering”, Med. Biol. Eng. Comput., 2004, 42,407-412, 2004.

[3]. Rebecca Romo-Vazquez, Radu Ranta,Valarie Louis-Dorr, Didier Maquin, “ Ocular artifacts removal in scalp EEG: Combining ICA and wavelet de noising”, Nancy – University, CNRS.

[4]. Senthil, R.Arumuganathan, K.Sivakumar, and C.Vimal, “Removal of ocular artifacts in the EEG through wavelet transform without using an EOG reference channel”, Int.J. Open Problems Compt.Math., Vol.1, No.3, December 2008.

[5]. P.Senthil, R.Arumuganathan, K.Sivakumar,

C.Vimal , “An adaptive method to remove ocular artifacts from EEG signals using Wavelet transform”, Journal of Applied Sciences Research, 5(7): 741-745, 2009.

[6]. S.G.Mallat, “ A theory for multi resolution signal decomposition: The wavelet representation,” IEEE Trans. On Pattern Analysis and Machine Intell., Vol.2, No.7, (1989), pp.674-693.

❑❑❑