Detection and Removal of artefacts from EEG signal using sign based LMS Adaptive Filters

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Abstract- In this paper we proposed signed LMS based adaptive filters for noise cancellation in the EEG signal. EEG is most commonly used for the diagnosis of brain disorders. Good quality EEG is generally required by the physician for interpretation and identification of brain disorders. But in real time, EEG signals are corrupted by artefacts. Different filter structures are proposed using signed LMS algorithms to eliminate Eye blink artefacts and ECG artefacts are the common artefacts present in EEG traces. Finally we have applied these algorithms on real EEG signals obtained from the CHB-MIT data base and compared the performance with the conventional LMS algorithm. Simulation results show that the performance of the signed regressor LMS algorithm is superior to that of conventional LMS algorithm in terms of computational complexity. Also the signal to noise ratio (SNR) values are very much closer to conventional LMS algorithm.

Keywords: Adaptive filtering, Artefact, ECG, EEG, LMS algorithm, Noise cancellation, Signal to Noise Ratio.

1 Introduction

The electroencephalogram (EEG) is a graphical representation of Brain's functionality and is an important tool used for diagnosis of brain disorders.The EEG identification is very complex due to the fact that the cerebral signals have several origins. Therefore, the noise removal is of the prime necessity to make easier data interpretation and representation and to recover the signal that matches perfectly a brain functioning. The purpose of this paper is to devise an efficient means for denoising EEG that is subject to pathological changes. A common problem faced during the clinical recording of the EEG signals is the Eye-blinks and movement of the eye balls that produce Ocular artefacts and ECG artefacts. Many approaches have been reported in the literature to address EEG enhancement [2]-[4]. C. Fortgens [2] proposed a method for removal of eye movement and ECG artifacts from the non-cephalic reference EEG. P.LeVan [3] introduced another strategy which automates the process of artefact removal based on independent component analysis and Bayesian classification. R.J. Croft [4] reviews a number of methods of dealing with ocular artefact in the EEG, focusing on the relative merits of a variety of EOG correction procedures. Several papers have been presented in the area of biomedical signal processing where an adaptive solution based on the LMS algorithm is suggested [5]-[7]. The objective of an adaptive filter [1] is to change 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. A Garces Correa [5] proposed a cascade of three adaptive filters based on a Least Mean Squares (LMS) algorithm to reduce the common artifacts present in EEG signals without removing significant information embedded in these records. SaeidMehrkanoon [6] proposed LMS algorithm for real time ocular and facial muscle artifacts removal from EEG signals. P. Senthil Kumar [7] proposed an adaptive filtering method for removing ocular artifacts from EEG recordings using wavelet transform. In [8] S. Romero et al. presented an application of Regression and Blind Source Separation methods for ocular artefact removal in EEG signals.

Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behavior according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. The adaptive filters essentially minimizes the mean-squared error between a primary input, which is the noisy EEG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with EEG in the primary input. Our work elaborates on LMS approach using improved signed versions of LMS algorithms. Thus far, to the best of the author's knowledge, sign based LMS algorithm is not used in the contest of EEG signal noise cancellation. These algorithms enjoy less computational complexity because of the sign present in the algorithm. In the literature, there exist three versions of the signed LMS algorithm, namely, the sign-regressor algorithm, the sign algorithm and the sign-sign algorithm. All these three require only half as many multiplications as in the LMS algorithm, thus making them attractive from practical implementation point of view [9] [10]. Finally to study the performance of the filter structures which effectively remove the artefacts from the EEG signal we carried out simulations on CHB-MIT database. The simulation results show that the performance of the sign based algorithms is comparable with LMS counterpart in terms of signal to noise ratio improvement (SNRI). The structure of the paper is as follows. In Section II, the fundamentals of LMS algorithms and developments of sign based algorithms are discussed. In Section III we have discussed about the Simulation results with Mat Lab using LMS, SRLMS, SLMS and SSLMS algorithms. Finally conclusions are presented in Section IV.

2 PROPOSED IMPLEMENTATION

2.1 Basic Adaptive Filtering Structure

Figure 1 shows an adaptive filter with a primary input that is an EEG signal s1 with additive noise n1. While the reference input is noise n2, possibly recorded from another generator of noise n2 that is correlated in some way with n1. If the filter output is y and the filter error e= (s1+n1)-y, then squaring on both sides results

$$e2= s_1^2 + (n_1 - y)^2 + 2s_1(n_1 - y) \qquad (1)$$

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$$E[e2]=E[s_1^2] + E[(n_1 - y)^2] \qquad (2)$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s1. The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs.

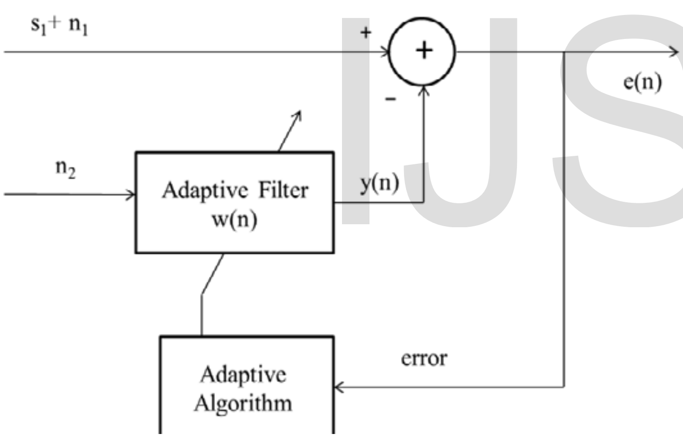

Fig.1 Adaptive filter Structure

2.2 Sign LMS based Adaptive Algorithms

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e(n) is minimized in the mean-square sense. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function ξ(n) = E[e2 (n)] by its instantaneous coarse estimate. The error estimation e(n) is

$$e(n) = d(n) – w(n)\ \Phi(n) \qquad (3)$$

Coefficient updating equation is

$$w(n+1) = w(n) + \mu\ \Phi(n)\ e(n) \qquad (4)$$

Where μ is an appropriate step size to be chosen as 0 < μ <(2 / tr R) for the convergence of the algorithm.
The most important members of simplified LMS algorithms are:

Signed-Regressor LMS Algorithm (SRLMS)

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap-input vector x(n) with the vector sgn{x(n)}. Consider a signed regressor LMS based adaptive filter that processes an input signal x(n) and generates the output y(n) as per the following:

$$y(n) = w\ t\ (n)x(n) \qquad (5)$$

where, w(n) = [w0(n), w1(n), … , wL-1(n)]t is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$w(n+1) = w(n) + \mu\ \mathrm{sgn}\{\Phi(n)\}e(n) \qquad (6)$$

Because of the replacement of Φ(n) by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

Sign LMS Algorithm (SLMS)

This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign. This leads to the following recursion:

$$w(n+1) = w(n) + \mu\ \Phi(n)\ \mathrm{sgn}\{e(n)\} \qquad (7)$$

Sign – Sign LMS Algorithm (SSLMS)

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$w(n+1) = w(n) + \mu\ \mathrm{sgn}\{\Phi(n)\}\ \mathrm{sgn}\{e(n)\} \qquad (8)$$

where sgn{ . } is well known signum function,

e(n) = d(n) – y(n) is the error signal.

The sequence d(n) is the so-called desired response available during initial training period

3 SIMULATION RESULTS

To show that sign based LMS algorithms are really effective in clinical situations, the method has been validated using several EEG recordings with a wide variety of wave morphologies from CHB-MIT scalp EEG database. We used the benchmark Massachusetts Institute of Technology and Children's Hospital Boston (CHB-MIT) scalp EEG database recordings as the reference for our work. The CHB-MIT Scalp

EEG database contains recordings grouped into 23 cases obtained from 22 subjects, studied by the BIH Laboratory ages 3 years to 22 years. Each case contains between 9 and 42 continuous files from a single subject. In most of the cases, the files contain exactly one hour of digitized EEG signals, although those belonging to some cases are two hours and four hours long in which seizures recorded are shorter. The recordings were digitized at 256 samples per second with 16-bit resolution. Most files contain 23 EEG signals (24 or 26 in a few cases). The International 10-20 system of EEG electrode positions and nomenclature was used for these recordings. In our experiments we have considered a dataset of five EEG records (chb01, chb02, chb03, chb04 and chb05) to ensure the consistency of results.

3.1 Eye Blink Artefact Removal

In our simulation, first we collected 600 samples of EEG signal and corrupted with Eye blink noise. This signal is applied as primary input to the adaptive filter shown in figure 1. The reference signal is an Eye Blink noise, the output of the filter is recovered signal. The experiment is performed over the dataset and average SNR is considered to compare the performance of the algorithms. These results for chb01 are shown in figure 2. In this simulation μ for all the filters is chosen as 0.001 and the filter length as 5. For all the figures in this section number of samples is taken on x-axis and amplitude on y-axis, unless stated. Table 1 shows the SNR for the dataset. In SNR measurements it is found that signed-regressor LMS algorithm gets average SNR as 7.0187 dB, sign LMS gets 6.6743 dB, sign-sign LMS gets 6.2527 dB and conventional LMS algorithm gets 7.1812 dB. From Table 1 it is clear that the sign regressor LMS algorithm filters the Eye Blink noise efficiently comparable to LMS filter with reduced number of computations.

Table 1: SNRI Contrast of sign based LMS algorithms for the removal of Eye Blink artefact

Record No	LMS	SRLMS	SLMS	SSLMS
Chb01	6.7289	6.4583	5.9205	5.5242
Chb02	7.3538	7.2734	6.9327	6.3485
Chb03	7.5329	7.3824	7.1943	6.7404
Chb04	6.4368	6.3865	6.0386	5.8139
Chb05	7.8539	7.5932	7.2854	6.8365
Average	7.1812	7.0187	6.6743	6.2527

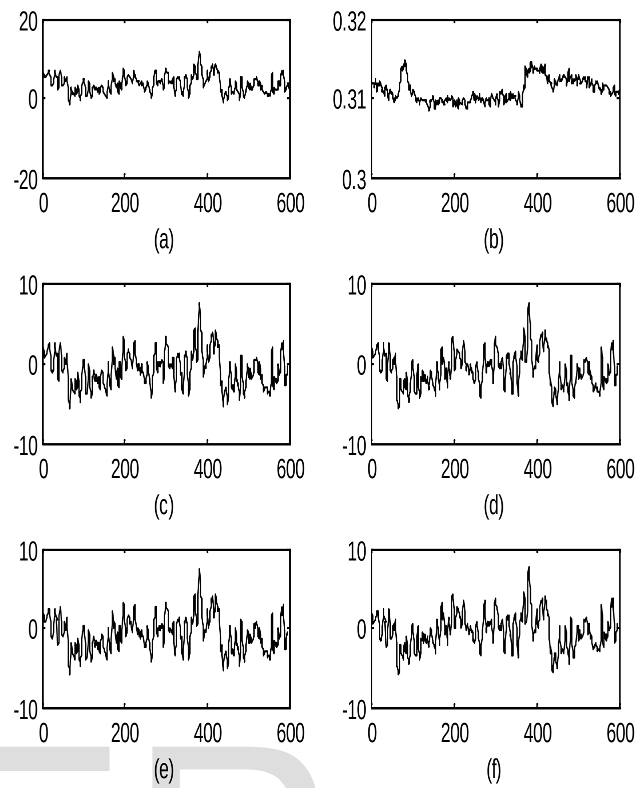

Fig.2: Typical filtering results for Eye Blink noise cancellation in EEG traces using sign based LMS algorithm: (a) EEG signal(chb01) combined with Eye Blink noise, (b) Real Eye Blink noise, (c) recovered signal using LMS algorithm, (d) recovered signal using SRLMS algorithm, (e) recovered signal using SLMS algorithm,(f) recovered signal using SSLMS algorithm.

3.2 Electrocardiogram(ECG) Artefact

In this experiment, first we collected 600 samples of EEG signal (chb01) and corrupted with real ECG artefact, it is used as primary input to the adaptive filter of figure 1. The algorithms are applied on entire dataset. Simulation results for chb01 are shown in figure 3. For evaluating the performance of the proposed adaptive filter structures we have measured the average SNR and compared with conventional LMS algorithm. The sign-regressor LMS algorithm gets average SNR as 7.3576 dB, sign LMS gets 6.9093 dB, sign-sign LMS improves 6.2387 dB and conventional LMS algorithm gets 7.5330 dB. From Table 2 it is clear that the sign regressor LMS algorithm filters the ECG noise efficiently comparable to LMS filter with reduced number of computations.

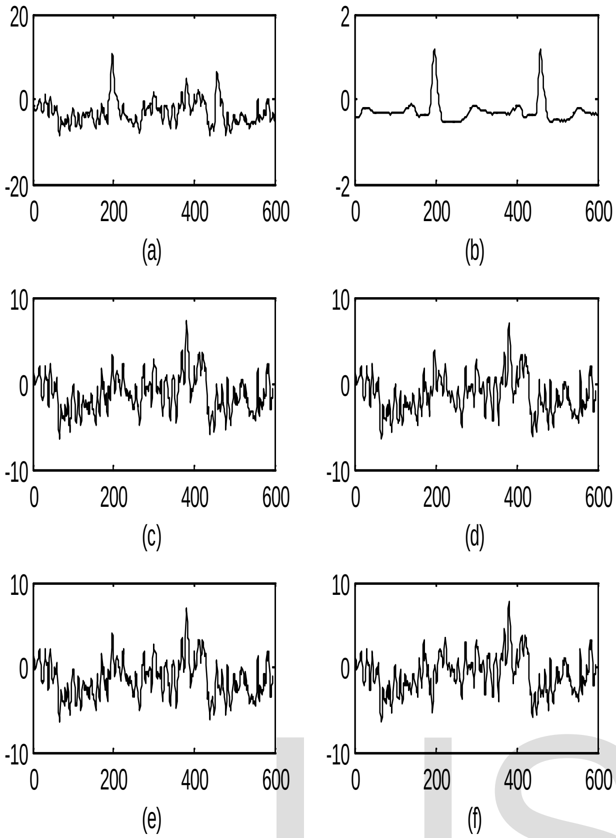

Fig.3: Typical filtering results for ECG noise cancellation in EEG traces using sign based LMS algorithm: (a) EEG signal(chb01) combined with ECG noise, (b) Real ECG noise, (c) recovered signal using LMS algorithm, (d) recovered signal using SRLMS algorithm, (e) recovered signal using SLMS algorithm, (f) recovered signal using SSLMS algorithm.

Table 2: SNRI Contrast of sign based LMS algorithms for the removal of ECG artefact

Record No	LMS	SRLMS	SLMS	SSLMS
Chb01	7.9145	7.8206	6.8235	5.2459
Chb02	7.4193	7.3204	6.8637	6.4183
Chb03	7.3274	7.1738	6.9375	6.4953
Chb04	7.3947	7.0438	6.7384	6.2486
Chb05	7.6193	7.4295	7.1837	6.7854
Average	7.5330	7.3576	6.9093	6.2387

4 CONCLUSION

In this paper the problem of noise removal from EEG using Signed LMS based adaptive filtering is presented. For this, the same formats for representing the data as well as the filter coefficients as used for the LMS algorithm were chosen. As a result, the steps related to the filtering remain unchanged. The proposed treatment, however exploits the modifications in the weight update formula for all categories to its advantage and thus pushes up the speed over the respective LMS-based realizations. Our simulations, however, confirm that the corresponding show-down effect with regard to the algorithm convergence is quite minor and is acceptable for all practical purposes. From the simulation results it is clear that the signed regressor LMS algorithm performs better than LMS in terms of computational complexity. Also the SNR values of SRLMS are very close to that of conventional LMS and hence it is more suitable.

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