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ELECTROENCEPHALOGRAM ENHANCEMENT USING SIGN BASED NORMALIZED ADAPTIVE FILTERING TECHNIQUES

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ABSTRACT

In this paper Adaptive filter is used as a primary method to filter the Electroencephalogram (EEG) or brain signal, as it does not require any priori information about the signal statistical characteristics. Several simple and efficient sign based normalized adaptive algorithms are presented to cancel the noise in EEG signal. These are Normalized sign regressor Least Mean Square (NSRLMS), Normalized sign Least Mean Square (NSLMS) and Normalized sign sign Least Mean Square (NSSLMS). These algorithms enjoy less computational complexity because of the sign present in the algorithm and good filtering capability because of the normalized term. The filters developed using these algorithms are computationally superior with multiplier free weight update loops. Based on these considerations NSRLMS, NSLMS and NSSLMS adaptive noise cancellers are developed for EEG signal enhancement. Power line interference (PLI) and Respiration artefacts are primarily considered for denoising. Finally we have applied the algorithms on EEG signals obtained from CHB-MIT database for comparison of performance. The comparison of proposed schemes and conventional LMS indicates that NSRLMS outperforms existing realizations in noise reduction.

KEYWORDS: Normalized adaptive algorithms, computational complexity, noise canceller, PLI.

INTRODUCTION

EEG recording is routinely used to check epilepsy and brain disorders. The EEG recording consists of numerous artefacts which should be minimized for clinical monitoring and good diagnosis. The predominant artefacts present in EEG signal include Power Line interference (PLI) and Respiration Artefact (RA). The extraction of high-resolution EEG signals from recordings which are contaminated with background noise is an important issue to investigate. In general most of the bioelectrical signals are nonstationary, so the filter which we use should change its coefficients in accordance with the input signal. Several filtering techniques are presented in literature for EEG analysis which includes both adaptive and nonadaptive techniques. Vandana Roy et al. [1] proposed NLMS Based Approach to remove artefacts from EEG Signals using ICA and Double Density Wavelet Transform. Recently Hongda Wang et al. [2] established a framework for seizure detection in EEG signal using Nonlinear adaptive filter and Kalman filter. For LMS algorithm based filters the reference inputs are deterministic functions and are defined by a periodically extended, truncated set of orthonormal basis functions. In such a case, the LMS algorithm operates on an instantaneous basis such that the weight vector is updated for every new sample within the occurrence based on an instantaneous gradient estimate. In a study, however, a steady state convergence analysis for the LMS algorithm with deterministic reference inputs showed that the steady-state weight vector is biased and thus the adaptive estimate does not approach the Wiener solution [3]. To handle this drawback another strategy was considered for estimating the coefficients of the linear expansion, namely, the block LMS (BLMS) algorithm [4], in which the coefficient vector is updated only once for every occurrence based on a block gradient estimation. The BLMS algorithm has been proposed in the

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case of random reference inputs and when the input is stationary, the steady state misadjustment and convergence speed is same as the LMS algorithm. A major advantage of the block or the transform domain LMS algorithm is that the input signals are approximately uncorrelated. . Apart from these several adaptive signal processing techniques are also published, e.g., In [5] NLMS algorithm with decreasing step size was proposed which converge to the global minimum, and Ning Li et al. [6] proposed a variable step size NLMS algorithm with faster convergence rate. S.C.Douglas [7], [8] and Markus Rupp [9] presented many data nonlinear LMS algorithms for noise reduction which can be specially utilized for biomedical applications.

In this paper we proposed several sign variants of Normalized LMS algorithm which are Normalized Sign Regressor LMS (NSRLMS), Normalized Sign LMS (NSLMS) and Normalized Sign Sign LMS (NSSLMS) algorithms. Based on these algorithms adaptive filters are designed which essentially reduces 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. Finally to evaluate the performance of these filter structures, we carried out simulations on CHB-MIT database. The performance of the considered algorithms is measured in terms of signal to noise ratio improvement (SNRI), EMSE and Misadjustment. The structure of the paper is as follows. In Section II, the fundamentals of NLMS algorithms and its sign variant algorithms for removal of PLI and Respiration artefacts are discussed. In Section III we have discussed about the Simulation results using Mat Lab for PLI and RA removal using LMS, NLMS, NSRLMS NSLMS and NSSLMS algorithms. Finally conclusions are presented in Section IV.

PROPOSED IMPLEMENTATION

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.

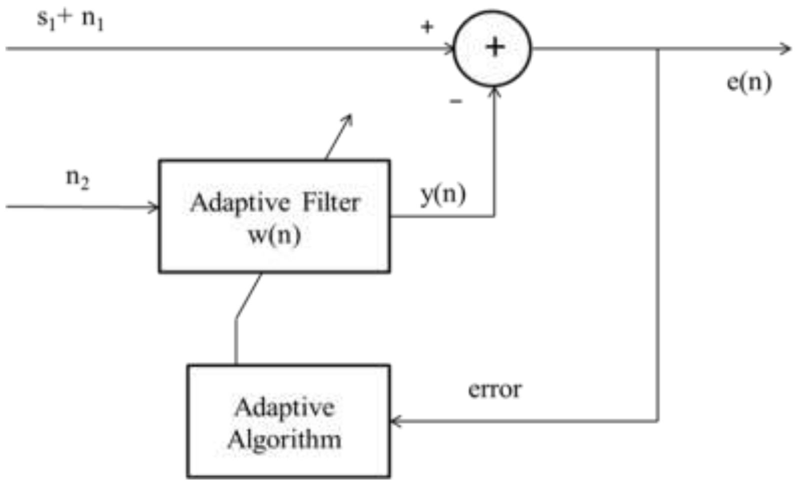

Figure 1 Adaptive Filter structure

2.1 Conventional LMS Algorithm & its Sign Variant Algorithms

The weight update equation of conventional LMS algorithm is

$w(n+1) = w(n) + \mu\, x(n)\, e(n)$ (1)

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)}.

$w(n+1) = w(n) + \mu\, \mathrm{sgn}\{x(n)\}e(n)$ (2)

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:

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w(n+1) = w(n) + μ x(n) sgn{e(n)} (3)

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) + μ sgn{x(n)} sgn{e(n)} (4)

2.2 Proposed Normalized LMS (NLMS)Algorithm

One of the problems in design and implementation of the LMS adaptive filter is the selection of the step size (μ). For the stationary process the LMS algorithm converges in the mean if $0 < \mu < \frac{2}{\lambda_{max}}$ and converges in the mean square if $0 < \mu < \frac{2}{tr(R_x)}$, however, since the R_x is generally unknown then either, λ_{max} or R_x, must be estimated in order to use these bounds. The bound on the step size for mean-square convergence:

$$0 < \mu < \frac{2}{\boldsymbol{x}^T(n)\boldsymbol{x}(n)}$$

More over the upper bound is given as

$$\mu(n) = \frac{\mu}{\boldsymbol{x}^T(n)\boldsymbol{x}(n)} = \frac{\mu}{||\boldsymbol{x}(n)||2}$$

To overcome the problem of small tap input vector x(n) we modify the above recursion by adding a small positive constant ε. The parameter ε is set to avoid denominator eing too small and step size parameter is too big. Now the step size parameter is written as,

$$\mu(n) = \frac{\mu}{\varepsilon + ||\boldsymbol{x}(n)||2} \quad (5)$$

where $\mu(n)$ is a normalized step size with $0 < \mu < 2$. Replacing μ in the LMS weight vector update equation (1) with μ (n) leads to the NLMS, which is given as

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{||\boldsymbol{x}(n)||2} e(n)\boldsymbol{x}(n) \quad (6)$$

With the normalization of the LMS step size by $||\boldsymbol{x}(n)||^2$ in the NLMS algorithm the noise amplification problem is diminished. Although the NLMS algorithm bypasses the problem of noise amplification, we now face a similar problem that occurs when $||\boldsymbol{x}(n)||$ becomes too small. So an alternative is to do the following modification to the NLMS algorithm:

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu}{\varepsilon + ||\boldsymbol{x}(n)||2} e(n)\boldsymbol{x}(n) \quad (7)$$

This normalization results smaller step size values than conventional LMS. The normalized algorithm usually converges faster than the LMS algorithm, since it utilizes a variable convergence factor aiming at the minimization of the instantaneous output error. The step size parameter μ of this algorithm is independent of the input signal power. But this algorithm required more computation to evaluate the normalization term $||\boldsymbol{x}(n)||^2$. At the same time NLMS requires less a priori information than LMS. So the resulting mean-square error of NLMS is larger than that of LMS.

2.3 Extension to Sign based realizations of NLMS algorithm

Less computational complexity is obtained by clipping either the input data or estimation error. The LMS algorithms based on clipping of error or data are SRLMS, SLMS and SSLMS. The combination of these three simplified algorithms with normalized algorithms provides fast convergence and reduced computational complexity. The advantage of the NLMS algorithm is that the step size can be chosen independent of the input signal power and the number of tap weights. Hence the NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm. On the other hand some additional computations are required to compute μ(n). In order to cope up with both the complexity and convergence issues without any restrictive tradeoff, we propose normalized sign based algorithms such as normalized signed regressor LMS (NSRLMS) algorithm, normalized sign LMS (NSLMS) algorithm and normalized sign–sign LMS (NSSLMS) algorithm for the removal of noise from EEG signal.

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2.3.1 Normalized Sign Regressor LMS (NSRLMS) algorithm

Normalized signed regressor LMS algorithm is a counter part of the NLMS algorithm; this is derived from SRLMS, where the normalizing factor for the SRLMS equals the absolute values of the input signal vector components. Here no multiplication operation is required to compute the normalization factor. NSRLMS enjoys the advantages of both SRLMS and NLMS algorithm. Due to the presence of normalizing factor, the steady state error does not depend on the reference input signal power. By combining (2) and (7) the weight update recursion for NSRLMS can be written as,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)e(n)Sign\{\boldsymbol{x}(n)\} \qquad (8)$$

2.3.2Normalized Sign LMS (NSLMS) algorithm

The sign algorithm takes the signum of the error signal. This algorithm is particularly attractive for its assured convergence in a disturbance and ease of implementation. The SLMS converges much slower than the LMS algorithm for the same steady state error. The combination of SLMS and NLMS enjoys the benefits of both less complexity and fast convergence. Using (3) and (7) the weight update recursion for NSLMS can be written as,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)\ Sign\ \{e(n)\}\boldsymbol{x}(n) \qquad (9)$$

2.3.3 Normalized Sign Sign LMS (NSSLMS) algorithm

Further simplification of the sign algorithm is sign-sign algorithm. Here the signum of the reference input is used in addition to the signum of error signal. Thus this requires only one bit multiplication. Similar to NSRLMS and NSLMS, NSSLSM can be obtained by combining SSLMS and NLMS algorithm. Using (4) and (7) the recursion for NSSLMS can be written as,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu(n)\ Sign\ \{e(n)\}Sign\{\boldsymbol{x}(n)\} \qquad (10)$$

SIMULATION RESULTS

To show that sign based NLMS 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 [10]. 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 Powerline Interference Artefact Removal

In our simulation, first we collected 600 samples of EEG signal and corrupted with PLI noise. This signal is applied as primary input to the adaptive filter shown in figure 1. The reference signal is an PLI 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. From SNR measurements it is found that NLMS algorithm outperforms conventional LMS algorithm with an average SNR of 16.0881. And NSRLMS gives high SNRI among all the sign variants of NLMS. Table 2 shows the comparison of EMSE and Misadjustment (M_{adj}) using normalized algorithms. Here also NLMS has lowest EMSE and M_{adj} followed by NSRLMS. But we consider NSRLMS algorithm as the best algorithm to filter PLI noise as its SNR, EMSE and M_{adj} values are very close to that of NLMS along with reduced number of computations.

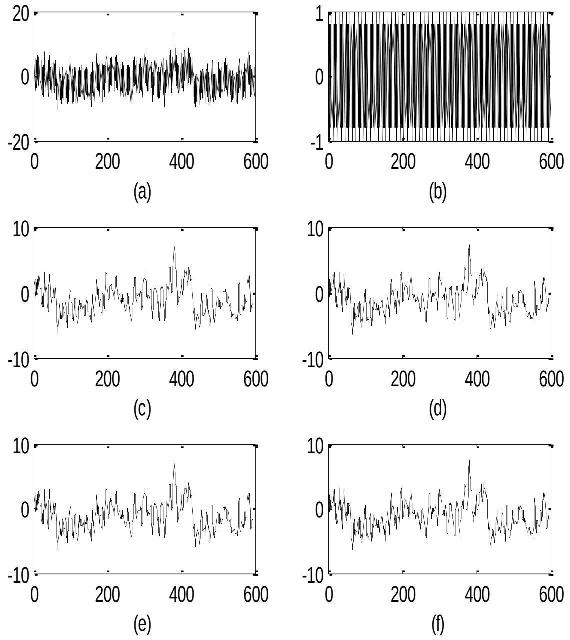

Fig. 2:Typical filtering results for PLI cancellation using data normalized adaptive filtering techniques: (a) EEG signal (chb01) with PLI, (b) real PLI noise (c) recovered signal using NLMS algorithm, (d) recovered signal using NSRLMS algorithm, (e) recovered signal using NSLMS algorithm, (f) recovered signal using NSSLMS algorithm.

Table 1 Performance Contrast of normalized algorithms for the removal of PLI

Rec.No.	LMS	NLMS	NSRLMS	NSLMS	NSSLMS
Chb01	7.1584	15.9545	14.7536	13.3458	11.9274
Chb02	7.9482	16.3824	15.3495	14.8354	12.3495
Chb03	7.4816	15.6843	14.2939	13.8494	11.7833
Chb04	6.8396	15.7291	14.8365	13.3672	11.7456
Chb05	8.4957	16.6902	15.2964	14.5203	12.8452
Average	**7.5847**	**16.0881**	**14.9059**	**13.9836**	**12.1302**

Table 2 Comparison of EMSE and M_{ad} for PLI artefact using data normalized algorithms

Rec.No.	NLMS		NSRLMS		NSLMS		NSSLMS	
	EMSE	**M_{adj}**	**EMSE**	**M_{adj}**	**EMSE**	**M_{adj}**	**EMSE**	**M_{adj}**
Chb01	-27.4025	0.0692	-25.5039	0.0912	-24.3178	0.1047	-21.2879	0.1082
Chb02	-27.3689	0.0487	-26.4842	0.0784	-24.7821	0.0746	-22.3047	0.0846
Chb03	-28.5368	0.0494	-26.9583	0.0628	-23.4926	0.0742	-21.9385	0.0921
Chb04	-28.1849	0.0538	-25.8524	0.0847	-23.9382	0.0926	-21.3819	0.1005
Chb05	-28.8743	0.0613	-27.2047	0.0734	-26.9239	0.0842	-23.8391	0.0926
Average	**-28.0731**	**0.0564**	**-26.4010**	**0.0781**	**-24.6911**	**0.0860**	**-22.1510**	**0.0956**

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3.2 Respiration Artefact Removal

In this simulation also, first we collected 600 samples of EEG signal and corrupted with Respiration noise. This signal is applied as primary input to the adaptive filter shown in figure 1. The reference signal is respiration 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 3. In this simulation µ for all the filters is chosen as 0.001 and the filter length as 5. Table 3 shows the SNR for the dataset. From SNR measurements it is found that NLMS algorithm outperforms conventional LMS algorithm with an average SNR of 16.007. And NSRLMS gives high SNRI among all the sign variants of NLMS. Table 4 shows the comparison of EMSE and Misadjustment (M_{adj}) using normalized algorithms. Here also NLMS has lowest EMSE and M_{adj} followed by NSRLMS. But we consider NSRLMS algorithm as the best algorithm to filter respiration noise as its SNR, EMSE and M_{adj} values are very close to that of NLMS along with reduced number of computations.

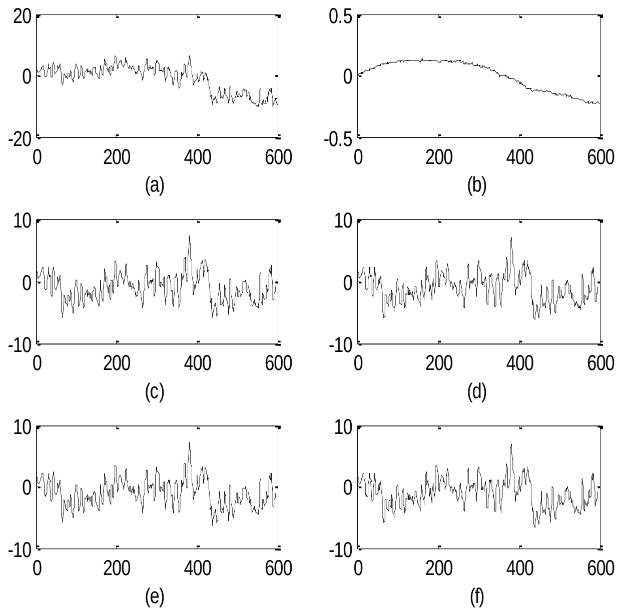

Figure 3: Typical filtering results for Respiration noise cancellation using data normalized adaptive filtering techniques: (a) EEG signal (chb01) with RA noise (b) real RA noise (c) recovered signal using NLMS algorithm, (d) recovered signal using NSRLMS algorithm, (e) recovered signal using NSLMS algorithm, (f) recovered signal using NSSLMS algorithm.

Table 3 Performance Contrast of normalized algorithms for the removal of Respiration Artefact.

Rec.No.	LMS	NLMS	NSRLMS	NSLMS	NSSLMS
Chb01	7.9214	16.0204	15.6743	13.5365	12.5687
Chb02	7.2396	15.6738	14.8273	12.8372	11.8271
Chb03	6.8238	15.4393	14.6268	12.3794	11.3842
Chb04	8.2458	16.9472	15.8374	13.9618	12.3943
Chb05	7.3846	15.9547	14.8146	12.2945	11.3172
Average	**7.5230**	**16.0070**	**15.1560**	**13.0018**	**11.8983**

Table 4 Comparison of EMSE and M_{ad} for Respiration artefact using data normalized algorithms

Rec.No.	NLMS		NSRLMS		NSLMS		NSSLMS	
	EMSE	**M_{adj}**	**EMSE**	**M_{adj}**	**EMSE**	**M_{adj}**	**EMSE**	**M_{adj}**
Chb01	-34.2308	0.0034	-32.9381	0.0059	-31.7092	0.0251	-28.2976	0.0334
Chb02	-31.3794	0.0082	-29.0349	0.0092	-25.4385	0.0112	-23.8502	0.0292
Chb03	-30.5329	0.0143	-26.9438	0.0235	-23.5938	0.0348	-21.4931	0.0391
Chb04	-34.7532	0.0086	-31.4925	0.0189	-29.4819	0.0229	-26.8493	0.0339
Chb05	-32.3672	0.0192	-28.4902	0.0241	-26.9485	0.0313	-25.9853	0.0348
Average	**-32.6531**	**0.0107**	**-29.7801**	**0.0163**	**-27.4340**	**0.0250**	**-25.2951**	**0.0340**

CONCLUSION

In this paper the EEG enhancement using sign based normalized LMS adaptive filters is proposed and tested on real EEG signals obtained from CHB-MIT data base. Simulation results confirm that the Normalized sign Regressor LMS (NSRLMS) filter reduces both PLI and Respiration noise efficiently with high signal to noise ratio, low EMSE and low Misadjustment along with reduced number of computations when compared to conventional LMS based filter.

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