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Simplified Algorithms for Artifact Removal in Brian Computer Interface Applications

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Abstract: In this paper some efficient and low computation complex signal conditioning algorithms are proposed for enhancement of electroencephalogram (EEG) signal in remote healthcare monitoring applications. In medical environment during EEG signal extraction, some artifacts contaminated and mask tiny features underlying EEG signal activity. Particularly in remote health care monitoring, low computational complexity filters are attractive. Hence, in this paper, we presented various efficient and less computation adaptive noise cancellers (ANCs) for enhancement of EEG signal. These methods mostly make use of simple addition and shift operations, and achieve considerable convergence speed over the other conventional methods. The proposed implementations are tested on real EEG signals recorded using emotive EEG system. Our experiments show that the proposed techniques give better performance compared to existing methods in terms of signal to noise ratio, computational complexity, convergence rate, excess mean square error and misadjustmen. This methodology is suitable in the analysis of brain computer interface (BCI) applications.

Keywords: Artifacts, Adaptive noise cancellers, Convergence, EEG, Health care monitoring.

1. INTRODUCTION

Electroencephalogram (EEG) is a test that records the electrophysiological activity of brain along the scalp. Due to its noninvasiveness, high temporal resolution, low cost and suitability for long-standing monitoring, EEG has been generally used for studying brain activity and pathological brain mechanisms [1]–[3]. These signals can be easily contaminated with various artifacts because they have small amplitudes and strong randomness. These signals are often contaminated with non-cerebral physiological activities. During the extraction EEG signal contaminated with various artifacts, which reduces the feature resolutions of the desired signal. The major artifacts are power line noise (PLN), ElectroMyoGram (EMG), Electrode Motion Artifacts (EMA), and Respiration Artifact (RA). Extraction of the EEG signal from these artifacts is mostly difficult task when compared to other types of noises associated to the electrocardiogram (ECG) and electrooculogram (EOG) [4]–[6]. To facilitate the neurologist these artifacts have to be eliminated for accurate diagnosis. Therefore high-resolution EEG signal extraction from the various artifact contaminations is an important task. The main aim of

EEG signal enhancement is to obtain the valid desired signal components from the artifacts and to present an EEG that facilitates easy and accurate analysis. Fixed coefficient filters are not suitable because the artifacts are random in nature. Based on the noise component the filter coefficients need to be updated automatically. For this we have to develop efficient adaptive noise cancellers (ANCs). However in practical cases, when the patient is in far location where a neurology specialist is not available for regular monitoring, biotelemetry based remote acquisition systems plays an important role in health care monitoring. To establish Brain Computer Interface (BCI) in a typical biotelemetry system the EEG recorder is interfaced with a computer.

In literature [7]–[10] several BCI systems are presented. BCIs were established to allow communication between human thought processes and a computer, with the goal of disabled patients assisting with motor function impaired as a result of disease, but whose mental functions are not affected severely [11]. The most advantageous selection for a BCI system reflects the equipment cost, as well as the spatial and temporal resolution essential for the particular application. Therefore a remote health monitoring network at the hospital establishes with the acquisition system, biotelemetry link, BCI, control station. In literature [12]–[15] several contributions are presented on enhancement of EEG signal using both adaptive and non-adaptive techniques. For a noise cancelation system less computational complexity is preferable, particularly in some specific applications such as wireless biotelemetry system, has remained a topic of intense research. As the EEG transmission data rate increases, the receiver filter's impulse response length also increases and thus the filter order. The resulting increase in complexity makes the real time operation of the biotelemetry system difficult.

In [16]-[18] less computational complexity techniques are used with a combination of Least Mean Square (LMS) algorithm to cardiac signal enhancement. By using the sign based algorithms the computational complexity can be reduced, namely, the signed regressor algorithm, the sign error algorithm and the sign-sign algorithm [19]. All these three algorithms are attractive from practical implementation point of view because they require only half as many multiplications as the LMS algorithm. The hybrid version of LMS and sign algorithms results Sign Regressor LMS (SRLMS), Sign LMS (SLMS) and sign LMS (SSLMS). In order to manage both the complexity and convergence issues without any restrictive tradeoff we developed various data normalized based adaptive filter [22] structures and block based [20] approach. These combinations result in six simplified adaptive algorithms namely, Normalized SRLMS (NSRLMS), Block Based NSRLMS (BBNSRLMS), Normalized Sign LMS (NSLMS), Block Based NSLMS (BBNSLMS), Normalized sign LMS (NSSLMS) and Block Based NSSLMS (BBNSSLMS). To study the filter structures performance which efficiently removes the artifacts from the EEG signals we carried out experiments on real signals recorded from humans. The theory of various algorithms and experimental results are presented in the next sections.

2. NORMALIZED SIGN BASED ADAPTIVE NOISE CANCELERS FOR EEG TELEMETRY

Let us consider a FIR filter with L coefficients. We take LMS algorithm for the filter weight coefficients adaptation. Using this LMS adaptive filter we constructed an ANC associated with an Emotive EEG recording system interfaced with a computer, the ANC structure is shown in Figure 1. $i(n)$ is the input sequence to the adaptive filter based on which the filter coefficients should be adjusted, desired signal is $d(n)$ which is recorded from patient, the weight update recursion is given as,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + \mathrm{S}\mathbf{i}(n)x(n) \tag{1}$$

where, $\mathbf{u}(n) = [u_0(n)u_1(n) \ldots u_{\mathrm{L}-1}(n)]^t$ is the tap weight vector at the n^{th} index, $\mathbf{i}(n) = [i(n)i(n-1) \ldots i(n-\mathrm{L}+1)]^t$, error signal $x(n) = d(n) - \mathbf{u}^t(n)\mathbf{i}(n)$ and S is the step-size parameter. In order to remove the noise from the EEG signal, the EEG signal $y_1(n)$ contaminated with noise signal $\eta_1(n)$ is applied as the desired sequence $d(n)$ to the adaptive filter shown in Figure 1. The reference signal $i(n)$ is $\eta_2(n)$ is a noise component and is correlated in some way with $\eta_1(n)$. Now the filter error becomes $x(n) = [y_1(n) + \eta_1(n)] - z(n)$. Where, z($n$) is the adapted FIR filter output and it is given by,

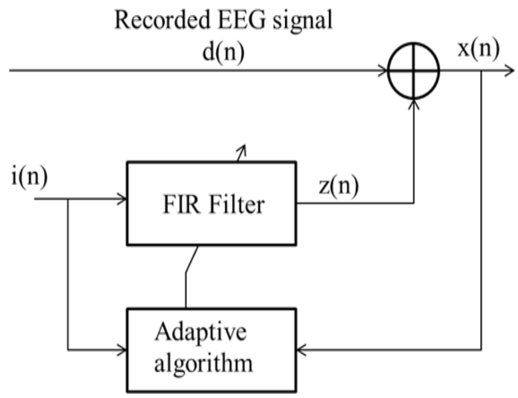

Figure 1: Structure of adaptive noise canceler

$$z(n) = \mathbf{u}^t(n)\mathbf{i}(n), \tag{2}$$

The mean-squared error (MSE) is calculated as,

$$\mathrm{E}[x^2(n)] = \mathrm{E}\{[y_1(n) - z(n)]^2\} + \mathrm{E}[\eta_1^2(n)] \tag{3}$$

Since $y_1(n)$ and $\eta_1(n)$ are uncorrelated, similarly $\eta_1(n)$ and $z(n)$ are uncorrelated the last two expectations are zero. MSE Minimization results in a filter output which is the best least-squares estimate of the signal $y_1(n)$.

The proposed ANCs make use of the *signum* function to either the error or the input data vector, or both [21], [19] have been derived from the LMS algorithm, for reducing the number of multiplications and additions. The weight update recursion of SRLMS, SLMS and SSLMS algorithms are given as follows,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + \mathrm{S}\ \mathrm{sgn}\{\mathbf{i}(n)\}\{x(n)\}, \tag{4}$$

$$\mathbf{u}(n+1) = \mathbf{u}(n) + \mathrm{S}\{\mathbf{i}(n)\}sgn\{x(n)\}, \tag{5}$$

and

$$\mathbf{u}(n+1) = \mathbf{u}(n) + \mathrm{S}\ \mathrm{sgn}\{\mathbf{i}(n)\}\mathrm{sgn}\{x(n)\}. \tag{6}$$

where, sgn$\{.\}$ is the well known signum function, i.e.,

$$\mathrm{sgn}\{x(n)\} = \begin{cases} 1 : x(n) > 0 \\ 0 : x(n) = 0 \\ -1 : x(n) < 0 \end{cases} \tag{7}$$

Among the above adaptive algorithms, the SRLMS, SLMS and SSLMS have a convergence rate and a steady-state error that are slightly poorer to those of the LMS algorithm. This can be explained as follows, Consider the SLMS algorithm with recursion equation,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + \mathrm{S}\{\mathbf{i}(n)\}\{x(n)/|x(n)|\}, \tag{8}$$

Since $\mathrm{sgn}[x(n)] = x(n)/|x(n)|$. This is rearranged as,

$$u(n+1) = u(n) + \left[\frac{\mathrm{S}}{|x(n)|}\right] i(n)x(n) \tag{9}$$

From the above equation it is clear that LMS algorithm with sign resembles a variable step size algorithm, $S'(n) = \{S/x(n)\}$. The $S'(n)$ increases, on an average, as the sign algorithm converges, since $e(n)$ decreases in magnitude. But as the filter converges and $x(n)$ becomes smaller in magnitude, $S'(n)$ becomes larger and increases convergence rate.

By making S to a value of power of two to make the hardware circuit simple with only Addition, subtraction and shift operations [21]. Normalized LMS (NLMS) algorithm is a fast convergent adaptive algorithm in which the step size is normalized with respect to input data vector [22]. The weight updates relation for NLMS algorithm is as follows,

$$u(n+1) = u(n) + \left[\frac{S}{a + i^t(n)i(n)}\right] i(n)x(n) \tag{10}$$

where, the variable step size parameter can be written as,

$$S(n) = \frac{S}{a + i^t(n)i(n)} \tag{11}$$

Here S is fixed step size as in LMS filter. a is set to avoid denominator becoming too small and step size parameter too big.

From the weight update equations of both LMS and NLMS given in (1) and (10), the update recursion of NLMS is a scaled version of LMS algorithm. The change in $u(n)$ is inversely proportional to the norm of input data vector $i(n)$. The $i(n)$ with a large normalized data quantity will cause some changes to $u(n)$ than a small normalization quantity. This normalization of data results smaller S values than LMS. The normalized filter usually converges quick than LMS filter, since it utilizes a variable convergence factor aiming at the minimization of the instantaneous output error. To accomplish less computational complexity we combine NLMS algorithm with sign based strategies to obtain NSRLMS, NSLMS and NSSLMS algorithms. The weight update recursions are written as,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S(n)\mathrm{sgn}\{\mathbf{i}(n)\}\{x(n)\}, \tag{12}$$

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S(n)\{\mathbf{i}(n)\}\mathrm{sgn}\{x(n)\}, \tag{13}$$

and

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S(n)\mathrm{sgn}\{\mathbf{i}(n)\}\mathrm{sgn}\{x(n)\}. \tag{14}$$

The additional strategies required to compute $S(n)$ in equations (12)-(14) can be reduced by using block based technique, in which the input data is divided into blocks and within each block with maximum magnitude is used to compute $S(n)$. With this, the weight update equation in (12)-(14) for $i_{Li} \neq 0$ and $c = 0$ takes the following form,

$$u(n+1) = u(n) + \frac{S}{i_{\mathrm{Li}}^2}\mathrm{sgn}\{i(n)\}\{x(n)\} \tag{15}$$

$$u(n+1) = u(n) + \frac{S}{i_{\mathrm{Li}}^2}\{i(n)\}\mathrm{sgn}\{x(n)\} \tag{16}$$

and

$$u(n+1) = u(n) + \frac{S}{i_{\mathrm{Li}}^2}\mathrm{sgn}\{i(n)\}\mathrm{sgn}\{x(n)\} \tag{17}$$

where, $i_{Li} = \max\{|i_k|, k \in B_i'\}$, $B_i' = \{i_L, i_{L+1}, ..., i_{L+L-1}\}$, $i \in B$. And for $i_{Li} = 0$ and $a = 0$ the equations (9)-(11) become $\mathbf{u}(n+1) = \mathbf{u}(n)$. These algorithms are known as BBNSRLMS, BBNSLMS and BBNSSLMS respectively.

The convergence characteristics of various algorithms discussed above are shown in Figure 2. From these characteristics it is conclude that NSRLMS is a little bit inferior to NLMS.

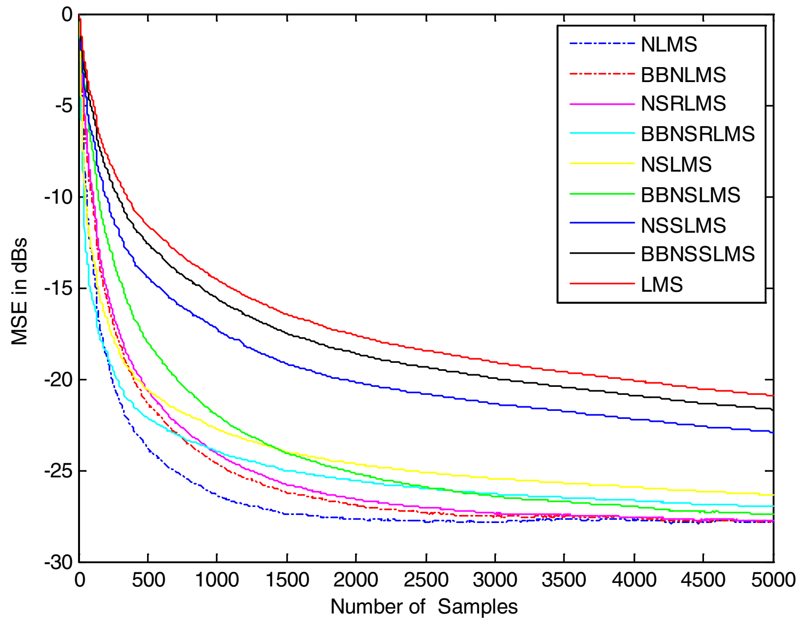

Figure 2: Convergence characteristics for various versions of LMS algorithm

3. SIMULATION RESULTS

To show that the proposed ANCs are really efficient in clinical situations, the method has been tested using a number of EEG recordings with a wide variety of wave morphologies recorded using the Emotive EPOC headset [24]. It has 14 data-collecting electrodes and 2 reference electrodes. The electrodes are placed in roughly the international 10-20 system and are labeled as such [25]. The encrypted data has been transmitted by headset wirelessly to a Windows-based machine; the wireless chip operates in the same frequency range as 802.11 (2.4GHz). We have recorded EEG signals using BCI with various artifacts from 6 subjects. All channels are sampled by head set at 128 samples/second, each of which is a 4-byte floating-point number equivalent to the single electrode voltage. The transmission rate of the EEG data from the relay laptop to the mobile phone is 4kbps per channel. In our experiment we have recorded 25,000 samples of EEG signal from a male person of age 41. For the performance analysis of proposed filter structures we have measured *Signal to Noise Ratio Improvement (SNRI)*, *Excess Mean Square Error (EMSE)*, *Misadjustment (MSD)* [15], [21] parameters, and compared with ANC with conventional LMS. The SNRI contrast of various artifact elimination is mentioned in Table 1. Table 2 gives the contrast of all algorithms in terms of EMSE, MSD for EEG record number 1. In our simulations we have taken a dataset of six EEG records: Record 1, Record 2, Record 3, Record 4, Record 5 and Record 6 to ensure the stability of results. Various ANCs are implemented using LMS, NLMS, BBNLMS, NSRLMS, BBNSRLMS, NSLMS, BBNSLMS, NSSLMS and BBNSSLMS algorithms. Our simulation model consists of a noise source, which produces a noise reference signal. This reference signal is a combination of PLN, EMG, RA and EMA artifacts. For all ANCs we give this signal as reference signal. Various experiments were performed to remove various artifacts from the recorded EEG signals. These results are shown in Figure 3 to Figure 6.

A. Adaptive Cancelation of Power Line Noise (PLN)

This experiment demonstrates Power Line Noise (PLN) cancelation. The input to the filter is EEG signal contaminated with PLN of frequency 50Hz and sampled at 160Hz recorded from a male person of age 41. The reference signal is taken from noise generator. The output of the filter is recovered signal. The EMSE behavior of several ANCs based on sign LMS algorithm are shown in Figure 3. We have done this experiment on six EEG records for ten times and averaged. Various performance measures like, SNRI, EMSE, MSD are tabulated in Tables 1 and 2. In SNRI measurements it is found that NLMS algorithm gets SNRI of 12.6327dB, BBNLMS gets 11.3835dB, NSRLMS gets 11.9273dB, BBNSRLMS gets 11.0373dB, NSLMS gets 8.3634dB, BBNSLMS gets 7.9464dB, NSSLMS gets 7.5735dB and BBNSSLMS gets 7.1745dB, where as the conventional LMS algorithm improves to 5.3735dB.

Table 1
Performance of various ANCs in terms of SNRI during EEG enhancement
(all values in dbs)

Noise	*Rec.no*	*LMS*	*NLMS*	*BBNLMS*	*NSRLMS*	*BBNSRLMS*	*NSLMS*	*BBNSLMS*	*NSSLMS*	*BBNSSLMS*
PLN	1	5.3735	12.6327	11.3835	11.9273	11.0373	8.3634	7.9464	7.5735	7.1745
	2	6.8473	14.6473	13.8692	13.5378	13.2527	9.6359	8.9362	8.3638	7.1837
	3	4.1736	11.8593	10.6427	10.3836	9.9363	7.7836	7.3749	6.9564	6.3638
	4	6.3632	15.7369	14.8468	14.6332	14.2743	11.3836	10.9372	10.3632	9.6645
	5	7.8854	14.7464	13.4837	13.2839	12.9604	12.4786	9.8847	9.4623	9.1236
RA	1	4.7343	11.8463	11.6058	10.6605	10.4729	9.7453	9.4856	7.7849	7.4217
	2	6.7653	13.3836	13.1107	12.7492	12.4728	11.7469	11.4904	9.7833	9.3342
	3	3.8762	10.6936	10.5836	9.8873	9.5053	8.7748	8.1063	6.9063	6.3967
	4	5.8835	12.7353	12.5832	11.9737	11.4895	10.8528	10.6574	8.7453	8.2846
	5	4.1735	10.2548	10.1038	9.3363	8.6648	7.9053	6.9037	4.8462	4.4241
EMG	1	4.8353	9.9363	9.5343	8.8363	8.4948	7.7462	7.4906	6.7738	6.2296
	2	6.8963	14.8463	14.4527	13.5420	13.1322	12.7352	12.3462	11.4895	11.3745
	3	5.7832	11.1835	11.0845	10.3729	9.5735	8.5274	8.2487	7.4867	6.5648
	4	7.7353	16.8458	16.2634	15.4837	15.2326	14.5527	14.0503	13.7483	13.2745
	5	5.6444	11.9484	11.6838	10.1293	9.9035	8.3027	8.1003	7.5903	7.2842
EMA	1	5.3795	9.4826	9.3729	8.8094	8.3067	7.9704	7.5097	7.1054	6.8809
	2	4.8836	8.8382	8.0353	7.8490	7.2219	6.8964	6.6907	6.4409	6.1067
	3	7.6353	11.6232	11.1837	10.7593	10.0869	9.8094	9.5872	9.2845	9.0453
	4	6.3783	10.9836	10.2437	9.5534	9.2264	8.6092	8.4539	8.1046	7.8453
	5	5.8943	9.7353	9.3452	8.7834	8.2063	7.7095	7.6984	7.3950	6.9043

Table 2
Performance of various ANCs in terms of EMSE and MSD during EEG enhancement for record number 1
(all values in dbs)

Noise	*Characteristic*	*LMS*	*NLMS*	*BBNLMS*	*NSRLMS*	*BBNSRLMS*	*NSLMS*	*BBNSLMS*	*NSSLMS*	*BBNSSLMS*
PLN	EMSE	–15.8464	–28.0731	–27.6372	–25.7734	–23.9742	–23.5629	–21.5362	–20.6352	–19.8363
	MSD	0.0938	0.0773	0.0787	0.0868	0.0896	0.0899	0.0538	0.0576	0.0593
RA	EMSE	–17.7456	–29.7745	–28.9362	–27.8363	–26.9763	–25.7453	–24.7345	–22.6352	–22.2735
	MSD	0.0854	0.0548	0.0653	0.0685	0.0698	0.0742	0.0769	0.0796	0.0863
EMG	EMSE	–17.6452	–30.6352	–29.8464	–28.6463	–27.5837	–26.5342	–25.7484	–25.3734	–24.6647
	MSD	0.0978	0.0659	0.0687	0.0737	0.0779	0.0799	0.0848	0.0877	0.0947
EMA	EMSE	–17.7332	–30.8353	–29.6693	–27.7386	–26.7295	–25.5371	–24.6638	–24.2746	–23.7962
	MSD	0.1385	0.0768	0.0825	0.0967	0.0907	0.0934	0.0976	0.1057	0.1265

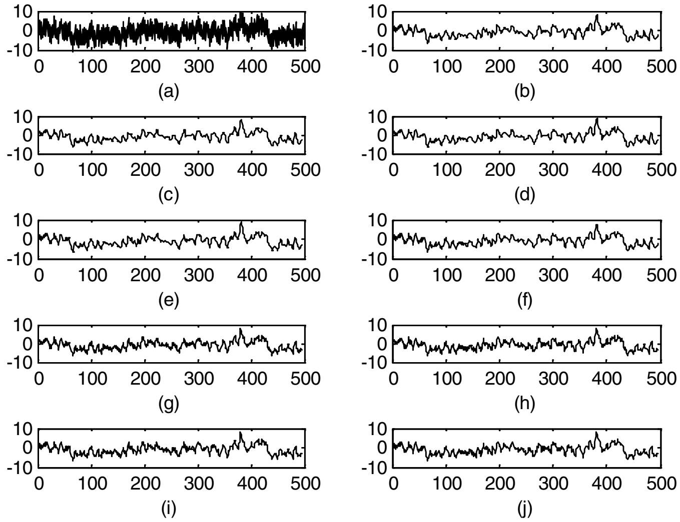

Figure 3: Typical brain signal enhancement results of PLN Cancelation (a) EEG Signal with PLN, (b) Filtered signal with LMS based ANC, (c) Filtered signal with NLMS based ANC, (d) Filtered signal with BBNLMS based ANC, (e) Filtered signal with NSRLMS based ANC, (f) Filtered signal with BBNSRLMS based ANC, (g) Filtered signal with NSLMS based ANC, (h) Filtered signal with BBNSLMS based ANC, (i) Filtered signal with NSSLMS based ANC, (j) Filtered signal with BBNSSLMS based ANC.

B. Adaptive Cancelation of Electro Mio Gram (EMG)

The contaminated EEG signal is applied as primary input to the adaptive filter of Figure 1, reference signal is taken from our noise generator. The Simulation results are shown in Figure 4. From the performance measure tabulated in Tables 1 and 2 it is clear that NLMS based noise canceller performs better than other algorithms. In SNRI measurements it is found that NLMS algorithm gets SNRI of 9.9363dB, BBNLMS gets 9.5343dB, NSRLMS gets 8.8363dB, BBNSRLMS gets 8.4948dB, NSLMS gets 7.7462dB, BBNSLMS gets 7.4906dB, NSSLMS gets 6.7738dB and BBNSSLMS gets 6.2296dB, where as the conventional LMS algorithm improves to 4.8353dB.

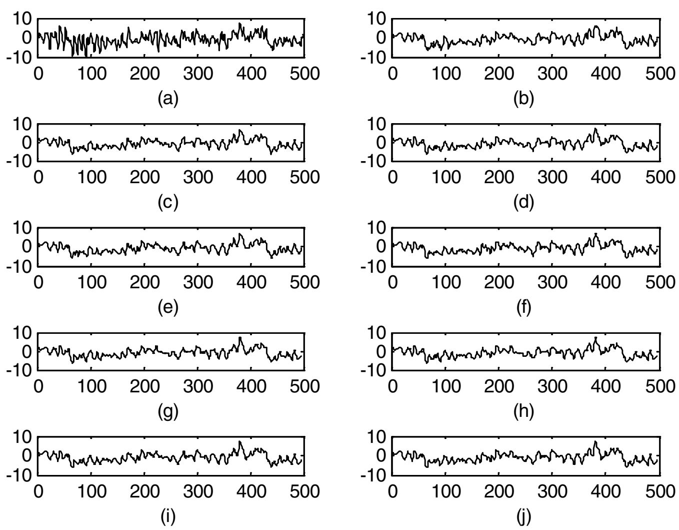

Figure 4: Typical brain signal enhancement results of EMG Cancelation (a) EEG Signal with EMG, (b) Filtered signal with LMS based ANC, (c) Filtered signal with NLMS based ANC, (d) Filtered signal with BBNLMS based ANC, (e) Filtered signal with NSRLMS based ANC, (f) Filtered signal with BBNSRLMS based ANC, (g) Filtered signal with NSLMS based ANC, (h) Filtered signal with BBNSLMS based ANC, (i) Filtered signal with NSSLMS based ANC, (j) Filtered signal with BBNSSLMS based ANC

C. Adaptive Cancelation of Respiration Artifact (RA)

Due to the patients breathing activity the EEG signal base line is wandering it causes some physiological artifact in the EEG signal. In our experiments we performed the cancelation of such artifact from EEG signal. The output signals from various ANCs are shown in Figure 5. Various performance measuring characteristics are tabulated in Table 1 and Table 2. In SNRI measurements it is found that NLMS algorithm gets SNRI of 11.8463dB, BBNLMS gets 11.6058dB, NSRLMS gets 10.6605dB, BBNSRLMS gets 10.4729dB, NSLMS gets 9.7453dB, BBNSLMS gets 9.4856dB, NSSLMS gets 7.7849dB and BBNSSLMS gets 7.4217dB, where as the conventional LMS algorithm improves to 4.7343dB.

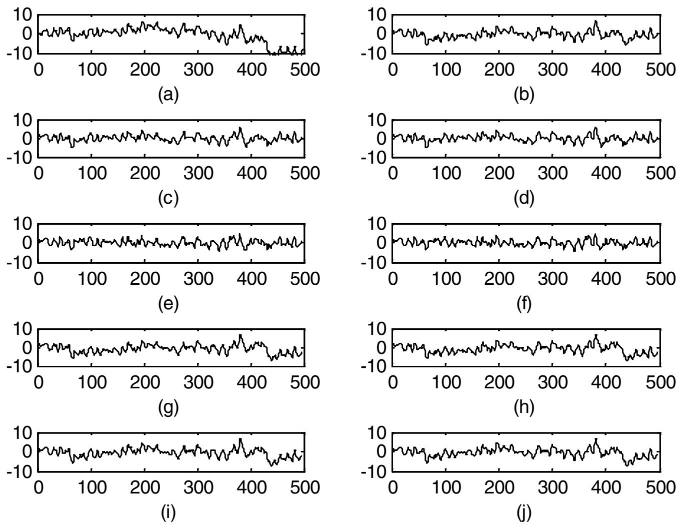

Figure 5: Typical brain signal enhancement results of RA Cancelation (a) EEG Signal with RA, (b) Filtered signal with LMS based ANC, (c) Filtered signal with NLMS based ANC, (d) Filtered signal with BBNLMS based ANC, (e) Filtered signal with NSRLMS based ANC, (f) Filtered signal with BBNSRLMS based ANC, (g) Filtered signal with NSLMS based ANC, (h) Filtered signal with BBNSLMS based ANC, (i) Filtered signal with NSSLMS based ANC, (j) Filtered signal with BBNSSLMS based ANC.

D. Adaptive Cancelation of Electrode Motion Artifact (EMA)

In this experiment the noise contaminated EEG signal is given to ANC structure shown in Figure 1, the reference is taken from noise generator. Noise free EEG signals after the elimination of EMA are shown in Figure 6. Various performance measuring characteristics are tabulated in Table 1 and Table 2. In SNRI measurements it is found that NLMS algorithm gets SNRI of 9.4826dB, BBNLMS gets 9.3729dB, NSRLMS gets 8.8094dB, BBNSRLMS gets 8.3067dB, NSLMS gets 7.9704dB, BBNSLMS gets 7.5097dB, NSSLMS gets 7.1054dB and BBNSSLMS gets 7.8809dB, where as the conventional LMS algorithm improves to 6.5.3795dB.

4. CONCLUSION

In this paper we proposed some efficient ANCs for wireless embedded BCI system. In order to enhance the ability of ANCs various variants are adapted in the weight update equation of filtering section. The proposed ANC structure is a fourteen channel EEG acquisition unit. To ensure stability, convergence, filtering and less computational complexity we have combined the characteristics like mean square error, normalization and signum in a single ANC. Several EEG signals with various artifacts are recorded and tested with proposed ANCs. In all the cases the proposed ANCs outperforms the LMS based ANC. Among the proposed ANCs NLMS based ANC performs better than other ANCs but the computational complexity is high. By applying signum this complexity

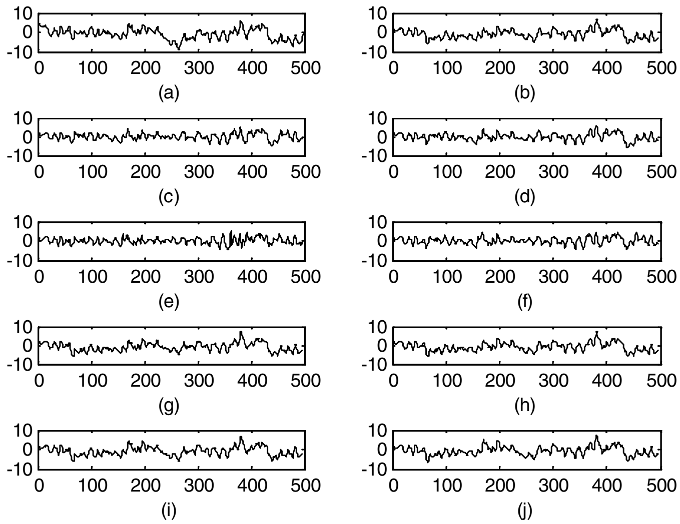

Figure 6: Typical brain signal enhancement results of EMA Cancelation (a) EEG Signal with EMA, (b) Filtered signal with LMS based ANC, (c) Filtered signal with NLMS based ANC, (d) Filtered signal with BBNLMS based ANC, (e) Filtered signal with NSRLMS based ANC, (f) Filtered signal with BBNSRLMS based ANC, (g) Filtered signal with NSLMS based ANC, (h) Filtered signal with BBNSLMS based ANC, (i) Filtered signal with NSSLMS based ANC, (j) Filtered signal with BBNSSLMS based ANC

is reduced in NSRLMS based ANC; its performance is nearly same as to NLMS with reduction in computational complexity. The filtering outputs were presented in Figure 3 to Figure 6. We have used the block size as 5 in our simulations. The filtering speed increases as the block size increases, but the output signals contain residual noise. From the performance analysis (Tables 1 and 2) it is clear that the proposed adaptive filters are superior than conventional LMS. Hence these ANCs are more suitable for remote EEG monitoring system.

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