International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075, Volume-9 Issue-1, November 2019

Artifact Elimination from EEG Signals using Error Normalized algorithms for Brain Computer Interface Systems

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***Abstract:** In this paper some efficient and low computation complex signal conditioning algorithms are proposed in distant health tracking applications, for improvement of the electroencephalogram (EEG) signal. Few artifacts are contaminated also mask small characteristics underlying EEG signal activity in medical environments during extraction of EEG signal. Low computational difficulty filters are appealing especially within distant healthcare surveillance. Therefore, we provided several effective and less computing adaptive noise cancellers (ANCs) in this work to improve EEG signal. Most of these techniques use easy addition as well as shift calculations also attain significant convergence performance compared to other standard techniques. Real EEG signals collected using emotional EEG systems are verified for proposed implementations. Using several performances measures our studies demonstrate that techniques suggested provides best performance than prevailing methods. This methodology is suitable in the analysis of brain computer interface (BCI) applications.*

***Index Terms**: Artifacts, Adaptive noise cancellers, Convergence, EEG, Health care monitoring.*

I. INTRODUCTION

According Electroencephalogram (EEG) test records activity of brain electrophysiology along the scalp. Because it is non-invasive, time-resistant, inexpensive and suitable for a long-term surveillance, EEG was usually used to study activity of brain also brain pathology [1]–[3]. These signals can be readily contaminated using several artifacts, since tiny amplitudes as well as strong uncertainty are present. These signals are often contaminated with non-cerebral physiological activities. During the extraction EEG signal contaminated with several artifacts that reduces resolutions of feature for desired signal. Major artifacts include ElectroMyoGram (EMG), Power Line Noise (PLN), 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]. These devices must be removed for accurate diagnosis to facilitate the neurologist. High-resolution EEG signal extraction from multiple artifact contaminations is therefore a significant job. The primary purpose of EEG signal improvement is to acquire the valid signal parts of the artifacts also to present an EEG for simple and precise evaluation. Filters with static coefficient are not suitable because artifacts are random in nature. Depending on component of noise, the filter coefficients need to be updated automatically. This requires the development of effective adaptive noise cancellers. In practical instances, however, biotelemetry based remote acquisition systems play a significant role in healthcare surveillance, when the patient is located where a neurology expert is not regularly accessible for surveillance.

In literature [7]–[10] several BCI systems are presented. BCIs have been developed to allow communication between human thought procedures and computers, for the purpose of handicapped patients, to help with motor function due to illness, but whose mental functions are not significantly impacted [11]. The most advantageous selection of a BCI system reflects the equipment cost, along with temporal also spatial resolution essential for particular application. Therefore, a remote health monitoring network at the hospital establishes with the biotelemetry link, BCI, acquisition system, and control station. In literature [12]–[15] several contributions are presented on enhancement of EEG signal with both non-adaptive also adaptive techniques. For a noise cancelation system less computational complexity is preferable, particularly in some specific applications like wireless biotelemetry system became a topic of intense research. As the EEG information transfer rate of data rises, the response duration of the receiver filter rises also therefore the filter order. The resulting complexity rise makes it hard to operate the biotelemetry system in real time.

In [16]-[18] methods with LMS algorithm used to improve cardiac signal offers less computational difficulty which can be reduced with use of sign-based algorithms such as signed regressor, signed error as well as sign-sign algorithms respectively [19]. From a practical perspective, all the three algorithms are appealing, because they need only half as much multiplication as the LMS algorithm. We have developed various data-standardized adaptive filter structures [22] with a block-based strategy in order to handle both the problems of complexity and convergence without restrictive tradeoff [20]. These combinations produce six simplified adaptive algorithms, specifically Error Normalized SRLMS (ENSRLMS), Block Based ENSRLMS (BBENSRLMS), Error Normalized Sign LMS (ENSLMS), Block Based ENSLMS (BBENSLMS),

Revised Manuscript Received on November 08, 2019.

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Error Normalized Sign Sign LMS (ENSSLMS) as well as Block Based ENSSLMS (BBENSSLMS).

We have experimented with actual human signals to study the efficiency of filters structure, which effectively removes the artefacts from EEG signals. The theory and experimental outcomes of multiple algorithms will be provided in the following parts.

II. SIGNED NORMALIZED ADAPTIVE NOISE CANCELLERS FOR EEG TELEMETRY

Take into account an L-coefficient FIR filter. For weight adjustment of the filter, we bring LMS algorithm. A typical adaptive filter for artifact elimination from EEG signals is shown in Fig.1. This LMS adaptive filter was used to build an ANC scheme connected with a computer interface. i(n) is an adaptive filter input sequence. The brain signal is recorded from patient is called as d(n). Therefore, the tap update recursion is expressed as,

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S\mathbf{i}(n)\, x(n) \qquad (1)$$

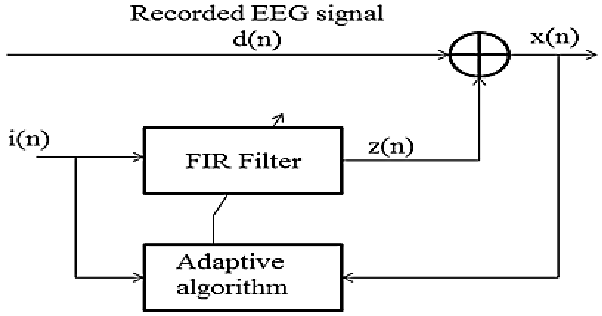

Figure 1: A typical structure of adaptive artifact canceller Let z*(n)* be the output of adaptive artifact canceller,

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

The mean-squared error (MSE) is measured as

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

The two last expectations are zero, because $y_1(n)$ and $\eta_1(n)$ are uncorrelated, and similarly $\eta_1(n)$ and $z(n)$ are uncorrelated. Minimizing the MSE results in the highest estimate of the signal $y_1(n)$ as filter output.

In order to reduce multiplication and addition rates, the proposed ANCs utilize the *signum* function either to the input data vector or error or both remains derived from the LMS algorithm [21],[19]. The SRLMS, SLMS and SSLMS algorithms are provided according to weight update recursion as below.

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

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

and

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S\, sgn\{\mathbf{i}(n)\}sgn\{x(n)\} \qquad (6)$$

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

The SRLMS, SLMS also SSLMS has the inferior convergence than the other counterparts. Consider the recursion expression of SLMS algorithm as given by,

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

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

As the sign algorithm converges, the S'(n) rises on average since e(n) falls in magnitude. However, with the filter converging and x(n) becoming narrower, S'(n) grows also improves convergence speed.

By creating S to an energy value of two, the circuit is simplified by subtractions; additions also shift calculations [21]. The Error Normalized LMS (ENLMS) technique is an adaptive fast converging due to normalization [22]. It's weight expression is written as

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

$$S(n) = \frac{S}{a + x^t(n)x(n)} \qquad (11)$$

The updated weight recursion expression of ENLMS is a scaled version of the LMS algorithm from the weight updates of both LMS and NLMS as indicated in (1) and (10). The shift in u(n) corresponds in reverse with norm of input information vector i(n). Smaller S values are achieved in this data normalization than LMS. The normalized filter uses a variable convergence factor, to reduce the instantaneous output error as it converges quickly than LMS filters. We merge ENLMS algorithm with sign-based methods to get ENSRLMS, ENSLMS, in order to achieve less computational difficulty.

The resultant update expressions are given by,

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

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

and

$$\mathbf{u}(n+1) = \mathbf{u}(n) + S(n)\, sgn\{\mathbf{i}(n)\}sgn\{x(n)\} \qquad (14)$$

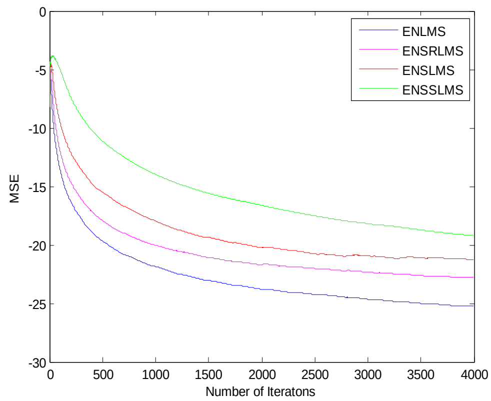

Figure 2: Typical Convergence Curves of ENLMS and its sign versions for artifact removal from Brain signals.

For calculating S(n) in expressions (12)-(14), additional strategies can be minimized with block-based approach. Thus, weight update relation in (12)-(14) for $i_{Li} \neq 0$ and $c = 0$ takes the following form,

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

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

and

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

where, $i_{Li} = max\{|i_k|, k \in B_i'\}$, $B_i' = \{i_L, i_{L+1}, \ldots, i_{L+L-1}\}$, $i \in B$. These new versions of techniques are BBNSRLMS, BBNSLMS and BBNSSLMS. Figure 2 illustrates the convergence characteristics of the above-mentioned techniques.

III. SIMULATION RESULTS

The technique was studied with a number of brain wave components with several waves morphologies collected using the Emotive EEG acquisition system to demonstrate that the suggested ANCs are effective in clinical situations [24]. It consists of 14 electrodes and two electrodes of reference. The EEG electrodes are as per the international system 10-20 and marked as such [25]. The encrypted information was transferred to the Windows-based device by headset wirelessly; the wireless module works. We have registered EEG signals with BCI from six topics with multiple artifacts.

The samples are taken in all channels by heading at 128 samples / second, each equal to a single electrode voltage. We have registered 25,000 EEG signal samples from a male with 41 years old in our experiment. We evaluated SNRI, EMSE, MSD [15] and ANC's parameters with standard LMS in the performance analysis of suggested filter structures. Table 1 mention the contrast between different artifact disposal by the SNRI. The comparison of all EMSE, MSD, EEG record number 1 algorithms is given in table 2. In our simulations, we have recorded six EEG signals for our experiments. Different ANCs are implemented with algorithms LMS, ENLMS, BBENLMS, ENSRLMS, BBENSRLMS, BBENSLMS, ENSSLMS and BBENSSLMS. Our simulation model includes a source of noise that generates a reference signal for noise. For all ANCs we provide this signal as a reference signal and experimentation has been carried out to extract multiple artifacts from registered signals of EEG. These findings are shown in Fig. 3 to Fig. 6. This reference signal is a mixture of PLN, E MG, RA and EMA artifacts.

A. REMOVAL OF POWER LINE INTERFERENCE (PLI)

The test shows the cancelation of PLI. The filter input is an EEG signal contaminated by 50Hz PLI and sampled at 160 Hz from a 41-year-old male. A noise generator is used to receive the reference signal. The filter output is the signal retrieved. EMSE component in several ANCs are displayed in Figure depending sign LMS technique. For ten occasions and on average, we performed this test on six EEG records. Tables 1 and 2 show several performance measurements, such as SNRI, EMSE, and MSD.

B. ELECTRO MIOGRAM (EMG) REMOVAL FROM EEG SIGNALS

As the main input for the adaptive filter in Fig.1, the contaminated EEG signal is implemented. 1, our noise generator receives a reference signal. Figure shows the simulation outcomes.

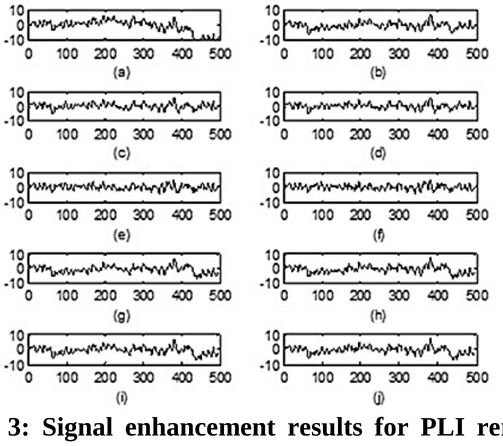

Figure 3: Signal enhancement results for PLI removal (a). Brain wave component with PLI, (b). Signal Enhancement using LMS-ANC, (c). Signal Enhancement using ENLMS-ANC, (d). Signal Enhancement using BBENLMS-ANC, (e). Signal Enhancement using ENSRLMS-ANC, (f). Signal Enhancement using BBENSRLMS-ANC, (g). Signal Enhancement using ENSLMS-ANC, (h). Signal Enhancement using BBENSLMS-ANC, (i). Signal Enhancement using ENSSLMS-ANC, (j). Signal Enhancement using BBENSSLMS -ANC.

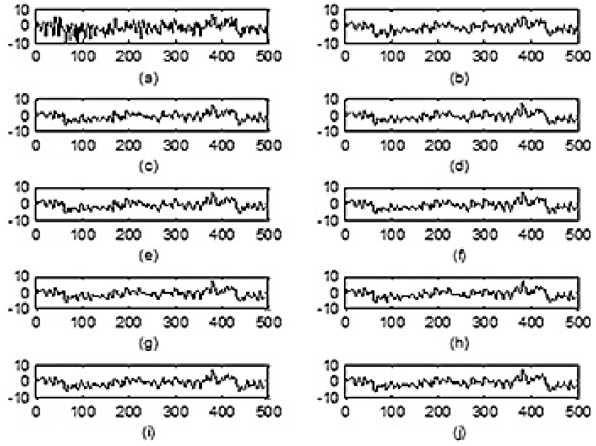

Figure 4: Signal Enhancement results for EMG Removal (a). Brain wave component with EMG, (b). Signal Enhancement using LMS-ANC, (c). Signal Enhancement using ENLMS-ANC, (d). Signal Enhancement using BBENLMS-ANC, (e). Signal Enhancement using ENSRLMS-ANC, (f). Signal Enhancement using BBENSRLMS-ANC, (g). Signal Enhancement using ENSLMS-ANC, (h). Signal Enhancement using BBENSLMS-ANC, (i). Signal Enhancement using ENSSLMS-ANC, (j). Signal Enhancement using BBENSSLMS -ANC.

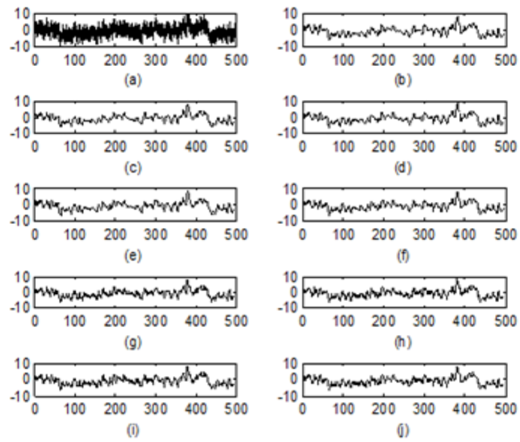

Figure 5: Signal Enhancement results for BW Removal (a). Brain wave component with BW, (b). Signal Enhancement using LMS-ANC, (c). Signal Enhancement using NLMS-ANC, (d). Signal Enhancement using BBENLMS-ANC, (e). Signal Enhancement using ENSRLMS-ANC, (f). Signal Enhancement using BBENSRLMS-ANC, (g). Signal Enhancement using ENSLMS-ANC, (h). Signal Enhancement using BBENSLMS-ANC, (i). Signal Enhancement using ENSSLMS-ANC, (j). Signal Enhancement using BBENSSLMS -ANC.

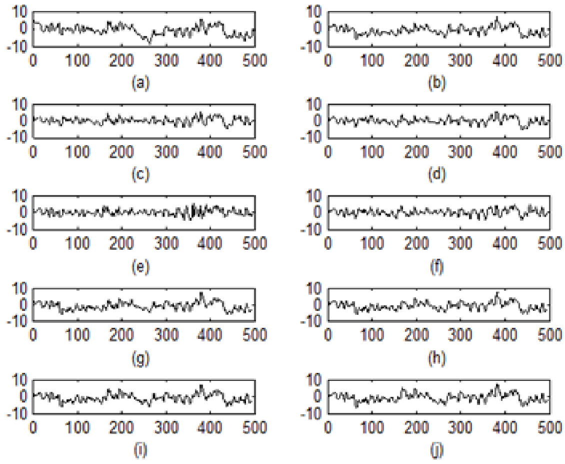

Figure 6: Signal Enhancement results for MA Removal (a). Brain wave component with MA, (b). Signal Enhancement using LMS-ANC, (c). Signal Enhancement using ENLMS-ANC, (d). Signal Enhancement using BBENLMS-ANC, (e). Signal Enhancement using ENSRLMS-ANC, (f). Signal Enhancement using BBENSRLMS-ANC, (g). Signal Enhancement using ENSLMS-ANC, (h). Signal Enhancement using BBENSLMS-ANC, (i). Signal Enhancement using ENSSLMS-ANC, (j). Signal Enhancement using BBENSSLMS -ANC.

C. BASELINE WANDER (BW) FROM BRAIN WAVES

The brain wave contaminated signal is provided in this experiment to ANC as in Fig. 1, which is a reference from the noise generator. The EEG noise free signals are shown after BW removal, in Fig. 5, the performance measures are shown in Table 1 and Table 2.

D. MOTION ARTIFACT (MA) FROM BRAIN WAVES

The brain wave contaminated signal is provided in this experiment to ANC as in Fig. 1, which is a reference from the noise generator. The EEG noise free signals are shown after MA removal, in Fig. 6, the performance measures are shown in Table 1 and Table 2.

IV. CONCLUSIONS

We have suggested in this work some effective ANCs for the BCI scheme with WIFI integration. Various variants in the tap recursion equation of the filter section are tailored to improve the capability of ANCs. The ANC design presented is an EEG acquisition unit of 14 channels. We combine the features of a medium square error, normalization and sign in a single ANC to guarantee stability, convergence, and filtering as well as low computational difficulty. Various EEG signals are considered also tested with multiple artefacts using suggested ANCs. The proposed ANC's exceed the ANC based on the LMS in every case. Among the suggested NLMS-based ANCs, computational difficulty of NLMS remains better than other ANCs. This complexity in NSRLMS-based ANC is reduced by the use of the signum. It has almost the same performance as NLMS, which reduces computational difficulty. The filter outputs were shown in Fig.3 through Fig. 6. In our simulations, we used the block size to be equal to 5. The filtering velocity improves as block size rises, while residual noise is present in the output signals. The assessment of results from Tables 1 and 2 indicates that the adaptive filters suggested are higher than standard LMS. These ANCs are therefore better suited for the EEG remote monitoring systems.

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Table I. Performance of various ANCs in terms of SNRI (dBs) during EEG Enhancement

Noise	*Rec.no*	*LMS*	*ENLMS*	*BBEN LMS*	*ENSR LMS*	*BBENSR LMS*	*ENS LMS*	*BBENS LMS*	*ENSS LMS*	*BBENSS LMS*
PLI	1	5.3735	10.6478	9.2387	9.8921	8.6579	7.7623	7.2385	6.8743	6.2745
	2	6.8473	12.5465	11.7145	11.8732	10.5764	8.9846	7.5738	7.8754	7.1352
	3	4.1736	10.2308	9.6379	9.9832	8.7645	8.9625	7.7334	7.9572	6.4567
	4	6.3632	13.4357	12.1785	12.8752	11.3471	10.8732	9.2746	9.9860	8.4584
	5	7.8854	12.3254	11.4379	11.9864	10.5439	10.9857	9.1325	9.4549	8.7842
BW	1	4.7343	9.8954	8.4671	8.8753	7.8734	7.9652	7.1348	7.8503	7.4365
	2	6.7653	11.5683	10.3284	10.7630	9.9854	9.8743	8.3487	8.8974	8.3254
	3	3.8762	9.3207	8.2150	8.8542	8.2721	7.4387	7.3841	6.9845	6.1245
	4	5.8835	10.3698	9.2358	9.9872	8.6523	9.4851	8.9843	9.0351	7.6585
	5	4.1735	9.8923	8.3465	8.8721	8.5432	7.9543	6.8723	7.2385	6.4583
EMG	1	4.8353	8.2142	7.4354	7.9874	7.1042	7.9844	6.8487	7.5853	5.9856
	2	6.8963	12.3289	11.3265	11.9258	10.8732	10.7643	9.2875	9.8473	8.8943
	3	5.7832	9.5983	8.9843	9.1479	7.9086	7.9865	7.1285	6.7383	6.3465
	4	7.7353	14.0954	13.5663	13.8923	12.8967	12.7649	11.2563	11.5731	10.5672
	5	5.6444	10.7647	9.9591	10.3829	8.8745	8.9874	8.3585	7.4587	7.2134
MA	1	5.3795	8.8941	7.3756	7.8923	7.1643	7.6734	6.9853	7.4294	6.4358
	2	4.8836	7.4572	6.4359	7.5483	6.2783	7.3472	6.4567	6.8737	5.4576
	3	7.6353	10.3952	9.9832	10.1094	9.6543	9.8756	8.1458	8.7694	8.1528
	4	6.3783	9.5489	8.3439	8.8936	7.6854	7.9853	6.9851	7.5382	7.1624
	5	5.8943	8.6591	7.3581	7.7961	7.1579	7.8734	6.4086	6.8742	6.2316

Table II. Performance of various ANCs in terms of EMSE (dBs)

Noise	Performance Measure	LMS	ENLMS	BBEN LMS	ENSR LMS	BBENSR LMS	ENSLMS	BBENS LMS	ENSS LMS	BBENSS LMS
PLI	EMSE	-15.8464	-27.4373	-26.2384	-24.7232	-22.2342	-22.5935	-20.4983	-19.9823	-19.0234
	MSD	0.0938	0.0778	0.0791	0.0871	0.0899	0.0904	0.0908	0.0914	0.0927
BW	EMSE	-17.7456	-28.6754	-27.6986	-26.8765	-25.4389	-24.9863	-23.5676	-21.4365	-20.9864
	MSD	0.0854	0.0556	0.0675	0.0694	0.0712	0.0764	0.0781	0.0799	0.0866
EMG	EMSE	-17.6452	-29.8765	-28.9830	-27.4369	-26.4369	-25.4358	-24.8730	-24.4354	-23.8674
	MSD	0.0978	0.0663	0.0691	0.0754	0.0787	0.0824	0.0878	0.0889	0.0956
MA	EMSE	-17.7332	-29.7382	-28.2735	-26.7239	-25.8373	-24.2842	-23.2389	-24.2892	-22.9234
	MSD	0.1385	0.0779	0.0847	0.0975	0.0987	0.0995	0.1032	0.1081	0.1296