International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I7P232

Volume 69 Issue 7, 255-262, July, 2021
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An Efficient Adaptive Learning Algorithm for EEG Analysis in Brain Computer Interface Applications

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Abstract *- For brain signal enhancement several adaptive signal processing techniques are available. In clinical environments while doing electroencephalogram (EEG) records it encounter with several artifacts and it may affect brain activities. To get high resolution brain wave signals, new adaptive learning technique is proposed in health care monitoring applications. In this paper logarithmic normalized mean least square (LNLMS) algorithm is proposed then it is compared with conventional least mean square (LMS) algorithm. Input brain waves are contaminated with EMG and EMA artifacts, these artifacts are reduced by LNLMS algorithm. Further applied sign regressor, sign and sign sign variants to adaptive algorithm. Using these sign variants, computational complexity is also reduced. Among these three variants sign regressor based LNLMS (SR-LNLMS) algorithm is preferred because its low computational complexity and also it is best suited for health care monitoring applications. Experimental results show that proposed algorithm perform well by means of signal to noise ratio, excess mean square error with values of 17.6214dB and -34.5856dB respectively.*

Keywords — *Adaptive algorithm, Brain waves, EEG, health care monitoring, noise canceller.*

I. INTRODUCTION

Electroencephalogram (EEG) is the tool that records neurological activity used for clinical as well as research scenarios. Basically, it is used to observe the activities of brain through arranging the electrodes on the scalp. EEG was generally used to observe the brain activity and brain pathology [1]–[3], since it is inexpensive, non-invasive, and appropriate for enduring observation. Any abnormalities in brain waves lead to several medical ill situations. Based on the reports of world health organization [4] any disorders in the brain wave subjected to majority of mortality. Hence, brain waves become an important tool for the diagnostic process. So, EEG signals with high resolution are essential in the clinical purposes. During the extraction process EEG signals are corrupted with many artifacts that degrade the resolution of the desired signal components. The neural response can be obtained by placing electrodes at several places on scalp. Due to the contamination of noise the response has low quality it is one of the reason of artifacts and also due to biological or technical issues signal evaluation is prone to artifacts. Biological artifacts are raised because of eyes blinking, head movement, contraction with muscles while talking, teeth clenching or because of cardiac actions. While technical artifacts are raised due to equipment problems it causes power line noises in the impedance of electronic circuits during the recording of signal values. For skin electrodes, artifacts can be eliminated before placing electrodes on scalp skin is cleaned or gel is also applied to contac with skin electrodes. Biological artifacts elimination is the essential task, because the desired EEG signal brain dynamics are combined with noises. Removal of artifacts is an important task in EEG signal to get desired information from brian functionalities

The most important artifacts include ElectroMyoGram (EMG) and Electrode Motion Artifacts (EMA) [5]–[7]. The artifacts degrade the quality of signal, it masks tiny features of brain signal, it is very important in diagnosis process. To facilitate neurologist in diagnosis, process these artifacts should be removed. Extracting high resolution EEG signal from contaminated artefacts is significant task. Basic purpose of improvement in EEG signal is to get desired part of signal and also to represent EEG signal for easy and accurate evaluation. Due to random nature of artifacts, stationary coefficients are not predfered with filters. For efficient filtering the coefficients of the filter needs to updated automatically depends on noise components for development of adaptive noise cancellers. However, in the practical scenarios, biotelemetry-based health care monitoring play major role in medicare supervision, if patient is not regularly accessible for supervision of neurology expert. Adaptive filtering techniques have the ability to adjust coefficients depends on input signal. The EEG signal has a very non-stationary model. For the removal of artifacts in the EEG signals conventional filters are not preferable. Thus, adaptive FIR filtering techniques are suitable for this process. A number of adaptive filtering techniques are implemented for the removal of artifacts from desired signals. Due to technological advancements in the analysis of brain waves a number of techniques such as brain computer interface (BCI), remote health care monitoring, source localization, machine learning, etc., pre-processing is also done for EEG signal so that greater resolution EEG signal components is obtained for exact diagnosis. Several BCI models are presented in [8]–[11].

BCIs are implemented for allowing communication involving computers and human mind actions, with motor functions helped handicapped patients due to illness, but mental activities will not affect systems [12]. BCI selection models does not reflect on equipment costs, for particular applications spatial and temporal resolutions are considered. In hospital remote health care systems equipped with signal extraction system, BCI and controlling mechanism. Artifacts are eliminated by using BCI prior to the EEG signal processing. Several signal enhancement techniques for EEG signals are presented in [13]– [16] with non-adaptive and adaptive filtering techniques. A smaller amount computational complexity is required for healthcare monitoring system, particularly for the applications such as biotelemetry wireless system, stayed as an area of extensive research. Methods for low complexity in computations were presented using Least Mean Square (LMS) technique for enhancement of cardiac signal in [17]-[19]. By using sign-based algorithms the computational complexity can be reduced, specifically, sign regressor (SR), sign error (S) and sign sign (SS) algorithms which becomes attractive in practice since it needs half as many multiply operations as LMS [20]. The hybrid variants of LMS combined with sign algorithms gives SRLMS, SLMS and SSLMS algorithms.

In the processing of brain waves under crucial conditions, some EEG samples are turn out to be zero, due to poor excitation their coefficients vary considerably yields to weight drift problem. This can be solved by Logarithmic Normalized Mean Least Squares (LNMLS) Algorithm. In this technique, the weight drift problem can be overcome. With this technique enhancement of stability, improve effects for excitation; and reduces the unwanted effects such as bursting, stalling, etc. Performance of the algorithm with comprehensive analysis is specified in [21]-[24] an application of hybrid version of the logarithmic based algorithm is described in [25]. To improve the stability, convergence rate, filtering capability and to minimize the computational burden we constructed several hybrid versions of adaptive artifact eliminator (AAE) for the processing of EEG signal. To reduce the computation complexity, we combine LNMLS algorithm with three sign variants. That yields SR-LNMLS, S-LNMLS and SS-LNMLS algorithms. With these variants we developed several adaptive noise cancellers. The mathematical modelling of these cancellers is described in the following section.

II. ADAPTIVE LEARNING METHODS FOR BRAIN WAVES USING LOGARTHMIC ADAPTIVE ALGORITHM

LNMLS is a variety form of adaptive algorithm used for updating coefficients of adaptive filter. In the implementation of the LMS adaptive filter the key issue is step size selection. This LNMLS algorithm is taken as a unique application of LMS algorithm that takes variations in the signal level at the output of filter also implements a logarithmic normalized cost function that facilitates faster converging and stable adaptation. LNMLS technique overcomes LMS limitations further it improves the convergence speed and tracking ability.

Mathematical Modelling

w(n) is the weight vector with the elements mentioned in a row vector

$$= [\mathrm{w(n)}\ \mathrm{w(n-1)}\ \ldots\ldots..\mathrm{w(n-T+1)}]^T$$

Here vector ω_o is considered with a linear function as

$$d(n) = \omega_o{}^T x(n) + n_t \quad (1)$$

Here x(n) is input signal, desired signal d(n) and n_t is noise. System vector is determined using adaptation process by reducing cost function. Generally to converge on the overall least amount error gradient descent techniques use convex and unimodal cost functions. For improved approximation of optimization error, a combination of LMS and LMF family of algorithms are used.

$$\nabla e^*(n) = -x^*(n) \quad (2)$$

The $\Delta_\mathrm{w}.\mathrm{F}(\mathrm{e(n)})$is first gradient of (4), the step size parameter $\mu > 0$ and the design parameter $\alpha > 0$.

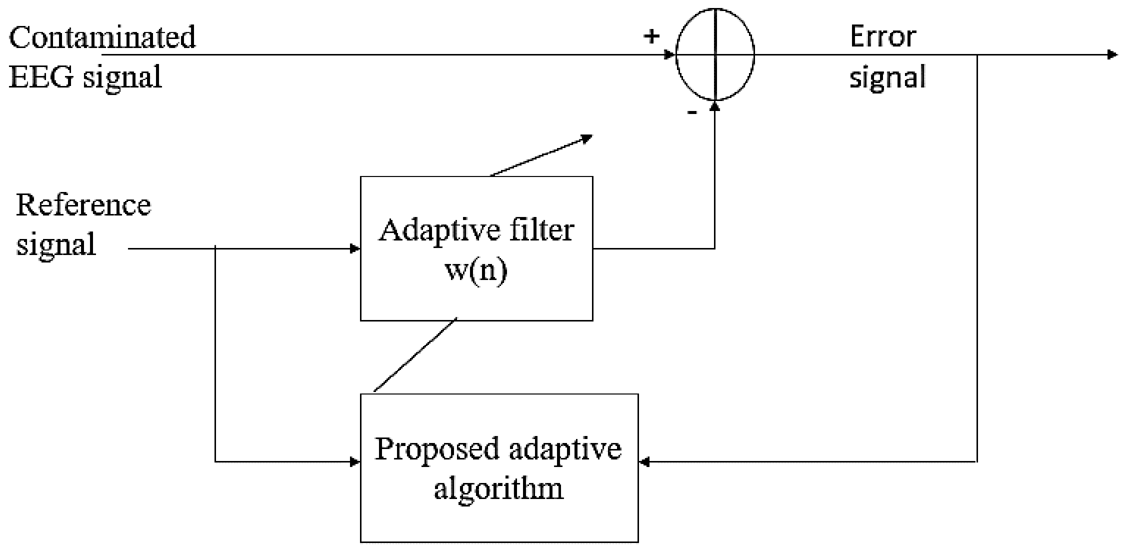

Fig. 1 Schematic diagram of brain analysis using adaptive learning methodology

Now, the weight up-dation is specified by

$$w(n+1) = w(n) + \mu . x(n) \frac{\partial f(e(n))}{\partial e(n)} \left[\frac{\alpha f(e(n))}{1+\alpha f(e(n))} \right] \quad (3)$$

It is related to LMF error updating, whereas it resembles LMS for large error perturbations. This exhibits low MSE in steady state for the error statistics of fourth order for small perturbations and greater stability of least-squares algorithms. From the weight recursion equation of LMS, the time variable parameter $\mu(n)$ such that a posterior error,

$$e^*(n) = d(n) - w^T(n+1)\, x(n) \quad (4)$$

is reduced in terms of magnitude. The below expression marks in reducing $[e^*(n)]^2$ respect to $\mu(n)$ that yields e*(n) to zero.

$$\mu(n) = \frac{1}{2\, x^T(n)\, x(n)} \quad (5)$$

Thus, the resultant expression is formulated as

$$w(n+1) = w(n) + \frac{1}{2\, x^T(n)\, x(n)}\, e(n) x(n) \quad (6)$$

The parameter μ' is dimensionless for the LNMLS algorithm, whereas it has reverse power dimensions for the LMS. The LNMLS algorithm can be viewed as a LMS algorithm using time dependent step size parameter on logarithmic cost function. The LNMLS has the ability to resolve the gradient noise amplification problem also weight drift related to LMS filter. Numerical complications may raise in this situation and we should divide the $\|x(n)\|^2$ by a small value. The flow diagram of brain wave enhancement using LNMLS algorithm is shown in Figure 2.

The LNMLS mathematical recursion is given by

$$w(n+1) = w(n) + \mu(n).\, x(n) e(n) \left[\frac{\alpha (e(n))^2}{1+\alpha (e(n))^2} \right] \quad (7)$$

Here $\mu(n) = \frac{\mu'}{\varepsilon + \|x(n)\|^2}$ is the normalized step size parameter with $0 < \mu < 2$.

Parameter μ in the LMLS weight update equation is replaced with μ(n) that contributes to the LNMLS algorithm, the tap update recurssion is given by,

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \frac{\mu'}{\|\boldsymbol{x}(n)\|2}\; x(n) e(n) \left[\frac{\alpha (e(n))^2}{1+\alpha (e(n))^2} \right] \quad (8)$$

LNMLS algorithm is one of the variants of higher order adaptive filter. To reduce the computation burden we combine LNMLS with simplifie algorithms. The combination of LNMLS with SRA, SA and SSA results in SR-LNMLS, S-LNMLS, and SS-LNMLS respectively. Their weight update expressions are given by,

$$w(n+1) = w(n) + \frac{\mu'}{\varepsilon + \|x(n)\|2}\; \mathrm{Sign}\{x(n)\} e(n) \left[\frac{\alpha (e(n))^2}{1+\alpha (e(n))^2} \right] \quad (9)$$

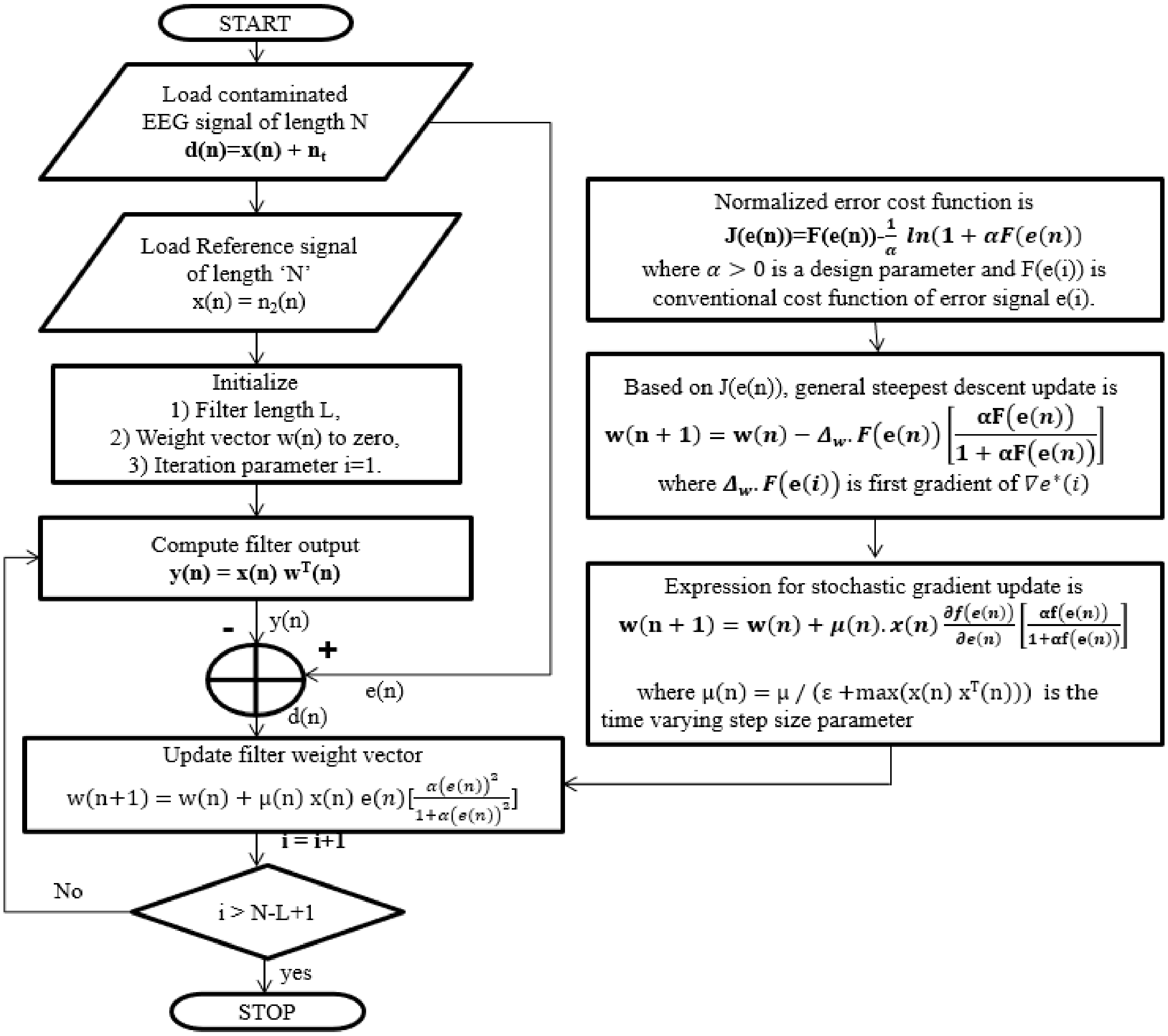

Fig. 2. Flow chart diagram for LNLMS based Brain Wave Enhancer

$$w(n+1) = w(n) + \frac{\mu'}{\varepsilon + ||x\,(n)||2}\; x\,(n)\ \mathrm{Sign}\left\{e\,(n)\left[\frac{\alpha\big(e(n)\big)^2}{1+\alpha\big(e(n)\big)^2}\right]\right\} \qquad (10)$$

$$w(n+1) = w(n) + \frac{\mu'}{\varepsilon + ||x\,(n)||2}\; \mathrm{Sign}\{x\,(n)\}\ \mathrm{Sign}\left\{e(n)\left[\frac{\alpha\big(e\,(n)\big)^2}{1+\alpha\big(e(n)\big)^2}\right]\right\} \qquad (11)$$

Out of these three SR-LNMLS algorithms exhibits good convergence performance and fine tracking capability due to its lower computational complexity.

III. SIMULATION RESULTS

The proposed techniques are examined with a several EEG components with various morphologies taken using Emotive acquisition system to show that the proposed adaptive noise cancellers are helpful in clinical scenarios. The system contains a total of 16 electrodes. The encrypted data from the headset is transmitted to the Windows-based device wirelessly. By using brain computer interface, brain signal are recorded. The samples are extracted from all channels with sampling rate of 128 samples / second. In our experiment, an EEG signal with 25,000 samples obtained from 41 years old male person is used. We measured SNRI and average EMSE of the proposed techniques and compared with conventional adaptive technique. Several adaptive noise cancellers are implemented with LMS, LNMLS, SR-LNMLS, S-LNMLS and SS-LNMLS. The reference component used in our experiments are a randon noise component.

A. Electro Miogram (EMG) removal from EEG signals

EEG component contaminated with elecro miogram is given as input the adaptive learning based noise canceller. A reference component is given for learning the algorithm such that the tap weights are trained to make the reference component some what correlated with the actual noise components present in input EEG signal. In Fig. 3 filtering results are shown. In Fig. 3 (a) is the input EEG signal conmtaminated with EMG artifact, from this figure it is clear that the amplitude of the signal is between 10 to -10, which indicates the present of high amplitude noise component. Fig. 3 (b) shows the enhanced signal with LMS based learning, in which the noise is eliminated littlebit, so that the amplitude of the EEG is appears as between 5 to -5. In Fig. 3(c), the EEG component is filtered using LNMLS is in a better manner when compared to other techniques. This is evident from the filtered signal as well as from the SNRI and EMSE tables. Again, it is clear that the filtering due to SR-LNMLS is just inferiour than LNMLS as shown in Fig. 3. In the Fig. 3 (e) and (f) due to clipping the error component, much residual component is present in the signal component. The noise free EEG signals after EMG removal are shown in Fig. 3. The SNRI performance found that LNLMS algorithm get 16.7203 dB, 13.9566 dB and for EMSE performance got -32.4710dB and -32.3986 they are shown Table 1 and Table 2 with corrsposnding bar diagrams in Figure 5 and Figure 6.

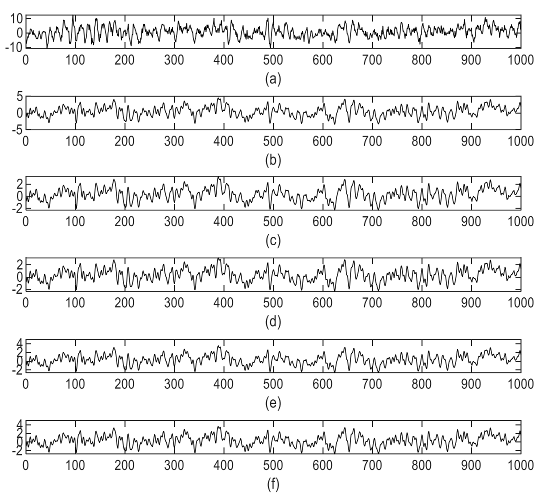

Fig. 3 Brainwave artifact elimination for EMG noise (a). EEG Siganl with EMG contamination, (b). artifact elimination using LMS learning, (c). artifact elimination using LNMLS learning, (d). artifact elimination using SR-LNMLS learning, (e). artifact elimination using S-LNMLS learning (f). artifact elimination using SS-LNMLS learning.

B. Electrode Motion Artifacts (EMA) removal from EEG signals

The EEG signal correpted with EMA componet is given as input signal in the experiemnts, a random signal is given as a reference component. The filtering results are shown in Fig. 4. In Fig. 4 (a) is the input EEG signal conmtaminated with EMG artifact, from this figure it is clear that the amplitude of the signal is between 10 to -10, which indicates the present of high amplitude noise component. Fig. 4 (b) shows the enhanced signal with LMS based learning, in which the noise is eliminated littlebit, so that the amplitude of the EEG is appears as between 5 to -5. In Fig. 4(c), the EEG component is filtered using LNMLS is in a better manner when compared to other techniques. This is evident from the filtered signal as well as from the SNRI and EMSE tables. Again, from Fig. 4 it is clear that the filtering due to SR-LNMLS is just inferiour than LNMLS. In the Fig. 4 (e) and (f) due to clipping the error component, much residual component is present in the signal component. In Table 1 and Table 2 performance metrics SNRI and EMSE are shown respectively. In Figure 5 and Figure 6, SNRI performance and EMSE performance are shown.

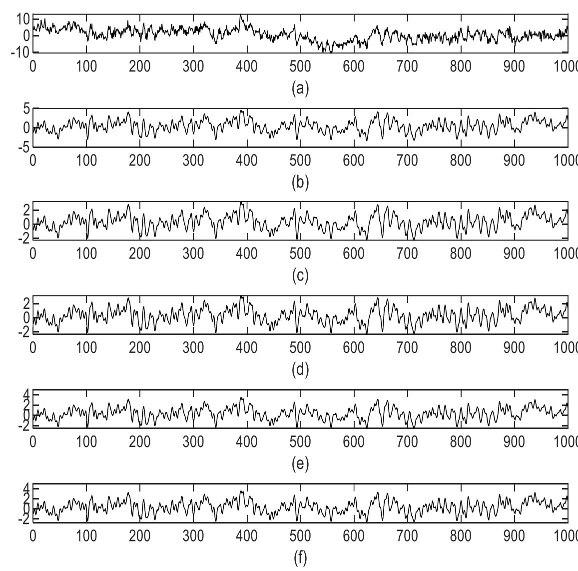

Fig. 4 Brainwave artifact elimination for EMA noise (a). EEG Siganl with EMA contamination, (b). artifact elimination using LMS learning, (c). artifact elimination using LNMLS learning, (d). artifact elimination using SR-LNMLS learning, (e). artifact elimination using S-LNMLS learning (f). artifact elimination using SS-LNMLS learning.

Table 1: SNRI (dB) for various algorithm for EEG signal enhancement

Artifact Type	Sample No.	SNR (dBs) before	SNR (dBs) after filtering				
			LMS	**LNMLS**	**SR-LNMLS**	**S-LNMLS**	**SS-LNMLS**
EMG	I	2.5	10.8619	16.1412	17.5276	24.1994	23.9658
	II	2.5	11.4464	17.8754	18.4715	23.9748	22.3578
	III	2.5	10.3482	16.3523	17.8524	25.1854	23.4842
	IV	2.5	11.4461	17.6546	18.4832	23.7824	22.9756
	V	2.5	11.0614	15.5782	17.5821	24.2149	23.7065
	AVG		**11.0328**	**16.7203**	**17.9833**	**24.2713**	**23.2979**
EMA	I	2.5	9.5259	13.6743	17.4049	24.8743	23.8567
	II	2.5	11.7581	14.6709	18.5182	23.3957	22.9672
	III	2.5	9.8661	13.9658	17.6458	24.9317	23.8701
	IV	2.5	11.1582	14.1857	18.2639	23.9458	22.2547
	V	2.5	8.5083	13.2867	16.2742	24.5309	23.9631
	AVG		**10.1632**	**13.9566**	**17.6214**	**24.3356**	**23.3823**

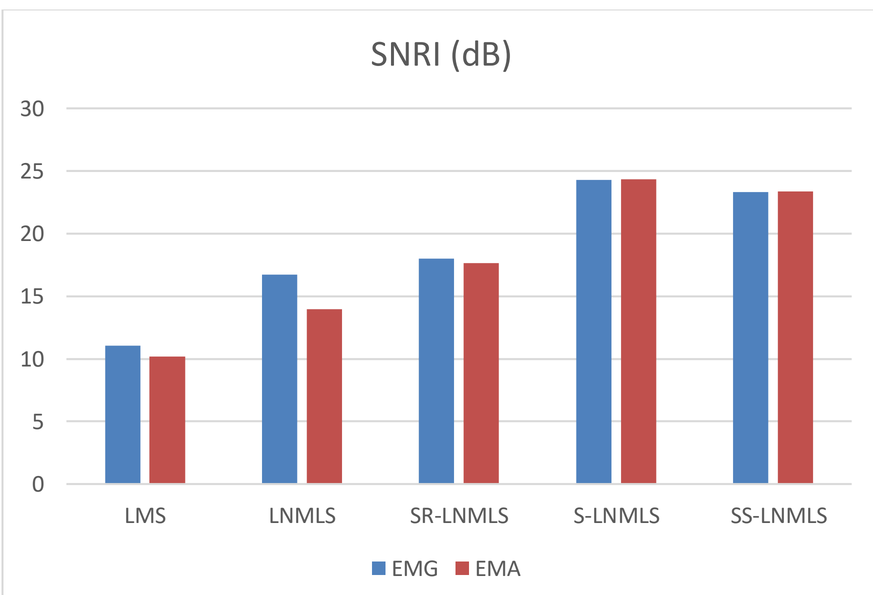

Fig. 5 Performance comparison of various logarithmic adaptive learning algorithms in brain wave enhancement experiments in terms of SNRI (dBs)

Table 2: EMSE (dB) of various algorithm for EEG signal enhancement

Artifact Type	Sample No.	EMSE (dBs) for various algorithms used in the development of ANCs				
		LMS	LNMLS	SR-LNMLS	S-LNMLS	SS-LNMLS
EMG	I	-17.6452	-32.2635	-33.7851	-37.2846	-36.1265
	II	-17.6863	-32.4137	-33.2458	-37.5275	-36.6328
	III	-17.7126	-32.3796	-33.6245	-37.3596	-36.3017
	IV	-17.6988	-32.6458	-33.5218	-37.4927	-36.1524
	V	-17.7234	-32.6527	-33.6307	-37.5817	-36.2921
	AVG	**-17.6932**	**-32.4710**	**-33.5615**	**-37.4492**	**-36.3011**
EMGA	I	-17.7332	-32.3583	-34.4528	-38.2837	-37.5847
	II	-17.8456	-32.2468	-34.4975	-38.4687	-37.6987
	III	-17.7762	-32.6129	-34.6825	-38.6218	-37.4853
	IV	-17.8128	-32.4957	-34.8426	-38.8675	-37.6348
	V	-17.7984	-32.2793	-34.4528	-38.5438	-37.4587
	AVG	**-17.7932**	**-32.3986**	**-34.5856**	**-38.5571**	**-37.5724**

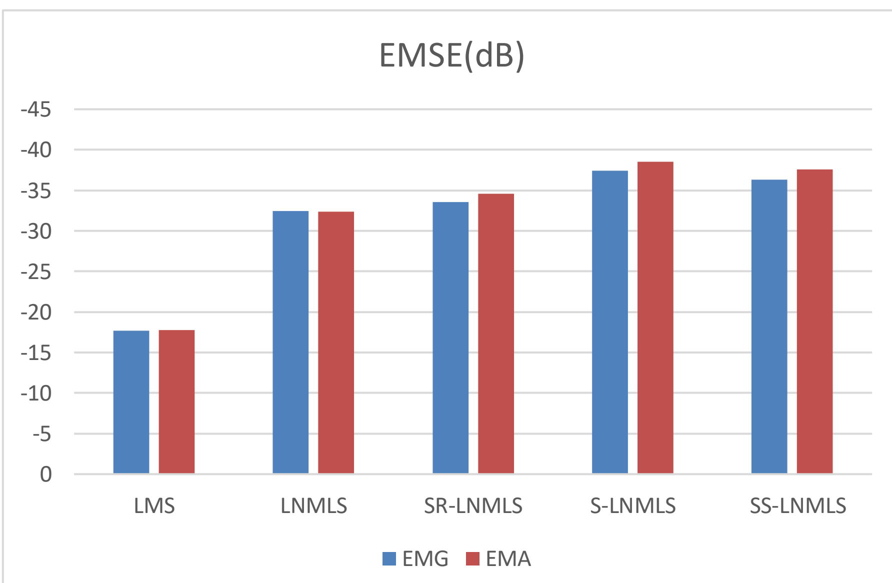

Fig. 6 Performance comparison of various logarithmic adaptive learning algorithms in brain wave enhancement experiments in terms of EMSE (dBs).

IV. CONCLUSION

From this work we have suggested some effective adaptive noise cancellers for the BCI scheme. Several modifications in weight recursion equation of adaptive filters are performed for improing performance of adaptive noise cancellers. In proposed methods, sign regressor based adaptive noise cancellers performs better than the remaining methods. The computation complexity in SR-LNMLS based adaptive noise cancellers is reduced with the usage of the signum function. For EMG and EMA noise types, signal to noise ratio and excess mean square error parameters are considered. Sign regressor based LNLMS algorithm SNR and EMSE values are 17.9833dB and -33.5615 dB, it is clear that it has better value when compared to LMS and LNLMS algorithms. Also from simulation results, observed that SR-LNMLS based adaptive noise cancellers exhibits enhanced performance Hence these adaptive noise cancellers are useful in real time applications.

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