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An Artifact Eradication in Brain Waves using Variable step sizeML Algorithms

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ABSTRACT: This paper proposes novel adaptive signal processing techniques for brain waves in patient care monitoring applications. Based on Leaky Least Mean Square algorithm using sign regressor and sign of step value and/or sign of signal, these novel algorithms are developed. In this work, we developed various adaptive signal conditioning techniques for BW suitable for remote patient care monitoring. Our proposed hybrid techniques mainly designed for simplicity with respect to complexity. In order to achieve better performance of the artifact elimination process a combination of normalized least mean square algorithm, leaky and variable step size algorithm is utilized. This hybrid version is variable step size leaky least mean square (VSNL^{2}MS) algorithm. The experimental results confirm that this algorithm is better in terms of convergence and filtering ability than the counter parts. Further, to minimize computational complexity, the proposed VSNL^{2}MS is combined with sign-based algorithms. Among the versions of signum based algorithms the sign regressor VSNL^{2}MS based noise canceller is well suited for patient care monitoring systems.

INDEX TERMS: Artifacts,Adaptive Artifact Eliminators; Brain Wave Analysis; Variable Step Size; Wireless EEG monitoring

I. INTRODUCTION

Electroencephalogram (EEG) illustrates the graphical representation of brain function. Any disorder in brain waves causes various medical ill conditions. According to world health organization reports [1] brain wave disorders responsible majority of mortality. Thus, in most of the diagnostic techniques brain wave become a key tool. Therefore, high resolution EEG signals are needed to be facilitated in clinical scenarios. But, during acquisition of the brain wave several artifacts like power line noise (PLN), respiration artifacts (RA). The projected artifacts contaminate signal quality and tiny brain wave activity features are masked, which is significant for process of diagnosis. Hence, process of eliminating the artifacts is a vital preprocessing methodology for monitoring the health care. Among the various techniques of artifact removal, the adaptive artifact elimination is a promising method. This is because adaptive techniques present inherent capability to alter the coefficients of filter based on input signal features. Also, among various physiological signals, the brain wave has a very non-stationary pattern. Thus, conventional filtering techniques are not suitable for artifact elimination in brain waves. Hence, adaptive FIR filters are the preferred way out in this process. Several adaptive filtering techniques are developed to eliminate artifacts from physiological signals. These are presented in several contributions like [2] -[15]. Due to technological developments in the brain wave analysis several techniques like brain computer interface (BCI), source localization, remote health care monitoring, machine learning, etc., also needs pre-processing of brain waves to facilitate high resolution EEG components for diagnosis. Several such contributions are found in the literature [16] –[19]. BCIs were established to allow communication between human thoughtprocesses and a computer, with the goal of disabled patients, assisting with motor function impaired because of disease, but whose mental functions are not affected severely [18]. The most advantageous selection of a BCI system reflects the equipment cost, as well as the spatial and temporal resolution essential for the application. Therefore, a remote health monitoring network at the hospital establishes with the acquisition system, biotelemetry link, BCI, control

ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

station. Less computational complexity is desirable for a usual healthcare remote monitoring system, specific to applications like 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 [20]-[22]. 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 brain wave processing under critical conditions, few samples of EEG signal turn out to be zero, with poor excitation and their weights vary significantly resulting in the problem of weight drift. This can be resolved by consideration of low leakage factor using Leaky LMS (L^2MS) technique. In this technique, the weight coefficient vector leaks out whenever its input is turned off. Towards increasing the stability of finite and precise operation, improve effects for excitation that is non-persistent; also decrease unwanted effects such as bursting, stalling, etc. Performance of L^2MS algorithm with comprehensive analysis is discussed in [25], an application of hybrid version of the leaky based algorithm is presented in [9]. The theory and analysis of leaky LMS and its variants are presented in [26]-[28]. Therefore, to increase the stability of the algorithm, to increase convergence, filtering ability and to minimize the computational complexity we develop a hybrid version of adaptive artifact eliminator (AAE) for brain wave pre-processing. To the best of our knowledge for the cancellation of artifacts in EEG components this hybrid version is not used till in the literature. Based on these considerations, we developed a new hybrid adaptive algorithm, which is a combination of circular leaky algorithms, variable step size algorithm and simplified algorithms. This resulting algorithm is called as variable step sizeL^2MS (VSL^2MS) algorithm, again thru combining this with a sign regressor algorithm (SAR) we realize sign regressor variable step size circular leaky LMS ($SRVSL^2MS$) algorithm; by combining with sign algorithm with VSL^2MS, we realize sign VSL^2MS ($SVSL^2MS$) algorithm; by combining with sign sign algorithm with VSL^2MS, we realize sign signVSL^2MS ($SSVSL^2MS$) algorithm. In this paper using these algorithms we design adaptive artifact eliminator (AAE) and demonstrate the pre-processing of the brain wave component by removing several kinds of artifacts that are non-physiological and physiological. In section II we present various algorithms and methodology for building an efficient AAE for remote brain wave monitoring facility, experimental results are discussed in section III, and conclusions in section IV are presented.

II. METHODOLOGY OF ADAPTIVE ARTIFACT ELIMINATION IN BRAIN WAVES

In the artifact elimination process the key element is the adaptive algorithm, which trains the FIR filter to change its coefficients. Let us consider 'L' to be the length of FIR filter. To facilitate ability to alter coefficients of filter in accordance to the artifact component this FIR filter is associated with an adaptive algorithm initially. Based on this strategy and using the framework of artifact elimination in [8] we develop an efficient adaptive artifact eliminator (AAE) which has better convergence, filtering ability, stability and less computational complexity. Fig. 1 shows a typical schematic diagram of an AAE. Let E= $e_1 + a_1$, here, E is the recorded signal of EEG, which combines the definite brain activity component (e_1) and artifact component (a_1).In adaptive artifact elimination process, a reference signal is needed and we give a random component a_2 as reference component. Consider filter weight vector as w(n), h(n) as the FIR filter's impulse response, also y(n) as convolution between w(n) and h(n).The adaptive algorithm trains a_2, become close to a_1,so that the summer performs the operation of $e_1 + a_1 - a_2$. As the number of iterations are going on, $a_1$and a_2 come close to each other and maximum of their components get

ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

cancel with each other and actual brain wave component B(n)will come out of AAE. The component f(n) is the feedback signal, it drives the adaptive algorithm as error signal, based on this the weight updating process will be repeated. The mathematical expression for the weigh update process of a typical LMS driven adaptive FIR written as,

$$w(n+1) = w(n) + s. E(n). f(n).$$

Here, w(n+1) is next weight coefficient for FIR adaptive filter, w(n) remains present coefficient of weight, 's' stands out to be step size of adaptation, E(n) stands as input brain wave which is contaminated with physiological and non-physiological artifacts, f(n) is the feedback signal based on which adaptive algorithm trains the filter coefficients.

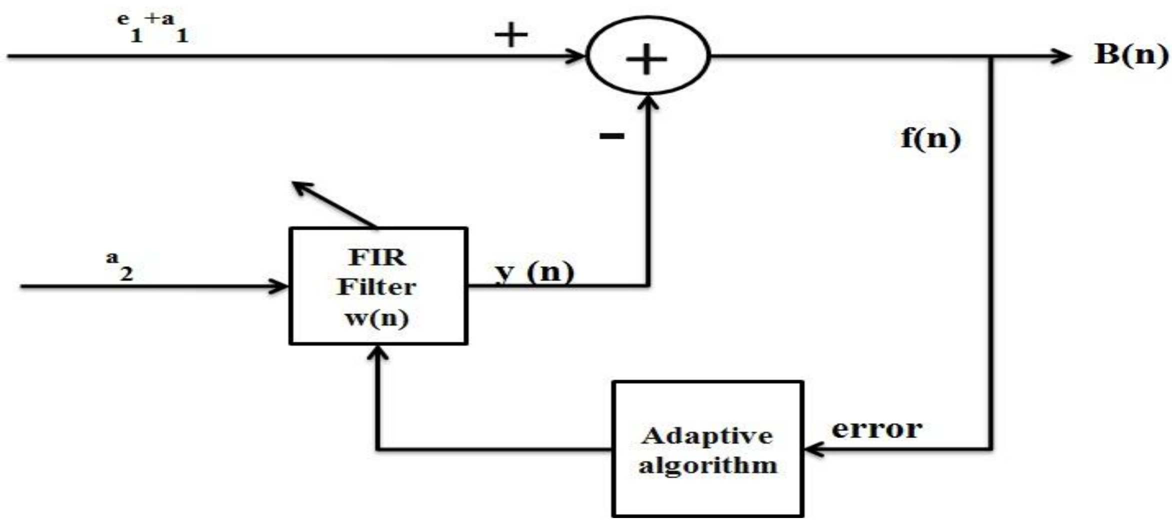


FIGURE 1. Typical block diagram of signal enhancement unit for brain wave analysis.

Even though, LMS algorithm is a better realization of adaptively updating the filter coefficients it suffers with two practical problems. The vector of input data is directly relational to the LMS weight update relation and fixed step size. A technique should be designed in a way for handling weak along with strong signals. Therefore, depending upon fluctuations in output and input of the filter, coefficients of tap vector must be altered consequently. As a result, LMS method undergoes a problem of gradient noise amplification for larger input data vector [29]-[30]. Normalized LMS (NLMS) is the better solution to overcome these problems. By doing so the adjustment applied to weight vector coefficient of the filter stands normalized pertaining to input vector's Euclidean squared norm in every iteration. The speed of convergence is slower in LMS due to fixed step size. In this regard, using an adjustable convergence factor helps in increasing the speed of convergence for LMS though estimates of the input correlation matrix were not used. The size of the step is varied iteratively due to normalization also it is relational inverse of the whole energy expected from immediate values of input vector data coefficients. Speed of convergence is typically faster in NLMS compared to LMS, as a variable factor of convergence aimed to reduce the immediate error output is used [31]-[32].

Now, mathematical recursion for Normalized LMS technique is written as,

ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

$$w(n+1) = w(n) + \frac{s}{\varepsilon + \max\|E(n)\|^2} E(n)f(n)$$

From this expression in this version of LMS, the step size is not a constant, rather than it is a variable quantity. In this version of normalization, we normalized the algorithm using maximum value of vector data E (n). It minimizes the computational complexity in the denominator of the weight update recursion.
This is the mathematical recursion for NL^2MS algorithm. In order to improve the convergence characteristics and filtering ability of the algorithm we combine this NL^2MS algorithm with NLMS and results normalized non-linear LMS (N^2L^2MS) algorithm. The weight update expression for this algorithm is given as,

$$w(n+1) = w(n) + s(n)g\{e(n)\}x(n)$$

where $s(n) = \frac{s}{\varepsilon + \|x(n)\|^2}$

A generalized flow diagram for the proposed SEU for brain wave enhancement is shown in Fig.2.
NLMS filter introduces its own problem to overcome noise amplification problem of gradient in case of LMS. Difficulties could arise here numerically due to smaller value of tap vector input E(n). Since squared norm needs should be divided with a small value for squared norm. A trivial positive constant ε needs to be used in order to evade divisor being too small and for larger step size.
Here, new variable parameter of step size becomes,

$$s(n) = \frac{s}{\varepsilon + \max\|E(n)\|^2}$$

For NLMS algorithm, the mathematical expression is written for instance,

$$w(n+1) = w(n) + s(n)x(n)f(n)$$

In physiological signal monitoring applications to increase stability we combine the NLMS algorithm with a leaky LMS algorithm. This result normalized leaky LMS algorithm (NL^2MS), its weight update recursion expressed as –

$$w(n+1) = (1 - s\gamma)w(n) + s(n)E(n)f(n)$$

It's selected in above expression in a way that product $s\gamma$ remains greater but close to zero. For improving the adaptive filter characteristics, LLMS technique has been used in order to to efficiently cancel the noise from EEG signals [27]. This algorithm will be overcome such problems numerically with the use of smaller leakage factor γ for the weight vector of the tap. In leaky algorithm, input signal that is ill conditioned is used to improve properties of convergence for the ill-conditioned correlation input matrix. Forovercoming the divergence of FIR adaptive filter under critical conditions, step size in the conventional leaky algorithm is improved based on the framework presented in [28], the complete mathematical analysis is presented in [28]. The major modifications in our proposed technique are as follows:
To achieve better performance we introduce a factor called adaptation factor '$\delta(n)$' in the algorithm.

$$\delta(n) = \frac{s(n)\text{fmod}(n)}{\varepsilon + \max\|E(n)\|^2}$$

Where, fmod(n) is the modified feedback signal.
A generalized flow diagram for a typical AAE for brain wave enhancement is shown in Fig.2.

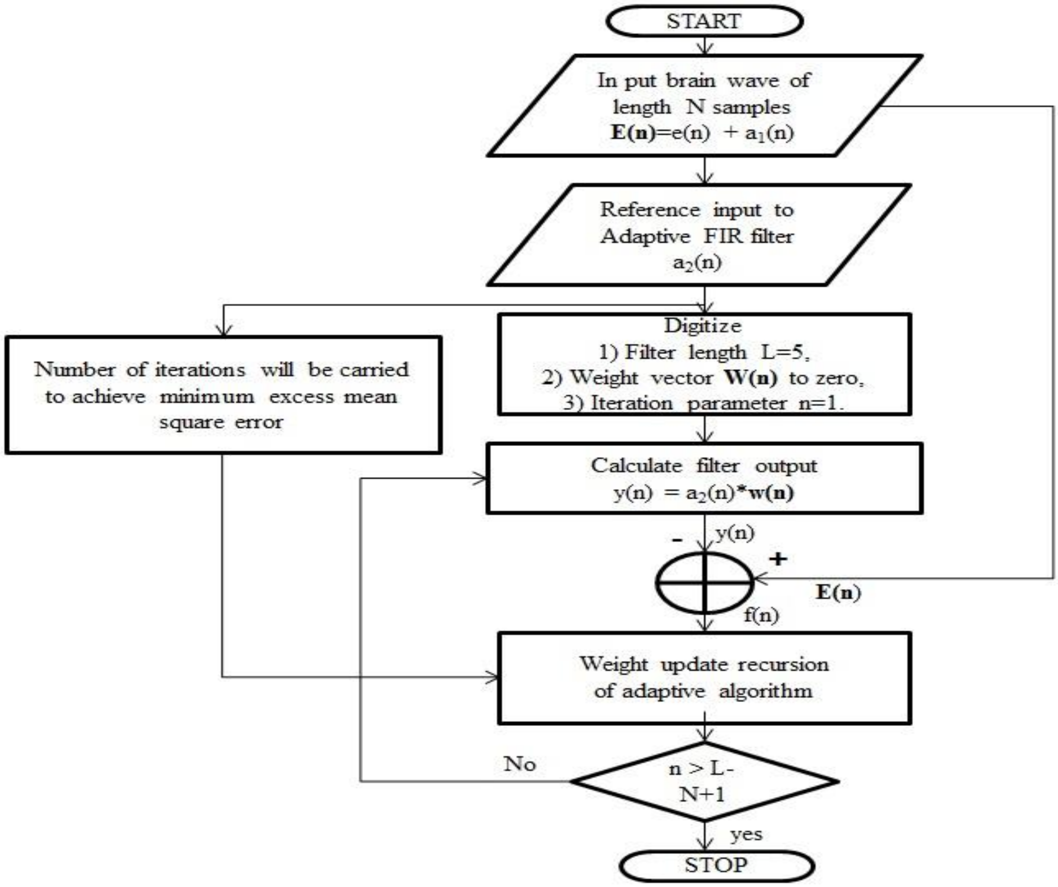


FIGURE 2. Flow chart of adaptive artifact cancellation algorithm for brain wave enhancement.

If the computational complexity of the algorithm increases, at the input of a wireless remote health care monitoring device the data samples overlap on each other as causes inter symbol interference. To overcome this problem, the impulse response of the receiver must be increased, but minimizing the complexity in computations for technique of signal conditioning is an optimum solution. So, we developed hybrid versions of adaptive algorithms by combining VSL^2MS and sign based algorithms. The three-familiar sign based algorithms are elaborated in [20]. The hybrid versions of VSL^2MS and signed algorithms are named as, sign regressor VSL^2MS ($SRVSL^2MS$), sign VSL^2MS ($SVSL^2MS$), sign signVSL^2MS ($SSVSL^2MS$) algorithms.

The weight update recursions for $SRVSL^2MS$is represented as,

$$w(n+1) = (1 - s\gamma)w(n) + \delta(n)\mathrm{sgn}\{E(n)\}f(n)$$

The weight update recursions for $SVSL^2MS$ becomes,

$$w(n+1) = (1 - s\gamma)w(n) + \delta(n)E(n)\mathrm{sgn}\{f(n)\}$$

The weight update recursions for $SSVSL^2MS$is expressed as,

$$w(n+1) = (1 - s\gamma)w(n) + \delta(n)\mathrm{sgn}\{E(n)\}\mathrm{sgn}\{f(n)\}$$

ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

Therefore, using these algorithms, namely, VSL^{2}MS, SRVSL^{2}MS, SVSL^{2}MS and SSVSL^{2}MS we develop various AAEs to eliminate artifacts from brain waves. We compare these implementations with familiar LMS and NLMS based AAEs. Typically, for estimating and comparing the complexity of algorithm, number of multiply operations needed is taken as a metric to complete the operation.The computational complexity for various algorithms in terms of number of multiplications is shown in Table 1.In signal processing circuits, the signum based techniques require less number of multiplications than their counterparts because of clipping operations. So, we have used these signum based hybrid versions in our realizations to minimize the computational burden of the proposed AAEs.

Table 1: Complexity of various adaptive algorithms for artifact elimination in brain waves.

S.No.	Algorithm	Multiplications
1.	LMS	L+1
2.	NLMS	L+2
3.	NL^{2}MS	L+3
4.	VSL^{2}MS	2L+3
5.	SRVSL^{2}MS	L+3
6.	SVSL^{2}MS	2L+3

Among the three sign-based algorithms SRVSL^{2}MS, SVSL^{2}MS and SSVSL^{2}MS, the SSVSL^{2}MS has less computational complexity. The SVSL^{2}MS has the complexity in terms of multiplications equal to VSL^{2}MS, also by clipping feedback signal its resolution is inferior than VSL2MS. So, SVSL^{2}MS is also not a good candidate for artifact elimination process. Whereas, in SRVSL^{2}MS the data vector is clipped and its computational complexity is nearly equal to conventional LMS in terms of multiplications with increased convergence characteristics. Therefore, from the analysis of various methods based on complexity in computations and their speed of convergence, the SRVSL^{2}MS is seems to be a better candidate for brain wave analysis.

III.RESULTS AND DISCUSSION

Towards demonstrating the proposed AAEs performance in health care monitoring contest we have recorded several brain waves in various physiological scenarios using the Emotive EPOC brain wave acquisition headset [33].This accusation system consists of 2 electrodes for reference and 14 electrodes for bio-potential. These are arranged according to a grid as per the international 10-20 system, these are designated as per the method presented in [34]. For the experiments, 10,000 samples of EEG signal are collected from the subject. To facilitate a signal of high resolution, 1000 samples for brain data are presented. The performance of several AAEs aimed at process of signal conditioning is measured using excess mean square error (EMSE) and signal to noise ratio improvement (SNRI). These performance measures are measured in ten experiments on individual data and averaged. These results are shown in Tables 2, 3. Gaussian noise using 0.01 variances commencing from mean of the brain wave data is added to resemble channel noise in a wireless EEG system. In our work, we used five diversified samples of brain data, the data set consists of: brain wave (BW) 1, BW 2, BW 3, BW 4 and BW 5 to obtain consistent results from AAEs. To perform experiments using the recorded data, we developed various AAEs using LMS, NLMS, VSL^{2}MS, SRVSL^{2}MS, SVSL^{2}MS and SSVSL^{2}MStechniques. Our model for simulation

ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

facilitated with a generator of noise to provide an adequate reference noise signal. This reference signal is a combination of PLN, impulsive noise, random noise, RA, EMA and EMG artifacts. Theexperimental findings of artifact elimination are described case by case in the following sub-sections.

A.ADAPTIVE ARTIFACT ELIMINATION OF POWERLINE NOISE FROM BRAIN WAVES

This experiment proves the PLN elimination process from brain wave component. The raw brain wave component is taken as input for AAE for instance is shown in Fig.1, component of input is a combination of actual brain action potential and non-physiological noise contamination, it is designated as $e_1 + a_1$. The reference signal given to the adaptive FIR filter is a_2.The adaptive technique trains the coefficients of FIR filter, in a way $a_2$becomes closer toa_1. The experimental results after artifact elimination are shown in Fig.3. From this figure, it is depicted that Fig. 3 (e) and (f) are showing high-resolution brain wave components than other subplots. These are results are obtained due to AAEs based on VSL^{2}MS and SRVSL^{2}MS algorithms. Again, by examine the performance measures using excess mean square error, SNR, among various algorithms VSL^{2}MS based AAE achieves highest performance measures. But, among all the algorithms SRVSL^{2}MS based AAE requires less amount of complexity in computations and multiply operations by an amount equal to length of the filter, in this case it is 'L', shown in Table 1. However, in terms of other performance measures SRVSL^{2}MS is little bit inferior than VSL^{2}MS algorithm based AAE. This fact is depicted by examine Tables 2, 3. Therefore, as a tradeoff the little bit inferior performance of SRVSL^{2}MS based AAE could be tolerated than AAE based on VSL^{2}MS, as SRVSL^{2}MS needs lesser number of multiplications by an amount 'L', which is filter length in this case. Hence, SRVSL^{2}MS based AAE is suitable for elimination of artifacts from brain waves for EEG analysis in remote health care monitoring applications.

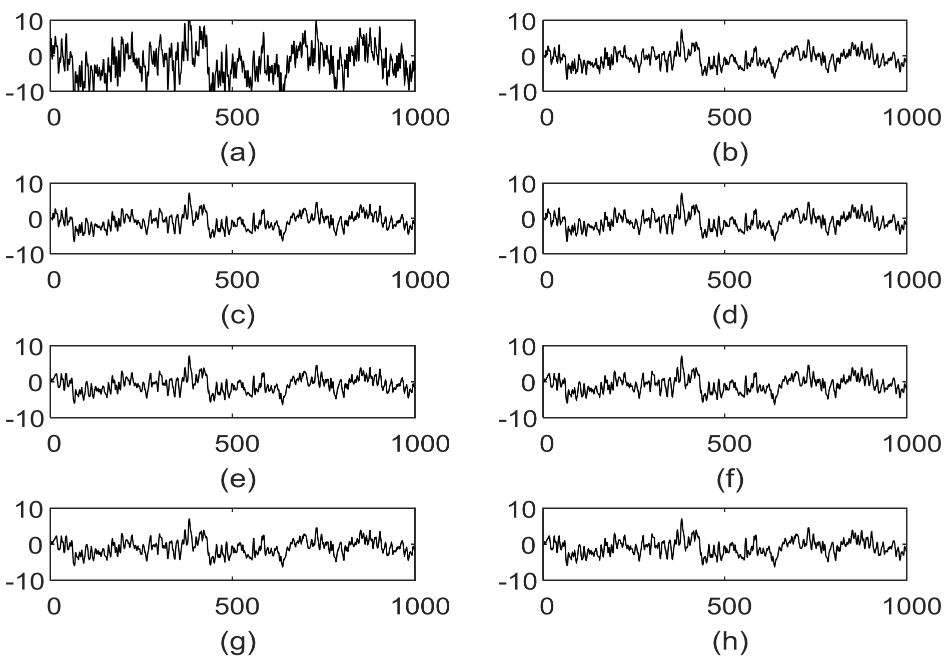
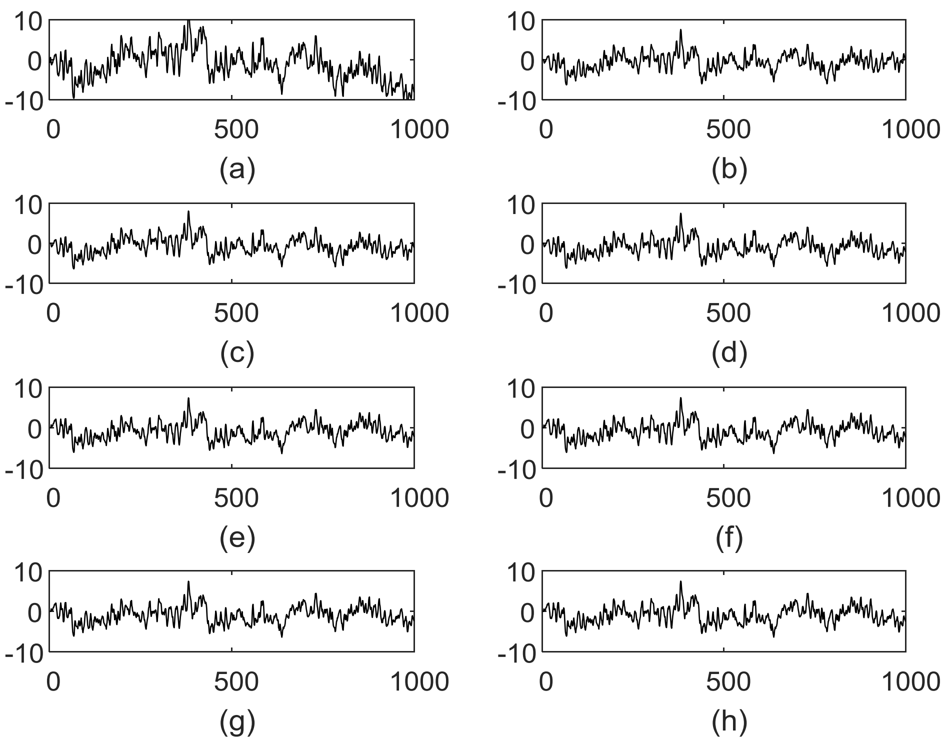


FIGURE 3. Adaptive artifact elimination results of PLN from brain waves: (a). Noisy raw brain wave component, (b). artifact elimination using LMS based AAE, (c). artifact elimination using NLMS based AAE, (d). artifact elimination using NL^{2}MS based AAE, (e). artifact elimination

using VSL^{2}MS based AAE, (f). artifact elimination using SRVSL^{2}MS based AAE, (g). artifact elimination using SVSL^{2}MS based AAE, (h). artifact elimination using SSVSL^{2}MS based AAE. (Number of samples on x-axis, signal amplitude on y-axis amplitude are considered)

B.ADAPTIVE ARTIFACT ELIMINATION OF RESPIRATION ARTIFACT FROM BRAIN WAVES

This experiment proves the respiration artifact elimination process from brain wave component. The raw brain wave component is taken as input for AAE as depicted in Fig.1, the component for input is a combination of actual brain action potential and non-physiological noise contamination, it is designated as $e_1 + a_1$. The reference signal given to the adaptive FIR filter is a_2.The coefficients of FIR filter are trained using adaptive technique in a way that $a_2$becomes closer to a_1. The experimental results after artifactelimination is shown in Fig.4. From this figure, it is depicted that Fig. 4 (e) and (f) are showing high-resolution brain wave components than other subplots. These are results are obtained due to AAEs based on VSL^{2}MS and SRVSL^{2}MS algorithms. Again, by examine the performance measures based on, excess mean square error, SNR, among various algorithms VSL^{2}MSbased AAE achieves highest performance measures. But, among all the algorithms SRVSL^{2}MS based AAE requires less amount of complexity in computations using multiply operations by an amount equal to length of the filter, in this case it is 'L', shown in Table 1. However, in terms of other performance measures SRVSL^{2}MS is little bit inferior than VSL^{2}MS algorithm based AAE. This fact is depicted by examine Tables 2, 3. Therefore, as a tradeoff the little bit inferior performance of SRVSL^{2}MS based AAE could be tolerated than AAE based on VSL^{2}MS, as SRVSL^{2}MS needs lesser number of multiplications by an amount 'L', which is filter length in this case. Hence, SRVSL^{2}MS based AAE is suitable for elimination of artifacts from brain waves for EEG analysis in remote health care monitoring applications.



ISSN- 2394-5125 VOL 07, ISSUE 04, 2020

FIGURE 4. Adaptive artifact elimination results of respiration artifact from brain waves: (a). Noisy raw brain wave component, (b). artifact elimination using LMS based AAE, (c). artifact elimination using NLMS based AAE, (d). artifact elimination using NL^{2}MS based AAE, (e). artifact elimination using VSL^{2}MS based AAE, (f). artifact elimination using SRVSL^{2}MS based AAE, (g). artifact elimination using SVSL^{2}MS based AAE, (h). artifact elimination using SSVSL^{2}MS based AAE. (Number of samples on x-axis, signal amplitude on y-axis amplitude are considered)

TABLE 2
COMPARISON OF FILTERING ABILITY OF VARIOUS ADAPTIVE ALGORITHMS IN BRAINWAVE ANALYSIS IN TERMS OF SNR BEFORE AND AFTER FILTERING(IN TERMS OF DECIBELS)

Artifact Type	Sample No.	SNR before filtering	SNR after filtering						
			LMS	NLMS	NL^{2}MS	VSL^{2}MS	SRVSL^{2}MS	SVSL^{2}MS	SSVSL^{2}MS
PLN	BaseWave 1	10.3717	17.7995	21.6407	22.7224	29.0039	27.7017	26.2850	25.1666
	BaseWave 2	10.1767	16.3403	18.82455	19.2450	25.4954	24.8384	24.0095	23.2887
	BaseWave 3	10.3726	17.8001	21.6414	22.7237	29.0859	27.7017	26.2782	25.2536
	BaseWave 4	10.1768	16.3548	18.8242	19.6885	25.4944	24.8392	24.5463	23.2597
	BaseWave 5	10.1029	16.9683	20.4382	21.0695	29.0584	27.6737	26.1786	25.0265
RA	BaseWave 1	2.5	8.5564	11.3676	12.9364	22.8865	20.5128	19.4982	18.5782
	BaseWave 2	2.5	10.9618	13.0811	14.9397	21.8450	19.8097	18.9304	18.8531
	BaseWave 3	2.5	8.9786	11.5648	12.8268	22.8765	20.8114	19.3579	18.5776
	BaseWave 4	2.5	10.6749	13.3921	14.3395	21.3289	19.6498	18.7653	18.1147
	BaseWave 5	2.5	7.8658	9.2125	11.3507	22.9007	20.5224	19.5053	18.4826

TABLE 3
COMPARISON OF FILTERING ABILITY OF VARIOUS ADAPTIVE ALGORITHMS IN BRAINWAVE ANALYSIS IN TERMS OF EXCESS MEAN SQUARE ERROR AFTER FILTERING(IN TERMS OF DECIBELS)

Artifact Type	Sample No.	Various algorithms used in the development of AAEs						
		LMS	NLMS	NL^{2}MS	VSL^{2}MS	SR VSL^{2}MS	S VSL^{2}MS	SS VSL^{2}MS
PLN	BaseWave 1	-15.8464	-28.0731	-30.6759	-34.2562	-33.72848	-32.6717	-31.9846
	BaseWave 2	-15.5343	-28.0345	-30.6826	-34.3423	-33.52364	-32.5234	-31.6234
	BaseWave 3	-15.7236	-28.1723	-30.7534	-34.4826	-33.86231	-32.6863	-31.7282
	BaseWave 4	-15.8723	-28.2673	-30.8632	-34.3947	-33.72845	-32.7521	-31.9523
	BaseWave 5	-15.9634	-28.0626	-30.8737	-34.4972	-33.69823	-32.8236	-31.8958
RA	BaseWave 1	-17.7456	-29.7745	-31.3848	-35.6278	-34.6472	-33.7584	-32.5267
	BaseWave 2	-17.6234	-29.8631	-31.3923	-35.7653	-34.5923	-33.8723	-32.6872
	BaseWave 3	-17.7923	-29.7852	-31.4682	-35.6986	-34.6834	-33.7724	-32.7274
	BaseWave 4	-17.8645	-29.9635	-31.5318	-35.7912	-34.7386	-33.8964	-32.7025
	BaseWave 5	-17.7983	-29.8624	-31.3942	-35.5928	-34.6955	-33.7842	-32.6987

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IV.CONCLUSION

This research demonstrates a new method for developing adaptive artifact eliminator to facilitate high-resolution brain waves for wireless EEG monitoring, remote health care monitoring applications in the contest of BCI. The proposed VSL^{2}MS based AAEs achieved good filtering ability, less computational complexity of the adaptive algorithms. To examine these characteristics various AAEs based on NL^{2}MS, VSL^{2}MS, SRVSL^{2}MS, SVSL^{2}MS, SSVSL^{2}MS algorithms are developed and demonstrated the brain wave enhancement. These implementations are compared with the performance of AAEs based on conventional LMS and NLMS algorithms. Among these implementations VSL^{2}MS based AAE achieved highest values of performance measures like SNR, EMSE, except computational complexity. This is evident from Tables 1, 2, 3. From the experimental results among LMS, NLMS, NL^{2}MS and VSL^{2}MS based AAEs the VSL^{2}MS out performs. Again, when comparing VSL^{2}MS and its hybrid versions of sign algorithms the performance of SVSL^{2}MS, SSVSL^{2}MS diverges more than VSL^{2}MS due to error clipping, data error clipping. When we compare the performance measures of VSL^{2}MS and SRVSL^{2}MS based AAEs in terms of SNR, EMSE, the performance of SRVSL^{2}MS is little inferior than VSL^{2}MS. But, the computational complexity of SRVSL^{2}MS is 'L' times less than VSL^{2}MS. Hence, it becomes more attractive for wireless and remote health care monitoring applications.

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