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Artifact Elimination in EEG Signal using Block and Sign Based Normalized Least Mean Square Techniques

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Abstract:** In this research the efficient and low computation complex signal acclimatizing techniques are projected for the improvement of Electroencephalogram (EEG) signal in remote health care applications. In clinical practices the EEG signal is extracted along with the artifacts and with some small constraints. Mainly in remote health care situations, we used low computational complexity filters which are striking. So, for the improvement of the EEG signal we introduced efficient and computation less Adaptive Noise Eliminators (ANE's). These techniques simply utilize addition and shift operations, and also reach the required convergence speed among the other predictable techniques. The projected techniques are executed on real EEG signals which are stored and are compared with the effecting EEG arrangement. Our realizations visualize that the projected techniques offer the best concert over the previous techniques in terms of signal to noise ratio, mathematical complexity, convergence rate, Excess Mean Square error and Mis adjustment. This approach is accessible for the brain computer interface applications.

I. INTRODUCTION

EEG resembles the visual illustration of the brain activities. If any disturbance occurs in the brain causes the mental illness. From the World Health Organization and other reports from [1]-[4] says that the brain signal disturbances cause the imbalance in the health both to the physical and mental health. So, in most of the cases the outcome of the clinical methods related to brain becomes an important tool. Such that we mostly focused on the high-resolution EEG signals in accordance with the clinical reports. But, at the time of analyzing the brain wave there are several number of artifacts like Power Line Interference (PLN), Eye Blink Artifact (EBA), Electromyogram (EMG), Cardiac Signal Artifact (CSA), Respiratory Artifact (RA) and Electrode Motion Artifact (EMA).These artifacts will disturbs the signal strength and hides some characteristics of the brain in accordance with the clinical reports. So that the artifact cancellation is the key part and this is the first step in health care observation. Such that they introduced several methods for the elimination of artifacts caused due to the head movement and finding the artifacts automatically by the Influential Independent components and for detection of Epileptic Seizure from the EEG. Usually the recognition and elimination of artifact in Multichannel scalp EEG through Wavelet ICA. By giving a reference signal to find the EEG artifacts caused due to restrained progressions. The elimination of EKG artifact from the EEG by using independent component analysis and Continuous Wavelet transformation. And also uses the principal component analysis for the declination of stimulated artifacts in EEG. In support of the removal of muscle artifact from a small number of sources with the new adaptive method as EMD and CCA whether it may be single or multi-channel to be used and also with the help of Independent Vector Analysis. Intended for the portable application in adaptive filtering and independent component analysis in additional it detects the driver tiredness from EEG spectrum and also for the elimination of electrooculography artifact and for single channel EEG using
wavelet technique, to take out the EOG artifacts from the single channel using singular spectrum analysis and Adaptive Noise Cancellers furthermore they are utilizing feature learning technique in EEG in the course of DWT and ANC mainly for portable appliances for the recognition and elimination of ocular artifacts. Furthermore, the unrecognized Eye Blink Artifact (EBA) in EEG can be recognized with modified High-Speed Eye Tracker. And also uses the Cyclo-stationary Source Extraction technique for the removal of Ballisto-cardiogram artifact in EEG and uses the independent vector analysis while for the moving related technique for the exclusion of gradient artifact from EEG is illustrated in [5]-[26]. Because of the technological improvements in brain signal movement i.e. EEG that can be measured with Noninvasive Neural Prostheses utilizing mobile and wireless EEG. And the wearable EEG sensor is used to evaluate the signal quality during mental stress. The Wearable and wireless EEG approaches used in daily life purposes. A hybrid BCI's and near-infrared spectroscopy (NIRS) is used for signal analysis in EEG. The stored EEG artifact for cochlear implant in synthetic brain for difficult audio stimuli and the ability of cochlear implant noise innovative technique is used and it can be eliminated using Auditory Evoked Potentials [28]. For more efficiency, they used the Brain-Computer interfacing for the removal of the artifacts. The EEG artifacts can be removed mainly in the portable relevance's. The innovative technology is used to find the brain activity is the EEG spectrum, which is used to eliminate the EOG artifact and to know the driver tiredness.

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Some important signal stipulating methods are used to detect the EEG and also the Thoracic Electrical Bio-Impedance (TEB) activity in Remote Health monitoring Network. In extent the proficient block practicing of lengthy period bio-telemetric brain statistics for health care monitoring is explained in [27]- [38]. The authors mainly focused on the Computational difficulty, to overcome this disadvantage they use the linear predictor and Cyclo-stationary Source Extraction technique for the removal of Ballisto-cardiogram artifact in EEG. The unrecognized Eye Blink Artifact (EBA) in EEG can be recognized with modified Multi-scale Sample Entropy, Kurtosis and Wavelet ICA. And in favor the Efficient Neural Network in adaptive filtering approach. Anda innovative methodology for decreasing the artifacts removal techniques in physiological signals is found in [39]-[43]. The ICA and multi-variate Emphirical Mode Decomposition are also used for the computational complexity diminishing in EEG artifacts they also used wavelet techniques have been designed and proved practically for the mathematical difficulty drawback. The performance [42] and the computational difficulty is achieved and the artifact removal in physiological signal is being described.

II. NORMALIZED SIGN RELATED ADAPTIVE NOISE ELIMINATORS FOR EEG TELEMETRY

Consider a FIR filter with M coefficients. We had taken the FIR filter because of the concept filter coefficient weight adaptation. Utilizing the FIR filter, we designed an ANE linked with a sensitive EEG recording structure and it is again connected to the computer which is shown in the Fig.1. In this structure s(n) is defined as input sequence applied to the adaptive filter which regulates the filter coefficients and the desired signal is p(n) which is traced from patient, and the weight modernize recursion equation can be written as

$x(n+1) = x(n) + V\, s(n)\, r(n)$ (1)

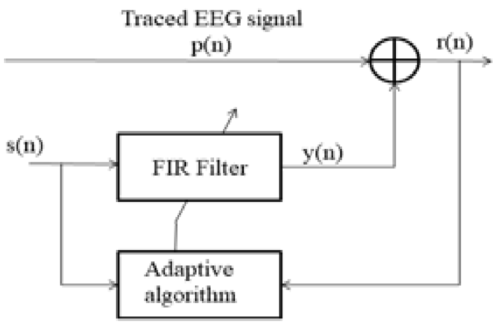

Fig. 1. Configuration of Adaptive Noise Eliminator

Where, $x(n) = [x_0(n), x_1(n),\ldots x_{M-1}(n)]^t$ is the filter weight vector at the n^{th} key, $s(n) = [s(n), s(n-1),\ldots.s(n-M+1)]^t$, error signal $r(n) = p(n) – x^t(n)\, s(n)$ and V is the step-size constraint. In order to extract the noise from the EEG signal, the EEG signal $z_1(n)$ is imputed with a noise signal $g_1(n)$ which is functional with the desired succession p(n) to the adaptive filter visualized in the Fig.1. The allusion signal s(n) is added with another noise component $g_2(n)$ and it is again correlated with $g_1(n)$. The filter error equation can be written as $r(n) = [z_1(n) + g_1(n)] – y(n)$, where y(n) is the adaptive filter output and its equation can be written as

$y(n) = x^t(n)\, s(n)$ (2)

The Mean squared error (MSE) is computed as,

$E[r^2(n)] = E\{[z_1(n) -y(n)] – y\ (n\ ]^2\} + E[g_1^2(n)]$ (3)

Since $z_1(n)$ and $g_1(n)$ are uncorrelated, likewise $g_1(n)$ and y(n) are uncorrelated and the last two expectations are zero. MSE reduces the filter outcomes which is the best least square estimate of the signal $z_1(n)$.

The projected ANEs will utilize the signum function to the error or to the key information vector, or for the two of them are being gained from the LMS algorithm, for minimizing the number of multiplications and additions. The weight modernize recursion of SRLMS, SLMS and SSLMS techniques are taken as follows,

$x(n+1) = x(n) + V\, sgn\{s(n)\}\, \{r(n)\}$ (4)

$x(n+1) = x(n) + V\, \{s(n)\}\, sgn\{r(n)\}$ (5)

and

$x(n+1) = x(n) + V\, sgn\{s(n)\}\, sgn\{r(n)\}$ (6)

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

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

Amongst the above adaptive techniques, the SRLMS, SLMS and SSLMS will have a poorer convergence rate and a steady state error when compared to the LMS algorithm. And this is elucidated as ensues, and the SLMS equation can be written as

$x(n+1) = x(n) + V\, \{s(n)\}\, \{r(n)/|r(n)|\},$ (8)

Here $sgn\{r(n)\} = r(n)/|r(n)|$. This is reorganized as,

$$x(n+1) = x(n) + \left\lfloor \frac{V}{|r(n)|} \right\rfloor s(n)\, r(n) \quad (9)$$

The variable step size technique can be represented by applying the sign to the LMS technique, the

V' (n) = {V/r (n)}. The V' (n) raises, the sign technique converges due to error r (n) downs in magnitude. So that the filter converges and r(n) changes to smaller in magnitude then V' (n) happens to larger and automatically raises the convergence rate.

By creating the V to a value of power of two then the hardware circuit becomes simple the arithmetic operations gets reduced, while in the Normalized LMs technique there is an achievement of quick convergence by normalizing the step size relating it to primary input. And that updated equation can be written as follows,

$$x(n+1) = x(n) + \left\lfloor \frac{V}{k + r^t(n)r(n)|} \right\rfloor s(n)\, r(n) \quad (10)$$

The step size parameter V(n) can be written as,

$$V(n) = \left\lfloor \frac{V}{k + r^t(n)r(n)|} \right\rfloor \quad (11)$$

In this V is the predetermined step size as announced in the LMS technique. And the k is the constant kept for the sake of denominator not to be equal to zero such that the step size constraint V befalls as larger value. Commencing the weight update equations of LMS and NLMS, the equations (1) and (10) resembles that the NLMS technique is the extended adaptation of LMS technique. The variation in x(n) is indirectly proportional to custom of primary data vector s(n). The s(n) with large normalized data quantity will sources some modifications to x(n) than a small normalization quantity. Because of the normalization of information outcome with smaller V estimation when defined with the LMS. The normalized filter typically works faster than the LMS filter becauseof utilization of variable step size for the constraints convergence rate and the low error estimation at the output.

The main aim of this is to achieve the less computations when we added up the NLMS with sign techniques. So that they should be visualized as NSRLMS, NSLMS and NSSLMS techniques. The weight modernized equation can be written as

x(n+1) = x(n) + V(n) sgn{s(n)} {r(n)} (12)

x(n+1) = x(n) + V(n) {s(n)} sgn{r(n)} (13)

x(n+1) = x(n) + V(n) sgn{s(n)} sgn{r(n)} (14)

The further requirements are to calculate the V(n) from the equations (12) – (14) can be minimized by utilizing block-based algorithms, in this the primary key is decomposed into blocks and each block consists of high extent is utilized to calculate V(n). With this the weight modernized equation can be written by considering the equations (12) – (14) and then S_{Li} = 0 and f=0 exhibits the following form,

$$x(n+1) = x(n) + \frac{V}{s_{Li}^2} sgn\{s(n)\}\ \{r(n)\} \quad (15)$$

$$x(n+1) = x(n) + \frac{V}{s_{Li}^2} \{s(n)\}\ sgn\{r(n)\} \quad (16)$$

and

$$x(n+1) = x(n) + \frac{V}{s_{Li}^2} sgn\{s(n)\}\ sgn\{r(n)\} \quad (17)$$

And at which $S_{Li} = \max \{|s_j|,\ j \in C_s'\}$, $C_s' = \{S_L, S_{L+1}, \ldots S_{L+L-1}\}$, $S \in C$. while for S_{Li} = 0 and k=0 the equations (9)-(11) can be seen as x(n+1) = x(n).These techniques can be written as BBNSRLMS, BBNSLMS and BBNSSLMS correspondingly. The convergence distinctive of several techniques is described at above as shown in Fig.2. So, from these distinctive it is claimed that NSRLMS works better when compared to NLMS.

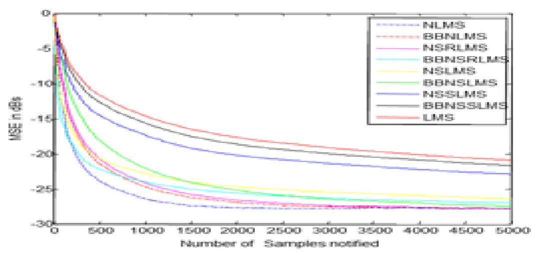

Fig.2. Distinctiveness of Convergence for several adaption's of LMS Algorithm.

III. SIMULATION RESULTS

Our outcome shows that the visualized ANE's gives the better results at clinical practices, for this we have taken the number of EEG recordings and compared them with the past experiences which have the noisy components in the EEG. We had taken the 14 information collective electrodes and two reference electrodes and these are kept for the 10-20 systems. That information will be encrypted by the transmitter which is placed at the headset without wires based on the windows-based appliance and that wireless equipment works at the 802.11 (2.4 GHz). And we took artifacts with 6 subjects. And the sampling capacity is 125samples/second with a 4-byte floating number of equals to one electrode amplitude. The transmission speed from laptop to mobile is 4kbps. The experiments are done for 25,000 samples from male, of age 41. For the concert analysis we measured Signal to Noise ratio Improvement (SNRI). Excess Mean Square Error (EMSE) and Mis-adjustment (MSD) constraints and those are evaluated with the predictable LMS. The SNRI distinction with different artifact cancellation is shown in Table 1. Whereas, Table 2gives the distinctive measures of all techniques in remarks of EMSE, MSD for the EEG record number 1. In the outcome we have achieved the datasets with 6 EEG records as Record 1, Record 2, Record 3, Record 4, Record 5 and Record6 to make certain the ability of the outcomes. Several ANE's are realized utilizing LMS, NLMS, BBNLMS, NSRLMS, BBNSRLMS, NSSLMS and BBNSSLMS techniques. This experiment has a noise source, which generates the noise reference signal. This reference signal contains PLI, EMG, RA and EMA noises. All the ANE's the input is the reference signal. Several experiments are being evaluated to eliminate the noise from the original signal. These outcomes are visualized in Fig.3 to Fig.6.

Table 1. Concert of several ANE's in terms of SNRI throughout the EEG Improvement (all values are in dB's)

Noise	Rec.no	LMS	NLMS	BBNLMS	NSRLMS	BBNSRLMS	NSLMS	BBNSLMS	NSSLMS	BBNSSLMS
PLI	1	**5.3737**	**12.6427**	**11.3845**	**11.9293**	**11.1373**	**8.3784**	**7.9672**	**7.6137**	**7.1921**
	2	6.8482	14.6524	13.8731	13.5397	13.2592	9.6379	8.9371	8.3642	7.1901
	3	4.1762	11.8603	10.6902	10.4032	9.9367	7.7922	7.3809	6.9573	6.3903
	4	6.4072	15.8032	14.9211	14.7103	14.3106	11.3927	10.9472	10.4210	9.7219
	5	7.9123	14.8241	13.5243	13.3019	12.9902	12.5102	9.9467	9.5407	9.2134
RA	1	**4.8273**	**11.9126**	**11.7213**	**10.7506**	**10.5123**	**9.8234**	**9.9821**	**7.7924**	**7.5213**
	2	6.8104	13.4231	13.1903	12.8213	12.4821	11.7613	11.5042	9.7923	9.3421

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	3	3.8924	10.7013	10.5947	9.9134	9.5107	8.7891	8.2098	6.9123	6.4013
	4	5.8927	12.7423	12.5936	11.9824	11.4967	10.9345	10.7126	8.8148	8.3145
	5	4.2159	10.3190	10.1124	9.3569	8.7213	7.9124	6.9219	4.9167	4.5189
EMG	1	**4.9120**	**9.9472**	**9.5678**	**8.9148**	**8.5067**	**7.7568**	**7.5013**	**6.7216**	**6.2378**
	2	6.9013	14.8792	14.4621	13.5642	13.2179	12.7452	12.3567	11.4952	11.3987
	3	5.7956	11.2017	11.1257	10.4128	9.5892	8.6287	8.3156	7.5287	6.5728
	4	7.7489	16.9128	16.3128	15.4985	15.2765	14.5631	14.1279	13.8469	13.3892
	5	5.6742	11.9587	11.6934	10.1563	9.9146	8.4203	8.2106	7.6439	7.3693
EMA	1	**5.4295**	**9.5697**	**9.5423**	**8.8127**	**8.3218**	**7.9807**	**7.5123**	**7.1267**	**6.9109**
	2	4.8927	8.8467	8.1093	7.8926	7.3497	6.9023	6.7203	6.5609	6.1107
	3	7.6782	11.6537	11.2109	10.8193	10.1249	9.8921	9.6129	9.3149	9.1293
	4	6.3986	10.9984	10.3193	9.6219	9.3156	8.7147	8.5179	8.2178	7.9784
	5	5.9126	9.8926	9.4689	8.8936	8.5632	7.9834	7.7219	7.4532	6.9129

Table 2. Concert of several ANE's in terms of EMSE and MSD throughout the EEG Improvement For record number1 (all values are in dB's)

Noise	characteristic	LMS	NLMS	BBNLMS	NSRLMS	BBNSRLMS	NSLMS	BBNSLMS	NSSLMS	BBNSSLMS
PLI	EMSE	-15.7462	-28.0245	-27.5998	-25.6983	-23.9698	-23.5598	-21.5289	-20.6289	-19.8298
	MSD	0.0947	0.0781	0.0789	0.0879	0.0899	0.0899	0.0549	0.0586	0.0598
RA	EMSE	-17.7397	-29.7689	-28.9287	-27.8269	-26.9689	-25.7386	-24.7298	-22.6287	-22.2689
	MSD	0.0864	0.0549	0.0657	0.0692	0.0699	0.0753	0.0775	0.0798	0.0879
EMG	EMSE	-17.6398	-30.6239	-29.8397	-28.6398	-27.5783	-26.5296	-25.7342	-25.3679	-24.6579
	MSD	0.0982	0.0678	0.0692	0.0741	0.0784	0.0801	0.0867	0.0897	0.0952
EMA	EMSE	-17.7299	-30.8297	-29.6599	-27.7296	-26.7198	-25.5169	-24.6548	-24.2679	-23.7892
	MSD	0.1388	0.0779	0.0839	0.0987	0.0912	0.0949	0.0982	0.1063	0.1273

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A. Adaptive Elimination of Power line Interference (PLI)

This evaluation describes the Power Line Interference (PLI) elimination. The key to the filter is the EEG signal mixed with the noisy PLI of frequency 50Hz and sampled at the 160Hz record taken from male of age 41. Here the reference signal is noise and the pure signal can be extracted at the output. The EMSE result related on sign LMs technique are visualized in Fig.3. We evaluate this result by using six EEG records for ten times and then averaged. Several concerts like SNRI, EMSE and MSD are tabulated in Tables 1 and 2. In SNRI evaluation it is clear that NLMS gives 12.6427 dB, NSLMS gives 8.3784 dB, BBNSLMS gets 7.9672 dB, NSSLMS gives 7.6137 dB and BBNSSLMS gives 7.1921 dB, whereas the predictable LMS raises to 5.3737dB.

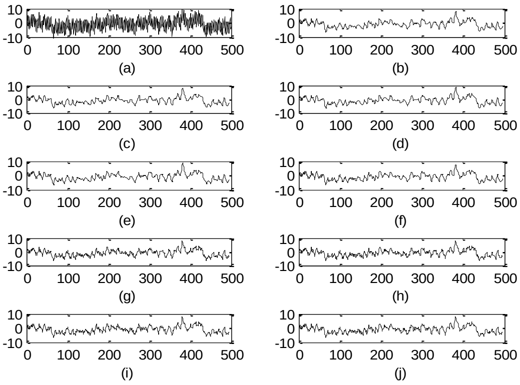

Fig.3. Distinctive outcome of PLN artifact for improved brain signal (a). EEG signal with PLN(b)Purified signal with LMS related ANE(c)Purified signal with NLMS related ANE (d) Purified signal with BBNLMS relatedANE, (e) Purified signal with NSRLMS related ANE, (f). Purified signal with BBNSRLMS related ANE(g)Purified signal with NSLMS related ANE. (h). Purified signal withBBNSLMS related ANE, (I). Purified signal with NSSLMS related ANE, (j). Purified signal with BBNSSLMS relatedANE.

B. Adaptive Elimination of Electromyogram (EMG)

The impure EEG signal is pertained as the key to the adaptive filter of Fig.1, the noise is reference signal taken from noise generator. The outcomes are visualized in Fig. 4. So that from the concert evaluation the Tables 1 and 2 shows the NLMS related noise elimination techniques results better over the other techniques. In SNRI it is shown that NLMS technique gives 9.9472 dB, NSLMS gives 7.7568 dB, BBNSLMS gets 7.5013 dB, NSSLMS gives 6.7218 dB and BBNSSLMS gives 6.2378 dB, whereas the predictable LMS raises to 4.9120 dB.

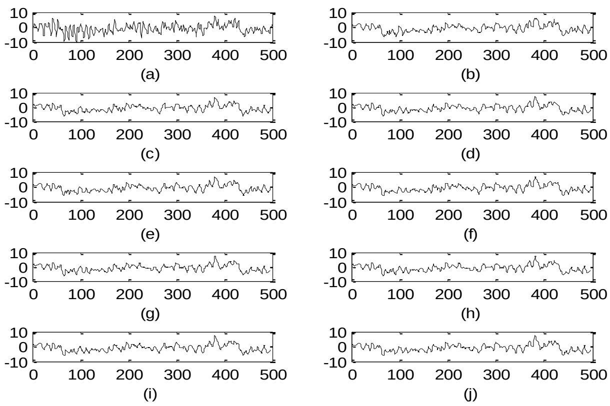

Fig.4. Distinctive outcome of EMG artifact for improved brain signal. (a). EEG signal with EMG, (b). Purified signal with LMS related ANE(c)Purified signal with NLMS related ANE(d)Purified signal with BBNLMS related ANE(e)Purified signal with NSRLMS related ANE, (f). Purified signal with BBNSRLMS related ANE(g)Purified signal with NSLMS related ANE(h)Purified signal with BBNSLMS related ANE(i)Purified signal with NSSLMS related ANE, (j). Purified signal with BBNSSLMS related ANE.

C. Adaptive Cancellation of Respiration Artifact (RA)

Because of patient inspiration and expiration activity the EEG signal base line gets wanders which causes physiological noise. Our aim is to remove this artifact from the EEG signal. The resultant signals from several ANE's are visualized in Fig. 5. Several concerts are being calculated and tabulated in Table 1 and Table 2. In SNRI the results of NLMS technique gives 11.9126 dB, NSLMS gives 9.8234 dB, BBNSLMS gets 9.9821 dB, NSSLMS gives 7.7924 dB and BBNSSLMS gives 7.5213 dB, whereas the predictable LMS raises to 4.8273 dB.

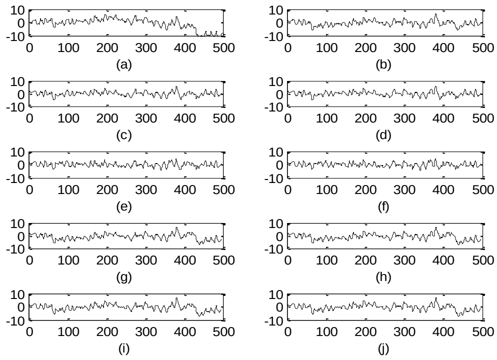

Fig.5. Distinctive outcome of RA artifact for improved brain signal (a). EEG signal with RA, (b). Purified signal with LMS related ANE, (c). Purified signal with NLMS related ANE, (d). Purified signal with BBNLMS related ANE, (e). Purified signal with NSRLMS related ANE, (f). Purified signal with BBNSRLMS related ANE, (g). Purified signal with NSLMS related ANE. (h). Purified signal with BBNSLMS related ANE(i)Purified signal with NSSLMS related ANE(j). Purified signal with BBNSSLMS related ANE.

D. Adaptive Elimination of Electrode Motion Artifact (EMA)

In this paper the EEG signal gets impure with the noise such that this impure signal is given to the Adaptive filter that is ANE. The purified EEG signal can be visualized in Fig. 6. Several concerts are measured and tabulated in Table 1 and Table 2. In SNRI evaluation it is clear that the NLMS Technique gives 9.5697 dB, NSLMS gives 7.9807 dB, BBNSLMS gets 7.5123 dB, NSSLMS gives 7.1267 dB and BBNSSLMS gives 6.9109 dB, whereas the predictable LMS raises to 5.4295 dB.

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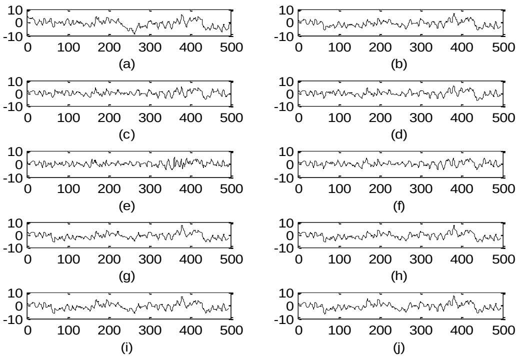

Fig.6. Distinctive outcome of EMA artifact for improved brain signal. (a). EEG signal with EMG, (b). Purified signal with LMS related ANE, (c). Purified signal with NLMS related ANE, (d). Purified signal with BBNLMS related ANE, (e). Purified signal with NSRLMS related ANE, (f). Purified signal with BBNSRLMS related ANE, (g). Purified signal with NSLMS related ANE. (h). Purified signal with BBNSLMS related ANE, (i). Purified signal with NSSLMS related ANE, (j). Purified signal with BBNSSLMS related ANE.

IV. CONCLUSION

In this research paper we projected a few resourceful ANE's for wireless surrounded BCI structures. To facilitate and to improve the capability of ANE's several modifications are personalized in the weight modernized equation of filtering structure. The future ANE system is a fourteen channel of EEG acquisition unit. To make certain the ability, convergence, filtering and with less computations, and we mixed up the constraints of mean square error, normalization and signum in single ANE. Various EEG signals with different artifacts are recorded and calculated with the projected ANE's. From all these functions the projected ANE's performs better among the LMS related ANE's. From all these projected ANE's NLMS related ANE's achieves better result over the all other ANE's but it has high computational complexity. This can be overcome by relating the signum to the NLMS then it becomes NSRLMS related ANE, its characteristics are nearly same to NLMS with minimization of computational complexity. The purified signals are figured out in Fig.3 to Fig. 6. And we utilized the block size as 5 in these experiments. If the filtering speed rises as the block size maximizes, but the output signal consists of residual noise. From the concert analysis (Table 1 and 2) it is clear that projected adaptive filters are higher than the predictable LMS. Hence these ANE's are most suitable for remote EEG health care system.

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