International Journal of Scientific & Engineering Research, Volume 3, Issue 11, November-2012
ISSN 2229-5518

Clearing Artifacts using a Constrained Stability Least Mean Square Algorithm from Cardiac Signals

Anitha Boge, V.Vijaya, Prof.K.Kishan Rao

Abstract -- In this paper, a novel least-mean-square (LMS) algorithm for filtering artifacts in the adaptive noise cancelation (ANC) is proposed. It is based on the minimization of the squared Euclidean norm of the difference weight vector under a stability constraint defined over a posteriori estimation error. The Lagrangian methodology has been used in order to propose a nonlinear adaptation rule defined in terms of the product of differential inputs and errors which means a generalization of the normalized LMS algorithm, the resultant algorithm is called as Constrained Stability Least Mean Square (CSLMS) algorithm. Different filter structures are presented to eliminate the diverse forms of noise like LMS, NLMS etc., Proposed algorithm is applied on real ECG signals obtained from the MIT-BIH (Massachusetts Institute of Technology-Beth Israel Hospital) data base and compared its performance with the conventional LMS algorithm. A simulation result demonstrates superior performance of this proposed algorithm.

Keywords--Adaptive Noise Cancelation, Artifacts, CSLMS algorithm, ECG signals, LMS algorithm.

1 INTRODUCTION

A desired signal corrupted by additive noise can often be recovered by an adaptive noise canceller (ANC) using the least mean squares (LMS) algorithm. As a tool for predicting stationary signals, the Least Mean Squares (LMS) algorithm is widely used. Adaptive filtering techniques permit to detect the time varying potentials and to track the dynamic variations of the signals. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Major artifacts in ECG signals are Baseline wanders and power line interference. The baseline wander is caused by varying electrode-skin impedance, patient's movements and breath. This kind of disturbances is especially present in exercise electrocardiography, as well as during ambulatory and Holter monitoring. Power-line interference (PLI) is a significant source of noise during bio-potential measurements, occurs due to power fluctuations.

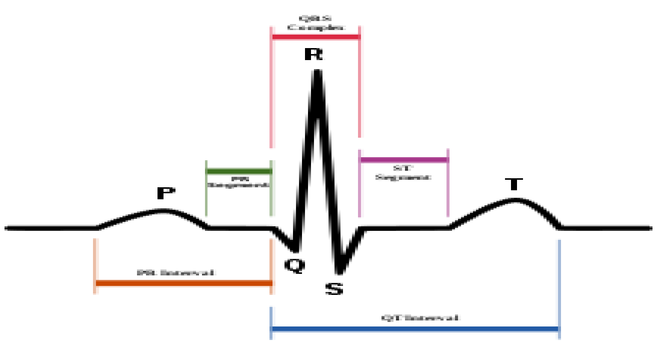

Figure 1--Standard ECG Signal

As shown in the figure-1, the electrocardiographic (ECG) signal is the electrical representation of the heart activity, represented as PQRST waveform. Computerized ECG analysis is widely used as a reliable technique for the diagnosis of cardiovascular diseases, and the ECG signal is the most commonly used biomedical signal in clinical practice. The artifacts effects & degrades the signal quality, frequency resolution, and produces large amplitude signals in ECG that can resemble PQRST waveforms and masks tiny features in ST segment which are important for clinical monitoring and diagnosis. For better diagnosis and accurate interpretation of electrocardiographic (ECG) signals it is must to remove/clear these artifacts.

A number of algorithms have been developed for ECG enhancement using both adaptive and non-adaptive techniques [5, 10]. Thakor[2] proposed an LMS based adaptive recurrent filter to acquire the impulse response of normal QRS complexes and then applied it for arrhythmia detection in ambulatory ECG recordings. NLMS algorithm with decreasing step size, which converges to the global minimum [11], a variable step size NLMS algorithm with faster convergence rate [12], Costa [13] proposed a noise resilient variable step size LMS which is specially indicated for biomedical applications. Several modifications are presented in literature to improve the performance of the LMS algorithm [14, 20]. Recently Rahman[21] presented several less computational complex adaptive algorithms in time domain.

But these algorithms exhibits slower convergence rate. A major disadvantage of the LMS algorithm is its excess mean-squared error, or misadjustment, which increases linearly with the desired signal power. The proposed algorithm, which applies non-linearity's to the error and input signal sequences, which can be derived using the Lagrange multiplier method as a generalization of the normalized LMS. Under certain conditions the adaptive noise cancellers (ANC) based on the CSLMS algorithm shows improved performance by decreasing the excess mean squared error and misadjustment compared to conventional algorithms like, LMS and NLMS algorithms.

2 ALGORITHMS

2.1 PREVIOUS ALGORITHMS

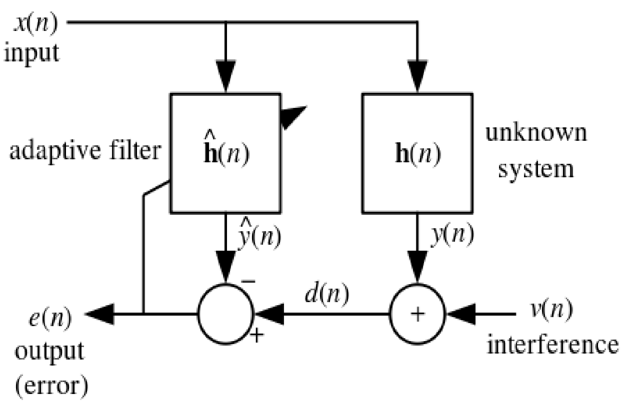

Figure 2--Adaptive filter

Fig. 2, LMS based adaptive filter takes an input sequence x(n),e(n) error output, desired response d(n),y(n) Filter output as follows,

$$x(n) = [x(n), x(n-1), \ldots\ldots, x(n-p+1)]^T \quad (1)$$

$$h(n) = [h_0(n), h_1(n), \ldots\ldots, h_{p-1}(n)]^T \;,\; h(n) \in C^p \quad (2)$$

$$h^H(n) = [h_0^*(n), h_1^*(n), \ldots\ldots, h_{p-1}^*(n)] \quad (3)$$

$$y(n) = h^H(n).x(n) \quad (4)$$

$$d(n) = y(n) + v(n) \quad (5)$$

$$e(n) = d(n) - \hat{y}(n) \quad (6)$$

The weight updates is as shown below

$$h(n+1) = h(n) + \mu x(n)e(n) \quad (7)$$

Where μ is step-size parameter

The mean square error is given as

$$E[e^2(n)] = E\{[s_1(n) - y(n)]^2\} + E[p_1^2(n)] \quad (8)$$

In Normalized LMS (NLMS) adaptive algorithm used to train the coefficients of the adaptive filter. This algorithm takes into account variation in the signal level at the filter output and selecting the normalized step size parameter that results in a stable as well as fast converging algorithm. The weight update relation for NLMS algorithm is as follows

$$h(n+1) = h(n) + [\frac{\mu}{p + x^t(n)x(n)}]x(n)e(n) \quad (9)$$

Here, parameter μ is fixed convergence factor to control maladjustment. Convergence condition is: $0 < \mu < 2$. Since $0 < \mu < 2/\lambda_{\max}$

2.2 PROPOSED ALGORITHM

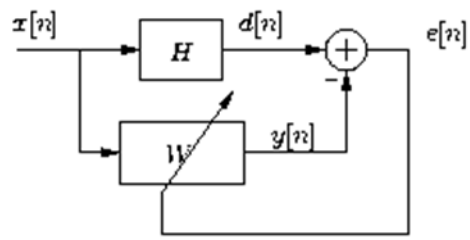

Figure 3--CSLMS filter structure

A common major drawback of adaptive noise canceller based on LMS and NLMS algorithms is the large value of excess mean-square error which results in signal distortion in the noise-canceled signal. In the CSLMS algorithm the time-varying step-size that is inversely proportional to the squared norm of the difference between two consecutive input vectors rather than the input data vector as in the NLMS. This algorithm provides significant improvements in decreasing mean-squared error (EMSE) and consequently minimizing signal distortion.

The weight update relation for CSLMS is as follows

$$h(n+1) = h(n) + [\frac{\delta x(n)\delta e(n)}{\|\delta x(n)\|^2}] \quad (10)$$

Where,

$\delta x(n) = x(n) - x(n-1)$ is the difference between two Consecutive input vectors, and $\delta e(n) = e(n) - e(n-1)$ is the difference between error sequences.

The weight adaptation rule can be made more robust by introducing a small P and by multiplying the weight increment by a constant step size μ to control the speed of the adaptation. This gives the weight update relation for CSLMS algorithm in its final form as follows,

$$h(n+1) = h(n) + \mu\left[\frac{\delta x(n)\delta e(n)}{p + \|\delta x(n)\|^2}\right] \quad (11)$$

The parameter P is set to avoid denominator being too small, step size parameter too big and to prevent numerical instabilities in case of a vanishingly small squared norm. The convergence characteristics of both the algorithms are shown in Fig. 4.

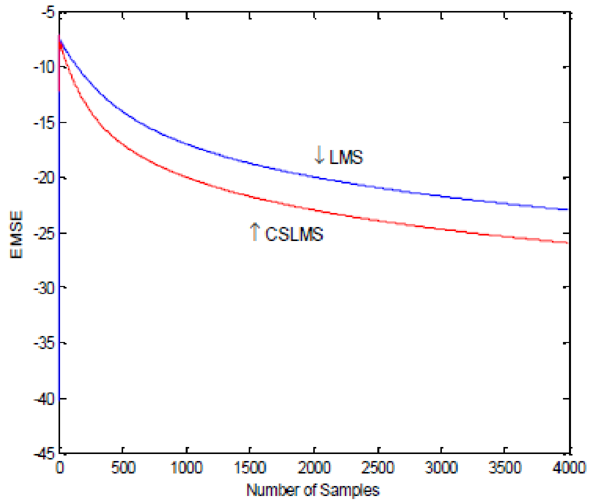

Figure 4--typical convergence curve of LMS and CSLMS for PLI cancellation

3 SIMULATION RESULTS

The method has been validated using several ECG recordings with a wide variety of wave morphologies from MIT-BIH arrhythmia database, to show that CSLMS algorithm is really effective in clinical applications. The benchmark MITBIH arrhythmia database ECG recordings and MIT-BIH Normal Sinus Rhythm Database (NSTDB) real noise are used for reference. In simulations both stationary (PLI) and non-stationary (BW) noises are considered. The arrhythmia data base consists of 48 half hour excerpts of two channel ambulatory ECG recordings, which were obtained from 47 subjects, including 25 men aged 32-89 years, and women aged 23-89 years. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

In simulation 4000 samples of ECG signal and a random noise with variance σ of 0.001, 0.01 and 0.1 is added to the ECG signals to evaluate the performance of the algorithm in terms of minimum MSE (MMSE), MSE, excess MSE (EMSE) and maladjustment (M). In experiments a data set of five records (records 101, 102, 103, 104 and 105) are used, but due to space constraint simulation results for record 105 are shown in this paper. For evaluating the performance of the proposed adaptive filter measured the SNR improvement and compared with LMS algorithm. Table I shows the comparison of MMSE, MSE, EMSE and M for LMS, NLMS and CSLMS algorithms. Table II gives the contrast of the considered algorithms in terms of SNR improvement (SNRI).

3.1 BASELINE WANDER REDUCTION

For reduction of base line wander, the 4000 samples of the pure ECG signal from the MIT-BIH arrhythmia database(data105) are taken and it is corrupted with real baseline wander (BW as in fig.5) taken from the MIT-BIH Noise Stress Test Database (NSTDB). This database was recorded at a sampling rate of 128Hz from 18 subjects with no significant arrhythmias. The contaminated ECG signal is applied as primary input to the adaptive filter of Fig.2. The real BW is given as reference signal. Different filter structures were implemented using the LMS and CSLMS algorithms to study the relative performance and results are plotted in Fig.6. On average LMS algorithm gets SNR improvement 3.1428dB, where as CSLMS gets 4.7613dB.

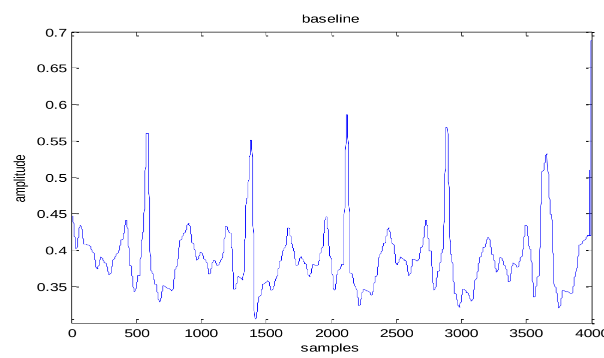

Figure 5--baseline signal

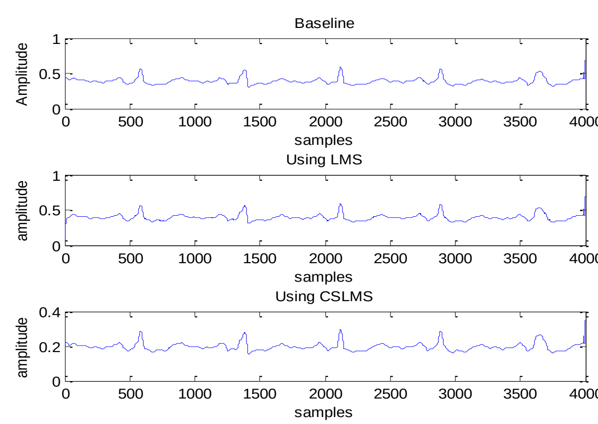

Figure 6--baseline wander reduction using LMS & CSLMS

3.2 PLI REDUCTION

For power line interference (PLI) cancelation also same MIT-BIH record number 105 is taken. The input to the filter is ECG signal corresponds to the data 105 corrupted with synthetic PLI with amplitude 1mv and frequency 60Hz, sampled at 200Hz. The reference signal is synthesized PLI, the output of the filter is recovered signal. These results are shown in Fig.7. In SNR measurements it is found that CSLMS algorithm gets SNR improvement 13.7365dB, where as the LMS algorithm improves 6.3702dB. Fig.5 shows the power spectrum of the noisy signal before and after filtering with LMS and CSLMS algorithms.

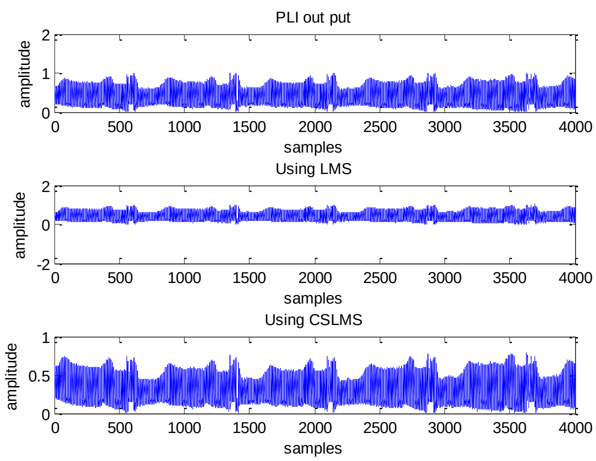

Figure 7--PLI canceller using LMS & CSLMS

Fig.8 shows the power spectrum of the noisy signal before and after filtering with LMS and CSLMS algorithms. It shows CSLMS has less magnitude compared to LMS.

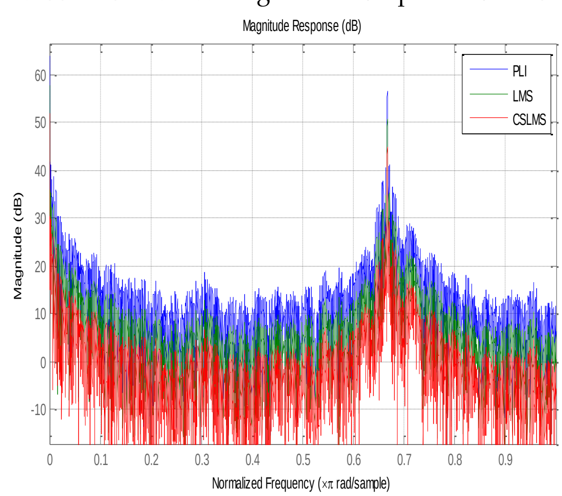

Figure 8--frequency spectrum of ECG

Recently G. P. Nason [23] used Stationary Wavelet Transform (SWT) to de-noise the corrupted EEG signals. R.Arumuganathan [24] a method based on Donohue's de-noising method is used. EEG signals with artifacts are as in fig.9 and the results are as shown in fig.10.

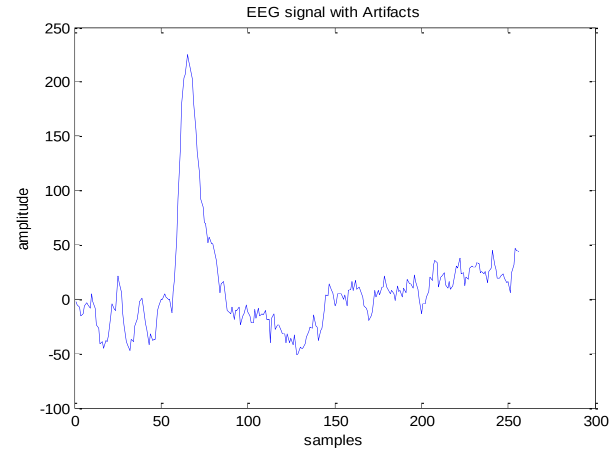

Figure 9--EEG signal with artifacts

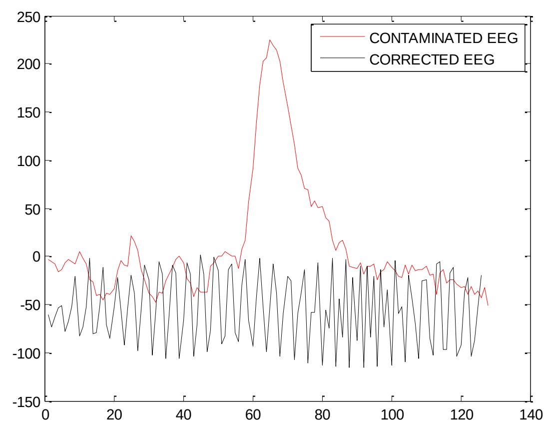

Figure 10--Clear EEG

4 CONCLUSIONS

A novel adaptation filter for clearing artifacts from ECG signal, called CSLMS algorithm is presented in this paper which shows an improved simulation results compared to conventional algorithms LMS and NLMS. This is achieved by changing the weight update formula. The performance of the CSLMS is better than the LMS algorithm in terms of SNRI, MSE and maladjustment, this is shown in tables I and II. This algorithm is also applied to EEG signals for noise cancellation, and the results show a better performance over conventional once. Hence CSLMS based adaptive noise canceller may be used in all practical applications.

Table 1--Performance contrast of LMS & CSLMS in terms of SNRI

Noise	Rec. No.	SNRI(LMS)	SNRI(CSLMS)
BW	101	2.2772	4.0204
	102	3.7013	4.9917
	103	3.3064	4.4690
	104	3.1798	4.9360
	105	3.2497	4.8894
PLI	101	6.1393	13.9129
	102	7.3513	14.0535
	103	5.7684	13.1728
	104	6.2568	13.3995
	105	5.9655	14.1440

Table 2--Comparison of MMSE, MSE of LMS, NLMS & CSLMS

μ	Σ	Algorithm	Min. MSE	MSE
0.1	0.001	LMS	0.3243	0.1586
		NLMS	0.3243	0.1525
		CSLMS	0.3243	0.1450
	0.01	LMS	0.3222	0.1565
		NLMS	0.3222	0.1502
		CSLMS	0.3222	0.1429
	0.1	LMS	0.3047	0.1371
		NLMS	0.3047	0.1317
		CSLMS	0.3047	0.1251
0.5	0.001	LMS	0.3243	0.2404
		NLMS	0.3243	0.1860
		CSLMS	0.3243	0.1453
	0.01	LMS	0.3222	0.2370
		NLMS	0.3222	0.1833
		CSLMS	0.3222	0.1432
	0.1	LMS	0.3028	0.2056
		NLMS	0.3028	0.1592
		CSLMS	0.3028	0.1260

REFERENCES

[1] Y.Der Lin and Y.Hen Hu, "power-line interference detection and suppression in ECG signal processing," IEEE Transactions on Bio medical Engineering, vol.55, pp.354-357, January, 2008.

[2] N. V. Thakor and Y. S. Zhu, "Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection," IEEET Transactions on Biomedical Engineering, vol.38, no. 8, pp.785-794, August, 1991.

[3] J. M. Leski and N. Henzel, "ECG baseline wander and power line interference reduction using nonlinear filter bank," Signal Processing, vol.85, pp. 781-793,2005.

[4] C. Meyer, J. F. Gavela, and M. Harris, "Combining algorithms in automatic detection of QRS complexes in ECG signals," IEEE Transactions on information tech. in Biomedicine, vol. 10, no. 3, pp. 468-475, July,2006.

[5] S. Olmos and P. Laguna, "Steady-state MSE convergence analysis in LMS adaptive filters with deterministic reference inputs for biomedical signals," IEEE Transactions on Signal Processing, vol. 48, pp. 2229-2241, August,2000.

[6] C. Brouse, G. A. Bumont, F. J. Herrmann, and J. M. Ansermino, "A wavelet approach to detecting electrocautery noise in the ECG," IEEE Eng. Med. and Biol. Mag., vol. 25, no. 4, pp. 76-82, August,2006.

[7] M. Kotas, "Application of projection pursuit based robust principal component analysis to ECG enhancement," Biomedical Signal Processing and Control, vol. 1, pp. 289-298, February, 2007.

[8] Floris. E, A. Schlaefer, S. Dieterich and A. Schweikard, "A Fast Lane Approach to LMS prediction of respiratory motion signals," Biomedical Signal Processing and Control, vol. 3, pp. 291-299, July. 2008.

[9] G. Mihov and I. Dotsinsky, "Power-line interference elimination from ECG in case of non-multiplicity between the sampling rate and the power-line frequency," Biomedical Signal Processing and Control, vol. 3, pp. 334-340, June,2008.

[10] P.Laguna, T. Jan,S. Olmos, N. V. Thakor, H. Tix, and P. Caminal, "Adaptive estimation of QRS complex by the Hermit model for classification and ectopic beat detection ," Med. Biol. Eng. Comp., vol. 34, no.1, pp. 58-68, January,1996.

[11] Ching-An LAI, "NLMS algorithm with decreasing step size for adaptive IIR filters," Signal Processing, vol. 82, pp. 1305-1316, 2002.

[12] Ning Li, Y. Zhang, Yanling. H and J. A. Chambers, "A new variable step size NLMS Algorithm designed for applications with exponential decay impulse responses," Signal processing vol. 88, pp. 2346-2349, March,2008.

[13] M. H. Costa and J. C. M. Burmudez, "A noise resilient variable step size LMS Algorithm," Signal Processing, vol. 88, pp. 733-748,2008.

[14] Ning Li, Y. Zhang, Yanling. H and Y. Zhao, "An improved variable tap length LMS Algorithm," Signal Processing, vol. 89, pp. 908-912, 2009.

[15] S. Zhao, Z. Mahb, S. Khoo and Hong. R. W, "Variable step-size LMS algorithm with a quotient form," Signal Processing, vol. 89, pp. 67-76, 2009.

[16] A. I. Sulyman and A. Zerguine, "Convergence and steady-state analysis of a variable step-size NLMS algorithm," Signal Processing, vol. 83, pp. 1255-1273, 2003.

[17] D. S. Brito, E. Aguiar, F. Lucna, R. C. S. Freire, Y. Yasuda and A. K. Barros," Influence of low frequency noise in adaptive estimation using the LMS algorithm," Signal Processing, vol. 89, pp. 933-940, 2009.

[18] V. E. DeBrunner and D. Zhou, "Hybrid filtered error LMS algorithm: Another alternative to F-XLMS," IEEE Transactions on CircuSyst., vol. 53, pp. 653-661, march, 2006.

[19] S. Olmos, L. Sommo and P. Laguna, "Block adaptive filter with deterministic reference inputs for event-related signals : BLMS and BRLS," IEEE Transactions on Signal Processing, vol. 50, pp. 1102-1112, may, 2002.

[20] J. E. Greenberg,"Modified LMS algorithm for speech processing with an adaptive noise canceller," IEEE Transactions on Speed Audio Process., vol. 6, pp. 338-351, July, 1998.

[21] M. Z. U. Rehman, S. R. Ahmed and D. V. R. K. Reddy, "Efficient sign based normalized adaptive filtering techniques for cancellation of artifacts in ECG signals: Application to wireless biotelemetry," Signal Processing, vol. 91, pp. 225-239, February 2011.

[22] J. M. Grriz, J. Ramerez, S. C. Alvarez, C. G. Puntonet, E. W. Lang, and Deniz. E,"A novel LMS algorithm applied to adaptive noise cancellation," Signal Processing Letters, vol. 16, pp. 34-37, January 2009.

[23] G. P. Nason and B. W. Silveman , "Stationary Wavelet Transform and Some Statistical applications," Tech. Rep. BS8 1Tw, University of Bristol(1995).

[24] P. Senthil Kumar, R. Arumuganathan, K. Sivakumar, "A Wavelet based statistical method for De-noising of Ocular Artifacts in EEG signals," IJCSNS, vol. 8, no. 9, September 2008.

Anitha Boge, currently Pursuing M.Tech in DSCE in Vaagdevi College of Engineering and Technology, Warangal, Andhra Pradesh.Obtained B.E.from M.J.C.E.T. Osmania University,Hyderabad.PH:9908966598,E-mail:anithaboge@gmail.com.

V.Vijaya obtained her B.Tech Degree in Electronics &Communication Engg., from (JNTU) Jawaharlal Nehru Technological University College of Engg., Ananthapur, and M.Tech. Degree in Instrumentation and Control Systems, from JNTUK College of Engg Kakinada & Pursuing PhD at JNTUH Hyderabad. She worked at APEL Radio Communication Systems, Hyderabad and presently, she is working as Assoc. Professor in the ECE Dept Vaagdevi College of Engineering at Warangal. She has 11 years of Teaching Experience and 2 years of Industrial Experience. Attended 15 workshops/refresher courses/short term courses at various places. She has published no of papers in national and international conferences

Prof. K. Kishan Rao is a Senior Professor in Electronics and Communications Engg.Department and is presently The Director, Vaagdevi group of colleges. He has more than 100 Research Publications to his credit so far. He has produced 5 PhDs and many more Research Scholars are working under his Guidance. . He has over 38 years of Experience in Teaching and Research. He has implemented number of Research Projects and developed many Laboratories in the Department.Prof. K. Kishan Rao has Post-Graduate from Osmania University and Ph.D Degree from Indian Institute of Technology (I.I.T) Kanpur. He had held number of administrative positions in the National Institute of Technology (REC) including that of Academic and Planning, Principal etc