Impulsive Noise Cancellation from Cardiac Signal using Modified WLMS Alogorithm based Adaptive Filter

Sarthak Panda, Mihir Narayan Mohanty*

Abstract— For clean signal, noise cancellation techniques are explored day-by-day. At the user end the clean signal is highly essential for different purposes. In this authors have considered the bio-medical signal that is corrupted with impulsive noise. It is very important to separate from the signal, as its occurrence is sudden and often similar to the signal. The popular adaptive algorithms have been tested for cancellation of impulsive noise. Further most used Wilcoxon LMS is also verified for impulsive noise case. Finally it has been modified for the same purpose. The result found excellent in terms of less MSE, SNR improvement and faster convergence.

Keywords— Adaptive Algorithm, ECG, Impulsive noise, LMS, MA-WLMS, NLMS, WLMS

I. Introduction

As per World Health Organization review, about 20 million individuals may bite the dust in the year 2017 because of the heart attack. Heart related issues are expanding day by day and Electrocardiogram (ECG) signal is vital in determination of heart related issues. The ECG signal is utilized to know the cardiovascular state of a human. ECG is obtained by the electrical movement of the heart and can be measured by interfacing electrodes on the skin surface of particular parts of the body. As the ECG is a recording of the electrical exercises of the heart, it can help one get an idea of a human's heart exercises and can likewise help in recognizing variations in heart action, for example, cardiovascular infractions or unequal beat intervals.

ECG signal contains various noises; these noises need to be expelled before monitoring, from the receiver perspective, so that a right decision can be taken for treatment. It is important to evacuate the different types noises present in the ECG signal consequently there is a need of filtering the ECG signal. In a practical case the majority of the signals are non-stationary and the filter, which we use must change its coefficient as indicated by the input signal. Different noises can be associated with ECG signal are: Base line wander, 50 Hz power line interference, motion artifact electromyogram (EMG) etc. Actually, most sorts of noises are not stationary, it implies, that the noise power measured highlights some variability.

The noise generated by the human muscle is the most difficult noise that ought to be removed. The switching transient in power, incidental pulses in phone lines add to impulsive noises. Such wonders happen in bio-medical signal in diathermia, while utilizing surgical gadgets, in electro cardiology (muscle noise). Also this type of noise gets included in ECG signal at the time of signal acquisition. To accomplish better noise reduction from non-stationary signals like ECG, different adaptive algorithm can be utilized. As adaptive filters don't have fixed channel coefficients, these channels can change their coefficients to lessen the noise present in the signal through adjustment.

A little amount of the works related with this area of investigation has been accomplished. Some major works are cited in the accompanying section. In this piece of work, we have endeavored to develop a system which will nullify the impulsive noise from ECG signal by using adaptive filtering theory. We have modified the Wilcoxon norm based LMS algorithm in a new way to weight variation. We have compared the Signal to Noise ratio (SNR) improvement of various adaptive filters. Also we have compared the Mean Square Error of those filters.

This paper is organized as follows. Section II, introduces the related literature. In segment III, our proposed method along with some other existing adaptive filtering techniques has been explored. Section IV introduces the results and discussion. Finally section V finishes up this paper with conclusion.

II. Related Literature

Adaptive algorithms have been used in many applications since two to three decades. One of the important applications is noise cancellation. This has been attempted by many researchers also. But the variant of noise with variation of applications are less used till date. Some of the works based on adaptive algorithm for noise cancellation is cited in this section.

Authors have introduced a new family of algorithms to exploit sparsity in adaptive filters. They have tested this algorithm on application of system identification and acoustic echo cancellation problem. This algorithm was based on minimization of cost function with respect to a time dependent norm of filter update. They assumed that their problem has not a closed form solution so they have proposed an approximate solution followed by asymptotic behavior [1]. Conventional

Sarthak Panda is with the Department of Electronics and Communication, Institute of Technical Education and Research, S 'O'A University, Odisha, (e-mail: sarthak216@rediffmail.com).

*Mihir Narayan Mohanty is with the Department of Electronics and Communication, Institute of Technical Education and Research, S'O'A University, Odisha, (e-mail: mihir.n.mohanty@gmail.com).

linear system's performance becomes poor when data is distorted with non-Gaussian noise. So, S.R Kim *et. al.* have proposed an adaptive pre-processor to minimize the impulsive components when the background noise is correlated with Gaussian process. The proposed pre-processer can be applied in real time environment and that does not require any iterative method. Their proposed method can adapt to the changes happened in the real time environment. They have successfully minimized the effect of impulsive noise from the system by using the pre-processer. It can be helpful for detection theory, PSD estimation and impulsive noise suppression in real time domain [2]. Two robust affine projection sign (RAPS) algorithms were proposed by authors and both of which minimize the mixed norm of and of the error signal. The direction vector of the RAPS algorithms was obtained from the gradient of a norm-based objective function, while two related norm-based minimization problems were solved to obtain the line search of the two RAPS algorithms. The norm-based direction vector reduces the impact of impulsive noise, where as the norm-based line search produces an unbiased solution in the proposed algorithms. In addition, one of the two RAPS algorithms shares the data selective adaptation used in the set-membership (SM) affine projection (SMAP) algorithm. The proposed algorithms were shown to offer a significant improvement in the convergence speed as well as a significant reduction in the steady-state misalignment relative to the pseudo affine projection sign (PAPS) algorithm. In addition, the proposed algorithms offer robust performance with respect to impulsive noise and improved tracking of the unknown system in comparison to that provided by the PAPS and Affine projection sign (APS) algorithms. These features of the proposed algorithms were demonstrated using simulation results in system-identification and echo-cancellation applications [3]. Generally feedback cancellation uses FXLMS algorithm. But when outliers are present this algorithm does not gives satisfactory result. So authors have proposed two new techniques to cancel out the feedback in hearing aids one of them is Filtered-X Wilcoxon LMS and other is Filtered-X least mean log square. Both of them are basically learning algorithms which are robust in nature [4]. A solution to many problems like environment sensing, target tracking, data collection is Distributed wireless sensor network. Wireless sensor networks are energy efficient, can have high estimation accuracy as well as fast convergence rate. T Panigrahi *et. al.* have used cost function like Wilcoxon norm and error saturation nonlinearity in impulsive noise environment to solve the robust adaptive estimation problem. According to them the incremental scheme is not useful to impulsive type environment so that they have used Wilcoxon norm to the incremental scheme to estimate the desired parameters in the existence Gaussian corrupted impulsive noise [5]. Noise cancellation from speech and bio-medical signal can be done by adaptive filtering. LMS algorithm is one of the generally utilized algorithms in many adaptive signal processing tasks. The adaptive filtering algorithm with averaging (AFA) algorithm is a development over the LMS algorithm and has an enhanced performance. So for speech signal processing authors have proposed a modification in the AFA algorithm. Their proposed modification was verified for noise cancellation from speech signal. Their proposed modified algorithm has a better performance in terms of improved signal-to-noise ratio [6]. LMS algorithm can be used to recover a signal distorted by an additive noise. This problem can be achieved by using adaptive noise cancelling technique. Excess mean square error is the major disadvantage in LMS algorithm. This causes performance degradation when desired signal has large power fluctuation. So authors have proposed two methods that can be associated with LMS algorithm. One of them is weighted sum method and another is sum method. They have also reduced the number of steps required for weight updating calculation. They have compared the weighted sum method with the sum method. According to them Analysis of the two modified LMS algorithms indicates that either one provides significant upgrades in the existence of strong desired signals and identical performance in the presence of weak desired signals, with respect to the conventional LMS algorithm [7]. In [8] authors have proposed an adaptive filtering with averaging algorithm for active control of noise. They have named their averaging algorithm as Filtered-x Adaptive Filtering with Averaging (FxAFA). They have used the averages of information and correction term to update the weight value. They have simulated for single channel feed forward noise controller system. Also they have compared their result with FxRLS algorithm on the basis of computational complexity and stability. G.G Yin *et. al.* have generated two sequences $\{x_n\}$ and $\{\overline{x_n}\}$. They have considered that $\{\overline{x_n}\}$ is the arithmetic average of $\{x_n\}$. By taking the averaging scheme they have developed an averaging procedure in adaptive algorithm. They have obtained optimal convergence with this algorithm with respect to the traditional approach. According to them averaging approach is efficient one [9]. In [10], an adaptive impulse correlated filter (AICF) for event-related signals was proposed by the authors .This filter removes the noise which is nor correlated with the stimulus even though the noise is colored noise and estimates the deterministic component of the signal. They have taken two inputs one is primary input and other is the reference input. Then they have used the traditional LMS algorithm to update the weights of the filter. Their first aim was to show that the AICF algorithm is equal to the exponentially weighted averaging (EWA) algorithm when they are using LMS. They have also performed the performance analysis in terms of signal-to-noise ratio, convergence and misadjustment error. Then they have changed the averaging techniques like ensemble averaging (EA) and moving window averaging (MWA) techniques. They have taken high resolution ECG signal for all processing. Signal characteristics changes so fast in case of noise cancellation process. So authors have used adaptive algorithms which has higher convergence rate. According to them their best choice was RLS algorithm. When they have tested RLS algorithm they found that this algorithm has high computational complexity and stability issues. So to avoid this kind of problem they have used adaptive filtering with averaging (AFA) algorithm for noise cancellation procedure. They found that AFA algorithm has high convergence rate as compared to that of the RLS algorithm and low computational complexity and robust in fixed-point calculation. They have implemented the algorithm in presence of car noise and office noise in speech signal [11]. In [12], authors have developed a new application of Widrow's adaptive noise cancellation scheme. They have applied the method to which there is an acoustic barrier present in between primary and reference inputs. During silence they have obtained that ANC can provide noise cancellation with a little speech distortion by updating the weights. They have applied the modified ANC system to the aircraft pilots who have worn oxygen mask. Finally they have obtained that if noise environment has been created with a single source, up to 11 dB SNR improvements can be achieved by involving an reference input to the outside of the face mask. They have taken 50 point ANC filter for this type of environment. Authors have executed four sorts of AC and DC noises as indicated by their essential properties. After that, these noises have been blended with ECG signal and they have invalidated these noises utilizing the LMS and the RLS algorithms. Then they have done the performance analysis between these algorithms in view of their parameters furthermore they have talked about the impact of channel length and the correlation coefficients. They have found that DC bias noises can't be taken care of by the LMS algorithm though the RLS can deal with both sorts of noises. Additionally, it was valid for both algorithms the channel length is proportional to MSE (Mean Square Error) rate and it was taking more time to converge for both calculations. But at the end they found that in RLS algorithm error has gone below as compared to LMS algorithm [13]. M.Z U Rahman *et. al.* have executed a straightforward and effective normalized signed regressor LMS (NSRLMS) algorithm, that can be connected to ECG signal with a specific end goal to expel different noises. This algorithm has less computational complexity due to the sign present in the calculation and great filtering capacity due to the standardized term. Accordingly it is especially reasonable for applications requiring substantial signal to noise proportions with less computational complexity [14]. In [15], authors have proposed several adaptive filters for noise cancellation and arrhythmia detection. According to them adaptive filters minimizes the mean squared error between a reference input and a primary input. Distinctive filter structures were introduced to kill the assorted types of noises such as baseline wander, 60 Hz power line interference, muscle noises, and motion artifacts. Mark Yelderman *et. al.* have proposed a technique by utilizing the concept of adaptive noise canceller and signal processing to improve ECG signal observation by nullifying the noise. Huge measures of interference are dispensed with by radio frequency protecting, active and passive low-pass filtering, and optical isolation. Then they have used LMS algorithm to remove the remaining noises. They have obtained a large improvement in SNR roughly 110 dB. Clean electrocardiograms have been obtained with electrocute gear in operation [16]. A few basic and proficient sign and error non linearity-based adaptive filters, which are computationally best having multiplier free weight upgrade loops, are utilized for cancellation of noise in electrocardiographic (ECG) signals by the authors. They have done the performance analysis as compared to existing algorithms in terms of SNR and computational complexities [17].

Though many approaches are there, still regarding impulsive noise cancellation the works are not sufficient. For the real time social application, we have considered the cardiac signal contaminated with impulsive noise. The proposed algorithm is explained in the following section.

III. Proposed Adaptive Algorithm For Impulsive Noise Cancellation

The bio-medical signals are recorded with a disturbance at the time of signal acquisition. An extensive variety of noise exists in bio-medical signal. One of the noises is a waveform of an electrical movement made by human muscles. In some cases this noise can be impulsive in nature. Impulsive noise can be due to internal i.e. from the human muscle or can be from eternal i.e. from the environment. So separating of this sort of noises is a fundamental need as impulsive noises are sudden burst having high amplitudes. Adaptive filtering theory can be utilized to remove impulsive noise from ECG signal ad adaptive filters can change their coefficients according to the environment.

The proposed block diagram of the adaptive noise cancellation for ECG signal is as follows,

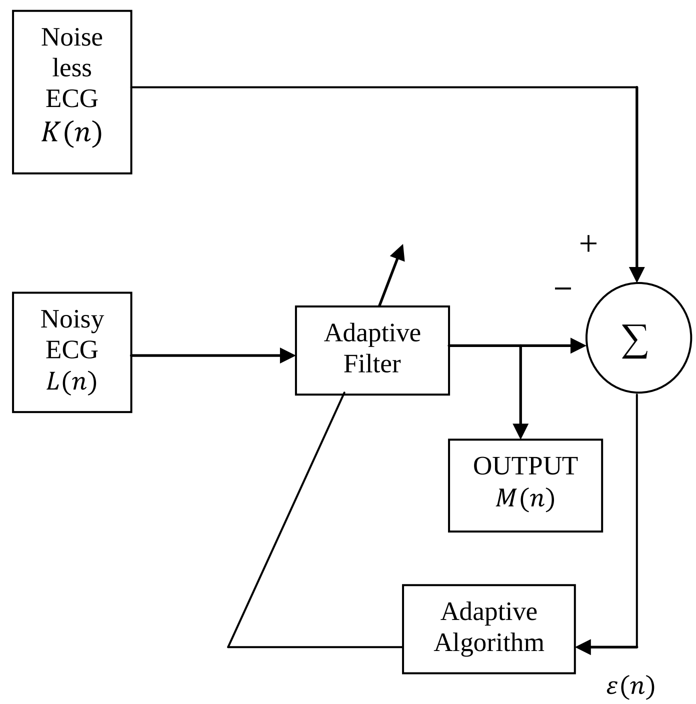

Fig. 1 Structure of Adaptive Noise Cancellation Procedure

The most common utilized structure as a part of the implementation of adaptive filters is the transversal structure. It considered as the desired signal as $K(n)$ which is noise less ECG signal. For input $L(n)$ we have picked an impulsive noise influenced ECG signal. The error signal which is obtained by taking the difference between the desired signal and the output signal gathered by passing the input signal through a adaptive channel is meant by $\varepsilon(n)$ [18].

The error signal $\varepsilon(n)$ can be calculated as,

$$\varepsilon(n) = K(n) - L(n) \quad (1)$$

The adaptive changes its weights as demonstrated by the noise signal. Whenever the error will be minimum, ideal point will be reached and at this instance of time we will get our clean

ECG signal without impulsive noise. The adaptive output is given by the following relation,

$$M(n) = \omega(n)^T L(n) \quad (2)$$

$\omega(n)$ is the weights of the adaptive filter. Some adaptive algorithms we will explore now to update the weights so as to achieve the noise cancellation task.

A. Least Mean Square (LMS) Algorithm

When we are analyzing a noisy signal to get the clean signal adaptive algorithm plays a vital role to eliminate the noise. LMS algorithm can be used for changing the weights of the adaptive filter. The weight adaption relation can be demonstrated by the following relation [19],

$$\omega(n+1) = \omega(n) + 2\mu\varepsilon(n)L(n) \quad (3)$$

Where, $\omega(n+1)$ is the next weight value to be updated and μ is the convergence coefficient, whose value is generally between 0 to 1. Also μ controls the stability of the system and convergence rate.

B. Normalized Least Mean Square (NLMS) Algorithm

Norm is associated with LMS algorithm and the normalized version of LMS algorithm is said to be NLMS algorithm. Due to normalization it has a greater stability than LMS algorithm and convergence rate is also higher. The weight update relation of NLMS algorithm can be as follows [18, 19],

$$\omega(n+1) = \omega(n) + \mu \,.\, \varepsilon(n) . \frac{L(n)}{\delta + \|L(n)\|^2} \quad (4)$$

Here δ is the small correction factor. Norm can be zero so if the denominator part will be zero then the equation will be invalid. So we are considering one small correction factor to avoid this problem.

C. Wilcoxon Least Mean Square (WLMS) Algorithm

Let us think over a linear combiner with its n number of weights to be upgraded by an algorithm determined utilizing the Wilcoxon norm as cost function. In building up the WLMS algorithm, iteration based training is utilized. In each experiment, the weights of the combiner are trained for x samples. To characterize Wilcoxon norm of an error vector ε of length x this we need a score function. Using standard LMS the weights of the model are updated, which expels the norm consistently. The score function can be defined as [4, 5, 20, 21],

$$\beta(i) : [0,1] \rightarrow \mathrm{R} \quad (5)$$

Which is non-diminishing such that,

$$\int_0^1 \beta^2\,(i)di < \infty \quad (6)$$

The score related with the score function ∂ can be defined by,

$$=> d(j) = \beta\left(\frac{j}{l+1}\right) \quad (7)$$

Where, l is a positive number. It can be demonstrated that the accompanying cost function which is a pseudo norm on R^l.

$$J(y) = \|\varepsilon\|_\omega = \sum_{k=1}^{l} d\big(\mathrm{R}(\varepsilon_k)\big)\,\varepsilon_k$$
$$= \sum_{k=1}^{l} d(k)\varepsilon_{(k)} \quad (8)$$

Where, $\mathrm{R}(\varepsilon_k)$ represents the rank of ε_k among all $\varepsilon_1, \dots, \varepsilon_l$. And it can be sort by $\varepsilon_1, \leq \dots \leq, \varepsilon_l$ and $d(j) = \beta\left(\frac{j}{l+1}\right)$ and $\beta(i) = \sqrt{12}(i - 0.5)$ Now we can call $\|\varepsilon\|_\omega$ as in equation (8) as the Wilcoxon norm of the error vector ε.

To determine the Wilcoxon LMS algorithm we need to use the steepest descent method,

$$\omega(y+1) = \omega(y) + \mu\big(\nabla_\omega J(y)\big) \quad (9)$$

Where, $\nabla_\omega J(y)$ can be evaluated as,

$$\frac{\partial J\,(y)}{\partial\,\omega_y} = \sum_{k=1}^{l} d\big(\mathrm{R}(\varepsilon_k)\big)\,\varepsilon_k = \sum_{k=1}^{l} d(k) i_k \quad (10)$$

D. Modified Averaging Wilcoxon Least Mean Square (MA-WLMS) Algorithm

To reduce the computational complexity and to make the system stable instead of conventional algorithms adaptive algorithm with averaging can be considered. For applications where fast converging is required conventional LMS, NLMS algorithms are not applicable [11]. Also WLMS can be adaptable but it has stability issues. Similarly RLS algorithm can also be adaptable but due to its recursive structure it has more complexity. So in order to overcome all the issues above we have presented a modification to WLMS algorithm based on adaptive filtering with averaging so called Modified Averaging Wilcoxon Least Mean Square (MA-WLMS) algorithm. Adaptive filtering with averaging (AFA) can be realized by as followed [6],

Noise can be estimated as,

$$N(n) = \sum_{k=0}^{M} \omega(n) N_1(n-k) \quad (11)$$

Where, M is the filter order and N_1 is the noise component present in the signal.

To minimize the mean square error the filter coefficients are adjusted recursively so as per [8, 11] a standard algorithm can be considered for approximating the vector of filter weights as,

$$\omega(n+1) = \omega(n) + \mu L(n)\varepsilon(n) \quad (12)$$

Here $L(n)$ is the input signal vector, $\omega(n)$ is the adaptive coefficient vector and $\varepsilon(n)$ is the error vector. μ is a positive scalar.

Taking the averages of $\omega(n)$ equation (12) can be transformed to,

$$\omega(n+1) = \overline{\omega(n)} + \frac{1}{n^\mu} L(n)\varepsilon(n) \quad (13)$$

Where we can represent the averages of $\omega(n)$ as follows,

$$\overline{\omega(n)} = \frac{1}{n}\sum_{k=1}^{n} \omega(n) \quad (14)$$

The value of μ lies in between 0.5 to 1.

According to the analysis present in the upper given algorithm is not stable initially because only the averages of the coefficients have been considered. So to enhance the stability also the averages of the input signal and the error signal is also considered. So the adaptive filtering with averaging can be obtained as,

$$\omega_k(n+1) = \overline{\omega_k(n)} + \frac{1}{n^{\mu}}\overline{L(n)\varepsilon(n)} \qquad (15)$$

Where, $k = 0,1,\ldots,M$

$\overline{\omega_k(n)}$ and $\overline{L(n)\varepsilon(n)}$ can be calculated from their past values, so averaging here does not make extra burden to the calculation. Here covariance matrix is not present so the estimate of covariance is not needed. Automatically computational complexity reduces as well as stability increases.

On application to impulsive noise cancellation from LMS and NLMS algorithm WLMS has better performance. So in order to improve the performance with respect to Signal-to-Noise ratio (SNR) we have modified the WLMS algorithm in corporation with adaptive filtering with averaging by introducing the Wilcoxon norm to it. And the Modified Averaging Wilcoxon LMS (MA-LMS) algorithm can be given by,

$$\omega_k(n+1) = \overline{\omega_k(n)} + \frac{1}{n^{\mu}}\frac{\overline{L(n)\varepsilon(n)}}{\|L_w(n)\|^2} + AVG\left[\frac{1}{n^{\mu}}\frac{\overline{L(n)\varepsilon(n)}}{\|L_w(n)\|^2}\right] \qquad (16)$$

The proposed adjustment was evaluated and tested for impulsive noise cancellation in ECG signal.

IV. Result And Discussion

For simulation we have collected the ECG signal from MIT-BIH database [22]. We have tried to cancel out the impulsive noise by considering the following parameters,

Table 1: Parameters for Impulsive Noise cancellation

Parameters	**Values**
μ for adaptive algorithms	0.08
δ for NLMS algorithm	0.001
No. of iteration	3600
Tap-weight	16

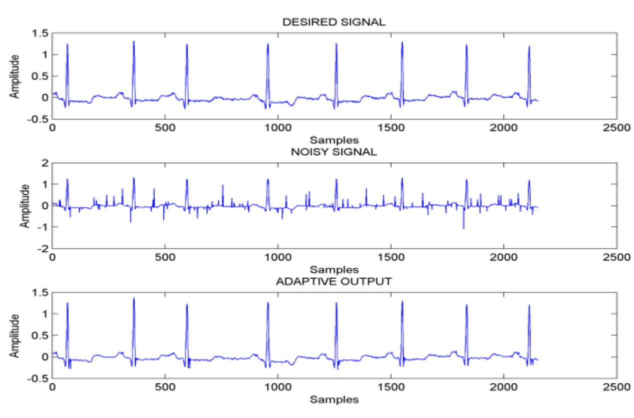

Fig .2 Impulsive noise cancellation using LMS algorithm

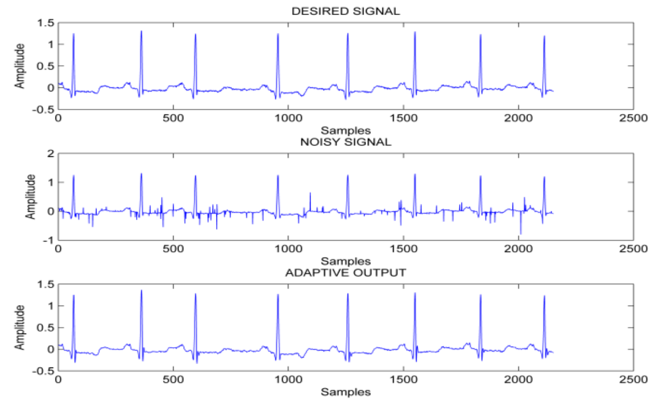

Fig .3 Impulsive noise cancellation using NLMS algorithm

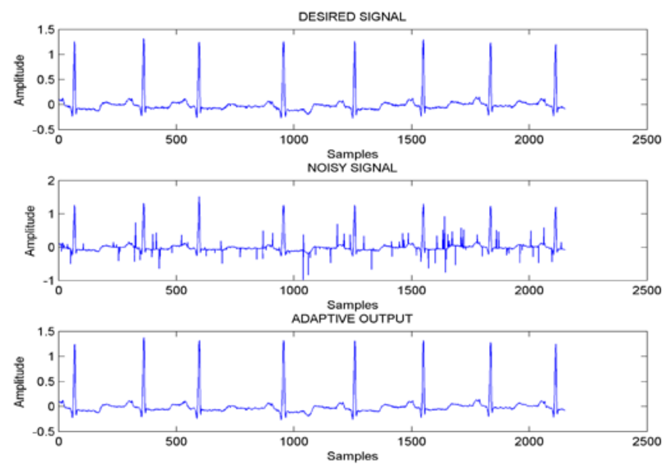

Fig .4 Impulsive noise cancellation using WLMS algorithm

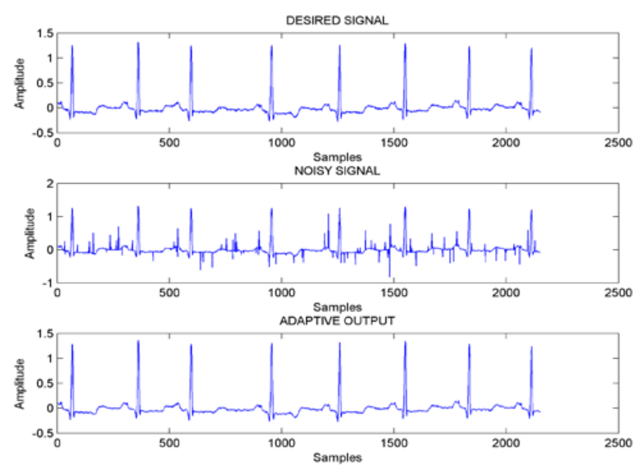

Fig .5 Impulsive noise cancellation using MA-WLMS algorithm

Fig.2 to Fig.5 demonstrates the impulsive noise cancellation from ECG sign utilizing LMS, NLMS,WLMS and MA-WLMS algorithm separately. In all cases noise is removed so to know which calculation is better we have compared the Mean Square curve of each algorithm.

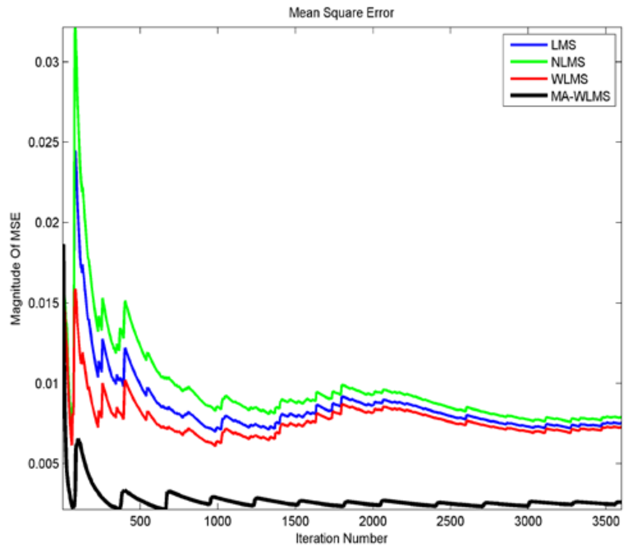

Fig .6 MSE comparison between LMS, NLMS, WLMS and MA-WLMS algorithm

Also we have obtained the performance of the proposed algorithm with respect to SNR.SNR before filtering and SNR after filtering has beeen calculated an. At that point we have also calulated the SNR improvement.From Table.2 MA-WLMS algorithm has preferred SNR improvement than LMS, NLMS and WLMS.

Table 2: SNR comparison between LMS, NLMS, RLS and SSRLS

FILTER TYPE	SNR BEFORE FILTERING	SNR AFTER FILTERING	SNR IMPROVEMENT
LMS	7.8499 dB	11.3658 dB	3.5159 dB
NLMS	7.0176 dB	12.5551 dB	5.5375 dB
WLMS	7.1397 dB	15.4473dB	8.3076dB
MA-WLMS	7.1086 dB	16.8498 dB	9.7412 dB

V. Conclusion

The proposed algorithm is shown excellence for noise removal. Though impulsive noise is complex, it is removed using the proposed algorithm and the SNR has been improved almost three times than standard LMS algorithms. It is suitable for the sensitive bio-medical applications. The algorithm may be verified for other signals and can be suitably used for real time application. The implementation of the algorithm can be useful for modern medical equipments and can be extended for future work.

References

[1] Leonardo Rey Vega, Hernán Rey, Jacob Benesty, Sara Tressens, “A Family of Robust Algorithms Exploiting Sparsity in Adaptive Filters”, *IEEE Trans. Audio, Speech, Language Process*, Vol. 17, NO. 4, pp.572-581, MAY 2009.

[2] Seong Rag Kim and Adam Efron, “Adaptive Robust Impulse Noise Filtering”, *IEEE Trans. Signal Process*, vol. 43, no. 8, pp. 1855-1866, AUG 1995.

[3] Md. Zulfiquar Ali Bhotto, M. Omair Ahmad, M. N. S. Swamy, “Robust Shrinkage Affine-Projection Sign Adaptive-Filtering Algorithms for Impulsive Noise Environments”, *IEEE Trans. Signal Process*, vol. 62, no. 13, pp. 3349-3359, JUL 2014.

[4] Vasundhara, Ganapati Panda, N.B. Puhan, “Robust feedback cancellation in hearing aids in the presence of outliers”, International Conference on Signal Processing and Integrated Networks (SPIN), pp.25-29, 2014.

[5] T Panigrahi, G Panda, B Mulgrew, Babita Majhi, “Robust Incremental LMS over Wireless Sensor Network in Impulsive Noise”, International Conference on Computational Intelligence and Communication Networks, pp. 205-209, 2010.

[6] V. R. Vijaykumar, P. T. Vanathi, P. Kanagasapabathy, “Modified Adaptive Filtering Algorithm for Noise Cancellation in Speech Signals”, *Electronics and Electrical Engineering, Elektronika IR Elektrotechnika*, vol. 2, no.74, pp. 17-20, 2007.

[7] Julie E. Greenberg, “Modified LMS Algorithms for Speech Processing with an Adaptive Noise Canceller”, *IEEE Speech Audio Process*, vol. 6, no. 4, pp.338-351, JUL 1998.

[8] Muhammad Tahir Akhtar, Masahide Abe, Masayuki Kawamata, “Adaptive Filtering With Averaging-Based Algorithm for Feed forward Active Noise Control Systems”, *IEEE Signal Process. Lett.* vol . 11, no. 6, pp.557-560, JUNE 2004.

[9] Gang George Yin, Yunmin Zhu, “Averaging Procedures in Adaptive Filtering: An Efficient Approach”, *IEEE Trans. Autom. Control*, vol. 37, no. 4, pp.466-475, 1992.

[10] Pablo Laguna, Raimon JanC, Olivier Meste, Peter W. Poon, Pere Caminal, HervC Rix, Nitish V. Thakor, “Adaptive Filter for Event-Related Bioelectric Signals Using an Impulse Correlated Reference Input: Comparison with Signal Averaging Techniques”, *IEEE Trans. Biomed. Eng*, vol. 39, no. 10, pp. 1032-1044, OCT 1992.

[11] Georgi Iliev, Nikola Kasabov, “Adaptive filtering with averaging in noise cancellation for voice and speech recognition”, Department of Information Science, University of Otago, 2001.

[12] William A. Harrison, Jae S. Lim, Elliot Singer, “A New Application of Adaptive Noise Cancellation”, *IEEE Trans. Acoust., Speech, Signal Process*, vol. 34, no. 1, pp. 21-27, FEB1986.

[13] Syed Zahurul Islam, Syed Zahidul Islam, Razali Jidin, Mohd. Alauddin Mohd. Ali, “Performance Study of Adaptive Filtering Algorithms for Noise Cancellation of ECG Signal”, 7th International Conference On Information, Communications and Signal Processing, 2009.

[14] Mohammad Zia Ur Rahman, Rafi Ahamed Shaik, D V Rama Koti Reddy, “An Efficient Noise Cancellation Technique to remove noise from the ECG signal using Normalized Signed Regressor LMS algorithm”, International Conference on Bioinformatics and Biomedicine, pp.257-260, 2009.

[15] Nitish V. Thakor, Yi-Sheng Zhu, “Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection”, *IEEE Trans. Biomed. Eng*, vol. 18. no 8, pp. 785-794, AUG 1991.

[16] Mark Yelderman, Bernard Widrow, John M. Cioffi, Edward Hesler, Jeffrey A. Leddy, “ECG Enhancement by Adaptive Cancellation of Electrosurgical Interference”, *IEEE Trans. Biomed. Eng*, vol. 30. no 7, pp. 392-398, JUL 1983.

[17] Muhammad Zia Ur Rahman, Rafi Ahamed Shaik, D. V. Rama Koti Reddy, “Efficient and Simplified Adaptive Noise Cancelers for ECG Sensor Based Remote Health Monitoring”, *IEEE Sensors J*, vol. 12, no. 3, pp. 566-573, MAR 2012.

[18] B. Widrow and S. D. Stearns, ‘Adaptive Signal Processing’, 2nd Edition, Pearson Education.

[19] Simon Haykin, 'Adaptive Filter Theory', Prentice Hall, 2002, ISBN 0-13-048434-2.
[20] Sidhartha Dash, Mihir Narayan Mohanty, "Analysis of outliers in system identification using WLMS algorithm", International Conference on Computing, Electronics and Electrical Technologies (ICCEET), pp. 802-806, Kanyakumari, 21-22 March 2012.
[21] Sarthak Panda, Mihir Narayan Mohanty, "Analysis Of Norms in Adaptive algorithm On Application of System Identification", Information Systems Design and Intelligent Applications, Advances in Intelligent Systems and Computing 433, pp 579-588,2016, DOI 10.1007/978-81-322-2755-7_60.
[22] https://www.physionet.org/physiobank/database/mitdb/