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Analysis of Removing Noise from Modeled ECG Signals by using Adaptive Noise Cancellation Model

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Abstract: In this paper an adaptive noise cancelation (ANC) model is presented to remove baseline wander (BW) noise from mathematically modeled ECG signals. The ANC model is designed to have a trade-off between the correlation properties of noise and reference signals. Matlab is used to simulate ECG signals artificially, to represent different sinus rhythms and leads of ECG waveform. Furthermore contamination of an important artifact (baseline wander) is simulated for normal ECG lead II, and then identified using LMS algorithm and its preconditioned versions: NLMS and TDLMS algorithms, to get denoised ECG signals. Experimental results are presented for a comparison of these adaptive algorithms, which shows preference of TDLMS algorithm and Fx LMS algorithm over the rest.

Index Terms: Mathematical model, almost periodic, adaptive algorithm, adaptive noise canceler.

I. INTRODUCTION

Adaptive filters can be identified as self-designing systems that rely on a recursive algorithm to become able to perform adequately in an environment where knowledge of the relevant statistics is not available. They have ability to detect time varying potentials and to track the dynamic variations of biomedical signals. An important biomedical signal processing application is denoising of the electrocardiogram (ECG) signals. ECG signals are non-stationary bioelectrical signals, used to detect the beats of heart rate variability (HRV). These signals can be split into different segments and intervals according to the phases of cardiac conduction. ECG signal include valuable clinical information, but frequently the valuable clinical information is corrupted by various kinds of noise, including baseline wander (BW), which is caused by variable contact between the electrodes and the skin. The least mean square (LMS) algorithm is a widely used adaptive filtering algorithm and have found its place in biomedical signal processing community as well [1]–[3].

LMS algorithm is a stochastic gradient algorithm which offers the easiest and reliable adaptive method to denoise and identify a signal. Its performance depends on the power spectral density (i.e. eigenvalue spread) of the input autocorrelation matrix [4]. When contamination of noise in the desired signal increases, its spectral power increases and this results in poor performance of LMS algorithm. Several approaches have been put forward to improve the performance of LMS algorithm, two such approaches are Normalized LMS (NLMS) algorithm and transform domain LMS algorithm [5]. Application of these techniques in biomedical signal processing is very limited. This study proposes a mathematical development of ECG waveform by employing the almost periodic nature of the waveform. The generating function is obtained by taking the superposition of linear combination of basis functions, while Fourier coefficients, and values of model parameters (amplitude, duration, time) for ECG lead-II are employed from the online model [6]. Afterwards an adaptive noise canceler (ANC) is presented for identification and removal of BW artifacts from modeled ECG. The reference signal of this noise canceler is obtained by using a novel technique for setting a trade-off between the correlation properties of input noise and reference signal. It is done by passing noise signal through an unknown filter, to have a reference signal with different correlation properties. After that performance of NLMS and discrete cosine transform based TDLMS algorithms is analyzed in identification and removal of estimated BW noise from contaminated ECG signals. Experimental results are obtained for noise cancelation of normal ECG waveform and it is observed that in case of BW noise of frequency 0.25 Hz, DCT-TDLMS algorithm has better convergence properties as compared with NLMS and LMS algorithms

II. ADAPTIVE NOISE CANCELER FOR REMOVAL OF BASELINE WANDER (BW) FROM MODELED ECG SIGNALS

The block diagram of proposed adaptive noise canceler (ANC) for denoising ECG signals is shown in Figure1. The signal x (n), consists of the desired clean signal ecg(n) and contaminated noise g(n) = BW(n), such that

$$x(n) = ecg(n) + BW(n) \qquad (1)$$

The noise source produces a noise signal which is recorded simultaneously with noise BW(n) and the reference signal(n), obtained by passing noise signal(n) = BW(n) through an unknown filter with frequency response:

$$H(z) = \frac{\sqrt{1-\alpha 2}}{1-\alpha z^{-1}}$$

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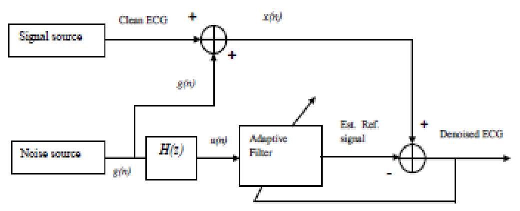

Fig. 1. Proposed Adaptive Noise Cancelation model for Denoising Modeled ECG signal.

Where $|\alpha| < 1$, α is a correlation parameter and controls the spectral properties of input signals. $\alpha = 0$ corresponds to the case when condition number is close to 1, condition number increase with an increase in the value of α. The ECG signals and contamination of noise is obtained by using a mathematical model which is based upon the superposition of linear combination of basic functions, and is summarized below.

A. Mathematical Simulation of ECG Signals

An ECG waveform is comprised of peaks and troughs with P, Q, R, S, T, and U events, associated with the artrial and ventricular depolarization/repolarization. These activities produce potential variation between the ECG electrodes positioned on different limbs and chest wall, and result in a time varying waveform. ECG model parameters are used for mechanical detection and classification of various sinus rhythms. Modeling the ECG signal is concerned with making the best simulation of the signal followed by obtaining the parameters of the model. More accurate model parameters will make the simulator more reliable. The proposed Mathematical model is designed by employing the almost periodic nature of ECG waveform and is based on three model parameters: amplitude (measured in mV), duration (in sec.) and incident time (in sec.) of events. Let us denote the number of heartbeat per minute by Nhb, and take the set of significant waveforms of ECG lead as J = P, Q, R, S, T, U. Then an event $j \in J$ in the ECG waveform, at time t, can be identified by an almost periodic function E (t) of time period $\tau hb(t)$ such that $Ej(t) \approx Ej(t+\tau hb(t))$, and the Fourier series representation of Ej(t) would be [7]

$$Ej(t) = Aj + \sum_{n=1}^{Nhb} Uj(n)\cos\{2\pi n \int_{tj}^{t} fhb(t)dt\} \qquad (2)$$

Where $fhb(t) = 1/\tau hb(t)$ is the fundamental frequency of heartbeat. A_j and $U_j(n)$ are Fourier coefficients, while parameter t_j is the incident time of event $j \in J$. Generally almost periodic behavior of waveform is governed by time dependent period $\tau hb(t)$, but for ease of computations, we assume that it is function of heartbeat only, i.e.
$1/\tau hb(t) = 60 fhb(t)$. Simplifying
$whb(t) = 2\pi fhb(t) = 2\pi/\tau hb(t)$, (2) yields

$$Ej(t) = Aj + \sum_{n=1}^{Nhb} Uj(n)\cos\{whb(t-tj)n\} \qquad (3)$$

If aj and dj denote respectively the amplitude and duration of event $j \in J$, then each event is supposed to occur in a cycle of period $\tau j = \tau hb(t)/dj$ with frequency $fj = 1/tj$. Given the values of model parameters aj dj and tj, for each $j \in J$, an appropriate choice of functions can be made to find the determine Fourier coefficients Aj & Uj (n) independently, as is done in appendix-A. The superposition of events Ej can be a good approach to develop a comprehensive set of all the waveforms in the ECG lead. For a known value of Nhb, the ECG waveform is approximated as:

$$ECG(t) = \sum_{j\in J} Ej(t)$$
$$= A_o + \sum_{j\in J}\sum_{n=1}^{Nhb} Uj(n)\cos\{whb(t-tj)n\}$$

Where $A_o = \sum_{j\in J} Aj$
adjusts the deviation of base line of ECG waveform from zero voltage. Since occurrence of an event in Independent of Nhb, (4) can be rewritten as:

$$ECG(t) = \sum_{j\in J}\sum_{n=1}^{Nhb} Uj(n)\cos\{whb(t-tj)n\} \qquad (5)$$

Most simple ECG machines are capable of recording at least three leads: lead I, lead II and lead III. The most commonly used lead is Lead II, which is the best lead for interpreting the heart's rhythm. Lead II is the view from the patient's right arm to his left leg. All further discussion is made for ECG lead II waveform, whose model parameters (Amplitude(mV), Duration(sec.), Time(sec.)) are employed from an online model [6], and are given in table-I. Starting with event P, the signals are sampled with 1mSec resolution for 5 seconds time, with

$$N = 0.001: 0.001: 5.$$

TABLE I: PARAMETERS FOR ECG LEAD-II.

PARAMETERS	P	Q	R	S	T	U
AMPLITUDE	0.25	0.15	1.6	0.25	0.35	0.035
DURATION	0.09	0.066	0.11	0.066	0.142	0.0476
TIME	0.1	0.25	0.3	0.39	0.545	0.733

Figure2 (b) shows the waveform of normal ECG-lead II, while the waveform shown in Figure2 (a) is contaminated by BW noise. The noise signal BW(n) is simulated by the mathematical function $A\sin(2\pi f_{bwn})$, where f_{bw} is the high frequency component of respiratory sinus arrhythmia (RSA), and A is amplitude of wandering from baseline.

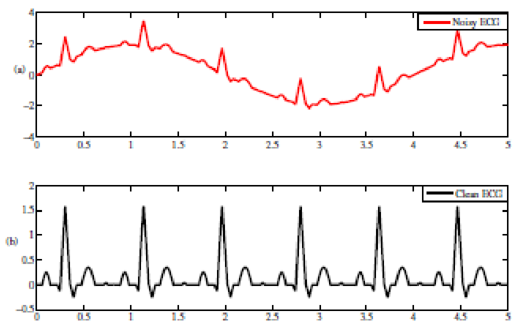

Fig. 2. Simulated ECG signal of normal sinus rhythm: (a). Contaminated by BW of $f_{BW} = 0.25$, (b) Clean for $\alpha = 0.8$.

III. LMS BASED ADAPTIVE NOISE CANCELERS

Consider an FIR filter of length N with a tap-weight vector Wn, at instant n. The LMS algorithm minimizes the

Instantaneous objective function (MSE)

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J(n) = e2(n) where e(n) = s(n)-$w_n^T a_n$ The vectors $a_i \in R^N$ are formed by input signals u(i) in such a way that

$$a_i = [\ u(i)\quad u(i-1)\quad \cdots\quad u(i-N+1)\ ]^T;\ 1 \le i \le n$$

Using input signals we can define the $n \times N$ data matrix A_n as:

$$A_n = \begin{pmatrix} u(1) & 0 & \cdots & 0 \\ u(2) & u(1) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ u(N) & u(N-1) & \cdots & u(1) \\ u(N+1) & u(N) & \cdots & u(2) \\ \vdots & \vdots & \ddots & \vdots \\ u(n-1) & u(n-2) & \cdots & u(n-N) \\ u(n) & u(n-1) & \cdots & u(n-N+1) \end{pmatrix}$$

Define X = E[$a_n a_n^T$] as the autocorrelation matrix of input vectora_n, and p= E[$a_n s_n$] as the cross correlation vector. The mean square error J(n) is minimized by continuously updating the weight vector $\mathbf{w}_n$ as each new input signal is received, according to the equation:

$$W_{n+1} = W_n + 2\mu e(n) a_n \qquad (6)$$

Where μ is a positive constant that controls the rate of convergence. To ensure the stability of the adaptive process, value of μ must satisfy the condition:

$$0 < \mu < \frac{1}{\lambda_{\max}} \qquad (7)$$

λmax is the largest eigenvalue of the autocorrelation matrix X = E[ananT] and is given by the maximum of the power spectrum of input signala_n For stationary input and an appropriate choice of μ, the minimum value of e(n) generates a Cauchy sequence{Wn}n=1∞ from (6) in RN. But since RN is a Banach space [8], there exists an optimum weight vector wo ∈RN, such that wo→ wn as n→∞. Value of w*o*, as given by Wiener-Hopf equation [4], is:

$$W_o = X^{-1} p \qquad (8)$$

Let us define the misalignment vector m_n as:

$$m_n = w_o - w_n$$

Then m*n* = ‖ mn ‖ 2 = ‖ wo-wn ‖ 2→ 0 as n→∞. It is not difficult to show that under independence assumption,

$$E[m_{n+1}] = (I - 2\mu X) E[m_n] \qquad (9)$$

This relation is used in literature [4], [9] to show that convergence behavior of the LMS algorithm is directly linked to the eigenvalue spread of X. For highly correlated input, X has high eigenvalue spread, and convergence of the algorithm can be extremely slow. To improve the convergence speed, we need to reduce eigenvalue spread of X by using some decorrelation techniques.

We may overcome this problem by employing preconditioning theory from numerical linear algebra. Here we briefly describe some algorithms which have been derived from conventional LMS algorithm by using techniques similar to that theory.

A. Normalized LMS Algorithm

The normalized LMS (NLMS) algorithm, which was developed as a constrained optimization problem [9], can be considered as a preconditioned LMS algorithm. The preconditioner $(\psi I + a_n a^T{}_n)^{-1} a_n$ is a regularized inverse of$a_n a^T{}_n$, whereψ≈0.

The update equation is given by:

$$W_{n+1} = W_n + \mu e(n)(\psi I + a_n a^T{}_n)^{-1} a_n$$

Using matrix inversion lemma, we have

$$W_{n+1} = W_n + \mu e(n)(\psi I + a_n a^T{}_n)^{-1} a_n \qquad (10)$$

Where ψ is selected to be small enough when compared with$a^T{}_n a_n$. NLMS has fast convergence as compared with the conventional LMS algorithm, but has a drawback of increased maladjustment.

B. TD-LMS Algorithm

Transform domain LMS algorithms is a class of robust preconditioned algorithms having good tracking capabilities in non-stationary environments. Application of an orthogonal transform, followed by a power normalization step, has the ability to reduce the eigenvalue spread of input correlation matrix, which results in an increase of convergence speed of the algorithm [4]. Here we give a brief description of the TDLMS algorithm.

The input vector an, and weight vector wn are transformed to an =T wn and Ŵ_n=T Wn respectively, through an orthogonal transform T. With error estimate

e(n) = s(n)- Ŵ_n

an and power normalization

$$\sigma_n^2(i) = \beta \sigma_{n-1}^2(i) + (1-\beta)\hat{a}_n^2(i) \quad ; \ i = 0, 1, \cdots, N-1,$$

where $0 < \beta < 1$, the weight vector update equation is:

$$\hat{W}_{n+1} = \hat{W}_n + 2\mu D^{-1} e(n) \hat{a}_n \qquad (11)$$

With

$$D = \mathrm{diag}[\sigma^2{}_n(0), \sigma^2{}_n(1), \dots, \sigma^2{}_n(N-1)]$$

An analytical approach [10] has shown significant decrease in the eigenvalue spread of the input correlation matrix of a first order Markov signal after application of discrete Fourier (DFT) and discrete cosine (DCT) transforms, followed by power normalization. For current noise cancelation problem, we use DCT based TDLMS algorithm, because it has better control on the eigenvalue spread of reference signals. Moreover it has better compatibility with our model of ECG waveform.

C. FxLMS algorithm

The most popular adaptive algorithm used for ANC applications is the filtered-x least mean square (FxLMS) algorithm which is a modified version of the LMS algorithm. The FxLMS algorithm is computationally simple, but its convergence speed is slow. Different ANC algorithms, with improved convergence properties, have been proposed, viz., 1) lattice-ANC systems; 2) infinite impulse response (IIR) filter-based LMS algorithms called filtered-u recursive LMS (FuRLMS), and filtered-v

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algorithms; 3) recursive least squares (RLS) based algorithms called filtered-x RLS (FxRLS) and filtered-x fast-transversal-filter (FxFTF); and 4) frequency-domain-ANC systems.

x(n) is the input signal to a linear filter at time n y(n) is the corresponding output signal d(n) is another input signal to the adaptive filter S(z) is the impulse response of the secondary path ys(n) is the signal from the secondary path e(n) is the error signal that denotes the superposition of d(n) and ys(n)
$\hat{S}(z)$ is the estimation of S(z)
x^s(n) is the resulting output signal from $\hat{S}(z)$

Assuming that W(z) is an FIR filter of tap-weight length Lw, the secondary signal y(n) is expressed as

y=WT(n)x(n)

W(n)=[W0(n),W1(n),………,WLw-1(n)]T
Is the tap-weight vector, and
x(n)=[x(n),x(n-1),…….,x(n-Lw+1)]
Is an Lw–sample vector the reference signal x(n).

The residual error signal e(n) is given as
e(n)=d(n)-ys(n)
Where d(n) = p(n) * x(n) is the primary disturbance signal, ys(n) = s(n) * y(n) is the secondary cancelling signal,
* denotes linear convolution, and p(n) and s(n) are impulse responses of the primary path
P(z) and secondary path S(z), respectively.

Minimizing the mean squared error (MSE) cost function;

j(n)=E $\left\{e^2(n)\right\} \approx$ e2(n)

Where E{·} is the expectation of quantity inside; the FxLMS update equation for the coefficients of W(z) is given as

W(n+1)=w(n)+ μ_w e(n)x^s(n)

Where μ_w is the step size parameter?

X^s(n)=[X^s(n), X^s(n),…….., X^s(n)]T

Is filtered-reference signal vector being generated as
x^s(n)=s^(n)*x(n)

Where s^(n) is impulse response of the secondary path modeling filter s^(z).

IV. EXPERIMENTAL RESULTS

In order to compare the performance of iterative algorithms for identification of BW noise in modeled ECG signal and then generation of denoised ECG curve, we make use of Matlab to apply LMS, NLMS and DCT-TDLMS algorithm on our modeled ECG signals contaminated by BW noise of frequency 0.25. Learning curves of MSE are noted for all the three algorithms (Figure3), for an ECG recording of 5 second duration with 1mSec resolution of sampling and time n=0.001: 0.001: 5. Furthermore denoised ECG waveform obtained by application of these algorithms is compared with clean ECG waveform in all cases (see Figure 4). Although all the three algorithms are found efficient in cancelation of noise components and identification of clean ECG signals from contaminated ones, but from a closer look at learning curved of ECG waveform in Figure 5(a) & Figure5 (b), preference of DCT-TDLMS is found over the rest. For all computations, correlation parameter is kept fixed at α = 0.8, and filter length is N = 5. Checking performance of all algorithms for different values of BW-amplitudes, it is found that because of its invariance under the correlation properties of reference signals, DCT-TDLMS algorithm can perform well even for amplitude of BW noise equal to amplitude of event R wave,while performance of rest two becomes poor for amplitude higher than that of three-fourth of event R.

An appropriate representation of E_j (t), for event j ∈ {P, T, U} is:

$$E_j(t) = a_j \cos\left(\pi \frac{\tau}{2L}\right) \quad ; \quad \frac{-L}{\tau_j} \le t \le \frac{L}{\tau_j} \qquad (12)$$

Then, $A_j = \frac{1}{2L}\int_{-\frac{L}{\tau_j}}^{\frac{L}{\tau_j}} a_j \left(\pi \frac{\tau_j}{2L} t\right) dt = \frac{2a_j}{\pi\tau_j}$

And, $U_j(n) = \frac{1}{L}\int_{-\frac{L}{\tau_j}}^{\frac{L}{\tau_j}} a_j \cos\left(\pi \frac{\tau_j}{2L}\right) \cos\left(\frac{n\pi}{L} t\right) dt$

$$= \frac{4a_j\tau_j}{\pi(\tau_j{}^2 - 4n^2)} \cos(\frac{n\pi}{\tau_j})$$

Next for j ∈ {R}

$$E_j(t) = \begin{cases} \frac{a_j\tau_j}{L} t + a_j & , \quad \frac{-L}{\tau_j} \le t \le 0 \\ -\frac{a_j\tau_j}{L} t + a_j & , \quad 0 \le t \le \frac{L}{\tau_j} \end{cases} \qquad (13)$$

Then, $A_j = \frac{1}{2L}\left\{\int_{-\frac{L}{\tau_j}}^{0} (\frac{a_j\tau_j}{L} t + a_j) dt\right\} = \frac{a_j}{2\tau_j}$

And, $U_j(n) = \frac{1}{L}\left\{\int_{-\frac{L}{\tau_j}}^{0} \left(\frac{a_j\tau_j}{L} t + a_j\right) \cos\left(\frac{n\pi}{L} t\right) dt + \right.$

0Lτj−ajτjLt+ajcosnπLtdt

$$= \frac{2a_j\tau}{(n\pi)^2}\left\{1 - \cos(\frac{n\pi}{\tau_j})\right\}$$

The waveforms of events Q and S are similar to that of reciprocal of waveform of event R. Therefore, it is enough to find the Fourier coefficients of E_j (t) for j ∈ {R} only, because functions corresponding to j ∈ {Q, S} are just negative of E_R(t).

V. FIGURES AND TABLES

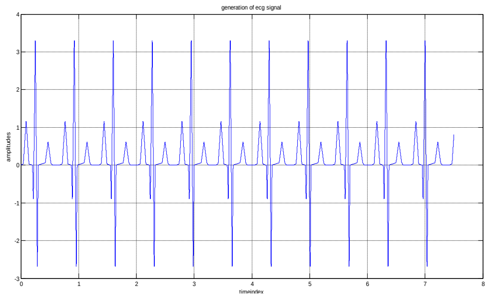

Fig 7.1: Generation of ECG signal

The above figure shows the generation of ECG signal with total number of Samples 2700 by using a MATLAB built in function ECG.

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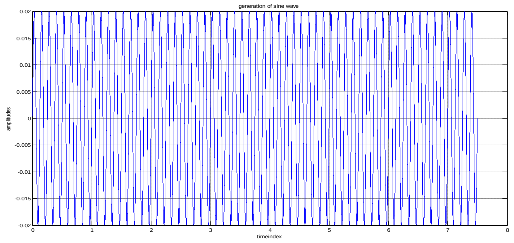

Fig 7.1: Generation of Sine wave

The above simulation results shows the generation of ECG

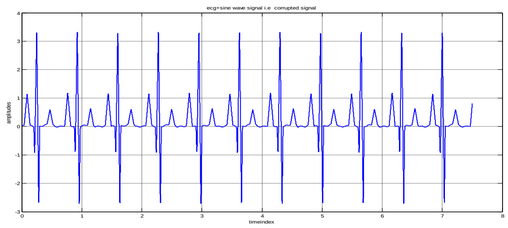

Fig 7.3: Simulated noise corrupted ECG signal

The above waveforms shows the simulated results of noisecorrupted ECG signal, by adding noise to original signal

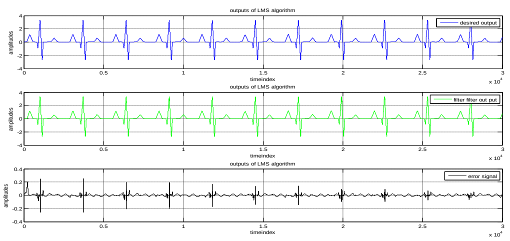

Fig 7.4: Simulated results of noise corrupted ECG signal by using LMS algorithm.

The above waveforms shows the simulation results of desired output, filtered output and error signal by using LMS algorithm.

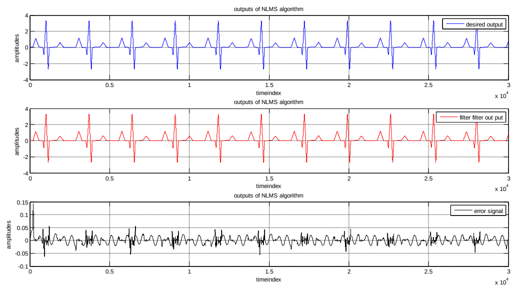

Fig 7.5: Simulated results of noise corrupted ECG signal by using Normalized LMS algorithm.

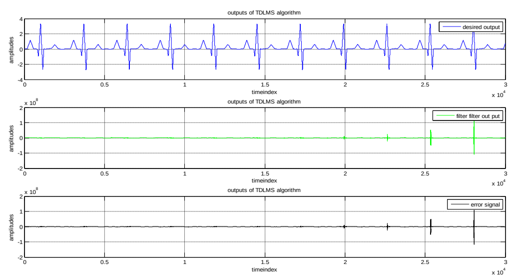

Fig 7.6: Simulated results of noise corrupted ECG signal by using TDLMS algorithm.

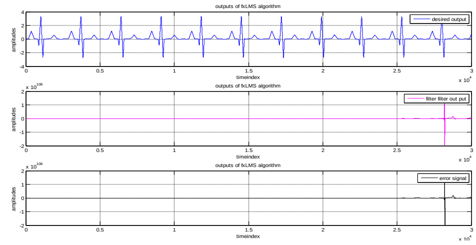

Fig 7.7: Simulated results of noise corrupted ECG signal by using Filtered-x LMS algorithm.

VI. CONCLUSION

The mathematical model presented in this paper is able to simulate complete ECG waveform of different leads with model parameters. Furthermore, it is flexible enough to be modeled with added noises, such as artifact of baseline wander (BW). This model is then used to compare the performance of LMS, NLMS and DCT-TDLMS,Fx LMS algorithms for cancelation of BW noise from modeled ECG signals. An adaptive noise canceler is designed for the purpose by offering a tradeoff between the correlation properties of noise and reference signals. Experimental results for MSE learning curves and denoised ECG waveforms are presented to show the comparative performance of three algorithms. This comparison results in preference of TDLMS algorithm under given circumstances. A summary of the performance of the adaptive filtering algorithms is expressed in table is shown in below Fig 7.8. The performance of the adaptive algorithms can be measured by using the parameters SNR, DISTORTION characteristics and Root Mean Square value. It is also noticed that the SNR, Distortion characteristics and attenuation values are better when we using LMS algorithm. It is also noticed that Filtered-x LMS algorithm is suitable for real time analysis because the average error value is minimum.

Type Of algorithm	Average Error Value	SNR	Distortion	RMS VALUE
LMS	0.0153	31.7205	-34.8081	0.0182
NLMS	0.0124	34.2035	-37.2911	0.0137
TDLMS	0.0124	-128.4368	125.3486	1.8511E+06
FXLMS	0.000456	-2.0963E+03	2.0932E+03	4.5845E+104

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