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An Efficient Normalized Fractional LMS Algorithm Used To Enhance the Quality of ECG Signal

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Abstract: *Adaptive filters are primary methods to remove the power line interference noise from the ECG signal. The frequency range of ECG signal is generally 0.05 Hz to 100 Hz, and that of the power line interference noise is 50 Hz which lies in the ECG signal. So, it has become very crucial to remove the power line interference from the ECG signal. In this paper Normalized fractional least mean square (NFLMS) algorithm had compared with others. The Normalized fractional least mean square algorithm essentially minimizes the mean square error and removes the 50Hz power line interferences. The experimental results show that the Normalized fractional least mean square algorithm is more effective compare to other algorithms.*
Keywords: *Power line interference; ECG signal; NFLMS; SNR*

I. Introduction

There are various biomedical signals present in the human body, by examining these biomedical signal one can check the health condition whether that person is clinically fit or not. Electrocardiogram is one of them [1]. ECG signal is electric representation of the activity of human's heart. Various cardiac diseases can be recognized with the help of ECG signal. While recording process of ECG signal, several types of noises may encounter in it. The common type of noises are power line interference (PLI), electrode motion noise (EM), muscle artifacts, baseline wander etc. It is essential to remove or minimize these interferences prior to further diagnosis for any medical application [2]. The QRS segment is very important and it is predominantly used for clinical observation. So if the noise changes the amplitude or time duration of the segment then recognizing the true condition of patient is very difficult task. Therefore the primary concern is to preprocess the ECG signal [3]. The objective is to separate the valid signal component from the undesired noises so that the accurate interpretation of ECG could be done. With the latest advancements in electronics, several techniques are used for removal of unwanted entities from signals especially that are implied in the most sophisticated applications. The removal of power line interference from most sensitive medical monitoring equipment's can also be removed by implementing various useful techniques [4]. The power line interference (50/60 Hz) is the main source of noise in most of bio-electric signals [5]. The thesis report presents the removal of power line interference from ECG signal using the different adaptive techniques. The Different types of digital filters (FIR and IIR) have been used to denoise the ECG signal [6]. However, it is difficult to apply these filters with fixed coefficients to reduce the power line interference noise, because the ECG signal is known as a non-stationary signal [7]. Recently, Adaptive filtering has become one of the effective and popular methods for the processing and analysis of the ECG signal [8]. It is well known that adaptive filters with LMS algorithm show good performance for processing and analysis of the most of the biomedical signals which are non-stationary. And in this study, we have used adaptive filters to remove the power line interference from the ECG signal [9]. We have used different adaptive filter algorithms, such as, LMS, NLMS, Fractional LMS, and Normalized fractional LMS algorithm [10],[11]. The original ECG signal is taken from MIT-BIH Arrhythmia Database [13] and the noise signals are generated by using MATLAB. We have used the Signal Processing Toolbox of the mentioned algorithms built in MATLAB.

II. Adaptive Filters

The so-called adaptive filter, is the use of the result of the filters parameter a moment ago, automatically adjusts the filter Parameters to the present moment, to process the unknown Signal and noise or over time changing statistical properties in order to achieve optimal filtering. Adaptive filter has "self-regulation" and "tracking" capacities. Filter out an increase noise usually means that the contaminated signal through the adaptive filter aimed to a check noise and signal relatively unchanged. For the purpose of the adaptive filter can be fixed, and can also be adaptive. Fixed filter designers assume that the signal characteristics of the statistical computing environment fully known, it must be based on the prior knowledge of the signal and noise [5]. However, in most of the cases it is very difficult to satisfy the conditions; most of the practical issues must be determined using adaptive filters. Adaptive filter is through theaction of the existing signal to interpret statistical properties, to adjust parameters automatically, to change their performance, so its design does not require of the prior knowledge of signal and noise characteristics.

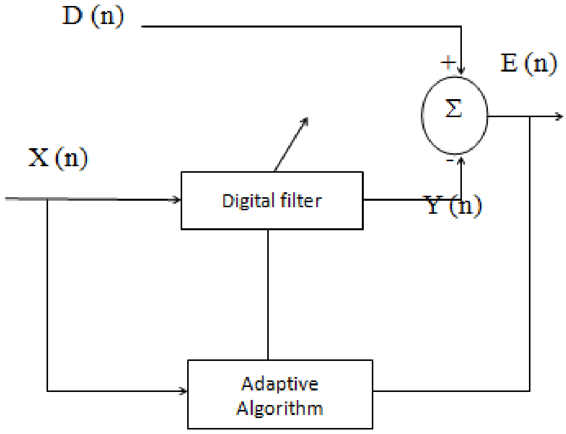

Figure1. Configuration for adaptive noise cancellation

The figure above is given the adaptive filtering display digital filters carries on filtering on the input signal x(n), produce output signal y(n). Adaptive filters adjusts the filter coefficient included in the vector w (n), in order to the error signal e(n) to be the smallest. Error signal is the difference of desired signal d(n) and the digital filter output y(n). Therefore, adaptive filter automatically carry on a design based on the characteristic of the input signal x(n)and the desired signal d(n). Using this method, adaptive filter can be adapted to the environment set by these signals [6]. When the environment changes, filter through a new set of factors, adjusts for new features. The most important property of adaptive filter is that it can work effective in unknown environment, and to track the input signal of time-varying characteristics. Adaptive filter is through the observation of the existing signal to understand statistical properties, which in the normal operation to adjust parameters automatically, to change their performance, so its design does not require of the prior knowledge of signal and noise characteristics.

2.1. Least Mean Square (LMS) Algorithm:

Least Mean Squares Algorithm is based on steepest descent algorithm where weight vector is updated from sample to sample as follows

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \mu e(n)\mathbf{x}^*(n) \quad (1)$$

Where μ is the step size and controls the convergence rate. Small value of μ leads to more convergence time. Large value of μ causes the algorithm to diverge and degrades the performance of adaptive filter [12]. Therefore selecting a step size is very important.

In LMS has more Complexity it requires $(p+1)$ multiplications and $(p+1)$ additions to update the filter coefficients. One addition to compute the error $e(n) = d(n) - \hat{d}(n)$ and one multiplication to compute $\mu e(n)$and $(p+1)$ multiplications and p additions to compute the output sample $\hat{d}(n)$ of the adaptive filter [13].

2.2. Normalized LMS Algorithm:

One of the difficulties in the implementation of the LMS adaptive filter is the selection of step size μ. For WSS processes,

LMS converges in mean if $0 < \mu < \frac{2}{\lambda_{max}}$ and converges in mean squareif $0 < \mu < \frac{2}{tr\,(\mathbf{R}_x)}$.

Since $\mathbf{R}_x$ is generally unknown, then either λ_{max} or $\mathbf{R}_x$ must be estimated in order to use these bounds. For stationary processes,

$$tr(\mathbf{R}_x) = (p+1)E\{|x(n)|^2\}. \quad (2)$$

This leads to the following bound for mean square convergence $0 < \mu < \frac{2}{\mathbf{x}(n)^H\mathbf{x}(n)}$

One way to incorporate this bound into the LMS adaptive filter is to use a time-varying step size

$$\mu(n) = \frac{\beta}{\mathbf{x}(n)^H\mathbf{x}(n)} = \frac{\beta}{\|\mathbf{x}(n)\|^2} \quad (3)$$

Where β is a normalized step size with $0 < \beta < 2$

The weight vector update in the NLMS algorithm is

$$\boldsymbol{w}(n+1) = \boldsymbol{w}(n) + \beta \frac{\mathbf{x}^*(n)}{\|\mathbf{x}(n)\|^2} e(n) \quad (4)$$

In the LMS algorithm, the correction that is applied to w_n is proportional to input vector $\mathbf{x}(n)$. Therefore when $\mathbf{x}(n)$ is large, the LMS algorithm experiences a problem with gradient noise amplification [11]. With the normalization of step size by $\|\mathbf{x}(n)\|^2$ in NLMS this noise amplification problem is diminished. A similar problem occurs when $\|\mathbf{x}(n)\|^2$ is too small. Hence typically the following equation is used

$$\boldsymbol{w}(n+1) == \boldsymbol{w}(n) + \beta \frac{\mathbf{x}^*(n)}{\epsilon + \|\mathbf{x}(n)\|^2} e(n) \quad (5)$$

Where ε is small positive number. NLMS algorithm converges faster than the LMS algorithm because it uses time varying step size calculation.

2.3. Fractional LMS Algorithm

In LMS, weights are optimized in a manner that the error is minimized in mean-square sense. The cost function is given by

$$J(n) = E[e(n)e^*(n)] = E[|e(n)^2|](6)$$

The weight update equation for the k^{th} element,having only the first derivative term, is given by

$$w_k(n+1) = w_k(n) - \mu \frac{\partial J(n)}{\partial w_k}, (k = 0,1,2, \ldots\ldots, M-1) \quad (7)$$

Where *M* is the number of tap weights and *n* is the current time index. In deriving the fractional LMS (FLMS) algorithm, we have to use fractional derivatives, in addition to the first derivative [10]. The update relation for the k^{th} element of the weight vector is given by

$$w_k(n+1) = w_k(n) - \mu_1 \frac{\partial J(n)}{\partial w_k} - \mu_f \frac{\partial^v J(n)}{\partial w_k^v} \quad (8)$$

Where v ($0 < v < 1$) is a real number and μ_f is the fractional step-size.

After calculating the derivative terms and doing some simplifications, we obtain the final update relation for the weight vectors of the FLMS algorithm as

$$\boldsymbol{w}_k(n+1) = \boldsymbol{w}_k(n) + \mu_1 e(n)\boldsymbol{X}(n-k) + \mu_f e(n)\boldsymbol{X}(n-k) \frac{w_k^{1-v}(n)}{\Gamma(2-v)} \quad (9)$$

Where Γ(.) denotes the gamma function.

2.4 Normalized Fractional LMS Algorithm

In this section, we compared our normalized version of the fractional Least-Mean-Squares algorithm to other algorithms.

The new idea is based on the fact that the normalized version of LMS algorithm has better performance than standard LMS filters. Furthermore, it has been shown that the fractional LMS (FLMS) algorithm, which is an improved version of the conventional LMS, has faster convergence than the LMS algorithm [9]. Thus, it is expected that using normalized version of FLMS (NFLMS) instead of the FLMS adaptive filter leads to a better performance of the adaptive filter. The update rule for the NFLMS algorithm is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\delta + \|\mathbf{u}(n)\|^2} e(n)\mathbf{u}(n) + \frac{\mu_f}{\delta + \|\mathbf{u}(n)\|^2} e(n)\mathbf{u}(n) \frac{w^{1-v}(n)}{\Gamma(2-v)}. \quad (10)$$

2.5Performance Measurements

To assess the performance of the proposed filters for removal of noise and to evaluate their comparative performance, different standard performance indices have been used in the thesis. These are defined as follows:

A) Signal to Noise Ratio Improvement (SNR)

SNRI in dB is defined as the difference between the Signal to Noise Ratio (SNR) of the restored signal in dB and SNR of noisy signal in dB[12] i.e.

SNRI (dB) = SNR of restored signal in dB- SNR of noisy signal in dB

The higher value of SNR reflects the better visual and restoration performance.

B) Mean square error (MSE):

A small minimum MSE is an indication that the small portion PLI signal is occur at the output ECG signal system [13].

III. Results And Discussion

For our simulations, we use four ECG signals from the MIT-BIH Arrhythmia Database.Four LMS-based algorithms (i.e., LMS, NLMS, FLMS, and NFLMS) are compared. The experimental conditions for these algorithms are shown in fig 2, fig 3, fig 4, & fig 5.

The original ECG signal is taken from MIT-BIHArrhythmia Database[13] and the noise signal are generated by using MATLAB whose sampling frequency is 200 Hz for each beat and amplitude is 1mv. The 50 Hz power line interference is also generated with sampling frequency of 3000 Hz. The power line interference is then added to the original ECG signal to get the mixed signal. Finally, the power line interference is removed using different adaptive filters based on different algorithms, such as, LMS, NLMS, FLMS and Normalized Fractional LMS algorithm.

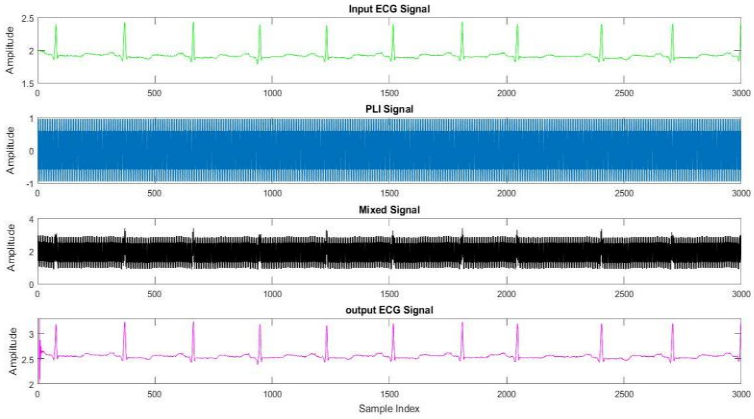

Figure2. Power line interference removing using LMS filter

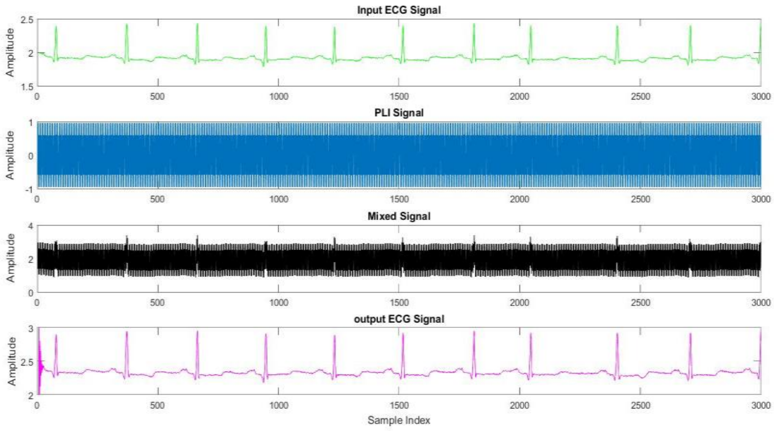

Figure3. Power line interference removing using NLMS filter

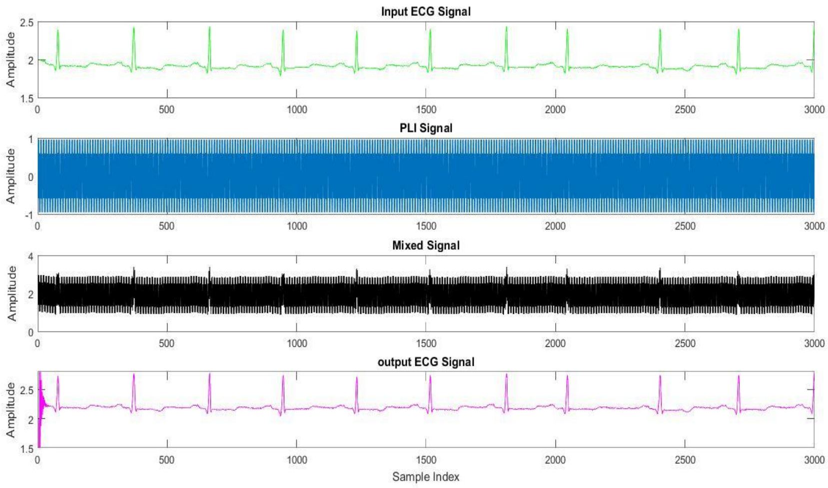

Figure 4. Power line interference removing using FLMS filter

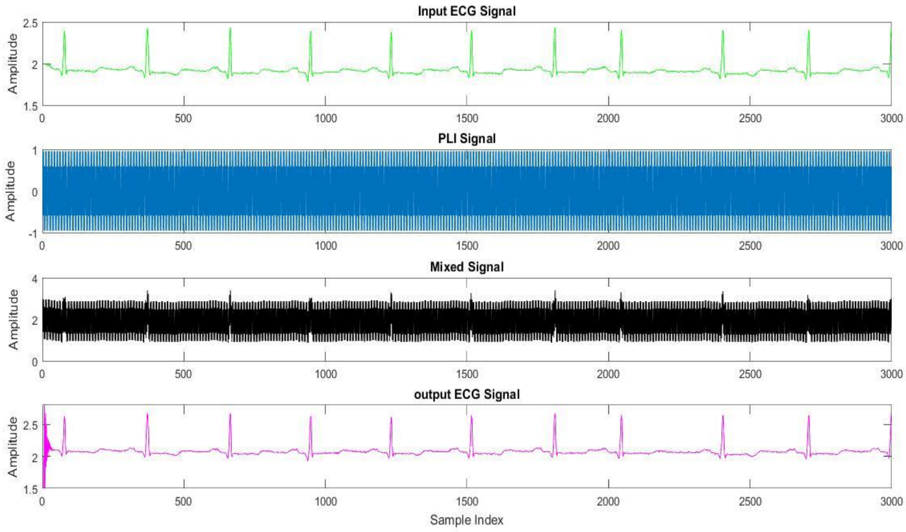

Figure 5. Power line interference Removing using NFLMS filter

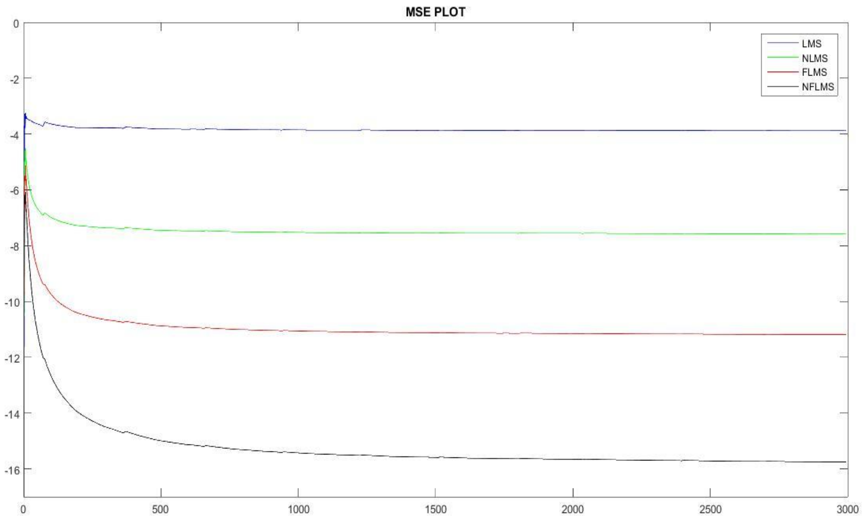

Figure 6. MSE Plot for LMS, NLMS, FLMS and NFLMS.

If the amplitude of the reconstructed signal increases, then there will be high distortion and vice versa. When the value of μ equal to 0.05, then we see that some noise also appear on the signal peak compared with the value of μ equal to 0.001.But when the value of μ is 0.001, then the reconstructed signal amplitude is less than the original signal as well as all other measuring values, such as, the SNR, MSE decreases with low distortion. So we can say that the SNR for step size μ of 0.05 is better but exhibits some distortion.

Table I shows the SNR and MSE of LMS,NLMS,FLMS and NFLMS algorithm for different types of noise in the case of record no. 100, record no 111, record no 200 and record no. 230 respectively. The tabular analysis indicate that the reconstructed ECG signal obtained from the adaptive NFLMS filter has high SNR and MSE than the LMS,NLMS,FLMS algorithms for all type of noises.

The convergence criterion shows that, the fast adaption of filtering signal with the original signal. The convergence of LMS, NLMS, FLMS and NFLMS filtering reconstructed signal is depicted in Fig. 6. We can see that, the NFLMS filtering signal adapts in far less iteration to original signal than the all algorithms. In this study, we find that adaptive NFLMS algorithm shows better performance compare to remain algorithms.

Table1. Values of performance parameters of adaptive filters:

Noises	Reconstructed Signal's Adaptive Filters	SNR					MSE				
		Patient Data 100	Patient Data 111	Patient Data 200	Patient Data 230	Average	Patient Data 100	Patient Data 111	Patient Data 200	Patient Data 230	Average
Power Line Interference	LMS	9.4864	9.4877	9.4792	9.4909	9.48605	0.4148	0.4468	0.4489	0.4227	0.4333
	NLMS	13.113	13.115	13.096	13.124	13.1119	0.1801	0.1938	0.1952	0.1831	0.18805
	FLMS	16.557	16.568	16.525	16.588	16.5599	0.0814	0.0875	0.0886	0.0825	0.0850
	NFLMS	20.623	20.447	20.282	20.590	20.4859	0.0319	0.0358	0.0373	0.0328	0.03445

IV. Conclusion

From table 1, the Normalized Fractional LMS Algorithm has better performance compare to other adaptive techniques. It is more efficient, low computation complexity; minimize the error and less power line interference. The SNR of reconstructed ECG signal of Normalized Fractional LMS Algorithm is higher than that of the other Algorithm. So, the Normalized Fractional LMS Algorithm is more appreciable for removing the power line interference from the ECG signal.

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