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A STUDY OF POWER LINE INTERFERENCE CANCELLATION USING IIR, AAPTIVE AND WAVELET FILTERING IN ECG

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Abstract- Background: It is essential to reduce these disturbances in ECG signal to improve accuracy and reliability. The bandwidth of the noise overlaps that of wanted signals, so that simple filtering cannot sufficiently enhance the signal to noise ratio. The present paper deals with the digital filtering method to reduce 50 Hz power line noise artifacts in the ECG signal. 4th order Butterworth notch filters(BW=.5 Hz) is used to reduce 50 Hz power line noise interference(PLI) from ECG signals and its performance is compared with Adaptve filters. Method: ECG signal is taken from physionet database. ECG signal (with PLI noise of different frequencies) were processed by Butterworth notch filters of bandwidths of 0.5 Hz. Ringing Artifact is observed in the output. ECG signal (with PLI noise of different frequencies) were processed by Adaptive filters no ringing effect seen. Wavelet filtering applied clean ECG were observed. Result: Performance is compared based on SNR and MSE of Butterworth notch filter and adaptive filters and output of wallet filtering were observed. Conclusion: RLS adaptive filter give better performance as compared to IIR Butterworth and LMS. Clean ECG were seen when filtering using symlet8 wavelet was done.

Keywords*- Power line interference (PLI) Electrocardiogram(ECG),Ringing Artifact(RA) , 3-dB stop band bandwidth(SBW), wavlet.*

I. INTRODUCTION:

Bio-potential signals, such as electrocardiogram (ECG), often suffer from power-line interference (PLI, 50 or 60 Hz) since the recorded signal is an output of the electric fields of coupling states surrounding main power lines (PLs) and the power of the body. PLI is probably the most common problem encountered in the processing of Bio-potential signals. Essentially, a notch filter is adapted for minimizing PLI because of its ability to reject narrow band noise. Indeed, the second-order, infinite impulse response (IIR) notch filter is routinely applied for this purpose [1-3]. Because of the transient response effect of the notch filter, the impulse response of this type filter generally has an oscillatory behavior, which may cause microvolt-level ringing artifacts(RAs, typically ranging between 0 and 40 µV) in the immediate regions of input signal with sharp transitions. Besides, it will cause undesirable attenuation in signal components at frequencies close to the center frequency (50 or 60 Hz). Tolerable signal distortion needs a narrow stop band bandwidth (SBW); however, a narrower SBW results in a longer transient response time (TRT); whilst a longer TRT often incurs more serious RAs. It is an inherent contradiction. When an ECG signal is being processed, the RAs occur in the right side of QRS complexes, and consequently, this implies that many cardiac components are lost in ST-T regions. Serious distortion (signal distortion caused by the SBW itself and the appreciable RAs) may make the ECG signal more difficult to interpret, particularly for the ST-T segment analysis, QT interval estimation, the detection of Ventricular Late Potentials (VLPs) and so on [4-6]. Removal of PLI however should be done with utmost stringent efforts not to eliminate or distort the raw signals without introducing artifacts nor losing vital information [7-9]. Many sophisticated digital methods have been investigated to cope with either 50 or 60 Hz interference [10-12], and they satisfy the requirement for suppression and even elimination of PLI during ECG signals acquisition. However, it is impossible to design an IIR notch filter to remove PLI without causing distortion [13-15], and this problem is still unsolved in practice. This can be reduced to minimum by adaptive filters.

Notch Filter:

Noisy ECG is directly applied to 4th order Butterworth notch filter(BW=.5 Hz) at PLI frequency of 50 Hz.

Simulation Result:

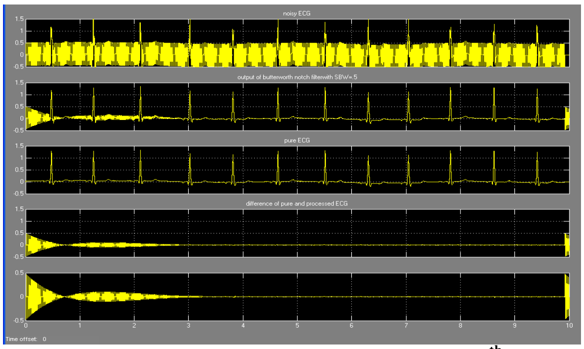

Figure 1: shows noisy ECG, pure ECG ,output of 4th order Butterworth notch filter , difference between processed ECG and pure ECG with the 3- dB stop band bandwidth of .5(49.75–50.25).

From the simulation it is evident that difference between processed ECG and pure ECG shows RA to the right side of QRS complex duration of transient response time of RA is up to 3 second.

Adaptive filter design:

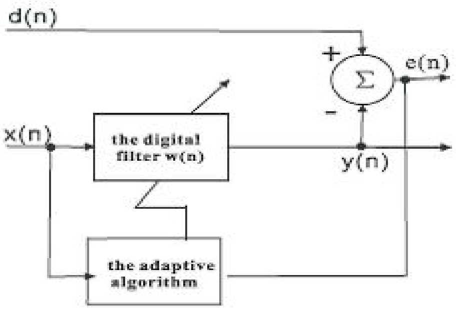

Figure 2: general Adaptive filtering diagram

The figure above is general adaptive filtering diagram. A digital filter is applied on the input signal x(n), produce output signal y(n). Adaptive algorithm adjusts the filter coefficient included in the vector w(n), in order to let the error signal e(n) be the smallest. Error signal is the difference of desired signal d(n) and the filter output y(n).The adaptive filter [12] has a Finite Impulse Response (FIR) structure. For such structures, the impulse response is equal to the filter coefficients. The coefficients for a filter of order N are defined as

$$W(n) = [W_n(0), W_n(1), ... W_n(N-1)]^T$$

The output of the adaptive filter is y(n) which is given by

$$y(n)=W(n)^T x(n)$$

The error signal or cost function is the difference between the desired and the estimated signal

$$e(n)=d(n)-y(n)$$

He variable filter updates the filter coefficients at every time instant

$$W(n+1)=W(n)+\Delta W(n)$$

Where $\Delta W(n)$ is a correction factor for the filter coefficients. The adaptive algorithm generates this correction factor based on the input and error signals.

LMS algorithm:
It is a stochastic gradient descent method in which the filter weights are only adapted based on the error at the current time. According to this LMS algorithm[8]-[9] the updated weight is given by
$W(n+1)=W(n)+2.\mu.x(n).e(n)$ where μ is step size.
RLS algorithm:
RLS algorithm iteration expressions are following:
$\pi(n)=P(n-1)x(n)$
$k(n)= \pi(n)/(\lambda+x^T(n)\pi(n))$
$e(n)=d(n)-w^T(n-1)x(n)$
$w(n)=w(n-1)+k(n)e(n)$
$P(n)=\lambda-1P(n-1)-\lambda-1k(n)xT (n)P(n-1)$

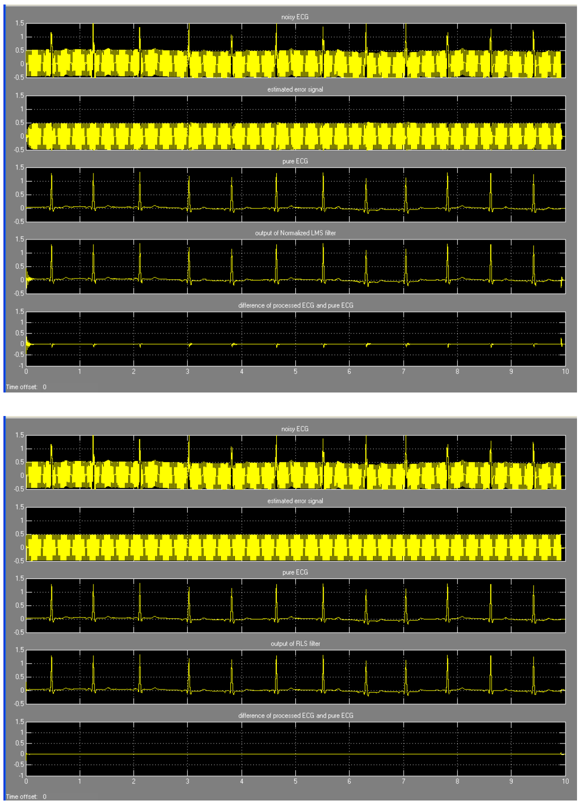

Figure 3:The noisy ECG signal processed by Adaptive filters based on Normalized least mean square (LMS) algorithm and recursive least squares (RLS) algorithm.

From the simulation it is evident that difference between processed ECG and pure ECG shows RA to the right side of QRS complex in Adaptive filters based on Normalized least mean square (LMS) algorithm and transient response time is 0.1 sec .For Adaptive filters based on recursive least squares (RLS) algorithm transient response time is very small and RA is almost absent.

Wavelet Method:
The noisy signal shown is de-noised by using discrete wavelet transform. For this, we have chosen symlet8 wavelet because it has energy spectrum concentrated around the low frequencies like the ECG signal. The symlet8 wavelet also resembles the QRS complex of the ECG signal. Figure 4 shows the result of wavelet filtering.

Figure 4: ECG signal after passing through symlet8.

Result: For performance measures SNR and mean square error MSE are considered.

PLI frequency of 50 Hz is taken for table given below.

$MSE=\sum_0^N(x^\wedge[n]-[n])^2/(N)$

$SNR_o=10\log(So/No)$

$x^\wedge[n]$ is estimated ECG and x[n] is original ECG

N is number of Samples

S_o and N_o are mean square power of estimated ECG and residual noise

Algorithm	MSE	SNR of output ECG
4^{th} order Butterworth notch filters	0.002174	2.904dB
LMS	0.0001249	13.601dB
Normalized LMS	0.00007355	14.4 dB
Sign error LMS	0.1755	-0.731 dB
Sign data LMS	0.0002247	14.17 dB
Sign Sign LMS	0.774	-0.3851 dB
RLS	0.000003441	26.954 dB

CONCLUSION:

Performance of Butterworth notch filters(BW=.5) and adaptive filters are measured by calculating SNR and MSE. RLS adaptive filter give best performance as observed from table having MSE and SNR 0.000003441 and 26.954 dB. To the artificial PLs used in this study, fo was set to 50 without varying. However, fo of real PLs, similar to its bandwidth, may fluctuate over a small range. We observed that adaptive filter gives a better performance as compared to non-adaptive 4^{th} order IIR Butterworth notch filter when the frequency of line varies. Wavelet filtering can be applied in this case symlet8 wavelet were used and result shows clean ECG as shown in Figure 4.

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