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Power Line Interference (PLI) Reduction in Electrocardiogram (ECG) Using Multiple Sub-Adaptive Filters Approach

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Abstract: One of the main problems in biomedical data processing like electrocardiography is the separation of the wanted signal from noises. In this paper a type of multiple sub-adaptive filters are considered to reduce the Electrocardiogram (ECG) signal noises like Power Line Interference (PLI). Results of simulations in MATLAB are presented. The results were compared with the pervious approaches used in this field of search.

Keywords: **Biomedical, Electrocardiogram (ECG), Multiple, Power Line Interference (PLI), MATLAB.**

I. Introduction

ECG records carry information about abnormalities or responses to certain stimuli in the heart. Some of the characteristics of these signals are the frequency and morphology of their waves. These components are in the order of just a few up to 1mV and their frequency content within 0.5Hz and 100Hz depending on individual. The morphology and frequency are analyzed by physicians in order to detect heart disorders and heart related pathologies. Schematic representation of normal ECG waveform is shown in figure 1. Different researchers have worked on powerline interferences in ECG using adaptive filters. Daniel Olguin Olguin et al worked on the use of adaptive noise canceller (ANC) with variable step size parameter and LMS algorithm for the elimination of powerline interferences in the recording of EEG signals[1]. Hong Wan et al used a variable step size least mean square (LMS) adaptive filtering algorithm to eliminate the 50Hz powerline interferences for which its frequency has small fluctuations from ECG signal[2]. Yufeng Wu et al presented an unbiased and normalized adaptive noise reduction (UNANR) system to suppress random noise in eectrocardiographic signals[3]. Guohua Lu et al evaluated the performance of adaptive noise cancellation filter in removing electrocardiogram interference from surface EMGs using recursive least square (RLS) algorithm[4]. Sachin Singh and K. L. Yadav carried a performance evaluation of different adaptive filters for ECG signal processing [5]. FC Chang et al carried out evaluation measures for adaptive PLI filters in ECG signal processing [6]. Wilfried Philips presented a time-warped polynomial filter (TWPF)and a new interval-adaptive filter for removing stationary noise from non stationary biomedical signals[7]. Abdel-Rahaman Al-Qawasmi and Khaled Daqrouq worked on ECG enhancement using wavelet transform[8]. J. Mateo et al worked on the adaptive approach to remove baseline wander from ECG recordings using Madeline Structure[9-10]. Yun-Li Liu et al suggested the use of adaptive algorithm for canceling power line interference in biopotential measurement[11]. Mikhled Alfaouri and Khaled Daqrouq considered ECG signal denoising by wavelet transform thresholding[12].

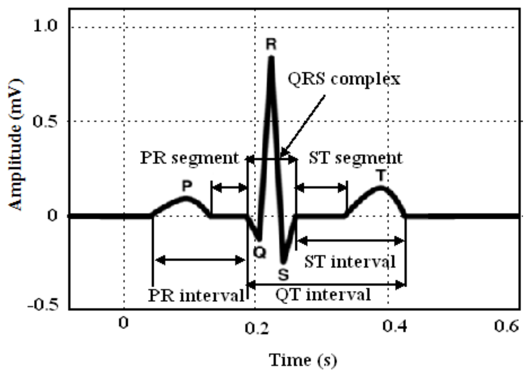

Fig.1 Schematic representation of normal ECG waveform.

II. Types of noise in ECG signals

a) Power line interference

This type of noise occurs through two mechanisms: capcaitive and inductive coupling. Capacitive coupling referes to the transfer of energy between two circuits by means of a coupling capacitance present between the two circuits. The value of the coupling capacitance decreases with increasing separation of the circuits. Inductive coupling on the other hand is caused by mutual inductance between two conductors. When current flows through wires it produces a magnetic flux, which can induce a current in adjacent circuits. The geometry of the conductors as well as the separation between them determines the value of the mutual inductance, and hence the degree of the inductive coupling [11-12]. Typically, capacitive coupling is responsible for high frequency noise while inductive coupling introduces low frequency noise. For this reason inductive coupling is the dominant mechanism of power line interference in electrocardiology. Ensuring the electrodes are applied properly, that there are no loose wires, and that all components have adequate shielding should help limit the amount of power line intererence.

B) Basline Wander

Baseline wander which is the extragenoeous low-frequency highbandwidth components, can be caused by:

1. Perspiration (effects electrode impedance).
2. Respiration.
3. Body movements.

Baseline wander can cause problems to analysis, especially when exmining the low-frequency ST-T segment. There are two main approaches used for baseline wander filtering which are linear filtering (time-invariant and time-variant) and polynomial fitting [13, 14].

C) Muscle contraction

Generally muscle contraction is produced due to muscle electrical activity. The signals resulting from muscle contraction is assumed to be transient bursts of zero-mean band-limited Gaussian noise [15]. Elecrtomyogram (EMG) interferences generate rapid fluctuation which is very faster

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than ECG wave. Its frequency content is dc to 10 KHz and duration is 50 ms [15]. To remove the interference of due to EMG a morphological filter of a unit square-wave structuring (best width is 0.07 s) is used [16].

III. Adaptive Noise Cancellation Configuration

There are four major types of adaptive filtering configurations; adaptive system identification [17], adaptive noise cancellation [18], adaptive linear prediction [19], and adaptive inverse system [20]. All of the above systems are similar in the implementation of the algorithm, but different in system configuration. All four systems have the same general parts; an input x(n), a desired result d(n), an output y(n), an adaptive transfer function w(n), and an error signal e(n) which is the difference between the desired output d(n) and the actual output y(n). In this paper only adaptive noise cancellation configuration is given.

The adaptive noise cancellation configuration is as shown in Figure (2). In this configuration the input x(n), a noise source $N_1(n)$, is compared with a desired signal d(n), which consists of a signal s(n) corrupted by another noise $N_0(n)$. The adaptive filter coefficients adapt to cause the error signal to be a noiseless version of the signal s(n). Both of the noise signals for this configuration need to be uncorrelated

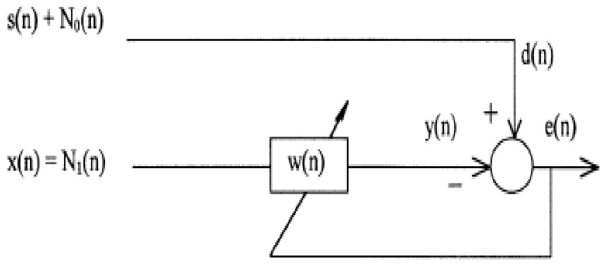

Fig.2 The adaptive noise cancellation configuration

Figure 2 shows an adaptive filter with a primary input that is an ECG signal s_1 with additive noise n_1. While the reference input is noise n_2, possibly recorded from another generator of noise n_2 that is correlated in some way with n_1. If the filter output is y then the filter error is given in following equations

$e = (s_1 + n_1) - y$ (1)

$e^2 = (s_1 + n_1)^2 - 2y(s_1 + n_1) + y^2$ (2)

Equation 2 can be write as follow

$e^2 = (n_1 - y)^2 + s_1^2 + 2 s_1 n_1 - 2ys_1$ (3)

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$E(e^2) = E[(n_1-y)^2] + E[s_1^2]$ (4)

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_1

$SNR = P_s / P_n$ (5)

Where P_s is the power of signal and P_n is the power of noise

$P_s = s_1^2$ (6)

$P_n = E[(n_1-y_1)^2]$ (7)

Therefore

$SNR = s_1^2 / E[(n_1-y_1)^2]$ (8)

IV. The Proposed Design

When the doctors are examining the patient on-line and want to review the ECG of the patient in real-time, there is a good chance that the ECG signal has been contaminated by noise. The predominant artifacts present in the ECG includes: Power-line Interference (PLI), Baseline wander (BW), Muscle artifacts (MA) and Motion artifacts (EM), mainly caused by patient breathing, movement, power line interference, bad electrodes and improper electrode site preparation. The low frequency ST segments of ECG signals are strongly affected by these contaminations, which lead to false diagnosis. To allow doctors to view the best signal that can be obtained, we need to develop an adaptive filter to remove the noise in order to better obtain and interpret the ECG data. The proposed adaptive filter was introduced as shown in figure (3). Here the design depends on the idea of using multiple sub-adaptive filters instead of using single adaptive filter. The connection of multiple sub-adaptive filters is depending on decomposition of error signals. The noise signal is assumed to be PLI only.

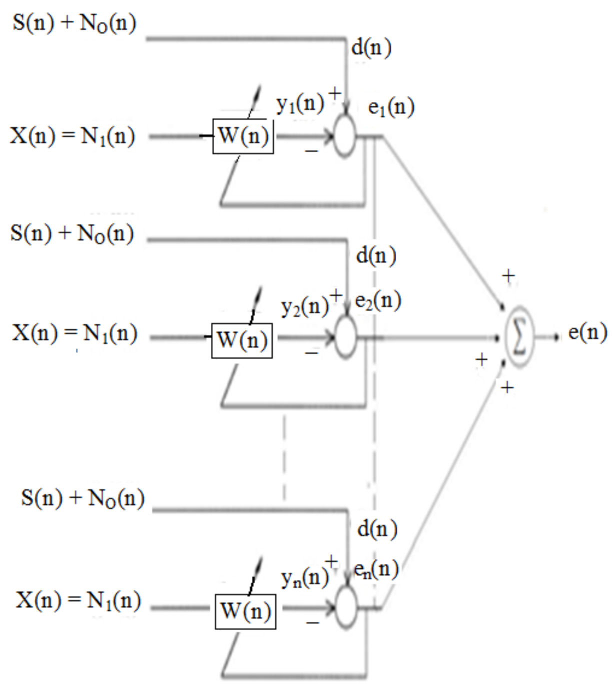

Fig. 3 The proposed design

V. Equations of the proposed design

$e(n)=e_1(n)+e_2(n)+........e_n(n)$ (9)

$e^2 = (s_1 + n_1)^2 - 2y_1(s_1 + n_1) + y_1^2 + (s_1 + n_1)^2 - 2y_2(s_1 + n_1) + y_1^2 + ... + y_n^2 + (s_1 + n_1)^2 - 2y_n(s_1 + n_1) + y_n^2$ (10)

Equation 10 can be write as follow

$e^2 = (n_1 - y_1)^2 + s_1^2 + 2 s_1 n_1 - 2y_1 s_1 + (n_1 - y_2)^2 + s_1^2 + 2 s_1 n_1 - 2y_2 s_1 + ...+ (n_1 - y_n)^2 + s_1^2 + 2 s_1 n_1 - 2y_n s_1$ (11)

Since the signal and noise are uncorrelated, the mean-squared error (MSE) is

$E(e^2) = E[(n_1-y_1)^2] + E[s_1^2] + E[(n_1-y_2)^2] + E[s_1^2] + ...+ E[(n_1-y_n)^2] + E[s_1^2]$ (12)

$SNR=P_s/P_n$

Where P_s is the power of signal and P_n is the power of noise

$P_s=s_1^2$ (13)

$P_n = E[(n_1-y_1)^2] + E[(n_1-y_2)^2] +....+ E[(n_1-yn)^2]$ (14)

Therefore

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$$SNR = s_1^2 / (E[(n_1-y_1)^2] + E[(n_1-y_2)^2] + \ldots + E[(n_1-y_n)^2]) \quad (15)$$

VI. Results and discussions

The simulation results of the proposed design and the previous approaches are shown in figure (4).The previous approaches which are to be considered are by using single adaptive filters or by using constant coefficients filters as fir filter and butterworth filter. The values of the parameters used in this simulation are shown in table 1

Table 1: Parameters values for simulation results of figure 4

Parameter name	Value
Sampling Frequency	1000Hz
Heart beat per minute	72
ECG duration	1.5sec.
ECG amplitude	1000µV
Noise level of PLI	10 µV
Order of the filters	10
Step size	0.05

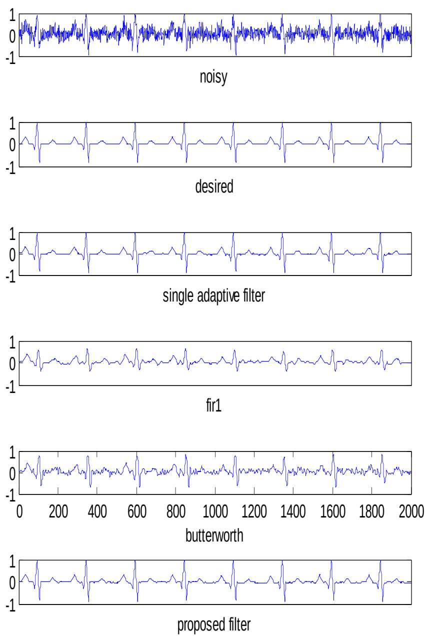

Fig. 4 Simulation result for given parameters in table 1

By calculating MSE and SNR, we obtain excellent results for the proposed technique. These results is illustrated in table 2

Table 2: MSE and SNR of different approaches

Technique	MSE	SNR
Fir	5.2×10^{-6}	0.89
Butterworth	4.7×10^{-6}	0.91
Single adaptive filter	2.25×10^{-6}	10.87
Three sub-adaptive filters	1.98×10^{-6}	12.53

The simulation shown in figure 4 is also repeated for different number of sub-adabtive filters with the same value of the other parameters given in table 1.
MSE and SNR with the assumed number of sub-adabtive filters are shown in table 3

Table 3: MSE and SNR with the assumed number of filters

Technique	MSE	SNR
Three sub-adaptive filters	1.98×10^{-6}	12.53
five sub-adaptive filters	1.45×10^{-6}	14.6
seven sub-adaptive filters	1.26×10^{-6}	17.8
ten sub-adaptive filters	1.14×10^{-6}	20.4

This simulation is repeated also for different order of three sub-adative filters with the same value of the other parameters given in table 1. The results with the assumed orders are shown in table 4

Table 4: MSE and SNR with the assumed order

Order of adaptive filters	MSE	SNR
10	1.98×10^{-6}	12.53
20	1.62×10^{-6}	14.6
25	1.35×10^{-6}	17.8
30	1.12×10^{-6}	20.4

VII. Conclusions

The proposed Multiple sub-adaptive filters achieved better SNR and MSE compared with the previous approaches. As the number of the sub-adaptive filters increased, Better SNR and better MSE were achieved. This is on the expanse of the complexity of design and cost. The performance of multiple stage filters is improved with increasing of the filter length.

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