Power Line Interference Noise Removal from ECG Signal using Adaptive Filter LMS Algorithms

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Abstract—The electrocardiogram (ECG) is the most commonly used for diagnosis of heart diseases. Good quality ECG are utilized by physicians and biomedical researchers for interpretation and identification of physiological and pathological phenomena. However, in real situations, ECG signals are corrupted by artifacts like 50Hz power line interferences, electrode motion, muscles movements etc. So the noise removal is a classical problem in ECG records, that generally produces artifactual data when measuring the ECG parameters. In recording a heart beat, which is being corrupted by a 50 Hz noise means, the frequency coming from the power supply in many countries. One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might varies between 47 Hz and 53 Hz. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Besides, they modify their behaviour according to the input signal. Therefore, they can detect shape variations in the ensemble and thus they can obtain a better signal estimation. In this paper we are using adaptive filter based on the LMS algorithm in biomedical signal processing.

Keywords: Adaptive filtering, artifact, ECG signal, LMS algorithm.

1. Introduction

It is also a non-invasive test that records the electrical activity of the heart over time and it is very useful in determining whether a person has heart disease. The voltage of the electrode signal got by surface ECG (Electrocardiograph) is mV-level, and low amplitude is vulnerable. Power frequency noise on ECG is most important in the various kinds of interference from the outside world. So it is necessary to remove the noise for detecting the correct nearly accurate reflection of information given by ECG signal. For example a cardiac arrhythmia in recording of an ECG, which is being corrupted by a 50 Hz noise coming from the power supply in many countries. One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power to the hospital, the exact frequency of the power supply might changes between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, because these noises could degrade the quality of the ECG signal since the ECG would also likely have frequency components in the rejected range. To prevent this potential loss of information, an adaptive filter has been used. The adaptive filter take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates. Such an adaptive technique generally allows for a filter with a smaller rejection range, which means, in our case, that the quality of the output signal is more accurate for medical diagnoses.

The extraction of high-resolution ECG signals from recordings contaminated with background noise is an important issue to investigate. The goal for ECG signal enhancement is to separate the valid signal components from the undesired artifacts, so as to present an ECG that facilitates easy and accurate interpretation. Many approaches have been reported in the literature to address ECG enhancement. In recent years, adaptive filtering has become one of the effective and popular approaches for the processing and analysis of the ECG and other biomedical signals. Adaptive filters permit to detect time varying potentials and to track the dynamic variations of the signals. Here we are using adaptive filter based on the LMS algorithm in biomedical signal processing.

1. Adaptive Filter

The most commonly used structure in the implementation of adaptive filters is the transversal structure. Fig. 1 shows an adaptive filter with a primary input that is an original ECG signal s(k) with additive noise n(k). Signal after adding noise is given by

\[ p(n) = s(n) + N(n). \]  

If the filter output is y(k) and the filter error, \( e(n) = (s(n) + N(n)) - y(n) \)  

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

\[ \text{MSE} = \mathbb{E}[e^2(n)] \]  

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s(n). The adaptive filter extracts the signal, or eliminates the noise, by iteratively minimizing the MSE between the primary and the reference inputs.
where

\[ w(n) = [w_0(n) \quad w_1(n) \quad \cdots \quad w_{L-1}(n)]^T \]  

is the tap weight vector at the \( n \)th index,

\[ x(n) = [x(n)x(n-1) \cdots x(n-L+1)]^T \]  

and \( e(n) = d(n) - w^T(n) x(n) \) for the LMS algorithm depicted in Fig. 3. If the noise signal \( p_2(n) \), possibly recorded from another generator of noise that is correlated in some way with \( p_1(n) \), is applied at the input of the LMS filter, then a weighted error becomes

\[ e(n) = [s_1(n) + p_1(n)] - y(n) \].

The filter output \( y(n) \) is given by

\[ y(n) = w^T(n)x(n) \]  

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

\[ E[e^2(n)] = E[(s_1(n) - y(n))^2] + E[p_2(n)] \]  

Minimizing the MSE results in a filter output that is the best least-squares estimate of the signal \( s_1(n) \).

New algorithms that make use of the signum (polarity) of either the error or the input signal, or both, have been derived from the LMS algorithm for the simplicity of implementation, enabling significant reductions in computing time, particularly the time required for "multiply and accumulate" (MAC) operations. This algorithm is attractive for its assured convergence and robustness against disturbances in addition to the ease of implementation. In the paper we consider the signed algorithm (SA), for which the weight update relation is given as

\[ w(n+1) = w(n) + \mu x(n) \text{sgn}(e(n)) \]  

Simulation Results

Fig. 2 illustrates another situation where the ECG is recorded from several electrode leads. The primary input \( s_1 + n_1 \) is a signal from one of the leads. A reference signal \( s_2 \) is obtained from a second lead that is noise free. The signal \( s_1 \) can be extracted by minimizing the MSE between the primary and the reference inputs. Generally in biomedical signal processing the filter structure shown in Figure 1 as it is difficult to obtain a noise free signal. Using a procedure similar to equation (3) we can show that

\[ E[e^2] = E[(s_1 - y)^2] + E[n^2] \]  

Minimizing the MSE results in a filter error output \( y \) that is the best least-squares estimate of the signal \( s_1 \),

\[ s_1 + n_1 \]

Fig. 4. Original ECG signal
These results matlab code developed in Matlab(R2010a)7.10.0.

**Signal Measurement And Signal Analysis**

The Multifunctional physiological data acquisition system MP35 (Biopac System Inc.) was utilized for signal measurement for ECG and EEG signals (by module SS2LA). The user friendly analysis package Biopac Student Lab 3.7.6 was used for the signal measurement and Biopac Student Lab PRO 3.7.6 for management, including the signal quality pre-screening, data storage and retrieval. The sampling frequency was 500 Hz for ECG & 250 Hz for EEG. The signals were verified visually by a well-trained technician. If the signal quality was poor, the signal would be excluded from further analysis and the subject was asked to repeat the experiment once again.

Figure 9.Multichannel Data Acquisition Unit
In this paper the process of noise removal from ECG signal using LMS algorithms based adaptive filtering is presented. For this, the input and the desired response signals are properly chosen in such a way that the filter output is the best least squared estimate of the original ECG signal. Our simulations shows how the 50 Hz noise removes from the ECG signal.

**References**


