Artifact Cancellation from Cardiac Signals in Health Care Systems using a Zoned Adaptive Algorithm

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Abstract: Electrocardiogram (ECG) is a noninvasive technique for indirect evaluation of volume of stroke, output related to cardiac is monitored by observation of added parameters that are hemodynamic thru changes related to blood volume is done within the body. Changes taking place in the blood volume inside a certain body segment due to several physiological processes are extracted in the form of the impedance variations of the body segment. The Analysis of ECG facilitates the heart stroke volume in sudden cardiac arrest. In the clinical environment ECG signals are affected by various physiological and non-physiological artifacts. As these artifacts are not stationary, we propose adaptive filtering techniques to improve ECG signals. In this paper we used normalized version of Dead Zone Least Mean Square (NDZLMS) adaptive techniques to remove artifacts in ECG signals. So as to minimize the computational complexity, this DZLMS is combined with sign algorithms and results Sign Regressor NDZLMS (SRNDZLMS), Sign NDZLMD (SNNDZLMS), Sign Sign NDZLMS (SSNDZLMS) algorithms. Based on these algorithms, several adaptive signal enhancement units (ASEUs) are developed and validated on the real ECG signal components. To ensure the ability of these algorithms, four experiments were performed to eliminate the various artifacts such as sinusoidal artifacts (SA), respiration artifacts (RA), muscle artifacts (MA) and electrode artifacts (EA). Among these techniques, the ASEU based on SRNDZLMS performs better with respect to process of filtering. The signal to noise ratio improvement (SNRI) for this algorithm is calculated as 21.8684 dB, 8.4544 dB, 8.6966 dB and 8.7101 dB respectively for SA, RA, MA and EA. Hence, the SRNDZLMS based ASEUs are more suitable for filtering ECG signal in real health care monitoring systems.

Index Terms: adaptive filter, artifacts, electrocardiogram, signal enhancement, stroke volume

I. INTRODUCTION

Ischemia Heart disease remains one of the leading causes of death worldwide based on World Health Organization (WHO) reports[1]. Hemodynamics is a popular method to measure the cardiac activity, in which the flow of the blood throughout the body is often measured. Impedance plethysmography methods that use electrical impedance changes on the body surface to measure tissue volume changes. Electrocardiogram (ECG) is a simple, inexpensive and noninvasive method to monitor electrical impedance changes for thorax, which is initiated thru periodic changes in the volume of blood in aorta. An appropriate thorax model can be used to estimate Cardiac Output (CO), Stroke Volume (SV), also additional factors that are hemodynamic [2]. Bio-impedance in electrical form identifies the variations related to thoracic impedance using electric current stimulation. The output related to Cardiac stands constantly evaluated by means of electrodes by analyzing the variation of the signal that occurs with various mathematical models. The Research has been stared within area of ECG thru study related to fluids flow within cardiac area with the use of methods for Impedance Plethysmography[3]. In [6] the investigation of ECG is presented in subjects with heart diseases during the exercises. With the advancement in technology, wearable devices with ECG sensors are designed to facilitate recordings of long termalsorelieffor patients [7]. From origin of ECG, an increase within reliability asehancement related to cardiac parameter’s measurement is presented [8–12]. While extracting the ECG signal, the desired signal components are contaminated with undesired artifacts. Minute features related to desired signal are masked by artifacts, which causes ambiguities during diagnosis [6]. The leading artifacts are Sinusoidal Artifacts (SA), Respiratory Artifacts (RA), Muscle Artifacts (MA) and Electrode Artifacts (EA). Hence, to facilitate high resolution ECG signal for estimating intensity of stroke volume these artifacts need to be eliminated. In the real-time situations, these artifacts are not stationary and that's why conventional fixed weighted filters are not appropriate for ECG filtering. Thus, adaptive filtering techniques are suitable to change the filter weights in accordance to the error component [13]. Until now, several authors are proposed techniques to enhance the ECG signal using several adaptive signal enhancement techniques [14–17]. The drawbacks of these techniques are high steady state error, weight drift, round off error and impulsive noise. To overcome these drawbacks and to enhance the performance of artifact cancellation we developed some hybrid algorithms. With these hybrid algorithms we can achieve less computation complexity also. In [18-21] Rahman et al. developed some adaptive noise cancellers to enhance the cardiac signal and brain activity using various LMS variants. We considered the same framework for the development of ECG signal filtering techniques. The performance of ASEUs for ECG analysis in a typical health care monitor system can be improved by various hybrid signal processing techniques. The characteristics of interest in any typical health care monitor system are signal enhancement capability, convergence rate, and computational complexity. To achieve these
features, we developed various adaptive algorithms. The basic adaptive algorithm is Least Mean Square (LMS) algorithm. In some critical situations, zoning the signal conditioning with the help of some threshold is needed. In that aspect we developed ASEU based on NDZLMS and its signum variants.

II. ENHANCEMENT OF ELECTROCARDIOGRAM SIGNALS USING HYBRID VERSIONS OF DZLMS ALGORITHM

In the real time clinical environment various artifacts encountered with the ECG signal and causes ambiguity in the diagnosis. Hence the artifacts should be eliminated in order to enhance the desired ECG signal. The physiological components are not stationary in nature that we have to apply adaptive filtering techniques to suppress the clutter components in the noisy input signal. Fig. 1 shows the block diagram of typical health care system for ECG analysis. System input remains as raw signal of ECG recorded from the corresponding electrodes. To identify the noise, type the recorded quantities are subjected to normalized power testing. For this, a reference generator is considered that consists of several artifact samples. Once the artifact is identified the noisy signal is fed as an input to ASEU. The correlated signal of noise component stands to be provided as input reference to ASEU. Fig. 2 shows the internal structure of an ASEU. ASEU is the key block in the typical health care system. Therefore, this paper presents several signal processing techniques for developing ASEU.

![Block diagram of proposed ECG signal analyzer](image1)

**Figure 1:** Block diagram of proposed ECG signal analyzer

![A typical adaptive signal enhancement unit (ASEU)](image2)

**Figure 2:** A typical adaptive signal enhancement unit (ASEU).

An ASEU consists of a FIR filter also an adaptive mechanism for updating the weights. Several adaptive techniques are developed. Thus, an LMS adaptive filter remains considered using length of the tap L. Input given for the EU remains x(n). This includes impedance component h(n) and artifact component N(n). η(n) is the correlated noise signal generated by the reference generator. Let q(n) is the FIR filter impulse response, z(n) is output for FIR filter, ε(n) as error signal.

The weight updating mechanism for an LMS based SEU can be mathematically written as,

\[ q(n+1) = q(n) + \lambda x(n) \varepsilon(n) \]  

(1)

where, \( q(n) = [q_0(n) \ q_1(n) \ldots q_L(n)]^T \) stands nth tap weight vector, \( x(n) = [x(n) \ x(n-1) \ldots x(n-L+1)] \) remains input sequence, \( \varepsilon(n) = x(n) - q(n) \eta(n) \) also ‘\( \lambda \)' represents a step-size.

Within clinical environment the smaller values of \( \varepsilon(n) \) may stand for disturbances but may also result from numerical instability. In an ECG noise canceller, the small and large errors may create additional filtering operations, leading to a delay in decision making. Under typical conditions the decision must be made instantaneously. These extra computations are avoided by setting a threshold value for the error. The Dead Zone LMS (DZ-LMS) is used in various signal processing applications to reduce the problems with rounding errors. The algorithm applies nonlinearity of the dead zone. If the error signal falls below the pre-defined threshold value then the algorithm stops uploading the tap-weight vector. We use this property of DZ-LMS in filtering the ECG signal. This Dead Zone nonlinearity is defined as,

\[ d(m) = \begin{cases} m - \alpha, m > \alpha > 0 \\ 0, -\alpha < m < \alpha \\ m + \alpha, m < -\alpha \end{cases} \]  

(2)

where \( \alpha \) is threshold.

The weight update recursion is given by,

\[ q(n+1) = q(n) + \lambda x(n) d(\varepsilon(n)) \]  

(3)

The data normalization version DZLMS is nothing but Normalized Dead Zone LMS (NDZLMS), whose weight update relation remains given by,

\[ q(n+1) = q(n) + \lambda(n) x(n) d(\varepsilon(n)) \]  

(4)

Now the SRNDZLMS, SNDZLMD, SSNDZLMS algorithms are given respectively as follows,

\[ q(n+1) = q(n) + \lambda(n) \text{sign}(x(n)) d(\varepsilon(n)) \]  

(5)

\[ q(n+1) = q(n) + \lambda(n) x(n) \text{sign}(d(\varepsilon(n))) \]  

(6)

\[ q(n+1) = q(n) + \lambda(n) \text{sign}(x(n)) \text{sign}(d(\varepsilon(n))) \]  

(7)

Based on these mathematical recursions several ASEUs are
developed also verified with actual ECG signals taken as of MIT-BIH data bank. The experimental results are presented in the next section.

III. SIMULATION RESULTS

Towards demonstrating that project techniques stand truly efficient within clinical applications, techniques are evaluated with various ECG signals. In the simulation experiments we have samples related to ECG signal taken as of five distinct persons. Proposed techniques are verified through considering Signal to Noise Ratio Improvement (SNRI) for five trials, averaged also related thru ASEU developed based on conventional LMS. Table I give the SNRI calculations in the process of signal enhancement. In the experiments five ECG samples record 101, record 102, record 103, record 104 and record 105 are used. These ECG records are influenced by artifacts such as SA, RA, MA and EA. Various ASEUs for ECG enhancement is developed using the NDZLMS, its three sign variants also related with LMS technique. Signal analyzer consists of reference generator that generates four types of artifacts synthetically by using the real artifacts features of MIT-BIH databases. Artifact tester compares power spectral density (PSD) for contaminated noisy input signal also synthesized artifact obtained from the reference generator. By doing so, reference generator can identify the type of noise in the input signal so that the similar type of correlated component of noisemains applied as reference signal for ASEU. This ASEU is influenced for updating the weights of the filter thru adaptive techniques based on input data. Based on these considerations, in our experiment, we have implemented five ASEUs using the algorithms discussed in above section. These ASEUs are operated under four modules to remove the artifacts SA, RA, MA and EA respectively. Due to space considerations, we have shown the experimental results for removal of all the artifacts for record 105 only. These experimental outputs are shown in Figures 3 to 6 respectively for SA, RA, MA and EA.

A. Filtering of Sinusoidal Artifacts (SA) Using Adaptive Algorithms

In this experiment SA components are removed from the input signal. The input signal to the ASEU is raw ECG from Fig.3(a). Desired component of ECG also sinusoidal artifacts are present in the input, and are given as input to ASEU shown in Fig. 2. By comparing the input signal PSD components, artifact tester and reference generator gives a reference signal to the ASEU. The reference signal is correlated to artifact component present in the ASEU input. Adaptive technique based ASEU inevitably updates coefficients of filter based on error components. Adaptivetechnique involves reference signal so that it correlated as much as possible with noise component and cancels each other, to update coefficients of filter. The performances of techniques remain compared with respect to SNRI. These are averaged for five experiments for each artifact and are tabulated in Table I. From the experimental results we can observed that SRNDZLMS based ASEU filters the SA from desired ECG signal almost completely. This could be preferred for real time applications due to its smaller number of multiplications due to the presence of SR function. Based on these performance measures it may be concluded that DZLMS based ASEU performs better in SA filtering of ECG signals. Hence, this technique is recommendable for the implementation in real time health care monitoring devices and wearable remote health care systems.

![Graphs showing ECG enhancement results for SA cancellation](image)

Figure 3: Typical ECG enhancement results for SA cancellation (a) ECG signal contaminated with SA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SSNDZLMS algorithm, (f) ECG filtered with DSNDZLMS algorithm. (x-axis number of samples also y-axis amplitude in millivolts).

B. Filtering of Respiration Artifact (RA) using Adaptive Algorithms

This experiment shows the enhancement process of desired ECG component contaminated with RA. Here also the raw ECG is fed to ASEU as shown in Fig. 2. A correlated respiration activity, component obtained from a reference generator after PSD comparison analysis is given to ASEU. The ECG affected with RA remains depicted in Fig.4(a). Fig.4 depicts simulation results for our experiments. Performance measures for five samples based on SNRI are presented in Table I. The SRNDZLMS based ASEU performs better among all algorithms. This enables SRNDZLMS related artifact canceller is better than all other counterparts. By comparing the performance measures among all the
algorithms, it seems as SRNDZLMS based ASEU is better with reference to computational complexity, SNRI, convergence and filtering ability. Hence, this realization is well suited for real time implementations.

![Figure 4](image)

Figure 4: Typical ECG enhancement results of RA cancellation (a) ECG signal contaminated with RA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples and y-axis amplitude in millivolts).

C. Filtering of Muscle Artifact (MA) using Adaptive Algorithms

This experiment demonstrates the enhancement process of ECG component encountered with MA. The desired ECG signal is affected by muscle artifact is applied as the input signal to ASEU is depicted from Fig. 2. In correlation thru artifact present within noisy input signal, a signal produced thru muscle activity remains provided as reference signal to adaptive ASEU. ECG affected with MA remains presented in Fig.5(a). Fig 5 depicts simulation results for removal of MA. The performance measures for five samples based on SNRI are depicted from Table I. The SRNDZLMS dependent ASEU performs better among all algorithms. By comparing the performance measures among all the algorithms, it seems that the above said algorithm based ASEU is better with reference to computational complexity, SNRI, convergence and filtering ability. Hence, this realization is well suited for real time implementations.

![Figure 5](image)

Figure 5: Typical ECG enhancement results of MA cancellation (a) ECG signal contaminated with MA, (b) ECG filtered with LMS algorithm, (c) ECG filtered with NDZLMS algorithm, (d) ECG filtered with SRNDZLMS algorithm, (e) ECG filtered with SNDZLMS algorithm, (f) ECG filtered with SSNDZLMS algorithm. (x-axis number of samples and y-axis amplitude in millivolts).

D. Filtering of Electrode Artifact (EA) using Adaptive Algorithms

This experiment shows that the enhancement process of ECG component influenced by EA. The desired ECG signal is affected by electrode artifact is applied as an input for ASEU is presented from Fig. 2.

Noise signal remains produced thru electrode activity in correlation artifact available within noisy input stands applied to be reference signal to ASEU. ECG affected with EAremainds depicted from Fig.6(a). Performance metrics derived using five samples based on SNRI is presented in Table I.

The NDZLMS related ASEU performs better among all algorithms. This enables NDZLMS based artifact canceller is better than all other counterparts. But, due to less computational complexity conducted.
better as this algorithm is independent of tap length of the filter. Hence, this realization is well suited for real time implementations.

![Figure 6: Typical ECG enhancement results of EA cancellation.](image)

**REFERENCES**


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