# Embedded Realisation of Amplitude-Phase Adaptive Filter for Bio-Potential Signals

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***Abstract*— Superposition of noise with the bio-potential signals causes plethoric information loss and misinterpretation in human-computer interference systems. Here, we have proposed a novel method to design a digital signal filter which is capable of filtering four major bio-potential signals viz. Electroencephalography (EEG), Electrooculography (EOG), Electrocardiography (ECG) and Electromyography (EMG). Different sampling frequencies for different bio-potential signals are manually selected through two select lines added as external inputs to the microcontroller based system. The filter has two sections in cascade, a conventional sixth order digital filter followed by an adaptive interference canceller (AIC). The AIC has a remarkable property of eliminating most of the interfering power line noise adaptively without consuming much time or space complexity of the embedded processor used. A variant of Least Mean Square (LMS) filtering algorithm called Amplitude-Phase Adaptive LMS (APALMS) is implemented here. Convergence behaviors of the adaptive parameters are simulated and finally verified on real time bio-potential signals extracted from different subjects using low cost embedded processor. In this paper, we have found that our proposed filter transition frequencies are small with least variation in adaptation time.**

**Keywords- Human-computer Interfacing, Bio-potential signals, Adaptive Interference Canceller, Least Mean Square Filtering, Embedded processor**

## I. INTRODUCTION

Bio-potential signal based human-computer interface (HCI) systems [1] are a new and evolving field of applied biological and cognitive sciences. The need of communication channels and new tools to process, classify and analyze them was strongly felt for the disabled people, who cannot move, cannot talk or have certain physical shortcomings, or in a single phrase has certain problems to communicate with the outside world. Thus, the idea is why not to use several bio-potential signals generated in their organs due to different stimuli to communicate. But in time of building these systems researchers faced a great problem in case of extracting the signals and to turn them into interpretable data due to lack of proper tools and instrumentation. The bio-potential signals are characterized by having very low amplitude and low frequency. Thus proper acquisition and preprocessing of the signals is essential for extracting relevant information from them required for diagnosis and human computer interactive purposes. The fundamental preprocessing step includes appropriate filtering and artifact removal of the acquired signals.

These bio-potential signals are often tainted by various noises like power line interference and movement artifact. Sometimes in absence of proper filtering, the relevant information from these signals is lost. Generally the interference wave parameters are random in nature and may not be removed completely by conventional notch filtering. Thus in this paper we address this problem by designing an adaptive filter which can be applied to any bio-potential signal, irrespective of their diverse amplitude and bandwidth ranges. Previous real time implementations on filters [2], [8] are mostly designed for a single purpose (specific applications like ECG or EEG filters etc.) but cannot be used as a generalized filter. Researchers in [2], [8] have compared various adaptive algorithms for effective removal of interferences but their realizations are complex as well as costly for general purpose.

Here, we have dealt with the real time implementation of a bio-potential signal filter, which is capable of filtering four important bio-potential signals: Electroencephalography (EEG), Electrooculography (EOG), Electrocardiography (ECG) and Electromyography (EMG). The novel features of our proposed filter includes an adaptive suppression [3], [4] of the 50/60 Hz power- line interference wherever necessary and a user-specified selection of the required bio-potential signal. A simple yet effective algorithm is implemented on a General Purpose (GP) Microcontroller Unit (MCU) Atmega-8 [5].Due to its low cost realization and simplicity, this filter finds great use as a generalized bio-potential signal filter.

For our study, we have considered a recursive algorithm Amplitude-Phase Adaptive LMS which is based on gradient descent approach and is similar to LMS algorithm [6], [3]. It is convenient to apply on a low cost GP Microcontroller (Atmega-8) [5] without sacrificing much of throughput.

A novel approach towards adaptive interference cancellation (AIC) is implemented in this study. One of the conventional approaches of interference reduction is passing the signal through a adaptive notch filter, but its implementation is a little more complex in comparison to an

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adaptive cancellation algorithm. Since the interfering frequency is approximately 50Hz, the amplitude and phase can be adaptively approximated and subtracted from the noisy signal to completely remove the interfering wave. The amplitude and phase are updated according to steepest descent [7] algorithm.

The rest of the paper is organized as follows: The proposed methodology is discussed in Section II, followed by description of the experiments performed in Section III. Section IV gives a discussion on the experimental results. The concluding remarks are outlined in Section V.

## II. METHODOLOGY

Bio-signals, when acquired, contain various interferences and artifacts. Of these, power line noise is the most common and disturbing factor during processing of the signals which often causes misinterpretation in HCI systems. The noise can be removed using notch filtering [8]-[10] or adaptive cancellation.

Here, we have proposed Amplitude-Phase Adaptive LMS (APALMS) algorithm for noise cancelation. The key principle of our approach is to cancel out the interference adaptively and recover the original signal. Since the amplitude and phase parameters of the interfering sinusoid are random, for effective cancellation adaptive procedures must be initiated.

It is known that the power-line interferences are sinusoidal signals found in the 50Hz (approx.) frequency component of unknown amplitude and phase. The interfering sinusoid $x\left(kT_S\right)$ can be represented as

$$x\left(kT_S\right)=\alpha\cdot cos\ \left(\omega_0 kT_S+\o\right) \tag{1}$$

where, $k$ (=0, 1, 2 …N) is the integral time index and $T_S$ is the sampling interval of the signal. $\alpha$ and $\phi$ are unknown amplitude and phase respectively, and angular frequency $\omega_0$ is represented as

$$\omega_0=\frac{2\pi\cdot 50}{f_S} \tag{2}$$

where, $f_S$ is the sampling frequency.

Thus, the acquired signal $d(kT_S)$ consists of the original signal and line interference noise as follows,

$$d\left(kT_S\right)=u\left(kT_S\right)+x\left(kT_S\right) \tag{3}$$

where, $u(kTs)$ and $x(kT_S)$ denote the original noise-free signal and the interfering noise respectively.

By conventional approaches as shown in [8]-[10], one can design a notch filter to attenuate interfering signal power at specific frequencies. But major disadvantages of these methods are the higher computational complexity, which cannot be implemented using general purpose embedded processor. To overcome these disadvantages a simple yet effective cancellation scheme is implemented in the proposed APALMS method, which is depicted in Fig.1.

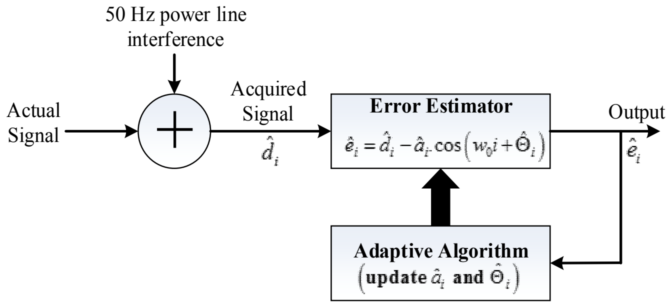


Fig.1. Block Diagram of the Adaptive Filter

In this approach the amplitude and phase is obtained recursively by minimizing the expectation value (power) [4], [11] of the error signal $e(kT_S)$, to match those of the interfering signal appropriately.

Since in APALMS algorithm, there is no provision for feeding desired response to the filter, we have to feedback the output signal $e(kT_S)$ to the adaptive block as an error signal as shown in Fig.1. This is also the estimated recovered signal of our concern.

The output of the adaptive block is the estimate of the interfering wave $y(kT_S)$, which when subtracted from the corrupted signal $d(kT_S)$gives an estimate of our desired signal $e(kT_S)$, which is the output itself, as shown below,

$$e(kT_s)=d\left(kT_s\right)—y\left(kT_S\right) \tag{4}$$

and the estimated interference is given in (5),

$$y\left(kT_S\right)=\hat{a}\left(kT_s\right)\cdot cos\ \left(\omega_0\cdot kT_s+\Theta\left(kT_s\right)\right) \tag{5}$$

where, $\hat{a}$ and $\Theta$ are close estimates of amplitude and phase of the interfering wave.

Thus, combining eqn. (1), (3), (5) with (4) we get,

$$\begin{aligned}e(kT_s)=&u\left(kT_s\right)+\alpha\cdot cos\left(\omega_0 kT_S+\o\right)\\&-\hat{a}\left(kT_s\right)\cdot cos\left(\omega_0 kT_s+\Theta\left(kT_s\right)\right)\end{aligned} \tag{6}$$

Taking partial derivatives of (6) with respect to the estimated amplitude and phase, respectively, we get

$$\frac{\partial e^2}{\partial\hat{a}}=-2.e.cos\ \left(\omega_0 kT_s+\Theta\left(kT_s\right)\right) \tag{7}$$

$$\frac{\partial e^2}{\partial\Theta}=2.e.\mathbf{\hat{a}}.\sin\left(\omega_0 kT_s+\Theta\left(kT_s\right)\right) \tag{8}$$

Therefore adaptation of wave parameters according to gradient descent rule [8] is presented below.

$$\begin{aligned}\hat{a}\left(kT_s+T_s\right)&=\hat{a}\left(kT_s\right)—\frac{\mu_{\hat{a}}}{2}\frac{\partial e^2}{\partial\hat{a}}\\&=\hat{a}(kT_s)+\mu_{\mathbf{\hat{a}}}.e.\cos(\omega_0 kT_s+\Theta\left(kT_s\right))\end{aligned} \tag{9}$$

$$\begin{aligned}\Theta\left(kT_s+T_s\right)&=\Theta\left(kT_s\right)—\frac{\mu_\Theta}{2\hat{a}}.\frac{\partial e^2}{\partial\Theta}\\&=\Theta\left(kT_s\right)—\mu_\Theta.e.\sin(\omega_0 kT_s+\Theta\left(kT_s\right))\end{aligned} \tag{10}$$

These equations govern the updating behavior of the filter coefficients.

There is an optional way to avoid computation of sine and cosine functions through constructing an appropriate *LOOK UP TABLE* (LUT).

Generally, a LUT is a vector $\vec{\mathbf{M}}$ of length N and contains the following elements:

$$\vec{\mathbf{M}} = \begin{bmatrix} 1 & \cos(\frac{\pi}{N}) & \cos(\frac{2\pi}{N}) & \cdots & \cos(\frac{(N-1)\pi}{N}) \end{bmatrix} \quad (11)$$

Since $\vec{\mathbf{M}}$ already contains values of cosine function for a uniform discrete set of arguments thus calculation in the MCU is unnecessary. Sine function can be found out by a half wavelength phase shift.

For different bio-potential signals different filter transfer functions are designed as a conventional IIR filter(Least $P^{th}$ approach) [12], which can externally be selected with two select lines A, B as shown in Table I.

TABLE I. FILTERING SPECIFICATIONS OF BIO POTENTIAL SIGNALS

| A | B | Bio-signal | Sampling frequency(Hz) | Bandwidth(Hz) |
|---|---|---|---|---|
| 0 | 0 | EEG | 128 | 0.5-30 |
| 0 | 1 | EOG | 128 | 0.5-20 |
| 1 | 0 | ECG | 512 | 0.5-100 |
| 1 | 1 | EMG | 512 | 0.5-250 |

## III. EXPERIMENTAL SET-UP AND PROGRAM OVERVIEW

An experimental test bench is prepared along with a DAC circuit assembly, which is used to see the output in analog form. The filter coefficients are computed and the program is developed in embedded C-language. Finally, the program is loaded in the general purpose MCU chip and then tested on real-time bio-potential signals.

### A. Setup overview

User's purpose to choose between different filters is implemented through a pair of external select lines A, B, where A selects sampling frequency and B selects signal type. The difference equations are realized in ATmega specific C-language, compiled and the generated '.hex' file is burned into the program-memory of Atmega8 MCU.

After programming the ATmega MCU the experimental setup is tested. This experiment aims to acquire, filter and visualize the output signal on a Digital Storage Oscilloscope (DSO) by employing DAC0800.

### B. Filter design

All filters coefficients are first computed and rounded up as fixed point integers for embedded platform. The filter transfer functions designed as $6^{th}$ order (three 2nd order sections in cascade) IIR filter rather than a traditionally used $4^{th}$ order filter. Because classification of Bio-potential signals, especially EEG, often requires closely spaced separate frequency bands fed to different parts of a classifier which needs sharp cutoff at band edges. The filter pass-bands and sampling frequencies are specified in Table I.

### C. Program description

The internal ADC (10-bit accuracy) of the MCU takes care of data sampling and acquisition so that the A/D is configured accordingly. Sampling interval is accurately controlled through overflow interrupt of a hardware timer TMR0. So data acquisition and buffering is done in a special routine called TMR0 overflow interrupt service routine (ISR).

The ISR contains raw data management and it calls other functions for further processing of data. The other functions called henceforth are conventional filtering routines like '*EEG_filt*', '*EOG_filt'*, '*ECG_filt'* and '*EMG_filt'* according to status of select lines, A and B. The adaptive part of filtering is also implemented in form of a routine, '*adapt*' which is also called from this ISR, when ECG or EMG filtering is chosen, so as to remove the 50/60 Hz power line noise. The adaptive routine of the program is described in the following section.

### D. Implementation of the adaptive updation

As discussed earlier, after deriving equations (9) and (10), we will avoid computation of trigonometric functions as they are difficult to calculate in an 8-bit GP MCU. Instead we defined an array containing 40 discrete values of cosine and sine functions $\vec{\mathbf{M}}$, which is similar to LUT as specified in (11), which provided a resolution of 0.025π in phase. The pseudo-code for APALMS algorithm is as follows:

*Step1.* // Initializations//

1.1 Initialize amplitude parameter $\hat{a}$ and phase parameter $\Theta$.

1.2 Define an array $\vec{\mathbf{M}}$ containing 40 uniformly spaced values of a unit amplitude sine function for angles ranging from 0 to π.

*Step2.* //Error signal estimation//

2.1 Calculate estimation of interference signal $\mathrm{d}_i$ using initial amplitude and phase as shown in (4).

2.2 Error output signal *e* is calculated as follows,

$$e_i = d_i - \hat{a}_i * M[shift]$$

*Step3.* //Updating parameters//

3.1 Amplitude and phase updates are calculated using (9) and (10)

$$\hat{a}_{i+1} = \hat{a}_i + U_A * e * M[cos\_shift]$$

$$\Theta_{i+1} = \Theta_i - U_P * e * M[sin\_shift]$$

where *sin_shift* and *cos_shift* give necessary shift in index of $\vec{\mathbf{M}}$ to get sine and cosine values as per (10) and (11). $U_P$ and $U_A$ are respective updating coefficients.

*3.2.* Reinitialize amplitude and phase parameters for next iteration. S

$$\hat{a}_i \leftarrow \hat{a}_{i+1}; \qquad \Theta_i \leftarrow \Theta_{i+1};$$

*3.3.* Go to *step2.*

The values of $U_A$ and $U_P$ are set as 0.03 and 0.0004 respectively, after several simulations, to satisfy both fast and accurate convergence as well as less quantization error in the embedded domain.

## IV. RESULTS AND DISCUSSIONS

In this section we present the results obtained after the implementation of the adaptive filter on the following bio-potential signals: EOG, EMG ECG and EEG.

### *A. Filtering of EOG signal*

The EOG filtering shown in Fig. 2, is mainly concerned with removal of both high frequency and low frequency noise, so that the pattern defining pulses are smoothened and preprocessed for further processing. From Table I, it is known that the bandwidth selected for EOG signals is from 0.1 – 20 Hz. Thus, only the conventional filter is employed for this signal.

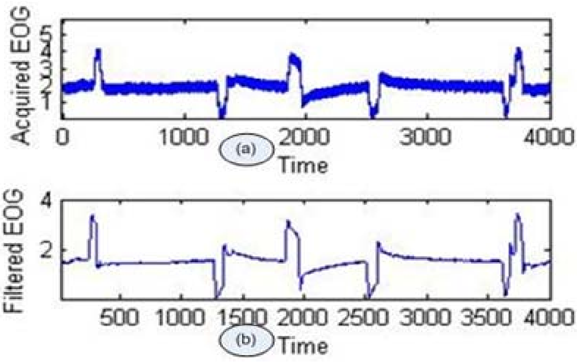


Fig.2. EOG signal denoised. (Signal depicted in plot (a) is the raw EOG signal and plot (b) is the filtered EOG signal)

### *B. Filtering of ECG Signal*

The required bandwidth for the ECG signal, as mentioned in Table I, is 0.1-100 Hz. Thus, here both the conventional and adaptive filter would be implemented to retrieve the relevant components of the ECG, which is shown in Fig. 3.

The adaptive filter realized intends to remove the 50/60 Hz component present in ECG signal. To visualize its characteristics we have intentionally corrupted an ECG signal with a 50 Hz sinusoid as shown in Fig. 3(a) and 3(b). Fig. 3(c) shows the successful de-nosing of the ECG waveform using our proposed adaptive 50 Hz noise cancellation technique.

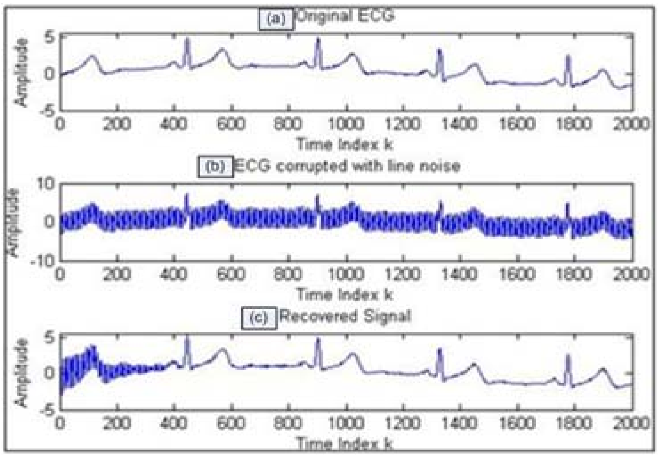


Fig.3. An ECG signal recovery from 50 Hz interference.

### *C. Filtering of EMG signal*

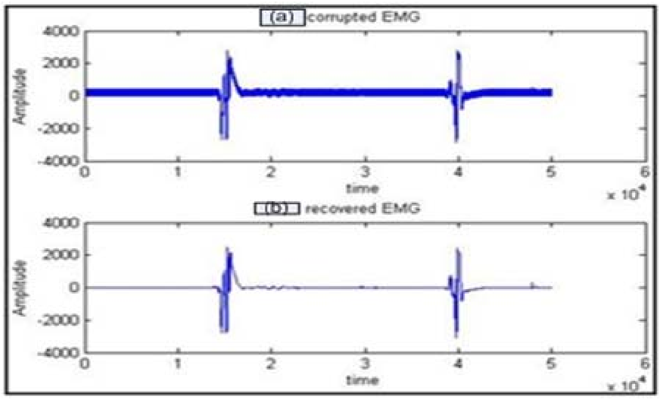


Fig.4. Recovery of EMG signal

According to Table I, the required bandwidth for EMG signals (in this study) is 0.1-250Hz. Here, the line noise interference is cancelled by our proposed adaptive filter. In Fig. 6 we have shown the successful retrieval of EMG components from its noisy counterpart.Filtering of the EEG signal.

### *D. Filtering of the EEG signal*

The waveforms in Fig. 7 are raw EEG and band pass filtered respectively. As shown in Fig. 7(a), the noisy EEG consists of a large DC offset and noise. We have band-pass filtered the noisy EEG within 0.1-30Hz range. As shown in Fig.7 (b), the baseline drift of the noisy EEG is corrected.

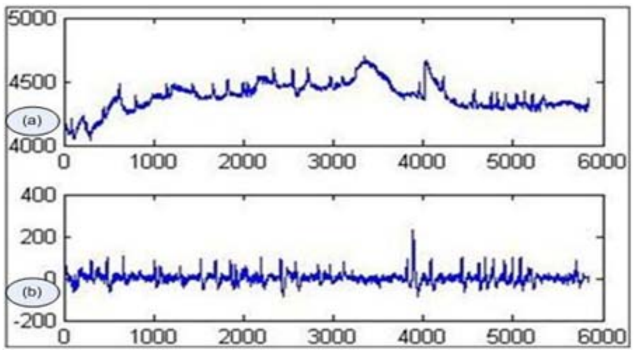


Fig.5. EEG offset removal and filtering

Summary of all results are shown on Table II. Some of them especially filter bandwidth and adaptation time; have slightly deviated from their ideal counterparts in case of their realization on standalone embedded platform. This can be explained by the effect of quantization noise caused by lower word length used for calculation within the given microcontroller domain. Higher word lengths for calculation could be possible, but that multiplied computational complexity and the processing time on an 8-bit microcontroller domain like Atmega-8 [5]. This delay becomes quite a significant factor in case of real time systems.

During simulation, FFT is done on both signals prior to and after filtering is done. Observing the frequency domain waveforms, a drastic reduction in high frequency noise as well as the 50 Hz noise is noticed. In real time, noise removal is verified with the help of a spectrum analyzer where patterns before and after filtering are compared. Due to lack of available space, simulation and real-time results cannot be provided.

TABLE II. EXPERIMENTAL RESULTS SUMMARY

| Signal filter | Theoretical Results | | | Standalone real-time Results | | |
|---|---|---|---|---|---|---|
| EEG | ***$F_S$ (Hz)*** | ***Bandwidth(Hz)*** | | ***$F_S$ (Hz)*** | ***Bandwidth(Hz)*** | |
| | 128 | 0.1-30 | | 128 | 0.1-31 | |
| EOG | ***$F_S$ (Hz)*** | ***Bandwidth(Hz)*** | | ***$F_S$ (Hz)*** | ***Bandwidth(Hz)*** | |
| | 128 | 0.1-20 | | 128 | 0.1-23 | |
| ECG | ***$F_S$ (Hz)*** | ***Band-width (Hz)*** | ***Adaptation time (sec)*** | ***$F_S$ (Hz)*** | ***Band-width (Hz)*** | ***Adaptation time (sec)*** |
| | 512 | 0.1-100 | 1.17 | 510 | 0.1-102 | 1.5 |
| EMG | ***$F_S$ (Hz)*** | ***Band-width (Hz)*** | ***Adaptation time (sec)*** | ***$F_S$ (Hz)*** | ***Band-width (Hz)*** | ***Adaptation time (sec)*** |
| | 512 | 0.1-250 | 1.56 | 510 | 0.3-249 | 2 |

*$F_s$ is the sampling frequency

## V. CONCLUSIONS AND FUTURE DIRECTION

In this paper a bio-potential signal filter is described which is capable of filtering four types of bio-potential signals with different origins and features along with a provision of adaptive cancellation of 50/60 Hz power-line noise. We have not limited our proposed filter structure to theory but also implemented it in the embedded platform. The major advantage of our proposed filter over the conventional ones is that it is a cheap general purpose filter which can used for low frequency bio-potential signals without any considerable loss of information. This practical implementation in a low cost microcontroller chip and the excellent performance with real time signals show the novelty and importance of our proposed method.

Experimentally the settling time is observed to be little longer than theoretical, due to rounding up of learning rates and other variables as 16 bit fixed point variables in a 8- bit MCU domain.

Though a typical EMG signal has larger bandwidth, a smaller bandwidth is considered here and thus limiting its use to few specific applications, also manual switching is implemented here due to lack of fast signal feature extraction and processing capability needed to identify different signals and switch automatically which opens up a scope for future research.

As noted from these points, a few area of concern still remains in the design of the filter. We are looking forward to remove these few concerns in the near future, so that it can be automatically switched and may be able to extract some signal features of profound interest and feed them to a classifier for characterization.

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