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# An Improved Adaptive Filtering Technique for De-Noising Electro-Encephalographic Signals

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***ABSTRACT-*** An electro-encephalographic (EEG) signal is a biomedical signal generated by the electrical activity of the brain. An encephalography is a test that detects this signal using small, flat metal disc (electrodes) attached to the scalp. A finite impulse response (FIR) adaptive filter for removing artifact electrocardiographic signal artifact from electroencephalographic signal was designed and implemented. It incorporates a new adaptive algorithm called Han-windowed algorithm which is a modification of least mean square algorithm. Based on the new algorithm, sampling frequency of 1000Hz with filter order of 122 and step size of 0.0011 were used in de-noising of the electro-encephalographic (EEG) signal of electrocardiographic (ECG) artifacts. A comparison of the new windowed algorithm with un-windowed algorithm in de-noising electro-encephalographic signals was made. It shows that the electro-encephalographic signal at 0.1621 normalized frequency has a signal power of -14.79dB when un-windowed. However, the EEG signal power was lowered to -15.21dB when windowed with least mean square algorithm. The signal to noise ratios in filtering with the new algorithm and the existing un-windowed algorithm based on the above stated parameters are 12.291dB and 11.234dB respectively. This implies that de-noising electro-encephalographic signal of electrocardiographic physiological artifact with Han-windowed adaptive algorithm delivers an enhanced signal output compared to the existing un-windowed algorithm.

***KEY WORDS:*** *Least Mean Square Adaptive algorithm, Han-window Function and Adaptive Filter*

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## I. INTRODUCTION

An adaptive filter is a type of digital filter that adjusts its transfer function or coefficients in accordance with an algorithm driven by an error signal. In order to minimize the error, it adapts to the change in signal characteristics (Rajvansh & Buta, 2016). An adaptive filter has wide applications such as in adaptive noise cancellation, frequency tracking, system identification and removing of artifact signals from the clinical signal of interest. An electro-encephalographic (EEG) signal is a biomedical signal generated by the electrical activity of the brain. An encephalography is a test that detects this signal using small, flat metal disc (electrodes) attached to the scalp. The activities of the brain cells appear on the EEG machine as they communicate through electrical impulses. These activities are active at all times (Hemant & Zahra, 2010). The EEG signal appears as a waveform of varying amplitude and frequency measured in micro voltages of the order 100µv and frequency range between 0,5Hz and 100Hz or above it depending on the state of the patient.

However, the EEG signal waveforms convey a lot of clinical information regarding the health condition of human brain. This information include: alertness, coma, brain death, location of head injury, stroke and tumour growth, investigating epilepsy and sleep disorders (Teplan 2002; Tatum, 2014). Sometimes, EEG signals are contaminated by other biomedical or non biomedical signals called artifacts. These biomedical signal include: electrocardiographic signals, which are generated by the electrical activities of the heart (Leila, 2010; Suresh & Puttamadappa, 2008), an electro-oculographic signal which is generated by the electrical activity of the eyes (Raduntz etal, 2015; Carlos & Angel, 2009; Gamick et al, 2004; Carrie et al, 2004). Non biomedical signal includes power-line interference, which is the 50Hz/60Hz frequency signal from the monitoring or measuring equipment due to its connection to the mains power supply (Guruva-Reddy & srilatha, 2013; Raduntz etal, 2015; Rohtash etal, 2010). Furthermore, to obtain a reliable interpretation of the EEG signal, artifacts which compromise the EEG result must be removed from the EEG signal. This enables one to obtain a clean and uncompromised EEG signal. In this research, effort was made to devise a method of removing this ECG artifact from EEG signal. The adaptive filtering technique was used to denoise EEG signals of ECG artifact because the frequency of the ECG signal (05-100Hz) overlaps with the frequency of EEG (0.5-100Hz and above). Finite Impulse Response (FIR) adaptive filters are suitable for removing this ECG artifact from EEG signal because of its linearity characteristic which makes its phase stable. Using only FIR adaptive filters alone may not give an almost ECG free EEG signal. In other to compensate for the limitation of FIR adaptive filter, a window function has to be applied to an adaptive filter for the purpose of removing the ECG artifact from EEG signal. Therefore, in this work, a windowed FIR adaptive filter was used to remove ECG artifact from EEG signal.

## II. REVIEW OF RELATED WORKS

Many researchers have studied and implemented the use of several methods in denoising ECG artifacts from human EEG. Ille et al, 2002 used spatial filters based on artifact and brain signal topographies. They proved that this spatial method can remove artifacts completely without distortion of relevant brain activity. Iriate et al 2003 used Independent Component Analysis (ICA) to remove artifacts from EEG. The authors studied eight samples of recordings with spikes and evident artifacts of ECG, eye movements, 50Hz interference, muscle or electrode artifacts. The ICA components were calculated using Joint Approximate Diagnolization of Eigen Matrices (JADE) algorithm. Their result shows that ICA produced an evident clearing-up of signals in all the samples. Shogi et al, 2007 used fully automated correlation method based on regression analysis to reduce electrooculagram artifact in EEG. The authors applied the method to 18 recordings with 22 channels and approximately 6m in each and concluded that the method is very viable option for reducing EOG artifacts. Tzyy-ping et al, 2000 proposed a method for removing a wide variety of artifacts from EEG records based on blind source separation by independent component analysis (ICA). Their results on EEG data collected from normal and autistic subjects show that ICA can effectively detect, separate and remove contamination from a wide variety of methods. Radunez et al, 2015 achieved automated artifact elimination in EEG using linear discriminate analysis (LDA) for classification of feature vectors extracted from ICA components via image processing algorithms.

## III. ADAPTIVE FILTER WITH LEAST MEAN SQUARE ALGORITHM

Having defined what adaptive filtering is all about in our introduction, we can now try to combine it with an algorithm. This is because an adaptive filter must have an algorithm that is used to adjust the filter coefficient. The workability of an adaptive filter will not be obtainable if there is no adaptive filter algorithm incorporated with it. In this work, we used least mean square algorithm to adjust the transfer function in line with the characteristics of the input signal so as to produce the best obtainable output. Figure 1 depicts the block diagram of the adaptive filter with a least mean square algorithm.

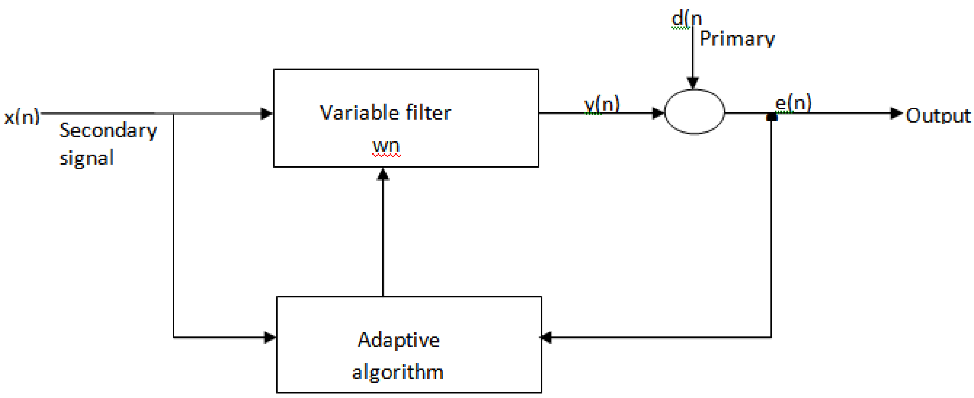


**Figure 1: Adaptive filter with least mean square algorithm**

## IV. METHODOLOGY

The adaptive filter was used in this work because of its self-adjusting ability. The filter varies its coefficients in line with the characteristics of the signal being filtered. Its transfer function takes the same form as of ordinary static filter. But its coefficients change during adaptation process until convergence is achieved. The FIR filter was used in this work with a least mean square algorithm for the generation of the adaptive filter coefficients. The adaptive filter coefficients were used to adjust the transfer function in other to get the correct filtered signal. The final output signal (EEG) was weighted through a Han-window function. The following equations represent the transfer function of the FIR adaptive filter.

$$H(Z) = \sum_{k=0}^{M-1} h(k) z^{-k} \quad (1)$$

Expanding (1) results in (2)

$$Hz)=h(0)+(h1)z^{-1}+(h2)z^{-2}+(h3)z^{-3}+(h4)z^{-4}+(h5)z^{-5}+\ldots\ldots.+h(k)z^{-L} \quad (2)$$

where k varies from 0 to M-1 or L and M is the number of samples considered. M-1=L where L is the order of the filter and h(k) the impulse response of the filter or filter coefficients.

To implement our algorithm, these ten steps are involved in the design and its realization. They are as follows; modeling of LMS adaptive algorithm, modeling of Han window, development of windowed-adaptive algorithm, obtaining responses of the filter based on the developed algorithm, and input variables of filter order, step size parameter and sampling frequency, determining the optimum order of the filter, determining the optimum step size parameter of the filter, structural realization of the filter, generation of results, calculation of signal to noise ratio of the filter, and finally comparative analysis of the proposed algorithm and other similar algorithms in use for the processing of EEG signal.

## V. MODELING OF LMS ADAPTIVE ALGORITHM

The mathematical modeling of FIR-LMS adaptive algorithm can be done by considering the adaptive noise canceller of fig. 2. There is a primary signal d(n) which in this case is the EEG signal plus ECG artifact, and the secondary or reference signal x(n) which in this case is the ECG artifact. The filter produces an output y(n) which is subtracted from d(n) to compute an error e(n) which in this circumstance is the output of the system (denoised EEG).

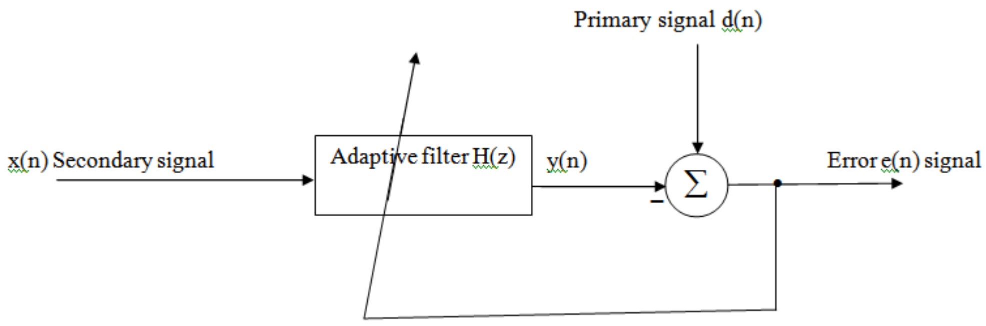


**Fig 2: Adaptive noise Canceller for Removing ECG from EEG signal**

The objective of the above filter is to change or adapt the coefficients, and hence its frequency response to generate a noise similar to the ECG noise present in the EEG signal to be filtered. The adaptive process involves minimization of cost function, which is used to determine the filter coefficients. In effect of this LMS scheme, the adaptive filter adjusts its coefficients to minimize the squared error between its output and primary signal. The coefficients will change with time, according to the signal variation, thus converging to an optimum filter. The adaptation is directed by the error signal between the primary signal and the filter output. The optimizing criterion is the Least Means Square (LMS) algorithm. Ascertaining how the optimizing criterion adapts the filter coefficients is possible by analytical means. Normally, the output of FIR filter is a convolution of the input and the filter coefficients given by the difference equation of (3):

$$y(n) = \sum_{k=0}^{L} h_k . x(n-k) \quad (3)$$

Where L is the order of the filter, x(n) is the secondary input signal, $h_k$ are the filter coefficients and y(n) is the filter output. The error signal e(n) is defined as the difference between the primary signal d(n) and the filter output y(n). That is to say;

$$e(n) = d(n) - y(n) \tag{4}$$

Substituting for y(n) will give

$$e(n) = d(n) - \sum_{k=o}^{L} h_k .x(n-k) \tag{5}$$

The Square Error is

$$e^2(n) = d^2(n) - 2d(n)\sum_{k=0}^{L} h_k .x(n-k) + \left[\sum_{K=0}^{L} h_k .x(n-k)\right]^2 \tag{6}$$

The Square Error expectation for N samples is given by

$$E\left[e^2(n)\right] = \sum_{K=0}^{N} e^2(n) \tag{7}$$

**Modeling of Han Window Function**

The window chosen for weighting the adaptive filter is Han window function and the mathematical model is presented (Mbachu &Nwabueze , 2013, Mbachu, 2015) in eqn(3). The diagrammatic representation is shown (Mbachu &Nwabueze, 2013) in fig. 3.

$$w(k) = 0.54 - 0.46\cos\left[\frac{2\pi k}{(M-1)}\right], \quad 0 \leq k \leq M-1 \tag{8}$$

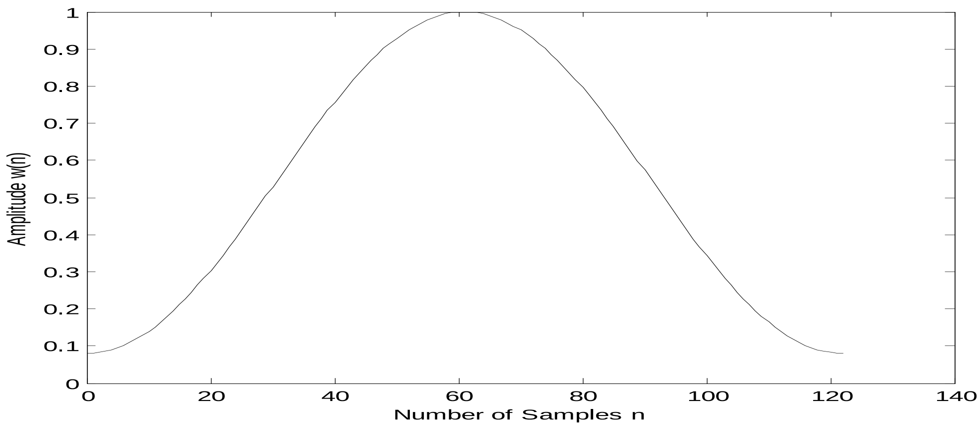


**Fig. 3: Han Window Function**

## VI. RESULT AND ANALYSIS

The results from our algorithm show that it is possible to remove ECG artifacts from human EEG signal. Firstly, we considered the proposed Han-windowed filter. The uncontaminated and filtered EEG signals are shown below in Fig. 5 & Fig. 8 respectively.

**Filtration with the Proposed Filter**

An uncontaminated electroencephalographic (EEG) signal was captured practically from an EEG machine while measuring a patient in a hospital. The code was transformed into matlab code in a matlab environment and the signal generated in a matlab environment using the code is shown in fig. 4. An uncontaminated ECG signal was generated using matlab function as shown in fig.5. The EEG signal was mixed with the ECG signal to form a corrupt EEG signal as presented in fig. 6. The corrupt EEG signal was applied to the proposed filter and the filter output was shown in fig. 7 while the filtered signal is presented in fig. 8. The filter output is the noise estimated by the filter which is similar to the corrupting noise and which the filter will subtract from the contaminated signal. The filtered signal is the system output and represents the desired signal remaining after the noise has been removed.

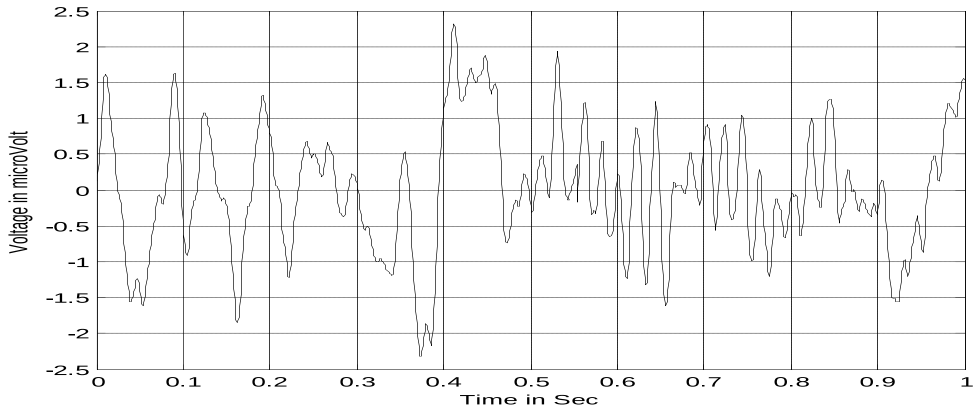


**Fig. 4: Uncontaminated EEG Signal**

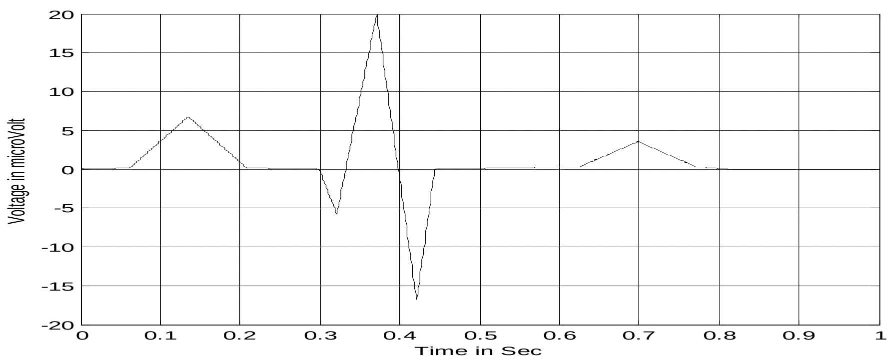


**Fig. 5: Uncontaminated ECG Signal**

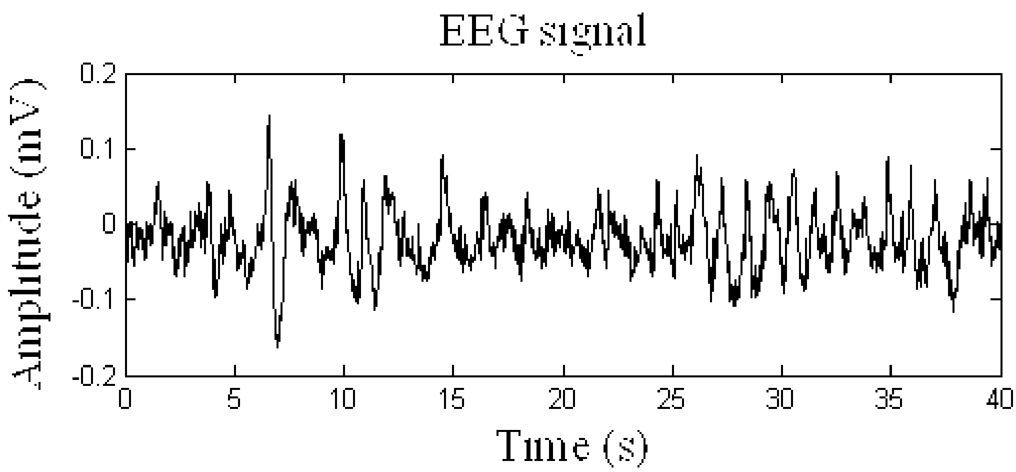


**Fig. 6: EEG Signal Contaminated with ECG**

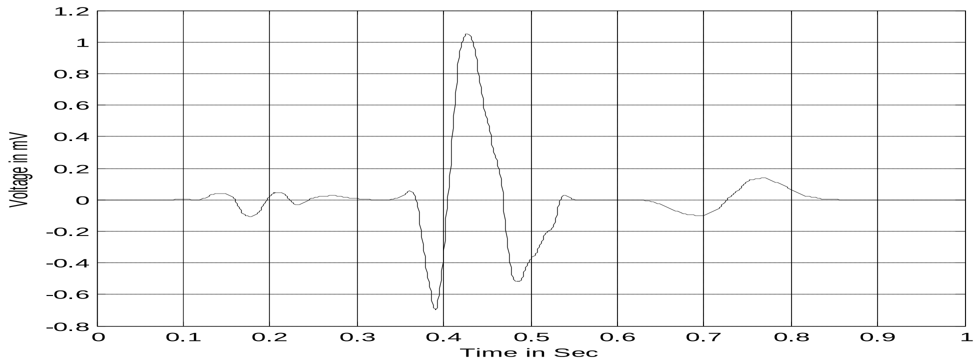


**Fig. 7: Filter output or Estimated Noise**

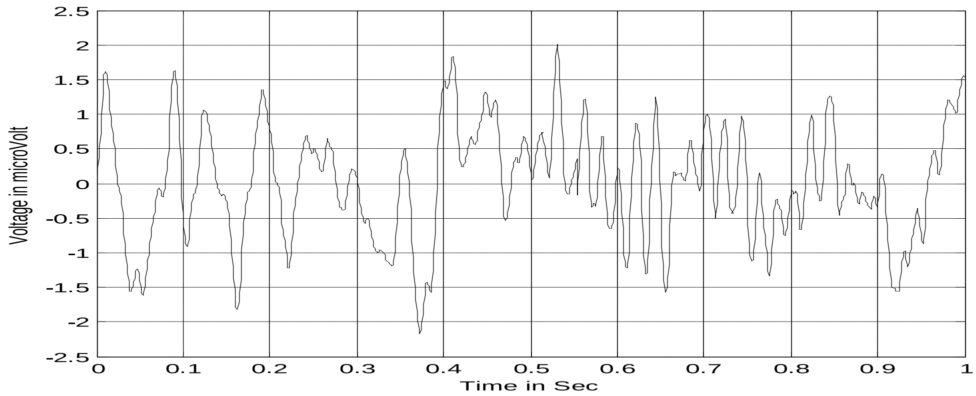


**Fig. 8: Filtered EEG Signal**

Examining the corrupt and filtered EEG signals as depicted in fig. 6 and fig. 8, respectively indicate that the filter substantially removed the ECG artifact that was in the corrupt EEG signal. The estimated noise signal of fig. 7 is very close to the original noise signal of fig. 6 which is another clear indication that the filter is performing.

## VII. CONCLUSION

In this research, a new adaptive algorithm known as Han-windowed adaptive filter was developed and used in a finite impulse response adaptive filter to effectively de-noise electroencephalographic signal of electrocardiographic artifact of a patient in a hospital. The analytical and simulated results show that power outputs when the signal output was passed through Han-windowed adaptive filter and when it was not were -15.79dB and -14.79dB respectively at the same normalized frequency of 0.1621. This implies that Han-windowed adaptive filter yields 0.42dB better than the un-windowed adaptive filter at the same 0.1621 normalized frequency with the optimum parameter values of 122 order and 0.0011 step size.

## VIII. RECOMMENDATION FOR FURTHER STUDIES

Future works need to be done in applying the Han-windowed adaptive filter in processing other signals such as Electrocardiogrphic, baseline wander, electromyographic and even audio signals. This is to verify whether the new Han-windowed adaptive filter will give the desired filtered output when applied to these signals. However, some other adaptive filter criterion, such as Recursive Least Square and Simple Matrix Inversion needed to be applied with the FIR adaptive filter as to know the criteria that attains convergence faster and stability still maintained.

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