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EEG Signal Enhancement and Estimation using Adaptive Filtering

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***Abstract*— In this paper the application of adaptive filtering is discussed in context of removing the random noise from an EEG signal. An experimental model is presented to mix the random noise of varying magnitude and frequency with EEG signals and consequently to estimate and remove the noise signal using the adaptive filtering approach. The variable random noise is projected as if there were multiple physiological artifacts like ocular signal, motion artifacts, myographic noise etc. getting merged with an EEG signal. The model can be used as an estimation and removal tool of artifacts in EEG signal from multiple origins. The filter performance is measured and analyzed on the basis of parameters like root mean square error (RMSE), normalized correlation coefficient (NCC) and % improvement in SNR.**

I. INTRODUCTION

The electroencephalogram (EEG) is an important physiological signal to measure and analyze the neuronal activities of the human brain. Many clinical uses have been found including the mental state (relaxed or vigorous) of a person, epileptic episodes' occurrences (instants and amplitudes), sleep disorders studies etc. to name a few. There are various sources of artifacts, e.g. other physiological signals like ECG, EMG and EOG; line interference (50/60 Hz noise); electrode motion artifacts etc., that merge with EEG signal. In order to provide artifacts-free EEG signals to the physicians for carrying better clinical observations and diagnosis, various filtering techniques have been proposed. These techniques include principal and independent component analysis (PCA and ICA), autoregressive and autoregressive moving average (AR and ARMA) modeling, adaptive filtering, wavelet transform, cyclostationary source extraction, sparse component decomposition, selective average subtraction, recurrent neural networks [1]-[5] and many more. Among the above stated methods the adaptive filtering based methods have been found more suitable as they can be used not only for filtering/cancelling the noise signals but also for estimating the noise signals. The estimated noise signals can then be subtracted to obtain the clean signal of interest.

An epilepsy diagnosis algorithm based on hybrid adaptive filtering (HAF) and higher-order crossings (HOC) is proposed and implemented in [6]. In this algorithm, HAF is developed to isolate the seizure and non-seizure EEG characteristics and facilitating the task of the feature vector extraction. HOC analysis is employed to select the effective feature from the HAF-filtered signals. The extracted features by HAF-HOC scheme can create maximum distinction between two classes. For classification and recognition of seizures through EEG signals, Quadratic Discriminant Analysis (QDA) and Mahalanobis Distance (MD) are used. A common problem faced during the clinical recording of the electroencephalogram (EEG) signals is the eye-blinks and movement of the eye balls. Eye blinks cause changes to the electric fields around the eyes, and consequently over the scalp. As a result, EEG recordings are often significantly distorted, and their interpretation becomes problematic. In [7], a method for removal of ocular artifacts is proposed using ARMA (auto-regressive moving average) method with wavelets. In [8], an adaptive filtering approach which includes radial EOG (REOG) signal as a third reference input has been proposed for removing ocular artifacts from EEG. The authors have analyzed the performance of adaptive algorithms using two reference inputs i.e. VEOG and HEOG and three reference inputs i.e. VEOG, HEOG and REOG. EEG signals, when recorded within the strong magnetic field of an MRI scanner are subject to various artifacts, of which the ballistocardiogram (BCG) is one of the most prominent artifacts affecting the quality of the EEG. The BCG artifact varies slightly in shape and amplitude for every cardiac cycle making it difficult to identify and remove. A novel method for the identification and elimination of this artifact using the shape basis functions of the new dilated discrete Hermite transform has been proposed in [9]. In [10] authors have implemented a novel filtering procedure, Hybrid Adaptive Filtering (HAF), for an efficient extraction of the emotion-related EEG characteristics was developed by applying Genetic Algorithms to the Empirical Mode Decomposition-based representation of EEG signals. In addition, Higher Order Crossings (HOCs) analysis was employed for feature extraction realization from the HAF-filtered signals. The introduced HAF-HOC scheme incorporated four different classification methods to accomplish a robust emotion recognition performance. Through a series of facial-expression image projection, as a Mirror Neuron System-based emotion elicitation process, EEG data related to six basic emotions (happiness, surprise, anger, fear, disgust, and sadness) have been acquired from 16 healthy subjects using three EEG channels. In [11] and [12], adaptive filtering combined with wavelet transform is used for artifact removal and extraction of evoked potential responses.

In this paper we have implemented a model for adaptively filtering the random noise, of varying amplitude and frequencies, from an EEG signal. The variable random noise is projected as if there were multiple physiological artifacts like ocular signal, motion artifacts, myographic noise etc. getting merged with an EEG signal. The model

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can be used as an estimation and removal tool of artifacts in EEG signal from multiple origins. The organization of the paper is as follows: section II provides a brief discussion on adaptive filtering concepts and models, section III provides the insight of the simulation model followed by results in section IV and conclusion in section V.

II. ADAPTIVE FILTERING: CONCEPT AND APPLICATIONS

A. Introduction

The general set up of an adaptive filtering environment is illustrated in Fig. 1, where k is the iteration number, *x(k)* denotes the input signal, *y(k)* is the adaptive filter output signal, and *d(k)* defines the desired signal. The error signal *e(k)* is calculated as *d(k) - y(k)*. The error signal is then used to form a performance (or objective) function that is required by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive-filter output signal is matching the desired signal in some sense.

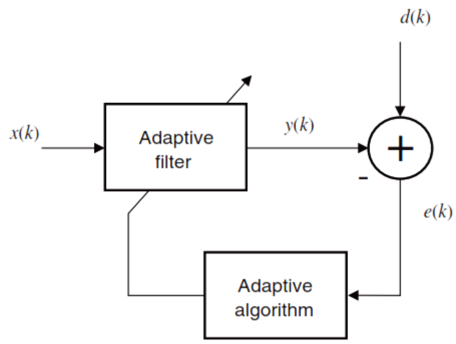
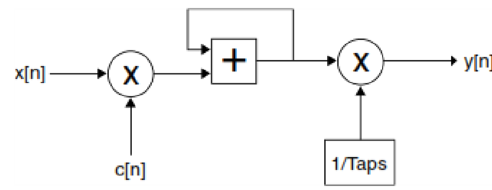


Figure 1. General adaptive filter configuration

B. The LMS Algorithm

An adaptive algorithm is used to estimate a time varying signal. There are many adaptive algorithms such as Recursive Least Square (RLS) and Kalman filters, but the most commonly used is the Least Mean Square (LMS) algorithm. It is a simple but powerful algorithm that can be implemented to take advantage of Lattice FPGA architectures. Developed by Window and Hoff, the algorithm uses a gradient descent to estimate a time varying signal. The gradient descent method finds a minimum, if it exists, by taking steps in the direction negative of the gradient. It does so by adjusting the filter coefficients to minimize the error.

The LMS reference design consists of two main functional blocks - a FIR filter and the LMS algorithm. The FIR filter is implemented serially using a multiplier and an adder with feedback. The FIR result is normalized to minimize saturation. The LMS algorithm iteratively updates the coefficient and feeds it to the FIR filter. The FIR filter than uses the coefficient *c(n)* along with the input reference signal *x(n)* to generate the output *y(n)*. The output *y(n)* is then subtracted to from the desired signal *d(n)* to generate an error, which is used by the LMS algorithm to compute the next set of coefficients. FIR filter is implemented serially using a multiplier and an adder with feedback. The FIR result is normalized to minimize saturation. The LMS algorithm iteratively updates the coefficient and feeds it to the FIR filter. The FIR filter than uses the coefficient *c(n)* along with the input reference signal *x(n)* to generate the output *y(n)*. The output *y(n)* is then subtracted to from the desired signal *d(n)* to generate an error, which is used by the LMS algorithm to compute the next set of coefficients.



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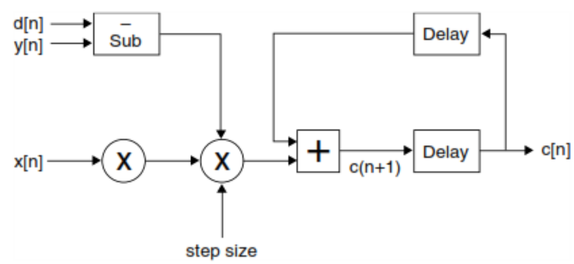


(b)

Figure 2. LMS algorithm implementation using FIR filter

C. Applications

Some of the classical applications of adaptive filtering are system identification, channel equalization, signal enhancement, and prediction. In the system identification application, the desired signal is the output of the unknown system when excited by a broadband signal, in most cases a white-noise signal. The broadband signal can also be used as input for the adaptive filter. When the output MSE is minimized, the adaptive filter represents a model for the unknown system. The channel equalization scheme consists of applying the originally transmitted signal distorted by the channel plus environment noise as the input signal to an adaptive filter, whereas the desired signal is a delayed version of the original signal. This delayed version of the input signal is in general available at the receiver in a form of standard training signal. In a noiseless case, the minimization of the MSE indicates that the adaptive filter represents an inverse model (equalizer) of the channel.

In the signal enhancement case, a signal *x(k)* is corrupted by noise *n1(k)*, and a signal *n(k)* correlated to the noise is available (measurable). If *n(k)* is used as an input to the adaptive filter with the signal corrupted by noise playing the role of the desired signal, after convergence the output error will be an enhanced version of the signal. Finally, in the prediction case the desired signal is a forward (or eventually a backward) version of the adaptive-filter input signal. After convergence, the adaptive filter represents a model for the input signal, and can be used as a predictor model for the input signal.

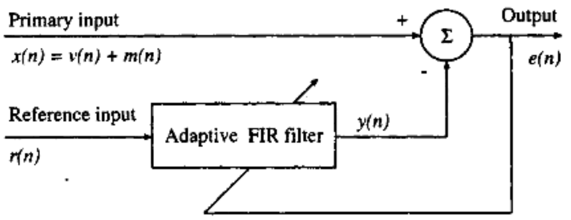


Figure 3. Signal enhancement ($n_1(k)$ and $n_2(k)$ are noise signals correlated to each other) using Adaptive filtering [13].

In this work we have utilized the model shown in fig. 3 [13] above for enhancing/ predicting an EEG signal. In the first approach we used *the noise signal* as the reference to *enhance* the EEG signal and in the other approach *the EEG signal* is used as the reference signal to *predict* the desired signal from the noisy EEG signal.

III. Simulation Model

The simulation model for the experiments is shown in fig. 4. A random noise signal, η, filtered with fourth order butterworth lowpass filter, is added with an EEG signal. The amplitude and frequency levels of noise can be controlled by A and B, respectively. The mixture signal is then filtered with an adaptive filter scheme shown in fig. 4. The output of the adaptive filter will be either an enhanced EEG signal or an estimated noise signal, which can be obtained by two versions of the adaptive filter.

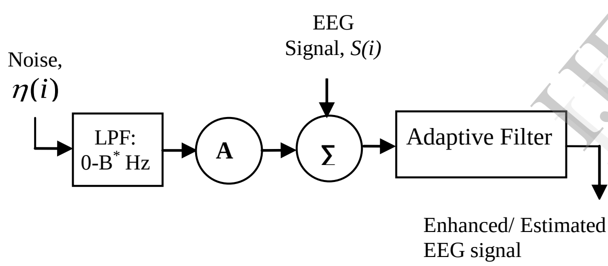
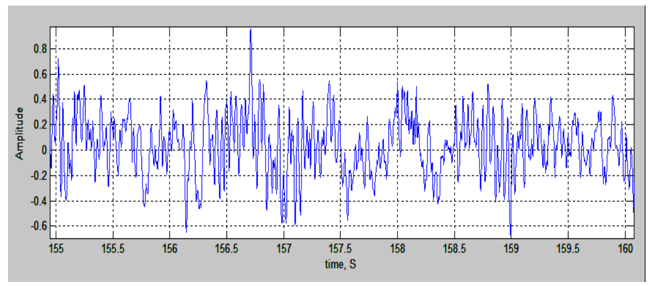


Figure 4. Simulation Model for Enhancement of EEG signal using Adaptive filter

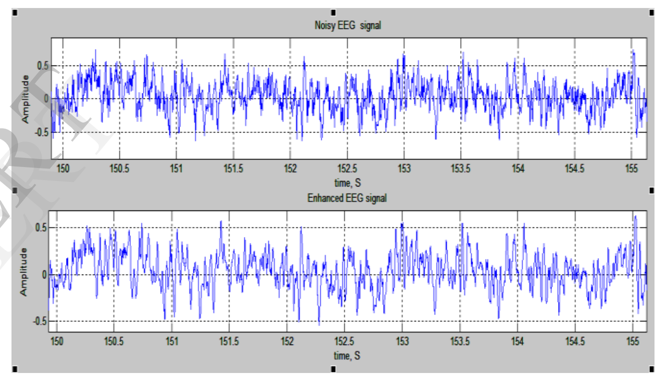
IV. Experimental Results

The simulations have been performed using the model shown in fig. 4. A low-pass filtered noise with three different frequencies-20 Hz, 30 Hz and 45 Hz and three different amplitude levels- is added with EEG signal. The EEG signal is a typical alpha rhythm as shown in fig. 5. Table I shows the simulation results for *enhancement of EEG signal* using adaptive filtering and table II shows the simulation results for estimation of EEG signal using the adaptive filtering. In the former case the noisy EEG signal is fed to the adaptive filter block with a correlated noise signal as a reference signal, whereas in the later case the original EEG signal is used as the reference signal for the adaptive filter block. Standard performance measuring parameters like RMSE and normalized correlation coefficient (NCC) have been used for the analysis.

The simulations results indicate that as the noise level and cut-off frequency/bandwidth of the noise increase, the % improvement in SNR decreases. The maximum % improvement obtained for *EEG signal enhancement* case is 60.49% which is essentially for the lowest noise frequency (B) - 20 Hz and lowest noise level (A) = 0.09 combination. The same for *EEG signal estimation* case is 48.37% for B = 20 Hz and A = 0.125 combination. Fig. 5 (a) and (b) show the original and the noisy EEG signals. Fig. 5 (c) and (d) indicate the output for enhanced EEG signal with SNR of 42.35 dB and the output for estimated EEG signal with SNR of 31.96 dB, respectively.



(a)



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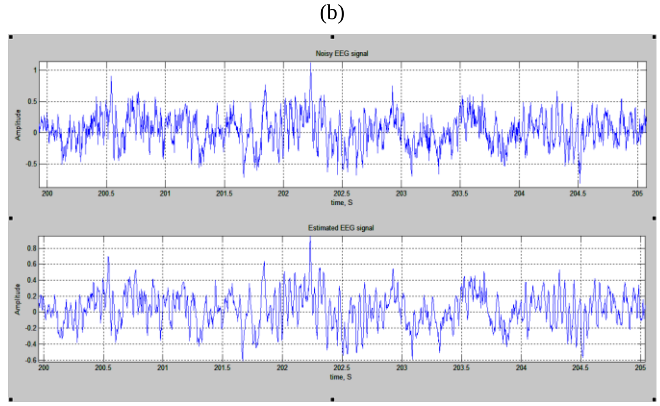

(c)

Figure 5. (a) Original EEG signal; (b) noisy EEG signal with SNR = 14.47 dB and *Enhanced EEG signal* with SNR = 17.95 dB (24.06% improvement in SNR) and (c) noisy EEG signal with SNR = 14.47 dB and *Estimated EEG signal* with SNR = 17.21 dB (19.20% improvement in SNR)

Table I: Simulation Results for EEG Signal Enhancement case

Noise freq-uency, B	**Noise level, A**	**RMSE**	**NCC**	**SNR, dB**		**Improve -ment in SNR**
				Before filtering	**After filtering**	
45 Hz	0.09	0.0608	0.9627	19.35	26.04	34.65%
	0.11	0.0711	0.9488	16.32	21.11	29.35%
	0.125	0.0779	0.9382	14.47	17.95	24.06%
30 Hz	0.09	0.0537	0.9710	22.91	33.93	48.13%
	0.11	0.0631	0.9599	19.75	28.49	43.92%
	0.125	0.0698	0.9507	17.75	24.97	40.74%
20 Hz	0.09	0.0473	0.9776	26.25	42.16	60.49%
	0.11	0.0561	0.9684	23.05	36.58	58.48%
	0.125	0.0626	0.9605	20.95	32.95	56.65%

TABLE II: SIMULATION RESULTS FOR EEG SIGNAL ESTIMATION CASE

Noise freq-uency, B	Noise level, A	RMSE	NCC	SNR, dB		Improve -ment in SNR
				Before filte-ring	After filte-ring	
45 Hz	0.09	0.0617	0.9617	19.35	24.70	27.68%
	0.11	0.0715	0.9481	16.32	20.32	24.28%
	0.125	0.0783	0.9376	14.47	17.21	19.20%
30 Hz	0.09	0.0562	0.9683	22.91	31.63	38.60%
	0.11	0.0648	0.9576	19.75	26.87	36.33%
	0.125	0.0713	0.9485	17.75	23.82	34.27%
20 Hz	0.09	0.0497	0.9753	26.35	38.38	45.67%
	0.11	0.0585	0.9656	23.05	33.91	47.34%
	0.125	0.0650	0.9573	20.95	31.06	48.37%

V. CONCLUSION

We have presented a model for offline enhancement and estimation of EEG signal using adaptive filtering method. The simulation results indicate that adaptive filtering model for signal enhancement (the one which uses correlated noise as reference signal) outperforms the other model used for signal estimation. This type of analysis may be quite useful when multiple noise sources (e. g. ECG, EMG, EOG etc.) have merged with an EEG signal. Having correlated reference signals, these noise sources can easily be estimated with the adaptive filtering method and hence the EEG signal can be enhanced for better carrying out diagnosis.

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