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Denoising and Classification of EEG Signals Using Adaptive Line Enhancer in VlSI

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Abstract

Artifacts in electroencephalogram (EEG) signal are affected by various factors, like power line interference, electrode interferences, head movement and other external interferences. These noise sources increase the arduousness in carefully studying the EEG signals and to get clear medicine based information. Hence, it is obligatory to design particular filters to decrease such artifacts and noises in EEG signal. The proposed adaptive filters are based on adaptive algorithms like Least Mean Squares, Recursive Least Square, and Kalman Filter algorithm. The adaptive filter uses a Finite impulse Response filter, which is used to vary the each stage coefficient of the adaptive filter through the adaptive algorithm. There are two kind of adaptive filter architecture employed and a filter of minimum order of the FIR filter with respect to the minimum input values of the EEG signal. The output of the adaptive system extract and are separate the EEG signal from the noise signal. The proposed technique was implemented in MATLAB and Verilog HDL in cadence 90nm environment.

Keywords: Adaptive Line Enhancer, Least Mean Squares, Adaptive Noise Cancellation

INTRODUCTION

Biomedical signal processing is one of the most effective procedures for EEG signal processing. The EEG signals carry the information about the human brain neuron activities or abnormalities. The main characteristics of EEG signals are microbiological effect or movement of the frequency waves. The signals have the minimum amplitude wave like less than 200μV, and their frequency varies with respect to the different neurological waves like as beta, delta, theta and gamma wave. The different waves are analyzed to detect the normal, cerebral pathologies and abnormal disorders in human brain for the physicians [1]. During the EEG signal recording the artifacts and noise occurred and it affects the quality of original EEG signals. The artifacts and noises are classified into two different categories such as physiological and electronics artifacts. In EEG signal observation or recording the physiological artifacts are often due to the muscular activity, head movement, eye and heart movement (ECG, EMG, EOG). However, these EEG signals are typically blended with other biomedical signals, for instance alpha is normally blended the EOG and ECG. In EOG, opening and shutting or movements of the eyes produces artifacts in the EEG [2]. The mechanical movement of valves from the heart produce the ECG and it interfere with the EEG signal, and also the heart sound is high amplitude when compared with EEG signal so the ECG sound easily interfere with the EEG signal. In other hand the power line interfaces from electrodes have a noise ranging from 50/60Hz on the scalp and transducer artifacts [3]. Because of the line interference artifacts, it is exceptionally hard to find the EEG signal, it might present spikes and make a mistaken with neurological wave. In this way, noise and undesirable signals must be eradicated from the EEG signal to make sure an exact analysis and diagnosis. Both kinds of artifacts occur during the EEG recording it must be eliminated with the help of denoising techniques.

However, the ECG waveforms will typically be misguided for epileptic type movement once the ECG is scarcely observable within the EEG. Muscle activity: Another normal artifact is caused by electrical action of the muscles, measured on the body surface by the electromyogram [4]. This kind of artifact is mainly encountered once the patient is conscious and happens throughout ingesting, grimacing, frowning, gnawing, talking, sucking, and hiccupping [5]. Eye movement and flicker: Eye movement turns out electrical action in the EOG that is powerful enough to be obviously noticeable within the electroencephalogram. The blinking artifact sometimes produces a additional and sudden change in the wave than eye movement, and, consequently, the blinking artifact have additional high-frequency elements. In addition to this Power line noises from recording medical specialty devices can also introduce distortion to recorded signals and, as a result, compromise their integrity and negatively have an effect on their interpretations [6]. Consequently, in fields like neural engineering, surgery, cardiology, and drug discovery we have to refine information by eliminating power line noise. Adulteration of neural signals by power line noise makes it troublesome to grasp the properties of particle channels and the way ensembles of neurons move to perform specific computations for determining behaviors. As a result of the instability of medical specialty signals, the distribution of signals filtered out might not be focused at 50/60 Hz. As a result, self-correction strategy area unit is required to optimize the performance of those filters [7-8].

RELATED WORK

Biomedical signal process field has been created substantial contributions over the past years. Noise cancellation in recent times, accomplished much thought as an approach to eradicate noise enclosed in helpful signals [9-10]. This method has been connected in various communication and mechanical apparatuses, like hands-free phones, hardwares, and transformers [11]. Additionally, noise cancellation has been enforced in medical specialty signals such as image process, echo cancellation, and speech improvement [12-13]. In acoustics applications, noise from the surroundings entirely diminishes the standard of audio and speech signals. Consequently, associate degree adaptive noise cancellation system is employed to restrain noise and improve speech and audio signal excellence. By means of the fundamental concept of unwanted signal suppression using adaptive filtering architecture primarily familiarized by Widrow [14]. The ANC uses two different inputs resulting from more than one signal sources and it’s affected from the high frequency noise components so the week signal is unpredictable. The adaptive filtering technique provides to predict the small amplitude signal because the filter weights are adjusted automatically with the help of adaptive algorithm. Based on the input signal weights the adaptive algorithms adjust the filter coefficients in each iteration. Investigators have developed various algorithms for active noise cancellation to develop adaptive filter, there are three kind of adaptive algorithms employed to predict and suppress the noise signal. The algorithms are LMS, RLS and Kalman Filter algorithm [15]. Some basic parameters are used to measure the adaptive algorithm performance like convergence rate, adaptation, etc., The Adaptive Line Enhancer are similar to the ANC, the only difference is the input signal taken as a reference signal in ALE but the ANC uses the two different input signals so the architecture is called as similar to ANC [16]. The ALE, in reality is a deteriorated sort of ANC, consisting of one detector and delay z-1 to supply a delayed version of d(n), denoted by x(n), that de-correlates the noise and whereas correlate the target signal element. Ideally, the output y(n) of the adaptive filter within the ALE is un estimate of the noise-free signal. Hence, the ALE capability to extract the periodic and random variable of a signal can even be called an adaptive self-tuning filter [17-18].The ALE becomes a stimulating application in noise reduction due to its simplicity and simple implementation. However, to get the most effective performance in its machine method, the optimum approach is to execute ALE on a stronger convergence rate of adaptive algorithm with a less complicated adaptive filter structure algorithm because of the ANC.

ADAPTIVE LINE ENHANCER

Several signals and statistics in natural world have periodic or cyclo-stationary parts. These signals square measure of noise or blended random signals. Removal of such repeated activities is necessary for observing the standing of a system. The ALE is introduced to separate low-level frequencies or narrow band signal from high frequency noise is a classical drawback has been overcome [21-22]. The basic architecture of the ALE is shown in Figure1. The ALE input *s(n)* is understood to be the addition of a input source signal *x(n)*, and a noise signal *n(n)*. The parameters of the prediction filter *w* coefficient custom-made in such an easiest way that the applied mathematical mean square error (MSE), $E\,[e^2(n)]$ is decreased. The ALE works by benefit of its difference among the desired signal *d(n)* and *x(n)*.The parameter delay Δ should be superior than the noise signal *n(n)*, however smaller than the input signal *x(n)*. During this case, it's achievable for *w* to create Δ-step further on to the prediction of *x(n - Δ)* supported by the current and past samples of *x(n - Δ)*. On the other hand, is not ready to forecast *x(t)* from information signal present and past samples of *x(n -Δ)*. Therefore, when the parameters of *w* have congregated near to their optimum values, *e(n)* error signal is around input *x(n)* and the filter output *y(n)* is with respect to the input *x(n)*. Despite the fact that the ALE architecture is an effective technique for single channel signal denoising, it utilizes filter order statistics of the information at intervals as step-down criteria.

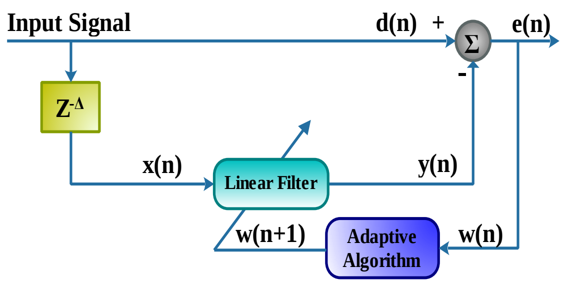

Figure 1: Traditional adaptive line enhancer

Moreover, the architecture is restricted to Gaussian noise digital signal processing. ALE is used as an efficient and dominant tool for bio medical signal prediction and denoising, video, audio etc., wherever tiny and extended, one-dimensional and 3D, stationary and non-stationary, nearly settled and least mean square measure to be analyzed. In associate degree adaptive filter, there square measures essentially have 2 processes:

1. A filtering method, a digital filter process with respect to the coefficient of input signal. During the process improves the linearity and stability of the excepted output signal so the FIR filter used to obtain the excepted result.

2. Adaptive line enhancer method, within which the transfer operate H(z) is adjusted in step with coefficient updation algorithm. The variation is intended for the error signal among the input source signal and output of the filter.

LMS Algorithm:

Achieving the maximum performance of adaptive filter needs of efficient adaptive algorithm with a quick convergence rate, less computational complexity and low machine quality. Most widely used adaptive algorithm for prediction and denoising uses LMS. There are different kind of adaptive algorithms employed to improve the convergence speed and reduce the computational complexity like NLMS, RLS, and Kalman filter. The adaptive filtering technique may be an account of the LMS algorithm, at the begging proposed by Widrow and Hoff [23-25]. The LMS is predicated with the technique namely steepest descent, gradient search to work out filter coefficients that diminish the mean square prediction of a filter. The origin of the LMS algorithm is,

$$y(n) = x(n)w(n) \qquad (1)$$

$$e(n) = d(n) - x(n)w(n) \qquad (2)$$

e(n) is the error signal adaptive mean square specified by the above equations. In these equations, x(n) is that the input signal, and w(n) is that the filter coefficient. Here, the equation uses the present evaluation of the coefficient updating. The coefficient updating algorithm of the standard LMS algorithm is given by equation 3.

$$w(n+1) = w(n) + \mu e(n)x(n) \qquad (3)$$

Where, the step size parameter is µ which is dominant in convergence rate at intervals and it varies appropriately. The step size price changes the length of coefficient of adaptive filter to a small price of µ which ends up in extraordinarily maximum convergence time to adapt the coefficient, whereas an elevation of µ causes the algorithm to adapt the coefficient with minimum convergence time, so minimizing the error rate of the adaptive filter. Consequently, selecting an acceptable level for the step size is critical while executing the LMS algorithm as adaptive filter. Figure 2 shows the function flow diagram for ALE – LMS algorithms in both environments.

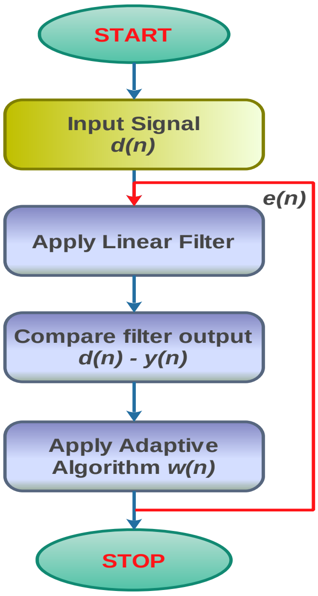

Figure 2: Flow diagram for ALE – LMS algorithm

RESULTS

The projected adaptive filter has filtered the artifacts in the EEG records. As we have said a tendency higher than, the primary stage constricts the line-frequency physical object, the x(z) filter adjusts the amplitude and also the section of the factitious curving signal d(n) so as to get a output of duplicate, y(n), of the line-frequency physical object gift within the graphical record. The EEG recorded source signal from www. commsp. ee. ic. ac. uk/~ mandic/research web site. Figure 3 illustrates the ability spectra of: (a) the first graphical record with the fifty rate interference, and (b) the primary stage output e1(n). Note within the previous one that this element is constricted in e1(n) and no alterations within the graphical record unique spectrum in alternative frequencies.

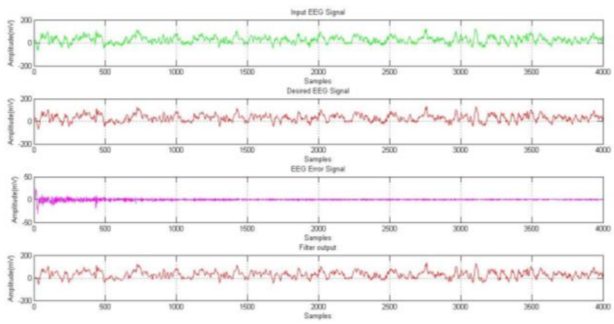

Figure 3: Output waveform for ALE – LMS EEG signal processing in MATLAB environment

The performance analysis such as Signal to Noise Ratio, Mean Square Error and the Computation Time of the proposed algorithm was shown in table 1 and the graphical representations are shown in figure 4.

Table 1: Performance Analysis of ALE LMS

Performance Analysis of ALE LMS				
Filter Order	**N=4**	**N=8**	**N=16**	**N=32**
SNR	25.672	11.437	6.20	4.6138
MSE	40.44	41.674	37.62	31.843
Time	2.142	1.4575	1.5605	1.8205

Figure 5 shows the simulated wave form through the Verilog HDL language used to simulate in Xilinx environment. In this process the input signal are converted to IEEE 754 single precession format 32 bit values.

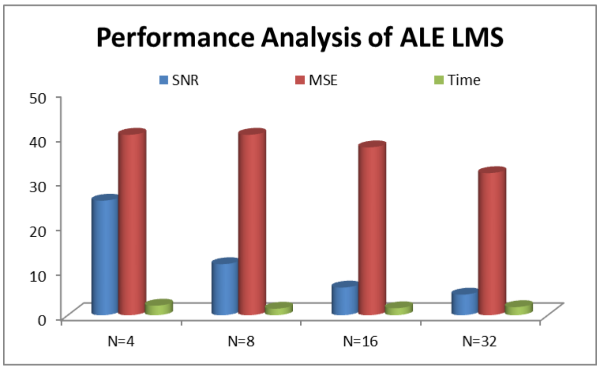

Figure 4: Performance Analysis of ALE LMS

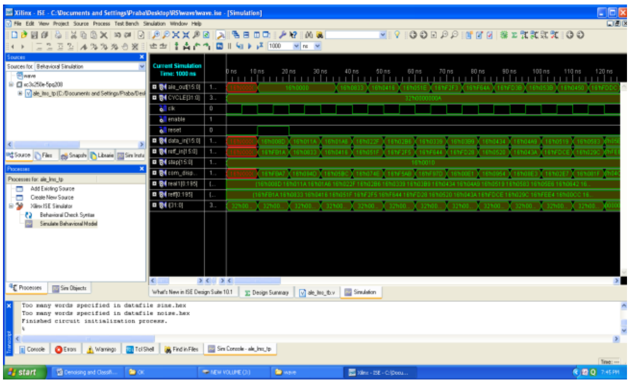

Figure 5: Output waveform for ALE – LMS in Verilog HDL in Xilinx

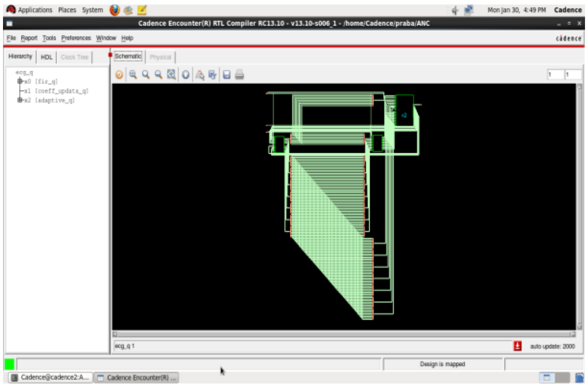

Figure 6: RTL view of ALE – LMS

Table 2: Utilization summary

ALE_LMS in TMSC 90nm	
Gates	9285
Area (µm)	83622
Power (nW)	5050192
Time (ps)	823352

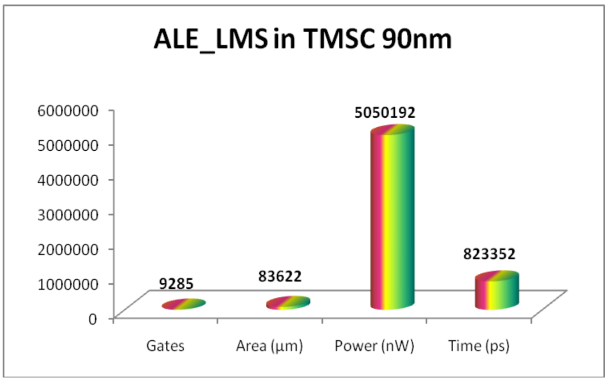

Figure 7: ALE – LMS utilization summary in TMSC 90nm

The figure 6 shows the HDL to RTL view obtained from cadence RC lab at 90nm technology. The ALE- LMS consuming the area, power, no of gates are utilized and the total processing time are shown in table 2 and the graphical representation of the above said values are shown in figure 7.

CONCLUSION

In this paper the adaptive filter using ALE is used to reduce the noise instead of the ANC. ALE was extended based on the ANC, where both systems may utilize related adaptive algorithms and adaptive filter structures. The broadly utilized adaptive algorithm of ALE is the LMS in view of its quick convergence, speed and small computational intricacy. In any case, different adaptive algorithms have additionally been produced to get better performance contrasted with those of conventional LMS for different applications that should be moderately quicker and ease. The analysis conferred the structures of adaptive filters that have been applied to implement adaptive algorithms is obtained with filter order N=8 and step size is 2 the signal to noise ratio (SNR) is 11.437 and the mean square error (MSE) is 41.674 and the other hand the system s consuming area 1443µm, power 182mW and the execution time of the algorithm 1567ps. Using the diverse adaptive filter and adaptive algorithm for improving the system performance like computational intricacy, convergence speed, and design of filter structure, along with adaptation algorithms, which can be used for future implementation.

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