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VLSI Implementation of Adaptive Noise Cancellation for EEG Signal

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Abstract:

Nowadays the Adaptive Noise Cancellation is one of the major techniques of estimating signals corrupted by noise or interference. The main advantage is no acceptable estimates of signal or noise, levels of noise rejection getable that may be troublesome or not possible to attain by different signal process strategies of removing noise. Its cost, inevitably, is that it wants two input signal such as original signal and noisy signal. The reference input is adaptively filtered and ablated from the first input to get the signal estimate. Reconciling filtering before subtraction permits the treatment of inputs that settled or random, stationary or time-variable. The result of unrelated noises in primary and reference inputs, and presence of signal parts within the reference input on the ANC performance is investigated. it's shown that within the absence of unrelated noises and once the reference is freed from signal, noise within the primary input may be basically eliminated while not signal distortion. A configuration of the reconciling noise canceller that doesn't need a reference input and is extremely helpful several applications is additionally use of ANC while not a reference input for canceling periodic interference, reconciling self-tuning filter, antenna aspect lobe interference canceling, cancellation of noise in EEG signals, etc.

Keywords: ANC, FIR, LMS, EEG, EMG, Adaptive Signal Processing

I. INTRODUCTION

Noise cancellation is that the methods of removing background from EEG signal. The degradation of EEG due to the presence of several other noises cause difficulties in varied signal process tasks like EEG recognition, ECG, EMG etc [1]. Several strategies are widely familiar to eliminate noise from EEG signal like linear and nonlinear filtering strategies, adaptive noise cancellation, total variation denoising. EEG improvement aims in up the standard of the EEG signal by reducing the background. Quality of EEG signal is weighed by its clarity, understandability and pleasantness [2]. EEG improvement may be a preliminary procedure within the EEG process space, as well as EEG recognition, EEG synthesis, EEG analysis and EEG writing. In power line EEG signal is typically corrupted with short period noises like impulsive noise. To listeners, these interferences are extremely invasive and will be suppressed so as to boost the standard and understandability of EEG signal. Most of the EEG-signal process algorithms are supported the idea that the noise follows Gaussian distribution and is additive in nature [3].

Adaptive filtering is thought of as a method during which the parameters used for the process of signals changes per some criterion [4]-[6]. Sometimes the criterion is that the predictable mean square error or the correlation. The adaptive filters are time-varying since their parameters are regularly ever-changing so as to satisfy a performance demand. During this sense, an adaptive filter is taken as a filter that performs the approximation tread on -line. Sometimes the definition of the performance criterion needs the existence of a reference signal that's sometimes hidden within the approximation step of fixed- filter style. The overall architecture of adaptive filtering is shown in Figure 1, wherever k is that the iteration range, x(k) denotes the input, y(k) is that the adaptive filter output, and d(k) defines the specified signal. The error signal e(k) is calculated as d(k)- y(k). The error is minimized to improve the performance in this filtering technique from various filter orders and adjusting the filter coefficients with the help of different adaptive algorithm. The reduction of the target operate implies that the adaptive filter signal is matching the specified signal.

II. LITERATURE REVIEW

The least mean square LMS adaptive algorithm is sometimes concerned in several applications like system identification, channel identification, echo and noise cancellation [7]. But there are a unit many drawbacks incorporating with application of such a way. For acoustic noise cancellation applications, the procedure necessities is extremely high, notably once realizing on digital signal processors, since in several cases long impulse responses, representing noise ways needed to be sculptured by adaptive filters. moreover, the convergence of the adaptive filter becomes terribly slow if the input to the adaptive filter could be a signal, with a high spectral dynamic vary attributable to the Manfred Eigen price unfold of the input autocorrelation matrix[8]. These problem particularly vital in moveable applications, wherever the process power should be unbroken minimum [9]. Several solutions are projected in literature. Block adaptive filtering, infinite impulse response IIR adaptive filtering, Least Square algorithm and RLS adaptive filtering examples [10-11]. Unfortunately, these solutions have their own drawbacks. On other hand, multi rate filter advised, to separate the spectrum of the signaling so adaptive filtering exploitation the sturdy LMS methodology may be enforced in sub bands, hopefully achieving quicker convergence, and higher noise cancellation performances [12]. The matter with this method is that the aliasing distortion related to the analysis stage attributable to non ideal analysis filters. A causative implementation may be achieved with terribly high order finite impulse response FIR filters; this suggests high procedure burden and substantial signal delay. If moderate order filters were used, aliasing is associate final aspect result. Aliasing causes the adaptive filters in branches to below model [13] that leaves high residual noise, at the output of the system. One suggestion to beat this drawback is that the use of band stop filters between sub bands; this comes at the expense of introducing signal distortion. Oversampled filter is one among the foremost applicable solutions to avoid aliasing distortion related to the utilization of critically sampled filter, but it implies higher procedure necessities than critically sampled one, additionally thereto, it has been incontestable in literature that oversampled filter themselves, color the signaling, that ends up in below modeling[14]. The special style of analysis/synthesis of the FIR filter projected in a remedy to the current drawback doesn't overcome the complexity problem [15-16].

III.ADAPTIVE NOISE CANCELLATION

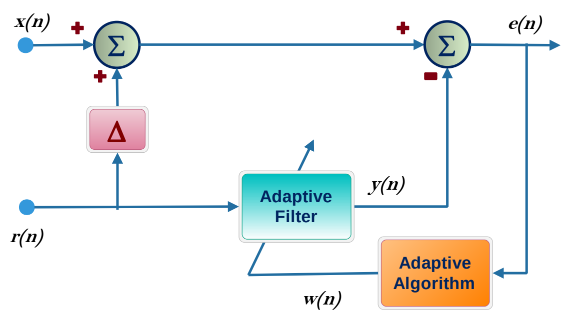

Figure 1 Adaptive Noise Cancellation (ANC)

Adaptive Noise Canceller (ANC) has 2 inputs – primary and reference. The first input receives a sign s from the signal supply that's corrupted by the presence of noise n unrelated with the signal. The reference input receives a noise n0 unrelated with the signal however correlate in how with the noise n. The noise no passes through a filter to provide an output nˆ that is an in depth estimate of primary input noise. This noise estimate is deducted from the corrupted signal to provide to estimate of the signal at sˆ, the ANC system output. In noise canceling systems a sensible objective is to provide a system output sˆ = s + n – nˆ that's a best slot in

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the smallest amount squares sense to the signal s. This objective is accomplished by feeding the system output back to the adaptive filter d adjusting the filter through an LMS adaptive algorithm to attenuate total system output power. In alternative words the system output is the error signal for the adaptive method.

Assume that s, n0, n1and y square measure statistically stationary and have zero means that. The signal s is unrelated with n0 and n1, and n1is correlate with n0.

$$s\hat{} = s + n - n\hat{} \quad (1)$$

$$\Rightarrow \; s\hat{}^2 = s^2 + (n - n\hat{})^2 + 2s(n - n\hat{}) \quad (2)$$

Taking expectation of both sides and realizing that ***s*** is uncorrelated with n_0 and nˆ,

$$E[\, s\hat{}^2] = E[s^2] + E[(n - n\hat{}\,)^2] + 2E[s(n - n\hat{})]$$

$$= E[s^2] + E[(n - n\hat{})^2] \quad (3)$$

The signal power $E[s^2]$ will be unaffected as the filter is adjusted to minimize $E[\, s\hat{}^2]$.

$$\Rightarrow \; \min E[\, s\hat{}^2] = E[s^2] + \min E[(n - n\hat{})^2] \quad (4)$$

Thus, once the filter is adjusted to attenuate the output noise power E[sˆ2], the output noise power E[(n- nˆ)2] is additionally decreased . Since the signal within the output remains constant, thus minimizing the whole output power maximizes the output ratio. Since (sˆ- s) = (n– nˆ) This is comparable to inflicting the output sˆ to be a best method of least squares estimates of the signal s.

IV. LMS ALGORITHM

Least mean squares (LMS) algorithms square measure one in every of the category of adaptive filters accustomed turn out a desired filter by finding the filter coefficients that turn out the smallest amount mean squares of the error signal (difference between the required and therefore the actual signal). The Least Mean Square (LMS) algorithm is adaptive algorithm that uses a gradient-based technique of steepest good [2]. LMS algorithm uses the estimates of the gradient vector from the out there knowledge. LMS follows unvarying procedure that creates sequent corrections to the burden vector that eventually results in the least mean square error The LMS algorithm could be a linear adaptive filtering algorithm that consists of 2 basic processes:

1) A filtering method that computes the output of a linear filter in response to signal generates an estimation error by examination this output with a desired response

2) Adaptive method that adjusts the parameters of the filter in accordance with the estimation error LMS algorithm is vital due to its simplicity and easy computation and since it doesn't need off-line gradient estimation or repetitions of knowledge

A. LMS algorithm Formulation:

The least mean square (LMS) is wide employed in adaptive signal process for its strength and ease. It is famed for its simplicity and its sensible steady state performance in stationary context [12]. Think about generally Associate in Nursing N-tap filter, with the burden vector w(n) at time instant n denoted by,

$$W(n) = [w_1(n) w_2(n) w_3(n) \ldots . w_n(n)]^T \quad (5)$$

Let be the input sequence and x(n)=[x(n)x(n-1)…x(n-N+1)]T be its vector illustration containing the immediate past N samples of . The filter output y(n)=wT(n)x(n) aims to follow a desired signal d(n), and therefore the estimation error e(n) is outlined by

$$e(n) = d(n) - y(n) \quad (6)$$

An adaptive filtering algorithm adjusts the filter faucet weight w(n) at when instant in line with the measured price of e(n). The quality LMS algorithms updates as [10]

$$w(n+1) = w(n) + \mu e(n) x(n) \quad (7)$$

Where μ is outlined because the step-size parameter that affects the convergence behavior of the filter weights.

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V. RESULTS

In this section we tend to judge the performance of every algorithm in noise cancellation setup as shown in Figure 1. The first, primary, and reference signals square measure from the reference.

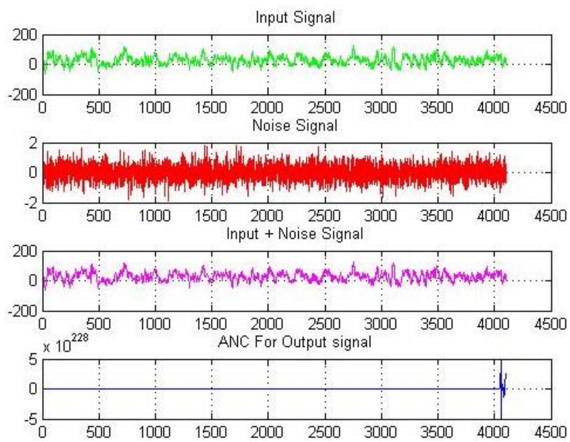

Figure 2 Simulated Output Waveform for ANC.

The first input is corrupted with internal noise. The signal to noise magnitude relation (SNR) of the first signal is -10.2180 dB. The order of the filter was set to M=8. The parameter P was set to 0.002 within the LMS. Figure.2 shows the input signal, noise signal and the filtered output signal and therefore the mean square error (learning curve) within the LMS algorithm. The SNR, MSE and the computation time of the filtered signal is calculated for this experiment. The SNR improvement, MSE and the time are shown in table 1 and the graphical representation are shown in figure 3.

Table 1 Performance Analysis of ALE LMS.

Performance Analysis of ALE LMS				
	N=4	N=8	N=16	N=32
SNR	25.6725	11.4374	6.2007	4.6138
MSE	40.4433	40.4433	37.6231	31.8437
Time	2.142297	1.457516	1.56053	1.82054

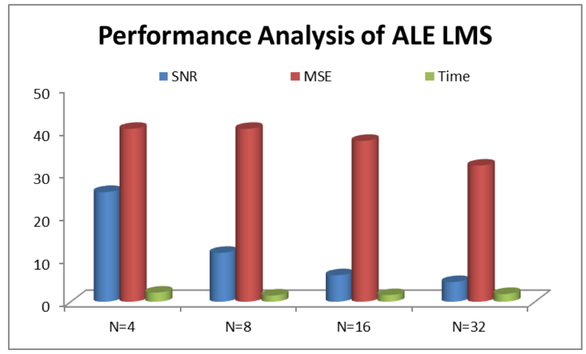

Figure 3 Performance Analysis of ALE LMS.

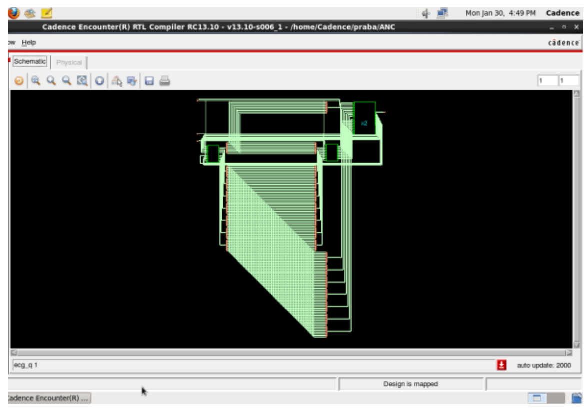

Figure 4. RTL View of ANC

The proposed teschnique was implemented in VLSI design through the Verilog HDL coding. The entire design was simulated and verified in Cadence Encounter TMSC 90nm. The RTL view of ANC are shown in figure 4. In this simulation the entire design are utilizing the no of components like sequential, logical and inveters with respect to the components the design utilizing the area total area is 108594µm, the each components values and areas are shown table 2. The graphical representation of the components and area shown in figure 5. In this manner the device utilizing the power (leakage and dynamic) are shown in table 3 and its represented the figure 6. The time utilization of the proposed design was shown in table 4 and the graphical representation are shown in figure 7.

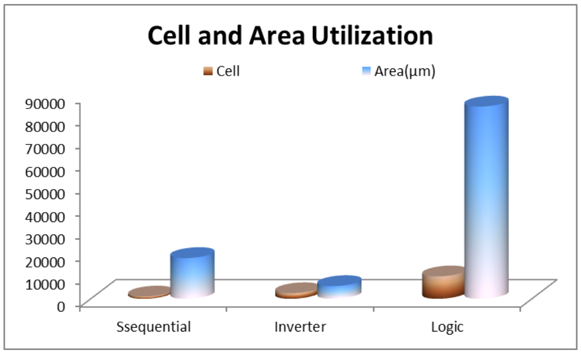

Figure 5. Cell and Area Utilization

Table 2 Utilization of Cells and Area

Cell and Area Utilization		
ANC	Cell	Area(µm)
Sequential	1008	18006
Inverter	2473	5615
Logic	9896	84973
Total	13377	108594

Table 3 Utilization of Power

Power Utilization			
Cells	Static Power(nW)	Dynamic Power (nW)	Total Power(nW)
13377	445118	4043420	4488538

Table 4 Utilization of Time

Time Utilization		
Fall Time (pS)	Rise Time (pS)	Total Time (pS)
2935	6573	9508

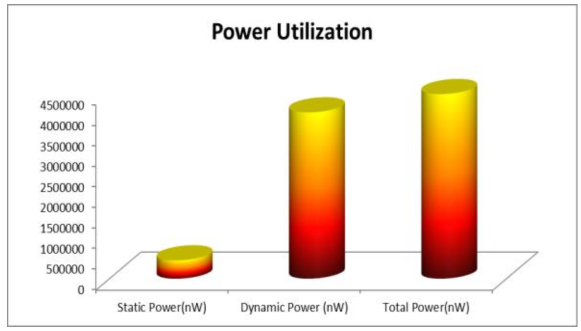

Figure 6. Utilization of Power

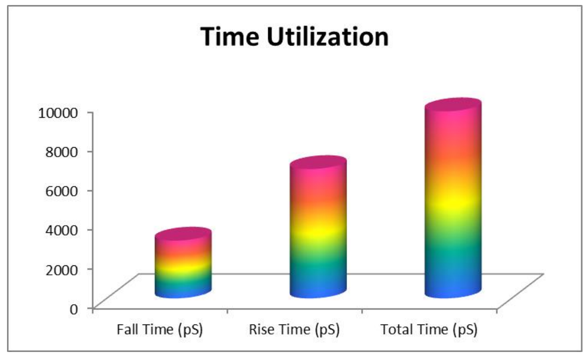

Figure 7. Utilization of Time

VI. CONCLUSIONS

In this paper, we've given a noise reduction technique for EEG and record EEG signals by applying adaptive linear filtering technique. The noise reduction drawback has been developed as a filtering drawback that is expeditiously resolved by exploitation the LMS technique. Additionally, the tactic pays attention to the non-stationary nature of some EEG signal. Simulation results indicate that the proposed technique will improve the performance the standard of EEG signal. Through the simulations, we have incontestable that the projected technique is kind of effective in noise reduction, particularly within the case of stationary white Gaussian noise.

REFERENCES

[1] B.Widrow and S.D. Steams, Adaptive signal processing,Penti-Hall,Inc,NewJersey1985.

[2] S. Hykin, Adaptive filter Theory, 4th edition, Prentice-Hall,UpperSaddleRiver,2002.

[3] K.Tam, H.Sheikhzadeh ,T.Schneider "Highly oversampled sub band adaptive filters for noise cancellation on low resource DSP system", Proc.7thInt. Conf.On Spoken Language Processing,ICSLP,DenverCO,September16-20, 2002.

[4] IShynk, "Multirate Adaptive Filters for The Frequency Domain" IEEE signal processing magazine, January 1992,ppI4-37.

[5] F.Beaufays, "Transform- domain adaptive filters: an analytical approach", IEEE Trail. Signal processing Vol.43,No.2,February1994,pp422-431.

[6] A.Gilloir, M.Vetterli "Adaptive Filtering in Sub bands with Critical Sampling; Analysis, Experiments and Application to Acoustic Echo Cancellation", IEEE Transaction on Signal Processing, Vol40,No.8 Aug. 1992,pp1862-1875.

[7] A.Akansu, M.Smith, "Sub band and Wavelet transforms" CHI2, Kluwer Academic Puplisher, Boston U.S.A,1995.

[8] P.Deleon, D.Etter "Experimental Results with Increased Bandwidth Analysis Filters in Oversampled, Sub band Acoustic Echo Cancellers", IEEE Signal Processing Lettes,Vol2,No.1,January1995,pp1-3.

[9] A.Keya,O.Donmez,D.Oktem, "Subband Adaptive Filters with Statistical Approach" IJCI, Proceedings of International Conference on Signal Processing, Vol.l, No.2, September2003, ISSN1304-2386.

[10] K.Kayabol, E.Tufan, "The Peak-Constrained Optimization of Stable, Linear-Phase IIR PRQMF bank", Int. 1. Electron. ComnlUn. (AEU) 59, pp8-14.

[11] lKliewer, E.Brka, "Near-perfect-reconstruction low-complexity two-band IIR/FIR QMF banks with FIR phase-compensation filters Near-perfect-reconstruction low- complexity two-band IIR/FIR QMF banks with FIR phase- compensation filters", Elsevier Signal Processing 86 ,2006,ppI71-181.

[12] S.Iwarmura, T. Suzuki, U.Tanaka, M.Ikehara, "Design of M-Channel Perfect Reconstruction Filter Banks with IIR-FIR Hybrid Building Block", IEICE Trans. Fundamentals, Vol.E9O-A, No.8 ,August 2007, pp1636-1642.

[13] A.Klouche-Djedid, "Design of Mixed IIR/FIR Two-Channel QMF bank" ,Elsevier Signal Processing, Vol 82,Issue 3,March 2002,pp507 520.

[14] E1. Eliasa, P. Lowenborgb, H.Johansson, LWanhammar, "Tree-structured IIR/FIR uniform-band and octave-band filter banks with very low-complexity analysis or synthesis filters", Elsevier Signal Processing,Vol83,Issue 9,September2003,pp1997-2009.

[15] P.P.Vaidyanathan, "Multirate Digital Filters ,Filter Banks, Poly phase Networks, and Applications: A Tutorial", Proceedings of IEEE, Vol 78,No I, January 1990,pp56-93.

[16] O.Ekiz, A.GConstantinides, "Phase Non-Linearitty in Polyphase Filters", Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing ICASSP, Vol l,5-9June2000,pp321-323.

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