Efficient Variable Step Size Least Mean Squares Adaptive Filter Performance Analysis using Earthquake Seismic Data Records

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***Abstract*—This work will review a newly introduced framework for automated detection of the P-wave arrival for real-time earthquake early warning systems. These systems are prone to suffering from erroneous detection due to high background noise. The original authors introduced an enhanced variable step-size least mean square (EVSSLMS) algorithm that has been shown to considerably improve P-wave detection accuracy [2]. The authors have additionally shown how to implement such filters in VLSI digital hardware design using methods that are suitable for large scale, low-cost, real time monitoring stations. To determine relative efficacy of the EVSSLMS algorithm, its mean square error (MSE) performance and convergence time is compared to several other common algorithms of the least mean square (LMS) variation using seismic sensor data source from Stanford University's Earthquake Dataset [3].**

***Index Terms* — Coordinate rotational digital computer (CORDIC), earthquake early warning system (EEWS), FPGA and ASIC design, half-unit biased (HUB) format, short-time average/long-time-average (STA/LTA) algorithm.**

I. INTRODUCTION

The precise detection of the P-wave arrival time to identify the onset time of an earthquake event is a critical step for correct measurement of different parameters like ground motion period (t_c), high-pass filtered vertical displacement amplitude (P_d), earthquake magnitude and location that can be used for developing an earthquake-early-warning-system (EEWS) [1].

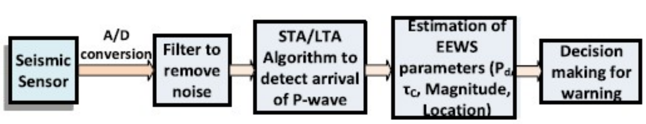

Figure 1: Block diagram of the set-up for EEWS based signal processing.

Traditional short-term average (STA) and long-term average (LTA) earthquake detection algorithms suffer from reduced accuracy when capture data has low signal to noise ratio (SNR). As is seen in Figure 1, it is proposed that a real time adaptive filtering strategy be inserted into the traditional EEWS receiver architecture. This has direct applicability to the EEE 606 course on adaptive filtering, since an adaptive LMS solution is intended to be utilized to improve the EEWS accuracy in low SNR environments.

II. PROPOSED METHODOLOGY

The proposed solution is to implement the EVSSLMS adaptive filter in VLSI as part of a real time adaptive filtering strategy. The EVSSLMS algorithm is detailed via pseudocode in Figure 2 [2].

Algorithm 1 EVSSLMS

Input: Tap Length (N), Input Data ($\mathbf{x}(k)$), Desired Data ($d(k)$), u_{max}, u_{min}, u_{EXTRA}

Output: $y(k)$, $e(k)$, $\theta_m(k)$

Initialization $\theta_m(0) = 0$, $0 \le m \le N-1$

For $k = 1, 2 \ldots .$

Input new $\mathbf{x}(k)$ and $d(k)$

For $m = 0, 1, \ldots, N-1$

$$y(k) = \sum_{i=0}^{N-1} \sin \theta_i(k)\mathbf{x}(k-m)$$

$$e(k) = d(k) - y(k)$$

$$\theta_m(k+1) = \theta_m(k) + u(k)\Delta(k)e(k)\mathbf{x}(k-m)$$

End For

If $(k < k'_{\min}) \&\& u_{\min} < u(k+1) < u_{\max})$ **then**

$$u(k+1) = u(k) + u_{EXTRA} sign(e(k))$$

Else If $(k \ge k'_{\min}) \&\& u_{\min} < u(k+1) < u_{\max})$ **then**

$$u(k+1) = 2^{-r}u(k) - u_{EXTRA} sign(e(k))$$

Else If $(u(k+1) > u_{\max})$ **then**

$$u(k+1) = u_{\max}$$

Else

$$u(k+1) = u_{\min}$$

End If

End For

Figure 2: EVSSLMS Algorithm Pseudocode [2]

The EVSSLMS algorithm is particularly well suited for the application at hand due to two key features. To improve low SNR signal filtering performance, the sign of the residual error is used to influence the coefficient weighting updates once the residual error is below a specified tolerance threshold, detailed in Figure 3.

$$c = \begin{cases} 2^{-r}, & k \geq k'_{\min} \\ 1, & otherwise \end{cases}$$

$$sign(e(k)) = \begin{cases} +1, & e(k) > \xi_{tol} \\ 0, & |e(k)| < \xi_{tol} \\ -1, & e(k) < -\xi_{tol} \end{cases}$$

Figure 3: Signum function error extraction and convergence coefficient (c) [2]

This contrasts with traditional LMS like algorithms which influence coefficient weight updates with both the sign and magnitude of the residual error. In low SNR environments the residual error power can be significant relative to the signal power which in turn can influence an adaptive filter to diverge. The complete weight update equation is provided in Figure 4.

$$u(k+1) = \begin{cases} cu(k) \\ \quad +u_{EXTRA} sign(e(k)), & u_{\min} \leq u(k) \leq u_{\max} \\ u_{\max}, & u(k) > u_{\max} \\ u_{\min}, & otherwise \end{cases}$$

Figure 4: Step size update logic of the EVSSLMS algorithm [2]

Secondly, the EVSSLMS algorithm was developed with VLSI implementation as a forethought. The mathematical operations required by the algorithm can be easily implemented with digital design primitives of low complexity. This results in a resource efficient design that has similar convergence properties of other VLSI adaptive filters.

III. Simulation Results

The performance of the EVSSLMS algorithm was evaluated by using Stanford's Earthquake Dataset [3] as a test stimulus input. The EVSSLMS algorithm was modelled in MATLAB, along with the normalized-LMS (NLMS), the variable step-size LMS (VSSLMS), and the variable-alpha step-size LMS (VASSLMS). The input stimulus was normalized and then AWGN was applied to reduce the SNR to 7 dB.

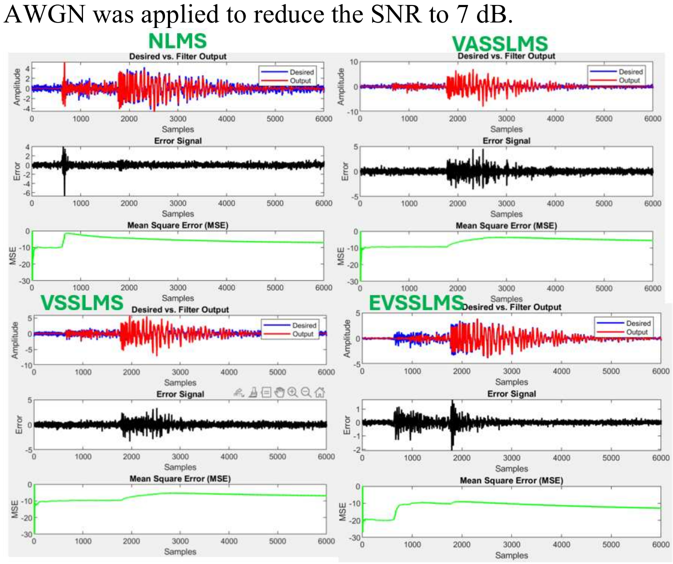

Figure 5: Simulated adaptive filter MSE with STEAD dataset

Figure 5 shows the simulated results with the principal comparison factor being the mean-square error (MSE) in dB. We can see that all of the filters did converge in the steady-state, with the EVSSLMS filter discussed attaining the best average MSE over the course of the sample dataset (6k samples at 1 ksps).

IV. VLSI Implementation

The EVSSLMS filter is easily implemented in VLSI due to subtle reductions in mathematical complexity by implementing power of 2 multiply and divide operations, along with utilization of the CORDIC processor to realize the weighting update term. The entire system can be realized with pipelined multipliers, pipelined CORDIC processor blocks and logic primitives as seen in Figure 6.

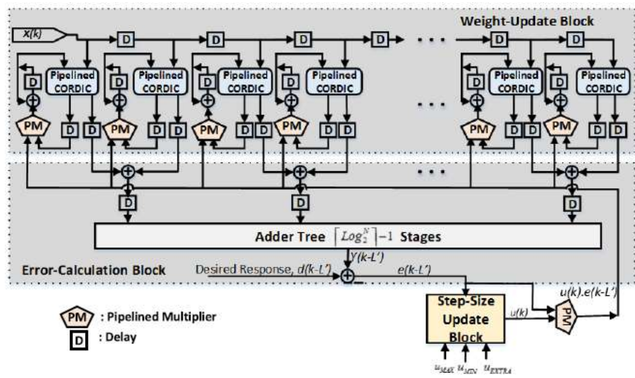

Figure 6: VLSI block diagram of EVSSLMS FIR implementation [2]

V. Conclusion

The EVSSLMS filter is an attractive solution for systems that require low-cost, large-scale, real-time adaptive filtering solutions. The NLMS filter does not perform as well due to its inability to adapt its learning rate as residual error power decreases, which can result in slower convergence rates and increased divergence at low SNR [5]. The VSSLMS and VASSLMS algorithms feature the ability to vary their learning rates, but at the cost of increased mathematical and algorithmic complexity (difficult to scale, larger resource utilization) [6]. The EVSSLMS capitalizes on these weaknesses by providing similar, if not better, MSE performance metrics, while easily being implemented in VLSI due to its low complexity power of 2 multiply/divide and its resourceful utilization of the CORDIC rotational algorithm. In this work the EVSSLMS filter stimulated with real earthquake seismometer data demonstrated its efficacy and usefulness for such EEWS real-time filtering applications.

References

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