

Computationally-Efficient DNLMS-Based Adaptive Algorithms for Echo Cancellation Application

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Abstract—This paper investigates the application of the delayed normalized least mean square (DNLMS) algorithm to echo cancellation. In order to reduce the amount of computations, DNLMS is modified by using computationally-efficient techniques including the M-Max algorithm, a Stop-and-go (SAG) algorithm, and Power-of-two (POT) quantization. For the SAG algorithm, a new stopping criterion related to the regressor energy is presented. Cumulatively, these modifications lead to reductions in power and/or area. Simulation results and comparisons with the normalized least mean square (NLMS) algorithm are included to show the advantages of the computationally-efficient algorithms.

Index Terms—adaptive filtering, echo cancellation, NLMS, DNLMS

I. INTRODUCTION

Adaptive filters on the order of 100 or even 1000 are typically applied in echo cancellation. When considering VLSI implementation, such long filters would result in large resource and high power consumption. Therefore, there is a need for adaptive filtering algorithms geared towards efficient implementation for echo cancellation application.

One of the most common adaptive filtering algorithms used in echo cancellation is the NLMS algorithm. Recently, computationally-efficient techniques have been applied to NLMS for echo cancellation [1]. The modifications to NLMS included adding power-of-two (POT) quantization [2] of the error and regressor, selective-partial coefficient update (namely the M-Max algorithm [3]), and a simple stop-and-go (SAG) algorithm.

In this paper, the application of the delayed NLMS (DNLMS) algorithm is considered. DNLMS has the advantage of allowing pipelining in the error feedback [4], [5]. Pipelining is useful in VLSI design because it facilitates low-power or high-speed architectures [6]. Moreover, DNLMS algorithm is modified with computationally-efficient techniques that lead to reduced power and/or area requirements. These techniques include the M-Max algorithm, a SAG algorithm with a new stopping criterion, and POT quantization of the error and regressor energy. Through analysis and simulations, the tradeoff between computational savings and performance degradation is shown for adaptive echo cancellation system using DNLMS algorithm that uses computationally-

efficient techniques. It is also shown how the proposed algorithm has adequate performance in network and acoustic echo cancellation while achieving significant savings in the amount of computations.

The remainder of this paper is organized as follows. Section II provides background information on echo cancellation, while Section III provides background information on the NLMS and DNLMS algorithms. Section IV discusses computationally-efficient techniques which are applied to DNLMS. Simulation results of network and acoustic echo cancellation are given in Section V followed by conclusions in Section VI.

II. ECHO CANCELLATION BACKGROUND

Echoes are delayed or distorted versions of a sound or signal which have been reflected back to the source [7]. They become distinct and disruptive when their round trip delay is longer than a few tens of milliseconds. In telecommunications, echoes are categorized as either network echoes or acoustic echoes.

Network echoes appear in telephone calls over the public switched telephone network (PSTN). The link connecting the two users is comprised of a two-wire line to connect both phones to their respective local central office and two separate unidirectional lines that make a four-wire inter-office link, as shown in Fig. 1. The hybrid transformer is the device that connects the two-wire circuit to the four-wire circuit. Ideally, the hybrid would transfer all energy from the incoming signal on the four-wire circuit to the two-wire circuit. However, due to imperfect impedance matching, some of the energy is reflected back to its source on the four-wire branch as an echo. Thus, hybrid or network echoes in the PSTN arise from hybrid devices.

Acoustic echoes occur in a loudspeaker-enclosure-microphone (LEM) system. In the LEM system, there exists an electro-acoustic coupling between the loudspeaker and the microphone, resulting in the microphone picking up signals from the loudspeaker as well as signal reflections off surrounding objects and boundaries [8], as illustrated in Fig. 2. Acoustic echoes occur in applications such as teleconferencing and hands-free telephony.

The basic principle of echo cancellation is to eliminate the echo by subtracting from it a synthesized replica. This

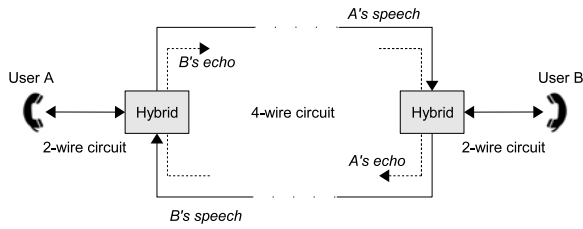


Figure 1. Network echoes over the PSTN.

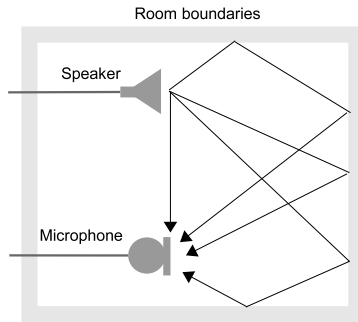


Figure 2. Acoustic echoes.

method of echo control is used to eliminate both network and acoustic echoes. Accordingly, the two different types of echo cancellation are network echo cancellation (NEC) and acoustic echo cancellation (AEC).

In order to create the synthetic echo, the unknown time-varying echo path impulse response is modelled using an adaptive filter. For network echoes, the echo path includes the hybrid transformer, which is different each time a link is arranged. For acoustic echoes, the echo path includes the LEM system, which is dependent on the physical environment. Figure 3 shows the system model used to simulate echo cancellation. When excited by the received signal, the adaptive filter outputs a synthetic echo. By subtracting the synthetic echo, the genuine echo is effectively removed prior to return-transmission. Usually during adaptation, the near-end signal is assumed to be simply noise. This is an adequate assumption because a double-talk detector (DTD) is usually implemented to pause the adaptive filter's adaptation, in order to avoid divergence, when both received and near-end signals are present, i.e. during double talk [9].

A typical measure of echo canceller performance is the echo return loss enhancement (ERLE) ratio, which is defined as

$$ERLE = 10 \log_{10} \frac{E[d^2(n)]}{E[(d(n) - y(n))^2]} \text{dB}, \quad (1)$$

where $d(n)$ is the desired signal (or the actual echo) and $y(n)$ is the output of the filter (or the synthetic echo).

III. NLMS AND DNLMS ALGORITHMS

The NLMS algorithm is commonly used in adaptive filtering, especially for echo cancellation, because of its simplicity and well-established stability characteristics

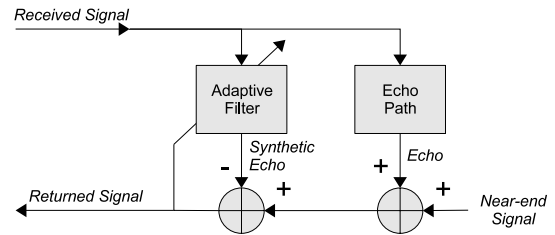


Figure 3. Adaptive echo cancellation system.

[10]. The coefficient update equation for the NLMS algorithm is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x}(n), \quad (2)$$

where $\mathbf{w}(n) = [w_0(n) w_1(n) \cdots w_{N-1}(n)]^T$ is the N -element adaptive filter coefficient vector at sampling instant n , and $\mathbf{x}(n) = [x(n) x(n-1) \cdots x(n-N+1)]^T$ is the N -element regressor vector containing the N last samples of the input $x(n)$ at sampling instant n , where N is the filter length. The error $e(n)$ and the step-size $\mu(n)$ are described by the relations

$$e(n) = d(n) - y(n) \quad (3)$$

$$\mu(n) = \frac{\alpha}{\|\mathbf{x}(n)\|^2 + \beta}, \quad (4)$$

where the output $y(n) = \mathbf{w}^T(n)\mathbf{x}(n)$, $0 < \alpha \leq 2$, β is a small constant preventing division by zero, and $\|\cdot\|$ is the l_2 norm operation. The quantity $\|\mathbf{x}(n)\|^2$ will be referred to as the regressor energy in the remainder of this paper.

It is the feedback error of NLMS that limits the speed of adaptation and prohibits pipelining. Pipelining is a technique of breaking up a signal path by inserting delays, thereby decreasing the critical path and facilitating either a low-power or high-speed architecture. To allow pipelining, (2) can be modified by inserting delays of D samples, resulting in the coefficient update equation for the DNLMS algorithm, i.e.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n-D)e(n-D)\mathbf{x}(n-D). \quad (5)$$

However, there is a tradeoff between the number of samples delayed, D , and the convergence performance of the algorithm.

IV. APPLICATION OF COMPUTATIONALLY-EFFICIENT TECHNIQUES TO DNLMS

In this section, the DNLMS algorithm given in (5) is modified to reduce the amount of computations.

A. M-Max Algorithm

Partial update algorithms update only a portion of the filter coefficients, effectively reducing the demand of memory resources and computation power when implementing adaptive filtering algorithms on digital signal processors (DSPs) [11]. Since the computational cost of adaptive filtering algorithms is proportional to the filter length, partial update algorithm are most effective in long

filter applications such as in echo cancellation applications. Partial update algorithms are considered for VLSI implementation because updating only a portion of the coefficients would decrease the switching activity in the device, thereby reducing the dynamic power consumption [12].

A straightforward selective-partial coefficient update algorithm is the M-Max algorithm [3]. The M-Max algorithm, which was originally applied to NLMS, only updates the taps corresponding to the M largest values of the regressor, where $M < N$. The M-Max-NLMS algorithm saves $N - M$ coefficient updates per iteration while maintaining close performance to NLMS. Extending this algorithm to DNLMS yields the M-Max-DNLMS algorithm, for which the coefficient update equation is given by

$$w_i(n+1) = \begin{cases} w_i(n) + \mu(n-D)e(n-D)x(n-i-D), & \text{if } i \text{ corresponds to one of the first } M \\ \text{maxima of } |x(n-i-D)| & \\ w_i(n), & \text{otherwise} \end{cases} \quad (6)$$

where $i = 0, \dots, N - 1$. The overhead cost of this M-Max algorithm includes implementing a sorting algorithm. If the SORTLINE sorting algorithm [13] is used, the amount of additional comparisons per iteration would be approximately $\lceil 2 \log_2 N \rceil + 2$.

B. SAG Algorithm

A SAG technique was first introduced in [14] to improve the convergence capabilities of decision-aided blind joint equalization and carrier recovery. The idea behind this algorithm is to “stop” adaptation or let it “go” based on the level of the error at the particular sampling time under consideration. In [1], the SAG concept is applied to NLMS in order to further reduce the amount of computations. In this SAG algorithm, when the magnitude of the error is below a pre-defined threshold, coefficient adaptation is stopped for that iteration. This reduces the amount of computations required for the coefficient updates. The coefficient update equation for the SAG-NLMS algorithm is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + f(n)\mu(n)e(n)\mathbf{x}(n) \quad (7)$$

where

$$f(n) = \begin{cases} 1, & |e(n)| > \kappa \\ 0, & |e(n)| \leq \kappa \end{cases} \quad (8)$$

In (8), κ is a positive real number and $f(n)$ is the flag indicating whether or not to update the coefficients. In [1], κ was determined by observing the statistics of $|e(n)|$ over a large number of iterations. Here, the SAG-threshold is related to the regressor energy.

Consider the instantaneous gradient estimate given by

$$\begin{aligned} \Delta \mathbf{w}(n) &= \mathbf{w}(n+1) - \mathbf{w}(n) \\ &= \frac{\alpha}{\|\mathbf{x}(n)\|^2} e(n) \mathbf{x}(n) \end{aligned} \quad (9)$$

where, for simplicity, the β term has been omitted. The coefficient update should be stopped when the $|e(n)|$ is small so that $|\Delta \mathbf{w}(n)|$ is significantly small and $\mathbf{w}(n+1) \approx \mathbf{w}(n)$. To ensure that this condition is true for all values in the vector $\Delta \mathbf{w}(n)$, let us define the stopping criterion in terms of the largest magnitude of $\Delta \mathbf{w}(n)$, which is associated with the largest magnitude of $\mathbf{x}(n)$. The new SAG-stopping criterion is defined as $\max\{|\Delta \mathbf{w}(n)|\} \leq \kappa$, where again κ is a positive real number. Substituting (9) into this condition gives

$$|e(n)| \leq \frac{\kappa}{\alpha \max\{|\mathbf{x}(n)|\}} \|\mathbf{x}(n)\|^2. \quad (10)$$

To avoid division, the stopping criterion in (10) can be rewritten as

$$\frac{\alpha}{\kappa} \max\{|\mathbf{x}(n)|\} |e(n)| \leq \|\mathbf{x}(n)\|^2, \quad (11)$$

where the ratio $\frac{\alpha}{\kappa}$ can be implemented as a single constant. Now, applying the SAG algorithm to DNLMS with the new stopping criterion gives SAG-DNLMS, for which the coefficient update equation is given by

$$\begin{aligned} \mathbf{w}(n+1) &= \\ \mathbf{w}(n) + f(n-D)\mu(n-D)e(n-D)\mathbf{x}(n-D) \end{aligned} \quad (12)$$

where

$$f(n-D) = \begin{cases} 1, & \|\mathbf{x}(n-D)\|^2 < \\ & \frac{\alpha}{\kappa} \max\{|\mathbf{x}(n-D)|\} |e(n-D)| \\ 0, & \|\mathbf{x}(n-D)\|^2 \geq \\ & \frac{\alpha}{\kappa} \max\{|\mathbf{x}(n-D)|\} |e(n-D)| \end{cases} \quad (13)$$

One overhead cost of the SAG algorithm is the calculations of $f(n-D)$, which requires one comparison and two multiplications per iteration. However, if the constants α and κ are power-of-two numbers, then one of the multiplications can be replaced with a shift operation. Another overhead cost is the implementation of a max selection algorithm. A fast algorithm for maximum/minimum calculation across a sliding data window has been proposed in [15] and was labeled the MAXLIST algorithm. This algorithm requires three comparisons and $O(\log N)$ memory locations on average for independent and identically distributed (i.i.d.) input signals. However, if the SAG algorithm is to be used with the M-Max algorithm, then the sorting algorithm also serve to find the maximum values of the regressor.

C. POT Quantization

POT error quantization has been applied to LMS in order to reduce multiplication to a shift operation, reducing the amount of computations [2]. The quantization is a nonlinear operation that results in the error being represented as a binary word with a single “1” bit. This idea can be extended to the regressor energy, thereby

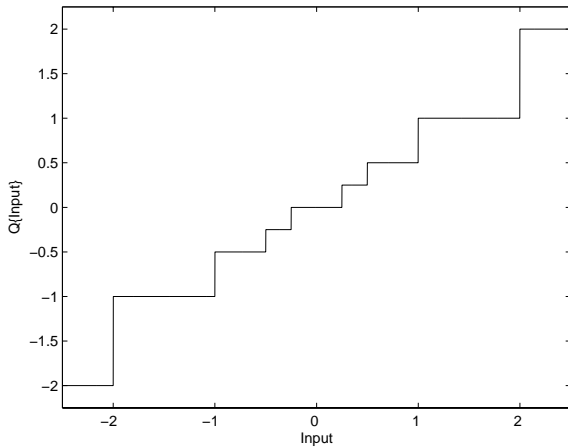


Figure 4. Transfer characteristic of POT quantizer for $a = 2$, $b = 2$, and $\tau = 0$.

allowing the division operation in (4) to be implemented as a shift operation. The POT quantization is given as

$$Q\{\cdot\} = \begin{cases} \text{sgn}\{\cdot\}2^{a-1}, & |\cdot| \geq 2^{a-1} \\ \text{sgn}\{\cdot\}2^{\lfloor \log_2(|\cdot|) \rfloor}, & 2^{-b} \leq |\cdot| < 2^{a-1} \\ \text{sgn}\{\cdot\}\tau, & |\cdot| < 2^{-b} \end{cases} \quad (14)$$

where $a \geq 0$ is the number of integer bits excluding the sign bit, $b \geq 0$ is the number of fractional bits, and τ is set to either 0 or 2^{-b} . Figure 4 illustrates the transfer characteristic of the POT quantizer for $a = 2$, $b = 2$, and $\tau = 0$.

By applying POT quantization to its error and regressor energy, DNLMS is modified to the Quantized-Error-Regressor-energy DNLMS (QER-DNLMS) algorithm, for which the coefficient update equation is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n-D)Q\{e(n-D)\}\mathbf{x}(n-D) \quad (15)$$

where

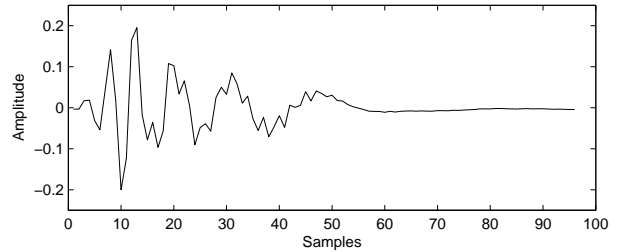
$$\mu(n-D) = \frac{\alpha}{Q\{\|\mathbf{x}(n-D)\|^2 + \beta\}}. \quad (16)$$

Note that if α is chosen to be a POT number, then QER-DNLMS coefficient update equation will consist of $N + 1$ shifts plus 2 POT quantizations in place of N multiplications and 1 division.

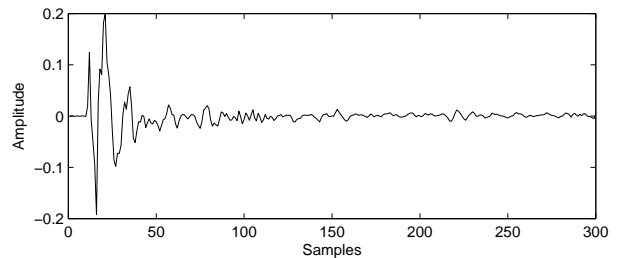
D. Proposed Algorithm

The proposed algorithm is the DNLMS modified with all the techniques previously mentioned in this section. Its coefficient update equation is given by equation (17), where $f(n-D)$ is defined in equation (18) and $\mu(n-D)$ is that in equation (16).

Table I summarizes the total number of multiplications, divisions, additions, shifts, and comparisons that execute over m input samples for each algorithm. The amount of computations was derived under the following assumptions: α is a POT number for all algorithms, resulting in at least one shift operation in the coefficient update calculation; the ratio $\frac{\alpha}{\mu}$ is implemented as a single constant equal to a POT number; the regressor energy is calculated recursively as $\|\mathbf{x}(n)\|^2 = \|\mathbf{x}(n-1)\|^2 + x^2(n) - x^2(n-N)$,



(a)



(b)

Figure 5. Impulse responses of (a) a hybrid echo path from ITU G.168 and (b) an acoustic echo path of the inside of a car.

requiring 2 multiplications and 2 additions per iteration; the SAG algorithms have only g out of m samples in the “GO” mode; and when the SAG algorithms are the “STOP” mode, $\mu(n)$ is not calculated. It can be seen that the proposed algorithm experiences the most reductions in multiplications, divisions, and additions at the expense of shifts and comparisons.

V. SIMULATION RESULTS

In this section, two simulation examples are considered to compare the performance of all algorithms previously discussed in Sections III and IV.

A. Network Echo Cancellation with White Gaussian Input

In this set of simulations, the performance of each algorithm mentioned in the previous sections is investigated under varying parameters for NEC. Simulations are carried out using an echo path impulse response model from the International Telecommunication Union (ITU) G.168 Recommendation [16], shown in Fig. 5(a). The input is white Gaussian noise (WGN) with signal-to-noise ratio (SNR) of 30 dB. The echo return loss (ERL), which is the ratio of the input signal power to the echo signal power, is 6 dB. The filter length is chosen to equal the channel length, i.e., $N = 96$. All simulations have parameters $\alpha = 0.5$ and $\beta = 0.008$. The mean squared error (MSE) is calculated as the average instantaneous squared error over 200 trials.

The first simulation shows how the adaptation delay affects NLMS performance. Figure 6 shows the results using different values of D for DNLMS, where $D = 0$ represents NLMS. It can be seen that as D increases, convergence time increases. Convergence time is defined

$$w_i(n+1) = \begin{cases} w_i(n) + f(n-D)\mu(n-D)Q\{e(n-D)\}x(n-i-D), & \text{if } i \text{ corresponds to one of the first} \\ & M \text{ maxima of } |x(n-i-D)| \\ w_i(n), & \text{otherwise} \end{cases} \quad (17)$$

$$f(n-D) = \begin{cases} 1, & \|\mathbf{x}(n-D)\|^2 < \frac{\alpha}{\kappa} \max\{|\mathbf{x}(n-D)|\} |Q\{e(n-D)\}| \\ 0, & \|\mathbf{x}(n-D)\|^2 \geq \frac{\alpha}{\kappa} \max\{|\mathbf{x}(n-D)|\} |Q\{e(n-D)\}| \end{cases} \quad (18)$$

TABLE I.
NUMBER OF OPERATIONS EXECUTED OVER m INPUT SAMPLES

Algorithm	No. of Multiplications	No. of Divisions	No. of Additions	No. of Shifts	No. of Comparisons
NLMS	$m(2N+2)$	m	$m(2N+3)$	m	0
DNLMS	$m(2N+2)$	m	$m(2N+3)$	m	0
M-Max-DNLMS	$m(M+N+2)$	m	$m(M+N+3)$	m	$m(2\lfloor \log_2 N \rfloor + 2)$
SAG-DNLMS	$gN + m(N+3)$	g	$gN + m(N+3)$	$g+m$	$4m$
QER-DNLMS	$m(N+2)$	0	$m(2N+3)$	$m(N+2)$	0
Proposed algorithm	$m(N+2)$	0	$gM + m(N+3)$	$g(M+2) + 2m$	$m(2\log_2 N + 3)$

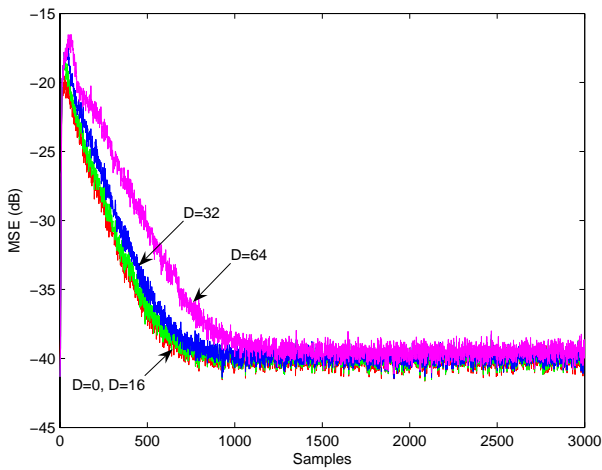


Figure 6. MSE curves of DNLMS for different D 's.

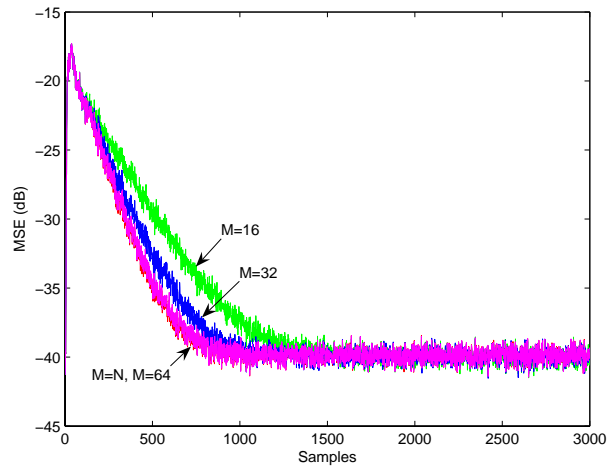


Figure 7. MSE curves of M-Max-DNLMS for different M 's.

as the time required for the MSE curve to reach 90% of its final MSE value. For the remaining simulations, $D = 32$ is used to obtain reasonable performance.

Next, the affects of using different values of M for M-Max-DNLMS are illustrated. Note that for $M = N$ the M-Max-DNLMS is reduced to DNLMS. Figure 7 shows that as M decreases, there is more degradation in convergence performance.

Next, simulations to investigate how varying κ affects the MSE learning curve of SAG-DNLMS are carried out. Note that $\kappa = 0$ represents DNLMS. It is shown in Fig. 8 that as κ increases, convergence time increases. Table II shows how often, on average over 200 trials, the SAG-DNLMS coefficients were updated before and after convergence. This table also includes results for the proposed algorithm, which will be discussed later. For SAG-DNLMS, it can be seen that as κ increases, the percentage of samples in the "GO" mode decreases drastically, especially after convergence.

The next simulation results show how DNLMS is affected by POT quantization. Quantized-Error DNLMS (QE-DNLMS) has POT quantization of the delayed error

TABLE II.
IMPACT OF SAG ALGORITHM UNDER WGN INPUT

Algorithm	κ	Percent Samples in "GO" mode	
		Before Convergence	After Convergence
SAG-DNLMS	0.0005	63.24	35.32
SAG-DNLMS	0.0010	31.64	6.75
SAG-DNLMS	0.0015	21.16	1.41
Proposed	2^{-11}	44.97	14.13

$e(n-D)$ to an 8-bit word ($a = 1, b = 6$). Quantized-Regressor-energy DNLMS (QR-DNLMS) has POT quantization of the delayed regressor energy $\|x(n-D)\|^2$ to an 8-bit word ($a = 7, b = 0$). As mentioned in the previous section, QER-DNLMS has POT quantization of both the delayed error and regressor energy to the same wordlengths used for QE-DNLMS and QR-DNLMS respectively. For QE-DNLMS, $\tau = 0$ and for QR-DNLMS, $\tau = 2^{-b}$ because both achieved better performances for those choices of τ . Figure 9 shows that, compared to DNLMS, QE-DNLMS converges slower but achieves a lower steady-state MSE, QR-DNLMS converges slower and achieves a higher steady-state MSE,

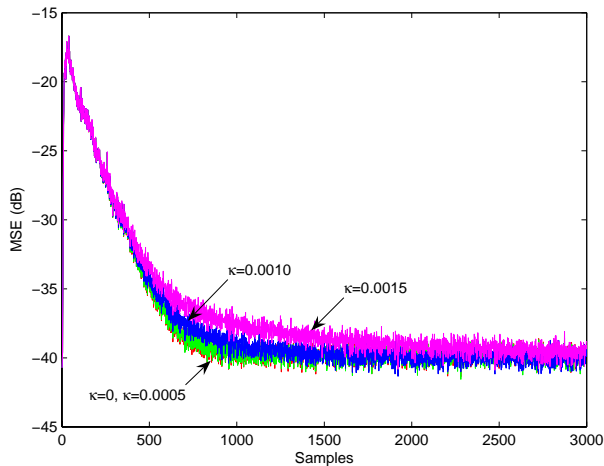
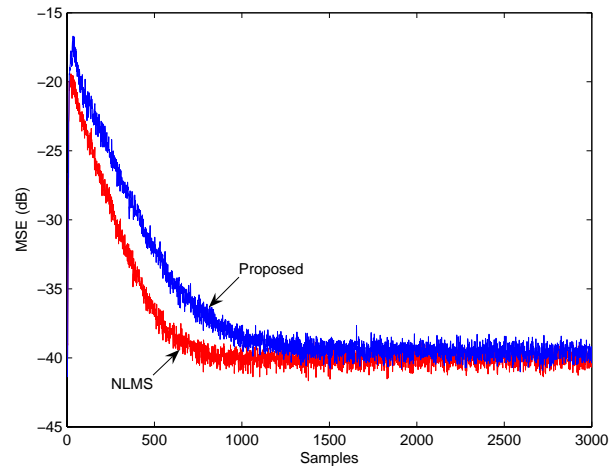
Figure 8. MSE curves of SAG-DNLMS for different κ 's.

Figure 10. MSE curves of NLMS and Proposed algorithm.

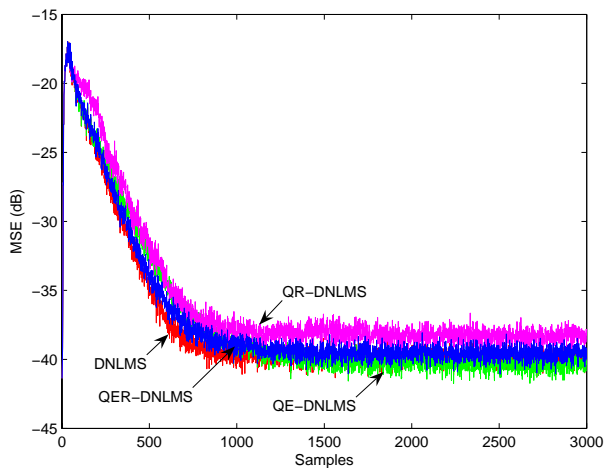


Figure 9. MSE curves of DNLMS under different quantization algorithms.

and QER-DNLMS achieves similar performance.

Finally, the performance of the proposed algorithm is compared to that of NLMS. The parameter chosen include $D = 32$, $M = 32$, $\kappa = 2^{-11}$, quantization of $e(n-D)$ to an 8-bit word ($a = 1, b = 6, \tau = 0$), and quantization of $\|x(n-D)\|^2$ to an 8-bit word ($a = 7, b = 0, \tau = 2^{-b}$). From Fig. 10, it can be seen that the proposed algorithm has moderate performance degradation when compared to NLMS. From Table II, it can be seen that the proposed algorithm experiences significant reductions in computations due to its SAG-related portion alone.

B. Network and Acoustic Echo Cancellation with Composite Source Signal Input

In this simulation example, NLMS and the proposed algorithm are simulated for both NEC and AEC applications. The input used in this simulation is the composite source signal (CSS) from ITU G.168. The CSS has been downsampled to 8 kHz. It is approximately 350 ms long and consists of a 48.62 ms duration voice signal, a 200 ms duration pseudo-noise signal, and a 101.38 ms duration

pause. This sequence is repeated as many times as needed, with an inversion at each repetition, to create a longer signal.

For NEC, the echo path shown in Fig. 5(a) is once again used. For AEC, the echo path impulse response model of the inside of a car, shown in Fig. 5(b), is used. The SNR is 30 dB. The filter lengths are given as $N = 96$ for NEC and $N = 300$ for AEC. Algorithmic parameters for NLMS and the proposed algorithm in both NEC and AEC simulations include $\alpha = 0.125$ and $\beta = 0.008$. Additionally, the proposed algorithm has the following parameters: $M = 32$ for NEC and $M = 128$ for AEC; $\kappa = 2^{-13}$ for NEC and $\kappa = 2^{-14}$ for AEC; and all remaining parameters are the same as the ones used in the first simulation example.

Figure 11 shows the residual echo and corresponding ERLE of NLMS and the proposed algorithm for NEC simulation. It is shown that the echo is effectively cancelled after the first CSS sequence for both algorithms. Also, the proposed algorithm achieves similar ERLE performance to NLMS.

For AEC simulation, Fig. 12 shows that the echo is effectively cancelled after the third CSS sequence. Although the proposed algorithm initially has a lower ERLE performance than NLMS in periods when the input is a voice signal, it achieves similar ERLE performance to NLMS in all other periods.

Finally, Table III shows, for the proposed algorithm under NEC and AEC simulations, how often the samples were in the "GO" mode over the voice, pseudo noise, and pause portions of the input. It can be seen that the proposed algorithm provides a significant amount of computational savings, especially during periods of pause.

VI. CONCLUSION

In this paper, computationally-efficient DNLMS-based algorithms have been considered for echo cancellation applications. Our interest in DNLMS stems from the fact that unlike NLMS, DNLMS allows pipelining, which

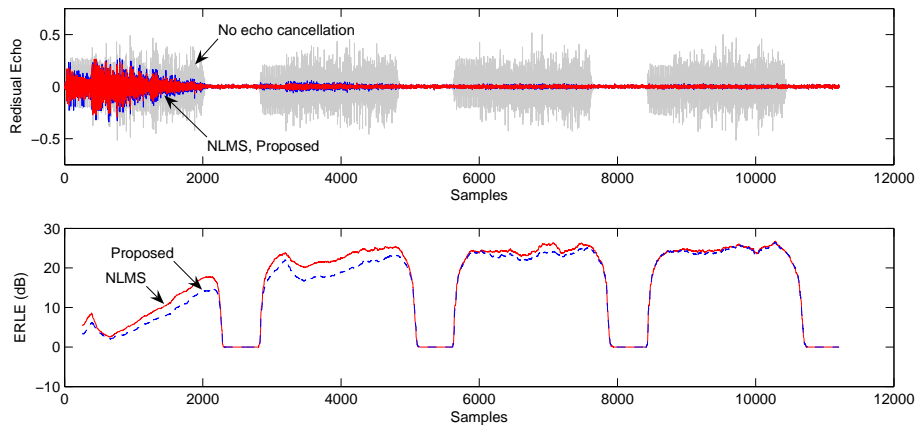


Figure 11. Residual echo and ERLE of NLMS and proposed algorithm for NEC.

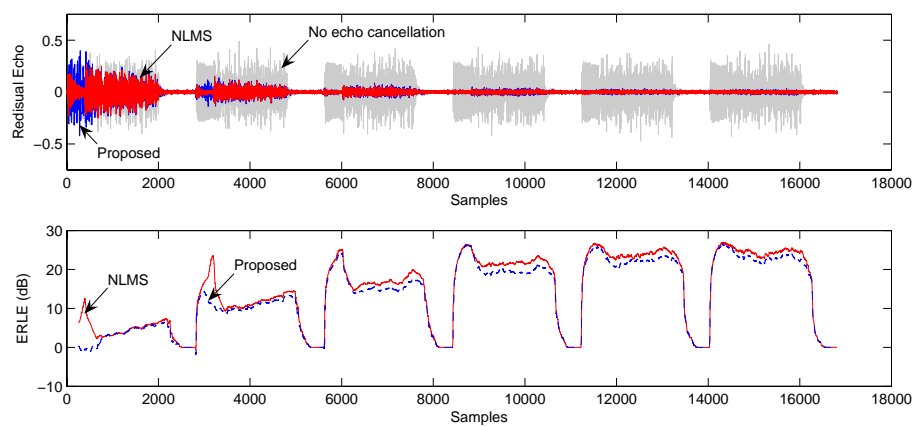


Figure 12. Residual echo and ERLE of NLMS and proposed algorithm for AEC.

TABLE III.
IMPACT OF SAG ON PROPOSED ALGORITHM UNDER CSS INPUT

	Percent Samples in "GO" mode		
	Voice	Pseudo Noise	Pause
NEC	32.13	42.23	2.42
AEC	34.33	50.54	6.28

in turn allows low-power or high-speed architectures when considering VLSI implementation. The DNLMS algorithm has been modified by using the M-Max algorithm and a SAG algorithm. This has decreased the amount of computations, which would result in reduced power consumption. For the SAG algorithm, a new and effective stopping criterion has been introduced. Power-of-two quantization was incorporated in DNLMS, which has reduced multiplication or division operation to a single shift, thus further reducing the amount of computations. NEC and AEC simulations have shown that, compared to NLMS, the proposed algorithm experienced only moderate performance degradation when using either WGN input or ITU G.168 CSS input.

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