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A low intricacy variable step-size partial update adaptive algorithm for Acoustic Echo Cancellation

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Abstract—*In this paper, adaptive filtering techniques based on partial update adaptive algorithms have been proposed which reduce the intricacy of the filter design. As the number of filter coefficients selected for adaptation reduces, the performance of partial update algorithm also reduces for MMax tap-selection algorithm which is one of the most popular tap-selection algorithms. A proposal of fast converging adaptive algorithm while keeping the complexity of the filter design low that exploits the MMax tap-selection is made. By deriving a variable step-size, fast convergence with low intricacy is achieved for the MMax normalized least-mean-square (MMax-NLMS) algorithm using its mean square deviation. Simulation results verify that the proposed algorithm achieves higher rate of convergence with low computational complexity compared to the NLMS algorithm.*

Index Terms— **Acoustic echo cancellation, Partial update adaptive filtering, Variable Step-size, Adaptive algorithms.**

I. INTRODUCTION

Adaptive filtering with finite impulse response (FIR) finds extensive application in signal processing. The normalized least-mean-square (NLMS) algorithm [2] [3] is treated as one of the most popular adaptive algorithms in many applications such as acoustic echo cancellation (AEC). By modeling the Loudspeaker-Room-Microphone (LRM) system using an adaptive filter, a replica of the echo can be generated for achieving effective echo cancellation as shown in fig 1. Challenges encountered when implementing an acoustic echo canceller are (i) the highly time-varying nature of the impulse response [4] and (ii) the long duration of the LRM system, which can require several thousands of filter coefficients for accurate modeling. Since the NLMS algorithm requires $O(2L)$ multiply accumulate (MAC) operations per sampling period, it is very desirable to reduce the computational workload of the processor, especially for the real-time implementation of AEC algorithms in portable devices where power budget is a constraint. Partial update adaptive algorithms differ in the criteria used for selecting filter coefficients to update at each of the iteration. It is found that as the number of filter coefficients updated per iteration in a partial update adaptive filter is reduced, the computational complexity is also reduced but at the expense of some loss in performance. The aim of this paper is to propose a low complexity, fast converging adaptive algorithm for AEC. It has been shown in [7] that the convergence performance of MMax-NLMS is dependent on the step-size when identifying an LRM system. Analysis of the mean-square deviation of MMax-NLMS is first presented and then a variable step-size in order to increase its rate of convergence is derived.

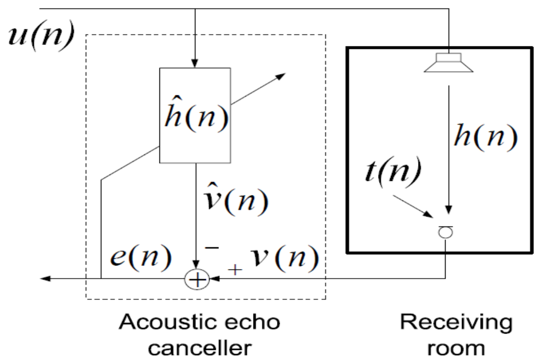

Fig.1. Acoustic Echo Canceller

The simulation results verify that the proposed variable step-size MMax-NLMS (MMax- NLMSvss) algorithm achieves higher rate of convergence with lower computational complexity compared to NLMS for both white Gaussian noise (WGN) and speech inputs.

II. MMAX-NLMS ALGORITHM

Fig.1 shows an echo canceller in which, at the nth iteration, $v(n) = \mathbf{u}^T(n)\mathbf{h}(n)$ where $\mathbf{u}(n) = [u(n). . . ., u(n - L + 1)]^T$ is the tap-input vector while the unknown LRM system $h(n) = [h_o(n),.....,h_{L-1}(n)]^T$ is of length L. An adaptive filter $\hat{h}(n) = [\hat{h}_o(n),.....,\hat{h}_{L-1}(n)]^T$ which assumed [3] to be of equal length to the unknown system $\mathbf{h}(n)$, is used to estimate $\mathbf{h}(n)$ by adaptively minimizing the *a priori* error signal $e(n)$ using $\hat{v}(n)$ defined by

$$e(n) = u^T(n)h(n) - \hat{v}(n) + g(n) \quad \text{— (1)},$$

$$\hat{v}(n) = u^T(n)\hat{h}(n-1) \text{ — (2)}$$

With $g(n)$ being the measurement noise. In the MMax-NLMS algorithm [5], only those taps corresponding to the M largest magnitude tap-inputs are selected for updating at each iteration with $1 \leq M \leq L$. defining the sub-selected tap-input vector

$$\hat{u}(n) = Q(n)u(n) \quad \text{— (3)}$$

where $\mathbf{Q}(n) = \text{diag}\{q(n)\}$ is an $L \times L$ tap selection matrix and $\mathbf{Q}(n) = [q_0(n), . . . , q_{L-1}(n)]^T$, the element $q_j(n)$ for $j= 0, 1, . . . , L - 1$ is given by,

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$$q_j(n) = \begin{cases} 1 & |u(n-j)| \in \{\text{M Maxima of } |\mathbf{u}(n)|\} \\ 0 & otherwise \end{cases} \quad (4)$$

Where $|\mathbf{u}(n)| = \left[|u(n)|, \ldots\ldots, |u(n-L+1)|\right]^T$.

Defining $\|.\|^2$ as the squared l_2-norm, the MMax-NLMS tap-update equation is then given by

$$\hat{\boldsymbol{h}}(n) = \hat{\boldsymbol{h}}(n-1) + \frac{\mu \mathbf{Q}(n)\mathbf{u}(n)e(n)}{\|\mathbf{u}(n)\|^T + C} \text{ — } (5)$$

where C is the regularization parameter. Defining $\mathbf{I}_{L\times L}$ as the LxL identity matrix, it is noted that if $\mathbf{Q}(n) = \mathbf{I}_{L\times L}$, i.e., with $M = L$, the update equation in (5) is equivalent to the NLMS algorithm. Similar to the NLMS algorithm, the step-size μ in (5) controls the ability of MMax-NLMS to track the unknown system which is reflected by its rate of convergence. To select the M maxima of $|\mathbf{u}(n)|$ in (4), MMax-NLMS employs the SORTLINE algorithm [8] which requires $2\log_2 L$ sorting operations per iteration. The computational complexity in terms of multiplications for MMax-NLMS is $O(L+M)$ compared to $O(2L)$ for NLMS. The performance of MMax-NLMS normally reduces with the number of filter coefficients updated per iteration. This tradeoff between complexity and convergence can be shown by first defining

$$\xi(n) = \frac{\|\boldsymbol{h}(n) - \hat{\boldsymbol{h}}(n)\|^2}{\|\boldsymbol{h}(n)\|^2} \text{ — } (6)$$

as the normalized misalignment. Fig.2 and Fig.3 show the variation in convergence performance of MMax-NLMS with M for the case of $L = 128$ and $\mu = 0.1$ using a white Gaussian noise (WGN) input. For this illustrative example, WGN $g(n)$ is added to achieve a signal-to-noise ratio (SNR) of 30dB. It can be seen that the rate of convergence reduces with reducing M as expected.

III. MEAN SQUARE DEVIATION OF MMAX-NLMS

It has been shown in [7] that the convergence performance of MMax- NLMS is dependent on the step-size μ when identifying an LRM system. Since the aim of this paper is to reduce the degradation of convergence performance due to partial updating of the filter coefficients, from Fig.2 it is clear that the convergence performance decreases as M=L/4. Fig.3 shows the Normalized misalignment verses Time. The MSD of MMax-NLMS can be obtained by first defining the system deviation as

$$\grave{o}(n) = \boldsymbol{h}(n) - \hat{\boldsymbol{h}}(n) \text{ — } (7),$$

$$\grave{o}(n-1) = \boldsymbol{h}(n) - \hat{\boldsymbol{h}}(n-1) \text{ — } (8)$$

Subtracting (8) from (7) and using (5), we obtain

$$\grave{o}(n) = \grave{o}(n-1) + \frac{\mu \mathbf{Q}(n)\mathbf{u}(n)e(n)}{\mathbf{u}^T(n)\mathbf{u}(\mathbf{n}) + C} \text{ — } (9).$$

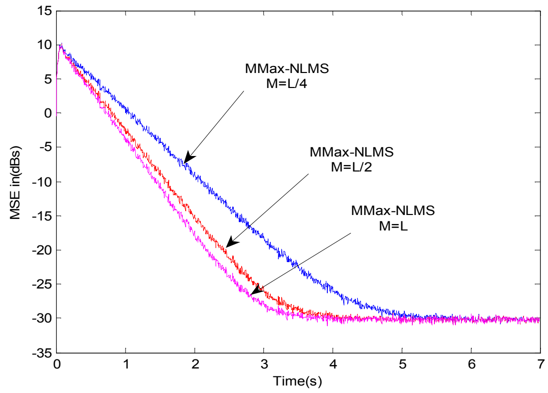

Fig.2. Convergence curves of MMax-NLMS for different M.

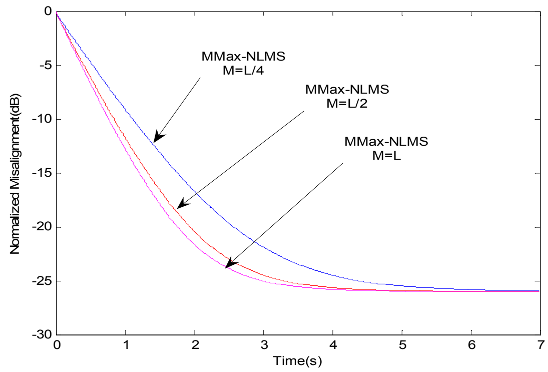

Fig.3 Normalized Misalignment curves for Different M.

Defining $\varphi\{.\}$ as the expectation operator and taking the mean square of (9), the MSD of MMax-NLMS can be expressed iteratively as (10)

$$\varphi\left\{\|\grave{o}(n)\|^2\right\} = \varphi\left\{\grave{o}^T(n)\grave{o}(n)\right\} = \varphi\left\{\|\grave{o}(n-1)\|^2\right\} - \varphi\{\Phi(\mu)\}$$

Where

$$\varphi\{\Phi(\mu)\} = \varphi\left\{\frac{2\mu\tilde{\mathbf{u}}^T(n)\grave{o}(n-1)e(n)}{\|\mathbf{u}(n)\|^2} - \frac{\mu^2\|\tilde{\mathbf{u}}(n)\|^2 e^2(n)}{\left[\|u(n)\|^2\right]}\right\}$$

— (11)

Assume that the effect of the regularization term Con the MSD is small. As can be seen from (10), in order to increase the rate of convergence for the MMax-NLMS algorithm, step-size µ is chosen such that $\varphi\{\Phi(\mu)\}$ is maximized.

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IV. THE PROPOSED MMAX-NLMS$_{VSS}$ ALGORITHM

Following the approach of [7], differentiating (11) with respect to μ and setting the result to zero,

$$\varphi\left\{\frac{\mu(n)\|\tilde{\mathbf{u}}(n)\|^2 e^2(n)}{\left[\|\mathbf{u}(n)\|^2\right]}\right\}=\varphi\left\{\delta^T(n-1)\tilde{\mathbf{u}}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}e(n)\right\}$$

giving the variable step-size

$$\mu(n)=\mu_{max}\times\frac{\delta^T(n-1)\tilde{\mathbf{u}}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\mathbf{u}^T(n)\delta(n-1)\|\mathbf{u}(n)\|^2}{\|\tilde{\mathbf{u}}(n)\|^2\delta^T(n-1)\mathbf{u}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\mathbf{u}^T(n)\delta(n-1)+\sigma_g^2 M(n)}$$

where $0 < \mu_{max} \leq 1$ limits the maximum of $\mu(n)$ and from [7]

$$M(n)=\frac{\|\tilde{u}(n)\|^2}{\|u(n)\|^2} \quad \text{— (12)}$$

is the ratio between energies of the sub-selected tap-input vector $\tilde{\mathbf{u}}(n)$ and the complete tap-input vector $\mathbf{u}(n)$, while $\sigma_g^2=\varphi\{g^2(n)\}$. To simplify the numerator of $\mu(n)$ further, considering

$\tilde{\mathbf{u}}(n)\mathbf{u}^T(n)=\tilde{\mathbf{u}}(n)\tilde{\mathbf{u}}^T(n)$ [1]

$$\mu(n)=\mu_{max}\times\frac{\delta^T(n-1)\tilde{\mathbf{u}}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\tilde{\mathbf{u}}^T(n)\delta(n-1)\|\mathbf{u}(n)\|^2}{\|\tilde{\mathbf{u}}(n)\|^2\delta^T(n-1)\mathbf{u}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\mathbf{u}^T(n)\delta(n-1)+\sigma_g^2 M(n)}$$

$\mu(n)$ can be further simplified by letting

$$\tilde{\mathbf{P}}(n)=\tilde{\mathbf{u}}(n)\left[\mathbf{u}^T(n)\mathbf{u}(n)\right]^{-1}\tilde{\mathbf{u}}^T(n)\delta(n-1) \quad \text{— (13)}$$

$$\mathbf{P}(n)=\mathbf{u}(n)\left[\mathbf{u}^T(n)\mathbf{u}(n)\right]^{-1}\mathbf{u}^T(n)\delta(n-1) \quad \text{— (14)}$$

from which it is then shown that [1]

$$\|\tilde{\mathbf{P}}(n)\|^2=M(n)\delta^T(n-1)\tilde{\mathbf{u}}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\tilde{\mathbf{u}}^T(n)\delta(n-1)$$

$$\|\mathbf{P}(n)\|^2=\delta^T(n-1)\mathbf{u}(n)\left[\|\mathbf{u}(n)\|^2\right]^{-1}\mathbf{u}^T(n)\delta(n-1)$$

Following the approach in [8], and defining $0 << \alpha < 1$ as the smoothing parameter, $\tilde{\mathbf{P}}(n)$ and $\mathbf{P}(n)$ are estimated iteratively by

$$\tilde{\mathbf{P}}(n)=\alpha\tilde{\mathbf{P}}(n-1)+(1-\alpha)\tilde{\mathbf{u}}(n)\left[\mathbf{u}^T(n)\mathbf{u}(n)\right]^{-1}e_a(n) \quad \text{— (15)}$$

$$\mathbf{P}(n)=\alpha\mathbf{P}(n-1)+(1-\alpha)\mathbf{u}(n)\left[\mathbf{u}^T(n)\mathbf{u}(n)\right]^{-1}e(n) \quad \text{— (16)}$$

Where $e(n)=\mathbf{u}^T(n)\delta(n-1)$ in (16) while the error $e_a(n)$ due to active filter coefficients $\tilde{\mathbf{u}}(n)$ in (15) is given as

$$e_a(n)=\tilde{\mathbf{u}}^T(n)\delta(n-1)=\tilde{\mathbf{u}}^T(n)\left[\boldsymbol{h}(n)-\hat{\boldsymbol{h}}(n-1)\right] \text{—(17).}$$

It is important to note that since $\tilde{\mathbf{u}}^T(n)\mathbf{h}(n)$ is unknown, $e_a(n)$ is to be approximated. Defining $\bar{\mathbf{Q}}(n)=\mathbf{I}_{L\times L}-\mathbf{Q}(n)$ [1] as the tap-selection matrix which selects the inactive taps, we can express $e_i(n)=\left[\bar{\mathbf{Q}}(n)\mathbf{u}(n)\right]^T\delta(n-1)$ as the error contribution due to the inactive filter coefficients such that the total error $e(n) = e_a(n) + e_i(n)$. As explained in [7], for $0.5L \leq M < L$, the degradation in M(n) due to tap-selection is negligible. This is because, for M large enough, elements in $\bar{\mathbf{Q}}(n)\mathbf{u}(n)$ are small and hence the errors $e_i(n)$ are small, as is the general motivation for MMax tap-selection [8]. We can then approximate $e_a(n) \approx e(n)$ in (15) giving

$$\tilde{\mathbf{P}}(n)\approx\alpha\tilde{\mathbf{P}}(n-1)+(1-\alpha)\tilde{\mathbf{u}}(n)\left[\mathbf{u}^T(n)\mathbf{u}(n)\right]^{-1}e(n) \quad \text{— (18).}$$

Using (16) and (18), the variable step-size is then given as

$$\mu(n)=\mu_{max}\frac{\|\tilde{P}(n)\|^2}{M^2(n)\|\mathbf{P}(n)\|^2+C} \quad \text{— (19)}$$

Where $C=M^2(n)\sigma_g^2$ Since σ_g^2 is unknown, it is shown that approximating C by a small constant, typically 0.0001 [9]. The computation of (16) and (18) each requires M additions. In order to reduce computation even further, and since for M large enough the elements in $\bar{\mathbf{Q}}(n)\mathbf{u}(n)$ are small, we can approximate $\|\mathbf{P}(n)\|^2=\|\tilde{P}(n)\|^2$ giving

$$\mu(n)=\mu_{max}\frac{\|\tilde{P}(n)\|^2}{M^2(n)\|\tilde{P}(n)\|^2+C} \quad \text{— (20).}$$

When $\mathbf{Q}(n) = \mathbf{I}_{L\times L}$, i.e., $M = L$, MMax-NLMS is equivalent to the NLMS algorithm and from (12), M(n) = 1 and $\|\tilde{P}(n)\|^2=\|\mathbf{P}(n)\|^2$. As a consequence, the variable step-size $\mu(n)$ in (20) is consistent with that presented in [9] for $M = L$.

V. SIMULATION RESULT

The performance of MMax-NLMS$_{vss}$ in terms of the normalized misalignment is determined and defined in (6) using both WGN and speech inputs. With a sampling rate of 8 kHz and a reverberation time of 256 ms, the length of the impulse response is $L = 1024$. Similar to [9], $C = 0.0001$, $\alpha = 0.15$ are taken, WGN $g(n)$ is added to v(n) to achieve an SNR of 30dB.The value of $\mu_{max} = 1$ is taken for MMax-NLMS$_{vss}$ while step-size μ for the NLMS algorithm is adjusted so as to achieve the same steady-state performance for all simulations.

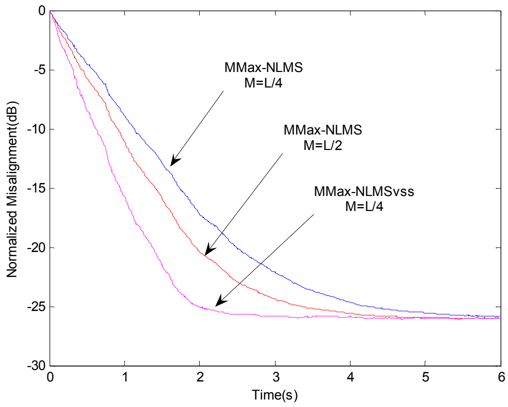

Fig.4. Improvement in convergence performance of MMax-NLMSvss over MMax-NLMS for different M.

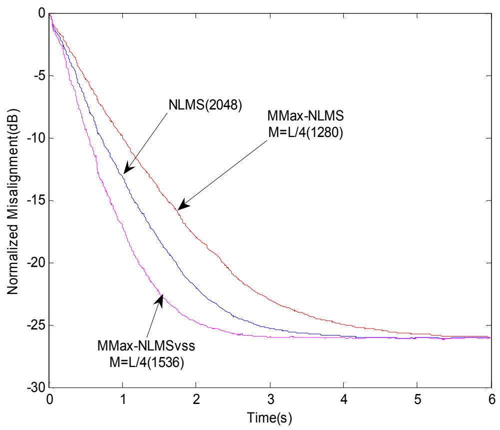

Fig.5. Comparison curves of Convergence performance of MMax-NLMSvss with NLMS and MMax-NLMS.

Fig.4 shows the improvement in convergence performance of MMax-NLMS$_{vss}$ over MMax-NLMS for the cases of M = L/4. The step-size of NLMS has been adjusted in order to achieve the same steady-state normalized misalignment. This corresponds to μ = 0.1. More importantly, the proposed MMax-NLMS$_{vss}$ algorithm outperforms NLMS even with lower complexity when M =256. This improvement in normalized misalignment of 7 dB (together with a reduction of 25% in terms of multiplications) over NLMS is due to variable step-size for MMax-NLMS$_{vss}$. The MMax-NLMS$_{vss}$ achieves the same convergence performance as the NLMSvss [9] when M = L. The performance of MMax-NLMS$_{vss}$ for a male speech input is depicted in Fig.6. For this simulation, L = 1024 and an SNR=30 dB are used as before. In order to illustrate the benefits of the proposed algorithm, M = 256 taken for both MMax-NLMS and MMax-NLMS$_{vss}$. This gives a 25% savings in multiplications per iteration for MMax-NLMS$_{vss}$ over NLMS. As can be seen, even with this computational savings, the proposed MMax-NLMS$_{vss}$ algorithm achieves an improvement of 1.5 dB in terms of normalized misalignment over NLMS.

VI. CONCLUSION

A low intricacy partial update MMax-NLMS algorithm is introduced with a variable step-size during adaptation. This is derived by analyzing the mean-square deviation of MMax-NLMS. In terms of convergence performance, the proposed MMax-NLMS$_{vss}$ algorithm achieves approximately 3 and 1.5 dB improvement in normalized misalignment over NLMS for both WGN and speech input respectively. More importantly, the proposed algorithm can achieve higher rate of convergence with lower computational complexity compared to NLMS.

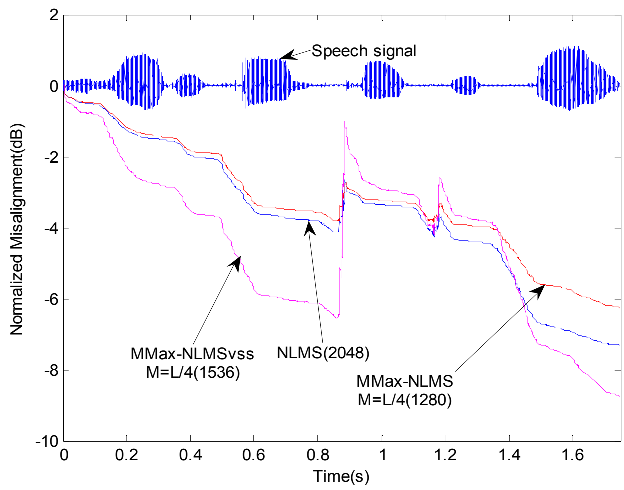

Fig.6. Speech Input: Comparison between convergence performance of MMax-NLMSvss with NLMS for L=1024, M=256, SNR=25dB.

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