A Noise Robust Adaptive Algorithm for Acoustic Echo Caneller

Young-Ho Lee*, Jeong-Hoon Park**, Jang-Sik Park***, Kyong-Sik Son*
Dept. of Electronics Eng., Pusan National University*,
Samsung Electronics Company**
Dept. of Visual Technologies, Dongeui Institute of Technology***
*yoholee@pusan.ac.kr

Abstract

Adaptive algorithm used in Acoustic Echo Canceller (AEC) needs fast convergence algorithm when reference signal is colored speech signal. Set-Membership Affine Projection (SMAP) algorithm is derived from the constraint, which is the minimum value adaptive filter coefficient error. In this paper, we test the characteristic about noise of the SMAP algorithm and proposed modified version of SMAP algorithm for using at AEC. As the projection order increase, the convergence characteristic of the SMAP algorithm is improved where no noise space. But if the noise uncorrelated with input signal exists, the AEC shows bad performance. In this paper, we propose normalized version of adaptive constants using estimated error signal for robust to noise and show the good performance through AEC simulation.

. Introduction

For highly correlated input signals, the recursive least squares(RLS) algorithms are known to present faster convergence than the least mean square(LMS) algorithm and its normalized version, the NLMS algorithm[1]. This advantage comes at the expense of a higher computational complexity. Data-reusing algorithms [2] are known to be a viable alternative to the RLS algorithm in terms of lower computational complexity in situations where the input signal is correlated. The penalty to be paid when increasing the number of data reuse is a slight increase in algorithm misadjustment. Tradeoff between final misadjustment and convergence speed is achieved through the introduction of a step-size, which is not the best solution. An alternative solution to this drawback is to employ the concept of set-membership filtering (SMF)[3] to data reusing algorithms. SMF specifies an upper bound on the estimation error and reduces computational complexity on the average due to its data-discerning property. The set-membership NLMS (SM-NLMS) algorithm proposed in [3] was shown to achieve both fast convergence and low misadjustment, and its data-selectivity and low computational complexity per update makes it very attractive in various applications [4]. An early attempt in this direction was the introduction of the set-membership bi-normalized data-reusing LMS algorithm (SM-BNDRLMS) [5]. As the projection order increase, the convergence characteristic of the Set-Membership Affine Projection algorithm is improved where no noise space. But if the noise uncorrelated with input signal existing, the acoustic echo canceller shows bad performance. In this paper, we propose normalized version of adaptive constants using estimated error signal for robust to noise and show the good performance through AEC simulation.

. Affine Projection (AP) Algorithm

The affine projection (AP) algorithm [5] is a gen eralization of the NLMS adaptive filtering algorithm. Under this interpretation, each tap weight vector upd -ate of NLMS is viewed as a one-dimensional affine projection. In AP algorithm the projections are made in multiple dimensions. As the projection dimension increases, so does the convergence speed of tap wei ght vector, and unfortunately, the algorithm's comput ational complexity. The general AP algorithm is de-fin ed by the following two equations:

$$\mathbf{e}(k) = \mathbf{d}(k) - \mathbf{X}^t(k)\mathbf{w}(k) \tag{1}$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \mu \mathbf{X}_k \left[\mathbf{X}_k^t \mathbf{X}_k\right]^{-1} \mathbf{e}_k \tag{2}$$

where L is the filter length of AP algorithm, P is the projection order of AP algorithm.

The membership set ψ_k suggests the use of more constraint-sets in the update. This section derives an algorithm whose updates belong to a set formed by P constraint sets. Let us express ψ_k as

$$\psi_k = \mathop{\mathrm{I}}_{i=1}^{k-P} H_i \mathop{\mathrm{I}}_{j=k-P+1}^{k} H_j = \psi_k^{k-P} \mathrm{I}\ \psi_k^P \tag{3}$$

where ψ_k^P is the intersection of the P last constraint sets, and ψ_k^{k-P} is the intersection of the $k-P$ first constraint sets. The objective is to derive an algorithm, whose coefficient update belongs to the last P constraint sets, i.e., $\mathbf{w}_{k+1} \in \psi_k^P$.

Let S_{k-i+1} denote the hyperplane, which contains all vectors $\mathbf{w}$ such that $d_{k-i+1} - \mathbf{w}^T \mathbf{x}_{k-i+1} = g_{k-i+1}$ for $i = 1,\dots,P$. The next section discusses the choices satisfying the bound constraint are valid. That is, if all g_{k-i+1} are chosen such that $|g_{k-i+1}| \le \gamma$, then $S_{k-i+1} \in H_{k-i+1}$. Let us state the following optimization criterion for the vector update whenever $\mathbf{w}_k \notin \psi_k^P$:

$$\begin{aligned} &\min \|\mathbf{w}_{k+1} - \mathbf{w}_k\|^2 \text{ subject to:} \\ &\mathbf{d}_k - \mathbf{X}_k^T \mathbf{w}_{k+1} = \mathbf{g}_k \end{aligned} \tag{4}$$

where

$\mathbf{d}_k \in R^{P\times 1}$ contains the desired outputs from the P last time instants;
$\mathbf{g}_k \in R^{P\times 1}$ specifies the point in ψ_k^P;
$\mathbf{X}_k \in R^{N\times P}$ contains the corresponding input vectors, i.e.

$$\begin{aligned} \mathbf{g}_k &= [g_k g_{k-1} \Lambda\ g_{k-P+1}]^T \\ \mathbf{d}_k &= [d_k d_{k-1} \Lambda\ d_{k-P+1}]^T \\ \mathbf{X}_k &= [\mathbf{x}_k \mathbf{x}_{k-1} \Lambda\ \mathbf{x}_{k-P+1}]^T \\ \mathbf{x}_k &= [x_k x_{k-1} \Lambda\ x_{k-N+1}]^T \end{aligned} \tag{5}$$

where $\mathbf{x}_k$ is the input-signal vector.

Using the method of Lagrange multipliers, the unconstrained function to be minimized is

$$f(\mathbf{w}_{k+1}) = \|\mathbf{w}_{k+1} - \mathbf{w}_k\|^2 + \lambda_k^T \left[\mathbf{d}_k - \mathbf{X}_k^T \mathbf{w}_{k+1} - \mathbf{g}_k\right] \tag{6}$$

where $\lambda_k \in R^{P\times 1}$ is a vector of Lagrange multipliers. Finally, the update equation is equation (7). Eq. (7) shows the general SM-AP algorithm.

$$\mathbf{w}_{k+1} = \begin{cases} \mathbf{w}_k + \mathbf{X}_k \left(\mathbf{X}_k^T \mathbf{X}_k\right)^{-1} (\mathbf{e}_k - \mathbf{g}_k), & \text{if } |e_k| > \gamma \\ \mathbf{w}_k, & \text{otherwise.} \end{cases} \tag{7}$$

In the case that a trivial choice would be $\mathbf{g}_k = 0$, i.e. force that the a posteriori errors to be zero at the last P time instants. Inserting $\mathbf{g}_k = 0$ in Eq. (7), leads to the recursions

$$\mathbf{w}_{k+1} = \begin{cases} \mathbf{w}_k + \mathbf{X}_k \left(\mathbf{X}_k^T \mathbf{X}_k\right)^{-1} \mathbf{e}_k, & \text{if } |e_k| > \gamma \\ \mathbf{w}_k, & \text{otherwise.} \end{cases} \tag{8}$$

The updating equation earlier is identical to the conventional affine-projection (AP) algorithm with unity step size whenever $\mathbf{w}_k \notin H_k$. The approach taken here allows a considerable reduction in complexity as compared with the conventional AP algorithm due to the data selectivity. But as the projection order increase, the convergence characteristic of the SM-AP algorithm is improved where no noise space. But if the noise is uncorrelated with existing input signal, the AEC shows bad performance.

. AEC Using modified SM-AP Algorithm

Hence, we propose noise robust SM-AP algorithm, which is normalized version of adaptive constants using estimated error signal for robust to noise and show the good performance through AEC simulation.

Inner product of input signal vector means power of input signal, therefore we can assume $\mathbf{X}_k^T \mathbf{X}_k \approx L\sigma_x^2(k)$.

In the same manner the cross correlation between reference input signal vector and estimated error signal $E[\mathbf{e}(k)\mathbf{X}(k)]$ is inferred as instantaneous gradient vector like equation (9)

$$\begin{aligned} \delta_n(k) &= \beta\delta_n(k-1) + (1-\beta)x_n(k)e(k) \\ n &= 0,1,\dots,L-1 \end{aligned} \tag{9}$$

$\delta_n(k)$ is running power estimate which infer the cross-correlation between reference input signal vector and estimated error signal from instantaneous gradient vector.

β is forgetting factor, $x_n(k)$ is input signal at n tap, none other than $x(k-n)$. L is order of the adaptive filter. Equation is (10)

$$\begin{aligned}\delta_n(k) &= \beta\delta_n(k-1)+(1-\beta)x_n(k)e(k)\\ &= \beta^k\delta_n(0)+(1-\beta)\sum_{i=0}^{k}\beta^{k-i}x_n(i)e(i)\end{aligned} \quad (10)$$

where, we assume $\delta_n(0)=0$ and adjust the past estimated cross- correlation from 0 to k_0 sample, the latest estimated cross- correlation from k_0+1 to k, then

$$\begin{aligned}\delta_n(k) &= \beta^{k-k_0}(1-\beta)\sum_{i=0}^{k_0}\beta^{k_0-i}x_n(i)e(i)\\ &+(1-\beta)\sum_{i=k_0+1}^{k}\beta^{k-i}x_n(i)e(i)\end{aligned} \quad (11)$$

$k-k_0$ is large enough, the first part of Eq. (11) is almost decreased, the second part remain mostly. Therefore, estimate as instantaneous gradient of LMS algorithm, the latest cross-correlation can be reflected. The more β is approach to 1, $k-k_0$ should have the larger value.

Equation (9) is normalized, as equation (12) to cross- correlation is smaller than 1 by summation of the reference input signal and estimated error signal.

$$\delta_k(k)=\beta\delta_n(k-1)+(1-\beta)\frac{x_n(k)e(k)}{\sigma_x^2(k)+\sigma_e^2(k)} \quad (12)$$

For computations saving, the instantaneous gradient of the maximum value of the adaptive filter's coefficient is defined adaptive constant.

$$\begin{aligned}N &= \max_k W(k)\\ \delta(k) &= \beta\delta(k-1)+(1-\beta)x_N(k)e(k)\end{aligned} \quad (13)$$

Therefore adaptive constants should be kept large many and few. The cross-correlation, $\delta_n(k)$ is low pass filtered like equation (14), the convergence speed of the adaptive filter should be kept fast.

$$c(k)=\beta c(k)+(1-\beta)\delta(k) \quad (14)$$

where, $c(k)$ is low pass filtered cross-correlation. $c(k)$ is normalized by the summation of the reference input signal and estimated error signal like equation (15) for the coefficient of the adaptive filter is not misadjusted by the surrounding errors.

$$\mu(k)=\frac{\alpha|c(k)|}{L\left(\sigma_x^2(k)+\sigma_e^2(k)\right)} \quad (15)$$

$\mu(k)$ is adaptive constant which adapts the coefficient of the adaptive filter, α is normalization adaptive constant. The reason absoluteness of the cross-correlation is if the adaptive constant is smaller than 0, the system can be unstable. The reason normalization using the summation of the input signal and estimated error signal is for reduce oscillation of the adaptive constant by the input signal and estimated error signal.

. Simulation Results and Investigation

Through simple simulations, the performance of the adaptive filter which has proposed normalized version of adaptive constants using estimated error signal for robust to noise and show the good performance through AEC simulation. Fig 1 shows the acoustic echo cancellation block. And Fig 2 represents input signals (far-end speech and near end speech) and echo signal. The speech signal is 8 kHz sampled and 16 bit quantized.

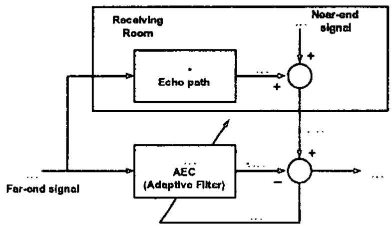

Fig 1. Acoustic Echo Cancellation Block

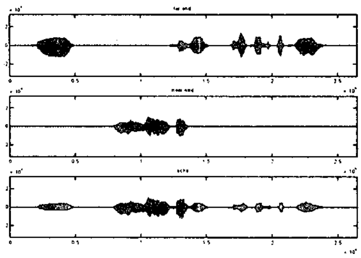

Fig 2. Input signals and echo signal

Fig 3, Fig 4 represents the performance of AEC using conventional SMAP algorithm. Fig 5, Fig 6 represents the performance of AEC using proposed normalized version of adaptive constants using estimated error signal. These simulation results show the good performance of our proposed algorithm than convention algorithm. 'p' represents SMAP filter order.

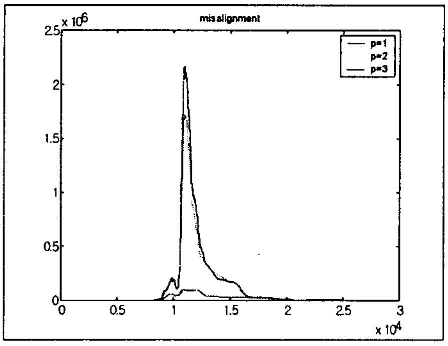

Fig 3. Misalignment of SM-AP algorithm

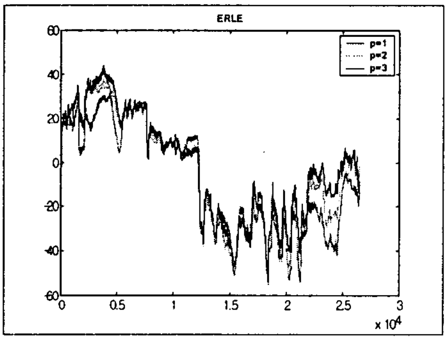

Fig 4. ERLE of SM-AP algorithm

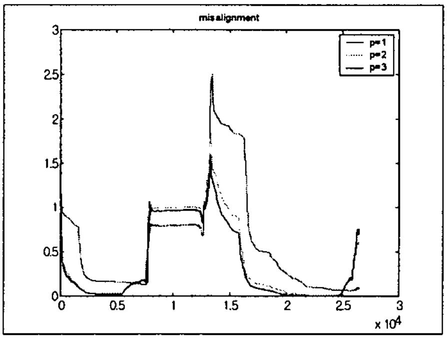

Fig 5. Misalignment of proposed algorithm

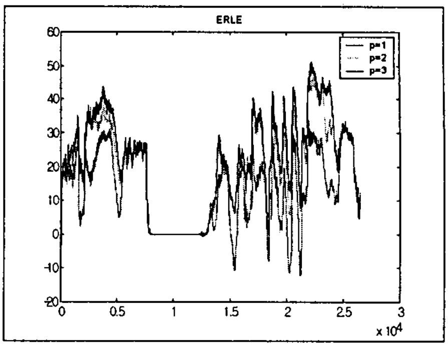

Fig 6. ERLE of proposed algorithm

. Conclusion

In this paper, we propose normalized version of adaptive constants using estimated error signal for robust to noise and show the good performance through Acoustic Echo Canceller simulation. The maximum instantaneous gradient is found among the coefficients of the adaptive filter, is low pass filtered and normalized by the summation of the input signal and the estimated error signals. Proposed algorithm is shown have good performance compare to the conventional algorithm. Quantitative analysis and experiment using DSP is needed

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