STEADY-STATE SOLUTIONS OF THE EXTENDED LMS ALGORITHM FOR STEREOPHONIC ACOUSTIC ECHO CANCELLATION WITH LEAKAGE OR SIGNAL CONDITIONING

Tetsuya Hoya, Jonathon A. Chambers, Neil Forsyth, and Patrick A. Naylor
Signal Processing and Digital Systems Section,
Dept. of Electrical and Electronic Engineering,
Imperial College of Science, Technology, and Medicine,
University of London, SW7 2BT, U.K.
email: {t.hoya,j.chambers,n.forsyth,p.naylor}@ic.ac.uk

ABSTRACT

Acoustic echo cancellers are widely employed in teleconferencing systems to reduce the undesired echos resulting from coupling between loudspeaker and microphone. The single-channel case has been widely studied. Of particular recent interest is the stereophonic case which is not difficult to solve due to the strongly correlated two-channel inputs. In this paper we compare the steady-state solutions of the Leaky eXtended LMS (XLMS) algorithm with XLMS having inputs conditioned by additional zero-memory non-linearities. Modification of the correlation matrix of the two channel-inputs is analysed. We also describe a new configuration for the zero-memory non-linearities which does not impact upon sound quality whilst maintaining improved algorithm convergence properties. Simulation results to support the analyses of these two different de-correlation methods are also included, which suggest that for deterministic parameter settings the performance of the Leaky XLMS algorithm is superior to the case where a half-wave rectifying non-linearity is used. Moreover, simulation results where time variations in the transmission room are considered in order to represent more realistic situations are given, which, on the other hand, suggest that the performance of the XLMS with a signal conditioning method using an Half-Wave Rectifier (HWR) is superior to that of the Leaky XLMS algorithm.

1 INTRODUCTION

The fundamental problem of Stereophonic Acoustic Echo Cancellation (SAEC) lies in the misalignment of the filter coefficients due to the strongly correlated two channel-inputs. This affects the convergence properties of the direct implementation of the conventional LMS type adaptive algorithms in SAEC. De-correlation of the two channel-inputs without affecting stereophonic perception is hence considered [1]. The eXtended LMS (XLMS) algorithm [2] is viewed as an extended version of the two-channel LMS algorithm which takes into account the cross-correlation between the two channel-inputs. Introducing a leakage factor in the update equation of the filter tap weight vector of XLMS [3] gives a similar, but improved effect to the direct addition of noise to the input signal because the input signal is not affected [4, 5]. Leakage has also been successful in channel equalisation [6] and ADPCM coders [7]. In this paper, the effect of the leakage factor within the Leaky XLMS algorithm is analysed in terms of modification to the correlation matrix of the two channel-inputs, and likewise the modification due to additional zero-memory non-linearities [8] in the two channel-inputs is investigated. Simulation work is also included to compare these two different de-correlation methods, where both deterministic and realistic situations are considered.

2 PROBLEM DEFINITION

The steady-state solution to the SAEC problem can be written in the form:

$$\boldsymbol{R}\boldsymbol{w}_{\rm opt} = \begin{bmatrix} \boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}} & \boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}} \\ \boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}} & \boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}} \end{bmatrix} \begin{bmatrix} \boldsymbol{w_1} \\ \boldsymbol{w_2} \end{bmatrix} = \boldsymbol{p} = \begin{bmatrix} \boldsymbol{p_{d,x_1}} \\ \boldsymbol{p_{d,x_2}} \end{bmatrix} \quad (1)$$

where, $\boldsymbol{R}$ is the correlation matrix of the two channel-inputs and $\boldsymbol{R}_{\boldsymbol{x_i},\boldsymbol{x_j}}$, $(i,j = 1,2)$ are the correlation sub-matrices of the original input vector $\boldsymbol{x_i} = (x_{i,1}, x_{i,2}, ..., x_{i,L})^T$ (T denotes transpose) and $\boldsymbol{x_j}$. However, due to the correlation between $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$, $\boldsymbol{R}$ may be near to singular. Thus, a steepest descent type algorithm used to find $\boldsymbol{w}_{\rm opt}$ will exhibit very slow convergence properties. To overcome this, direct and indirect methods have been proposed to modify $\boldsymbol{R}$ to yield much improved convergence.

3 STEADY STATE SOLUTION OF THE XLMS ALGORITHM WITH A ZERO-MEMORY NON-LINEARITY

In the recent paper by Benesty *et al* [8], the approach is to introduce Half-Wave Rectifiers (HWRs) within the path of the signals from the transmission room, which, intuitively, broadens the input spectrum and hence “whitens” the two channel-inputs, which aids de-correlation. The modified input to the XLMS algorithm is given by:

$$\begin{aligned} \tilde{x}_i(n) &= x_i(n) + \beta f(x_i), \ i = 1,2, \\ &= (1+\frac{\beta}{2})x_i(n) + \frac{\beta}{2}|x_i(n)| \end{aligned} \quad (2)$$

where β is a scalar variable which determines the amount of the additional non-linearity and where $f(x)$ is a half-wave rectifier, other non-linearities are possible but the HWR, significantly, preserves the shape of the input signal. The HWR is expressed as:

$$f(x) = \begin{cases} x & \text{if } x \geq 0, \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

The resulting modified input correlation matrix becomes

$$\boldsymbol{R}_{\rm rect} = \begin{bmatrix} \boldsymbol{R}_{\tilde{\boldsymbol{x_1}},\tilde{\boldsymbol{x_1}}} & \boldsymbol{R}_{\tilde{\boldsymbol{x_1}},\tilde{\boldsymbol{x_2}}} \\ \boldsymbol{R}_{\tilde{\boldsymbol{x_2}},\tilde{\boldsymbol{x_1}}} & \boldsymbol{R}_{\tilde{\boldsymbol{x_2}},\tilde{\boldsymbol{x_2}}} \end{bmatrix},$$

where $\boldsymbol{R}_{\tilde{\boldsymbol{x}}_i,\tilde{\boldsymbol{x}}_j}$, $(i,j=1,2)$ are the correlation submatrices of the conditioned input vectors $\tilde{\boldsymbol{x}}_i$ and $\tilde{\boldsymbol{x}}_j$. It is assumed that $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$ are zero-mean and jointly Gaussian distributed, and $\boldsymbol{R}_{|\boldsymbol{x_i}|,|\boldsymbol{x_j}|}$ denotes the matrix $E[\,|\boldsymbol{x_i}|\cdot|\boldsymbol{x_j^T}|\,]$.

Finally, the new steady-state solution of the XLMS algorithm with HWR signal conditioning is given by

$$\boldsymbol{R}_{\text{rect}}\boldsymbol{w}_{\text{opt}} = \boldsymbol{p}_{\text{rect}}, \tag{4}$$

where

$$\begin{aligned}\boldsymbol{R}_{\text{rect}} &= (1+\frac{\beta}{2})^2\cdot\boldsymbol{R}\\ &+\frac{\beta^2}{4}\cdot\begin{bmatrix}\boldsymbol{R}_{|\boldsymbol{x_1}|,|\boldsymbol{x_1}|} & \boldsymbol{R}_{|\boldsymbol{x_1}|,|\boldsymbol{x_2}|}\\ \boldsymbol{R}_{|\boldsymbol{x_2}|,|\boldsymbol{x_1}|} & \boldsymbol{R}_{|\boldsymbol{x_2}|,|\boldsymbol{x_2}|}\end{bmatrix}\end{aligned} \tag{5}$$

and

$$\boldsymbol{p}_{\text{rect}} = \begin{bmatrix}\boldsymbol{R}_{\boldsymbol{d},\tilde{\boldsymbol{x}}_1}\\ \boldsymbol{R}_{\boldsymbol{d},\tilde{\boldsymbol{x}}_2}\end{bmatrix} = (1+\frac{\beta}{2})\boldsymbol{p}+\frac{\beta}{2}\begin{bmatrix}\boldsymbol{R}_{\boldsymbol{d},|\boldsymbol{x_1}|}\\ \boldsymbol{R}_{\boldsymbol{d},|\boldsymbol{x_2}|}\end{bmatrix}. \tag{6}$$

4 STEADY-STATE SOLUTION WITH THE LEAKY XLMS ALGORITHM

A second method to de-correlate the inputs is to apply leakage in the XLMS algorithm. The filter coefficients $\boldsymbol{w_1}$, and $\boldsymbol{w_2}$ at time index $n+1$ with the Leaky XLMS algorithm are updated by:

$$\begin{aligned}\begin{bmatrix}\boldsymbol{w_1}(n+1)\\ \boldsymbol{w_2}(n+1)\end{bmatrix} &= (1-\gamma)\begin{bmatrix}\boldsymbol{w_1}(n)\\ \boldsymbol{w_2}(n)\end{bmatrix}\\ &+\alpha\boldsymbol{M}^{-1}(n)\begin{bmatrix}\phi(\boldsymbol{x_1}(n))\\ \phi(\boldsymbol{x_2}(n))\end{bmatrix}e(n),\end{aligned} \tag{7}$$

in which the function $\phi(\cdot)$ is a transformation of the input vector. γ is the leakage factor and α is the learning constant. The transformation $\phi(\cdot)$ is unit scaling in general but could be the non-linearity defined in (2), and then there would be no degradation of the transmission signals. In the above equation, $\boldsymbol{M}^{-1}(n)$ is given as:

$$\begin{aligned}\boldsymbol{M}^{-1}(n) &= \frac{1}{\det(\boldsymbol{M})}\cdot\begin{bmatrix}p_{22}(n) & -\rho r_{12}(n)\\ -\rho r_{12}(n) & p_{11}(n)\end{bmatrix},\\ \det(\boldsymbol{M}) &= p_{11}(n)p_{22}(n)-\rho^2 r_{12}^2(n),\end{aligned}$$

where ρ is a correlation coefficient that scales the cross-correlation by a variable amount and:

$$p_{11}(n)=\boldsymbol{x_1}^T(n)\boldsymbol{x_1}(n), p_{22}(n)=\boldsymbol{x_2}^T(n)\boldsymbol{x_2}(n),$$
$$r_{12}(n)=\boldsymbol{x_1}^T(n)\boldsymbol{x_2}(n).$$

Using the same assumption as in [4], we can write the error $e(n)$ and the desired response $d(n)$ as:

$$e(n) = d(n)-\sum_{i=1}^{2}\boldsymbol{w_i^T}(n)\boldsymbol{x_i}(n), \tag{8}$$

$$d(n) = \sum_{i=1}^{2}\boldsymbol{w_i^T}_{\text{opt}}\boldsymbol{x_i}(n)+\nu(n). \tag{9}$$

Then, the optimum filter coefficients for the two channels, $\boldsymbol{w_1}_{\text{opt}}$ and $\boldsymbol{w_2}_{\text{opt}}$, are given as the solution to the Wiener-Hopf equation [9]:

$$\boldsymbol{R}_{\text{leaky}}\begin{bmatrix}\boldsymbol{w_1}_{\text{opt}}\\ \boldsymbol{w_2}_{\text{opt}}\end{bmatrix} = \begin{bmatrix}\boldsymbol{p}_{\boldsymbol{d},\boldsymbol{x_1}}\\ \boldsymbol{p}_{\boldsymbol{d},\boldsymbol{x_2}}\end{bmatrix}, \tag{10}$$

where $\boldsymbol{p}_{\boldsymbol{d},\boldsymbol{x_1}}$ and $\boldsymbol{p}_{\boldsymbol{d},\boldsymbol{x_2}}$ are the cross-correlation vectors between the tap inputs of the filter and the desired response $d(n)$. In order to facilitate the analysis, we assume that the two channel-inputs are statistically stationary, then in steady-state we can have a constant matrix $\check{\boldsymbol{M}}^{-1}$ for $\boldsymbol{M}^{-1}(n)$ in the update Eqn. (7).

As time $n\to\infty$, the expected vector $\boldsymbol{w_1}^\infty$ can be written as:

$$\begin{aligned}\boldsymbol{w_1}^\infty &= E[\boldsymbol{w_1}(\infty)]\\ &= E[(1-\gamma)\boldsymbol{w_1}(\infty)+a\alpha(p_{22}\boldsymbol{x_1}-\rho r_{12}\boldsymbol{x_2})\\ &\quad\cdot\{d-\boldsymbol{w_1}^T(\infty)\boldsymbol{x_1}-\boldsymbol{w_2}^T(\infty)\boldsymbol{x_2}\}],\\ a &= \det(\check{\boldsymbol{M}}).\end{aligned} \tag{11}$$

Similarly, the expected vector $\boldsymbol{w_2}^\infty$ becomes:

$$\begin{aligned}\boldsymbol{w_2}^\infty &= E[\boldsymbol{w_2}(\infty)]\\ &= E[(1-\gamma)\boldsymbol{w_2}(\infty)+a\alpha(p_{11}\boldsymbol{x_2}-\rho r_{12}\boldsymbol{x_1})\\ &\quad\cdot\{d-\boldsymbol{w_1}^T(\infty)\boldsymbol{x_1}-\boldsymbol{w_2}^T(\infty)\boldsymbol{x_2}\}].\end{aligned} \tag{12}$$

Eqns. (11) and (12) yield the relations:

$$\begin{aligned}(p_{22}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}} &- \rho r_{12}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}}+\frac{\gamma}{a\alpha}I)\boldsymbol{W_1}^\infty\\ &-(\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}}-p_{22}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}})\boldsymbol{W_2}^\infty\\ &= p_{22}\boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_1}}-\rho r_{12}\boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_2}},\\ (p_{11}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}} &- \rho r_{12}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}}+\frac{\gamma}{a\alpha}I)\boldsymbol{w_2}^\infty\\ &-(\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}}-p_{11}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}})\boldsymbol{w_1}^\infty\\ &= p_{11}\boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_2}}-\rho r_{12}\boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_1}}.\end{aligned}$$

Finally, putting the above relations in matrix form, we obtain

$$\boldsymbol{R'}\boldsymbol{w}^\infty = \begin{bmatrix}p_{22} & -\rho r_{12}\\ -\rho r_{12} & p_{11}\end{bmatrix}\boldsymbol{p} = a\cdot\check{\boldsymbol{M}}^{-1}\boldsymbol{p}, \tag{13}$$

where,

$$\begin{aligned}\boldsymbol{R'} &= \begin{bmatrix}\boldsymbol{R'_{11}} & \boldsymbol{R'_{12}}\\ \boldsymbol{R'_{21}} & \boldsymbol{R'_{22}}\end{bmatrix}, \boldsymbol{W}^\infty = \begin{bmatrix}\boldsymbol{w_1}^\infty\\ \boldsymbol{w_2}^\infty\end{bmatrix},\\ \boldsymbol{R'_{11}} &= p_{22}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}}-\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}}+\frac{\gamma}{a\alpha}I\\ \boldsymbol{R'_{12}} &= -(\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}}-p_{22}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}})\\ \boldsymbol{R'_{21}} &= -(\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}}-p_{11}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}})\\ \boldsymbol{R'_{22}} &= p_{11}\boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}}-\rho r_{12}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}}+\frac{\gamma}{a\alpha}I\\ \boldsymbol{p} &= \begin{bmatrix}\boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_1}}\\ \boldsymbol{R}_{\boldsymbol{d},\boldsymbol{x_2}}\end{bmatrix}.\end{aligned}$$

Comparing Eqn. (13) with (1), $\boldsymbol{R}_{\text{leaky}}$ is given as

$$\boldsymbol{R}_{\text{leaky}} = \frac{1}{a}\check{\boldsymbol{M}}\boldsymbol{R'}. \tag{14}$$

After simplification, we obtain $\boldsymbol{R}_{\text{leaky}}$:

$$\boldsymbol{R}_{\text{leaky}} = \begin{bmatrix}\boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_1}}+p_{11}\frac{\gamma}{a^2\alpha}I & \boldsymbol{R}_{\boldsymbol{x_1},\boldsymbol{x_2}}+\rho r_{12}\frac{\gamma}{a^2\alpha}I\\ \boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_1}}+\rho r_{12}\frac{\gamma}{a^2\alpha}I & \boldsymbol{R}_{\boldsymbol{x_2},\boldsymbol{x_2}}+p_{22}\frac{\gamma}{a^2\alpha}I\end{bmatrix}. \tag{15}$$

Finally, the new steady-state solution that the Leaky XLMS algorithm will find is given by

$$\boldsymbol{R}_{\text{leaky}}\boldsymbol{w}_{\text{opt}} = \boldsymbol{p}. \tag{16}$$

5 SIMULATION RESULTS

5.1 DETERMINISTIC PARAMETER SETTINGS

For the deterministic parameter setting, the impulse responses from the source to each microphone, $\boldsymbol{g_1}$ and $\boldsymbol{g_2}$, in the transmission room were respectively set as [0.4 0.8 0.6] and [0.8 0.6 0.4]. These values were used to generate the two channel-inputs from the source signal. As assumed, the source input signal was generated by Gaussian random noise with zero-mean. On the other hand, the impulse responses, $\boldsymbol{h_1}$ and $\boldsymbol{h_2}$, in the receiving room were respectively fixed as [0.5 0.4 0.3 0.2 0.1] and [0.1 0.5 0.4 0.3 0.2]. In order to evaluate the misalignment performance, the Weight Error Norm (WEN):

$$\mathrm{WEN} = 10log(\frac{\|\boldsymbol{h} - \boldsymbol{h}_{\mathrm{opt}}\|_2^2}{\|\boldsymbol{h}_{\mathrm{opt}}\|_2^2}), \qquad (17)$$

is used, where the norm $\|\cdot\|_2^2$ denotes the sum of squared values of the vector argument. The WEN performance for $\boldsymbol{h_1}$ and $\boldsymbol{h_2}$ are respectively shown in Figs. 2 and 3. For the case where an HWR is used, the filter coefficients are updated by the ordinary XLMS algorithm. Fig. 1 shows the Mean Squared Error (MSE) of the filters.

Parameters for Figs. 1 - 3:

- H.W.R. + XLMS Algorithm/Standard XLMS Algorithm: $\alpha = 0.95$, $\rho = 0.3$, $\beta = 0.3$
- Leaky XLMS Algorithm: $\alpha = 0.95$, $\rho = 0.3$, $\gamma = 0.005$

5.2 REALISTIC PARAMETER SETTINGS

The room impulse responses in practical situations can be modelled with a combination of exponentially decaying and growing envelopes [10]. Moreover, the impulse responses can be modulated with variations simulated by a "random-walk" regression model.

To represent the impulse responses of the transmission room, $\boldsymbol{g_i}$ $(i = 1, 2)$ and those of the receiving room, $\boldsymbol{h_i}$, models based upon zero-mean Gaussian random variables modulated by exponentially decaying/growing envelopes are used. The filter $\boldsymbol{f_i} = [f_{i1}, f_{i2}, ..., f_{iL}]$, is fixed as:

$$f_{ij} = \begin{cases} [1 - exp(-a \cdot j)] \cdot kv_i(j) & j = 1, 2, ..., p, \\ exp(-b \cdot j) \cdot kv_i(j) & j = p+1, p+2, ..., L \end{cases} \qquad (18)$$

where a and b are positive scalar values to define the slope of the exponential function. For the simulation, the filter length $L = 50$ is chosen for both $\boldsymbol{g_i}$ and $\boldsymbol{h_i}$, where k is a positive scalar to determine the variance of $\{v_i(j)\}$, and where $v_i(j)$ are independent identically distributed Gaussian random variables. The filter coefficients in $\boldsymbol{g_2}$ are fixed in the form as $\boldsymbol{g_2} = [g_{11} + e_1, g_{12} + e_2, ..., g_{1L} + e_L]$, where $e_j = g_{1j} \cdot w(j)$ ($w(j)$ are chosen from independent Gaussian distributed random variables).

To simulate a more realistic situation, the impulse response of the transmission room $\boldsymbol{g_i}$ is modulated by a "random-walk" regression model, and the coefficients at time index $n+1$ are updated by:

$$g_i(n+1) = \alpha g_i(n) + \beta w_i(n) + g_i(0), \qquad (19)$$

where α and β are positive scalar values to determine the variance of the fluctuations in the filter coefficients.

In the simulation, the filter coefficients for both $\boldsymbol{g_i}$ and $\boldsymbol{h_i}$ $(i = 1, 2)$ are generated by (18) with $a = 0.25$ and $b = 0.03$, and only $\boldsymbol{g_i}$ are modulated by (19) with $\alpha = 0.1$ and $\beta = 0.05$. Fig. 4 shows a segmented ERLE performance comparison between XLMS, XLMS with HWR signal conditioning, and XLMS algorithm with a leakage factor, where independent Gaussian random noise signals are used as the channel-inputs. In Fig. 5 and 6, comparisons of misalignment performance of $\boldsymbol{h_1}$ and $\boldsymbol{h_2}$ are respectively shown. The performance shown is that averaged over five different channel-inputs. In Fig. 7 - 9, the performance comparison where a real recorded utterance, "PRESENT ZOOS ARE RARELY REACHED BY OFFICIAL TRANSPORTATION", is used is shown. The utterance used is recorded by a male speaker in a quiet room, sampled originally at 48KHz and down-sampled to 8KHz. For the simulation studies using both the random noise and the real speech as channel-inputs, the results are shown in the presence of noise in the echo-path in the receiving room at SNR=30dB. The noise in the echo-path is also assumed as an independent Gaussian random noise signal.

6 CONCLUSION

In this paper, analysis, with supporting simulations, of the XLMS algorithm with leakage and with the introduction of additional zero-memory non-linearities in the two channel-inputs has been presented. Simulation results with more realistic parameter settings has also been given. In the steady-state solution of the Leaky XLMS, only the original correlation matrix $\boldsymbol{R}$ is *artificially* shifted by additive terms as given in Eqn. (15) during the operation. In the method involving the non-linearities, however, not only $\boldsymbol{R}$ is modified but the cross-correlation vector $\boldsymbol{p}$, due to the underlying absolute operation and the scaling factors in Eqns. (5) and (6), which is considered to be particularly helpful for the de-correlation of the channel-inputs. Interestingly, the simulation results for the deterministic parameter settings as in Fig. 2 and 3 show that the appropriate setting of the leakage factor can improve the convergence performance of XLMS in terms of the misalignment of the filter coefficients in comparison with the additional non-linearities. In the simulations for the realistic parameter settings where time-variations are considered in the transmission room impulse responses, the performance with the Leaky XLMS, however, degraded for both the independent Gaussian random noise and the real speech channel-inputs, but the performance of the XLMS with HWR signal conditioning was superior to both the standard XLMS and the Leaky XLMS algorithm. Future works include the further investigation of the practical situations and the development of novel algorithms for SAEC.

References

[1] M. M. Sondhi and D. R. Morgan, "Stereophonic Acoustic Echo Cancellation", IEEE Signal Processing Letters, Vol. 2, No. 8, pp. 148-151, Aug. 1995.

[2] J. Benesty, F. Amand, A. Gilloire, and Y. Grenier, "Adaptive Filtering Algorithms For Stereophonic Acoustic Echo Cancellation", Proc. ICASSP-96, Vol. 5, pp. 3099-3102, Atlanta, 1996.

[3] T. Hoya, Y. Loke, J. A. Chambers, and P. A. Naylor, "Application Of The Leaky eXtended LMS (XLMS) Algorithm In Stereophonic Acoustic Echo Cancellation", submitted to European Signal Processing Journal: Special Issue on Acoustic Echo Cancellation, Aug. 1997.

[4] S. C. Douglas, "Performance Comparison of Two Implementations of the Leaky LMS Adaptive Filter", IEEE Trans. on SP, Vol. 45, No. 8, pp. 2125-2129, Aug. 1997.

[5] M. G. Bellanger, “Adaptive Digital Filters and Signal Analysis: Section 4.6 — Leakage Factor”, Marcel Dekker, Inc. 1987.

[6] R. P. Gitlin, H. C. Meadors, and S. B. Weinstein, “The Tap-Leakage Algorithm: An Algorithm for the Stable Operation of a Digitally implemented Fractionally Spaced Equaliser”, Bell Sys. Tech. Journal, Vol. 61, No. 8, pp. 1817- 1839, Oct. 1982.

[7] D. L. Cohn, and J. L. Melson, “The Residual Encoder: An Improved ADPCM System for Speech Digitisation”, IEEE Trans. on Communications, Vol. COM-23, pp. 935-941, Sept. 1975.

[8] J. Benesty, D. R. Morgan, and M. M. Sondhi, “A Better Understanding and an Improved Solution to the Specific Problems of Stereophonic Acoustic Echo Cancellation”, Proc. ICASSP’97, Vol. 1, pp.303-306, Munich, 1997.

[9] S. Haykin, “Adaptive Filter Theory, 2nd. Ed.”, Englewood Cliffs, NJ: Prentice-Hall, 1995.

[10] C. Antweiler and H. Symanzik, “Simulation of Time Variant Room Impulse Responses”, Proc. ICASSP-95, Vol. 3, pp. 3031-3034, 1995.

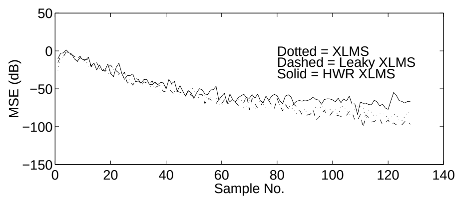

Figure 1: MSE

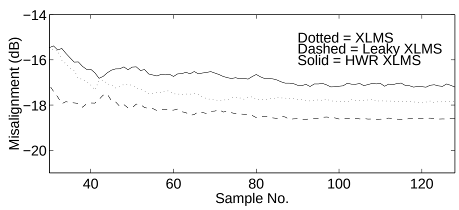

Figure 2: Misalignment in Filter 1

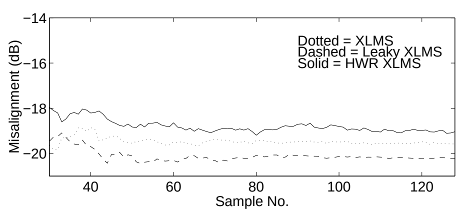

Figure 3: Misalignment in Filter 2

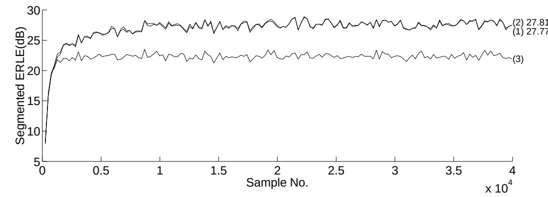

Figure 4: Segmented ERLE

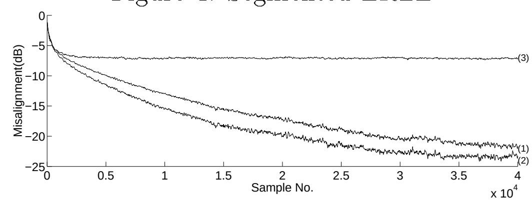

Figure 5: Misalignment in Filter 1

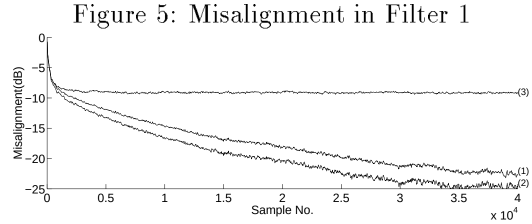

Figure 6: Misalignment in Filter 2 — (Fig. 4 - 6) Channel-Inputs: Independent Gaussian Random Noise Signals With Zero-Mean: (1) — XLMS, (2) — XLMS With Signal Conditioning with an HWR ($\beta = 0.3$), (3) — Leaky XLMS ($\gamma = 0.0005$)

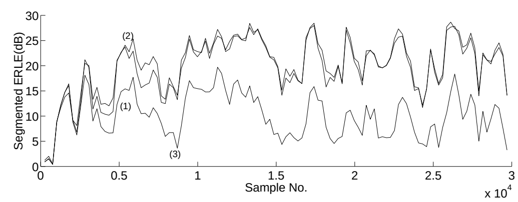

Figure 7: Segmented ERLE

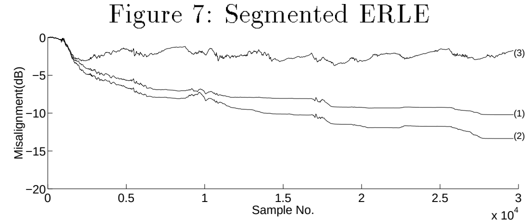

Figure 8: Misalignment in Filter 1

Figure 9: Misalignment in Filter 2 — (Fig. 7 - 9) Channel-Inputs: Real Speech Data — ”PRESENT ZOOS ARE RARELY REACHED BY OFFICIAL TRANSPORTATION”: (1) — XLMS, (2) — XLMS With Signal Conditioning with an HWR ($\beta = 0.3$), (3) — Leaky XLMS ($\gamma = 0.0005$)