

Leakage Factor: Its Application In Stereophonic Acoustic Echo Cancellation

Y. Loke and J. Chambers

Department of Electronic and Electrical Engineering
Imperial College Of Science, Technology And Medicine
email: y.loke@ic.ac.uk, j.chambers@ic.ac.uk

Abstract

Recent analysis on the leaky Least Mean Square (LMS) adaptive filter has justified the use of leakage factor in numerous applications. In this work, a similar leakage factor is introduced in the two-channel LMS, and the eXtended LMS (XLMS) algorithms for use in stereophonic acoustic echo cancellation. This is compared to the alternative of adding random white noise to the input stereo signals. Simulations and experimental results indicate that the leakage factor is superior compared to the direct addition of random white noise. Performance measures used are based on output error and weight error vector norms.

1 Introduction

The fundamental problem in stereophonic echo cancellation lies in the misalignment of two-channel adaptive filters. This can be understood by considering the two-channel echo cancellers in Fig. 1. At the remote room on the right, speech is transmitted via two acoustic paths characterised by the impulse responses g_1 and g_2 . In the near room, the signals from each loudspeaker will couple back into the microphone via the impulse responses h_1 and h_2 . Echo cancellation is achieved if the adaptive filters match the receiving room impulse responses. To simplify the diagram, coupling is only shown for one microphone, echo cancellation on the other microphone is essentially an identical process.

In the LMS algorithm, the error signal $e(n)$ is written as

$$e(n) = y(n) - \hat{h}_1^t x_1 - \hat{h}_2^t x_2 \quad (1)$$

where \hat{h}_1 and \hat{h}_2 are N -dimensional vectors of the adaptive filter coefficients, x_1 and x_2 are vectors comprising the N most recent samples, with superscript t denoting transpose.

Similarly, the signal $y(t)$ can be written as

$$y(n) = h_1^t x_1 + h_2^t x_2 \quad (2)$$

where h_1 and h_2 are the true impulse response vectors in the receiving room. We can denote the misalignments \tilde{h}_1 and \tilde{h}_2 as

$$\tilde{h}_1 = h_1 - \hat{h}_1 \quad \tilde{h}_2 = h_2 - \hat{h}_2 \quad (3)$$

Now assuming $e(n)$ has been driven to be zero. It follows that

$$\tilde{h}_1^t x_1 + \tilde{h}_2^t x_2 = 0 \quad (4)$$

From here, we can immediately see that unless x_1 and x_2 are linearly independent, this does not imply that $\tilde{h}_1 = \tilde{h}_2 = 0$. This illustrates the fundamental problem with stereophonic signals, because the signals are correlated, based on the fact that x_1 and x_2 are convolution of the same signal $s(n)$ with impulse responses g_1 and g_2 .

Thus the main strategy with stereophonic echo cancellation is to find a method to *decorrelate* x_1 and x_2 , and do this *without* affecting stereophonic perception. A few of these approaches are discussed in [1].

2 The Leaky eXtended LMS (XLMS) Algorithm

The leaky LMS adaptive algorithm has been found to be important in channel equalisation [2] and ADPCM coders [3]. Leakage is successful in stabilising the systems and in alleviating "stalling" of adaptive coefficients due to very low input signal. Similarly, the leakage factor can be incorporated into the XLMS algorithm [4], to yield the Leaky XLMS algorithm.

The Leaky XLMS algorithm is a direct approximation of the two-channel RLS algorithm with a leakage factor γ . Using the same notation as above, the main update in the algorithm is as follows:

$$\begin{bmatrix} \hat{h}_1(n+1) \\ \hat{h}_2(n+1) \end{bmatrix} = (1-\gamma) \begin{bmatrix} \hat{h}_1(n) \\ \hat{h}_2(n) \end{bmatrix} + \alpha_E \mathbf{M}^{-1}(n+1) \begin{bmatrix} x_1(n+1) \\ x_2(n+1) \end{bmatrix} e(n+1) \quad (5)$$

where α_E is the adaptation gain.

The matrix, $\mathbf{M}(n+1)$ is defined as:

$$\mathbf{M}(n+1) = \begin{bmatrix} p_{11}(n+1)\mathbf{I} & \rho r_{12}(n+1)\mathbf{I} \\ \rho r_{12}(n+1)\mathbf{I} & p_{22}(n+1)\mathbf{I} \end{bmatrix}$$

and:

$$p_{11}(n+1) = x_1^T(n+1)x_1(n+1)$$

$$p_{22}(n+1) = x_2^T(n+1)x_2(n+1)$$

$$r_{12}(n+1) = x_1^T(n+1)x_2(n+1)$$

$\mathbf{M}(n+1)$ can be interpreted as a simplified two-channel correlation matrix which takes into account the cross correlation between x_1 and x_2 . p_{11} and p_{22} are the sum squared data in the two channel input taps, and r_{12} is the sum squared cross channel coefficient. ρ is a correlation coefficient that scales the cross-correlation by a variable amount.

The stability conditions of XLMS are:

$$0 < \alpha_E < 1$$

$$0 \leq \rho < 1$$

$$0 \leq \gamma \ll 1$$

In stereophonic echo cancellation, the misalignment problem results from the strong correlation between input stereo signals. The main strategy [5],[6] involves *decorrelating* the input signals so as to reduce the misalignment. The Leaky XLMS algorithm does this by subtracting the correlated components from each tap input. This is shown by decoupling the first filter coefficient update equation in (5):

$$\hat{h}_1(n+1) = (1-\gamma)\hat{h}_1(n) + \frac{\alpha_E}{p_{11}p_{22} - \rho^2 r_{12}^2} x_e(n+1)e(n+1) \quad (6)$$

and:

$$x_e = [p_{22}x_1(n+1) - \rho p_{11}x_2(n+1)]$$

where it is seen that the effective data vector $x_e(n+1)$ is a linear combination of x_1 and x_2 controlled by the inter channel coefficients.

Having the leakage factor γ is equivalent to adding a white noise to the input signal [7]. For stereophonic signals, this has the desirable effects of reducing the input correlation [6] and helping the algorithm to adapt to non-stationary signals. More importantly, the introduction of a leakage factor has been proven to be superior to adding random white noise to the input signal [8]. The main advantage is that the leakage factor is implemented directly in the algorithm, and so will not affect the quality of the input signals. In addition, the leakage factor is found to decrease both the output error and weight error vector norm, whereas the addition of random white noise only decreases the weight error vector norm.

3 Simulations And Experimental Results

The experimental work performed can be divided into two sections. First, simulations were carried out using a real speech signal convolved with non-stationary room impulse responses [9] of the form:

$$h(n+1) = ah(n) + v(n) \quad (7)$$

where a controls the time constant of non-stationarity, elements of $v(n)$ consist of independent white gaussian noise process of zero mean and standard deviation $h(n)/200$. The impulse responses used were obtained from measurements of real room impulse responses truncated to 256 points. This was to verify the performance of XLMS against the conventional LMS and FLS algorithms. To compare the leakage factor against addition of white noise, the noise input was added into the inputs x_1 and x_2 at the position labelled Z , shown in Fig. 1. All results were obtained by averaging over 50 ensemble members. Performance measures were based on the average Echo Return Loss Enhancement (ERLE)

$$ERLE = -10 \lg \left(\frac{1}{k} \sum_{i=0}^k \frac{1}{l} \sum_{j=1}^l e^2(il+j) \right) \quad (8)$$

(where the ERLE was averaged over k blocks and l was approximately the period of stationarity in samples) and the weight error norm

$$\frac{\|\hat{h} - h\|_2^2}{\|h\|_2^2} \quad (9)$$

(where the norm $\|x\|_2^2$ represents the sum of squared values of the vector argument).

The ERLE performance of all the algorithms at various levels of additive input noise is compared in Fig. 2. All inputs and desired signals were normalised to unity power. The XLMS is shown to function well with highly correlated input signals, that is, input SNRs above 5dB, but its performance advantage over conventional LMS disappears with lower input SNRs. This corresponds with equation (6), since subtraction of non-correlated input signals will result in a more noisy and poorer adaptive process. Another important observation is that the ERLE performance deteriorates with higher noise levels. This is intuitively so because any input noise will disrupt the adaptive process. On the other hand, the leakage factor improves the ERLE performance of both LMS and XLMS.

Fig. 3 shows the weight error vector norm performance. The addition of more white noise is shown to improve weight error vector norm performance by at least 6dB. This is because the noise helps to decorrelate the input signals. The leakage factor approximates the effect of adding white noise, and is capable of reducing weight error vector norm to an extent of about 1dB.

In the second part of the experiment, real stereo signals were captured using a TASCAM DA-20 DAT recorder sampling at 44.1kHz. The same adaptive algorithms were used, with the adaptive filter length increased to 1000 points. The ERLE performance of XLMS and LMS for varying leakage factors is shown in Fig. 4. This is compared to the FLS, which achieved an ERLE of 28.47dB. The effectiveness of the leakage factors is more apparent for longer filter lengths, with an improvement of over 2.5dB for XLMS. The leaky XLMS thus gives a good performance at the expense of a slight increase in computational cost. The number of operations for leaky LMS, leaky XLMS and FLS are summarised in Table 1, where L denotes the length of the adaptive filter.

4 Conclusion

The use of leakage factor is found to improve the performance of two-channel gradient-based algorithms. This is preferred to the addition of white random noise which will result in a poorer signal quality and ERLE performance. The leaky XLMS algorithm has been proven to work well in both simulation and practical applications at a low computational cost. In addition, a maximum overall increase of 2.5dB in ERLE is obtained using a leakage factor for XLMS.

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Y. Loke was born in Singapore, in 1973. He will be graduating from Imperial College in June 1997 with the MEng degree in Electrical and Electronics engineering. Upon graduation, he will be working as an logistics engineer in the Republic of Singapore Navy.



J. Chambers was born in Peterborough, England, in 1960. He is a lecturer in Signal Processing with special interests in Adaptive Signal Processing and Spectral Estimation. He acts as a consultant and has published conference and journal papers in the area of adaptive signal processing. He is currently running research projects in adaptive signal processing and its application to mobile communications, condition monitoring and control. He is a member of the IEE, E5, professional group committee on Signal Processing, and an associate editor for the IEEE Trans. Signal Processing.

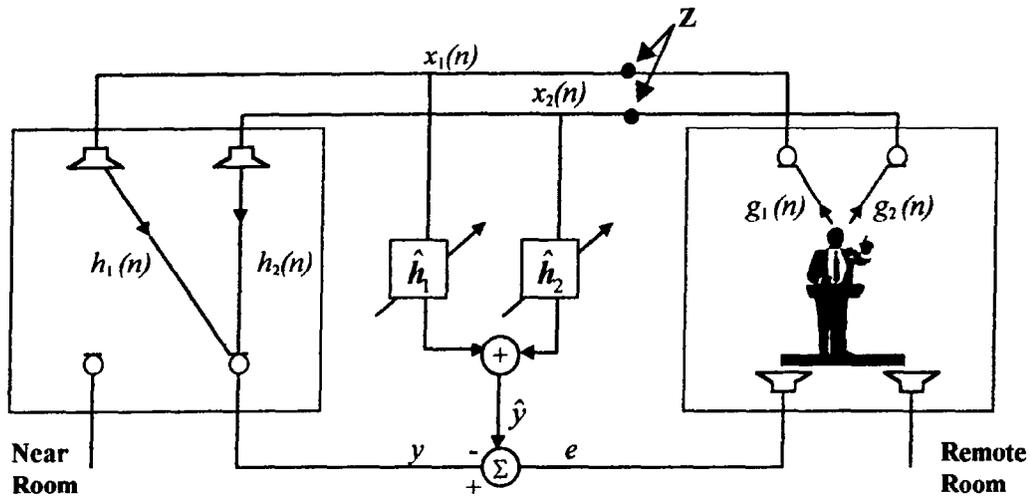


Figure 1: Schematic diagram of stereophonic echo cancellation

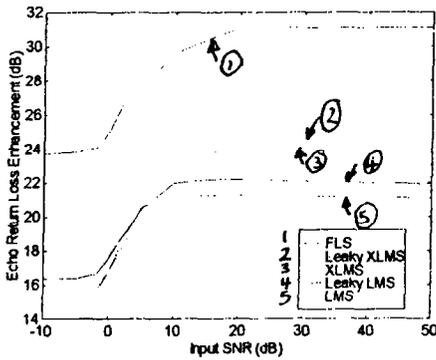


Figure 2: ERLE Performance Of Two Channel Algorithms

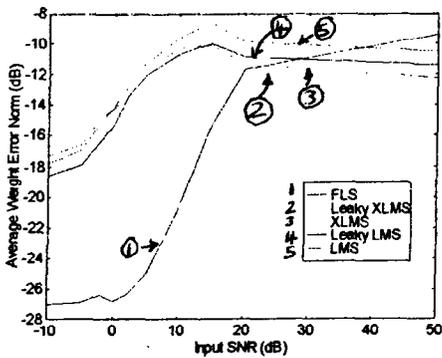


Figure 3: Average Weight Error Norm Performance Of Two Channel Algorithms

Parameters For Figure 2 & Figure 3:
 FLS: Forgetting Factor = 0.998
 Leaky XLMS: $\alpha_E = 0.8, \rho = 0.5, \gamma = 0.00015$
 XLMS: $\alpha_E = 0.8, \rho = 0.5$
 Leaky LMS: Adaptation Gain = 1.6, $\gamma = 0.00015$
 LMS: Adaptation Gain = 1.6

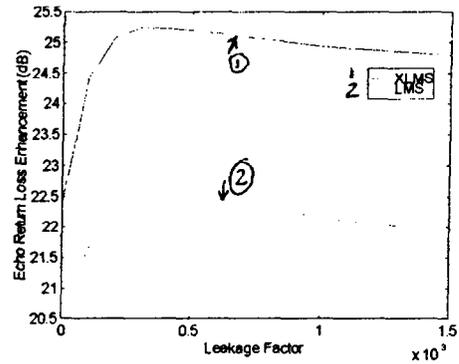


Figure 4: ERLE Performance Against Leakage Factor For LMS and XLMS

ERLE For FLS: 28.47dB

Parameters:
 FLS: Forgetting Factor = 0.9995
 XLMS: $\alpha_E = 0.85, \rho = 0.5$
 LMS: Adaptation Gain = 1

	Additions	Multiplications	Total
Leaky LMS	4L	6L	10L
Leaky XLMS	6L	8L	14L
FLS	28L	28L	56L

Table 1. Computational Complexity of leaky LMS, leaky XLMS and FLS Algorithms