References

1 CHANG, J.T.C.-S.: 'Effective bandwidth in high-speed networks', *IEEE J. Sel. Areas Commun.*, 1995, **13**, (6), pp. 1091–1100

2 GROSSGLAUSER, D.M.: 'Measurement-based call admission control: Algorithms and analysis'. IEEE INFCOM'97, April 1997,

3 RAGHAVAN, S.K.T.S.V.: 'Networked multimedia systems: concepts, architecture, and design' (Prentice Hall, 1998)

4 WIJESEKERA, D., and SRIVASTAVA, J.: 'Experimental evaluation of loss perception in continuous media', to be published in *Multimedia Syst. J.*, 1999

Noise robust alternating fixed-point algorithm for stereophonic acoustic echo cancellation

N.T. Forsyth, J.A. Chambers and P.A. Naylor

A novel algorithm specifically for use in stereophonic acoustic echo cancellation (SAEC) environments is introduced. It is based on an alternating fixed-point (FP) structure. Analysis provides bounds to ensure that the algorithm has the form of a contraction mapping (CM). Simulation results show improved performance over algorithms with similar computational complexity in the presence of noise.

Introduction: In communications using hands-free telephony and teleconferencing systems, there is often a need for some kind of echo cancellation. An acoustic echo canceller is designed to adaptively model the acoustic path through which speech travels. To give more spatial realism, two channels can be used, but new difficulties are experienced in identifying multiple echo paths uniquely [1]. Consider Fig. 1; the transmission room on the right has two microphones to pick up the source signal in stereo via the two acoustic paths with impulse responses $g_1(n)$ and $g_2(n)$. These signals then pass to loudspeakers in the receiving room on the left and are coupled to one of the microphones via paths $h_1(n)$ and $h_2(n)$; the signal $y(n)$ is then produced. Stereophonic acoustic echo cancellation (SAEC) is then undertaken on this signal $y(n)$, otherwise the same signal would be passed to the transmission room as an echo. The echo canceller derives an estimate using two finite impulse response filters $\hat{h}_1(n)$ and $\hat{h}_2(n)$ to model the two echo paths in the receiving room. The loudspeaker signals $x_1(n)$ and $x_2(n)$ then form the inputs to these estimated paths, the outputs of which are summed to produce $\hat{y}(n)$. This is then subtracted from the echo signal, $y(n)$, giving the error signal. Assuming the error is driven to zero, we have the relationship:

$$\left(h_1(n) - \hat{h}_1(n)\right) * x_1(n) + \left(h_2(n) - \hat{h}_2(n)\right) * x_2(n) = 0 \qquad (1)$$

where * denotes discrete convolution. It can be seen that unless $x_1(n)$ and $x_2(n)$ are linearly independent, the desired result $h_1(n) - \hat{h}_1(n) = h_2(n) - \hat{h}_2(n) = 0$, $\forall n$, cannot be guaranteed. Clearly this is not the case as $x_1(n)$ and $x_2(n)$ come from a common source and are inherently highly correlated. This coupling between the solutions leads to non-uniqueness in the solutions for both echo paths and something must be done to remedy this. The extended least mean square algorithm [1] takes into account the cross-correlation between the inputs signals, but its performance is limited. Other generalisations of single channel algorithms, such as normalised-LMS, (NLMS) and recursive least squares (RLS), to the two channel case either perform poorly or have an impractically high computational complexity due to the lengths of impulse responses involved, $O(1000)$, in room environments. A multichannel affine projection algorithm was proposed in [2], but it suffers from considerable sensitivity to noise. Therefore a robust algorithm for enhanced SAEC performance is needed.

Alternating fixed-point normalised least mean square two-channel algorithm (AFP-NLMS2): To avoid local minima associated with non-uniqueness, a new search-space is created by freezing one channel of the adaptive echo canceller and updating the other for a number of iterations. The proposed new algorithm is based on this concept, but at each sample we first use the ε-NLMS2 algorithm as a main loop to update both channels and then fix one channel and update the other in a fixed-point (FP) manner. The ε-NLMS2 algorithm is a two-channel NLMS algorithm with an adaptation gain $\mu = \mu'/(\varepsilon + \|\underline{x}\|_2^2)$ where $\underline{x} = [\underline{x}_1^T, \underline{x}_2^T]^T$, $[.]^T$ is a vector transpose and $\|.\|_2$ is an l_2 norm. After the main loop at the next time sample, the FP procedure alternates to the other channel. To try to make the solution unique, orthogonal projections in the form of Gram-Schmidt procedures are used within the fixed-point iterations (FPIs) to remove information that is deemed to be detrimental to the identification of a distinct echo path for that channel. The first FPI maps one channel onto a subspace that is orthogonal to the other channel at that time, denoted $\mathbf{P}^{\perp}_{x2(n)} x_1(n)$. This can be viewed as a cross-channel projection as it removes information in the data for one channel that is correlated to that in the other channel. The second FPI uses the previous channel input and removes information that is correlated with the present channel input, $\mathbf{P}^{\perp}_{x1(n)} x_1(n-1)$. The third is similar, but looks forward two iterations, $\mathbf{P}^{\perp}_{x1(n), x1(n-1)} x_1(n-2)$. These second and third FPIs are cross-through-channel projections as they remove data that are correlated to the future data in that channel. The number of FPIs can be increased further, although complexity increases with performance. The algorithm is formalised below (subscripts denote main loop iteration number, channel number; c denotes channel 1 or 2; main index denotes FPI number) with μ normalised as above.

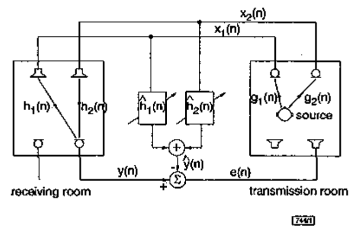

Fig. 1 *Schematic diagram of stereophonic acoustic echo cancellation*

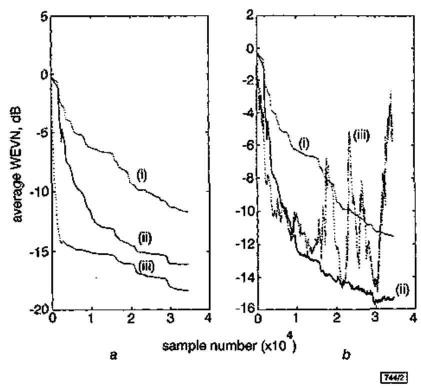

Fig 2 *Comparison of weight error vector norms of ε-NLMS2, AFP-NLMS2 and MCAPA algorithms*

a no noise; *b* SNR = 30dB
(i) ε-NMMS2, (ii) AFP-NLMS2 (N = 3), (iii) MCAPA (N = 3)

Main loop iterations – n:

$$\underline{\hat{h}}_{(n+1,1)} = \underline{\hat{h}}_{(n,1)} + \mu \underline{x}_{(n,1)} e_{(n)}$$
$$\underline{\hat{h}}_{(n+1,2)} = \underline{\hat{h}}_{(n,2)} + \mu \underline{x}_{(n,2)} e_{(n)} \qquad (2)$$

where $e_{(n)} = d_{(n)} - \underline{x}_{(n,1)}{}^T \underline{\hat{h}}_{(n,1)} - \underline{x}_{(n,2)}{}^T \underline{\hat{h}}_{(n,2)}$

Fixed-point iterations - k: If mod$(n) = 0$, $c = 1$, $\bar{c} = 2$, else $c = 2$, $\bar{c} = 1$

Initialisations: $\underline{\hat{h}}_{(c)}[1] = \underline{\hat{h}}_{(n+1,c)}$, $e[1] = e_{(n)}$

(i) First update $\underline{\hat{h}}_{(c)}[2] = \underline{\hat{h}}_{(c)}[1] + \mu e[1] \mathbf{P}^{\perp}_{\underline{x}(n,\bar{c})} \underline{x}_{(n,c)}$

(ii) Then calculate the new error $e[2] = d_{(n-1)} - \underline{x}^T_{(n-1,c)} \underline{\hat{h}}_{(c)}[2] - \underline{x}^T_{(n-1,\bar{c})} \underline{\hat{h}}_{(n+1,\bar{c})}$
with update $\underline{\hat{h}}_{(c)}[3] = \underline{\hat{h}}_{(c)}[2] + \mu e[2] \mathbf{P}^{\perp}_{\underline{x}(n-1,\bar{c}), \underline{x}(n,c)} \underline{x}_{(n-1,c)}$

(iii) The new error $e[3] = d_{(n-2)} - \underline{x}^T_{(n-2,c)} \underline{\hat{h}}_{(c)}[3] - \underline{x}^T_{(n-2,\bar{c})} \underline{\hat{h}}_{(n+1,\bar{c})}$
then update $\underline{\hat{h}}_{(c)}[4] = \underline{\hat{h}}_{(c)}[3] + \mu e[3] \mathbf{P}^{\perp}_{\underline{x}(n-2,\bar{c}), \underline{x}(n-1,c), \underline{x}(n,c)} \underline{x}_{(n-2,c)}$

For the general kth FPI

$$e[k] = \underline{d}_{(n-k+1)} - \underline{x}^T_{(n-k+1,c)}\underline{\hat{h}}_{(c)}[k] - \underline{x}^T_{(n-k+1,\bar{c})}\underline{\hat{h}}_{(n+1,\bar{c})}$$

$$\underline{\hat{h}}_{(c)}[k+1] = \underline{\hat{h}}_{(c)}[k] + \mu e[k]\mathbf{P}^{\perp}_{(\underline{x}_{(n-k+1,\bar{c})},\underline{x}_{(n-k+2,c)},\underline{x}_{(n-k+3,c)},\ldots,\underline{x}_{(n,c)})}\underline{x}_{(n-k+1,c)}$$

return the updated channel vector for the next main loop $\underline{\hat{h}}_{(n+2,c)} = \underline{\hat{h}}_{(c)}[k+1]$.

AFP-NLMS2 is contraction mapping (*CM*): To guarantee convergence we need to show that an algorithm is a CM. A proof is presented for AFP-NLMS2 drawing largely on the framework in [3]. The weight error vector $\underline{\varepsilon}_1(k) = \underline{h}_1 - \underline{\hat{h}}(k)$, is given by

$$\underline{\epsilon}_1(k+1) = \underline{\epsilon}_1(k) - \mu(k)\underline{\psi}_1(k)\left[\underline{\epsilon}_1^T(k)\underline{\phi}_1(k) + \underline{\epsilon}_2^T(k)\underline{\phi}_2(k) + v(k)\right] \quad (3)$$

where $\underline{\phi}_1(k)$ and $\underline{\psi}_1(k)$ give the input and projected input data vectors, respectively, and similarly for channel 2. The inhomogeneous noise term $v(k)$ is neglected in demonstrating that eqn. 3 is a CM. The second term in $\varepsilon_2^T(k)$ is fixed as this channel is frozen, so is assumed to be approximately constant and ignored for this proof. This gives the simplified state-space model:

$$\underline{\epsilon}_1(k+1) = \left(\underline{I} - \mu(k)\underline{\psi}_1(k)\underline{\phi}_1^T(k)\right)\underline{\epsilon}_1(k) \quad (4)$$

The contraction mapping (CM) theorem is as follows. If an operator **T** is defined on a domain D in a normed linear space and if there is a constant $0 < C < 1$ such that $\|Tx_2 - Tx_1\| \le C\|x_2 - x_1\|$ then T is a contraction operator (CO). Comparing this form with the squared l_2 norm of eqn. 4 we require

$$\|\underline{\epsilon}_1(k+1)\|_2^2 \le \left\|\left(\underline{I} - \mu(k)\underline{\psi}_1(k)\underline{\phi}_1^T(k)\right)\underline{\epsilon}_1(k)\right\|_2^2 = \|\underline{\epsilon}_1(k)\|_2^2 C(k) \quad (5)$$

where

$$C(k) = 1 - \frac{2\mu(k)\underline{\psi}_1^T(k)\underline{\epsilon}_1(k)\underline{\phi}_1^T(k)\underline{\epsilon}_1(k) - \mu^2(k)\|\psi_1(k)\|_2^2\left(\underline{\phi}_1^T(k)\underline{\epsilon}_1(k)\right)^2}{\|\underline{\epsilon}_1(k)\|_2^2} \quad (6)$$

The conditions such that $0 < C(k) < 1$ must be found, giving

$$0 < \left[2\underline{\psi}_1^T(k)\underline{\epsilon}_1(k) - \mu(k)\left\|\underline{\psi}_1(k)\right\|_2^2\underline{\phi}_1^T(k)\underline{\epsilon}_1(k)\right]\mu(k)\underline{\phi}_1^T(k)\underline{\epsilon}_1(k) < \|\underline{\epsilon}_1(k)\|_2^2 \quad (7)$$

Dividing by $\mu(k)\underline{\phi}_1^T(k)\underline{\varepsilon}_1(k)$ ensures that $\mu(k)$ must be positive if we assume an acute angle between $\underline{\phi}_1(k)$ and $\underline{\varepsilon}_1(k)$ for a contraction. We then neglect the upper bound as this describes how $\mu(k)$ behaves towards zero, leaving the lower bound as $\mu(k)\|\underline{\phi}_1(k)\|_2^2\,\underline{\phi}_1^T(k)\underline{\varepsilon}_1(k) < 2\,\underline{\phi}_1^T(k)\underline{\varepsilon}_1(k)$. Considering the descent of channel 1 with channel 2 frozen we have $\phi_1(k) = \underline{x}_1(k - M + 1)$, i.e. the channel 1 input, M FPIs ago. To describe $\underline{\psi}_1(k)$, the input data are arranged into a matrix with columns formed by the future inputs to the same channel and the input to the other channel M iterations ago:

$$\underline{X}_1(k) = [\underline{x}_1(k-M+1), \underline{x}_1(k-M+2), \ldots, \underline{x}_1(k-1), \underline{x}_1(k), \underline{x}_2(k-M+1)] \quad (8)$$

$$= \left[\underline{x}_1(k-M+1), \underline{\tilde{X}}_1(k)\right] \quad (9)$$

Vector $\underline{\psi}_1(k)$, is given by the channel 1 input, M iterations ago, projected onto a subspace that is orthogonal to the corresponding channel 2 input and future channel 1 inputs, i.e. the following linear combination $\underline{\psi}_1(k) = \underline{x}_1(k - M + 1) - \underline{\tilde{X}}_1(k)\underline{a}(k)$ for a vector $\underline{a}(k)$, whose elements are the normalised crosscorrelation coefficients between $\underline{x}_1(k - M + 1)$ and the columns of $\underline{\tilde{X}}_1(k)$. The second term encompasses all parallel components that must be removed to create the orthogonal subspace. The condition for CM is now written:

$$\mu(k) < \frac{2}{\|\underline{\psi}_1(k)\|_2^2}\frac{\left(\underline{x}_1^T(k-M+1) - \underline{a}^T(k)\underline{\tilde{X}}_1^T(k)\right)\underline{\epsilon}_1(k)}{\underline{x}_1^T(k-M+1)\underline{\epsilon}_1(k)} \quad (10)$$

Assuming orthogonality between the *a posteriori* errors and the input data, i.e. the weight error vector $\underline{\varepsilon}_1(k)$ is orthogonal to all columns of $\underline{\tilde{X}}_1(k)$, the second inner product in the numerator is zero and the bound on $\mu(k)$ reduces to

$$\mu(k) < \frac{2}{\|\underline{\psi}_1(k)\|_2^2} \quad (11)$$

Simulations: The performance of the AFP-NLMS2 algorithm is compared with that of the multi-channel affine projection algorithm (MCAPA) [2], and the ε-NLMS2 algorithm. Real speech data were used to test the algorithms for the noiseless case and for an SNR of 30dB. Fig. 2 shows the two cases with average weight error vector norm, WEVN = $\frac{1}{2}\sum_{i=1,2}(\|\underline{h}_i - \underline{\hat{h}}_i\|_2^2)/\|\underline{h}_i\|_2^2$, over both channels. For the noiseless case the performance of the AFP-NLMS2 far exceeeds that of the ε-NLMS2 and approaches that of the MCAPA of order 3. For the noisy case, the MCAPA becomes unstable due to noise amplification in the projection process, while the new AFP-NLMS2 stays stable and provides increased performance over ε-NLMS2.

Summary: A new algorithm for SAEC is introduced and analysed and is shown to outperform the MCAPA with real speech data. The AFP-NLMS2 of order 3 has lower computational complexity, $O(12L)$, than the MCAPA of order 3 $O(14L)$ and provides better noise immunity, where L is the adaptive filter length.

9 August 1999
Electronics Letters Online No: 19991271
DOI: 10.1049/el:19991271

N.T. Forsyth, J.A. Chambers and P.A. Naylor (*Communications and Signal Processing Division, Department of Electrical and Electronic Engineering, Imperial College of Science, Technology and Medicine, SW7 2BT, United Kingdom*)

References

1 BENESTY, J., *et al.*: 'Adaptive filtering algorithms for stereophonic acoustic echo cancellation'. Proc. ICASSP'95, Detroit, Michigan, USA, 1995, pp. 3099–3102
2 BENESTY, J., *et al.*: 'A multichannel affine projection algorithm with applications to multichannel acoustic echo cancellation', *IEEE Signal Process. Lett.*, 1996, 3, (2), pp. 35–37
3 RUPP, M.: 'Contraction mapping: An important property in adaptive filters'. Sixth IEEE DSP Workshop, Yosemite Nat. Park, CA, USA, 1994, pp. 273–276

Planar lightwave circuit design for programmable complementary spectral keying encoder and decoder

Chau-Han Lee, Shan Zhong, Xiao Lin, J.F. Young and Y.J. Chen

A planar lightwave circuit design for implementing complementary spectral keying encoders and decoders is presented. The design uses only one arrayed-waveguide grating integrated with arrays of thermo-optic phase shifters and attenuators in a reflective structure. The result is a compact, low component count, programmable spectral keying switch that can implement a variety of spectral encoding/decoding functions.

Introduction: Recently there has been considerable interest in optical code division multiple access (CDMA) systems as an efficient protocol for local area networks. Both coherent [1 – 3] and incoherent [4 – 6] systems have been investigated. Coherent approaches require picosecond or femtosecond pulsed lasers and phase detection systems that are generally complex, expensive, and cumbersome. Several different incoherent schemes have been proposed and demonstrated, some of which implemented bipolar coding as used in radio frequency CDMA and spread spectrum systems [6 – 9]. The most successful incoherent systems employ complementary spectral keying (CSK), in which one spectral pattern is transmitted for data '1' and the complementary pattern is transmitted for data '0'. CSK is a very powerful and general