

Acoustic Echo Cancellation using a Fast *QR*-RLS Algorithm and Multirate Schemes

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ABSTRACT

High quality acoustic echo cancellation is now required by hands-free systems used in mobile radio and teleconference communications. The demand for fast convergence, good tracking capabilities, and reduced complexity cannot be met by classical adaptive filtering algorithms. In this paper, a new echo canceller using multirate systems and a Fast *QR*-decomposition based RLS algorithm is investigated. Simulation results demonstrate the efficiency of this new combined structure for acoustic echo cancellation, and a fixed-point implementation of the proposed scheme confirms the expected numerical robustness of the Fast *QR*-RLS algorithm.

1. INTRODUCTION

With the increasing use of hands-free audio terminals in communication systems, the realization of a high quality hands-free function is a challenging research topic. The basic acoustic echo cancellation scheme is shown in fig. 1, and consists in modeling the echo path with an adaptive filter.

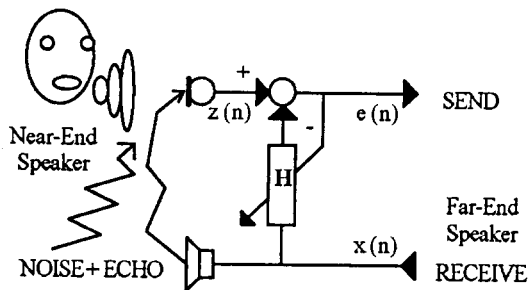


Figure 1 Principle of the acoustic echo canceller.

The ideal acoustic echo canceller would successfully cope with: the length of the impulse response (related to the reverberation times), the time-varying nature of the echo path (people moving, ...), the statistical properties of speech signals (highly correlated and nonstationary), the acoustic noise picked up by the microphone (office noise, car noise, ...), and the double-talk situations due to simultaneous near-end and far-end speech (approximately 10 % of a communication time). In the emerging field of mobile communications, the hands-free function appears to be one of the key features of telephone devices, as it has this dual advantage of improving the ergonomics of the communication as well as giving additional security when used in a car while driving. Thus, the context of use of such systems is new and technology demanding, [1]. As for example, in GSM

(the new European digital standard for radio communications) the high delay on the network (90 ms), the noise present in most communications, the nonstationarities of the acoustic path, the difficulty to characterise this environment a-priori, due to the wide range of possible ways of using the phone (various cars, offices, rooms, ...), are all factors that need to be addressed carefully so as to ensure adequate behaviour of the function. The well-known NLMS algorithm has generally been chosen for practical implementation. However, this algorithm performs poorly in the acoustic echo cancellation context. Recursive-Least-Squares algorithms are known to exhibit better performances, but suffer from complexity and instability. Stabilised versions of the Fast Transversal Filter, [2] have been developed, and Fast Newton Transversal Filters, using reduced prediction part, has been proposed [3], and used in the context of acoustic echo cancellation [4].

In this paper, we propose the use of an order recursive fast version of the *QR*-decomposition-based RLS algorithm, known for its good numerical properties, associated with multirate systems, [5][6], for reducing the overall complexity of the echo canceller. Different schemes are presented, taking advantage of the flexibility of the sub-band structure. Finally some simulation results are presented to assess the efficiency of the proposed fast *QR*-RLS-based echo canceller, in terms of performance, robustness to noise, double-talk and finite wordlength implementation.

2. *QR*-BASED RLS ALGORITHMS

The problem of recursive least-squares estimation is to find \mathbf{H} so as to minimize the following exponentially weighted cost function :

$$\xi(n) = \sum_{i=0}^n \lambda^{n-i} [z(i) - \mathbf{H}^T(n) \cdot \mathbf{x}(i)]^2 \quad (1)$$

where λ is a forgetting factor. The least-square solution to this problem is given by :

$$\mathbf{H}_{LS}(n) = \mathbf{C}^{-1}(n) \cdot \mathbf{r}(n) \quad (2)$$

where the autocorrelation matrix of the input signal matrix \mathbf{C} , and the cross-correlation \mathbf{r} between $z(n)$ and $\mathbf{x}(n)$ signals are recursively obtained with :

$$\mathbf{C}(n) = \lambda \cdot \mathbf{C}(n-1) + \mathbf{x}(n) \cdot \mathbf{x}^T(n) \quad (3)$$

$$\mathbf{r}(n) = \lambda \cdot \mathbf{r}(n-1) + \mathbf{x}(n) \cdot z(n) \quad (4)$$

Whereas the classical RLS algorithm exploits the matrix inversion lemma, the *QR*-RLS algorithm is based on the recursive updating of the *QR* decomposition of the input data matrix \mathbf{X} . The algorithm can then keep the initial dynamic range of the input signal. We suppose that at time $n-1$:

$$\mathbf{Q}(n-1) \cdot \mathbf{X}(n-1) = \begin{bmatrix} \mathbf{R}(n-1) \\ 0 \end{bmatrix} \quad (5)$$

where $\mathbf{Q}(n-1)$ is an $(n \times n)$ orthogonal matrix, and the matrix \mathbf{R} is an $(N \times N)$ upper triangular matrix. Using the last relation and a recursive formulation of the input data matrix, we get :

$$\begin{bmatrix} \mathbf{Q}(n-1) \\ 1 \end{bmatrix} \cdot \mathbf{X}(n) = \begin{bmatrix} \lambda^{1/2} \mathbf{R}(n-1) \\ 0 \\ \mathbf{x}^t(n) \end{bmatrix} \quad (6)$$

The orthogonal matrix \mathbf{Q} can now be updated using a set of N Givens rotations, known for their numerical robustness, according to:

$$\mathbf{Q}(n) = \mathbf{Q}_{N-1}^\theta(n) \dots \mathbf{Q}_0^\theta(n) \cdot \begin{bmatrix} \mathbf{Q}(n-1) \\ 1 \end{bmatrix} \quad (7)$$

Applying the orthogonal transformation to the error vector leads to the recursive equation :

$$\begin{bmatrix} \mathbf{z}_1(n) \\ \tilde{\mathbf{e}}(n) \end{bmatrix} = \mathbf{Q}_\theta(n) \cdot \begin{bmatrix} \lambda^{1/2} \mathbf{z}_1(n-1) \\ \mathbf{z}(n) \end{bmatrix} \quad (8)$$

where the orthogonal transformation matrix \mathbf{Q}_θ is reduced to rows and columns of \mathbf{Q} relative to the N Givens rotations. The *a-posteriori* error is then given, in terms of the square root of the conversion factor and the *rotated error* or *angle normalised*, by :

$$\mathbf{e}(n) = \tilde{\mathbf{e}}(n) \cdot \prod_{i=0}^{N-1} \cos \theta_i(n) = \tilde{\mathbf{e}}(n) \cdot \gamma(n) \quad (9)$$

with :

$$\gamma^2(n) = \mathbf{e}(n) / \mathbf{e}(n|n-1) \quad (10)$$

The derivation of fast *QR* algorithms (FQR) is based on recursive updating of the orthogonal transformation matrix using forward and backward prediction. Close relationships between fast *QR* algorithms and normalised least-squares lattice algorithms have been already pointed out in the literature [7][8].

Some similar investigations in electrical echo cancellation have been simultaneously carried out in [9], using the fixed-order Fast ROTOR's RLS algorithm [10]. Our contribution consists in using for the first time in the context of acoustic echo cancellation, an order-recursive version of the fast *QR*-based RLS algorithm [8][11]. The numerical stability and robustness of this algorithm [12], is one of our main motivations for its use in acoustic echo cancellers. The order recursive property of the fast *QR* algorithm chosen can also be used for dynamic adaptation to the impulse response length, in the context of

mobile hands-free systems used in various environments, car and office for instance.

3. PROPOSED STRUCTURES FOR ACOUSTIC ECHO CANCELLERS

In [13], the use of fast transversal RLS algorithms in a multirate scheme is proposed for acoustic echo cancellation. In a similar manner, we propose to use the fast *QR*-RLS algorithm in sub-band structures. This algorithm does not need any stability monitoring procedures like those required by fast transversal RLS algorithms, and the subsampling rate used in multirate schemes leads to significant computational reduction.

3.1. Double-Talk Detection

Double-Talk periods required quick and accurate detection for a correct behavior of the echo canceller. Classical detection methods feature slow response properties and are often unable to distinguish a double-talk period from a variation of the acoustic echo path. Moreover, they are inadequate for hands-free systems in noisy environments. We propose the use of a spectral distortion measure to compare the loudspeaker signal (related to the far-end speaker) with the signal picked up by the microphone (composed of the near-end speech, acoustic echo and background noise). It can be a classical Itakura-Saito-based distance between two AR models, or a cepstral-based distance, which can be derived from LPC predictor coefficients. Root-cepstral analysis is well-suited for a full-band double-talk detector in noisy environment [14]. A sub-band double-talk detection can also be performed, and in this case, the ratio of residual prediction error energies using small order AR models give good results.

3.2. Variable Length and Variable Forgetting Factor Adaptive Filters

One can take advantage of the order recursive property of the fast *QR*-RLS algorithm to obtain a variable-length adaptive filter. This structure is particularly interesting for reducing near-end speech distortion, and improving noise robustness, by selecting the output order of the adaptive filter according to short-term estimated level of the loudspeaker signal in each sub-band. A shorter adaptive filter is more robust to interference disturbance, and the residual echo in the corresponding sub-band will be partly masked by interference components, background noise or near-end speech.

The robustness of the fast *QR*-RLS algorithm to isolated forgetting factor variation, can also be used to reduce the misadjustment error, slowing down the adaptation process of the algorithm when interference is detected.

3.3. Mixed Structures

Some further improvements can be achieved in terms of complexity/performance trade-off, by using different adaptive algorithms with respect to the sub-band signal characteristics. An efficient algorithm (such as fast *QR*-RLS) is selected in lower frequency sub-bands due to the presence of high speech echo energy, and also for its robustness to noise interference,

4. SIMULATION RESULTS

The figures from 1 to 6 illustrates the results obtained by the two structures, on a real speech file. The figure 7 shows a comparison between a 16-bit fixed-point implementation and a floating-point implementation of the fast *QR*-RLS. It shows the

Subjective evaluations were performed by listeners for assessing near-end speech quality during "double-talk" periods and adverse conditions (car noise). The Fast *QR*-RLS scheme appeared to be significantly better than the NLMS one.

	SB NLMS	SB FQR-RLS
Mean ERLE	10.5 dB	17.5 dB
Maxi ERLE	21.0 dB	37.0 dB
Convergence Time to 10 dB of ERLE	320 ms	120 ms

5. CONCLUSION

ACKNOWLEDGEMENTS

REFERENCES

- 971

- [7] SLOCK D.T.M., "Reconciling Fast RLS Lattice and QR Algorithms", in IEEE ICASSP90, pp 1591-1594, 1990.
- [8] REGALIA P.A., and BELLANGER M.G., "On the Duality Between Fast QR Methods and Lattice Methods in Least Squares Adaptive Filtering", in IEEE Trans. SP, Vol.SP-39, No 4, pp 879-891, April 1991.
- [9] SIQUEIRA M.G., and ALWAN A., "New Adaptive-Filtering Techniques Applied To Speech Echo Cancellation", in Proc. ICASSP94, pp II-265-II-268, 1994.
- [10] CIOFFI J.M., "The Fast Adaptive ROTOR's RLS Algorithm", in IEEE Trans. ASSP, Vol. 38, No 4, pp 631-653, April 1990.
- [11] YANG B., and BOHME J.F., "Rotation-Based RLS Algorithms: Unified Derivations, Numerical Properties, and Parallel Implementations", in IEEE Trans. SP, Vol.SP-40, No 5, May 1992.
- [12] REGALIA P.A., "Numerical Stability Properties of a QR-Based Fast Least Squares Algorithm", in IEEE Trans. SP, Vol.SP-41, No 6, pp 2096-2109, June 1993.
- [13] HATTY B., "Recursive Least Squares Algorithms Using Multirate Systems for Cancellation of Acoustic Echoes", in Proc. ICASSP90, pp 1145-1148, 1990.
- [14] ALEXANDRE P., LOCKWOOD P., "Root Cepstral Analysis: A Unified View - Application to Speech Processing in Car Noise Environments", in Speech Communication 12, pp 277-288, 1993.
- [15] BOUDY J., MAGAN J., and GRENIER Y., "Description of the FRETEL database", submitted to EUROSPEECH 1995.

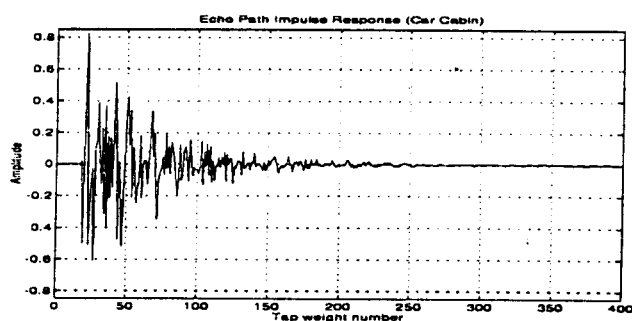


Figure 3. Acoustic Echo Path Impulse Response - Car AFE.

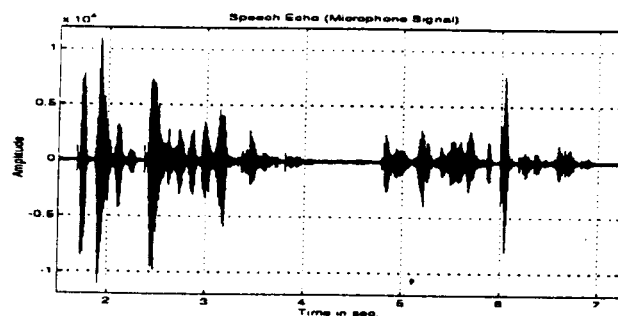


Figure 4. Real speech echo signal - Female Speaker - Car AFE.

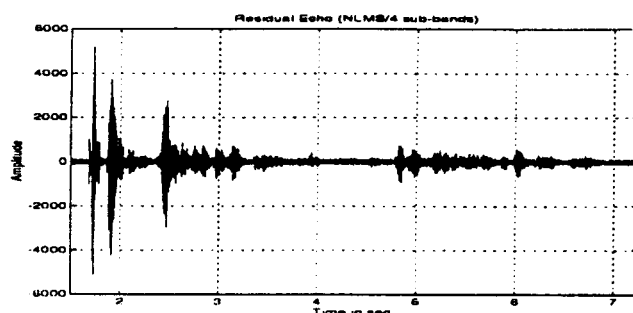


Figure 5. Sub-band (4) NLMS residual echo-64 taps/sub-band.

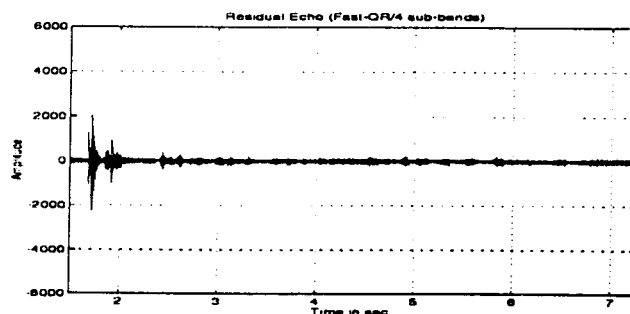


Figure 6. Sub-band (4) FQR-RLS residual echo-64 taps/sub-band.

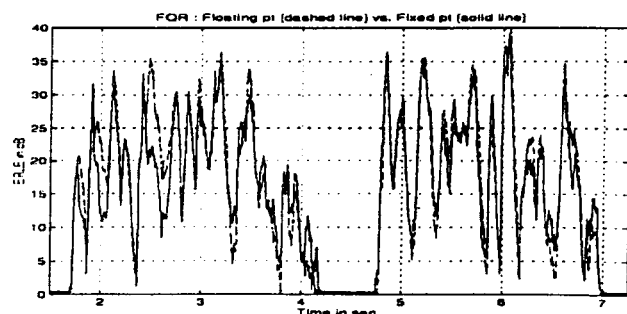


Figure 8. Fixed-point vs. floating point FQR-RLS (ERLE).

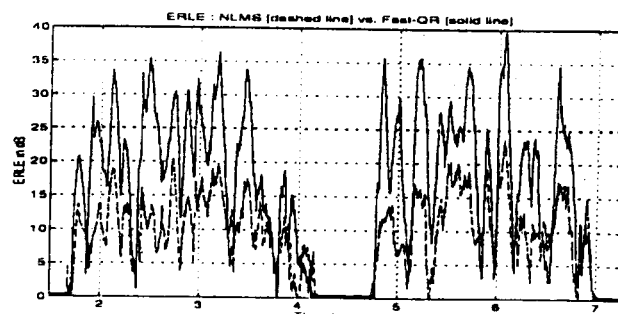


Figure 7. Comparative ERLE (max = 40 dB) curves.