CONTROLLED CONVERGENCE OF QR LEAST-SQUARES ADAPTIVE ALGORITHMS
- Application to Speech Echo Cancellation -

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ABSTRACT

With the increasing use of hands-free audio terminals in communication systems, the realization of a high quality hands-free function still remains a challenging research topic [1]. The use of Fast QR Least-Squares algorithms, combined with a multirate structure, have been proposed in [5] for good performances and reduced complexity. In this paper, we propose to modify QR Least-Squares adaptive algorithms in order to control the adaptation process in the context of acoustic echo cancellation. This modification is based on a similar idea developped for Fast Transversal Filters, [6], [7]. Simulation results demonstrate the efficiency of this modified adaptation process for QR-LS adaptive algorithms.

I. INTRODUCTION

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 ergonomy of the communication as well as giving additional security when used in a car while driving. The main difficulties encountered in acoustic echo cancellation are : the length of the impulse response, the time-varying nature of the echo path, the statistical properties of speech signals (highly correlated and nonstationary), the acoustic noise pickedup by the microphone, and the double-talk situations due to simultaneous near-end and far-end signals. Recursive-Least-Squares algorithms are known to exhibit better performances than the well-known NLMS algorithm, but suffer from complexity and instability. We suggested in [5] the use of Fast QR-based LS algorithms combined with a subband structure. In this paper, we propose to modify the adaptation of QR Least-Squares adaptive algorithms, known for their good numerical properties, to improve their tracking and convergence capabilty, as suggested in [6] and [7] for stabilized versions of Fast Transversal Filters. This modification can also be driven by a double-talk detector to slow down the adaptation process.

II. QR-BASED LEAST-SQUARES ALGORITHMS

Whereas classical RLS algorithms exploit the matrix inversion lemma, QR-based Least-Squares algorithms update the QR-decomposition of the input data matrix $\mathbf{X}$. These algorithms can then keep the initial dynamic range of the input signal. The basic QR-RLS algorithm is given by the three following relations :

$$\mathbf{Q}_{N+1,N+1}(n).\begin{bmatrix} \lambda^{1/2}.\mathbf{R}_{N,N}(n-1) \\ \mathbf{X}_N^t(n) \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{N,N}(n) \\ \mathbf{0}_N^t \end{bmatrix} \quad (1)$$

$$\mathbf{Q}_{N+1,N+1}(n).\begin{bmatrix} \lambda^{1/2}.\mathbf{Z}_N^{(1)}(n-1) \\ z(n) \end{bmatrix} = \begin{bmatrix} \mathbf{Z}_N^{(1)}(n) \\ e_N(n) \end{bmatrix} \quad (2)$$

$$e(n|n) = \gamma_N(n).e_N(n) \quad (3)$$

where the matrix $\mathbf{Q}_{N+1,N+1}(n)$ stands for the orthogonal transformation matrix, resulting from the product of N Givens rotations which annihilate the elements of the input signal vector $\mathbf{X}_N(n)$. The upper triangular matrix $\mathbf{R}_{N,N}$ results from the QR-decomposition. The a-priori and a-posteriori errors are noted e(n|n-1) and e(n|n). $\gamma_N(n)$ is the square-root of the conversion factor, or likelihood variable :

$$\gamma_N(n) = \prod_{i=0}^{N-1} \cos_i(n) = \left[\frac{e(n|n)}{e(n|n-1)} \right]^{1/2} \quad (4)$$

Finally, the so-called angle-normalized error, or mixed error, is related to the a-priori and a-posteriori errors according to :

$$e_N(n) = \sqrt{e(n|n-1).e(n|n)} \quad (5)$$

Several fast derivations of QR-type algorithms have been proposed, using either direct [2][3], or inverse [4], QR decomposition. Close relationships between fast QR algorithms and normalized least-squares lattice algorithms have been already pointed out in the literature [3].

III. MODIFIED ADAPTATION

As suggested in [6][7], the classical adaptation process (6) of fast transversal RLS algorithms can be modified for improved convergence according to (7) :

$$\mathbf{H}_N(n) = \mathbf{H}_N(n-1) + \mathbf{K}_N(n).e(n|n) \quad (6)$$

$$\tilde{\mathbf{H}}_N(n) = \mathbf{H}_N(n-1) + \alpha(n).\mathbf{K}_N(n).e(n|n)$$

with $\alpha(n) = \dfrac{1}{1 - \rho\gamma_N^2(n)}$ and $0 \le \rho \le 1.$ (7)

This modified adaptation process is obtained by annihilating the a-posteriori error :

$$\tilde{e}(n|n) = z(n) - \tilde{\mathbf{H}}_N^t(n).\mathbf{X}_N(n) = 0.$$

$$\tilde{e}(n|n) = e(n|n-1).\left[1 - \alpha(n).\left[1 - \gamma_N^2(n)\right]\right] = 0$$

We propose to modify the adaptation process of QR-based LS algorithms in a similar manner. To this end, we first recall that the optimum LS transversal filter can be obtained by solving the following set of equations :

$$\mathbf{Z}_N^{(1)}(n) = \mathbf{Z}_N^{(1)}(n|n) = \mathbf{R}_{N,N}(n).\mathbf{H}_N(n) \quad (8)$$

The modified rotated vector is then given by : (9)

$$\tilde{\mathbf{Z}}_N^{(1)}(n) = \left[1 - \alpha(n)\right].\mathbf{Z}_N^{(1)}(n|n-1) + \alpha(n).\mathbf{Z}_N^{(1)}(n)$$

where the rotated vector :

$$\mathbf{Z}_N^{(1)}(n|n-1) = \mathbf{R}_{N,N}(n).\mathbf{H}_N(n-1) \quad (10)$$

is obtained with a frozen adaptation process : (11)

$$\mathbf{Q}_{N+1,N+1}(n).\begin{bmatrix} \lambda^{1/2}.\mathbf{Z}_N^{(1)}(n-1) \\ z(n) - e(n|n-1) \end{bmatrix} = \begin{bmatrix} \mathbf{Z}_N^{(1)}(n|n-1) \\ 0 \end{bmatrix}$$

This modified adaptation process requires, at first sight, to compute the classical rotated vector according to relation

(2), the frozen rotated vector according to (11), and then the modified rotated vector according to (9). In fact, the overall complexity can be significantly reduced, by remarking that we only need to compute the a-priori error and get the modified updated rotated vector from a modified error :

$$\varepsilon(n) = \left[1 - \alpha(n)\right].e(n|n-1) \quad (12)$$

and

$$\mathbf{Q}_{N+1,N+1}(n).\begin{bmatrix} \lambda^{1/2}.\mathbf{Z}_N^{(1)}(n-1) \\ z(n) - \varepsilon(n) \end{bmatrix} = \begin{bmatrix} \tilde{\mathbf{Z}}_N^{(1)}(n|n) \\ \times \end{bmatrix} \quad (13)$$

This modified adaptation process can be used directly with fast QR-based LS algorithms, [2][4].

IV. APPLICATION TO ECHO CANCELLATION

In this section, the application ot the modifed adaptation process for QR-based algorithms is investigated in the context of speech echo cancellation.

IV.1. Background noise control

In the presence of acoustic background noise, the modified adaptation process given by (7) is no longer valid. The optimal value for $\alpha(n)$ is given by :

$$\alpha(n) = \frac{1 - \left[E\{\tilde{e}^2(n|n)\}/E\{e^2(n|n-1)\}\right]^{1/2}}{1 - \rho.\gamma_N^2(n)} \quad (14)$$

with $E\{\tilde{e}^2(n|n)\}$ equal to background noise energy.

An estimate E_{noise} of the background noise energy can be computed during speech pauses, and the a-priori error energy $E_e(n)$ can be recursively computed according to :

$$E_e(n) = \lambda.E_e(n-1) + (1-\lambda).e^2(n|n-1) \quad (15)$$

Finally, we get : $\alpha(n) = \dfrac{1 - \left[E_{noise}/E_e(n)\right]^{1/2}}{1 - \rho.\gamma_N^2(n)}$ (16)

IV.2. Double-Talk period control

When the interference signal is due to near-end speech (in double-talk periods), we cannot easily replace, in (16), the estimate E_{noise} by an estimate of the near-end speech energy. But as suggested in [6], we can still use the same

idea to slow down or freeze the adaptation process, when double-talk periods are detected, with $\alpha(n)$ driven by the double-talk detector in the range [0,1].

$\alpha(n) = 1$	classical adaptation process
$\alpha(n) = 0$	frozen adaptation process
$\alpha(n) = \dfrac{1 - \left[E_{noise}/E_e(n)\right]^{1/2}}{1 - \rho.\gamma_N^2(n)}$	modified adaptation in single-talk
$\alpha(n) = f(DTD)$ in $[0,1]$	modified adaptation in double-talk

table [IV.1] : $\alpha(n)$ value for controlled adaptation process.

IV.3. Multirate Structures

The use of a multirate structure for the realisation of the echo canceller [5], not only reduces the overall complexity, but also gives us the opportunity to tune the algorithms independently in each subband. This also applies to the modified adapation process. If background noise or near-end speech is located in some specific subbands, we can slow down or freeze the adaptation of corresponding algorithms, without affecting the convergence in the remaining subbands.

When using critically subsampled filter banks, it has been shown in [9] that aliased components can be cancelled by adding cross-band adaptive filters. This scheme can be advantageously applied to QR based LS algorithms. In particular, for order-recursive type algorithms [2][4] output errors are available for all intermediate orders, and cross-band adaptive filters can reuse the prediction part of the corresponding in-band adaptive filter, with a lower order than the in-band filter. The increased complexity is then only due to the modified filtering part.

V. SIMULATION RESULTS

The evaluation of the modified adaptation process is illustrated on figures [V.1], [V.2] for a speech signal, and on figures [V.3], [V.4] for a USASI (speech like) signal. The echo signals were obtained using a 512-tap impulse response, corresponding to a hands-free car-kit. A jump of the impulse response was applied for both the speech and USASI signals, in order to evaluate the improvement of the tracking capability. The jump is located at approximately 3.6 sec. for the speech signal, and 6.7 sec. for the USASI signal. The identification was performed using a 380-tap filter. The forgetting factor was equal to $(1-\frac{1}{5N})$, with ρ equal to 0.95. The convergence and tracking

capability improvements are clear for both speech and USASI signals. We can only notice an increased level of misadjustment for the USASI signal (fig.V.4 vs fig.V.3).

A comparison of ERLE performances is shown on fig. V.5, V.6, V.7., between a 4-subband structure based on classical CQF-32 analysis filters, with and without crossband filters. An FQR-LSL adaptive algorithm has been used with 64 taps for in-band filters and 16 taps for cross-band filters. The results are given for a car-kit acoustic front-end, using a speech signal. The ERLE improvement is clear for the first cross-band at 1 kHz, where speech is energetic. The overall improvement over a classical structure is about 5 dB.

VI. CONCLUSION

Fast QR-based Least Squares adaptive algorithms are an interesting alternative to classical transversal adaptive filters for acoustic echo cancellation. We have shown in this paper than modifications for improving convergence and tracking capabilities of Fast Transversal Filters can easily be applied to most QR-based algorithms. The derived modification of the adaptation process can then be used to both improve performances and control the adaptation in the presence of interference signals : double-talk or noise.

ACKNOWLEDGEMENTS

REFERENCES

[1] BOUDY J., LOCKWOOD P., BECKER T., and SITZMANN J., 1992, "Hands-free Radiotelephones For Car Application", in Conference DMR-V, Helsinki, December 1992.
[2] REGALIA P.A., and BELLANGER M.G., 1991, "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.
[3] SLOCK D.T.M., 1990, "Reconciling Fast RLS Lattice and QR Algorithms", in IEEE ICASSP'90, pp 1591-1594,1990.
[4] RONTOGIANNIS A.A., THEODORIDIS S., 1995, "New Fast Inverse QR Least Squares Adaptive Algorithms", in IEEE ICASSP'95, pp 1412-1415, 1995.
[5] CAPMAN F, BOUDY J., LOCKWOOD P., 1995, "Acoustic Echo Cancellation Using A Fast-QR-RLS Algorithm and Multirate Schemes", in IEEE ICASSP'95, Detroit, pp 969-972, 1995.
[6] SLOCK D.T.M., KAILATH T., 1991, "Numerically Stable Fast Transversal Filters for Recursive Least Squares Adaptive Filtering", in IEEE Trans. SP, Vol. 39, n° 1, pp 92-113, January 1991.
[7] BENALLAL A., GILLOIRE A., 1989, "Improvement of the Tracking Capability of the Numerically Stable Fast RLS Algorithms for Adaptive Filtering", in IEEE ICASSP'89, pp 1031-1034, 1989.
[8] TERRE M., BELLANGER M.G., 1995, "Application de l'algorithme QR rapide systolique à l'annulation d'écho", 15 ème colloque GRESTSI-Juan-Les-Pins, pp 435-438, September 1995.
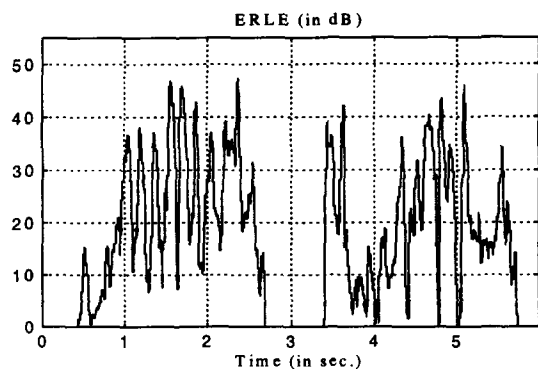
[9] GILLOIRE A., VETTERLI M., 1988, "Adaptive Filtering in Sub-Bands ", in IEEE ICASSP'88, pp 1572-1575, 1988.

ERLE (in dB)

figure [V.1] : Classical adaptation - Speech signal - IR jump at 3.6s.
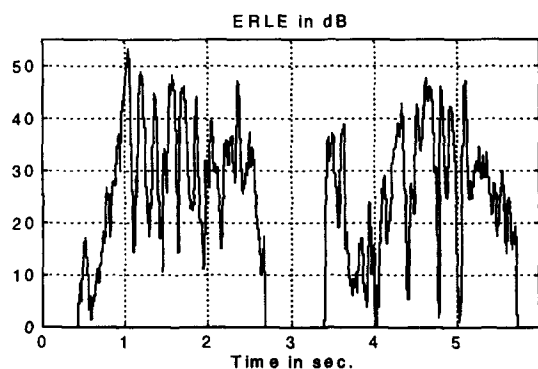
ERLE in dB

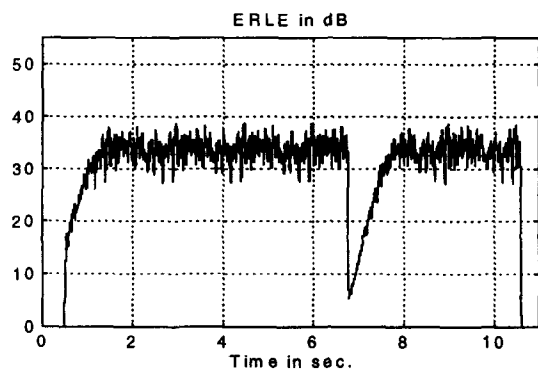figure [V.2] : Modified adaptation - Speech Signal - IR jump at 3.6 s.

ERLE in dB

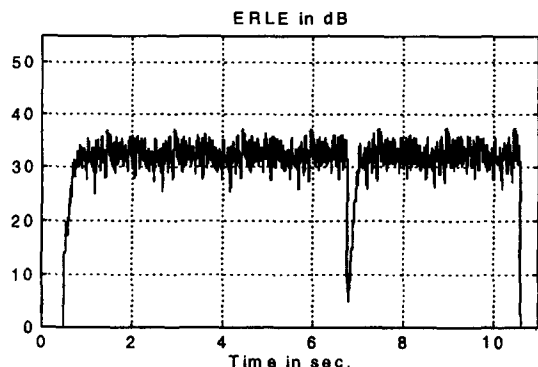figure [V.3] : Classical adaptation - USASI signal - IR jump at 6.7 s.

ERLE in dB

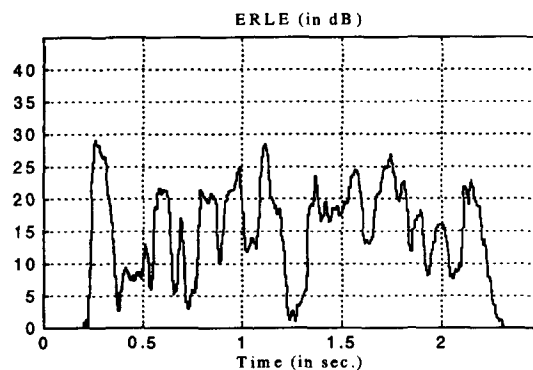figure [V.4] : Modified adaptation - USASI signal - IR jump at 6.7 s.

ERLE (in dB)

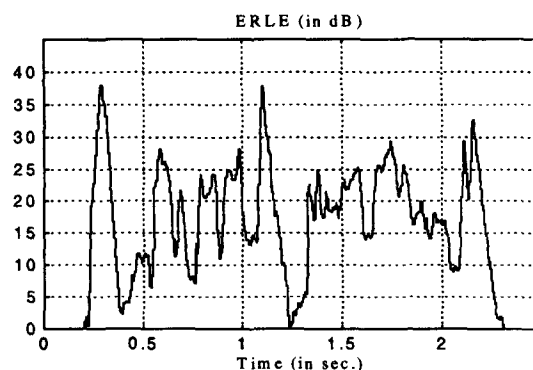figure [V.5] : ERLE (dB) - Subband FQR-LSL - Without cross-filters.

ERLE (in dB)

figure [V.6] : ERLE (dB) - Subband FQR-LSL - With cross-filters.
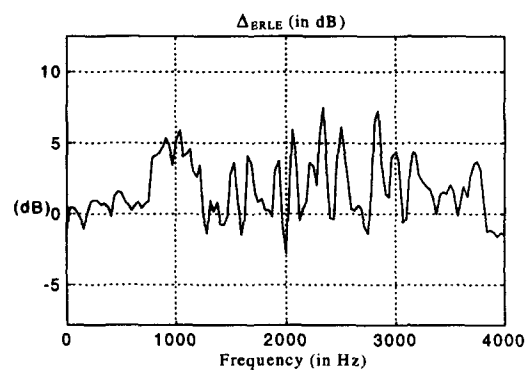
Δ_{ERLE} (in dB)

figure [V.7] : Frequency-domain ERLE (dB) improvement of the cross-filters based subband structure, over the classical subband structure (speech signal).