ON PERFORMANCE OF LINEAR ADAPTIVE FILTERING ALGORITHMS IN ACOUSTIC ECHO CONTROL IN PRESENCE OF DISTORTING LOUDSPEAKERS

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ABSTRACT

Echo attenuation obtained using linear adaptive filtering algorithms in the presence of distorting loudspeaker is discussed. Experimental evidence is given that, when the acoustic echo path is almost linear, computationally complicated algorithms (such as RLS or APA) give considerable better echo attenuation than normalized LMS, but this is not the case when there are considerable nonlinearities (i.e. acoustic distortion) in the echo path. However, it is illustrated that when a suitable nonlinear preprocessor is added to produce acoustic distortion to adaptive linear filter input then the more complicated algorithms give better overall echo attenuation than normalized LMS. Finally, it is shown that if there is acoustic distortion but no preprocessor the parameters of linear adaptive filter are the closest to the parameters of acoustic echo path that follows the nonlinearity in normalized LMS adaptation.

1. INTRODUCTION

This paper focuses to acoustic echo control in the presence of distorting loudspeakers. Acoustic echo path is modeled using FIR filter defined by

$$y(n) = \sum_{m=0}^{M-1} w_m x(n-m), \tag{1}$$

where $x(n)$ is input (far-end speech), $y(n)$ output (replica of the echo) and M is the number of filter parameters w_m, $m = 0, \ldots, M-1$.

According to [1] the normalized LMS algorithm has become the de facto standard for adapting (1) in acoustic echo cancellation and originally the algorithm was proposed in the late 1960's [2]. It is derived considering a constrained optimization problem where the sum $\sum_{m=0}^{M-1} (w_m(n) - w_m(n-1))^2$ is minimized subject to constraint

$$\sum_{m=0}^{M-1} w_m(n)x(n-m) = d(n), \tag{2}$$

where $d(n)$ is a microphone signal in near-end (desired output). The algorithm can be summarized by

$$\begin{aligned} y(n) &= \sum_{m=0}^{M-1} w_m(n-1)x(n-m) \\ e(n) &= d(n) - y(n) \\ w_m(n) &= w_m(n-1) + \frac{\mu e(n) x(n-m)}{\delta + \sum_{l=0}^{M-1} x(n-l)^2}. \end{aligned}$$

If the step size $\mu = 1$ and regularization factor $\delta = 0$ the exact solution of the constrained optimization problem is obtained in each step. However, in practice, it has been observed that adjusting μ and δ can improve the algorithm significantly (cf. e.g. [3]). The computational complexity of normalized LMS is low, $\mathcal{O}(M)$.

It has been long known that the normalized LMS algorithms suffers from slow convergence [2]. Thus, alternative algorithms such as RLS, and more recently affine projection algorithm (APA) have been proposed [2, 4]. They have fast initial convergence and, in acoustic echo control, they generally give good echo attenuation if the signals are measured using the high-quality equipment. However, when using measurements with inexpensive hands-free sets it seems that, after convergence, the normalized LMS gives as good or even better echo attenuation.

We assume that this is caused by the acoustic distortion in the loudspeaker. Such measurement noise is a filtered version of a signal dependent error signal, i.e. it is not additive. Thus, linear model is insufficient in the presence of distorting loudspeakers, especially in high volumes. Although loudspeakers are not completely memoryless devices, we consider modeling the echo path with a separable model, a memoryless nonlinearity followed by a linear filter, as illustrated in Figure 1. Previously we have successfully modeled acous-

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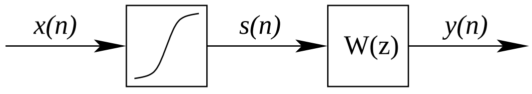

Figure 1: Model for acoustic echo path: a memoryless nonlinearity followed by a linear filter

tic distortion in loudspeakers using polynomial models [5, 6].

This paper is organized as follows. In Section 2, we review RLS and affine projection algorithms and discuss how they differ from normalized LMS. New results have been obtained in thorough simulations and they are presented in Section 3. Some final conclusions are drawn in Section 4.

2. ALGORITHMS

In this section we review the RLS and the affine projection algorithms (APA). They are computationally more complicated than normalized LMS. The underlying idea in both the algorithms is to fit more precisely to the data than it is possible with normalized LMS. In normalized LMS adaptation only previous values of filter parameters, current data and estimation error are used.

In least squares adaptive filter design the cost function

$$\begin{aligned}\mathcal{E}_{\mathrm{RLS}} &= \sum_{k=0}^{n} \lambda^{n-k} \left(d(k) - \sum_{m=0}^{M-1} w_m x(k-m) \right)^2 \\ &\quad + \lambda^{n+1} \delta \sum_{m=0}^{M-1} w_m^2 \qquad (3)\end{aligned}$$

is minimized at each iteration n by setting its gradient equal to zero with respect to parameters $w_0, \ldots, w_{M-1}$. The parameter λ is referred to as forgetting factor and its role is to control convergence and tracking speed. The RLS algorithm is known to suffer from numerical instability, but such problems can be almost completely avoided by using its square root variants, such as QR–RLS. The computational complexity of ordinary RLS and its square root variants is $(\mathcal{O}(M^2))$. There are also fast variants of RLS but they are numerically unstable [2].

The ordinary affine projection algorithm, APA, proposed in [7] is a generalization of the normalized LMS algorithm, where the constraint (2) is generalized to be

$$\sum_{m=0}^{M-1} w_m(n) x(n-m-p) = d(n-p), \quad p = 0, \ldots, P-1. \qquad (4)$$

The parameters μ (step size) and δ (regularization factor) are introduced again to improve the performance of the algorithm. The normalized LMS algorithm corresponds to the special case $P = 1$.

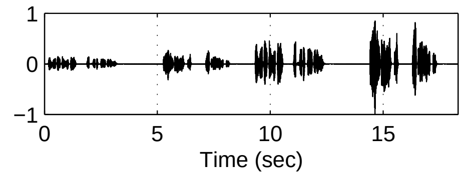

Figure 2: Far-end signal

The computational complexity of ordinary APA is $\mathcal{O}(MP + P^2)$, a tradeoff between RLS and normalized LMS, and it may also suffer from numerical instability. Thus, there have been quite many variants introduced recently [2].

3. SIMULATIONS

In simulations, we demonstrate that there is no significant difference between the adaptive linear filtering algorithms in the presence of distorting loudspeakers unless far-end signal is suitably preprocessed. Test signal, shown in Figure 2, consist of Finnish sentences *"Hän ei pelkää mitään. Lapsi opettelee puhumaan. Pöydällä on sanomalehtiä. Elokuva oli jännittävä."* said first in normal loudness level and repeated with the loudness of the hands-free set turned into maximum.

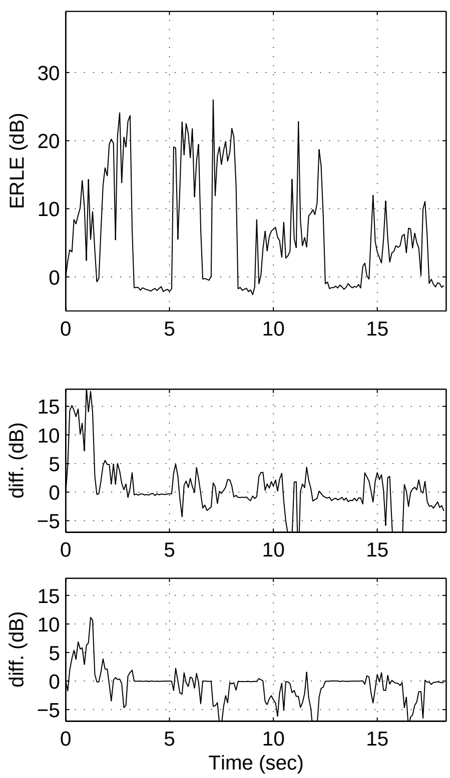

Figure 3: The echo attenuation (ERLE) obtained using normalized LMS (top) in the presence of distorting loudspeakers and how much it can be improved using QR–RLS (middle) and AP (bottom) algorithms

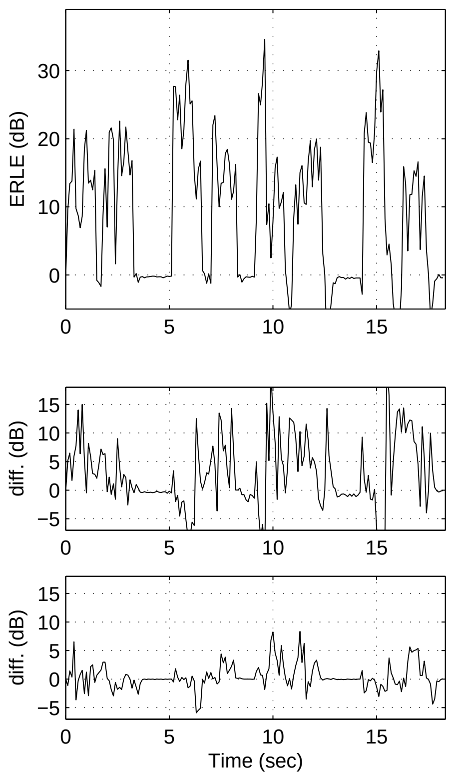

Figure 4: The echo attenuation (ERLE) obtained using normalized LMS (top) when the true echo path is linear and how much it can be improved using QR–RLS (middle) and AP (bottom) algorithms

The first simulations are carried out using NLMS, QR–RLS and AP (projection order $P = 6$) algorithms with $\mu = 0.8$, $\delta = 9 \times 10^{-5}$ and $\lambda = 0.999$. The measurements have been carried out in a car in garage using a hands-free set and high quality equipment. In Figures 3 and 4, we give some evidence that in terms of echo attenuation

$$\mathrm{ERLE} = 10 \log_{10} \frac{\mathrm{E}(d^2(n))}{\mathrm{E}(e^2(n))} \qquad (5)$$

($d(n)$ – echo, $e(n)$ – residual echo, measured in windows of 100 ms) QR–RLS and APA outperform normalized LMS when the measurements are carried out using high quality equipment, but there is no such difference in the presence of distorting loudspeakers. We also note that in the case of distorting loudspeakers the performance of linear adaptive filtering algorithms drops by 10–15 dB when the volume is turned to maximum.

Secondly, we consider separable homogeneous Volterra filter

$$y(n) = \sum_{m=0}^{M-1} \sum_{q=1}^{Q} w_m a_q x(n-m)^q, \text{ with } a_1 = 1, \qquad (6)$$

for compensating acoustic distortion in loudspeakers. It is of the general form illustrated in Figure 1 with

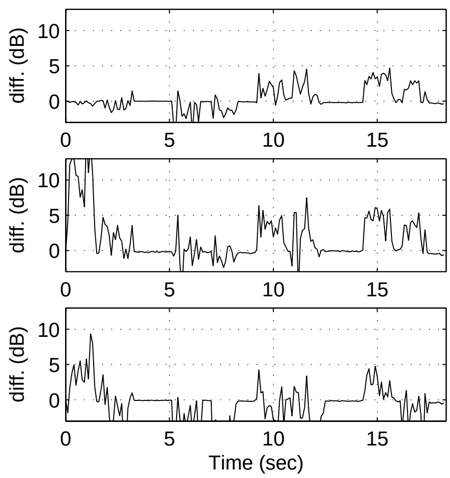

Figure 5: The improvement in echo attenuation (ERLE), compared to linear adaptive filter (adapted using normalized LMS), obtained using a fixed nonlinear preprocessor and normalized LMS (top) QR–RLS (middle) and AP (bottom) algorithms

$s(n) = \sum_{q=1}^{Q} a_q x(n)^q$ and $y(n) = \sum_{m=0}^{M-1} w_m s(n - m)$. We compute fixed parameters $a_1, a_2, \ldots, a_Q$ off-line and compare the performance of adaptive linear filtering algorithms with $s(n)$ as input and $d(n)$ as output. As shown in Figure 5, the QR–RLS adaptation of the linear part now gives slightly better improvement to echo attenuation compared to normalized LMS.

Finally, we use measurements from anechoic chamber as far-end signal $x(n)$ and generate the microphone signal

$$d(n) = \sum_{m=0}^{M-1} h_m s(n-m), \qquad (7)$$

from the measured loudspeaker output $s(n)$ using a fixed linear filter $H(z)$. Its coefficients were estimated from data simultaneously with the fixed nonlinearity of the previous example. In Figure 6, we compare the results of adaptive linear filters in terms of system error norm

$$\Delta w = 10 \log_{10} \mathrm{E} \left(\sum_{m=0}^{M-1} (h_m - w_m(n))^2 \right) \qquad (8)$$

estimated in windows of 100 ms. As shown in Figure 6, in terms of system error norm the best results are obtained using normalized LMS although in the beginning of speech activity QR–RLS gives parameters that are closer to the parameters of $H(z)$. In Figure 7, the results are compared in terms of overall echo attenuation.

4. CONCLUSIONS

We have simulated the performance of adaptive linear filtering algorithms in the presence of distorting loud-

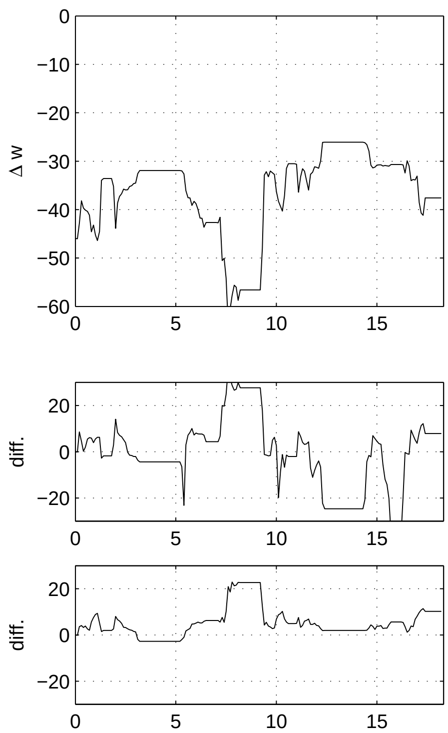

Figure 6: System error norm between the true and estimated linear echo path that follows an acoustic distortion measured in anechoic chamber. The echo path was estimated using normalized LMS algorithm (top) and compared to QR–RLS (middle) and APA (bottom).

speakers that decrease the performance of acoustic echo cancelers driven by normalized LMS algorithm by 10–15 dB in maximal volume levels.

We have shown that although in ideal environment, where acoustic echo path is almost linear, considerable improvement can be achieved using QR–RLS or AP algorithms, both algorithms fail in producing any significant improvement (besides faster convergence) in presence of distorting loudspeakers. The normalized LMS finds the parameters of the linear echo path that follows the nonlinearity most efficiently. If the acoustic distortion is compensated using a polynomial preprocessor the use of QR–RLS or APA can be justified in the performance point of view.

5. REFERENCES

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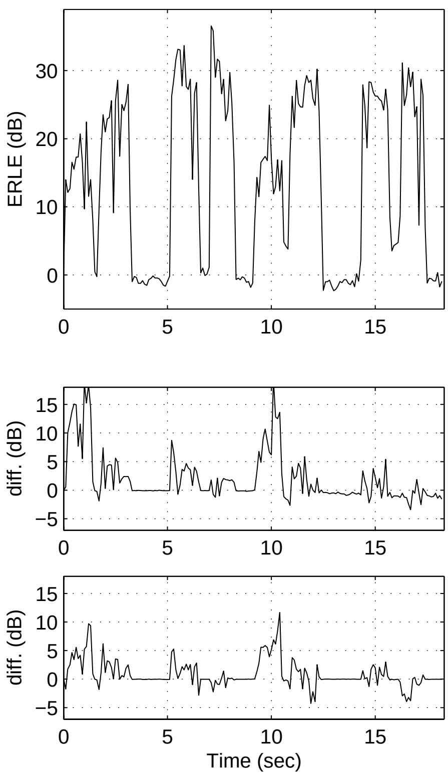

Figure 7: Comparison of the results presented in Figure 6 in terms of echo attenuation.

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