COMBINED ECHO AND NOISE CANCELLATION BASED ON GAUSS-SEIDEL PSEUDO AFFINE PROJECTION ALGORITHM

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ABSTRACT

In this paper, we propose an approach for combined acoustic echo and noise cancellation based on the Gauss-Seidel Pseudo Affine Projection algorithm (GS-PAP). It includes a simple residual echo cancellation scheme and a double-talk detector using a two-path model. Simulation results indicate that the proposed GS-PAP is stable, fast convergent and has good tracking abilities, which are attractive for acoustic echo cancellation.

1. INTRODUCTION

Adaptive filtering is essential in applications such as system identification, channel equalization, speech coding, and acoustic echo cancellation. In acoustic echo cancellation systems, an adaptive filter algorithm is used to reduce the echo. The well-known normalized LMS (NLMS) algorithm has been widely used but it has slow asymptotic convergence. The affine projection algorithm (APA) [1] can be considered as a generalization of the NLMS algorithm. It is known that the convergence performance of APA is between those of the LMS-based algorithms and the RLS-based algorithms. Some papers [2-5] address the decorrelation properties of the affine projection (AP) algorithm, which provides an improved convergence speed compared to stochastic gradient descent algorithms. It is shown in [2] that it is sensitive to a high level of noise. The implementation complexity of the original APA [1] is high. The fast version proposed in [6], when implemented with an embedded FRLS (Fast Recursive Least Squares) algorithm suffers from numerical instability. In [7], we proposed a simple and stable FAP algorithm, called the Gauss-Seidel Fast Affine Projection algorithm. In [4], a sub-optimal implementation of the AP algorithm, called the Pseudo Affine Projection (PAP) algorithm, was derived using the Levinson-Durbin recursion from the original APA algorithm under some realistic hypotheses. Starting from the same hypotheses as [4], we derive a new algorithm based on Gauss-Seidel method (GS-PAP) in section 2. In section 3, a double-talk detection algorithm based on the two-path model [8] is used and a simple residual echo cancellation method is proposed. Fig. 1 shows the combined acoustic echo and noise cancellation system. The system has an acoustic echo canceller (AEC), a double-talk detector (DTD), and a residual echo canceller (REC). The AEC is realized by an adaptive FIR filter to cancel the effect of the loudspeaker enclosure microphone system (LEM). The simulation results and the computational complexity of these algorithms are evaluated in section 4. Section 5 concludes this work.

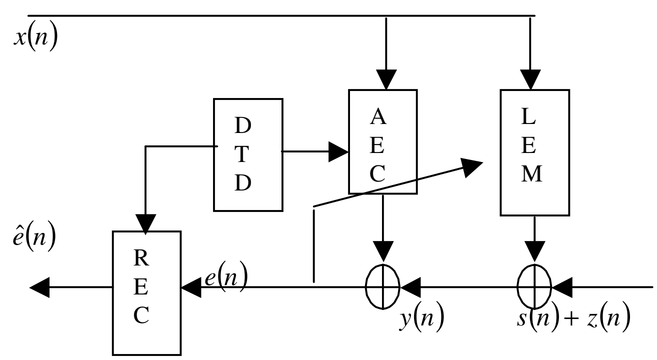

Fig. 1. Combined echo and noise cancellation.

2. GS-PAP ALGORITHM

We will adopt the notations from [7]. Starting from the original PAP algorithm [4], we replace the Levinson-Durbin procedure with the Gauss-Seidel procedure. The same approximation for the de-correlated input vector as [4] is used. In the following description, $x(n)$ is the input signal; $y(n)$ is the desired output signal; $e(n)$ is the output error; $z(n)$ is the ambient noise; N is the projection order; L is the filter length; $\mathbf{X}(n)=\left[x(n),...,x(n-L+1)\right]^T$; $\mathbf{R}(n)$ is the auto-correlation matrix of the signal (symmetric and positive definite); $\xi(n)=\left[x(n),...,x(n-N+1)\right]^T$; δ is a regularization factor that prevents the input auto-correlation matrix from becoming ill-conditioned; $\mathbf{U}(n)=\left[u(n),...,u(n-L+1)\right]^T$ is the approximated decorrelation vector; $\mathbf{b}$ is an N vector with only one non-zero element, which is unity at the top; $\mathbf{H}(n)=[h_1(n),...,h_L(n)]^T$ is the filter coefficients vector; $\mathbf{P}$ is also an N vector that can be updated less frequently (after p iterations). Table 1 summarizes the equations to be used in our Gauss-Seidel Pseudo Affine Projection (GS-PAP) algorithm.

$\mathbf{X}(-1)=\mathbf{0},\ \mathbf{R}(-1)=\delta\mathbf{I},\ \mathbf{P}(-1)=\mathbf{b}/\delta,$ $\mathbf{U}(-1)=\mathbf{0},\ \mathbf{H}(-1)=\mathbf{0}$	(1)
$\mathbf{R}(n)=\mathbf{R}(n-1)+\xi(n)\xi^T(n)-\xi(n-L)\xi^T(n-L)$	(2)
$\mathbf{R}(n)\mathbf{P}(n)=\mathbf{b}$	(3)
$e(n)=y(n)-\mathbf{X}^T(n)\mathbf{H}(n-1)$	(4)
$\mathbf{U}(n)=\frac{1}{\mathbf{P}_0(n)}\sum_{i=0}^{N-1}\mathbf{P}_i(n)\mathbf{X}(n-i)$	(5)
$\bar{e}(n)=\frac{\mu}{\mathbf{U}^T(n)\mathbf{U}(n)+\delta}e(n)$	(6)
$\mathbf{H}(n)=\mathbf{H}(n-1)+\mathbf{U}(n)\bar{e}(n)$	(7)

Table 1. The GS-PAP algorithm.

The Gauss-Seidel method used to solve (3) is guaranteed to converge because the matrix $\mathbf{R}(n)$ is symmetric and positive definite [9]. Due to its regular structure, the updating of $\mathbf{R}(n)$ is implemented efficiently by reorganizing the memory buffers. The normalized step size can be chosen within a range from 0 to 1. The Gauss-Seidel method computes an approximation of the optimal prediction coefficients. An advantage of the PAP and the GS-PAP algorithms is that they provide the filter coefficients unlike the other FAP algorithms that compute only auxiliary coefficients. A similar, but more complex algorithm, called the Gram-Schmidt Affine Projection (GS-AP) algorithm was proposed in [5] for stereophonic acoustic echo cancellers. It can be seen that (6) and (7) lead to similar update equations as the NLMS algorithm.

3. RESIDUAL ECHO CANCELLATION AND DOUBLE TALK DETECTION

We have chosen the two-path model proposed in [8] for handling the double-talk. In this method, the background filter tries to adapt to the signal and only decide if the filter has converged or not. The other filter, called the foreground filter, is not adaptive, but cancels the echo. The copying of the background filter coefficients to the foreground ones is made when a set of conditions are met [8]. This algorithm is not sensitive to echo path change, but the delay introduced by copying the coefficients slows down its convergence. Depending on the decision of the double-talk detector, there are several requirements for the residual echo cancellation (REC) system. It should reduce the residual echo, but should not attenuate the local speech signal if double-talk happens. The algorithm provides a smooth amplitude, in order to limit the dynamic range in the computations [10]. We define:

$$\chi_e(n)=(1-\gamma)\chi_e(n-1)+\gamma\left(\left|e(n)\right|\right) \tag{8}$$

$$\upsilon(n)=(1-\gamma)\upsilon(n-1)+\gamma\left(\left|z(n)\right|\right) \tag{9}$$

$$D(n)=1-\mu\times 2^{-\frac{\chi(n)}{\eta\upsilon(n)}} \tag{10}$$

where η is a constant that controls the level of the attenuation and $0<\gamma<1$. The final error is

$$\hat{e}(n)=e(n)\times D(n)=e(n)\times\left(1-\mu\times 2^{-\frac{\chi(n)}{\eta\upsilon(n)}}\right). \tag{11}$$

If there is no double talk, $D(n)$ is close or tends to zero. Therefore, a faster convergence is obtained (see Fig. 5b). When double talk occurs, $\chi_e(n)$ increases, and the local speech is slightly attenuated. The local speech is not attenuated when the filter weights are frozen ($\mu=0$) during the double talk (see Fig. 5b). Some multiplications from (8) and (9) can be replaced by a shift if γ is chosen to be a power of two $\left(\gamma=2^{-l}\right)$.

4. SIMULATIONS

We tested the algorithms with two different filter lengths ($L=256$ and 1024) representing a car cabin and a room impulse responses. For the first figure, as shown in [11], we truncated the impulse response of the car cabin to 259 coefficients, so that the theoretical minimum misalignment is -49.06 dB. The convergence of the algorithms was compared by using the squared norm of the difference between the LEM model and the adaptive filter (in dB) [11]. The comparative performance is focused on the GS-PAP and the NLMS algorithms for white noise, colored noise (or speech excitation). The signal was generated as shown in [11] by AR filtering a white noise signal with 15 LPC coefficients of a typical speech signal. As expected, no comparable difference between the GS-PAP and the NLMS algorithms performance for the case of a white noise excitation was visible in our simulations. A similar result was reported in [11] regarding the affine projection and the NLMS algorithms. The advantages of the GS-PAP compared to the NLMS are evident in the case of colored excitation signals (see Fig. 2) and speech excitation (see Fig. 3).

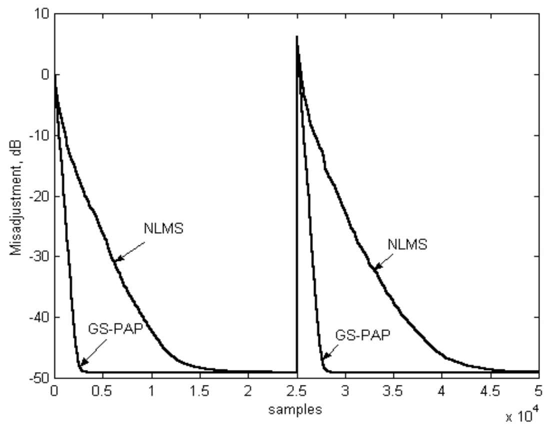

Fig. 2. Learning curves for GS-PAP and NLMS algorithms for colored excitation ($L = 256$, $N = 10$) under a sudden change in echo path.

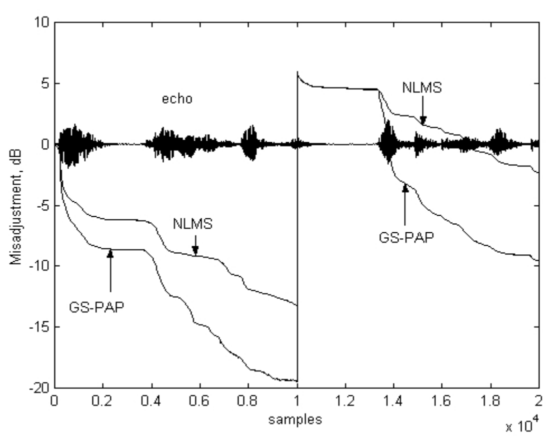

Fig. 3. Learning curves for GS-PAP and NLMS algorithms ($L = 1024$, $N = 10$) under a sudden change in echo path.

Fig. 2 shows that the theoretical minimum misalignment is reached by both algorithms so that the comparison of convergence rate and tracking performance is fair. In Fig. 3, the excitation signal was a speech signal, sampled at 8 kHz. The local noise level was 30 dB bellow the echo level. In these figures, the tracking ability of the algorithms is investigated by a sudden change in the echo path. It can be seen that the tracking performance of the GS-PAP algorithm is better than that of the NLMS in all the considered cases. Our simulations have shown that the convergence speed decreases with increasing filter length. As expected, the adaptation of the GS-PAP algorithm is slower in a speech excitation than in a colored excitation. Also, our simulations have shown that the GS-PAP algorithm retains the sensitivity to high level of noise of the original AP algorithm [2].

ALGORITHMS	$N = 2$	$N = 10$	$N = 20$
APA [1]	4124	21180	43760
FAP [6]	2088	2248	2448
GSFAP [7]	2061 (2058)	2189 (2099)	2529 (2169)
PAP [4]	2066 (2063)	2202 (2112)	2552 (2192)
GS-PAP	**2063 (2060)**	**2183 (2093)**	**2513 (2153)**
NLMS	2052	2052	2052

Table 2. Computational complexity (number of divisions and multiplies) of different FAP algorithms ($L = 1024$).

Table 2 compares the numerical complexity of the considered algorithms for three values of the projection order. The GS-PAP algorithm has $2L + N^2 + 3N + 5$ multiplies and divisions. It can be seen that all the fast affine projection algorithms are only marginally more complex than the NLMS. The GS-PAP algorithm is more efficient for high projection orders. Also, our simulations have shown that the simpler updating procedure further reduces the numerical complexity of the PAP, the GS-PAP, and the GSFAP without affecting their performances (see the values between parentheses in Table 2).

All these results were similar with those of [11] because the GS-PAP is a close approximation of the original AP algorithm. The step size for the NLMS and the GS-PAP was $\mu = 1$ and we updated $\mathbf{P}$ vector every 10 samples. We simulated the behaviors of the algorithm in 16-bit fixed point and 32-bit floating-point arithmetic. Fig. 4 shows some losses in performances due to reduced word-length precision. The GS-PAP finite word-length implementations were stable in all the simulations. Fig. 5a shows that the use of the residual echo reduction method leads to significant improvements of the echo return loss enhancement (ERLE) performance over those of the GS-PAP or the NLMS based AEC.

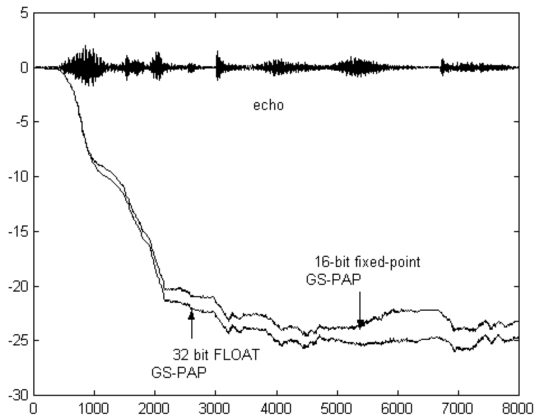

Fig. 4. Learning curves for 32-bit FLOAT and 16-bit fixed point GS-PAP implementations ($L = 256$, $N = 10$).

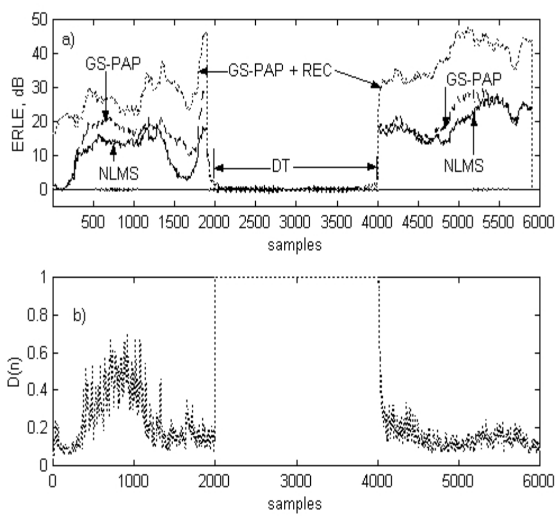

Fig. 5. a) ERLE curves for NLMS, GS-PAP, and GS-PAP + REC; b) Attenuation *D(n)* of REC system ($L = 256$, $N = 10$, $\eta = 10$).

5. CONCLUSIONS

It has been shown by simulations that the Gauss-Seidel Pseudo Affine Projection algorithm represents an attractive option for acoustic echo cancellation systems. It has a reduced complexity in comparison with other FAP algorithms, and good convergence and tracking properties. We showed its effectiveness in a combined acoustic echo and noise cancellation system. We intend to develop a more efficient and robust DTD algorithm, capable of operating in different noise environments. A comparison of our method with some sparse system identification methods is also envisaged.

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