AN EFFICIENT LOW-COMPLEXITY ALGORITHM FOR CROSSTALK-RESISTANT ADAPTIVE NOISE CANCELLER

Ludovick Lepauloux[1], *Pascal Scalart*[2], *and Claude Marro*[1]

[1]Orange Labs - TECH/SSTP, 2 Avenue Pierre Marzin, 22307 Lannion Cedex, France
[2]ENSSAT - IRISA/CAIRN, 6 Rue de Kerampont, B.P. 447, 22305 Lannion Cedex, France
E-mail: ludovick.lepauloux,claude.marro@orange-ftgroup.com; pascal.scalart@enssat.fr

ABSTRACT

This paper proposes an algorithmic and memory complexity reduction of the well-know crosstalk-resistant adaptive noise canceller (CTRANC). First, we show that the decorrelation approach is not accurate with the feedback structure. Consequently, a minimum based energy criterion approach more suitable with the cross-coupled structure, like the one proposed by Zinser et al., is proposed. Indeed, by using an additional stationarity assumption about the filter coefficients, we show that recursive gradient formulae could be rewritten as convolution operation. Simulation results show that the proposed algorithm is as efficient as the one proposed by Zinser despite its significantly lower complexity.

1. INTRODUCTION

Extracting a desired speech signal from noisy speech corrupted by additive noise is an important problem in digital voice communication systems. To deal with, adaptive noise cancellation represents one such potential effective technique for noise reduction [1]. The adaptive noise canceller (ANC) requires two inputs: i) a primary signal consisting of the desired signal (target) corrupted by additive noise (jammer) and ii) a reference signal that is correlated with the jammer and uncorrelated with the target. The reference signal is processed by an adaptive filter to generate a replica of the noise component in the primary input. However, to apply the ANC effectively, the reference noise picked up by the reference sensor must be highly correlated with the noise components in the primary signal. This condition requires a close spacing between the primary and the reference sensors. Unfortunately, it is also critical to avoid the speech signal components from the signal source being present in the reference sensor signal. This signal leakage (crosstalk) into the noise reference quickly results in signal distortion, slower convergence and poor noise cancellation.

For the crosstalk problem, many crosstalk-resistant noise cancellers [2]-[6] have been proposed to improve the ANC's performance. In this work we focus on the feedback structure (CTRANC) [7] described on Figure 1, which uses a second adaptive filter in estimating the crosstalk signal. This filter structure based on joint energy minimization of both outputs, allows a closer location of the sensors. A similar dual-channel signal separation by decorrelation was developed in [8] and further analyzed in [9]. According to the authors, energy minimization and output decorrelation could be considered as equivalent, which is intuitively true if we apply to the feedback structure the standard stochastic gradient algorithm independently on each adaptive filter. In this case, the time update equations of W_1 and W_2 (see Figure 1) are the same for both methods. Recently, to cope with this problem, we have proposed [10] a new adaptive filter structure and its learning algorithm that enable feedback implementation from a standard stochastic gradient algorithm point of view.

For these reasons, we propose in this paper to deeply analyze the optimal algorithm proposed by Zinser and Mirchandani [7, 11] that matches exactly the feedback structure for an energy minimization criterion. The remainder of the paper is organized as follows. Section 2 shows the inefficiency of the SAD algorithm [9] in the feedback implementation. Section 3 presents an overview of the different algorithms based on the minimization of the output energies in the backward structure. Section 4 gives the derivation of the proposed algorithm to reduce complexity. Section 5 describes the experimental results and we conclude and outline our future work in Section 6.

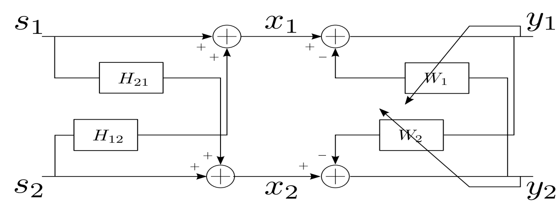

Figure 1: Mixing model and crosstalk-resistant adaptive noise canceller (CTRANC).

2. ENERGY MINIMIZATION VERSUS DECORRELATION

The most widely used approach to the two-channel signal enhancement or separation problem is described on Figure 1 where H_{12} and H_{21} represent the cross-coupling effects between the channels. In a more general formulation, the direct couplings will not be identities and then the solutions will be indeterminate up to a shaping filter. Although this case is somewhat restrictive, it represents an important and interesting problem of noise reduction. The main objective is to find a model, $y_{1,2}(n)$, of the original source signals $s_{1,2}(n)$. For this, it is sufficient to estimate separation filters W_i that removes the crosstalk introduced by the mixing process. The transfer function of this linear time invariant (LTI) system will be noted

$$H(z) = \begin{pmatrix} 1 & H_{12}(z) \\ H_{21}(z) & 1 \end{pmatrix}.$$

Hence, the model of the observed signals is written:

$$\begin{aligned} x_1(n) &= s_1(n) + h_{12}(n) * s_2(n) \\ x_2(n) &= h_{21}(n) * s_1(n) + s_2(n). \end{aligned}$$

Subsequently, it is assumed the following assumptions:

- $\mathscr{H}_1$: the filters $H_{12}(z)$ and $H_{21}(z)$ are causal,
- $\mathscr{H}_2$: the filter $H(z)$ is minimum phase i.e its inverse is stable; this can be written : $1 - H_{12}(z)H_{21}(z) \neq 0 \quad \forall z$,
- $\mathscr{H}_3$: the sources $s_1(n)$ and $s_2(n)$ are stationary and statistically independent or at least decorrelated (the case of non-stationary signals will be addressed in Section 5).

A necessary condition for correct implementation is that one of the zeroth-order coefficients of the adaptive and generating filters equals zero

$$w_1(0) = h_{21}(0) = 0 \quad \text{or} \quad w_2(0) = h_{12}(0) = 0.$$

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2.1 Minimization of the mean square errors

When a minimum energy criterion is considered to obtain an adaptive algorithm dedicated to produce optimal filter coefficients, the most commonly used performance criterion is the mean-squared error (MSE) defined as

$$\xi = E\left[e(n)^2\right] = E\left[(d(n) - \mathbf{w}^{\mathbf{T}}(n)\mathbf{x}(n))^2\right] \qquad (1)$$

where $d(n)$ stands for a primary signal, $\mathbf{x}$(n) a reference signal and $\mathbf{w}$(n) filter coefficients. Let us apply this process to the feedback structure of Figure 1 as described in [7]. Let $s_1(n)$ and $s_2(n)$ be real, discrete-time, random processes. The error signals at time n are given by

$$y_1(n) = x_1(n) - \mathbf{w_1}^T(n)\mathbf{Y_2}(n) \qquad (2)$$
$$y_2(n) = x_2(n) - \mathbf{w_2}^T(n)\mathbf{Y_1}(n) \qquad (3)$$

where ^{T} denotes the transpose operation, and

$$\mathbf{w_1}^T(n) = \left[w_1^0(n)\; w_1^1(n)\; w_1^2(n) \ldots w_1^N(n)\right]$$
$$\mathbf{w_2}^T(n) = \left[w_2^0(n)\; w_2^1(n)\; w_2^2(n) \ldots w_2^N(n)\right]$$

are the time-varying filter weights for the Nth-order filters W_1 and W_2, and

$$\mathbf{Y_1}^T(n) = [y_1(n)\; y_1(n-1) \ldots y_1(n-N)]$$
$$\mathbf{Y_2}^T(n) = [y_2(n)\; y_2(n-1) \ldots y_2(n-N)].$$

Thus, the mean square error on the primary channel associated with y_1 is

$$\xi_1 = E\left[y_1^2\right] = E\left[(x_1 - \mathbf{w_1}^{\mathbf{T}}\mathbf{Y_2})^{\mathbf{2}}\right]$$

where time index n is omitted for convenience and $\mathbf{Y_2}$ denotes the N taps-input vector of W_1. Differentiating this function with respect to $\mathbf{w_1}$ leads to

$$2 \cdot E\left[(x_1 - \mathbf{w_1}^{\mathbf{T}}\mathbf{Y_2})(-\mathbf{Y_2} - \mathbf{w_1}^{\mathbf{T}}\nabla_{\mathbf{w_1}}\mathbf{Y_2})\right]. \qquad (4)$$

Assuming that $\nabla_{\mathbf{w_1}}\mathbf{Y_2} = \mathbf{0}$, which is theoretically wrong according to the cross-coupled structure of Figure 1 and to the output equations (2) and (3), we get

$$2 \cdot E\left[(x_1 - \mathbf{w_1}^{\mathbf{T}}\mathbf{Y_2})(-\mathbf{Y_2})\right] = -2 \cdot E[y_1\mathbf{Y_2}]. \qquad (5)$$

This solution yields to the symmetric adaptive decorrelation (SAD) algorithm proposed by Van Gerven in [9], which corresponds to an intuitive stochastic gradient approach. On the contrary, if $\nabla_{\mathbf{w_1}}\mathbf{Y_2} \neq \mathbf{0}$, obvious solution according to the output equations, then (4) equals to

$$-2 \cdot E\left[y_1(\mathbf{Y_2} + \mathbf{w_1}^{\mathbf{T}}\nabla_{\mathbf{w_1}}\mathbf{Y_2})\right] \qquad (6)$$

which corresponds to the one proposed by Zinser and Mirchandani in [7, 11] and is thus more accurate.

2.2 Experimental results

These two different approaches given in equations (5) and (6) yield to the following coefficients update recursion respectively:

$$\mathbf{w_1}(n+1) = \mathbf{w_1}(n) + 2\mu_{sad}E[y_1\mathbf{Y_2}] \qquad \text{(a)}$$
$$\mathbf{w_1}(n+1) = \mathbf{w_1}(n) + 2\mu_{grad}E\left[y_1(\mathbf{Y_2} + \mathbf{w_1}^{\mathbf{T}}\nabla_{\mathbf{w_1}}\mathbf{Y_2})\right]. \qquad \text{(b)}$$

However and as it was explained before, applying SAD algorithm to the feedback structure by replacing the expected values by their stochastic estimates in (a) does not lead to the optimal solution. This is shown on Figure 2, where the convergence of the two adaptive filters W_1 and W_2 is plotted for a very simple case where the mixing filters and the optimal solutions are reduced to single tap filters, *i.e.* $H_{21}(z) = W_2(z) = 0.8$ and $H_{12}(z) = W_1(z) = -0.8z^{-1}$. In addition, the results for a standard deterministic gradient algorithm (b) (cf. *Algorithm B* in 3.1) is also plotted. Sources are two Uniform zero-mean white noises with power $\sigma_{s_1}^2 = 0.2$ and $\sigma_{s_2}^2 = 0.1$. According to these results, we show that the SAD algorithm is not accurate for the feedback implementation due to the lack of higher order components in the gradient formula.

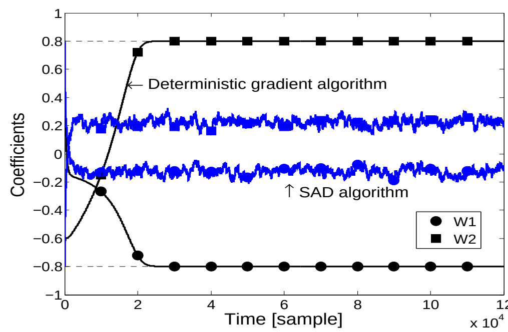

Figure 2: Coefficients of the two adaptive filters for Uniform zero-mean white noises. Step sizes are $\mu_{grad} = \mu_{sad} = 0.005$.

3. ALGORITHMS FOR ENERGY MINIMIZATION

3.1 Optimal filters

3.1.1 One approach, one algorithm

Different approaches to derive optimal filter coefficients $\mathbf{w_1}$ and $\mathbf{w_2}$ by using mean-square error minimization can be found. The main difference between these approaches lies in the way than ξ_1 and ξ_2 are minimized. According to these possible methods, we can list three algorithms.

$$Algorithm\ A = \begin{cases} \mathbf{w_1}(n+1) = \mathbf{w_1}(n) - \mu_1\nabla_{\mathbf{w_1}}\xi_1 \\ \mathbf{w_2}(n+1) = \mathbf{w_2}(n) - \mu_2\nabla_{\mathbf{w_2}}\xi_2 \end{cases}$$

$$Algorithm\ B = \begin{cases} \mathbf{w_1}(n+1) = \mathbf{w_1}(n) - \mu_1\nabla_{\mathbf{w_1}}\xi_1 \\ \mathbf{w_2}(n+1) = \mathbf{w_2}(n) - \mu_2\nabla_{\mathbf{w_2}}\xi_1 \end{cases}$$

$$Algorithm\ C = \begin{cases} \mathbf{w_1}(n+1) = \mathbf{w_1}(n) - \mu_1\nabla_{\mathbf{w_1}}\xi_2 \\ \mathbf{w_2}(n+1) = \mathbf{w_2}(n) - \mu_2\nabla_{\mathbf{w_2}}\xi_2 \end{cases}$$

Algorithm A was described more precisely by Mirchandani et al. in [11]. Let us consider s_2 as a noise source. Obviously, *Algorithm B* focuses essentially on the observation of the noise path h_{12}. Such behavior corresponds to an adaptive noise canceller scheme. Note that the inverse statement also holds for *Algorithm C*. In practice, this difference stands in the relative position of source and noise. As explained in [12], the causality of one of the generating FIR filter, associated to the source position regarding the sensors, is strictly related to the algorithm convergence.

3.1.2 Simulation results

Behavior of *Algorithms A* and *B* is given in Figures 3 and 4 where the system mismatch of W_1 and W_2 defined as $\Delta W(n) = 10log_{10}\left[\frac{\sum_{j=0}^{N}(w_{1,2}^j(n) - h_j(n))^2}{\sum_{j=0}^{N}h_j^2(n)}\right]$ are provided. All results were averaged over 30 trials. The transfer functions used in these simulations and satisfying $\mathscr{H}_2$ correspond to $H_{12}(z) = 0.5 +$

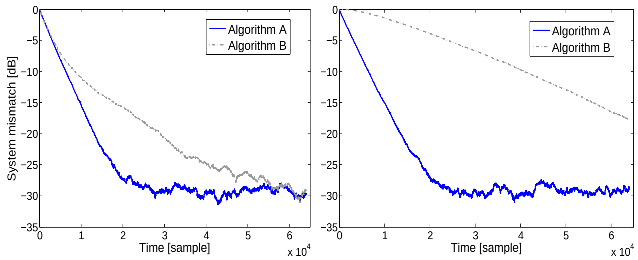

Figure 3: System mismatch of W_1 (left) and W_2 (right) in Uniform zero-mean white noises. Step sizes are $\mu_A = \mu_B = 0.0001$.

$0.2z^{-1} - 0.1z^{-2} - 0.2z^{-3}$ and $H_{21}(z) = -0.439z^{-1} + 0.366z^{-3} - 0.110z^{-4}$ and the sources'power equal to $\sigma_{s_1}^2 = 1$ and $\sigma_{s_2}^2 = 1$. We observe that correct and fast simultaneous convergence of the two adaptive filters is only found for *Algorithm A* (CTRANC). In contrast to the results of Figure 2, the convergence speed of *Algorithm B* is now disturbed by the stochastic gradient approximation of equation 5.

3.2 Complexity assessment

3.2.1 Memory cost

In the previous section, we have shown through simulations the outperformance of *Algorithm A*. The analytic demonstration of this effectiveness will be detailed in this section. Indeed, the CTRANC superiority is mainly due to the accuracy of the gradient equations $\nabla_{\mathbf{w_1}}\mathbf{y_1}(n)$ and $\nabla_{\mathbf{w_2}}\mathbf{y_2}(n)$. In fact, each gradient is a function of the two adaptive filter taps $w_1(k)$ and $w_2(k)$ and moreover it depends on the time index n which means that the last $2N(N+1)$ gradient values have to be stored as well as the last $2(N+1)^2$ coefficients for the two adaptive filters. Recursive formulae for the two gradients are

$$\nabla_{\mathbf{w_1}}\mathbf{y_1}(n) = C_0(n)\left[\sum_{k=1}^{2N} C_k(n)\nabla^k_{\mathbf{w_1}}\mathbf{y_1}(n-k) - \mathbf{Y_2}(n)\right] \quad (7)$$

$$\nabla_{\mathbf{w_2}}\mathbf{y_2}(n) = D_0(n)\left[\sum_{k=1}^{2N} D_k(n)\nabla^k_{\mathbf{w_2}}\mathbf{y_2}(n-k) - \mathbf{Y_1}(n)\right] \quad (8)$$

where the superscript k on the gradient operator implies differentiation with respect to weights evaluated at time $(n-k)$. Initially, analytic solution does not lead directly to these expressions, additional assumption is necessary to form these explicit recurrence relations. This assumption relies on the orthogonal principle and the slow time variations of the signals.

$$C_0(n) = D_0(n) = \frac{1}{1 - w_1^0(n)w_2^0(n)}$$

with

$$C_i(n) = \begin{cases} \sum_{j=0}^{i} w_1^j(n) w_2^{i-j}(n-j) & 1 \le i \le N \\ \sum_{j=i-N}^{N} w_1^j(n) w_2^{i-j}(n-j) & N+1 \le i \le 2N \end{cases}$$

$$D_i(n) = \begin{cases} \sum_{j=0}^{i} w_2^j(n) w_1^{i-j}(n-j) & 1 \le i \le N \\ \sum_{j=i-N}^{N} w_2^j(n) w_1^{i-j}(n-j) & N+1 \le i \le 2N \end{cases}$$

In contrast with SAD algorithm or misused LMS algorithm on each channel independently, all terms containing products of the type $w_1(m)w_2(n)$ are now considered. Thus, the algorithm described by (7) and (8) takes into account the intrinsic cross-coupling effect of the feedback structure.

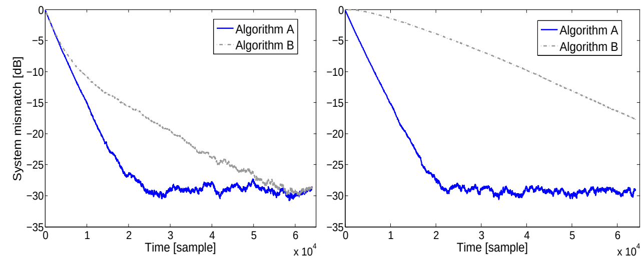

Figure 4: System mismatch of W_1 (left) and W_2 (right) in Gaussian zero-mean white noises. Step sizes are $\mu_A = \mu_B = 0.0001$.

Scalar gradient formula	Multiplications	Additions
$\frac{\partial y_k(n)}{\partial w_k^i(n)}$ $k = 1,2$	$2N^2 + 4N + 2$	$N^2 + 2N + 1$

Table 1: Algorithmic complexity in terms of number of real multiplications and real additions per sample instant.

4. LOW COMPLEXITY ALGORITHM FOR FEEDBACK STRUCTURE

4.1 Algorithmic simplifications

4.1.1 Concept

In the previous section, we have shown that the algorithm proposed by Mirchandani et al. is the most efficient. However, its complexity often led researchers to use other algorithms such as the SAD algorithm. In this section, we propose to reduce this complexity by assuming the following hypothesis:

- $\mathscr{H}_4$: the filter coefficients are slowly time varying which implies that $w_{1,2}^i(n) \approx w_{1,2}^i(n-k)$.

Such hypothesis enables us to rewrite recursive formulae (7) and (8) as a convolution operation and thus reduce the complexity as it will be shown in the following section.

4.1.2 Derivation of the new algorithm

Consider the signal estimates given in equations (2) and (3). Expanding the one concerning y_1, we obtain

$$\begin{aligned} y_1(n) &= x_1(n) - \sum_{k=0}^{N} w_1^k(n) x_2(n-k) \\ &+ \sum_{s=0}^{N} w_1^s(n) \sum_{t=0}^{N} w_2^t(n-s) y_1(n-s-t). \end{aligned} \quad (9)$$

Taking the gradient of this last equation, we get for each component in the resulting vector $\nabla_{\mathbf{w_1}}\mathbf{y_1}(n)$

$$\begin{aligned} \frac{\partial y_1(n)}{\partial w_1^l(n)} &= -y_2(n-l) + w_1^0(n) w_2^0(n) \frac{\partial y_1(n)}{\partial w_1^l(n)} \\ &+ w_1^0(n) \sum_{k=1}^{N} w_2^k(n) \frac{\partial y_1(n-k)}{\partial w_1^l(n)} \\ &+ \sum_{s=1}^{N} w_1^s(n) \sum_{t=0}^{N} w_2^t(n-s) \frac{\partial y_1(n-s-t)}{\partial w_1^l(n)}. \end{aligned} \quad (10)$$

The algorithmic complexity regarding gradient component calculation for each gradient vector in the CTRANC algorithm is given in Table 1. After factorization of the last two terms in (10) with respect to the partial derivative $\frac{\partial y_1(n-i)}{\partial w_1^l(n)}$, these one may be written as

$$
\begin{aligned}
&\ldots \quad w_1^0(n)\sum_{k=1}^{N} w_2^k(n)\frac{\partial y_1(n-k)}{\partial w_1^l(n)} \\
&+ \quad \sum_{s=1}^{N} w_1^s(n)\sum_{t=0}^{N} w_2^t(n-s)\frac{\partial y_1(n-s-t)}{\partial w_1^l(n)} \\
&= \quad \begin{cases} \sum_{j=0}^{i} w_1^j(n) w_2^{i-j}(n-j)\frac{\partial y_1(n-i)}{\partial w_1^l(n)} & 1 \le i \le N \\ \sum_{j=i-N}^{N} w_1^j(n) w_2^{i-j}(n-j)\frac{\partial y_1(n-i)}{\partial w_1^l(n)} & N+1 \le i \le 2N \end{cases}
\end{aligned}
$$

which corresponds to $C_i(n)\cdot\frac{\partial y_1(n-i)}{\partial w_1^l(n)}$. Applying now the hypothesis $\mathscr{H}_4$ to $C_i(n)$ without omitting the first term for $i=0$, it immediately follows that:

$$
\begin{aligned}
\sum_{i=0}^{N}\sum_{j=0}^{N} w_1^i(n) w_2^j(n-i) &\overset{\mathscr{H}_4}{\equiv} \sum_{k=0}^{N} w_1^k(n) w_2^{n-k}(n) \\
&= \mathbf{w_1}(n) * \mathbf{w_2}(n) = G(n) \qquad (11)
\end{aligned}
$$

where $*$ denotes the convolution operator.
Accordingly, the new gradients estimates become

$$\nabla_{\mathbf{w_1}}\mathbf{y_1}(n) = C_0(n)\left[\sum_{i=1}^{2N} G^i(n)\cdot\nabla_{\mathbf{w_1}}\mathbf{y_1}(n-i) - \mathbf{Y_2}(n)\right] \quad (12)$$

$$\nabla_{\mathbf{w_2}}\mathbf{y_2}(n) = D_0(n)\left[\sum_{i=1}^{2N} G^i(n)\cdot\nabla_{\mathbf{w_2}}\mathbf{y_2}(n-i) - \mathbf{Y_1}(n)\right]. \quad (13)$$

Analysis of the structure of the two gradient vectors (12) and (13) show that they exhibit a quasi-circularity property. By exploiting this property, it can be possible to reduce the computational complexity of (12) and (13) by computing only the first term of each gradient vector at each iteration. The two gradient vectors are then obtained by using a circular buffer mechanism in order to reintroduce this quasi-circularity property. Consequently, the complexity of the gradient vector computation is significantly reduced (at the expense of a small approximation in the gradients values). The overall memory required to store the gradient information between two consecutive time instant is also reduced since only $2N$ points have to be stored for each gradient.

The above assumption may be applied also to the second estimated signal y_2 given by (3).

4.1.3 *Memory cost*

Thanks to our assumption, each gradient is a function of the last adaptive filters estimates $\mathbf{w_1}(n)$ and $\mathbf{w_2}(n)$ and gradient vectors $\nabla_{\mathbf{w_1}}\mathbf{y_1}(n)$ and $\nabla_{\mathbf{w_2}}\mathbf{y_2}(n)$ which implies to store the last $2N$ gradient values as well as the last $2(N+1)$ coefficients for the two adaptive filters. Consequently, we reduce drastically the memory load in comparison with previous expressions given in (7) and (8).

4.1.4 *Algorithmic complexity*

The algorithmic complexity regarding gradient component computation for the presented method is given in the following Table 2. In comparison with previous results associated with CTRANC algorithm, we can see that N^2+N multiplications and $\frac{1}{2}N^2+\frac{1}{2}N$ additions have been saved per sample instant for each evaluation of gradient components.

Scalar gradient formula	Multiplications	Additions
$\frac{\partial y_k(n)}{\partial w_k^i(n)}$ $k=1,2$	N^2+3N+2	$\frac{1}{2}N^2+\frac{3}{2}N+1$

Table 2: Algorithmic complexity in terms of number of real multiplications and real additions per sample instant.

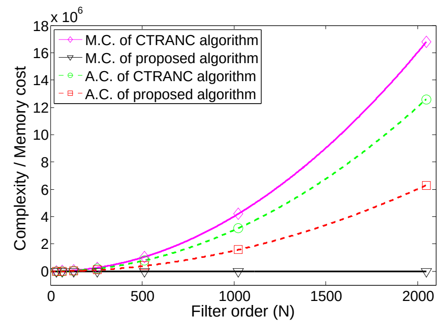

Figure 5: Behavior of memory cost (M.C.) and algorithmic complexity (A.C.) to compute one gradient component. M.C. is obtained by summing all the memory blocs to store each filters coefficient and gradient values needed. A.C. is the sum of the required multiplications and summations

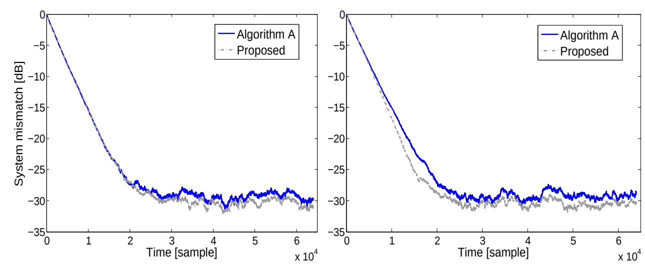

Figure 6: System mismatch of W_1 (left) and W_2 (right) in Uniform zero-mean white noises. Step sizes are $\mu_A = \mu_B = 0.0001$.

4.1.5 *Summary*

To easily compare the complexity gain, we compute the total memory cost (M.C.) obtained by adding all the necessary components for each studied algorithm. The same procedure is performed for the algorithmic complexity (A.C.) by summing respectively the required multiplications and additions given in Tables 1-2. Results are given in Figure 5.

4.2 Experimental results

As shown in Figures 6 and 7, the additional hypothesis $\mathscr{H}_4$ is valid since the same performance in terms of system mismatch are obtained. In other words, we have proved the ability of our algorithm to perform as efficiently as the original algorithm [11] but with a significantly lower complexity.

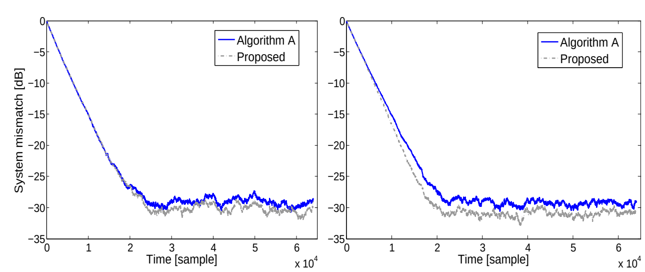

Figure 7: System mismatch of W_1 (left) and W_2 (right) in Gaussian zero-mean white noises. Step sizes are $\mu_A = \mu_B = 0.0001$.

5. APPLICATION TO SPEECH ENHANCEMENT

5.1 Experimentation procedure

To further illustrate the practical behavior of the proposed algorithm, we now consider an application in speech signal processing. The input SNRs are computed using the ITU-T recommendation P.56 speech voltmeter (SV56). Office noise was used as a noise source, and clean male voice as a signal source with a sample rate of 8 kHz. Synthetic noise path (H_{12}) and crosstalk path (H_{21}) impulse responses are used. The noise component is generated by convolution of the noise source with the noise path, and then added to the speech signal to create a noise-contaminated signal. The reference signal is generated by adding the noise to the crosstalk generated by convolution of the speech signal and the crosstalk path. The length of the adaptive and generating filters is set to $L = 64$ in order to avoid the modeling problem. In addition, due to the difficulty to set correctly the normalization procedures for the step sizes, we use an ideal vocal activity detection in the adaptation procedure in order to focus our study to the impact of the recursion and which is given here after.

5.2 Discussion

As in [11], the effect of the memory length (i.e the order $2N$ of the summation in (7), (8), (12) and (13)) on the convergence must be taken into account. According to the authors, there is a potential for instability when the poles of the recursion lie outside the unit circle. This problem has been solved by restricting the memory of the recursion, i.e. by setting the order of the summation to $2N = 20$. In case of non-stationary signal, we could imagine that some instability may occur due to the hypothesis $\mathscr{H}_4$. Indeed, assuming that the filter coefficients are slowly time varying could be in contradiction with the supposed speech signal stationarity period, especially when the memory of the recursion is longer than this one. However, under the filters order and the sampling frequency used in our simulations, we found that any observed instabilities were exclusively related to the memory length, not to our hypothesis. Finally, for all considered input SNRs, the proposed method provides the same performance as the one of *Algorithm A* (but with a lower memory and computational cost) in terms of cepstral distance.

6. CONCLUSION

After having emphasized the inaccuracy of the SAD algorithm with feedback structure, an overview of possible methods dedicated to the estimation of the optimal filters and based on minimum energy criterion has been given. Among these different approaches, the one proposed by Zinser has been pointed out as the most efficient but the most complex too. In this paper, the complexity of the original algorithm [11] has been reduced through an additional assumption, that enables us to rewrite recursive formula as a convolution operation. Doing so, the memory load is also reduced without a loss in performance. For further improvement, future work will be oriented towards the implementation of the algorithm in the frequency domain to take advantage of the capacity of the Fourier transform to implement a convolution operation as a simple vector product. Similarly, conditions for stability have to be analyzed.

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