INTERMITTENTLY-UPDATED AFFINE PROJECTION ALGORITHM

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ABSTRACT

Acoustic echo cancellation and feedback cancellation systems require robust and computationally efficient adaptive filtering techniques. In this paper, a new affine projection algorithm with intermittent update of the filter coefficients is proposed where the update interval is determined according to the adaptation state. Simulation results show that the proposed algorithm provides improved performance and reduced average computational complexity compared with other similar algorithms for acoustic echo cancellation and acoustic feedback cancellation applications.

Index Terms—Acoustic echo cancellation, acoustic feedback cancellation, affine projection algorithm, variable update interval

1. INTRODUCTION

There are many adaptive filtering algorithms proposed for echo cancellation [1], [2]. A common challenge for acoustic echo cancellation (AEC) systems is the large number of adaptive filter coefficients (of the order of hundreds) necessary for accurate modeling of the acoustic echo path. Acoustic feedback is also a difficult problem encountered in hearing aids. The acoustical coupling between the loudspeaker and the microphone combined with a high amplification is responsible for the feedback. Many adaptive feedback cancellation (AFC) techniques have been proposed to minimize the feedback effect on the hearing aids [3-6]. Adaptation control is difficult because the correlated input and feedback signals can lead to a biased filter and severe signal distortion at the hearing aid output [7].

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The algorithms for AEC and AFC should provide a compromise between fast convergence speed, low complexity, low steady-state mean-squared error (MSE), and good sound quality. The most commonly used algorithm for both applications is the normalized least mean square (NLMS) algorithm [1], [2]. Unfortunately, NLMS has a slow convergence, especially for colored inputs. The recursive least-squares (RLS) algorithm has a fast convergence but is often numerically unstable and computationally expensive [1]. The performance of the affine projection (AP) algorithm [8] lies between those of NLMS and RLS. Many fast versions of the AP algorithm have been proposed (see [9] for an extended overview of their evolution). It is known that there is a bias in the estimate of the feedback path in the case of AFC due to the correlation between the input and output signals of the hearing aids. Several solutions for this problem have been proposed based on decorrelation filters [6], [10]-[11]. Moreover, different AP algorithms employing variable step-size [12], variable regularization [13]-[14], set-membership filtering [15], and variable projection order [16]-[18] have also been proposed.

An AP algorithm with intermittent update of filter coefficients depending on a computed threshold has been proposed in [19]. Improved convergence and steady-state error has been obtained while reducing the number of updates. In this algorithm, the adjustment of the update interval depends on a threshold derived from the steady-state MSE formula given in [20]. However, a better estimation of the steady-state MSE has been proposed in [18]. Additionally, in [18], the projection order of the AP algorithm is varied depending on the adaptation state. For this purpose, a linear dependence of the projection order on the logarithm of the estimated variance of the filter output error is used. The algorithm of [18] was termed AP algorithm with selective projections (APA-SP).

In this paper, we propose to use the MSE estimation formula from [18] and adjust the *update interval* depending on the adaptation state in order to derive our algorithm, termed *intermittently-updated AP algorithm* (IU-APA). Simulation results demonstrate the superiority of the proposed algorithm over the conventional AP algorithm and the APA-SP of [18] in several AEC and AFC applications.

2. PROPOSED IU-APA

In a system identification problem, an unknown system may be identified by using an adaptive filter. For an AEC application, both the target system and the adaptive filter have finite impulse responses and are defined by the real-valued vectors $\mathbf{h} = [h_0, h_1, \dots, h_{L-1}]^T$ and $\hat{\mathbf{h}}(n) = [\hat{h}_0(n), \hat{h}_1(n), \dots, \hat{h}_{L-1}(n)]^T$, respectively, where superscript T denotes transposition, n is the time index, and L is the length of the echo path and the corresponding adaptive filter. The signal $x(n)$ is the far-end speech that goes through the acoustic echo path with impulse response, $\mathbf{h}$, and generates the echo signal, $y(n) = \mathbf{x}^T(n)\mathbf{h}$, where $\mathbf{x}(n) = [x(n), x(n-1), \dots, x(n-L+1)]^T$. This signal is picked up by the microphone together with the near-end noise signal, $v(n)$, yielding the microphone signal $d(n) = y(n) + v(n)$. The near-end signal can contain both the background noise, $w(n)$, and the near-end speech, $u(n)$.

The AP algorithm [8] is defined by the following relations:

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n-1) \tag{1}$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu\mathbf{X}(n)\mathbf{R}^{-1}(n)\mathbf{e}(n) \tag{2}$$

where $\mathbf{e}(n)$ is the *a priori* error vector, $\mathbf{d}(n) = [d(n), d(n-1), \dots, d(n-P+1)]^T$ is the desired signal vector, P denotes the projection order, and μ is the step-size parameter. The matrix $\mathbf{X}(n) = [\mathbf{x}(n), \mathbf{x}(n-1), \dots, \mathbf{x}(n-P+1)]$ is the input signal matrix and $\mathbf{R}(n) = \mathbf{X}^T(n)\mathbf{X}(n) + \delta\mathbf{I}$, where δ is a regularization factor and $\mathbf{I}$ is the identity matrix.

The average computational complexity of AP algorithm can be reduced using the intermittent update procedure introduce in [19]. Thus, the update equation of (2) can be replaced by

$$\hat{\mathbf{h}}(n) = \begin{cases} \hat{\mathbf{h}}(n-1) + \mu\mathbf{X}(n)\mathbf{R}^{-1}(n)\mathbf{e}(n) & \text{if } n \bmod i_n = 0 \\ \hat{\mathbf{h}}(n-1) & \text{otherwise} \end{cases} \tag{3}$$

where i_n is the variable update interval at time n.

We propose to compute i_n at each time instant by relating it linearly to the logarithm of the estimated variance of the filter output error, similar to the approach taken in [18] to vary the projection order. In this way, we are able to tune the update interval according to the adaptation state. Consequently, we have

$$\hat{\imath}_n = 1 + (i_{\max} - 1)\ln[\sigma_e^2(n)/\eta]/\ln(\gamma/\eta) \tag{4}$$

$$i_n = i_{\max} + 1 - \min\{i_{\max}, \max(1, \lceil \hat{\imath}_n \rceil)\} \tag{5}$$

where $i_{\max}$ is the maximum allowed value for i_n and $\sigma_e^2(n)$ is updated as in [18] using a time-varying forgetting factor and a moving average window. We set $\sigma_e^2(0) = \sigma_d^2$ where σ_d^2 is the desired signal variance that, if not known *a priori,* can be estimated during the first $i_{\max}$ samples as specified in [18]. The steady-state MSE, η, is approximated as

$$\eta = \sigma_v^2\sqrt{[1 + \mu P/(2-\mu)][1 + L\mu P/(L - 2\mu P + L\mu P)]} \tag{6}$$

where σ_v^2 is the variance of the noise signal, $v(n)$. Furthermore, γ is given by

$$\gamma = \eta(\sigma_d^2/\eta)^z \tag{7}$$

where z is computed as

$$z = \max\{1/12, \min[0.5, (i_{\max} - 2)/12]\}. \tag{8}$$

In the proposed algorithm, the update of the filter coefficients from (3) is performed only when

$$n \bmod i_n = 0$$

and not at every iteration as in (2). The proposed algorithm, called *intermittently-updated AP algorithm* (IU-APA), differs from the algorithm proposed in [19] because it uses a more accurate formula for predicting the steady-state MSE, η, and a different approach for computing the time-varying update interval, i_n. Extensive simulations of the proposed algorithm showed that $i_{\max} = P$ is a good choice and confirmed the similar findings of [19] and [21].

The IU-APA can be easily integrated in an adaptive feedback cancelation context. More information about these systems can be found in [22]. In a hearing aid system, the source signal is corrupted by the additive feedback signal generated by the output signal leaking to the input. The correspondence with the AEC system signals is the following: the acoustic source signal corresponds to the near-end signal, the feedback signal corresponds to the echo signal, and the output signal corresponds to the far-end signal. The hearing-loss has to be taken into account in order to generate the signals for the adaptive filter; otherwise, the algorithm equations are the same.

3. SIMULATION RESULTS

The first simulations were performed in the context of echo cancellation, where the input signal is either white Gaussian noise or speech. The performance of IU-APA, APA-SP1 [18], and AP algorithm (APA) was investigated by comparing the normalized misalignment and echo return loss enhancement (ERLE) curves. The echo path and the adaptive filter both had 300 coefficients. The simulated parameters were $i_{max} = 8$, $\mu = 0.2$, SNR = 20 dB, and $\delta = 0.01$. The minimum and maximum allowed values for the variable forgetting factor are also set to 0.1 and 0.99, respectively [18]. The misalignment curves of IU-APA, APA with $P = 1$ (corresponds to NLMS), APA with $P = 8$ and APA-SP1 are shown in Fig. 1(a). The tracking ability of the algorithms was examined by changing the sign of the echo path coefficients after 40,000 samples. It can be seen that IU-APA has the lowest steady-state error among the considered algorithms. It also has the best ERLE

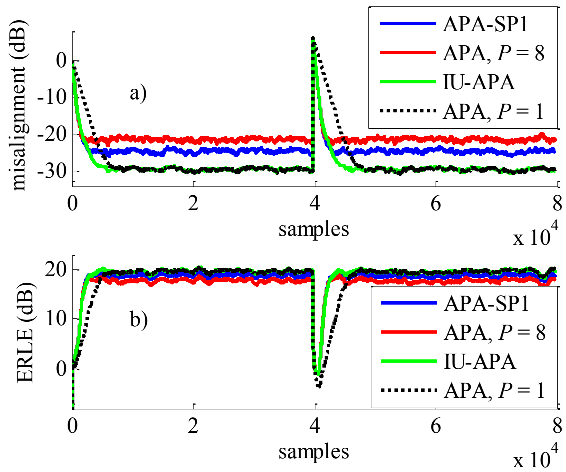

Fig. 1. Performance comparison of APA ($P = 8$), APA-SP1, and IU-APA for an AEC simulation using a white Gaussian input; a) misalignment curves, b) ERLE curves.

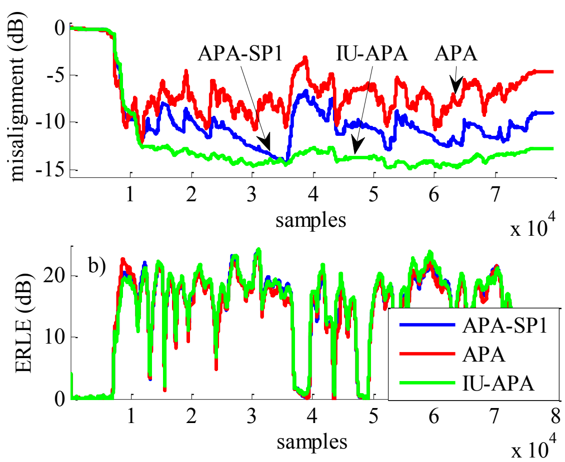

Fig. 2. Performance comparison of APA, APA-SP1, and IU-APA for an AEC simulation using a speech signal input; a) misalignment curves, b) ERLE curves.

performance, followed by APA-SP1 and APA as indicated by the curves plotted in Fig. 1(b).

It can be seen from Fig. 1(a) that IU-APA inherits both fast convergence of APA with $P = 8$ and lower steady-state error of APA with $P = 1$. It can also be noticed that the tracking performance of IU-APA is almost the same as that of APA-SP1 and APA with $P = 8$. Similar results regarding the convergence and tracking abilities were obtained for colored signals.

For the next simulations, $P = 8$ was used for APA. In Fig. 2, the input signal is a speech signal. The same conclusions as above can be drawn from Fig. 2(a) regarding the misalignment performances of the studies algorithms. It can be seen from Fig. 2(b) that the ERLE values of IU-APA are most of the time higher than those of APA or APA-SP1.

In Fig. 3, a variable background noise case is considered. The SNR decreases to 12 dB between the samples 30,001 and 50,000 while it is 20 dB otherwise. All the other conditions are the same as those of Fig. 2. It can be seen that IU-APA has the best misalignment performance. It can be noticed from Fig. 3(b) that the update intervals are closer to one in the region with high background noise level, therefore IU-APA's performance is closer to that of APA.

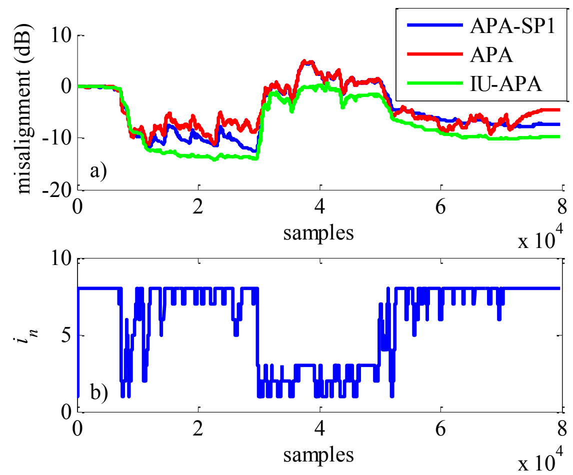

Fig. 3. Performance comparison of APA, APA-SP1, and IU-APA for an AEC simulation using a speech signal input and a higher background noise between the samples 30,001 and 50,000; a) misalignment curves, b) computed i_n values.

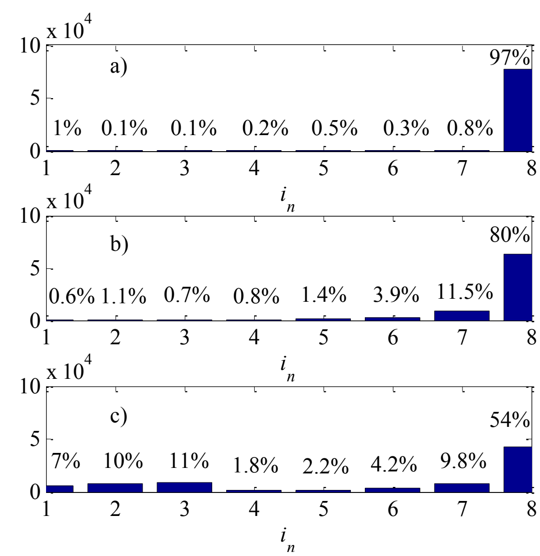

Fig. 4. The histograms of the computed i_n values; a) the white input signal case of Fig. 1, b) the speech input signal case of Fig. 2, c) the speech input and variable background noise case of Fig. 3.

In Fig. 4, the histograms of the updating interval values are plotted for the white and speech signal case from above. It can be noticed that most of the updating intervals are close to the maximum allowed case. Moreover, there are more values of $i_n = 8$ in the white noise case [Fig. 4(a)] than in the speech case [Fig. 4(b)].

The next simulations investigate the performance of APA, IU-APA and APA-SP1 in the acoustic feedback context.

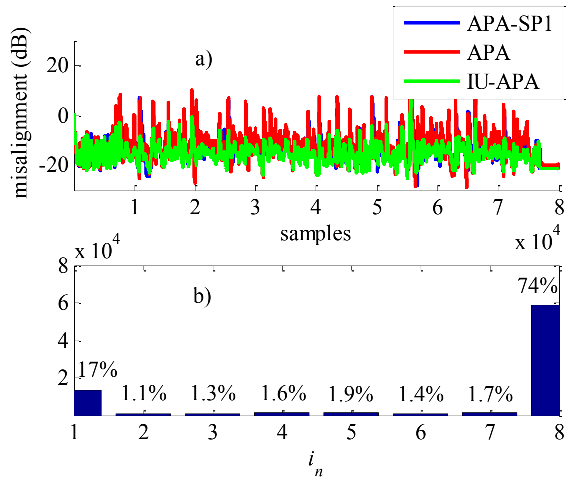

Fig. 5. a) Misalignment curves of APA, APA-SP1, and IU-APA for an AFC simulation using a speech signal, b) the histogram of the computed i_n values.

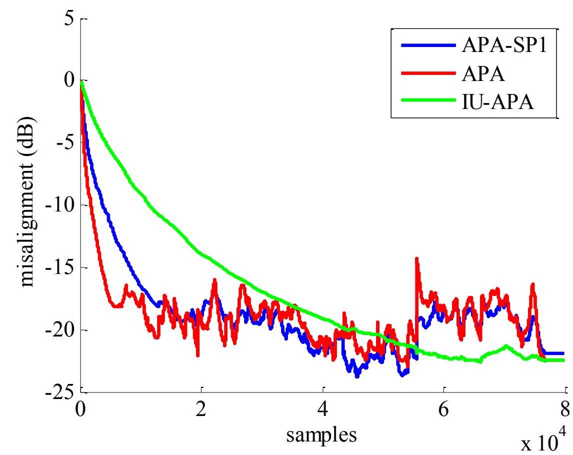

Fig. 6. Misalignment curves of APA, APA-SP1, and IU-APA for an AFC simulation using a speech signal when $\mu = 0.002$.

The feedback path was modeled as a finite-impulse-response filter with 64 coefficients. The adaptive filter had 64 coefficients too. A constant gain of 30 dB in the forward path and a delay of 60 were assumed. The other parameters are the same as in the above AEC simulations. It can be seen from Fig. 5(a) that most of the time, the performance of IU-APA is superior to APA and APA-SP1.

Significant average computational complexity reduction is achieved using IU-APA in comparison with APA in addition to the improved performance. The percentage of updates in IU-APA varied from 13% to 28% for the simulated scenarios. However, IU-APA may need up to 30% more multiplications than APA-SP1 in the AEC case. Our simulations have indicated that in order for IU-APA to perform well in AFC systems, a good estimation of the steady-state MSE is required.

Fig. 6 shows the misalignment curves of the investigated algorithms for a smaller step-size, $\mu = 0.002$, when all the other parameters are identical to those used for the simulations of Fig. 4. It can be observed that, for small step-sizes, both IU-APA and APA-SP1 converge slower than APA. This indicates that the steady-state approximation of (6) is not valid for very small step-sizes. The same observations were made for white and colored input signals. It is noteworthy that, compared with the traditional APA, the proposed algorithm reduces the average computational complexity and not the peak computational complexity that is almost the same as the peak complexity of its contenders, APA and APA-SP1.

4. CONCLUSION

An affine projection algorithm with a variable interval for updating the filter coefficients (called IU-APA) has been proposed for acoustic echo cancellation and adaptive feedback cancellation in hearing-aids applications. It was shown that the proposed algorithm outperforms other similar algorithms in several cases.

Future work will be focused on further reducing the complexity of IU-APA by using fast filtering techniques and variable-projection-order schemes. The extension of the ideas of this paper to sign algorithms (e.g., [22]) for AFC and AEC systems will be investigated too.

5. RELATION TO PRIOR WORK

The IU-APA adjusts its update interval by establishing a linear dependence of the update interval on the logarithm of the estimated variance of the filter output error. The work of [19] employs the approximate steady-state MSE formula proposed in [20]. However, IU-APA uses a more accurate steady-state MSE estimation formula proposed in [18] and does not utilize the evolutionary approach of [17] and [19] for computing the update interval. In addition, application of the proposed algorithm to acoustic feedback cancellation was considered, which has not been done in the earlier studies.

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