Acoustic Echo Canceller Using the Error Coded Affine Projection Algorithm

J. G. Avalos-Ochoa, F. A. Serrano-Orozco, and G. Avalos-Arzate

***Abstract*—Adaptive algorithms used in acoustic echo cancellers (AEC) must present high convergence speed and low misadjustment, therefore algorithms like the affine projection (APA) are frequently used, nevertheless its high computational complexity could be a problem for hardware implementations. In this paper, we present an acoustic echo canceller using the Error Coded Affine Projection Algorithm, which is a modification that assigns a code to the error and establishes a threshold to update the filter coefficients, in such way the coefficient update is not performed during each iteration. Results show the efficiency of the algorithm in terms of good convergence behavior, final misadjustment and a considerable reduced number of updates, making this a great option for AEC implementations.**

***Index Terms*—Acoustic echo canceller, Adaptive filters, Affine projection algorithm, Computational cost.**

I. Introduction

Nowadays, a vast variety of adaptive filter configurations are applied to diverse fields such as: telecommunications, radar, sonar, audio and video signal processing, among others. Since these applications are implemented on digital systems, high-speed and efficiency are required [1]-[3] which increase the technical challenges during the design.

The Least Mean Square algorithm (LMS) is widely used in many adaptive filter applications due to its low computational complexity although its convergence speed is slow; therefore, several modifications have been proposed to improve its performance. Some of the most common alternatives use variants of the quantization algorithms in order to reduce the computational complexity, but the misadjustment and convergence time are increased. On the other hand, algorithms like the Newton LMS and the Affine Projection Algorithm (APA) reduce the convergence time but increase the computational complexity and the misadjustment [4], which makes their implementation more complex [5]-[6]. For this reason, many efficient variations of the algorithm have been proposed in recent years to reduce the computational cost [5]-[10].

In this paper we present an acoustic echo canceller using a variation of the Affine Projection Algorithm that is called ECAPA [10], [11], also the stability of the algorithm is analyzed. The ECAPA is a modification that presents a high convergence speed and low computational complexity. The reduction in complexity is achieved by the fact that an adaptive filter does not need to be updated when the error signal is small; therefore the filter coefficients are updated only when the output estimation error is higher than a pre-determined threshold. This proposal has been validated through simulations. The results showed that the algorithm reduces the computational load while keeping the high-speed convergence, besides the proposal does not modify the structure of the original version since the algorithm is not altered.

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II. Error Coded Affine Projection Algorithm (ECAPA)

The APA algorithm [4] is based on affine subspace projections, where the coefficients are updated by using the most recent input vectors instead of one. In this way the convergence rate increases if more input vectors are used, nevertheless as the input vectors increase also the computational complexity is increased.

In order to reduce the computational load, it was proposed in [10] the Error Coded Affine Projection Algorithm, which is shown in (1).

$$\mathbf{w}(n+1)= \mathbf{w}(n)+\mu\mathbf{X}(n)[\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I}]^{-1}C[\mathbf{e}(n)] \quad (1)$$

where $\mathbf{w}(n)$ is the weight vector at instant n, $C[\mathbf{e}(n)]$ is the coded error, μ is the step size, $\mathbf{X}(n)$ is the input signal matrix $\mathbf{X}(n) = [\mathbf{x}(n), \mathbf{x}(n-1), \dots ,\mathbf{x}(n-L+1)]$, which groups the recent input vectors $\mathbf{x}(n)$ of length L, ϵ is a regularization parameter of the autocorrelation inverse matrix and the superscript ^{T} denotes vector transpose operation. The error signal $\mathbf{e}(n)$ is defined by $\mathbf{e}(n)=\mathbf{d}(n)-\mathbf{X}^{T}(n)\mathbf{w}(n)$, where $\mathbf{d}(n)$ is the desired input vector.

The error codification is based on the digital-analog conversion that consists in sampling the signal, the quantization and the conversion into a binary code word. To encode the error data is used $C[\mathbf{e}(n)]=round(\mathbf{e}(n)/Res)$, where $\mathbf{e}(n)$ is the error at the time instant n and Res is the encoder resolution, which is calculated with $Res=e_{max}/2^{b}-1$, where e_{max} is the maximum probable error (is assumed that is not greater than the 90% of the maximum amplitude of the signal), and b is the number of bits used to codify the data.

The round function quantizes the sample, while the digital code is obtained from the division between the error sample and the resolution. For high quantization levels the precision of the encoder increases, therefore more information of the error magnitude is obtained which is beneficial for the adaptive algorithm. The number of bits used for the codification determines the precision of the process; thereby with a bigger b the approximation will be better thus obtaining

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a good resolution. Numerically the resolution affects the error, thus a good resolution causes that the value of the coded error becomes greater than the real error, therefore the algorithm increases the size of the weights and so the convergence rate.

In order to do a simpler digital implementation, $C[\mathbf{e}(n)]=round(\mathbf{e}(n)J)$ is used, where $J=1/Res$. In this way the division is replaced by a multiplication since J is calculated before the process.

A. ECAPA Stability

The encoding process modifies the error magnitude and changes the step size. In (2) is shown the quantization effects produced on the ECAPA algorithm.

$$\mathbf{w}(n+1) = \mathbf{w}(n)+\mathbf{X}(n)[\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I}]^{-1}\{Q[\mathbf{e}(n)]/Res\}\mu \quad (2)$$

where $Q[\mathbf{e}(n)]$ is the quantized error. In (2) can be seen that the resolution affects the step size. In order to do a better analysis (2) is combined with Res to give:

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\mathbf{X}(n)[\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I}]^{-1}[\mu(2^{b}-1/e_{max})]Q[\mathbf{e}(n)] \quad (3)$$

In (3) the step size is inversely proportional to the resolution; therefore, encoding the error with a high number of bits will produce a good resolution, which causes a large step size and so the convergence rate increases. To guarantee the convergence in the affine projection algorithms the step size value must satisfy (4) [12].

$$\mu< 2/\lambda_{max}(E[\mathbf{X}(n)(\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I})^{-1}\mathbf{X}^{T}(n)]) \quad (4)$$

Taking into account the quantization effects of the ECAPA in (4) is obtained the relation that the step size must satisfy (5).

$$\mu/Res< 2/\lambda_{max}(E[\mathbf{X}(n)(\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I})^{-1}\mathbf{X}^{T}(n)]) \quad (5)$$

To obtain the relation between the number of bits and the step size, Res is combined with (5) as is shown in (6).

$$\mu< 2e_{max} /\lambda_{max}(E[\mathbf{X}(n)(\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon\mathbf{I})^{-1}\mathbf{X}^{T}(n)])(2^{b}-1) \quad (6)$$

B. Efficient Implementation of the ECAPA Algorithm

To reduce the computational load, the proposed method takes advantage of the encoding stage. In the ECAPA algorithm when the adaptation process advances the error signal is decreased, thus when the *round* function (3) is applied the algorithm behaves like the sign algorithm and the coded error becomes "0" or "1", therefore if the error signal remains in that threshold and does not increase its magnitude, is not necessary to recalculate the filter coefficients. The threshold established to update the coefficients is shown in (7).

$$\mathbf{w}(n+1)=\begin{cases} \mathbf{w}(n) & \text{otherwise} \\ \mathbf{w}(n)+\mu\mathbf{X}(n)(\mathbf{X}^{T}(n)\mathbf{X}(n)+\epsilon I)^{-1}C[e(n)] & \text{if } C[e(n)] \neq 0 \end{cases} \quad (7)$$

When (7) is used, the processing time and the computational load are reduced since calculation of coefficients is not required during this process.

III. Experimental Results

The Acoustic Echo Cancellers (AEC) is commonly used for hands–free communication in mobile environments and speakerphones for teleconferencing. Fig. 1 shows an AEC, in general, the signal $x(n)$ is the speech signal from a far end room, $d(n)$ is the sum of the echo of the incoming signal, $y(n)$, and other sound activities produced in the near end room, $e_0(n)$.

The objective of the AEC is to model the echo path and generate a replica of the echoed incoming signal in the near end room, in order to remove $y(n)$ and transmit only the residual signal $e(n) = e_0(n)$.

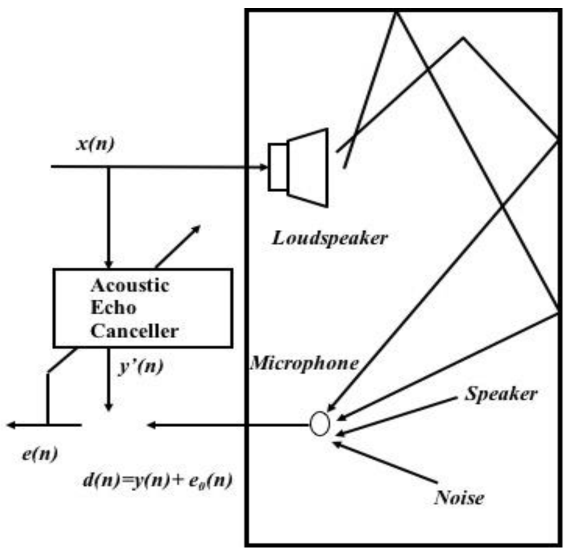


Fig. 1. Acoustic echo canceller.

The experimental results were done for a single-talk situation, and were obtained using MATLAB. The impulse response used is given in [13], which is of length 1000. In the first experiment the input signal was a speech sequence sampled at 8KHz, besides the echo signal was corrupted by a white Gaussian noise with SNR=30dB.

To measure the performance, it was obtained the echo return loss enhancement (ERLE), Fig. 2, and the normalized misalignment, Fig. 3, which is defined as $20\mathrm{Log}[\|\hat{\mathbf{w}}(n)-\mathbf{w}(n)\|^2/\|\hat{\mathbf{w}}(n)\|^2]$, where $\hat{\mathbf{w}}(n)$ are the coefficients of the impulse response of the echo path.

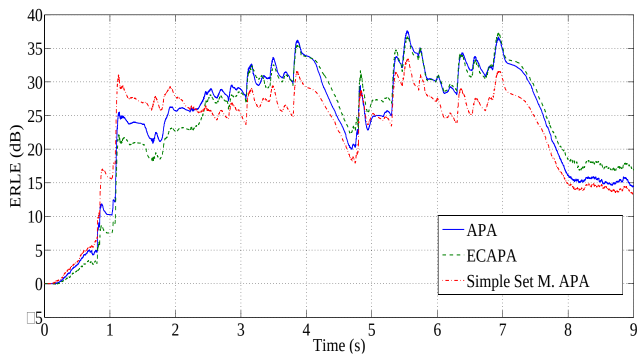


Fig. 2. ERLE curves for K=10, the length of the adaptive filter is the same as the echo path and K=10.

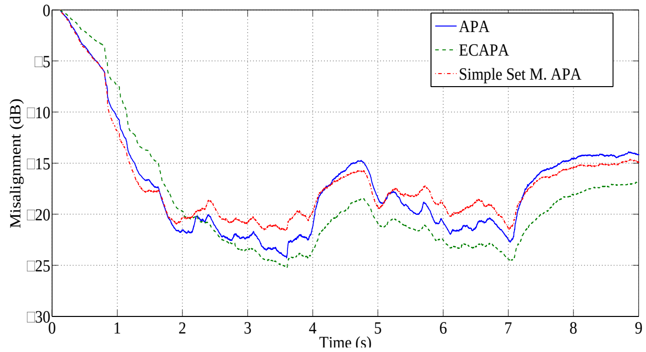


Fig. 3. Misalignment of the algorithms, the length of the adaptive filter is the same as the echo path and K=10.

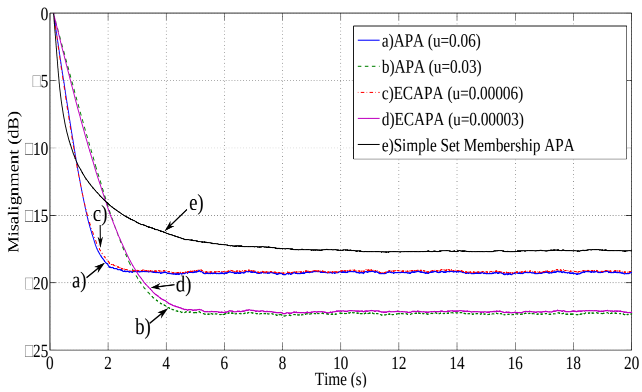
To demonstrate the effectiveness of the proposal, a comparison was performed between the original APA, the proposal and a variant that reduce the computational load, like the Set Membership APA, which is an algorithm that updates its coefficients based on an established bound [1]. The step size was chosen in a way that the algorithms reached their best performance, the error was coded to 16 bits and the projection order was 10 for all the algorithms.

The results demonstrate a faster convergence of the simple set membership APA, however the ECAPA obtained a slightly higher ERLE and a lower misalignment, but the most important feature is that the ECAPA updated its coefficients 40636 times while the simple set membership APA updated 46079 times and the APA 72982 times.

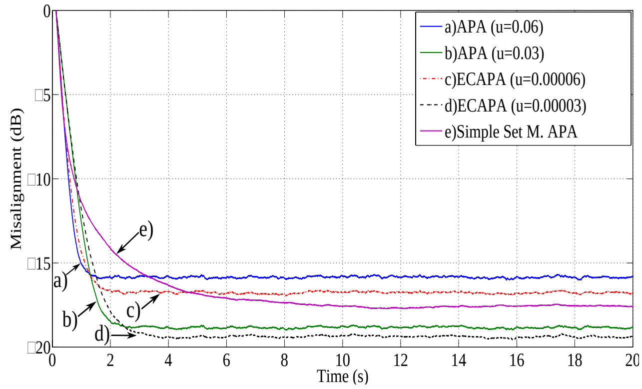
In the second experiment the input signal was an AR(1) process generated by filtering a white Gaussian noise through the system1/(1-0.95z-1), the echo path was the same used in experiment one and an independent white Gaussian noise with SNR=20dB was added to the echo signal. The length of the adaptive filter was set to 1000 coefficients, the projection orders used were K=5 and K=10, the error was coded to 10 bits and the results were averaged over 20 trials. Fig. 4 shows the misalignment obtained and the number of updates is shown in Table I.

TABLE I: NUMBER OF UPDATES AND UPDATE RATIOS

Algorithm	Updates for K=5 (ratio)	Updates for K=10 (ratio)
APA $\mu = 0.06$	3379840 (100%)	3379640 (100%)
APA $\mu = 0.03$	3379840 (100%)	3379640 (100%)
ECAPA $\mu = 0.00006$	2424865 (71.74%)	1581100 (46.78%)
ECAPA $\mu = 0.00003$	2497841 (73.9%)	1736586 (51.38%)
Simple Set M. APA	303629 (8.98%)	306327 (9.063%)



a)



b)

Fig. 4. a) Misalignment of the algorithms for K=5, b) Misalignment of the algorithms for K=10.

In the second experiment the step size was chosen in a way that the algorithms reached a proper solution. As can be seen from Fig. 4 the convergence speed and misalignment level are almost the same for the APA and ECAPA, however there is a noticeable difference in the number of updates, on the other hand the simple set membership APA reduces the number of updates but presents the higher misalignment. For K=10 the convergence speed and the misalignment were increased for all the algorithms.

When K is increased the number of updates is reduced for the ECAPA, in this case was reduced almost 50% than the APA and was obtained a lower misadjustment, which occurs because with a larger K the algorithm minimizes faster the error, thus the proposed method updates less due to the threshold established to calculate its coefficients is reached earlier. On the other hand, the ratio of updates of the simple set membership APA was the lower but its convergence speed was the slower.

IV. CONCLUSION

In this paper we presented a stability analysis of the error coded affine projection algorithm, and developed a relation that could be used to guarantee the convergence, also we demonstrated that the ECAPA can be a great alternative to implement Acoustic Echo Cancellers. The experimental results showed that the proposal maintains the fast convergence speed of the conventional APA, a lower misadjustment level and reduces the number of updates.

Using too many bits to codify the error increases the convergence speed but also the number of updates, however an important feature of the algorithm is that the computational load reduces if the projection order is increased.

The reduction of the number of updates could lead to simpler implementations on hardware, allowing liberating resources on the processors and maybe reducing the power consumption.

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