

Adaptive Noise Cancellation using Delta Controlled Affine Projection Algorithm

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Abstract—This paper presents the Adaptive Noise Cancellation using Delta Controlled Affine Projection Algorithm to adaptively filter the noise using a concept of minimum absolute mean square error. It is very simple with less computational complexity. All the computer simulations are carried out in Matlab software. Results are presented graphically to illustrate the improvement of performance. Performance in terms of Signal to noise ratio (SNR) is also presented in tabular form.

Keywords-component; formatting; style; styling; insert (key words)

I. INTRODUCTION

The principle of Adaptive noise cancellation is to obtain an estimate of the noise signal using an Adaptive Filter and subtract it from the corrupted signal. The error signal is used to adapt the tap weight vectors of adaptive filter so as to minimize the noise. By ANC, higher levels of noise rejection are attainable without a priori estimates of signal or noise. The level of cancellation of noise components in corrupted signal depend on the difference between the estimated characteristics and actual characteristics of unknown channel, which decides the accuracy of desired signal obtained at the output.

In the Least Mean Square (LMS) based adaptive noise cancellation less number of operations are required to make one complete iteration of the algorithm. However, since convergence rate is relatively slow, it allows the algorithm to adapt slowly to a stationary environment of unknown at higher speeds with less computational complexity [1].

APA is a generalization of the well known Normalized Least Mean Square (NLMS) algorithm. Under this interpretation, each tap weight update of NLMS is viewed as a one dimensional affine projection. In APA the projections are made in multiple dimensions. As the projection dimension increases, so does the convergence speed of the tap weight vector, and unfortunately, the algorithm's computational complexity [2]. APA updates the weights based on K previous input vectors, where, K is projection order of the APA [3]. Like NLMS algorithm, convergence **speed** and the steady state misalignment of the conventional APA is governed by the step size [4]. In conventional APA a matrix inversion is required, therefore some numerical problems arise caused by ill conditioned matrix. To avoid this problem a diagonal matrix is added to the matrix to be inverted. This diagonal matrix is often chosen as the identity matrix multiplied by a positive constant called the regularization parameter or delta [1], [5]. The

parameter delta is highly influenced by the level of the system noise. The rule of thumb for this is: the more is the noise, the larger the value of the delta [6]. The use of regularization factor makes the APA more robust to both perturbations and model uncertainties [7].

Here, in this paper, a delta controlled affine projection algorithm is proposed to adaptively filter the reference noise using a concept of minimum absolute mean square error. It is very simple with less computational complexity. The results are tabulated in SNR sense and the mean square error is graphically presented.

II. SYSTEM MODEL

The model for Adaptive Noise Canceller used throughout this paper is as shown in figure 1 followed with a description. The variables described here are used in the proposed algorithm.

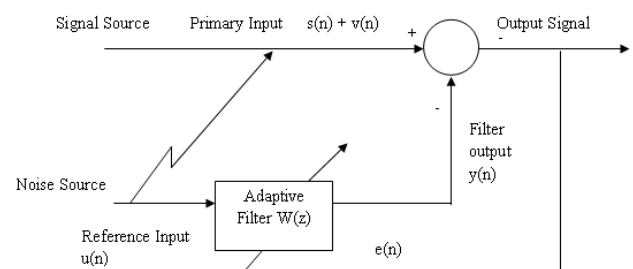


Figure 1. Model of Adaptive Noise Canceller

- An actual signal $\mathbf{s(n)}$ at primary input is corrupted with a noise signal $\mathbf{v(n)}$ to obtain a desired signal $\mathbf{d(n)}$. Here a sinusoidal signal of varying frequency is taken as $\mathbf{s(n)}$ and a white gaussian noise passed through an autoregressive process is considered as $\mathbf{v(n)}$. Thus, $\mathbf{d(n) = s(n) + v(n)}$. To simulate the proposed algorithm K recent samples of $\mathbf{d(n)}$

are considered at a time, so that, $\mathbf{d}(n) = [d(n), d(n-1), \dots, d(n-K+1)]^T$.

- Input to the adaptive filter, $\mathbf{u}(n)$ is is reference noise correlated with $v(n)$. In this deal, it is white gaussian noise passed through a moving average process.

$$\mathbf{u}(n) = [u(n), \dots, u(n-L+1)]^T \quad (1)$$

- $\mathbf{v}(n)$ and $\mathbf{u}(n)$ both are uncorrelated with $\mathbf{s}(n)$.
- $\mathbf{w}(n)$ is tap weight vector of adaptive filter, $\mathbf{w}(n) = [w_0(n), \dots, w_{L-1}(n)]^T$.
- $\mathbf{y}(n)$ is output of adaptive filter.
- This output is subtracted from desired signal to get error signal $\mathbf{e}(n)$, where,

$$\mathbf{e}(n) = [\mathbf{e}_0(n), \mathbf{e}_1(n), \dots, \mathbf{e}_{K-1}(n)]^T$$

- For Delta Controlled APA structure of excitation signal matrix $\mathbf{A}(n)$ for adaptive filter is L by N, such that,

$$\mathbf{A}(n) = [\mathbf{u}(n), \mathbf{u}(n-1), \dots, \mathbf{u}(n-K+1)] \quad (2)$$

- K is projection order of APA.
- L is length of the adaptive filter.
- I is K by K identity matrix.
- μ is adaptation constant in the range $0 \leq \mu \leq 1$.
- Filter structure is taken as finite impulse response (FIR).

III. DELTA CONTROLLED AFFINE PROJECTION ALGORITHM

To avoid any numerical problems caused by ill-conditioned matrix during matrix inversion in conventional APA, a diagonal identity matrix multiplied with a constant called delta is added. This parameter delta(δ) is highly influenced by the level of the system noise. As the noise increases, the larger value of delta is required. However it is not easy to tune the value of this constant in noisy environments [8].

In this brief, choice of the delta is based on attenuation of the effects of the noise in the adaptive filter estimate. By controlling the delta, it became possible to improve the convergence speed and the misalignment. The N^{th} order affine projection algorithm is defined as,

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{A}^T(n)\mathbf{w}(n) \quad (3)$$

$$\mathbf{S}(n) \triangleq \mu [(\mathbf{A}^T(n)\mathbf{A}(n) + \delta(n)\mathbf{I})]^{-1} \quad (4)$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{A}(n)\mathbf{S}(n)\mathbf{e}(n) \quad (5)$$

Here, $\mathbf{e}(n)$ is a priori error. In order to minimize the difference between the estimated and the true adaptive filter coefficients, the l_2 norm of the a posterior error $\mathbf{\varepsilon}(n)$ is equal to the noise variance and the a posteriori error is defined as,

$$\mathbf{\varepsilon}(n) = \mathbf{d}(n) - \mathbf{A}^T(n)\mathbf{w}(n+1) \quad (6)$$

Substituting for $\mathbf{d}(n)$ from equation (3) and then for $\mathbf{w}(n+1)$ from equation (5) it becomes,

$$\begin{aligned} \mathbf{\varepsilon}(n) &= \mathbf{e}(n) + \mathbf{A}^T(n)\mathbf{w}(n) - \mathbf{A}^T(n)[\mathbf{w}(n) + \mathbf{A}(n)\mathbf{S}(n)\mathbf{e}(n)] \\ &= \mathbf{e}(n) - \mathbf{A}^T(n)\mathbf{A}(n)\mathbf{S}(n)\mathbf{e}(n) \end{aligned} \quad (7)$$

$$\text{Or, } \mathbf{\varepsilon}(n) = [\mathbf{I} - \mathbf{A}^T(n)\mathbf{A}(n)\mathbf{S}(n)]\mathbf{e}(n) \quad (8)$$

To control the delta, the criterion is to minimize expectation of the l_2 norm of the system error and the system error is defined as,

$$\{E\|\mathbf{w}(n+1)\|^2 - E\|\mathbf{w}(n)\|^2\} \quad (9)$$

Thus, to minimize error, $\delta(n)$ is given by,

$$\delta(n) = \{E\|\mathbf{w}(n+1)\|^2 - E\|\mathbf{w}(n)\|^2\} \quad (10)$$

And the optimal value of delta is given by,

$$\delta_0(n) = \min_{\delta} \{E\|\mathbf{w}(n+1)\|^2 - E\|\mathbf{w}(n)\|^2\} \quad (11)$$

Since, signal to noise ratio is defined by,

$$SNR = \frac{\sigma_s^2}{\sigma_v^2} \quad (12)$$

Where,

$$\sigma_s^2 = E\{s^2(n)\} \text{ and } \sigma_v^2 = E\{v^2(n)\} \quad (13)$$

These are variances of $s(n)$ and $v(n)$ respectively.

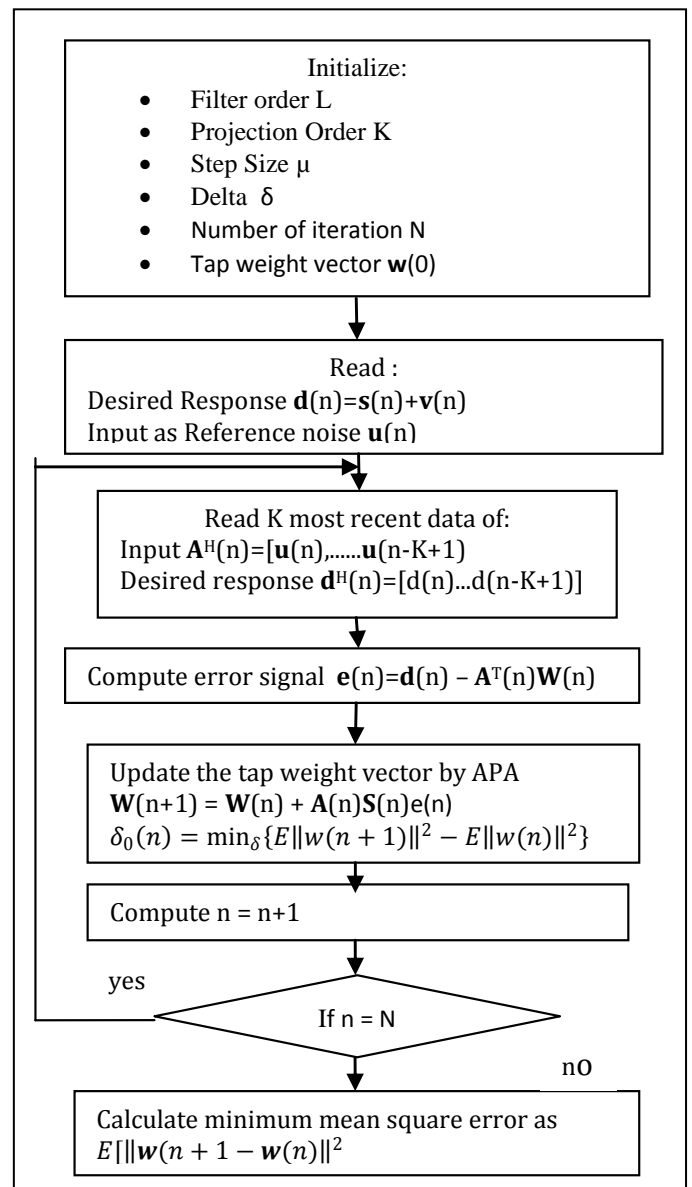


Figure 2. Flowchart for Delta Controlled APA

For minimum error, variance of estimated output power should approximate to actual signal power i.e.

$$E[\hat{s}^2(n)] = E[y^2(n)] \tag{14}$$

$$SNR = \frac{\sigma_y^2}{\sigma_n^2} \tag{15}$$

Where, σ_y^2 is variance of output. In order to attenuate the effects of the noise in the adaptive filter, it is reasonable to find δ in such a way that,

$$E[\|\varepsilon(n)\|_2^2] = E[\|v(n)\|_2^2] \tag{16}$$

IV. SIMULATION RESULTS

The simulation model is set to the following parameters :

- Number of iterations : 2000
- Order of filter : 20
- Projection order : 4
- Initial delta : 0.001
- Initial tap weight vector: [0,0,.....,0]
- Time response and frequency response of frequency varying sinusoidal signal applied as the actual signal at primary input is are shown in figure 3 & 4 respectively.
- Reference noise as input to adaptive filter is as shown in figure 4.
- Time and frequency response of unknown input signal at primary sensor i.e. noisy signal of which noise has to be cancelled and the filtered signal at output of Adaptive Noise Canceller are as shown in figure 6 and 7 respectfully.
- Mean square error of adaptive noise canceller is as shown in figure 8.
- For different values of variables SNR of output is tabulated in table I.

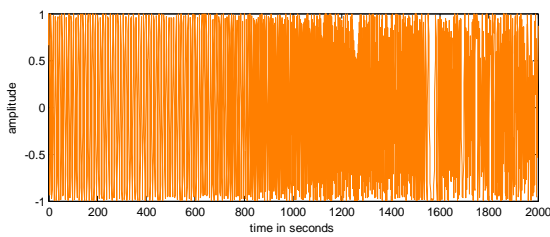


Figure 3. Time Response of Actual signal

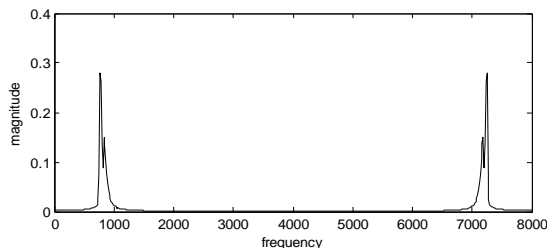


Figure 4. Frequency Response of Actual Signal

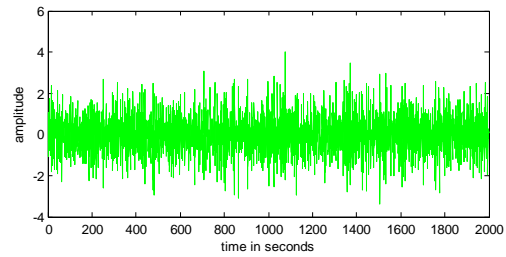


Figure 5. Time response of Input to Adaptive Filter

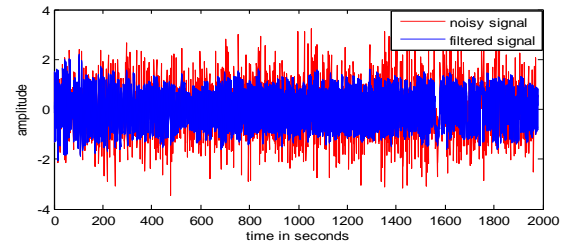


Figure 6. Time Response of Noisy and Filtered Signal for ANC

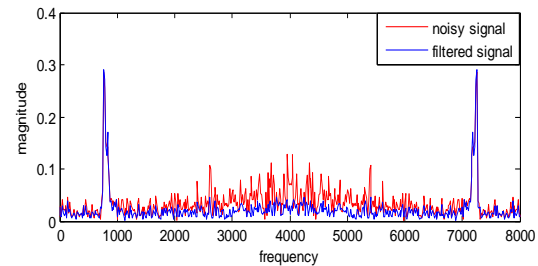


Figure 7. Frequency Response of Noisy and Filtered Signal for ANC

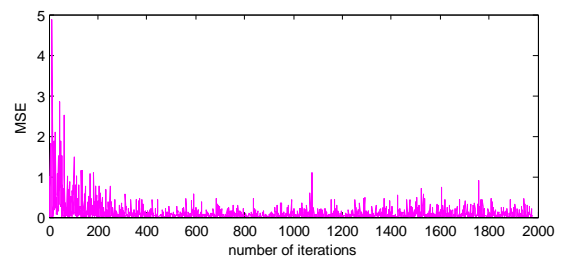


Figure 8. Mean Square Error

N	Final Delta *10 ⁻⁴	K	L	SNR in dB		Gain (b)-(a)
				Initial (a)	Final (b)	
2000	0.100	06	40	-1.9933	5.8611	7.8544
2000	1.290	06	20	-1.9933	6.4388	8.4321
2000	0.036	04	40	-1.9933	5.5332	7.5265
2000	0.620	04	20	-1.9933	6.6976	8.6909
2000	0.514	08	40	-1.9933	5.7106	7.7039
2000	2.529	08	20	-1.9933	5.9583	7.9516
1000	3.075	06	40	-1.7087	4.5977	6.3064
1000	2.165	06	20	-1.7087	5.6252	7.3339
1000	3.121	04	40	-1.7087	3.7111	5.4198
1000	3.535	04	20	-1.7087	5.4852	7.1939
1000	5.314	08	40	-1.7087	4.8952	6.6039
1000	8.082	08	20	-1.7087	5.4446	7.1533
10000	0.828	08	40	-2.2397	6.2770	8.5167
10000	0.897	06	40	-2.2397	6.9030	9.1427
10000	2.064	04	40	-2.2397	7.4869	9.7266

TABLE I. DATA FOR DELTA CONTROLLED APA

V. CONCLUSIONS

Here, delta of affine projection algorithm is controlled keeping step size parameter constant. It has increased the convergence speed. It removes the wide range of unwanted frequency components of noise signal than LMS algorithm and conventional APA with faster convergence rate. Thus, it can be concluded that this algorithm can cancel the noise components added suddenly due to varying channel response without

removing the signal components uncorrelated to noise. As seen from table, higher SNR gain can be obtained with less number of iterations and projection order increasing the speed.

REFERENCES

- [1] S.Haykin, Adaptive Filter Theory, 4thed. Upper Saddle River, NJ: Prentice-Hall, pp 27, 2002.
- [2] S. Gay and S. Thavathia, "The fast affine projection algorithm," in Proc. IEEE ICASSP 1995, Detroit, U.S.A., vol. 5, pp. 3023-3026, May 1995.
- [3] K. Ozeki and T. Umeda, "An adaptive filtering algorithm using an orthogonal projection to an affine subspace and its properties", Electron. Commun. Jpn., vol. 67-A, no. 5, pp. 19-27, 1984.
- [4] H.C. Shin and A.H. Sayed, "Mean-square performance of a family of affine projection algorithms," IEEE Trans. Signal Process., vol. 52, no. 1, pp. 90-102, Jan. 2004.
- [5] A. H. Sayed, Fundamentals of Adaptive Filtering. Hoboken, NJ: John Wiley & Sons, Inc., 2003.
- [6] J. Benesty, T. Gaensler, D. R. Morgan, M. M. Sondhi, and S.L. Gay, Advances in Network and Acoustic Echo Cancellation. Berlin, Germany: Springer-Verlag, 2001.
- [7] H. Rey, L. R. Vega, S. Tressens, and J. Benesty, "Variable explicit regularization in affine projection algorithm: Robustness issues and optimal choice," IEEE Trans. Signal Process., vol. 55, no. 5, pp. 2096-2109, May 2007.
- [8] T. van Waterschoot, G. Rombouts and M. Moonen, "Optimally regularized adaptive filtering algorithms for room acoustic signal enhancement," Signal Processing, vol. 88, pp. 594-611, Mar. 2008.