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An Effective Noise and Acoustic Echo Reduction System Based on Adaptive Algorithm for Speech Signals

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Abstract
This paper discusses about an effective noise and acoustic echo reduction system based on adaptive algorithm for speech signals. The Acoustic Echo Reduction system is most prominently used in mobile phones and pilot head phones. The requirements of an adaptive algorithm for Acoustic Echo Cancellation (AEC) are (i) high convergence and better tracking and (ii) low misadjustment and robustness against background noise variations. Affine Projection family of algorithms best satisfies these requirements. The basic APA (Affine Projection Algorithm) cannot meet these requirements together. A Variable Step-Size Affine Projection Algorithm (VSS-APA) solves this problem. This paper presents VSS-APA for speech signals with echo. In the presence of impulsive noise VSS-APA cannot perform well. For this APSA algorithms were proposed. A Memory Improved Proportionate Affine Projection Sign Algorithm (MIP-APSA) was found to perform well in impulsive noise environments with less computations and improved misadjustment. This paper simulates MIP-APSA for speech signals with echo and compares the misadjustment with that of APA and VSS-APA

Keywords: Acoustic Echo Cancellation (AEC), Affine Projection (AP) Algorithm**,** Variable Step-Size Affine Projection Algorithm (VSS-APA), Memory Improved Proportionate Affine Projection Sign Algorithm (MIP-APSA).

Introduction
The LMS algorithm and NLMS algorithm are commonly used algorithms in adaptive signal processing [1]. But for highly correlated inputs, their convergence is significantly low [2]. Even though the RLS algorithm could converge at a faster rate than LMS and NLMS, its computational complexity is very high [1], [3]. The Affine Projection (AP) algorithm proposed by Ozeki and Umeda in 1984 was a solution to this problem [4], [2]. The algorithm aims at increasing the convergence speed of the stochastic gradient algorithm. It was found that the convergence speed of NLMS could be increased if the update directions are orthogonal to the last p input vectors and thus decorrelates the input sequence. But the requirements of AEC are not met by the Ozaki-Umeda AP algorithm. The main application of AEC is in mobile phones and pilot headphones where it helps to reduce he echo generated by hand-free audio terminals [5]. In such a scenario, the adaptive filter should identify the acoustic echo path between the terminal's loudspeaker and microphone. The microphone signal is the sum of the near-end speech with noise and the far-end echoed speech. The output of the filter which is the convolution of the far-end speech and the filter taps is subtracted from microphone signal to cancel the echo.

The AEC faces several challenging problems [5]. First the echo path is extremely long and tine-varying. This could be due to slow speed of sound through air, multiple reflections of walls and may be due to objects in room. Again the impulse response of the room is time variant with the ambient temperature, pressure and humidity and also movement of objects and human bodies can rapidly change the acoustic impulse response. Thus the filter seems to work in an under modeling situation i.e. its length is less than the length of the acoustic impulse response. Hence the residual echo caused by the part of the system that cannot be modeled acts like an additional noise and alters the overall performance. Second the background noise present can be strong and highly non-stationary. Another important challenge faced is the non stationary nature of the speech signal and the fact that the speech signal is highly correlated. Finally, a major aspect that has to be considered in echo cancellation is behavior during double-talk.

Considering all these challenges an AEC demands some special characteristics for adaptive algorithms used. Ideally the algorithm should converge at a faster rate, should have good tracking capability and low misadjustment. Also apart from these requirements the algorithm should be computationally less complex. Neither LMS nor RLS algorithm nor any other algorithms belonging to their family could satisfy these requirements [2]. APA algorithm proposed in [4] and other algorithms belonging to its family turned to be a better option in AEC applications. The algorithm performs well for highly correlated inputs especially speech signals. It shows better convergence rate than NLMS algorithm.

Like LMS and NLMS algorithm, the convergence rate, misadjustment and stability of APA depends on the selection of the step-size parameter [2]. The basic APA fails to meet a compromise between convergence and fast tracking on one hand and misadjustment on the other. Thus various variable step-size algorithms were developed. This paper discuss about the performance of variable step size APA for speech input at different projection order.

It was found in [6] was found in [6] that the LMS and APA type algorithms are based on L_2-norm optimization, thus they suffer from performance degradation due to system output noise, which includes impulsive noises. The adaptive algorithms that are robust against robust against impulsive noises are based on L_1-norm optimization. The main challenge with these algorithms is that they have slow convergence rate. To overcome this drawback, affine projection sign algorithm (APSA) has been proposed. Even though APSA is also based on L_1-norm optimization approach, it has fast convergence rate due to multiple input vectors and its specific constraint. In this case we have to choose an optimum step-size so that we acquire the required convergence rate and a small steady state estimation error. In such a situation VSS-APSA was developed [7].

Similar to AEC, in a network echo cancellation (NEC) the adaptive filter has to model an unknown system, i.e. the echo path. The main difference is the way in which echo arises. In the network echo problem, there is an unbalanced coupling between the 2-wire and 4-wire circuits which results in echo, while the acoustic echo is due to the acoustic coupling of the microphone and loudspeaker. Proportionate affine projection sign algorithm was proposed for NEC [6]. The algorithm was computationally less complex compared to the AP algorithm family due to elimination of matrix inversion

A new proportionate affine projection sign algorithm MIP-APSA was proposed for network echo cancellation. It uses a recursive procedure and takes into account the previously computed proportionate coefficients. It is observed that the proposed algorithm can obtain a lower steady-state misalignment than other affine projection sign algorithms for different echo paths, impulsive interferences and step sizes. This paper also discuss about the behavior of MIP-APSA in an AEC environment with input speech signal. Also here we compare the performance of MIP-APSA with that of VSS-APA for AEC. The basic structure of both AEC and NEC is the same and is shown in Fig.1.

AP algorithm for AEC

Consider the input vector $\mathbf{u}(n)=[u(n),u(n-1),...,u(n-M+1)]$, which is a collection of M past input samples u(n) and let $\mathbf{w}(n)$ be the weight vector. The new estimate $\mathbf{w}(n+1)$ of M dimensional unknown plant parameter $\mathbf{w}$ is computed as in [2] from the old estimate of $\mathbf{w}(n)$ as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha \frac{\boldsymbol{\varphi}(n)}{\boldsymbol{\varphi}^{T}(n)\boldsymbol{\varphi}}\mathbf{e}(n) \quad (1)$$

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{w}^{T}(n)\mathbf{u}(n) \quad (2)$$

where, φ(n) defines the direction of the update. The desired vector d(n) consist of plant output and additive noise. We define φ(n) as

$$\boldsymbol{\varphi}(n) = \mathbf{u}(n) - \mathbf{U}(n)\mathbf{a}(n) \quad (3)$$

where, $\mathbf{U}(n)$ is the input matrix defined as $\mathbf{U}(n) = [\mathbf{u}(n-1),...\mathbf{u}(n-p)]$ and $\mathbf{u}(n),...\mathbf{u}(n-p)$ are p past input vectors. Here p is the projection order and $\mathbf{a}(n) = [\mathbf{U}^{\mathbf{T}}(n)\mathbf{U}(n)]^{-1}\,\mathbf{U}^{\mathbf{T}}(n)\mathbf{u}(n)$. If M is the order of the filter, then $\mathbf{U}(n)$ is a matrix of order Mxp, $\mathbf{u}(n)$ is an Mx1 vector and thus $\boldsymbol{\varphi}(n)$.

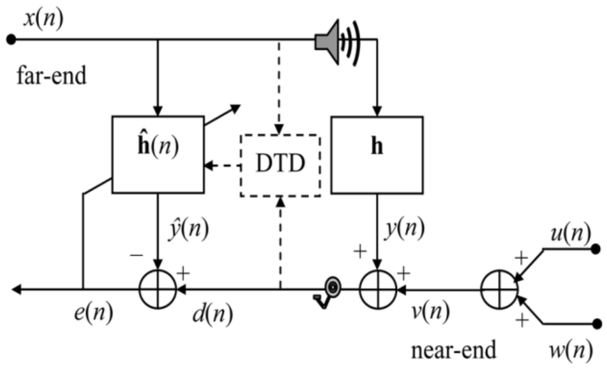


Fig.1. Basic Structure of an Echo Canceller

From the update equation we can conclude that the algorithm runs with a decorrelated direction vector $\boldsymbol{\varphi}(n)$ instead of the original correlated input $\mathbf{u}(n)$, thus the convergence of the algorithm becomes fast [2], [4]. In this paper we have simulated the affine projection algorithm in a application of AEC to recover the near-end speech signal as the output which appears as the error vector used to update the tap weights

VSS-AP Algorithm for AEC

The main aim of an acoustic echo canceller (AEC) is to identify an unknown system (i.e., acoustic echo path) using an adaptive filter [5]. Both the acoustic echo path and adaptive filter have finite impulse responses, defined as real valued vectors $\mathbf{h} = [h_0\ h_1\ \dots\ h_{N-1}]^T$ and $\mathbf{h}(n) = [h_0(n)\ h_1(n)\dots h_{M-1}(n)]^T$, where n is the time index, N is the length of echo path and M is the length of the adaptive filter. The far end speech signal x(n) is subjected to acoustic impulse response h, resulting in a far-end echoed signal, y(n). The far-end echoed signal together with near-end is picked up by the microphone resulting in a microphone signal d(n). The near end signal is a combination of near end speech, u(n) and background noise w(n). The output of the adaptive filter provides the replica of the echo, which is then subtracted from the microphone signal.

From classical APA as in [2] we have

$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{X}^T(n)\,\mathbf{h}(n-1) \tag{4}$$

$$\mathbf{h}(n) = \mathbf{h}(n-1) + \mu\, \mathbf{X}(n)[\mathbf{X}^T(n)\mathbf{X}(n)]^{-1}\mathbf{e}(n) \tag{5}$$

where, $\mathbf{d}(n)=[d(n),d(n-1),...,d(n-p+1)]$ is the input signal vector of length p, where p is the projection order and $\mathbf{X}(n)=[x(n),x(n-1),...,x(n-p+l)]$ is the input matrix of order Mxp, with l=0,1,...p-1.The constant μ is the step size parameter of the algorithm.

For a variable step size affine projection algorithm, the weight update equation can be modified as

$$\mathbf{h}(n) = \mathbf{h}(n-1)+\mathbf{X}(n)[\mathbf{X}^T(n)\mathbf{X}(n)]^{-}1\boldsymbol{\mu}(n)\mathbf{e}(n) \tag{6}$$

where,

$$\boldsymbol{\mu}(n) = \mathrm{diag}\{\mu_0(n),\mu_1(n),\ldots,\mu_2(n)\} \tag{7}$$

is a pxp diagonal matrix. The a posteriori error vector can be defined as

$$\boldsymbol{\varepsilon}(n) = \mathbf{d}(n)-\mathbf{X}^T(n)\mathbf{h}(n) \tag{8}$$

For the AEC in the fig.1, we have a combination of adaptive system identification and adaptive interference cancelling [5]. The aim of system identification part is to identify the acoustic echo path. The aim of the interference cancelling system is to recover the useful signal i.e. the near-end signal corrupted by an undesired perturbation. $\mathbf{v}(n)=[v(n),v(n-1),\ldots,v(n-p+1)]^T$ is the near-end signal.

To find the variable step size parameter μ(n) we modify the a posteriori error vector as

$$\boldsymbol{\varepsilon}(n) = [\mathbf{I}_p - \boldsymbol{\mu}(n)]\mathbf{e}(n) \tag{9}$$

$$\varepsilon_{l+1}(n) = [1-\mu_l(n)]e_{l+1}(n)=v(n-l) \tag{10}$$

where $\varepsilon_{l+1}(n)$ and $e_{l+1}(n)$ denote the (l+1)th elements of the vectors $\boldsymbol{\varepsilon}(n)$ and $\mathbf{e}(n)$, with l=0,1,…,p-1. Squaring and taking expectation on both sides we have

$$E\{\varepsilon^2_{l+1}(n)\}=E\{v^2(n-l)\}= [1-\mu_l(n)]^2 E\{e^2_{l+1}(n)\} \tag{11}$$

Solving "(11)" we get

$$\mu_l(n) = 1 \pm \frac{\sqrt{E\{v2\,(n-l)\}}}{\sqrt{E\{e\,2\,l+1\,(n)\}}} \tag{12}$$

but the value of step size parameter ranges between 0 and 1, we choose

$$\mu_l(n) = 1 - \frac{\sqrt{E\{v2\,(n-l)\}}}{\sqrt{E\{e\,2\,l+1\,(n)\}}} \tag{13}$$

in terms of power estimates we can write as

$$\mu_l(n) = 1 - \frac{\sigma v(n-l)}{\sigma e l+1(n)} \tag{14}$$

i.e.

$$\sigma^2_{el+1}(n) = \lambda\, \sigma^2_{el+1}(n-1) + (1-\lambda)\, e^2_{l+1}(n), \tag{15}$$

where, λ is the weighing factor and is chosen as 1-1/(KM) and K>1; the initial value of $\sigma^2_{el+1}(0)=0$ [5].

In this paper we have simulated VSS-APA for speech signals with echo and its performance is evaluated.

MIP-APSA for AEC

For an echo canceller and when the input contains impulsive noise neither APA nor VSS-APA provides the required misadjustment. Thus in this paper we propose to use Memory Improved Proportionate Affine Projection Sign Algorithm (MIP-APSA) which is computationally less complex and provides low misadjustment compared to any of the adaptive algorithms belonging to the Affine Projection family for AEC. The adaptive filter that models the true M-length echo path, **h**, is defined by $\mathbf{w}(n) = [w_0(n), w_1(n),..., w_{M-1}(n)]^T$, where superscript T denotes transposition, M is filter length, and n is the time index [6], [8], [10]. We note x(n) the far-end signal, z(n) and v(n) are the near-end and background noise signals, respectively.

The desired signal is given by

$$y(n) = \mathbf{x}^T(n)\mathbf{h} + z(n) + v(n), \tag{16}$$

where,

$$\mathbf{x}(n) = [x(n), x(n-1),..., x(n-M+1)]^T \tag{17}$$

is an M × 1 vector collecting the far-end signal, the output of the adaptive filter is

$$y(n) = \mathbf{x}^T(n)\mathbf{w}(n). \tag{18}$$

The output error is

$$\mathbf{e}(n) = \mathbf{y}(n) - \mathbf{X}^T(n)\mathbf{w}(n), \tag{19}$$

where,

$$\mathbf{y}(n) = [y(n), y(n-1),..., y(n-p+1)]^T, \tag{20}$$

p is the projection order and

$$\mathbf{X}(n) = [x(n), x(n-1),..., x(n-p+1)]^T \tag{21}$$

is the M × p input signal matrix.

The APSA algorithm was obtained by minimizing the l_1-norm of the a posteriori error vector, i.e.

$$\min_{w(n+1)} (\mathrm{norm}\{\mathbf{y}(n) - \mathbf{X}^T(n)\mathbf{w}(n+1)\}1) \tag{22}$$

with constraint on filter coefficients $\mathrm{norm}(\mathbf{w}(n+1) - \mathbf{w}(n))^2{}_2 \leq ß^{2,}$ where $ß^2$ is a parameter. The method of Lagrange multipliers as in is used and the filter coefficients are adapted proportionately by pre-multiplying the update vector with the proportionate matrix $\mathbf{G}(n) = \mathrm{diag}\{g_0(n),..., g_{p-1}(n)\}$ which contains the proportionate factors, $g_l(k)$ given by

$$g_l(k)=[(1-\alpha)/2L+(1+\alpha)\mathrm{abs}(w_l(n))]/[2$$

$$\sum_{i=0}^{L-1} \mathrm{abs}(wi(n)) + \varepsilon)] \tag{23}$$

where, l=1,…,L and $-1\leq\alpha<1$ and ε is a small constant which avoids division by zero. If we denote $\mathbf{P}(n)= \mathbf{G}(n)\mathbf{X}(n)$, then we have

$$\mathbf{P}(n)=[\mathbf{g}(n).\mathbf{x}(n)\ \mathbf{g}(n).\mathbf{x}(n-1)\ldots\mathbf{g}(n)\mathbf{x}(n-p+1)], \tag{24}$$

where, **g**(n) is a vector containing diagonal elements of **G**(n), which denotes Hadamard product. Considering the 'proportionate history' from the last p moments of time and approximate **P**(n) with

$$\mathbf{P}'(n) = [\mathbf{g}(n).\mathbf{x}(n)\ \mathbf{P}'_{-1}(n)], \quad (25)$$

Where, the matrix
$\mathbf{P}'_{-1}(n) = [\mathbf{g}(n-1).\mathbf{x}(n-1)\ldots$

$$\mathbf{g}(k-p+1).\mathbf{x}(k-p+1)], \quad (26)$$

contains the first p – 1 columns of $\mathbf{P}'(n-1)$. Therefore, in order to update $\mathbf{P}'(n)$,only the M × 1 vector **g**(n).**x**(n) has to be computed and this part simply requires M multiplications. An approximate M × 1 vector $\mathbf{x}g's(n)$ is then computed as

$$\mathbf{x}g's(n) = \mathbf{P}'(n)\mathrm{sgn}(\mathbf{e}(n)). \quad (27)$$

Finally, the weight update formula of the MIP-APSA is:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}g's(n)/$$

$$\mathrm{sqrt}(\delta + \mathbf{x}^T g's(n)\mathbf{x}g's(n)). \quad (28)$$

In this paper we have simulated MIP-APSA for speech input and compared the results with APA and VSS-APA.

Simulation

In this paper we compare APA with commonly used adaptive algorithms like LMS and RLS. Also we have simulated APA, VSS-APA and MIP-APSA for AEC using speech input and compared the performance of each. For LMS algorithm convergence is slow [9], thus tracking ability is less. Thus LMS algorithm cannot be used in real time applications or in the scenario of AEC where input is speech signal which is highly correlated. The RLS algorithm even though it converges at a faster rate [3], it can be used in real time applications. But RLS algorithm also doesn't perform well when the input is highly correlated.

It was found that the family of Affine Projection Algorithm performs well than any other adaptive algorithm when the input is highly correlated [2]. In this paper we have simulated the basic APA with sound input with 5000 samples for projection order 2, 4 and 8 with constant step size of 0.01 and also for different step-size. The weight updates equation for APA is computed using equations

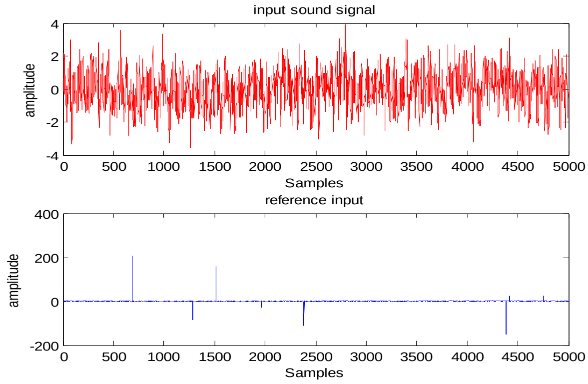
$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha \frac{\boldsymbol{\varphi}(n)}{\boldsymbol{\varphi}^T(n)\boldsymbol{\varphi}}\mathbf{e}(n) \quad (29)$$

and error vector is

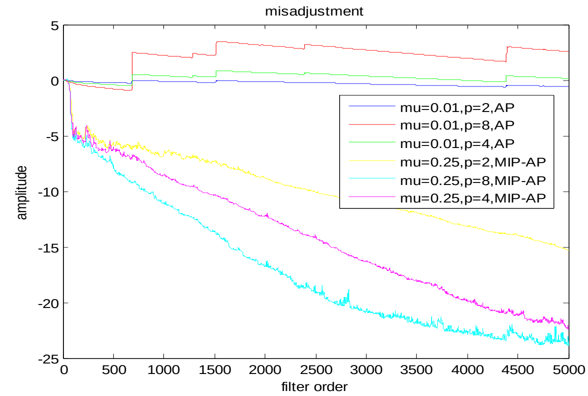
$$\mathbf{e}(n) = \mathbf{d}(n) - \mathbf{w}^T(n)\mathbf{u}(n) \quad (30)$$

The error vector denotes the output of the system and $\mathbf{w}^T(k)\mathbf{u}(k)$ denotes filtered far end speech signal. All the simulations are done for a filter order of 512. The performance at different projection order is evaluated in terms of normalised misadjustment (in dB) computed as $20\log_{10}(\mathrm{norm}(\mathbf{w}_0-\mathbf{w})/\mathrm{norm}(\mathbf{w}_0))$ [5]. Certain values are chosen for parameters ε, δ, and λ. The parameter ε which is a small constant is chosen to be 1, δ as 50 and λ as 0.001.

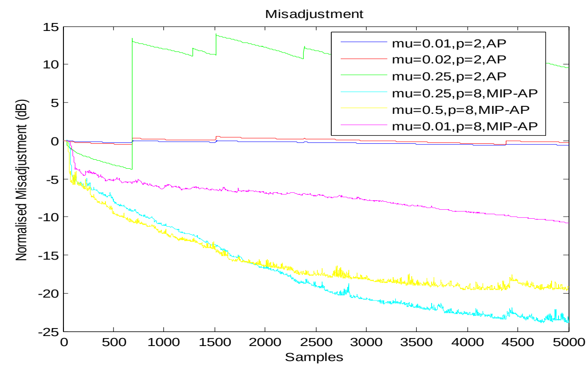
It is found that as the projection order is increased for APA the normalized misadjustment becomes more positive. Thus the optimum projection order is chosen to be 2. By setting projection order p=2 and simulating the algorithm for various values of step size parameter μ we can see that as the value is increased above 0.01 the normalized misadjustment becomes more positive. From Fig 2(b) and 2(c) we can infer that optimum APA is obtained at p=2 and μ=0.01.



2(a)



2(b)



2(c)

Fig 2: (a) input sound signal and reference sound signal of sample size 5000 and sample frequency 8000 Hz, (b) normalized misadjustment plot at p=2,4 and 8 with μ=0.01 for APA and 0.25 for MIP-APA and (c) normalized misadjustment plot at different μ and p=2 for APA and p=8 for MIP-APA.

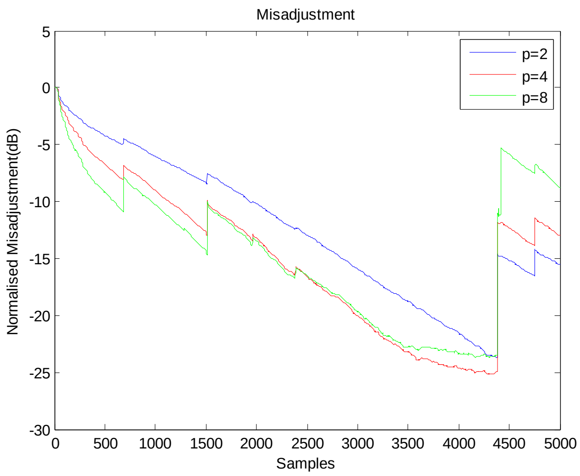
Since the misadjustment depends on weight updated we can also infer that when μ value is increased from 0.01 in addition to more positive misadjustment, the weight updates deviates more from zero. In all the cases we take $\varepsilon = 1$, $\delta = 50$ and $\lambda = 10^{\wedge -3}$.

The main difficulty faced by the basic constant step-size APA is the selection of optimum step-size that satisfies fast convergence and low misadjustment [5]. Thus variable step-size APA was developed which solves this problem and also reduces the error to a great extent. In this paper we have simulated VSS-APA for a sound input signal of sample size 5000 and also we have applied it in the scenario of AEC. The weight update for VSS-APA is given by

$$\mathbf{h}(n) = \mathbf{h}(n-1)+\mathbf{X}(n)[\mathbf{X}^T(n)\mathbf{X}(n)]^{-1}\boldsymbol{\mu}(n)\mathbf{e}(n) \qquad (31)$$

where,

$$\mathbf{e}(n) = \mathbf{d}(n)-\mathbf{X}^T(n)\mathbf{h}(n) \qquad (32)$$

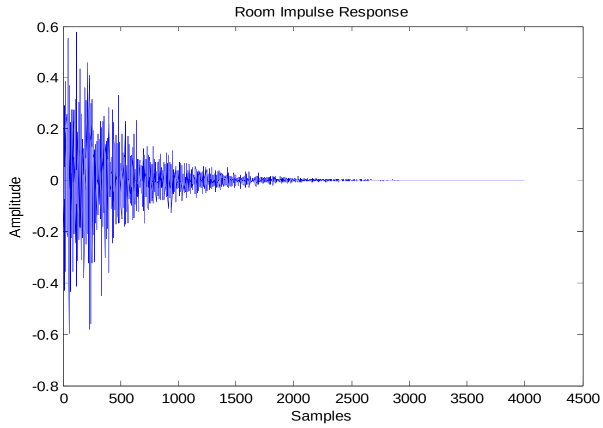


3(a)

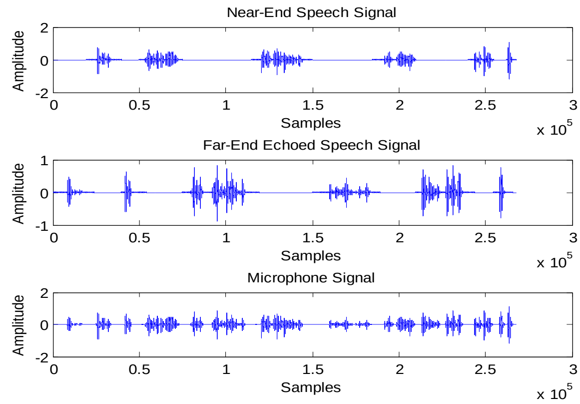
Fig: 3 (a) normalized misadjustment at p=2, 4 and 8 of order 512 with input sound of sample size 5000.

It is found that as projection order is increased from 2 to 8 there was no significant improvement in misadjustment. Thus by considering the number of computations we choose p=2 as the optimum case. While considering the scenario of AEC it is found that as the projection order p is increased the amount of echo at the output of the system is reduced. Thus we choose p=8 VSS-APA for AEC. Fig 3(a) shows the performance of VSS-APA in terms of misadjustment for the inputs shown in Fig 2(a).

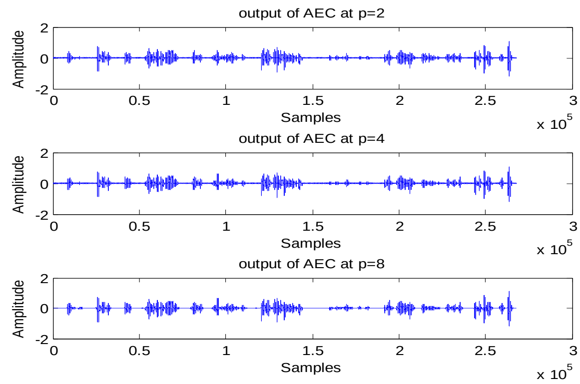
Fig 4(a) shows the measured impulse response of the room which imparts echo into the far-end signal, Fig 4(b) shows the input to the AEC system using VSS-APA, the near-end speech, the far-end echoed speech and the microphone signal which is the sum of far-end echoed speech and the near end speech along with the background nose. Fig 4(c) shows the output of the AEC system which is the calculated error vector that appears as the microphone signal with reduced echo for different projection order. As the projection order increases, we can see that the output becomes freer from echo.



4(a)



4(b)



4(c)

Fig: 4 (a) Room impulse response, (b) input to the AEC, Far-End speech signal, Near-End speech signal and Microphone signal and (c) output of AEC at p=2, 4 and 8 for VSS-APA.

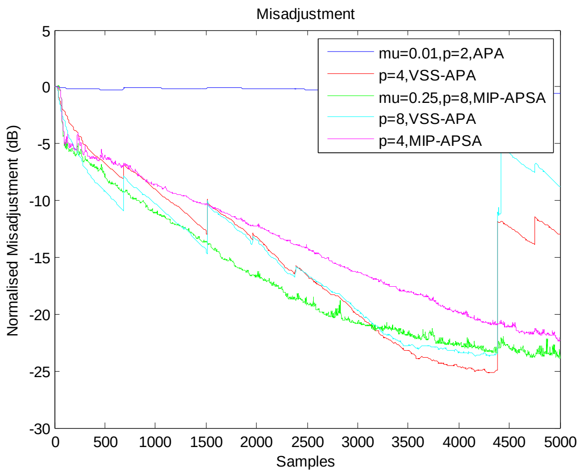
The main limitation of APA and VSS-APA is that they are less tolerant to impulsive noise. MIP-APSA was found to perform well in the impulsive noise environment [6]. In this paper we have simulated MIP-APSA for an input sound of sample size 5000 and it was found that as the projection order is increased the normalized misadjustment becomes more negative Thus we choose MIP-APSA with p=8 and step-size 0.25 and also we have simulated AEC with MIP-APSA at p=8 and step size 0.25. It was observed that MIP-APSA performs well than APA or VSS-APA in an acoustic echo environment. The weight update of MIP-APSA is given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \mathbf{x}g's(n)/\mathrm{sqrt}(\delta + \mathbf{x}^T g's(n)\mathbf{x}g's(n)). \quad (33)$$

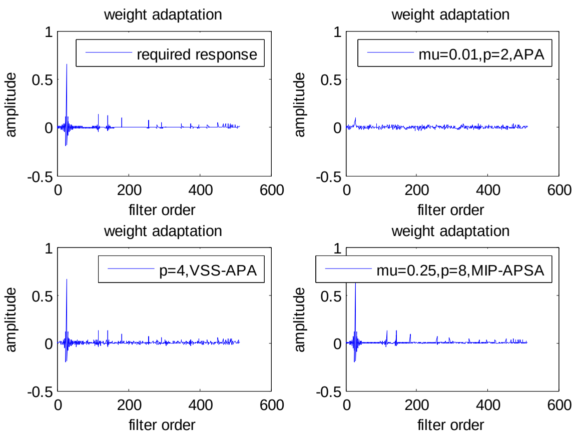
where,

$$\mathbf{x}g's(n) = \mathbf{P}'(n)\mathrm{sgn}(\mathbf{e}(n)). \quad (34)$$

From Fig 2(b) and (c) we can infer that optimum MIP-APSA is obtained at p=8 and μ=0.25.

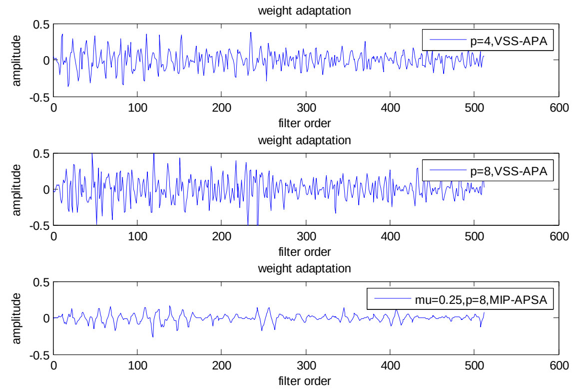


5(a)

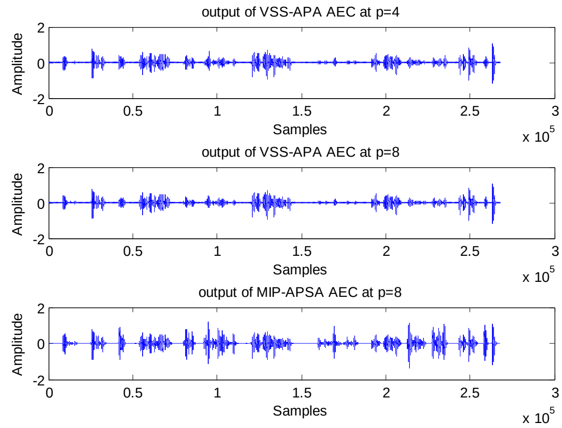


5(b)

Fig: 5 (a) normalized misadjustment for APA, VSS-APA and MIP-APSA and weight adjustment for APA, VSS-APA and MIP-APSA for an input sound signal of sample size 5000.



6(a)



6(b)

Fig:6 (a) weight adaptation for p=4 and 8 VSS-APA and p=8 MIP-APSA and (b) output of p=4 and 8 VSS-APA and p=8 MIP-APSA for AEC.

Fig 5(a) shows the comparison of different AP algorithms in terms of misadjustment and (b) shows the comparison in terms of weight adaptation. It is observed that among the three AP, VSS-AP and MIP-APSA, the best performance is obtained for p=8, μ=0.25 MIP-APSA. Thus we expect MIP-APSA to perform well in Acoustic Echo Cancellation than any other AP algorithm.

Fig 6(a) shows the performance of AEC using VSS-APA and MIP-APSA in terms of weight adaptation. It is observed that for MIP-APSA the weight update value is more close to zero than VSS-APA. Fig 6(b) shows the output of AEC for VSS-APA and MIP-APSA. It was observed that echo cancellation is performed well by MIP-APSA for p=8 and μ=0.25.

Conclusion

We know that mobile phones and aircraft headphones are often used in a noisy and reverberant environment. In hands-free mode the distance between the speaker and the microphone is usually larger than that encountered in handset mode. The received audio signal is degraded by the acoustic echo of the far end speaker, room reverberation and background noise. This problem can be solved by the use of different adaptive filters. The family of affine projection algorithm shows better performance than LMS and RLS algorithm. It was observed that for basic affine projection as step-size decreases convergence increases but mean square error decreases. Thus variable step size was introduced which could cancel p posteriori error at each iteration of the algorithm. The main disadvantage was that computation increases and takes more memory. Memory improved proportionate affine projection shows least misadjustment and consumes less memory. Also MIP-APSA performs well in acoustic echo cancellation.

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