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Modified Variable Step Size Normalized Least Means Square Algorithm in The Context of Acoustic Echo Cancellation

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Abstract— In this paper, we present a new approach to cancelling echoes, mostly occurrence in today's telecommunication system due to acoustic coupling between loudspeaker and a microphone. The proposed algorithm is a Modified VSS-NLMS-UM algorithm the popularity of this algorithm due to the solve a conflicting requirement of fast convergence and low misadjustment. Most of the algorithm was design under-modeling scenario the proposed algorithm doesn't require any prior information about acoustic environment. Due to the specific characteristic of this algorithm are equipped with good robustness feature against the near end signal variation and has a low computational complexity and low level data storage. So it's a reliable candidate for real world application.

Index Terms—Acoustic Echo Cancellation, Adaptive Filtering Algorithm (AFA), UMSI (Undermodeling System Identification).

I. INTRODUCTION

The word filter is used for any hardware or software that can be applied to a set of noisy data to extract the information about the prescribed quantity of interest. So a filter can be considered as a device which manipulates its input into desired output [1], [2]. The linear filter problem is to design a linear filter in such a way that for noisy data as input effect of noise can removed or suppressed at the output [2]. In statistical approach to solve the linear filtering problem, the availability of certain statistical parameter (i.e. means and covariance) of the useful signals and unwanted additive noise is assumed. The error is suppressed according to the statistical criterion. The useful criterion is minimization of the means square value of the error signal the resulting solution is known as Wiener filter [1], [2], which is said to be optimum in means square since. Wiener filter is not much popular in practical applications. For practical applications adaptive filters are used more realistic approach of gradient based adaption. The filter of this type is more generally used in time domain in tapped delay line form and the least means square algorithm are used to obtain the filter parameter.

The main drawback of the LMS algorithm is that convergence speed decrease as the ratio of the maximum to minimum eigenvalue of the autocorrelation matrix increase.

One approach to increase the convergence rate is to use NLMS and RLS adaptive algorithm. But RLS demand higher storage requirements and the computational intensive over LMS.

A very serious problem associated with LMS and NLMS is the choice of step-size parameter that is a tradeoff between steady state misadjustment and the speed of convergence [3].

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Adaptive filter have been successfully applied in a divers field including a communication, control and system identification [1] and is still in the field of the research reason is that it can be satisfactorily applied unknown environment. [2]. the context of acoustic echo cancellation adaptive filter will design a finite impulse response to estimate a echo path between the terminal's loudspeaker and microphone. The most popular adaptive algorithm is a NLMS algorithm frequently involved in the context of AEC, but NLMS suffer from a slow convergence speed so that it cannot optimized both conflicting requirement like a convergence speed and low misadjustment. To solve this.

Problem numbers of VSS-NLMS algorithm have been developed. The very famous VSS-NLMS algorithm was derived under modeling scenario is known as a VSS-NLMS-UM case where the length of adaptive filter is less than the length of echo path [3]. It was designed only for a single talk case but in AEC double talk happen frequently. If adaption is not halted during double talk case algorithm will be diverse.

The objective of this paper is to compare the VSS-NLMS algorithm with various adaptive algorithms in the context of echo cancellation.

System identification refers to the ability of an adaptive system to find the FIR filter that best reproduces the response of another system, whose frequency response is apriori unknown. System identification is mostly used in divergence application, setup is given below. Basic definition of the term using in this paper.

AEC - Device used to cancel to echoes that can be automatically adapt changing the echo environment.

AAEC- Acoustic Adaptive Echo Cancellation. Acoustic echo canceller applied to an acoustic environmental (Loudspeaker to microphone).

NAEC – Network AEC Acoustic echo canceller applied network environment (2-wire 4-wire hybrid).

ERLE - Echo Return Line Enhancement Amount of echo cancelled by AEC. Echo canceller is a one of the most widely device used in a digital device used in computer because each telephone call required a couples of canceller. Transversal filter which is adaptive modeling a echo path impulse response, generate a estimate of echo, with this an echo canceller is created and give a right time to cancel actual echo. Diagram show in below,

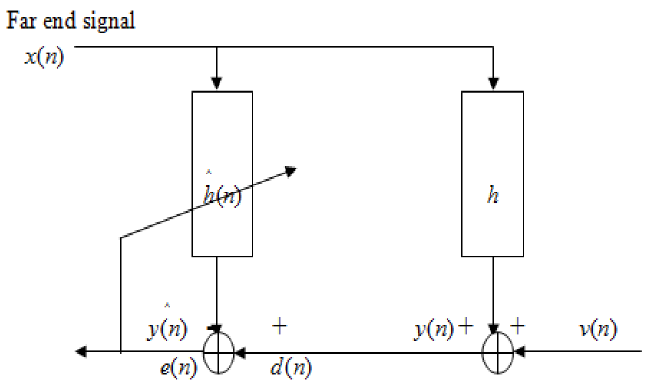

Fig.1 System identification

The FIR filter reproduces the behavior of the 'unknown system'. This works perfectly when the system to be identified has got a frequency response that matches with that of a certain FIR filter.

But if the unknown system is an all-pole filter, then the FIR filter will try its best. It will never be able to give zero output but it may reduce it by converging to an optimum weights vector. The frequency response of the FIR filter will not be exactly equal to that of the 'unknown system' but it will certainly be the best approximation to it.

Let us consider that the unknown filter is a time invariant, which indicate that the coefficient of the impulse response are constant and of finite extent (FIR). Therefore,

$$d(n) = \sum_{k=0}^{N-1} h_k x(n-k)$$

The output of the adaptive filter with the same number of the coefficient N, is given by

$$y(n) = \sum_{k=o}^{N-1} w_k x(n-k)$$

These two systems to be equal, the difference between $e(n) = d(n) - y(n)$ must be equal to zero. Under these conditions, the two set of the coefficients are also equal. It is the method of adaptive filtering that will enable us to produce an error, $e(n)$ approximately equal to zero and therefore will identify that $w_k\,'s \cong h_k\,'s$.

Where,

$x(n)$ Far-end signal

$v(n)$ Near-end signal

$d(n)$ Echo or desired signal

The problem then reduces to similar to the room echo path response h by an impulse response $\hat{h}(n)$ of the adaptive filter. So that feeding a same input to the adaptive filter the estimate of actual echo, $\hat{y}(n)$ is obtained. The use of adaptive filter in the echo cancellation is necessary because the path of echo's are highly time varying, so that the use of fixed filter is not suitable.

BASIC PROBLEMS-

In hand free telephony, the objective is to permit two or more people, sitting in two different rooms, two converge with each other. In simple configuration, there are two separate rooms one is far end room and another is near end room. Each room contains a microphone and a loudspeaker pair which is used by one speaker to converge with other..

The far-end signal broadcast to the near end signal $x(n)$ is broadcast to the near end room. The near end room has a microphone which is for the use of near end speaker but this near end speaker also receives a delayed and distorted version of the far end signal $x(n)$ as an echo $d(n)$ due to the room.

This echo passes through the near - end microphone and is broadcasted back to the far-end room, due to this, far - end receiver discomfort happens and who listen its own speech. There are two ways to overcome this problem,

- Echo suppression.
- Echo cancellation.

II. LITURATURE SERVE

Since last several decades, there has been a great deal of interest in the study of adaptive signal processing. An adaptive filter is defined as a self-designing system that relies for its operation on a recursive algorithm, which makes it possible for the filter to perform satisfactorily in an environment where knowledge of the relevant statistics is not available [1-2]. At present time most celebrated adaptive algorithm is LMS algorithm due to their simplicity and robustness, led to their wide use in variety of applications. Very important independence assumption, impractical in the case of adaptive filtering, is avoided [3], [6]. The error in LMS decreases over time as sum of exponential whose time constants are inversely proportional to eigenvalues of the autocorrelation matrix of filter input. But we know that the main disadvantage of LMSalgorithms is slow rate of convergence. This draw back can overcome with the new normalized adaptive algorithm, give certain computationally efficient, rapidly converging adaptive filtering algorithm has-been independently discovered many times [7] and performance of algorithm very well in acoustic echo cancellation application. The most common algorithms used for echo cancellation are the normalized least-mean-square (NLMS) and the affine projection (AP). The classical versions of these algorithms use a constant step-size parameter and need to as certain a tradeoff between several performance criteria e.g., high convergence rate versus low misadjustment. Letter presents a class of variable step-size NLMS and AP algorithms, which are designed to recover the near-end signal from the error of the adaptive filter [8-15]. The NPVSS adaptive algorithm that uses the power estimate of the background noise in order to control its step-size parameter and the step size of the proposed algorithm is adjusted according to the square of a time-averaging estimate of the autocorrelation of a priori and a posteriori error. Also, the affine projection algorithm (APA) and its some version [23-24], were found very attractive choices for echo cancellation. However there is still need to improve the performance of these algorithm for echo cancellation More importantly, it is necessary to find some way to increase the convergence rate and tracking of the algorithms since it is known that the performance of both NLMS and APA are limited for high length adaptive filters. This can be partially overcome the exploiting the character of system to identify the path of echo,

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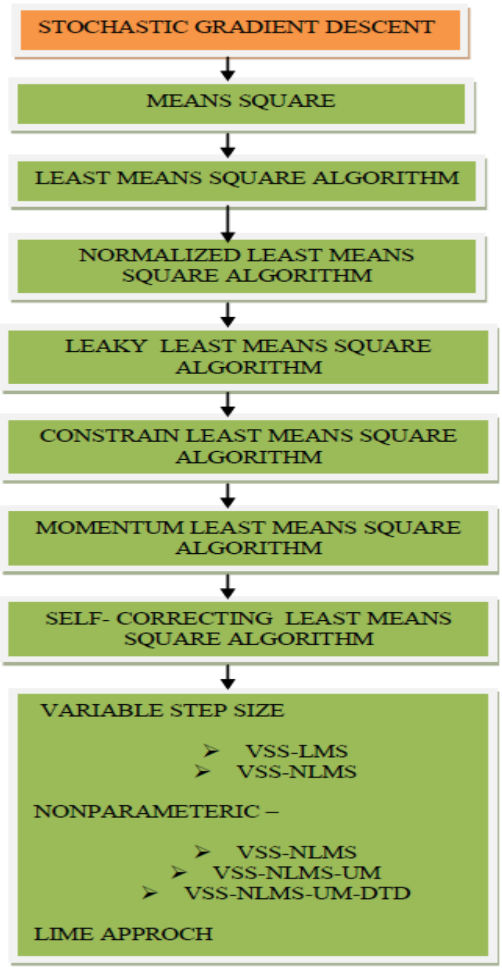
To overcome this problem by using a most attractive algorithm, VSS-NLMS-UM adaptive filtering algorithm [19], variable step-size normalized least-mean-square (VSS-NLMS) algorithm suitable for the under-modeling case is proposed. This algorithm does not require any a priori information about the acoustic environment; as a result very robust and easy to control in acoustic echo cancellation application. One of the most challenging problems in echo cancellation the double-talk situation, i.e. the talkers on both sides speaks simultaneously. For this reason, the echo canceller is usually equipped with a double-talk detector (DTD), in order to slow down or completely halt the adaptation process during double-talk periods .The main challenge for the DTD algorithm is to “feel” the presence of the near-end speech.

A lot of very interesting DTD algorithm have been proposed. The simplest one is well known P. Algren, [22], which provides an efficient and low-complexity solution, especially for acoustic echo cancellation. Other more complex algorithms have been proposed; more recent framework for designing robust adaptive algorithm can be found [21]. The algorithm is developed based on acoustic echo cancellation, where recover the near-end signal from error signal of adaptive filter. As consequence, these VSS algorithms are equipped with good robustness feature against near-end signal variation, like double talk.

III. CURRENT STATUS

Current status in the field of a adaptive algorithm is given below,



$$h = \left[h^T{}_L h^T{}_{N-L}\right]^T \tag{5}$$

Where

$$h_L = \left[h_0 \quad h_1 \quad \dots \quad h_{L-1}\right]^T$$

$$h_{N-L} = \left[h_L \quad h_{L+1} \quad \dots \quad h_{N-1}\right]^T$$

$$X_L(n) = \left[x(n) \quad x(n-1) \quad \dots \quad x(n-L+1)\right]^T$$

$$X_{N-L}(n) = \left[x(n-L) \quad x(n-L-1) \quad \dots \quad x(n-N+1)\right]^T$$

$$y_{N-L}(n) = X^T{}_{N-L}(n) h_{N-L}$$

The a priori and posteriori error signal can be written using afilter coefficient at time $n-1, n$

$$e(n) = d(n) - \hat{y}(n) \tag{5}$$

$$= d(n) - X_L{}^T(n) - \hat{h}(n-1)$$

$$= X_L{}^T(n)\left[h_L - \hat{h}(n-1)\right] + y_{N-L}(n) + v(n) \tag{6}$$

Posteriori error signal is defined as,

$$\varepsilon(n) = X_L{}^T(n)\left[h_L - \hat{h}(n)\right] + y_{N-L}(n) + v(n) \tag{7}$$

We know that weight updated equation

$$\hat{h}(n) = \hat{h}(n-1) + \mu(n) X_L(n) e(n) \tag{8}$$

Where $\mu(n)$ is a stepsize parameter and is positive scalar. The relation between a posteriori and a priori error signal is then

$$\varepsilon(n) = e(n)\left[1 - \mu(n) X_L{}^T(n) X_L(n)\right] \tag{9}$$

If $\varepsilon(n) = 0$, but assuming that $e(n) \neq 0, \forall n$. Therefore , step size is converted into

$$\mu(n)_{NLMS} = \left[X_L{}^T(n) X_L(n)\right]^{-1} \tag{10}$$

Which is the step size of classical NLMS Algorithm this approach hold good for noise free case and in exact modeling case. To cancel the posteriori in the presence of noise and in under modeling case.

$$X_L{}^T(n)\left[h_L - \hat{h}(n)\right] = -y_{N-L}(n) + v(n) \neq 0 \tag{11}$$

This will be the basis the adaptive estimate. In this situation requirement,

$$X_L{}^T(n)\left[h_L - \hat{h}(n)\right] = 0$$

$$\varepsilon(n) = e(n)\left[1 - \mu(n) X_L{}^T(n) X_L(n)\right]$$
$$= y_{N-L}(n) + v(n)$$

(12)

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$$E\{\varepsilon^2(n)\} = E\{y^2{}_{N-L}(n)\} + E\{v^2(n)\} \qquad (13)$$

The $y_{N-L}(n)$ and $v(n)$ are uncorrelated,Using approximation $x^T(n)x(n) = LE\{x^2(n)\}$, for $L \gg 1$,which is valid in AEC where the length of the adaptive filter is of the order of hundred. We obtained

$$E\{e^2(n)\}\left[1 - L\mu(n)E\{x^2(n)\}\right]^2 = E\{y^2{}_{N-L}(n)\} + E\{v^2(n)\}$$

Above equation is a quadratic equation and obtained a step size parameter

$$\mu(n) = \frac{1}{X_L{}^T(n)X_L(n)}\left[1 - \sqrt{\frac{E\{y^2{}_{N-L}(n)\} + E\{v^2(n)\}}{E\{e^2(n)\}}}\right]$$

Most problemetic terms is $E\{y^2{}_{N-L}(n)\}$. We know that $d(n) = y_L(n) + y_{N-L}(n) + v(n)$, squaring them and taking expextations and assuming that $y_L(n)$ and $y_{N-L}(n)$ are uncorrelated and only valid for a white input. $E\{y^2{}_{N-L}(n)\} = E\{d^2(n)\} - E\{y^2{}_L(n)\} - E\{v^2(n)\}$

Considering that adaptive filter coefficients have converged to certain degree, assumed that

$$E\{y^2{}_L(n)\} = E\left\{\hat{y}^2(n)\right\} \qquad (14)$$

The step size can be written as,

$$\mu(n) = \frac{1}{X_L{}^T(n)X_L(n)}\left[1 - \sqrt{\frac{E\{d^2(n)\} + E\left\{\hat{y}^2(n)\right\}}{E\{e^2(n)\}}}\right]$$

$$\mu(n) = \frac{1}{X_L{}^T(n)X_L(n)}\left[1 - in\sqrt{\frac{\hat{\sigma}^2_d(n) + \hat{\sigma}^2_{\hat{y}}(n)}{\hat{\sigma}_e(n)}}\right] \qquad (15)$$

In general, the parameter $\hat{\sigma}^2_\alpha(n)$ denotes the power estimate of the sequence $\alpha(n)$,and can be computed as

$$\hat{\sigma}^2_\alpha(n) = \lambda\hat{\sigma}^2_\alpha(n-1) + (1-\lambda)\alpha^2(n) \qquad (16)$$

Where λ is weighting factor chosen as $\lambda = 1 - \frac{1}{1-KL}$,with $K \succ 1$. The initial value is $\hat{\sigma}^2_\alpha(0) = 0$

Concluding, the stepsizeparameter of the proposed VSS-NLMS for under-modeling
(VSS-NLMS-UM) algorithm is

$$\mu(n) = \mu_{NLMS}(n) \quad \text{for} \quad n \le L$$

$$\frac{1}{X_L{}^T(n)X_L(n)}\left[1 - in\sqrt{\frac{\hat{\sigma}^2_\alpha(n) + \hat{\sigma}^2_{\hat{y}}(n)}{\hat{\sigma}_e(n)}}\right]$$

$n \succ L$

The NPVSS-NLMS algorithm derived in **(**19**)** is similar at first look to the VSS-NLMS-UM algorithm. It uses a step-size parameter computed as

$$\mu_{NPVSS}(n) = \frac{1}{x^T(n)x(n)}\left[1 - \frac{\sigma_v}{\sigma_e(n)}\right] \qquad (17)$$

When, $N = L$, so that $y_{N-L}(n) = 0$, and under the assumption (10), the NPVSS-NLMS algorithm is theoretically equivalent to the VSS-NLMS-UM algorithm. The NPVSS-NLMS algorithm. gives more accurate results,

when $N = L$ and σ_v is available. It should be also noted that the variance of the ambient noise may change in AEC applications. If this change does not happen during a silence period, the NPVSS-NLMS algorithm will be affected until the new value of the noise power is estimated. VSS-NLMS-UM algorithm uses only the parameters that are available from the adaptive filter [i.e., $d(n)$, $\hat{y}(n)$, a $e(n)$] and all the information concerning the change in the acoustic environment e.g., echo path change, ambient noise change is contained in the second ratio from the step size equation.

Needs to be paged per unit area and per time unit (second) is SIMULATION.

The convergence performance of the variable step size adaptive algorithm is simulated for the application of the system identification. Matlab 7.0 is chosen as a simulation platform due to simplicity and its own advantage in engineering applications. The echo path measured using an 8 kHz sampling rate. In this simulation setup the number of unknown plant coefficient is higher than the adaptive filter length, known as undermodeling. The input signal applied to the unknown system is either a white gaussian noise or speech signal. The output of the plant is mixed with noise such that the signal to noise ratio remain 20-dB. This signal is a desired signal for adaptive filter. The error vector obtained as the difference of desired and output vector is used to update output of adaptive filter. The initial weights of are initially set to zero. The simulation study has been carried out for NLMS, NPVSS-NLMS and VSS-NLMS-UM.

IV. SIMULATION RESULTS

A. NLMS and Nonparameteric VSS algorithm.

The acoustic coupling between microphone and microphone in hand free telephones generates echoes .To remove this echo, we need to identify impulse response of unknown system. Simulation results, input signal is consider as white gaussian signal or speech signal. An independent white gaussian noise signal is added to the output of unknown system at 30-dB. We also assume that power of noise signal is known. Parameters setting for simulations are $\hat{\sigma}_e^2(0) = 0$,

$\delta = 20\sigma_x^{\ 2}$ and $\lambda = 1 - \frac{1}{KL}$ and $K = 2$ for white gaussian noise signal. The performance of algorithm measured in terms of the normalized misalignment in (dB).

$$Misalignment\left(\hat{h}(t)\right) = 20\log\left(\frac{\left\|\hat{h}(t) - h\right\|}{\left\|h\right\|^2}\right)$$

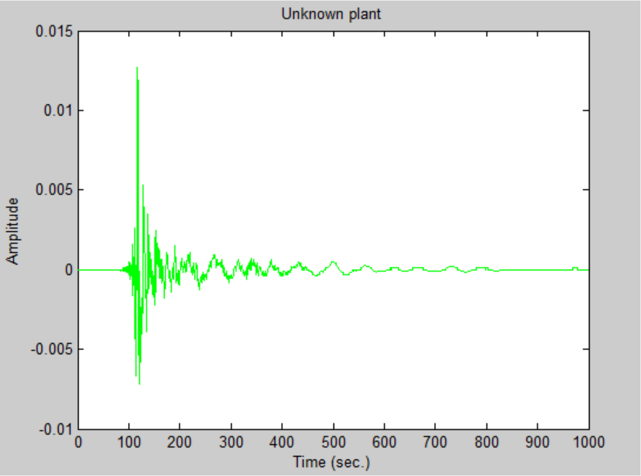

Fig.2 Unkown Plant

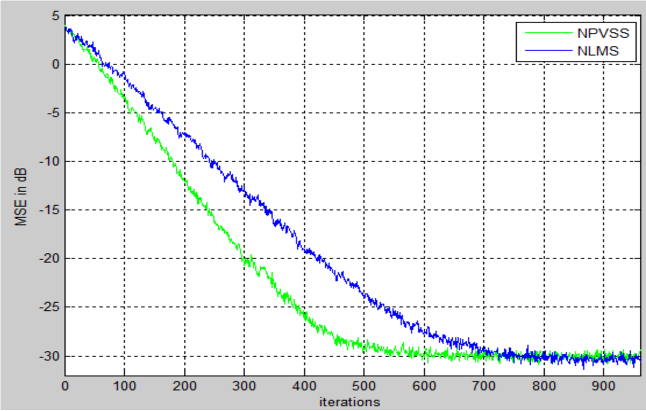

Fig.3. Misalignment of the NLMS algorithm at $\left[\delta + X^T(n)X(n)\right]^{-1}$ and the NPVSS-NLMS Algorithm.

The input signal is white gaussian noise, $L = 500$, $\lambda = 1 - \frac{1}{1-(2L)}$, and SNR = 30 dB

The simulation results show that NPVSS algorithm is better than NLMS algorithm. We have compared NPVSS and NLMS. The plot has been taken between numbers of iterations and corresponding MSE. The iteration range varied from 0 to 950 where as MSE value varies from 0 dB to 5 dB. It is clear from the above plot, fig.13 that NPVSS algorithm converges in 30 dB signal to noise ratio, which is lesser than NLMS algorithm.

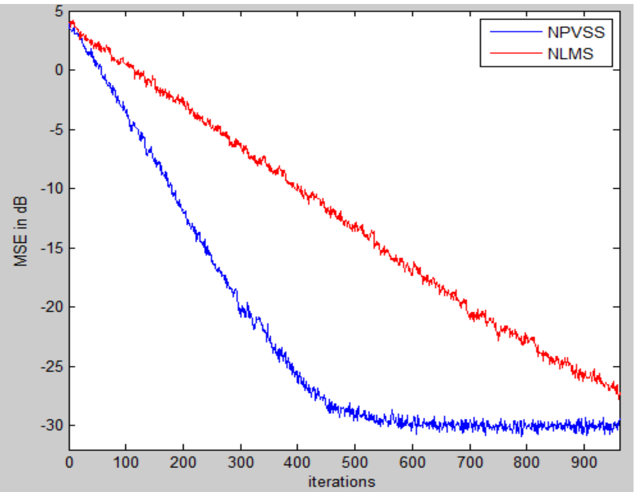

Fig.4 Misalignment of the NLMS algorithm at $0.04\left[\delta + X^T(n)X(n)\right]^{-1}$ and the NPVSS-NLMS Algorithm.

The input signal is white gaussian noise

$L = 500, \lambda = 1 - \frac{1}{1-(2L)}$, SNR = 30 dB

Tracking is a very important issue in adaptive algorithms. In applications like acoustic echo cancellation, it is essential that an adaptive filter tracks fast since impulse responses are not very stationary. Fig. shows that, when the impulse response has changed NLMS algorithm provides more erroneous results than the previous one, where as NPVSS algorithm shows the same results with more efficiency compare to NLMS algorithm.

B. Variable Step Size NLMS for Undermodeling case

In the simulation the acoustic echo path was measured using a sampling rate 8-kHz, impulse response of unknown plant h has $N = 950$ Coefficients and adaptive filter length is $L = 450$. The input signal is a either white gaussian noise or speech signal. Independent white gaussian noise added at the output of the unknown plant at 20 dB signal to noise ratio. we know that the noise power and weighting factor from a NPVSS. We fixed $\xi = 0.0001$ and regularization factor of the algorithm is $\delta = 30\sigma_x^{\ 2}$. Misalignment measure from equation (57).

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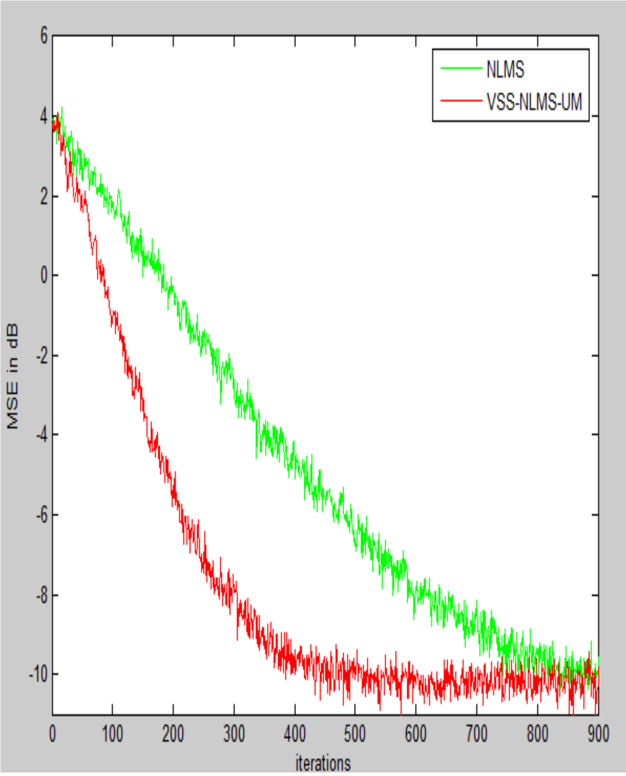

Fig.5. Misalignment of the NLMS algorithm at $0.04\left[\delta + X^T(n)X(n)\right]^{-1}$ and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda = 1-\frac{1}{1-(2L)}$ and SNR= 10 dB

The simulation results show that VSS-NLMS-UM algorithm is better than NLMS algorithm. We have compared VSS-NLMS-UM and NLMS. The plot has been taken between numbers of iterations and corresponding MSE. The iteration range varied from 0 to 900 where as MSE value varies from 0 dB to 6 dB. It is clear from the above plot, fig.13 that NPVSS algorithm converges in 10 dB signal to noise ratio, which is lesser than NLMS algorithm.

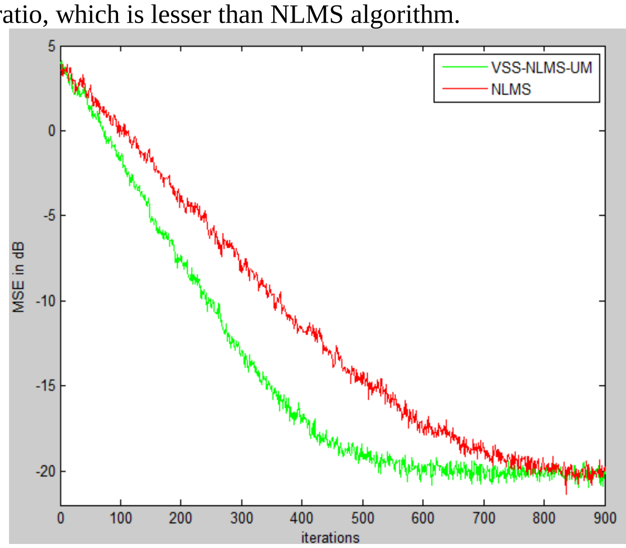

Fig.6 Misalignment of the NLMS algorithm at $0.05\left[\delta + X^T(n)X(n)\right]^{-1}$, NPVSS and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda = 1-\frac{1}{1-(2L)}$ and SNR= 20 dB

The simulation results show that VSS-NLMS-UM algorithm is better than NLMS algorithm. We have compared VSS-NLMS-UM and NLMS. The plot has been taken between numbers of iterations and corresponding MSE. The iteration range varied from 0 to 900 where as MSE value varies from 0 dB to 5 dB. It is clear from the above plot, fig.13 that NPVSS algorithm converges in 20 dB signal to noise ratio, which is lesser than NLMS algorithm.

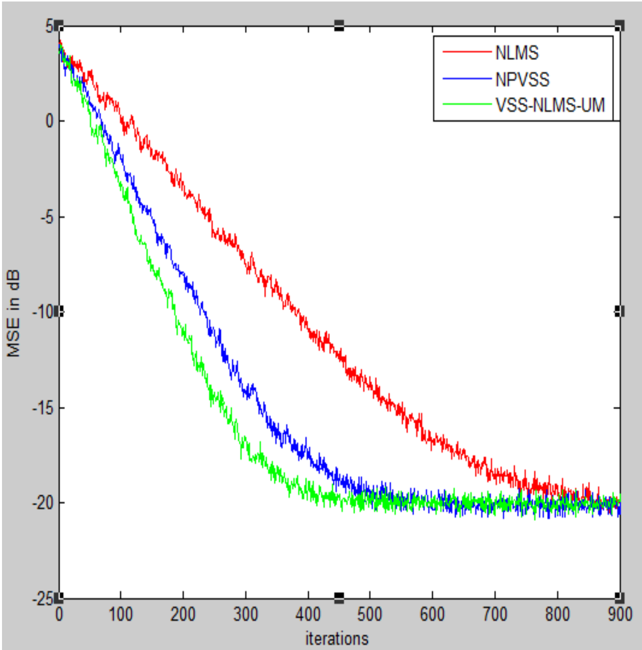

Fig.7 Misalignment of the NLMS algorithm at $0.05\left[\delta + X^T(n)X(n)\right]^{-1}$, NPVSS and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda = 1-\frac{1}{1-(2L)}$ and SNR= 20 dB

We have compared between three adaptive algorithms, NLMS, NPVSS and VSS-NLMS-UM. The result shows that VSS-NLMS-UM algorithm has batter performance and Quick response than the other two algorithm, as it converse very fast compare to the other. It has been clear from the plot, Fig. , that for the case of MSE variation from -25 dB to 5 dB with iteration values 0 to 900, VSS-NLMS-UM converses in 370 iteration and -20 dB MSE.

V. CONCLUSION

In AEC, the acoustic echo paths are extremely long. Therefore, the adaptive filter works most likely in under-modeling situation. The main property of the algorithm doesn't require any priori information about acoustic environment. It can be deduced from above figures that variable step size normalized least means square adaptive algorithm for undermodeling case perform better than the other two algorithms, NLMS and NPVSS in the context of echo cancellation. In NLMS algorithm, we need to find a compromise between fast convergence and low final misadjustment. In many applications, this compromise may not be satisfactory so a VSS-NLMS algorithm is required.

It should be noted that the idea of proposed algorithm can be used in coincidence with other NLMS-based algorithms This improves the convergence rate and reduced the computational complexity. So it is suitable for real world application.

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