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Acoustic Echo Cancellation and their Application in ADF

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Abstract- In this paper, we present an overview of the principal, structure and the application of the echo cancellation and kind of application to improve the performance of the systems. Echo is a process in which a delayed and distorted version o the original sound or voice signal is reflected back to the source. For the acoustic echo canceller much and more study are required to make the good tracking speed fast and reduce the computational complexity. Due to the increasing the processing requirement, widespread implementation had to wait for advances in LSI, VLSI echo canceller appeared.

Index Terms—*Acoustic Echo Cancellation, FIR, IIR Adaptive Filter, Non-Parameteric, System Identification, LMS, NLMS, VSS, VSS-NLMS-UM*

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I. INTRODUCTION

Acoustic echo cancellation is one of the most popular application of adaptive filter [1]. The role of the adaptive filter is to identify the acoustic echo path between the terminals loudspeaker and microphone.

Even though many interesting adaptive filtering algorithm have been developed and are applicable for acoustic echo cancellation [2], an application with limited precision and processing power, the least means-square (NLMS) algorithm [3] (e.g., frequency domain or subband versions [1]) are usually applied.

The standard least means square (LMS) algorithm is considered to be one of the simplest algorithms for adaptive filtering, but it is sensitive to the scaling of its input when choosing a step-size parameter to guarantee stability [2],[3].

The NLMS algorithms solve this problem by normalizing with the power of the input. For both algorithms, the parameter of step-size governs the convergence speed and the steady-state excess mean-square error. To better tradeoff the conflicting requirement of fast convergence rate and low misadjustment, various schemes for adjusting the step-size have been reported [4], [5], [6], [7],. To meet these conflicting requirements, the step size needs to be controlled. Thus, a number of variable step size NLMS (VSS-NLMS) algorithms have been proposed [8], [9] and references therein. In [5], elaborated and distribution free VSS-NLMS (DFVSS-NLMS) is proposed. This algorithm is gives the good performance in the context of acoustic echo cancelation [AEC].

II. BASIC FILTER STRUCTURE AND ALGORITHM

The echo canceller must accurately estimate the echo path characteristic and rapidly adapt to its variation. This involves the selection of an adaptive filter and an algorithm for the adaptation. The best selection depends on the particular application and on performance requirements. In this section, various alternatives for this selection are outlined.

(a) Filter Structure

Figure1. shown various type of filter based on their practical importance and table 1 indicate characteristics of the filters. Now consider that $X(z)$ and $Y(z)$ are polynomials of Z, a_k and b_k are coefficient of filter and highly vary with time

Types of adaptive filter structure.

1) FIR Structure
2) IIR Structure.
3) Lattice Structure
4) Frequency-Domain Structure
5) Echo Replica Memorization

The adaptive filter can be implemented in a number of different structures or realization. The choice of the structure can influence the computational complexity of the process and also the necessary number of iterations to achieve a desired performance level. Basically, there are two major classes of adaptive digital filter realization, distinguish in the form of the impulse response, namely the FIR filter and infinite impulse response filter (IIR). FIR filters are usually implemented with non-recursive structures, whereas IIR filter utilize recursive realizations. FIR filter is preferred for many applications for its stability duration adaption. IIR can normally achieve similar performance as FIR, with similar amount of coefficient and less computational complexity. However, as the complexity of the filter grows, the order of the IIR filter increases and the computational advantage is less dominant. Also IIR filter suffers from the instability problem. So the filters that are being used in present paper are of FIR type.

In the FIR filter, convergence is the fastest for white (uncor-related) signals, and the rate decreases for colored (correlated) signals. This can be a serious problem for FIR filters with voice input, particularly when a large number of taps is required. In such a case, the use of a white noise training signal must be considered. To circumvent this problem, a lattice-type pre-filter, as shown in Figure 3(d), has been proposed [9] [15] [16]. The weighted sum of signals obtained at each stage of the lattice

gives the echo replica. The weights are the filter coefficients, adapted in the same way as for the FIR filter. In effect, the lattice
Whitens the input signal so that rapid convergence is obtained. Another promising approach is to convert signals to the frequency domain using the Discrete Fourier Transform (DFT) and carry out echo cancellation in the frequency domain [131 [141. Convolution for a block of time-domain signals becomes simply coefficient multiplication, substantially reducing complexity. Figure 3(e) shows an example in which an echo canceller is provided for each frequency bin.
This structure is suitable
for data transmission, especially when the echo duration is short. Echo replicas corresponding to each sequence of transmitted data are stored in memory. Therefore, it is not necessary to compute the echo replica; just read it out of memory, using the data sequence as the address. This structure has an
advantage in that nonlinear effects in the echo path can also be included, since table look-up is not restricted to linear functions. But the required amount of memory grows exponentially as the data sequence size become large; hence, it is not suitable for long echo durations.

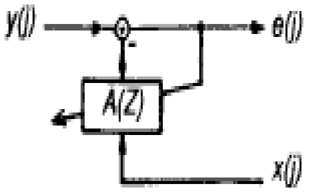

Fig1. FIR Structure

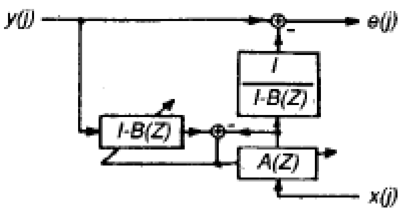

Fig2.IIR (Series-Parallel) Structure

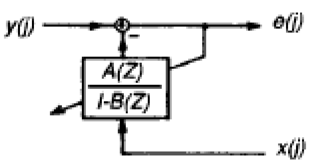

Fig3.IIR (Parallel) Structure

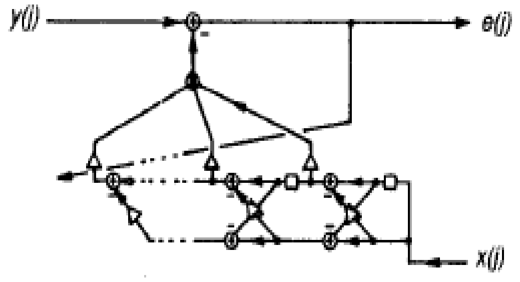

Fig3.Lattice Structure

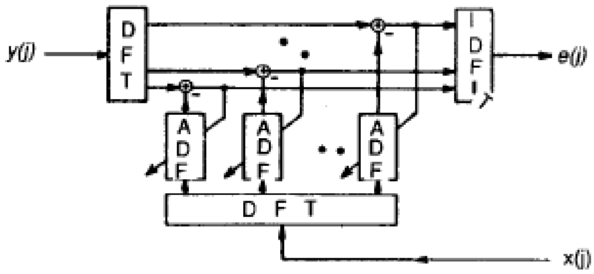

Fig4.Frequency Domain Structure

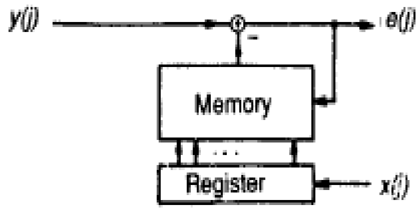

Fig5.Memory Type Structure

Table shown the adaptive structure and characteristics below-

Adaptive Filter Structure		**Characteristics**
FIR		• Basic Structure • In the LMS Algorithm the number of tap delay is directly proportional to the convergence rate.
IIR	Series-Parallel	• The same adaption algorithm as in the FIR Structure can be used. • Stability testing is required • Performance is limited due to background noise.
	Parallel	• Convergence property not affected by background noise • Converge to local minima. • Convergence is too slow • Stability testing is required.
Lattice		• Due to orthogonal zed , convergence is fast. • Stability Testing can be easily done. • When input time varying signal then LMS can not be applicable.
Frequency-domain Structure		• A transform operation is required

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	• Required operation is small. • The echo canceller is provided to each frequency bin.
Echo replica memorization	• Nonlinearity of the echo path can be canceled.

II. BASIC CONCEPTS OF ECHO CANCELLATION

Echo is a process which a delayed and distorted version of an original sound or signal is reflected back to source.

There are two types of echo

- Acoustic echo.
- Hybrid echo.

Acoustic Echo: Acoustic echo occur when some of the sound from the speaker part of the telephone gets picked up and transmitted back by the microphone.

There are two types of the source of echo.

(a) Acoustic Isolation echo

It is also known as a acoustic coupling is generated when the headset and microphone are poorly isolated from one another.

(b) Ambient Acoustic

Ambient acoustic echo is generated when a telephone conversation is held in an acoustically reflective environment.

In acoustic echo cancelation, the estimates of the near-end echo path response is computed which is used to generate an estimate of echo. The estimate of echo is subtracted from the near-end microphone output to subtract the actual echo.

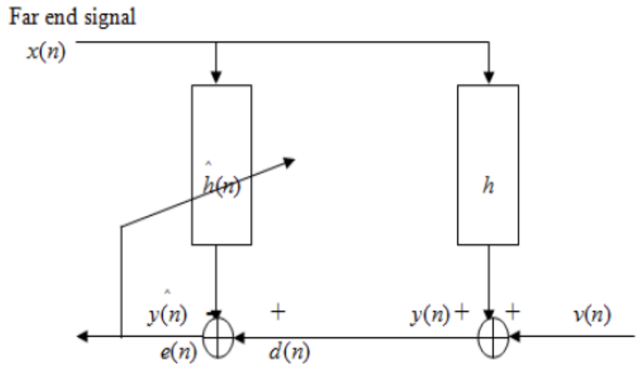

Fig6. Block diagram of the echo canceller

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.

III. BASICS 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.

(a) System Identification

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 Fig2.

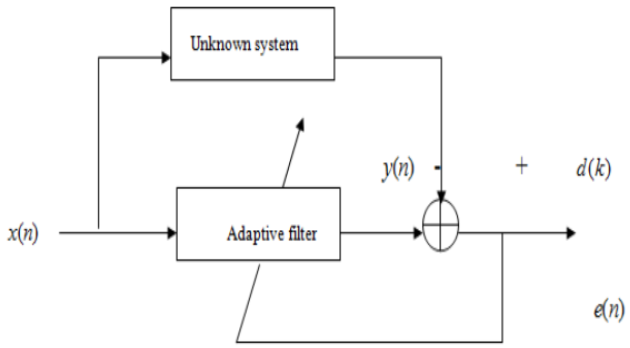

Fig7. System Identification

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,

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

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.

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$w_k \approx h_k$.

TableII. Echo Canceller Applications

Source of Echo	Application	Practical Example
Hybrid Transformer impedance mismatch	Voice Communication • Long-haul transmission Data Communication • Voice-band full-duplex data transmission • Baseband full-duplex data transmission	• Satellite Communication • Automatic Call Transfer • Electronic meeting with telephone. • ISDN Subscriber loop.
Acoustic Coupling	Speaker/Microphone System	• Teleconferencing system • Hand free telephone

Practical diagram shown below which indicate 4-ire-2-wire-4-wire source of echo

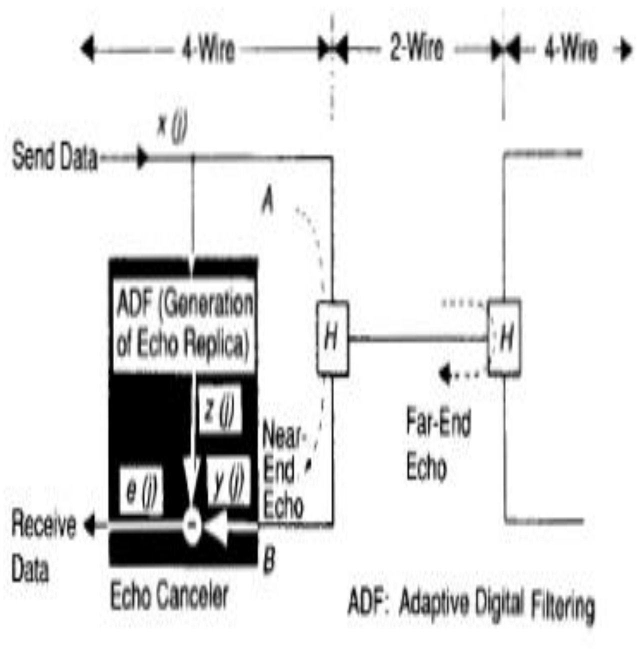


Fig7.Hybride transformer

IV. LITERATURE REVIEW

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 LMS algorithms 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, 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.

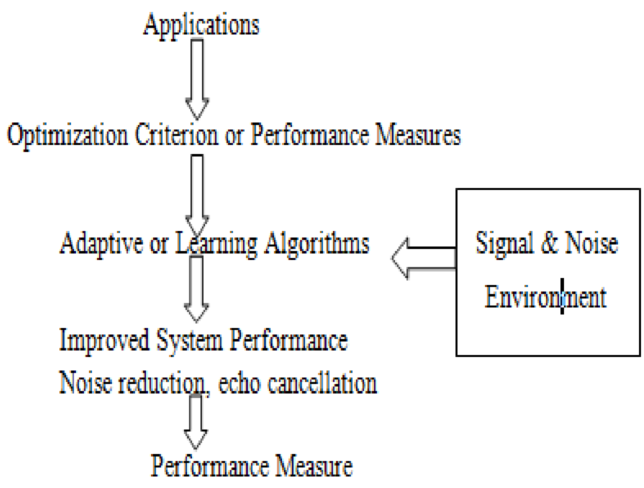
A lot of very interesting DTD algorithm have been proposed. The simplest one is well known P. Algren, [22], which provides an efficient and low-complexity solution, especially for acoustic echo cancellation. Other more complex algorithms have been proposed, more recent framework for designing robust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

V. ADAPTIVE ALGORITHM

For echo cancellation, we have know about various type adaptive algorithm. The adaptive filter solution has to be relatively simple, which often leads to the use of the conventional Least Mean Square (LMS) algorithm. However, the performance of the LMS algorithm is often sub-optimal and the convergence rate is small. This, therefore, provides the motivation to explore and study variable step-size LMS adaptive algorithms for various applications.

(a) Basic concept of adaptive filtering

The basic concept of the adaptive filter is given by using a signal flow diagram:



VI. PERFORMANCE PARAMETER OF ADAPTIVE FILTER

There are many factors to describe the performance of the algorithm given below:

Rate of convergence: The rate of convergence defined as a "the number of iterations required for the algorithm, in response to stationary inputs, to converge to close enough to the optimum wiener solution in the means square error sense".

Misadjustment: Misadjustment provide the quantitative measure of the amount by which the final value of the means square error, averaged over an ensemble of adaptive filters, deviates from the minimum mean-square error produced by the wiener filter.

$$M = J_{ex}(\infty) / J_{\min}$$
$$= \frac{\mu}{2}\sum_{n=1}^{N}\lambda_n$$

Where the $J_{ex}(\infty)$ is a excess means-square error

$$J_{ex}(\infty) = \frac{\mu J_{\min}}{2}\sum_{n=1}^{N}\lambda_n$$

Stability: In adaptive filter structure we generally preferred FIR) instead of the IIR filter because of their application in the field of adaptive filter is limited. The IIR filter easily become unstable since their pole may get shifted out of unit circle ($|z| = 1$). During adaption process the performance function of an IIR filter has many local minima points. This may results the convergence of filter to one of the local minima and not to desired global minima points of the performance surface.

Adaptive filters are recursive estimators. This recursive nature raises the question of stability. As they are stochastic systems, several criteria can be used. Mean and mean-square stability are preferred [1]. Stability is also important to study the steady-state and transient behavior. However, the stability issue is the most critical, because it determines when an adaptive filter can be implemented and be useful for the application of interest.

Computational Requirements: There are many factors to describe the computational requirement to the adaptive filter

The number of the operations like a addition, multiplication, division required to make one complete iteration of the adaptive algorithm.

The size of memory location required to store the data and program.

Echo Return Loses Enhancement (ERLE):

ERLE is the ratio of send-in power and the power of a residual error signal immediately after the cancellation. It is measured in dB. ERLE measures the amount of loss introduced by the adaptive filter alone. ERLE depends on the size of the adaptive filter and the algorithm design. The higher the value of ERLE, the better the echo canceller. ERLE is a measure of the echo suppression achieved and is given by

$$ERLE = 10\log_{10}(p_d / p_e)$$

Echo Return Losses: Measured in dB, ERL [2] is the ratio of receive-out and send- in power. ERL measures receive-out signal loss when it is reflected back as echo within the send-in signal.

$$ERL = 10\log_{10}(p_x / p_e)$$

Error Estimated: The performance of the filter is determined by the size of the estimation error, that is, smaller the estimation error better is the filter performance. As the estimation error approaches zero, the filter output approaches the desired signal.

Tracking: When the adaptive filtering algorithm operates on the no stationary environment, the algorithm is required to track statistical variation in the environment. The tracking ability of the algorithm is influenced by two factors:

- Rate of convergence.
- Steady-state fluctuation due to system noise.

Typical performance surface for a two tap adaptive FIR filter. Autocorrelation matrix coefficient of the given data $x(n)$ and the variance of the desired signal is $\sigma_d^{\,2} = 24.40$ and the cross-correlation vector be P_{dx} =[2,4.5]T.

$$J(w) = 24.40 - 4w_o - 9w_1 + w_o^2 + w_1^2$$

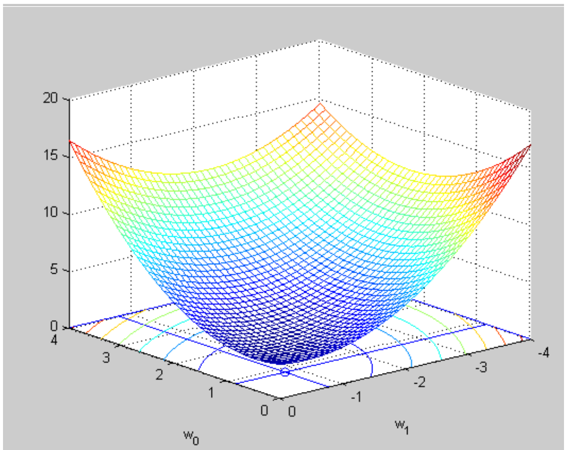


Fig. 8 Means – square error surface

Fig 8 shows the MSE surface. This surface is found by inserting the different values of the w_1 and the w_1 in the function . The values of the coefficients that correspond to the bottom of the surface are the optimum wiener coefficients. The vertical distance from the $w_0 - w_1$ plane to the bottom of the surface known as the minimum error, $J_{\min}$, and correspond to the optimum wiener coefficients. We observe that the minimum height of the surface corresponds to about $w_0 = 2$ and the $w_1 = 4.5$, which are optimum coefficients.

- geometrical properties of the error surface, the cost function can be written in the form, $w^T R_x w - 2p^T w - (J - \sigma_d^2) = 0$

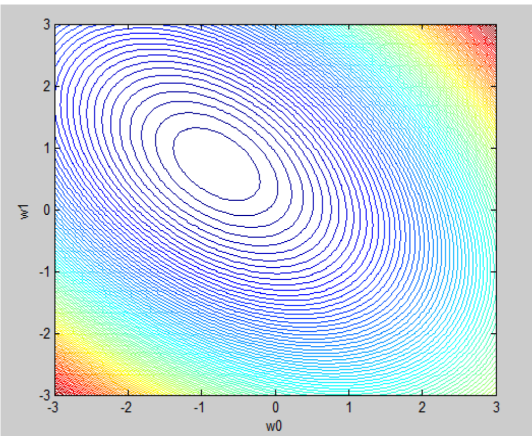


Fig.9 MSE contour at the w plane

Various type algorithms have been proposed to cancel echo in today's telecommunication system. Listed out the algorithm in order to improve the performance in the terms of misadjustment and convergence rate.

- LMS
- NLMS
- VSS-LMS
- VSS-NLMS
- NPVSS-NLMS
- VSS-NLMS-UM
- VSSNLMS-UM-DTD
- LIME Approach
- Affine Projection Algorithms

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 LMS algorithms is slow rate of convergence.

Step size represented by μ and not a function of time, Weight updated equation is given by,

$$w(n+1) = w(n) + 2\mu e(n)x(n)$$

The problem of the conventional LMS algorithm is that the fixed step-size governs the trade-off between the convergence rate and the steady state error. A large step reduces the transient time but will result in a larger steady state mean square error.

To ensure stability of the LMS algorithm, the step size parameter is bounded by the following equation [2] $0 \prec \mu \prec 2/\lambda_{\max}$.

a. Effect of Power Spectral Density of the Input Signal

The convergence rate of the LMS algorithm deteriorates with higher input correlation levels due to greater relations among the adaptive tap coefficients. To ensure improved convergence rate, the LMS algorithm requires input signals to have equal excitation over the whole range of frequency.

b. Effect of the filter length

The length of the LMS adaptive FIR filter should be sufficient to cover the impulse response of the unknown channel [36]. However, this may lead to increased computational complexity when the impulse response of the unknown channel is 'long'. Moreover, this may lead to poor convergence rates when the input signals are highly correlated [11].

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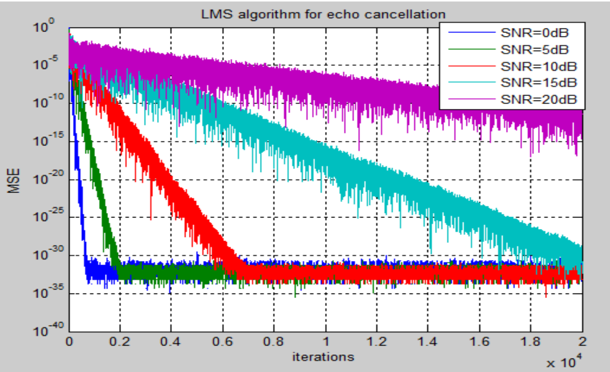

Fig 10 Plot between MSE vs Iterations

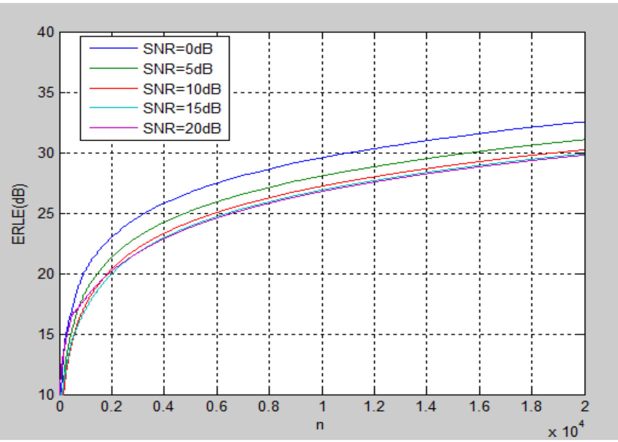

Fig. 11 Plot between ERLE vs iterations

The fig10and 11 are shows that, the comparison of LMS algorithm at different SNR with 20000 iterations and length of filter is 25000 with 0.09 step size in the context of acoustic echo cancellation. We conclude that the LMS algorithms converge quick at 20 dB signal to noise ratio.

LMS algorithm becomes unstable and therefore will not lead to the optimal solution. To deal with this problem, a modified version of LMS known as Normalized algorithm can be implemented.

NLMS Algorithm-

As we know that the weight updating equation of LMS algorithm,

$$w(n+1) = w(n) + 2\mu(n)e(n)x(n)$$

Where the step-size parameter varies with time and we conclude that the stability, convergence, stability and steady-state behavior of the recursive algorithm, are influenced by the length of filter and the power of the signal.

Determining the upper vault step size is a problem for the variable step size algorithm if the input signal to the adaptive filter is non-stationary. The fastest convergence is achieved with the choice of step size as follows:

$$\mu = 2/\lambda_{\max} + \lambda_{\min}$$

This means that faster convergence can be achieved when λmax is close to λmin, that is, the maximum achievable convergence speed depends on the eigenvalue spread of R.

Step size of the NLMS algorithm is given below and it is highly depends on input signal.,

$$\mu(n) = \frac{1}{2x^T(n)x(n)} = \frac{1}{2\|x(n)\|^2}$$

Weight pupation equations given below,

$$w(n+1) = w(n) + \frac{1}{\|x(n)\|^2}e(n)x(n)$$

A white noise signal has autocorrelation matrix R = σ2I, where σ2 is the variance of the signal. In this case all eigenvalues are equal, and the eigenvalue spread is the minimum over all possible matrices.

The common interpretation of this result is therefore that the LMS converges quickly for white input signals, and slowly for colored input signals, such as processes with low-pass or high-pass characteristics.

The convergence performance of the NLMS algorithm shown below

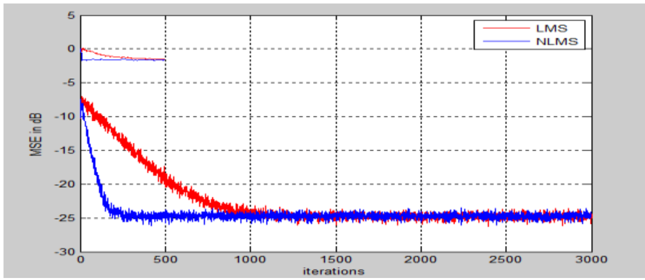

Fig 12 Comparison between LMS and NLMS

The simulation results shown that the NLMS adaptive algorithm converges quickly as compare to LMS algorithm. At 25 dB signal to noise ratio, 0.003 step size for LMS and 0.03 for NLMS algorithm.

(c)Variable step-size LMS Algorithm

We know that both the LMS and the NLMS algorithms have a fixed step size value for every tap weight in each iteration. In the Variable Step Size Least Mean Square (VSLMS) algorithm the step size for each iteration is expressed as a vector, μ(n). Each element of the vector μ(n) is a different step size value corresponding to an element of the filter tap weight vector, W(n) [32].

The VSS-LMS algorithm assists the conflicting requirements, whereas a large step-size parameter is needed for fast convergence and small step-size needed to reduce the misadjustment factor. When the adaption begins and $w(n)$ is far from its optimum value, the step-size parameter should be large in order for convergence to be rapid. As the filter coefficient $w(n)$ approach the steady state solution, the step-size parameter should decrease in order to reduce the excess MSE.

The step-size is proportional to the energy. The weight update recursion of the algorithm is of the form,

$$w_i(n+1) = w_i(n) + 2\mu_i(n)e(n)x(n-i),$$
$$i = 0,1,\ldots\ldots,M-1$$

Where the $w_i(n)$ is the i^{th} coefficient of $w(n)$ at iteration n and $\mu_i(n)$ is the associated step-size. The step-sizes are determined in an ad hoc manner, based on monitoring sign changes in the instantaneous gradient estimate, indicate that algorithm is close to its optimal solution, hence the step size must decrease. Reverse is also true.

The weight update recursion of the algorithm is of the form

$$w(n+1) = w(n) + \mu(n)e(n)x(n)$$

The $\mu(n)$ is the diagonal matrix with the following elements in the diagonal: $\mu_0(n), \mu_1(n), \ldots.\mu_{N-1}(n)$

The step size updated expression is

$$\mu(n+1) = \alpha\mu(n)\gamma e^2(n)$$

Where $0 \prec \alpha \prec 1$, $\gamma \succ 0$, and $\mu(n+1)$ is set to $\mu_{\min}$ or $\mu_{\max}$ when it fall below or above one of them. The algorithm has preferable performance over the fixed step size LMS. At the early stage of the adaption, error is large causing step size to increase to provide faster convergence speed. When the error decreases, the step decreases thus yielding smaller misadjustment.

(d) *Nonparaeteric Variable step size adaptive algorithm*

test which are not based on a normal distribution of data or on any other assumption. They also known as distribution free test. The aim of the VSS NLMS algorithmsis to try to solve the trade off between the low misadjusment and the convergence rate. Various type of VSS algorithm found in literatures with the common points of them, and have some drawback because they may not work very reliable, the depends on severl parameterand it is not simple to tune for the real world application. The draw back occures in VSS algorithm is overcome by using a Nonparametric VSSNLMS.

The step size parameter of a proposed nonparameteric VSS-NLMS lgorithm is given by:

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

Where $\alpha(n)$ is normalized step size, range is given $0 \le \alpha(n) \le 1$. The NPVSS-NLMS algorithm is

$$\hat{h}(n) = \hat{h}(n-1) + \mu_{NPVSS}(n)x(n)e(n)$$

(e) Variable step size NLMS algorithm for under modeling

The term ‘Undermodeling’ defines as according to the adaptive filtering forum, the length of adaptive filter is less than the acoustic echo path.

Most of the adaptive filter developed assuming an exact modeling case means the length of adaptive filter is equal to the length of acoustic echo path. The VSS-NLMS algorithm suitable for undermodeling case.This algorithm dosen’t required any priori information about the acoustic environment.The residual echo coused by the part of the system that can not be modeled can be interpreted as a additional noise. In such a case, a nonlinear processor is used to remove the residual echo.The goal of the nonlinear processor is to block this small unwanted signal if the signal magnitude is lower than certain small threshold value during single talking. The main purpose of nonlinear processor distorts and not blocks the near-end signal during double talking.

The step size can be written as,

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

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

(50)

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

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

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

Concluding, the stepsizeparameter of the proposed VSS-NLMS for under-modeling

(VSS-NLMS-UM) algorithm is

$$\mu(n) = \begin{cases} \mu_{NLMS}(n) & \text{for } n \le L \\ \frac{1}{X_L^{\ T}(n)X_L(n)}\left[1 - \sqrt{\frac{\hat{\sigma}_\alpha^2(n) + \hat{\sigma}_{\hat{y}}^2(n)}{\hat{\sigma}_e(n)}}\right] & n \succ L \end{cases}$$

The NPVSS-NLMS algorithm derived iis similar at first look to the VSS-NLMS-UM algorithm. It uses a step-size parameter computed as

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

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 $N = L$

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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., $d(n)$, $\hat{y}(n)$, $e(n)$] 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.

VII. SIMULATION

The analysis shown in previous section is demonstrated through computer simulation in the present section.

Simulation Setup -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 under modeling. 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. Their results are compared.

(a) NLMS and Nonparametric 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).

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

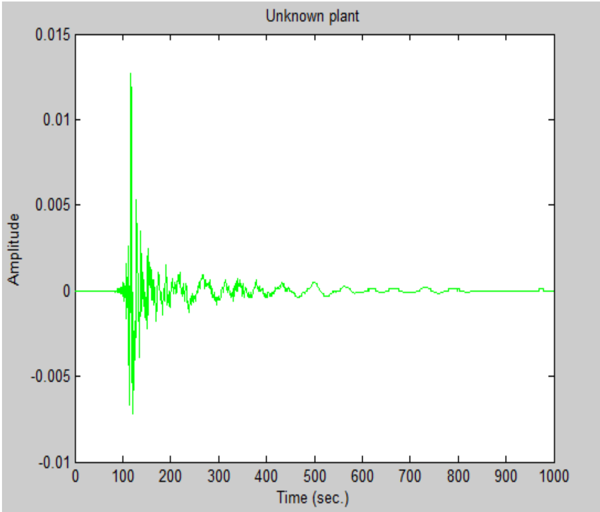

Fig. 13 Unkown plant

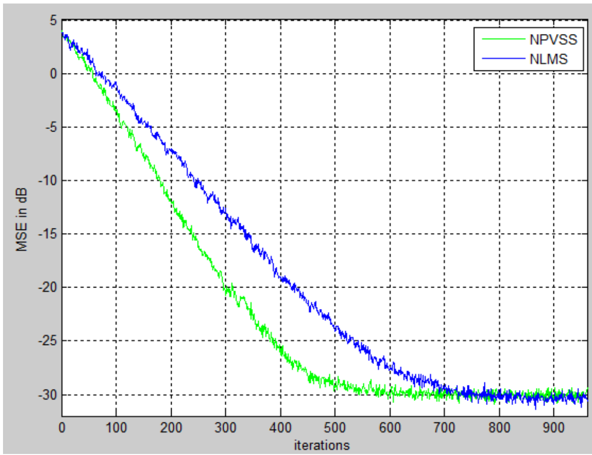

Fig.14 Misalignment of the NLMS algorithm at $\left[\delta+X^T(n)X(n)\right]^{-1}$ and the NPVSS-NLMS Algorithm. The input signal is white gaussian noise, $L=500$, $\lambda=1-\frac{1}{1-(2L)}$, and SNR = 30 dB.

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.

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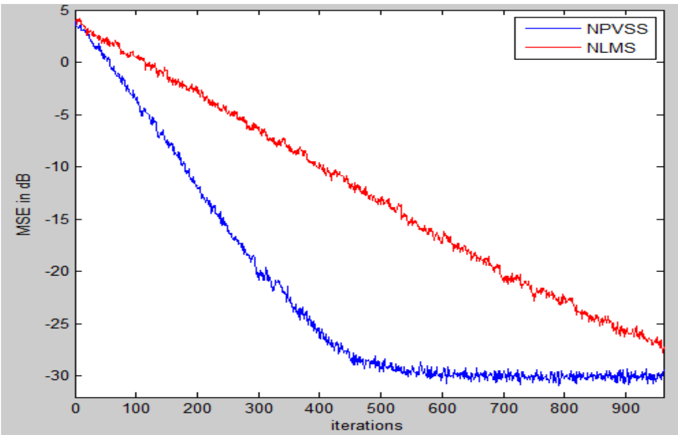

Fig.15 Misalignment of the NLMS algorithm at $0.04\left[\delta + X^T(n)X(n)\right]^{-1}$ and the NPVSS-NLMS Algorithm. The input signal is white gaussian noise $L=500, \lambda = 1-\dfrac{1}{1-(2L)}$, SNR = 30 dB

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 Under modeling 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.

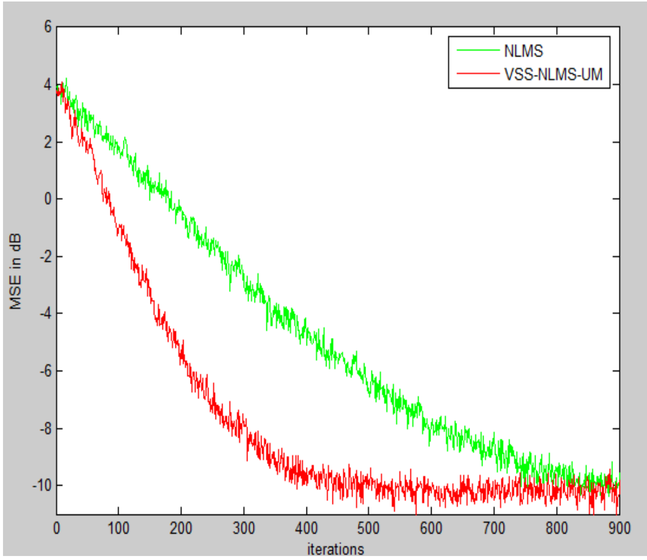

Fig.16 Misalignment of the NLMS algorithm at $0.04\left[\delta + X^T(n)X(n)\right]^{-1}$ and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda = 1-\dfrac{1}{1-(2L)}$ and SNR= 10 dB

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.

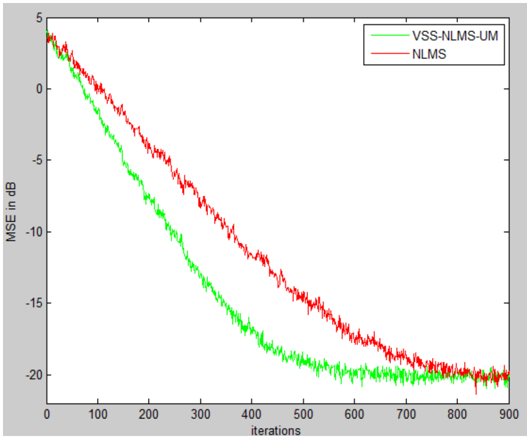

Fig.17 Misalignment of the NLMS algorithm at $0.05\left[\delta + X^T(n)X(n)\right]^{-1}$, NPVSS and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda = 1-\dfrac{1}{1-(2L)}$ and SNR= 20 dB

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.

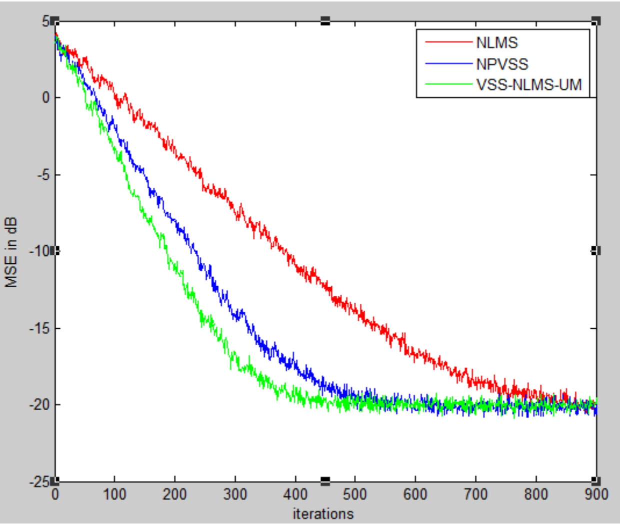

Fig.18 Misalignment of the NLMS algorithm at $0.05\left[\delta+X^{T}(n)X(n)\right]^{-1}$, NPVSS and the VSS-NLMS-UM Algorithm. The input signal is white gaussian noise, $N=900$, $L=450$, $\lambda=1-\frac{1}{1-(2L)}$ and SNR= 20 dB

We have compared between three adoptive 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.

VIII. CONCLUSIONS

This research paper presented an overview of the principle, structure, and applications of echo cancellers.

We have reviews lot of research paper and implement various algorithm in order to increase the convergence rate and minimized means square error.

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.

IX. BRIGHT FUTURE OF ECHO CANCELLER

It is, to be honest, remarkable that a technique which has been studied, favorably appraised, and implemented modified version of algorithms in upcoming years upto 2016 has still not been commercially applied. The obvious reason is that echo cancellers which perform better than echo suppressors have tended to cost much more than echo suppressors; it is intrinsically more difficult to discover and separate an echo from a mixture of signals than to block everything. Despite these difficulties, the combination of increasingly skillful design and new technology has brought the expected cost of effectives ho cancellation down to a reasonable level. During the next few years it is conceivable that echo cancellers will be introduced not only into the telephone network, but also into communication station equipment and other systems where an interference derived from a known reference signal must be modified or eliminated.

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