Acoustic Echo Cancellation for Noisy Signals

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ABSTRACT

Echo is the time delayed version of the original signal. Acoustic echo results from a feedback path set up between the speaker and the microphone in a mobile phone, hands-free phone .Echo can degrade the quality of service in telecommunication. Therefore echo cancellation is an important part of communication systems. A new approach based on the number of coefficients in an adaptive finite impulse response filter based acoustic echo cancellation setup is an important parameter, affecting the overall performance of the echo cancellation. Too few coefficients give under modeling and too many cause slow convergence and an additional echo due to the mismatch of the extra coefficients This paper focuses on the use of adaptive filtering techniques to cancel this unwanted echo thus increasing communication quality

General Terms

Echo cancellation, adaptive filtering algorithms.

Keywords

Echo ,adaptive filtering.

1. INTRODUCTION

Acoustic echo occurs when an audio signal is reverberated in a real environment, resulting in the original intended signal plus attenuated, time delayed images of this signal. Strong and delayed echo signals is very annoying and can make the conversation impossible The hands free telecommunication system has both an active loudspeaker and microphone input operating simultaneously. When a signal is received by the system, it is output through the loudspeaker into an acoustic environment. This signal is reverberated within the environment and returned to the system via the microphone input. It is then transmitted to the original sender as time delayed and attenuated images of the original signal. The occurrence of acoustic echo in speech transmission causes signal interference and reduced quality of communication. The method used to cancel the echo signal is known as adaptive filtering. Adaptive filtering constitutes one of the core technologies in digital signal processing and finds numerous application areas in science as well as in industry. Adaptive filtering can be useful in situations when speech signal is submerged in noisy environment. These applications involve processing of signals that are generated by systems whose characteristics are not known a priori. Under this condition, a significant improvement in performance can be achieved by using adaptive rather than fixed filters. Adaptive filters are used to track the variations in the input signal because the input signal is not stationary signal. Adaptive filters are dynamic filters which iteratively alter their characteristics in order to achieve an optimal desired output. An adaptive filter algorithmically alters its parameters in order to minimize a function of the difference between the desired output d(n) and its actual output y(n). This function is known as the cost function of the adaptive algorithm. The main aim of the adaptive filtering algorithm is to minimize the cost function. The echo canceller identifies the transfer function of the acoustic echo path i.e. the impulse response H(n) between the loudspeaker and the microphone. Since the impulse response varies as a person moves and varies with the environment, an adaptive filter echo replica y(n) is then subtracted from the echo signal d(n) to give the error e(n)= d(n) y(n).This is used to identify H(n).The characteristics of a filter can be expressed as a vector consisting of values known as tap weights that determines the performance of the filter. The desired signal is obtained by convolving the input signal with the impulse response of the acoustic environment and an echo replica is created at the output of the adaptive filter. The number of elements in impulse response vector corresponds to the order of the filter. The adaptive algorithm should provide real time operation, fast convergence, and high Echo Return Loss Enhancement (ERLE).

2. PROBLEM STATEMENT

An echo canceller has to deal with a number of challenges in order to perform robust echo cancellation

2.1 Avoiding Divergence

Near end speech will cause the adaptive filter to diverge if the echo canceller does not detect a double talk condition. Double talk detectors are used to detect if the far end signal is corrupted by the near end speech signal. Under specific conditions, certain algorithms are bound to diverge and corrupt the signal or even add echo to the line. Good echo cancellers are tuned to avoid divergence situations in nearly all conditions.

2.2 Handling doubletalk

In a normal conversation, both talkers often speak simultaneously or interrupt each other during which the echo and speech have similar characteristics and occupy same bandwidth. Those situations are called doubletalk. It may try to cancel the speech signal Doubletalk presents a special processing challenge to echo cancellers.

2.3 Preventing Clipping

Clipping occurs when a part of the speech is erroneously removed during a telephone conversation**.** Clipping results due to the lack of a precise Non-Linear Processor (NLP). Specifically, the NLP fails to start and stop at the right time. It replaces parts of words with background noise, which makes the conversation difficult to understand.

3. PROPOSED WORK

Various adaptive filter algorithms can be utilized to cancel the echo and to reduce the noise to a minimum value. The aim of an adaptive filter is to calculate the difference between the desired signal d(n) and the adaptive filter output, y(n) to obtain e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function(MSE). Cost function is used because it modify the transfer function to minimize cost on next iteration.Adaptive filters are required because some parameters of the processing operation are not known in advance .In acoustic echo cancellation the adaptive filter output will be equal to echoed signal. When the adaptive filter output is equal to desired signal the error signal goes to zero. In this situation the echoed signal would be completely cancelled. Here we are analyzing various adaptive filter algorithms and finding which algorithm shows best performance.MSE adaptive filters try to minimize the cost function equal to the expectation of squared difference between the desired signal and actual adaptive filter output .
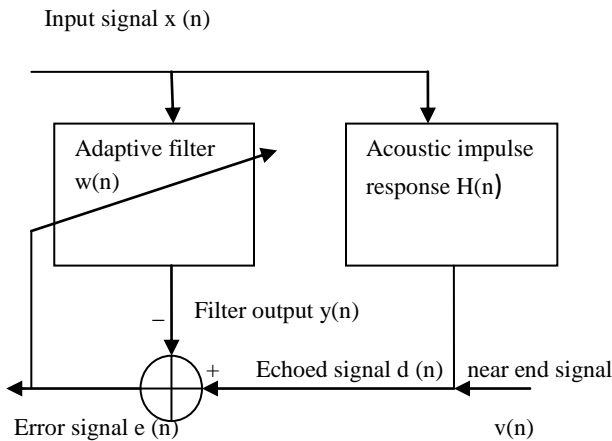

Fig 1. Adaptive echo cancellation system

3.1 LMS algorithm

LMS Algorithms are a class of adaptive filters that will mimic the desired filter by finding the filter coefficients. It will produce the least mean squares of the error signal .It uses stochastic gradient descent based method where filter is adapted based on error at the current time. This algorithm is widely used in digital signal processing. The fixed step size least mean square (FSS LMS) algorithm is an important member of the family of stochastic gradient algorithms. A path that changes the signal x is called h. Transfer function of this filter is not known in advance. The task of the LMS algorithm is to estimate the transfer function of the filter. Echo signal is obtained by convolving the input signal with impulse response of the echo path and is denoted by r. In this case r is the echo and h is the transfer function of the hybrid. The near-end speech signal v is added to the echo. The adaptive algorithm tries to create a filter w. The transfer function of the filter is an estimate of the transfer function for the hybrid. This transfer function in turn is

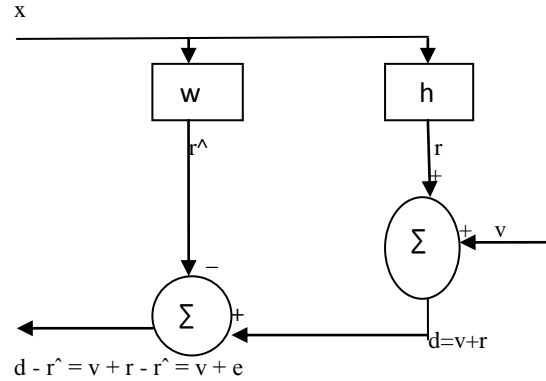used for calculating an estimate of the echo. The echo estimate is denoted by rˆ.

Fig 2. LMS algorithm

By the addition of signals the output signal from the algorithm is

$$v + r - r\hat{} = v + e \quad\quad (1)$$

where e denotes the error signal. The error signal and the input signal *x* are used for estimation of the filter coefficient vector w. Choosing the filter weight is one of the main problems because the path h is not stationary. Therefore, the filter weights must be updated frequently so that the adjustment to the variations can be performed. Updating of the filter weights is realized in accordance with

$$w(k + 1) = w(k) - \mu gw(k) \quad\quad (2)$$

for $k = 0,1,2,\cdots$ where gw(k) represents an estimate of the gradient vector and μ is the convergence factor or step size. This step size parameter controls the influence of updating factor. If the step size is too small it will take more time to converge. It does not require matrix inversion nor measurement of correlation function.The impulse response depend on the filter size and is obtained using impulse function for random number of iterations(i).

$$\text{impulse}(((i-1)*filter\_size/5)+1) = 1/i \quad\quad (3)$$

3.1.1 Derivation of LMS Algorithm

During every iteration the tap weight adaptation updates the tap weight vector w in the direction of minimizing cost function to find w_0 . Using the current tap weight vector and the current gradient of the cost function with respect to the filter tap weight coefficient vector, filter coefficient can be updated.

$$w(n+1) = w(n) - 2\mu\nabla\xi(n) \quad\quad (4)$$
$$\xi(n) = E[e^2(n)] \quad\quad (5)$$

Each recursion shifts the value of the filter coefficients closer toward their optimum value as the negative gradient vector points in the direction of steepest descent for the N dimensional quadratic cost function, , which corresponds to the minimum achievable value of the cost function, $\xi(n)$. Here the expectation for the error signal is not known so the instantaneous value is used as an estimate

$$w(n+1) = w(n) - \mu\nabla\xi(n) \quad\quad (6)$$
$$\xi(n) = e^2(n) \quad\quad (7)$$
$$\nabla\xi(n) = \nabla(e^2(n)) \quad\quad (8)$$
$$= \partial(e^2(n))/\partial w \quad\quad (9)$$
$$= 2e(n)\,\partial e(n)/\partial w \quad\quad (10)$$
$$= 2e(n)\,\partial(d(n)-y(n))/\partial w \quad\quad (11)$$
$$= -2e(n)\,\partial ew^T(n)x(n)/\partial w \quad\quad (12)$$
$$= -2e(n)x(n) \quad\quad (13)$$

Therefore the recursion for the LMS adaptive algorithm can be written as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu e(n)\mathbf{x}(n). \tag{14}$$

3.1.2 Implementation of LMS Algorithm

Each iteration of the LMS algorithm requires 3 distinct steps in this order:

a. The output of the FIR filter, y(n) is calculated using equation

$$y(n) = w^T(n)x(n). \tag{15}$$

b. The value of the error estimation is calculated using equation

$$e(n) = d(n) - y(n) \tag{16}$$

c. The tap weights of the FIR vector are updated in preparation for the next iteration.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu e(n)\mathbf{x}(n) \tag{17}$$

The main reason for the popularity of LMS algorithms in adaptive filtering is its computational simplicity, making it easier to implement than all other commonly used adaptive algorithms. For each iteration the LMS algorithm requires 2N additions and 2N+1 multiplications (N for calculating the output, y(n), one for 2μe(n) and an additional N for the scalar by vector multiplication).

3.2 VSLMS Algorithm

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).Variable step size is constrained to maximum and minimum step size value of LMS Algorithm to ensure stability. The major drawback with this algorithm is that it requires the user to select the initial step size to control the adaptive behavior of the step size sequence .

3.2.1 Derivation of VSLMS Algorithm

The VSLMS algorithm is as follows

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu g(n) \tag{18}$$

$$\text{where } g(n) = e(n)x(n) \tag{19}$$

Where g is a vector comprised of the gradient terms, $g_i(n) = e(n)x(n-i)$, i=0….N-1, the length corresponds to the order of the adaptive filter. The values for μ(n) can be calculated. The choice is dependent on the application

$$\mu(n) = \mu(n-1) + \rho \, sign(g(n)) sign(g(n-1)) \tag{20}$$

Here ρ is a small positive constant optionally used to control the effect of the gradient terms on the update procedure. In order to ensure the step size parameters do not become too large (resulting in instability), or too small (resulting in slow reaction to changes in the desired impulse response), the allowable values for each element in the step size are bounded by upper and lower values. As with the standard LMS algorithm statistics of the signal must be known in advance. It is necessary to guarantee optimal performance of the adaptive filter.

3.2.2 Implementation of VSLMS Algorithm

The VSLMS algorithm is executed by following these steps for each iteration . With ρ=1, each iteration of the VSLMS algorithm requires 4N+1 multiplication operations.

a. The output of the adaptive filter is calculated.

$$y(n) = \sum w(n)x(n-i) = w^T(n)x(n) \tag{21}$$

b. The error signal is calculated as the difference between the desired output and the filter output.

$$e(n) = d(n) - y(n) \tag{22}$$

c. The gradient, step size and filter tap weight vector for the next iteration. (23)

3.3 NLMS Algorithm

The primary disadvantage of the LMS algorithm is its fixed step size parameter for every iteration. So before starting adaptive filtering operation, statics of the input signals must be known in advance. In practice this is rarely achievable. Even if we assume speech signal as the only input to adaptive echo cancellation , there still many other factors such as signal input power and amplitude which will affect its performance. In order to achieve faster convergence speed and for non stationary input NLMS Algorithm is the most preferable choice. The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm. It selects a different step size value, μ(n), for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector **x**(n).When the variation of the input signal power is very large stability is not affected because of the normalization of step size with an estimate of the input signal variance. The recursion formula for the NLMS algorithm can be written as

$$w(n+1) = w(n) + e(n)x(n)/x^T(n)x(n). \tag{24}$$

3.3.1 Derivation of NLMS Algorithm

To derive the NLMS algorithm we consider the standard LMS recursion, for which we select a variable step size parameter, μ(n). This parameter is selected so that the error value , $e^+(n)$, will be minimized using the updated filter tap weights, w(n+1), and the current input vector, **x**(n).

$$w(n+1) = w(n) + 2\mu(n)e(n)x(n) \tag{25}$$

$$e^+(n) = d(n) - w^T(n+1)x(n) \tag{26}$$

$$= (1 - 2\mu(n)x^T(n)x(n))e(n) \tag{27}$$

Next we minimize $(e^+(n))^2$, with respect to μ(n). Using this we can then find a value for μ(n) which forces $e^+(n)$ to zero.

$$\mu(n) = 1/2x^T(n)x(n) \tag{28}$$

This μ(n) is then substituted into the standard LMS recursion replacing μ, resulting in the following.

$$w(n+1) = w(n) + 2\mu(n)e(n)x(n) \tag{29}$$

$$w(n+1) = w(n) + 1.e(n)x(n)/x^T(n)x(n) \tag{30}$$

$$w(n+1) = w(n) + \mu(n)x(n) \tag{31}$$

$$\text{where } \mu(n) = \mu/x^T x + \psi \tag{32}$$

Here the value of ψ is a small positive constant in order to avoid division by zero when the values of the input vector are zero.

3.3.2 Implementation of NLMS Algorithm

As the step size parameter is chosen based on the current input values, the NLMS algorithm shows far greater stability with unknown signals. This combined with good convergence speed and relative computational simplicity make the NLMS algorithm ideal for the real time adaptive echo cancellation

system. Each iteration of the NLMS algorithm requires 3N+1 multiplications, this is only N more than the standard LMS algorithm. Each iteration of the NLMS algorithm requires these steps in the following order

a. The output of the adaptive filter is calculated
$$y(n)=\sum w(n)x(n-i)=w^T(n)x(n) \qquad (33)$$
b. An error signal is calculated as the difference between the desired signal and the filter output.
$$e(n) = d(n) - y(n) \qquad (34)$$
c. The step size value for the input vector is calculated.
$$\mu(n)=1/x^T(n)x(n) \qquad (35)$$
d. The filter tap weights are updated in preparation for the next iteration
$$w(n+1)=w(n)+\mu(n)e(n)x(n) \qquad (36)$$

3.4 VSNLMS Algorithm
The VSLMS algorithm still has the same drawback as the standard LMS algorithm in that to guarantee stability of the algorithm, a statistical knowledge of the input signal is required prior to the algorithms commencement. the major benefit of the NLMS algorithm is that it is designed to avoid this requirement by calculating an appropriate step size based upon the instantaneous energy of the input signal vector. It is a natural progression to incorporate this step size calculation into the variable step size algorithm, in order increase stability for the filter without prior knowledge of the input signal statistics. In the VSNLMS algorithm the upper bound available to each element of the step size vector, $\mu(n)$, is calculated for each iteration. As with the NLMS algorithm the step size value is inversely proportional to the instantaneous input signal energy.

3.4.1 Implementation of VSNLMS Algorithm
It is essentially an extension of the implementation of the VSLMS algorithm with the added calculation of a maximum step size parameter for each iteration.

a. The output of the adaptive filter is calculated.
$$y(n)=\sum w(n)x(n-i)=w^T(n)x(n) \qquad (37)$$
b. The error signal is calculated as the difference between the desired output and the filter output.
$$e(n) = d(n) - y(n) \qquad (38)$$
c. The gradient, step size and filter tap weight vectors are updated using the following equations in preparation for the next iteration.

For i = 0,1,...,N -1
$$g(n)=e(n)x(n) \qquad (39)$$
$$\mu_i(n)= \mu_i(n-1)+ \rho g_i(n)g_i(n-1) \qquad (40)$$
$$\text{if } \mu_i(n)>\mu_{max}, \ \mu_i(n)= \mu_{max}(n) \qquad (41)$$
$$\text{if } \mu_i(n)<\mu_{min}, \ \mu_i(n)= \mu_{min}(n) \qquad (42)$$
$$w_i(n+1)=w_i(n)+2\mu_i(n)g_i(n) \qquad (43)$$
ρ is an optional constant the same as is the VSLMS algorithm. With ρ =1, each iteration of the VSNLMS algorithm requires 5N+1 multiplication operations.

4. SIMULATION RESULTS
Each of the adaptive filtering algorithms were implemented using MATLAB. MATLAB is a powerful, general-purpose, mathematical software package. Matlab possesses excellent graphics and matrix handling capabilities. The salient features of MATLAB are its in-built mathematical toolboxes and graphic functions. Echoed signal was generated by defining an

appropriate impulse response then convolving this with a vocal input wav file.
The MATLAB software environment suited the needs of this research for the following reasons:

a. The input signals (far-end and near-end talker signals) were voices. These voices were stored as wav files and can be easily imported into the code.
b. The intermediate signals and output signals were obtained as wav files.
c. The signal processing toolbox has in-built functions for almost all signal processing applications.
d. Since MATLAB supports graphics, the results of a simulation could be presented in a graphical format with ease.
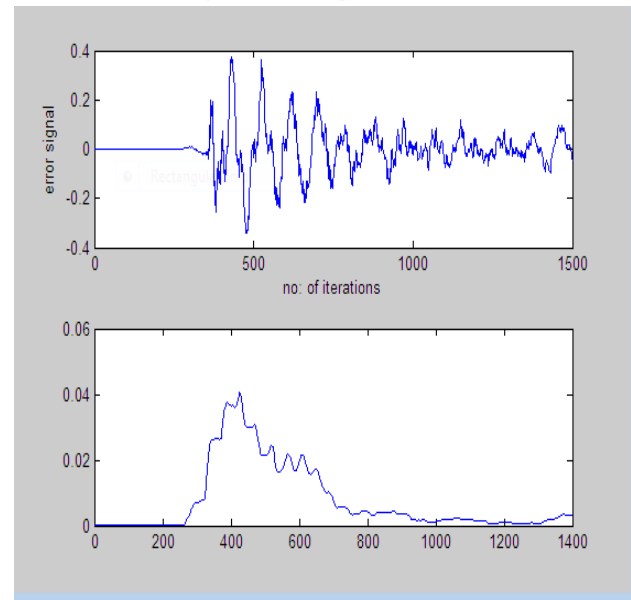
4.1.1 LMS Algorithm output

Fig 3. Error signal and cost function using lms algorithm

The MSE shows that as the algorithm progresses the average value of the cost function decreases, this corresponds to the LMS filters impulse response converging to the actual impulse response, more accurately emulating the desired signal and thus more effectively cancelling the echoed signal.The number of iterartions for the error function and cost function can be same or different.

4.1.2 NLMS Algorithm output
Fig 4 shows that error signal is smaller and the amplitude of the mean square error is in the order of ten times smaller than that of the standard LMS algorithm. This comes with the addition of only N more multiplication operations. Convergence rate of the NLMS algorithm is greater than that of the standard LMS algorithm because impulse response of NMLS is approximately twice than that of the LMS algorithm.NLMS algorithm works as best algorithm for acoustic echo cancellation.
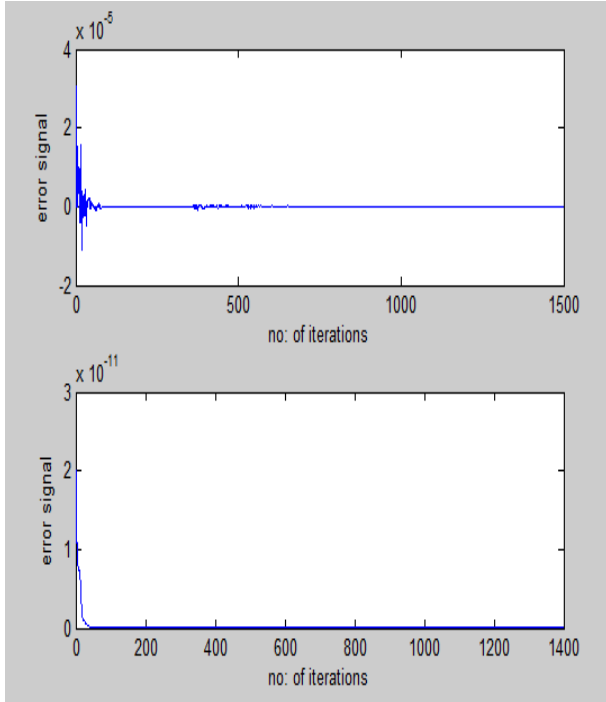
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Fig 4. Error signal and cost function using nlms algorithm

4.1.3 VSLMS Algorithm output

VSLMS algorithm performs poorly having a peak mean square error approximately greater than that of the standard NLMS algorithm. This is very poor considering each iteration of the VSLMS algorithm has 2N more multiplication operations.
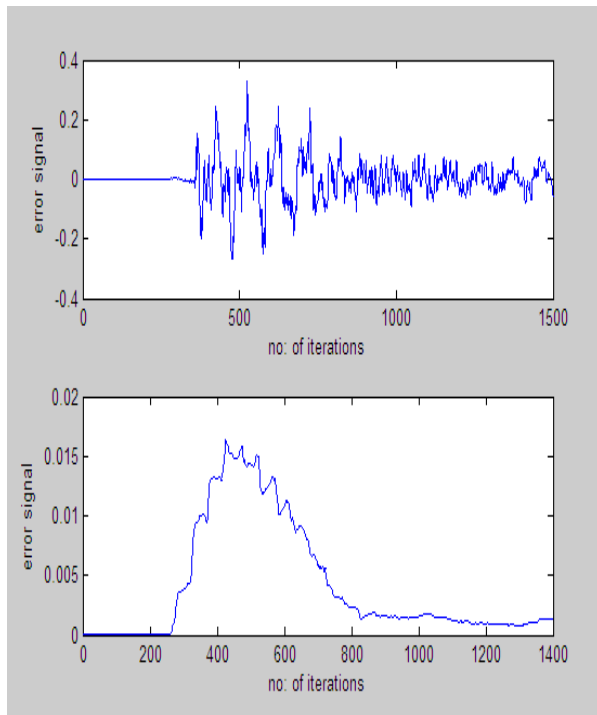

Fig 5. Error signal and cost function using vslms algorithm
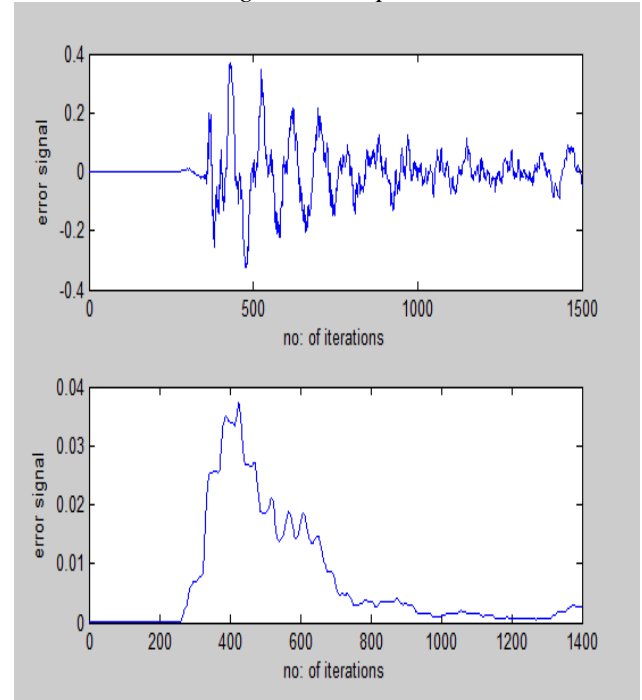
4.1.4 VSNLMS Algorithm output

Fig 6. Error signal and cost function using vsnlmsalgorithm

Fig 6 shows 1500 iterations of the algorithm with a minimum step size of 0, and a ρ value of 1. It can be seen that the results are virtually identical to those for the VSLMS algorithm because it does not calculate the actual step size ,although the upper step size boundary is calculated for each iteration.

5. EVALUATION OF ECHO CANCELLATION ALGORITHM

In order to evaluate the effective working of the algorithm, some basic tests were conducted.

5.1.1 Convergence Test

Several tests were performed on the simulated data to verify whether the filter coefficients have converged or not. If the filter coefficients are converged the code would be useful. The impulse response of NLMS algorithm is greater than LMS algorithm for the same number of iterations,this shows that convergence rate of NLMS algorithm is greater than LMS algorithm.
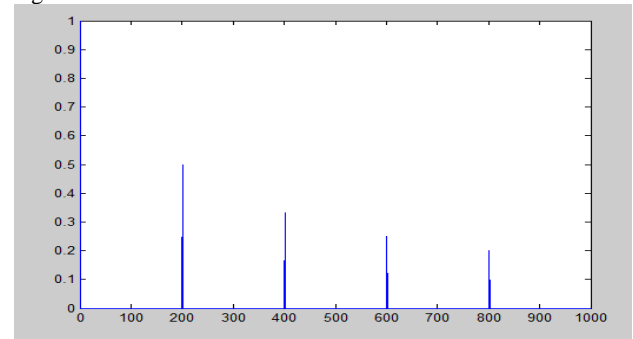

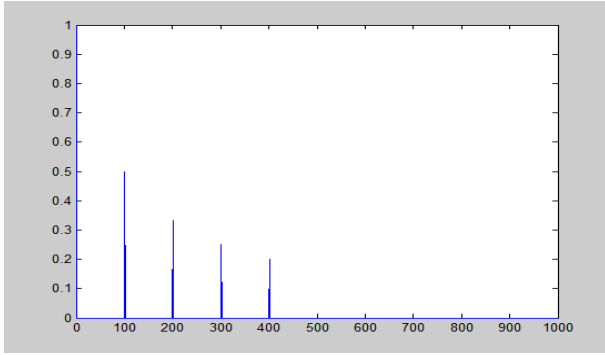**Fig 7. Impulse response of NLMS algorithm**

Fig 8. Impulse response of LMS algorithm

5.1.2 Echo Return Loss Enhancement (ERLE)

ERLE measures the amount of loss introduced by the adaptive filter alone. Quality of the echo cancellation can be evaluated by ERLE. It is defined as ratio of send in power to the power of the residual signal immediately after the cancellation. Higher the value ,better is the echo canceller. ERLE was obtained in range of 30-40 dB which is desirable for a good echo canceller.
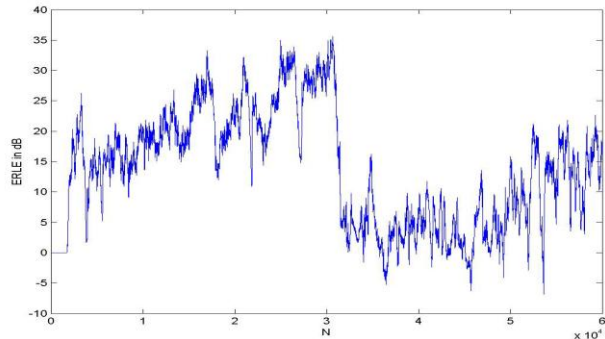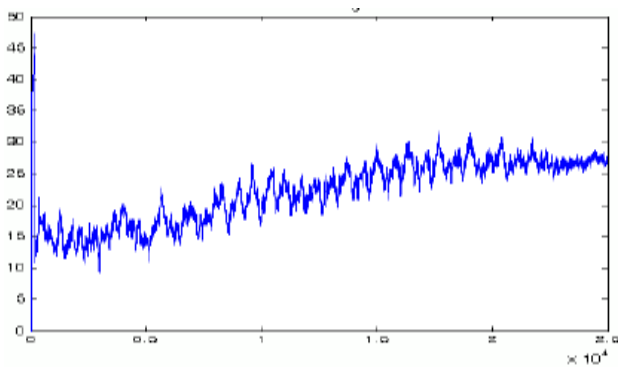

Fig 9. Plot of ERLE versus number of samples

Fig 10. Plot for the ERLE for NLMS algorithm

ERLE measured in dB is defined as the ratio of the instantaneous power of the signal d(n) and the instantaneous power of the residual error signal, e(n), immediately after cancellation. ERLE measures the amount of loss introduced by the adaptive filter alone.

ERLE=10log $p_d(n)/p_e(n)$=10log $E[d^2(n)]/E[e^2(n)]$ (44)

The average ERLE obtained is around 22.34 in decibels. The average ERLE obtained for LMS algorithm is 18.23 in decibels. The number of iterations is randomly selected.
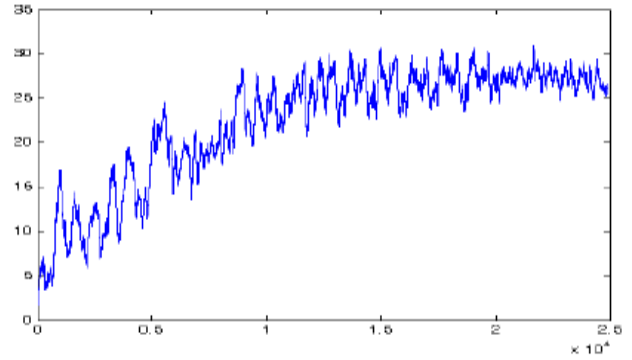

Fig 11. Plot of ERLE for LMS algorithm

5.1.3 Audio quality Test

The audio of the output signal was presented to a panel. The panel was almost not able to distinguish the near end signal v(n), and the output signal with the residual echo, e(n) was removed. Some discrepancies in the audio shows the fact that the real-time applications cannot escape the factor called noise.
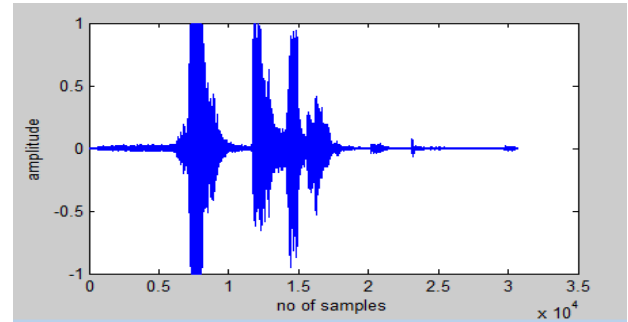

Fig 12. Plot of output signal

5.1.4 Recovery time

Recovery time after echo cancellation has been used to check whether the original signal is delayed. If the original signal is heared without any delay then there is no echo.

Table 1. comparison of algorithms

Algorithm	Iteration	Filter order(N)	MSE	Computation
LMS	1500	15	0.025	$2N+1$
NLMS	1500	15	0.006	$3N+1$
VSLMS	1500	15	0.01	$4N^2$
VSNLMS	1500	15	0.035	$5N+1$

6. CONCLUSION

The proposed adaptive length algorithms, based on estimation of the cost function is more robust and has better tuning possibilities for acoustic echo cancellation environment ,it can update the unknown coefficients. Among the four algorithms NLMS shows better performance and increased convergence rate, it requires no extra delay. The aim of every algorithm is to achieve minimum mean square error at a higher rate of convergence with lesser complexity. NLMS is one of the most popular algorithms in the field of adaptive digital signal processing, due to simplicity.

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