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A Comparative Analysis of Adaptive IIR Filtering Techniques using LabVIEW

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Abstract

Removal of noises from real-time speech signal is a typical problem. The signal interference initiated by background noise is a major problem in voice communication systems. Adaptive Filtering methods have emerged as an important technology for communication systems. This technique has been employed to improve the quality of the speech signal by cancelling the undesirable phenomenon such as acoustic noise. In this paper, for the removal of additional noise from speech signal an adaptive filter has been designed using LMS, NLMS, SLMS and VSS-LMS algorithms. This paper presents the instigation of Least Mean Square algorithm (LMS), Normalized Least Mean Square algorithm (NLMS), Sign Least mean square algorithm (SLMS) and Variable step size (VSS) algorithm on an infinite impulse response (IIR) filter using adaptive filter toolkit of LabVIEW software. User interface is designed using LabVIEW to obtain the learning curves for these adaptive algorithms. The final results show the comparison of the performance of the entire proposed algorithms with each other. The complete performance of the designed system in terms of stability and convergence rate has been observed.

Keywords: *Adaptive IIR Filter; Convergence Speed; LabVIEW; LMS Algorithm; Mean Squared error; NLMS Algorithm; Sign LMS Algorithm, VSS Algorithm*

1. Introduction

In transmission of information from the source to receiver, the information signal gets contaminated with the noise components present in the background. The noisy signal will contains two elements, one is the information of interest i.e. the useful signal; the other part carries noise which is present in the background of the useful signal [1].These errors are unwanted because they reduces the accuracy and perceived quality of signal. Therefore, the effective removal or reduction of noise in the field of signal processing is an active area of research. In order to keep tracking the frequencies changes in the input signal, the adaptive filters must be employed in the DSP system so as to update that system recursively [2, 3].

2. Background of Adaptive Filters

Adaptive Filtering is one of the most prominent domains of signal processing techniques. The noise cancellation method shows its effectiveness only if the method used and the nature of audio interferences is known to us [4]. The nature of noise plays a very important role in the processing of speech signals as it changes its behavior with respect to time so a special processing technique must be used for the automatic adjustment of noise characteristics. This special processing technique is dependent upon adaptive frequency algorithm which is designed to suppress broadband and periodic noises due to vibration, room and street noise or recording interferences [5, 6]. The method of filtration basically contains processing of two procedures i.e. subtraction of adaptive spectral noise that allow to increase the quality of speech and the extraction of adaptive background which will separate the background acoustic environment from the required signal. The adaptive filter is a special class of filters, used to regain the information carrying signal from the corrupted signal by adjusting its tap weights [1]. To design an adaptive filter,

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three major specifications are to be considered. Firstly the input signal to the system must be known. Secondly the structure of filter must be considered that whether it is an infinite impulse response (IIR) filter structure or a finite impulse response (FIR) filter. An adaptive IIR filter is made up of two basic components: a time varying IIR filter with input x(n) and output y(n), and an algorithm that updates the filter coefficients $\overline{w(n)}$ to optimize a nature of error signal, e(n) [7]. The property of this filter is to generate a suitable estimate y(n) of the desired output signal denoted by d(n). There are basically two classes of digital filter model i.e. Finite impulse response (FIR) filters and Infinite impulse response (IIR) filters. FIR filters are realized by moving average model which consists of zeros only where as an IIR filter can be realized by an autoregressive moving average model which consists of poles and zeros. It is desired that IIR filters can be economically and effectively modeled as compared to FIR models [8]. It is well known that IIR filter needs much lower filter length to meet the same magnitude specification as compared to its FIR counterpart. Effective research has been done to boost up the performance of FIR filter to the most versatile IIR configuration filter. A recursive IIR filter generally provides better performance than a FIR filter [9]. In the terms of complicatedness, IIR filters are more favorable than FIR filters for real time applications.

3. Implementation of LMS Algorithm

The IIR LMS algorithm is an extended version of the FIR LMS algorithm. To attain a desired level of performance an IIR filter needs less number of coefficients as compared to a FIR filter [3]. The LMS algorithm is chosen because of its easiness and directness. This algorithm basically minimizes the mean squared error (MSE) i.e. the difference of the expected output and the obtained output signal. This algorithm belongs to the steepest decent algorithm, which is simple, and very easy to realize. The weight's upgrading equation is expressed by the below mentioned equation

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

Where, x(n) act as an input signal to this filter, e(n) is the error signal, μ(n) is the step size and w(n) is the weight tap vector[3].

The standard LMS algorithm performs the following operations: (i) It smoothes the input signal x(n) by updating the step size to produce the output y(n). (ii) It estimates the value of error by simply subtracting the obtained output signal from the desired output signal by using this equation

$$e(n) = d(n) - y(n) \qquad (2)$$

(iii) It updates the filter coefficients.

This equation has a special parameter step size which is represented by μ, whose value is always kept constant for each and every iteration. This parameter is used in optimizing the results and in updating the coefficients of the filter. Now, to design an adaptive IIR filter, firstly an unknown system is designed in which the input signal is taken as a stimulus signal which is gaussian white noise signal represented by x(n). Then by using IIR filter virtual Instrument (VI) from signal processing toolkit of LabVIEW and assigning the values of reverse and forward coefficients, the response signal (output signal) is obtained which is the filtered form of gaussian white noise signal with a value of standard deviation as 0.001. Then this input signal (stimulus signal) and response signal both are added to form a desired signal, d(n) [6]. In Figure 1 the block diagram of the designed unknown system is shown below.

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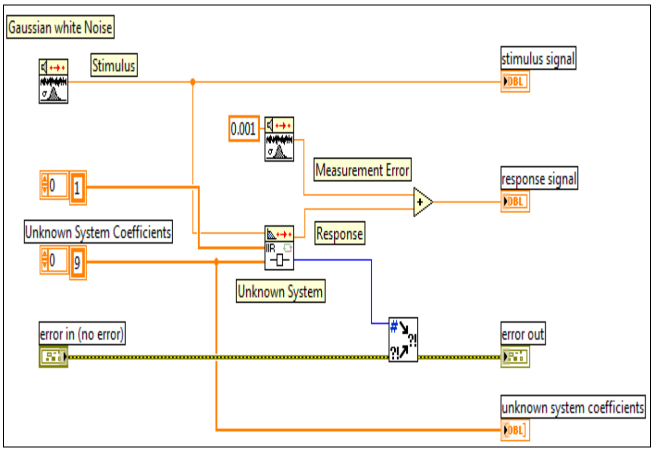

Figure 1. Block Diagram of an Unknown System

Then these input signal x(n) and the obtained response signal d(n) are used as an input to the adaptive filtering system so as to update the coefficients of LMS algorithm in a recursive manner. According to this algorithm filter weights are updated recursively. The Figure 2 shows the execution of adaptive IIR filter using LMS algorithm.

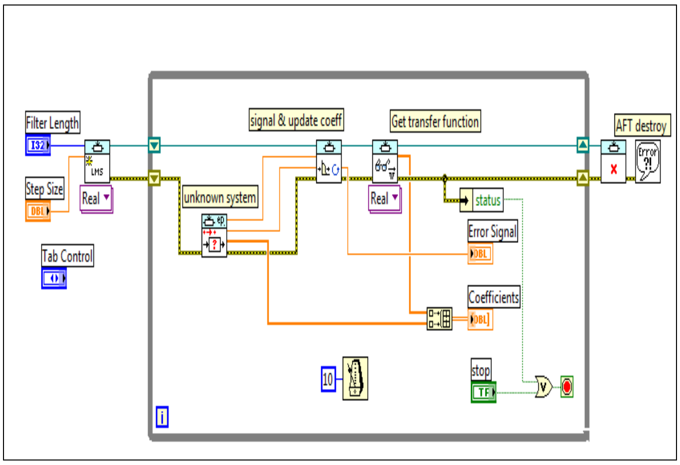

Figure 2. Block Diagram of Design of Adaptive IIR Filter using LMS Algorithm

This filter is used to reduce the value of mean square error (MSE). In Figure 3 the value of e(n) is shown, which depicts the decrease in the value of error signal as the number of iteration increases. This signal e(n) is obtained by using eq (2). When the value of MSE approaches zero, the system will become stable. The rate of convergence in this case is moderate.

The output obtained from the designed adaptive IIR filter is shown in Figure 4. The curve shows that how the adaptive coefficients (black coloured signal) get updated in accordance with the value of unknown coefficients (red coloured signal).

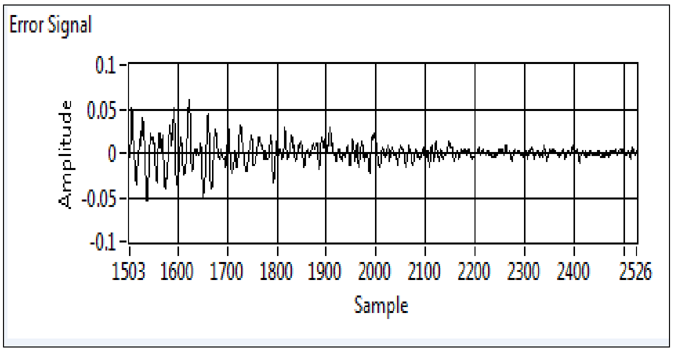

Figure 3. Error Signal using LMS Algorithm

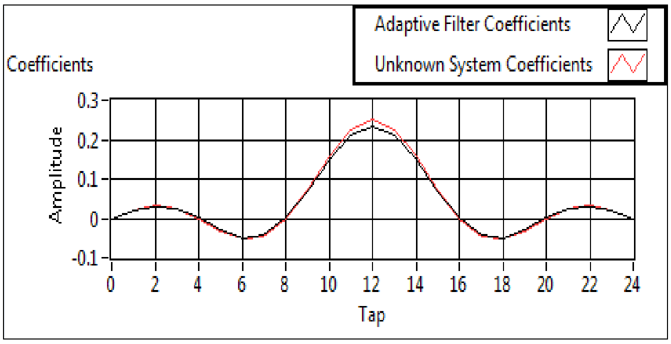

Figure 4. Adaptive IIR Filter output using LMS Algorithm

4. Implementation of NLMS Algorithm

A Similarly, an IIR filter is designed using normalized least mean square (NLMS) algorithm,which normalizes the value of step size (μ) by squaring the input signal. The NLMS algorithm is given by the following equation

$$w(n+1) = w(n) + \frac{\alpha}{c+\|x(n)\|^2} e(n)x(n) \qquad (3)$$

where α is an adaptation constant, which optimizes the convergence rate of algorithm. The value of α is practically less than 1 and c is constant term for normalisation. As in the above eq(3), the computational complexity increases with the manipulation of these different parameters. So, this algorithm gives slow convergence speed for small values of step size. To implement this algorithm in LabVIEW, AFT create NLMS (VI) is available, so create AFT LMS block in the previous designed IIR filter can be replaced with this block. The Figure 5. depicts the realisation of adaptive IIR filter using NLMS algorithm in LabVIEW.

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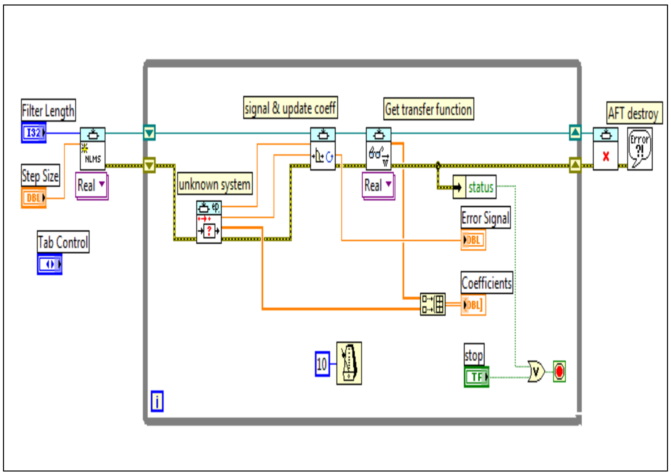

Figure 5. Block Diagram of Design of Adaptive IIR Filter using NLMS Algorithm

The Figure 6 shows the obtained error signal e(n). The value of e(n) will lie in between -0.5 to 0.5 but after some time with increase in number of iteration, the value of e(n) will approaches zero. The Figure 7 shows the obtained output of IIR Filter using NLMS algorithm.

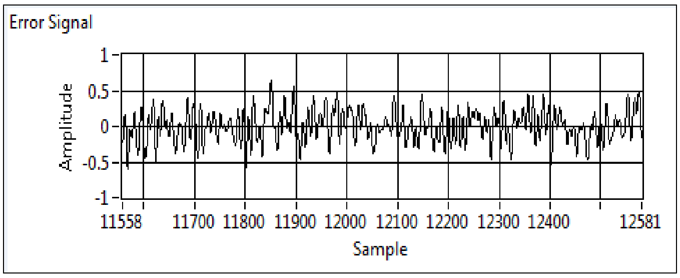

Figure 6. Error Signal using NLMS Algorithm

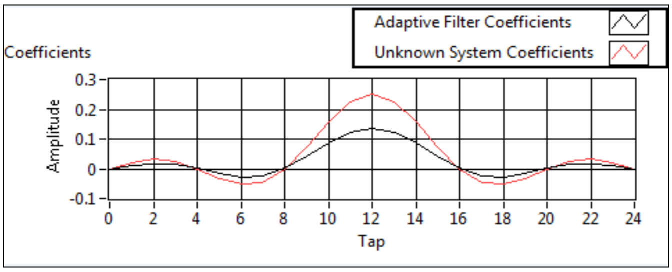

Figure 7. The Output of IIR Filter using NLMS Algorithm

The results obtained from the designed adaptive IIR filter are shows that the adaptive IIR filter updates its coefficients slowly in accordance with the value of unknown tap weights. But the convergence speed is very slow.

5. Implementation of Sign LMS algorithm

For high speed communication applications, the time is crucial; the fastest adaptation process is required. The sign function, as described by the following equation clarifies the functioning of LMS algorithm:

$$sgn\,(x) = \begin{Bmatrix} 1\,; & x > 0 \\ 0\,; & x = 0 \\ -1\,; & x < 0 \end{Bmatrix} \qquad (4)$$

When the sign function is applied to the standard LMS algorithm; it gives the following three types of sign LMS algorithms.

(i) Sign-error LMS algorithm - This employs the sign function to the error signal e(n) and this algorithm upgrades the taps of filter through the below mentioned equation:

$$\overrightarrow{w(n+1)} = \overrightarrow{w(n)} + \mu.sgn\big(e(n)\big).\overrightarrow{u(n)} \qquad (5)$$

It is noticed that when e(n) is zero, this algorithm does not perform multiplication operations. When e(n) is not zero, this algorithm performs only one multiplication operation.

(ii) Sign-data LMS algorithm – This employs the sign function on the input signal $\overrightarrow{u(n)}$ and this algorithm upgrades the taps of the filter by the following equation:

$$\overrightarrow{w(n+1)} = \overrightarrow{w(n)} + \mu.\big(e(n)\big).sgn\,(\overrightarrow{u(n)}) \qquad (6)$$

Where μ denotes the step size of the adaptive filter, $\overrightarrow{w(n)}$ denotes the filter coefficient vector, $\overrightarrow{u(n)}$ denotes filter input vector, and e(n) denotes error signal.

It is noticed that when $\overrightarrow{u(n)}$ is zero; this algorithm does not perform multiplication operations. When $\overrightarrow{u(n)}$ is not zero, this algorithm perform only one multiplication operations.

(iii) Sign-sign LMS algorithm – This employs the sign function to both the terms e(n) and $\overrightarrow{u(n)}$ and this algorithm basically upgrades the taps of the filter through the equation:

$$\overrightarrow{w(n+1)} = \overrightarrow{w(n)} + \mu.sgn\big(e(n)\big).sgn(\overrightarrow{u(n)}) \qquad (7)$$

It is noticed that when either e(n) or $\overrightarrow{u(n)}$ is zero, this algorithm does not perform multiplication operations. When neither e(n) nor $\overrightarrow{u(n)}$ is not zero, this algorithm perform only one multiplication operation.

The sign algorithm does less number of multiplication operations than other algorithms. When the value of step size factor μ equals a power of 2, the sign LMS algorithm will exchange the multiplication operations with shift operations. As compared to the standard LMS algorithm, the sign LMS algorithm possesses slow rate of convergence and more value of mean squared errors [7].

Though this above defined LMS algorithm is very easy in calculation terms but its mathematical analysis is very complex because of its stochastic and non-linear behaviour and so it's hardware implementation. So, to profound the execution and to have hardware consistency another LMS algorithm, called as sign sign algorithm is used in this paper. This algorithm deduces the error in terms of speed and hardware by assessing its gradient value in terms of its sign value as given in the above mentioned equations. In general terms it is a hardware friendly algorithm, which decreases the non linearity with its sign value [10].

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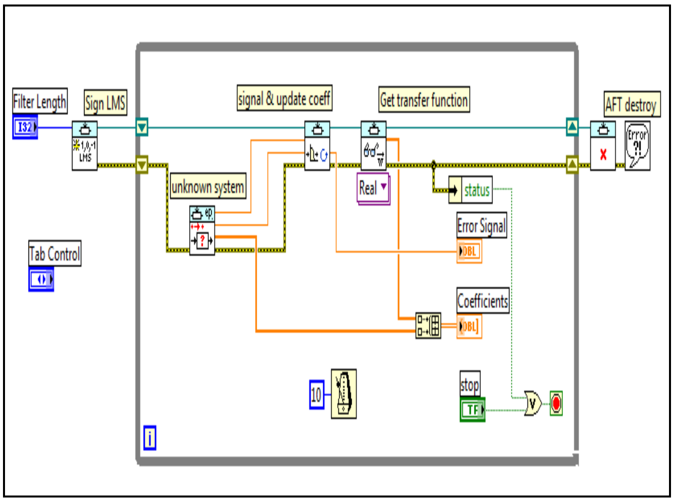

Figure 8. Block Diagram of SLMS Algorithm

The error signal, e(n) shown in Figure 2. depicts the value, which decreases as we increases the iterations. This filter is used to decrease the mean square error (MSE) and increase the convergence rate. When the value of MSE approaches zero, the system will become stable. The output obtained from the designed adaptive IIR filter is shown in Figure 3. The curve shows that how the adaptive coefficients (black coloured signal) get updated in accordance with the value of unknown coefficients (red coloured signal). The rate of convergence in this case is neither too fast nor too slow.

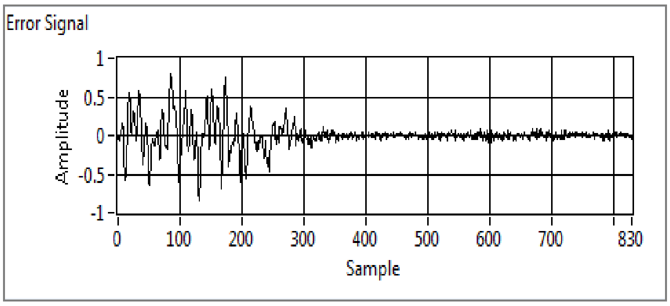

Figure 9. Error Signal using Sign LMS algorithm

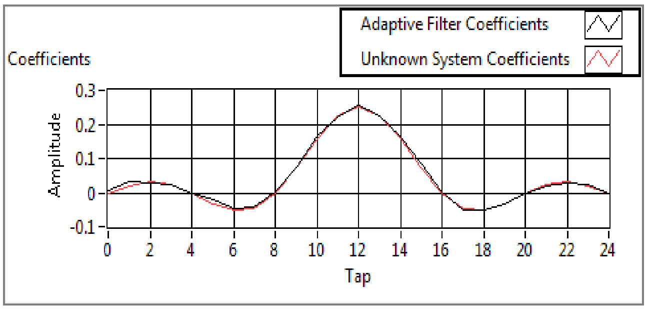

Figure 10. Adaptive IIR Filter output using Sign LMS algorithm

6. Implementation of VSS LMS Algorithm

As explained above the NLMS algorithm is used for limited precision and processing power. As per the stability conditions, the choice of this parameter step size reflects a trade off between fast convergence rate and good tracking ability on the one hand and low misadjustments on the other hand. To overcome this problem, the step size needs to

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be controlled. As taking large value of step size causes large error and fast convergence speed and taking small value of step size causes slow convergence speed [14]. The variable step size least mean square algorithm (VSSLMS) is a solution to this problem that arises between step size and Mean squared error. This algorithm was proposed by Kwong and Johnston in which step size is adjusted according to the square of prediction error. The lms algorithm is stated by the equation:

$$w(n+1) = w(n) + \mu(n)e(n)x(n) \qquad (8)$$

For varying step size,

$$\mu'(n+1) = \alpha\mu(n) + \gamma e^2(n) \qquad (9)$$

With $0 < \alpha < 1$ and $\gamma > 0$

As $\mu(n+1)$ is set to μ_{max} or μ_{min}. When its value goes below or above one of them, respectively. The step size updated equation is given as

$$\mu(n+1) = \alpha\left(\mu(n)\right) + \gamma \mathrm{E}^2\{e(n)e(n-1)\} \qquad (10)$$

This equation represents the behavior of variable step size algorithm. The block diagram of VSS-LMS algorithm has been designed using adaptive filter toolkit of LabVIEW as shown in Figure 11.

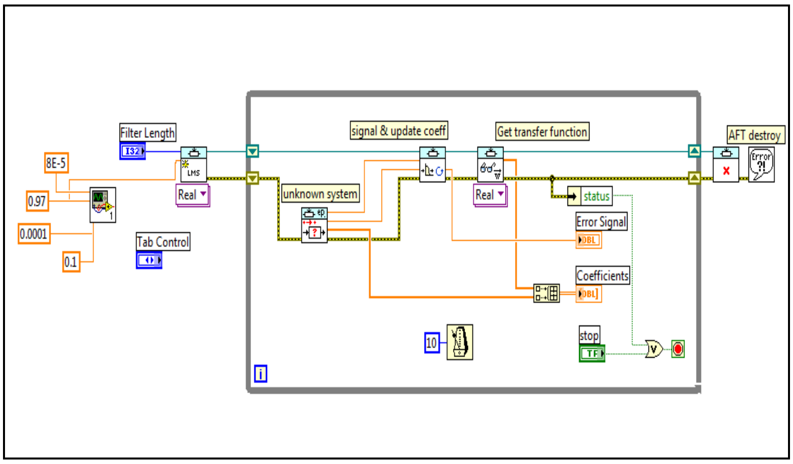

Figure 11. Block Diagram of VSS-LMS Algorithm

7. Implementation of Learning Curves

The plot between mean square error (MSE) and number of iterations is known as curve of the designed algorithm, and it depends upon the value of step size. This curve is used to measure the convergence rate and stability of the system [6]. Generally learning curves fall off exponentially to a constant value, with the increasing number of iterations, as it further decreases the mean squared error (MSE) value. To obtain these learning curves, adaptive filter toolkit (AFT) of LabVIEW is used [7]. The equation of mean squared error is given as

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e(n)^2 \qquad (11)$$

The Virtual Instrument (VI) blocks are available in AFT are AFT create LMS, AFT filter and update coefficients VI, AFT get transfer function VI and AFT destroy adaptive filter VI are used to execute these learning curves. To implement both the algorithms (LMS and NLMS) in Virtual Instrument (VI), case structure is used to attain learning curve of both the implemented algorithms. To compute MSE, VI is designed using array and numeric function palette. In Figure 8 the block diagram of learning curve is shown.

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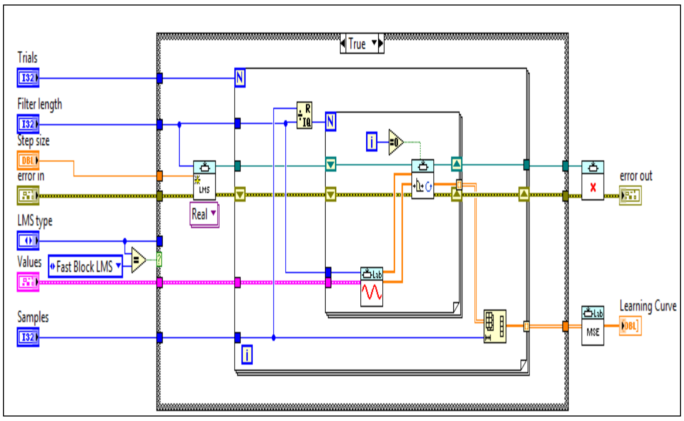

Figure 12. Block Diagram of Learning Curve

8. Simulation Results

The comparison of the least mean square (LMS) algorithm with normalized least mean square algorithm is based upon the factors on which these algorithms are designed to achieve the desired results. Both the algorithms are analyzed by taking the samples of noisy signal as input of unit variance and zero mean. The value of filter order considered in the analysis is 25. The results are observed by taking multiple independent trials.

The different values of parameter µ are taken to obtain the learning curve over multiple iterations. During its execution, the number of samples of an unknown system is considered as number of iterations. In Figure 13 the performance of least mean square algorithm for different step sizes is given.

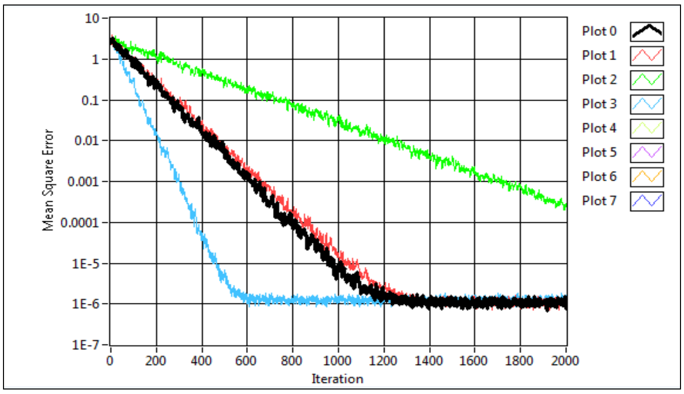

Figure 13. Learning Curve of LMS for different step sizes

The step size obtained through the simulation to plot learning curve for LMS algorithm is shown in Table I.

Table I. Different Step Size of LMS Algorithm

S.No	Algorithm	Step Size	Filter Length	Color of curve
1.	LMS	0.0072	25	Black
2.	LMS	0.0065	25	Red
3.	LMS	0.0024	25	Green
4.	LMS	0.0161	25	Blue

The results in Figure 14 shows the learning curve of LMS algorithm for step size 0.016 (blue curve), 0.0072 (black curve), 0.0065 (red curve), 0.0024 (green curve). The simulation results shows that at 500 iterations, the convergence speed obtained is best with μ=0.0161 as compared to the other stated values. In Figure 14 the learning curve is obtained for NLMS algorithm.

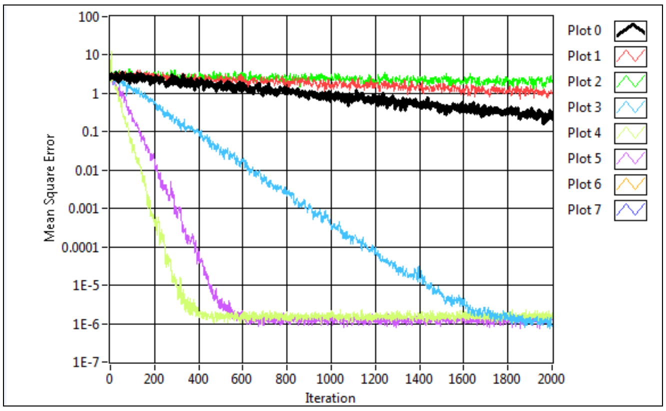

Figure 14. Learning Curve of NLMS algorithm for Different Step Size

The results shows the learning curve of normalized least mean square algorithm for step size 0.0161 (black curve), 0.0065 (red curve), 0.0024 (blue curve),0.1200 (green curve), 0.7000(olive green curve) and 0.4000(purple curve). The simulation result shows that if the value of μ, the convergence speed is good. The step size taken for the simulation of NLMS algorithm to plot the learning curve is shown in Table II.

Table II. Different Step Size of NLMS Algorithm

S.No	Algorithm	Step Size	Filter Length	Color of curve
1.	NLMS	0.0161	25	Black
2.	NLMS	0.0065	25	Red
3.	NLMS	0.0024	25	Blue
4.	NLMS	0.1200	25	Green
5.	NLMS	0.7000	25	Olive green
6.	NLMS	0.4000	25	Purple

To simulate the SLMS algorithm, the different values of parameter μ has been taken, so as to obtain the learning curve over 2000 samples. During the execution of learning curve, the number of samples of an unknown system is considered as number of iterations. The Figure 15 shows the learning curve of sign least mean square algorithm for five different values of step size.

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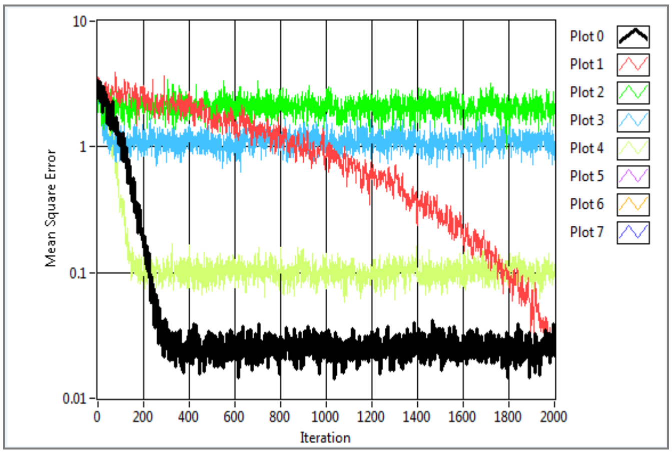

Figure 15. Learning Curve for Sign LMS Algorithm for Different Step Size

The step size obtained through the simulation to plot learning curve for SLMS algorithm by taking five different values of step size is shown in Table III.

Table III. Different Step Size of Sign LMS Algorithm

S.No	Algorithm	Step Size	Filter Length	Color of curve	MSE
1.	Sign LMS	0.001	25	Red	0.02202
2.	Sign LMS	0.066	25	Blue	0.02798
3.	Sign LMS	0.020	25	Olive green	2.17817
4.	Sign LMS	0.010	25	Black	1.11332
5.	Sign LMS	0.090	25	Green	0.11514

The results in Figure 15 shows the learning curve of SLMS algorithm for step size 0.001 (red curve), 0.066 (blue curve), 0.020 (olive green curve), 0.010 (black curve). The simulation results shows that at 2000 iterations, the convergence speed obtained is best with μ=0.010 as compared to the other stated values because the complete analysis is dependent upon the step size (μ), if the value of μ is very small, convergence speed will be too slow and if value of μ is very large then the adaptive filter will become unstable and its output diverges due to high convergence rate. Therefore, the value of μ is crucial.

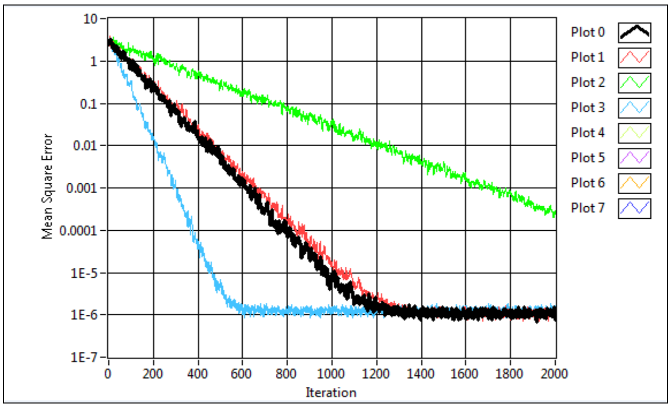

Figure 16. Comparison of VSS Algorithm with SLMS, LMS and NLMS Algorithm

From the obtained learning curve, it can be presumed that LMS algorithm with small value of step size converges faster as compared to the NLMS algorithm and SLMS algorithm. But faster convergence speed brings greater value of steady state errors so the best output is obtained with SLMS because it gives moderate convergence speed with smaller steady state error. The learning curve obtained in Figure 17. Depicts that at 2000 iterations, the SLMS algorithm converges faster than NLMS algorithm and converges slowly in comparison with the standard LMS algorithm. The step size taken to make comparison of SLMS algorithm with LMS and NLMS algorithm by plotting the respective learning curves is shown in Table IV.

Table IV. Comparison of VSS algorithm with LMS, SLMS and NLMS algorithm

S.No	Algorithm	Filter Length	Color of curve	MSE
1.	Sign LMS	25	Red	1.23E-06
2.	LMS	25	Black	0.020661
3.	NLMS	25	Green	0.524033
4.	VSS	25	Blue	0.00245

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