

Improved VSSLMS Algorithm For Noise Cancellation Using Adaptive Weight Updation And It's Performance Evaluation

Karri Dilleswara Rao¹, K. S. Rajasekhar², B. Bhaskara Rao³

^{1,2,3} Acharya Nagarjuna University, Guntur, Andhra Pradesh, India

Abstract- In this paper, a novel algorithm for cancelling noise from the speech signal is proposed. Least Mean Square (LMS) adaptive noise cancellers are widely used to recover signal corrupted by additive noise due to its simplicity in implementation. But it has limitation when the desired signal is strong, that the excess mean-square errors increase linearly with the desired signal power. This results in poor performance when the desired signal exhibits large power fluctuations. Later several algorithms were proposed to achieve maximum SNR value with minimum distortion, such as normalized least mean square algorithm (NLMS) and variable step size least mean square algorithm (VSSLMS). But in NLMS algorithm, selection of step size and filter length of adaptive filter for different type of noise with different noise level (dB) that gives maximum SNR is difficult. This needs various trials of step size and filter length to get optimum solution. In the proposed algorithm we use the benefits of both variable step size (VSS) LMS algorithm and Normalized LMS (NLMS) algorithm to deal with this situation. Finally, the proposed (VSSNLMS) algorithm yields maximum signal to noise ratio (SNR) with minimum mean square error (MSE) in simulations which were carried out using MATLAB software with different noise signals.

Keywords- Adaptive Noise Canceller, Step Size, Mean Square Error, NLMS, SNR, VSSNLMS.

I. INTRODUCTION

The goal of any filter is to extract useful information from noisy data. A normal fixed filter is designed in advance with knowledge of the statistics of both signal and the unwanted noise but if the statistics of the noise are not known priori, or change over time, the coefficients of the filter cannot be specified in advance. In these situations, adaptive algorithms are needed in order to continuously update the filter coefficient.

Adaptive filtering finds application in noise cancellation in speech called as Adaptive Noise cancellation (ANC) which involves in time-varying signals and systems. ANC is an effective method for recovering a signal corrupted

by additive noise and it is an important core area of the digital signal processing.

Fig.1 shows the basic problem and the adaptive noise cancelling solution to it. A signal $s(n)$ is transmitted over a channel to a sensor that also receives a noise n_0 uncorrelated with the signal. The primary input to the canceller is combination of both signal and noise $s + n_0$. A second sensor receives a noise n_1 uncorrelated with the signal but correlated with the noise n_0 . This sensor provides the reference input to the canceller. This noise n_1 is filtered to produce an output $y(n)$ that is as close a replica of n_0 . This output of the adaptive filter is subtracted from the primary input to produce the adaptive filter error $e(n) = d(n) - y(n)$.

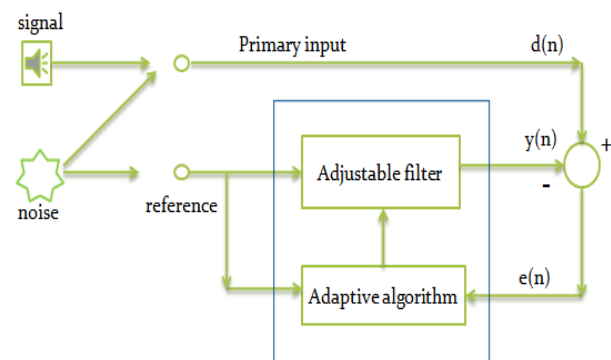


Fig:1 Adaptive Noise Canceller

Probably, one of the well-known algorithms in the field of adaptive filtering is the Least Mean Square (LMS) algorithm. Simplicity and easy implementation are the main reasons for the popularity of LMS algorithm. Some successful applications of the LMS filters are:

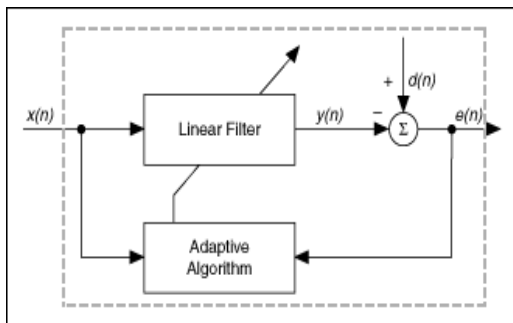
1. System identification.
2. Noise cancellation in speech signals.
3. Signal prediction.
4. Interference cancellation.
5. Channel equalization.
6. Echo cancellation and it has been widely used in noise cancellation.

II. ADAPTIVE ALGORITHMS

Several modified LMS algorithms have been proposed in the past years in order to simultaneously improve the tracking ability and speed of convergence of corrupted signal. They provide an extensive performance evaluation Compared to standard LMS algorithms, including the NLMS, VSSLMS and other recently proposed LMS algorithms.

A. Least Mean Square (LMS) Algorithm

The Least Mean Square (LMS) algorithm was first developed by Widrow and Hoff in 1959 through their studies of pattern recognition (Haykin 1991, p. 67). The least-mean-square (LMS) algorithm is the most widely used among various adaptive algorithms because of its simplicity and robustness. The block diagram illustrates the general LMS adaptive filtering algorithm. Here the adaptation process of the filter parameters is based on minimizing the mean squared error between the filter output and a desired signal.



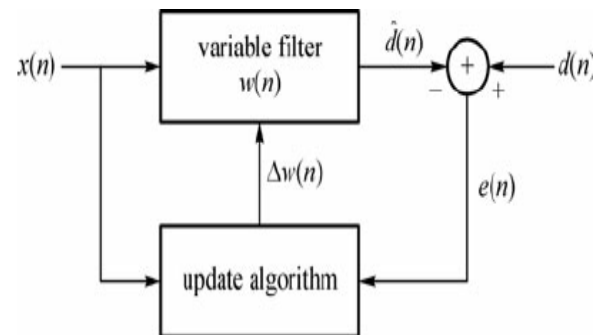
B. Normalised Least Mean Square (NLMS) Algorithm

One of the primary disadvantages of the LMS algorithm is having a fixed step size parameter for every iteration. This requires an understanding of the statistics of the input signal prior to commencing the adaptive filtering operation. In practice this is rarely achievable. Even if we assume the only signal to be input to the adaptive echo cancellation system is speech, there are still many factors such as signal input power and amplitude which will affect its performance. The normalised least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by selecting a different step size value, $\mu(n)$, 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 $\mathbf{x}(n)$.

C. Variable Stepsize Least Mean Square (VSSLMS) Algorithm

In the variable step-size algorithm for LMS adaptive filtering, Commonly the basic ideas for the variable step-size algorithm of LMS are as follows: In the initial stage of

convergence, step size should be bigger, this makes the algorithm has faster convergence speed. Then with the deepening of convergent gradually reduce the step size to reduce the static error. In the process of research for the variable step-size algorithm of LMS, also proposed to make $\mu(n)$ is proportional to $e(n)$, and proposed to make $\mu(n)$ is proportional to the evaluation of the cross-correlation function for $e(n)$ and $x(n)$, and so on. Practice shows that these algorithms can give attention to faster convergence rate and smaller maladjustment to a certain extent. Can effectively remove the irrelevant noise interference, and have fewer parameters and smaller amount of calculation of the algorithm itself.



D. Variable Stepsize Least Mean Square (VSSLMS) 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. Also, recall 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. This is what I have tried to achieve in developing the Variable step size normalized least mean square (VSNLMS) algorithm.

III. ANALYSIS OF ADAPTIVE ALGORITHMS

A. Least Mean Square (LMS) Algorithm

The LMS algorithm is a type of adaptive filter known as stochastic gradient-based algorithms as it utilises the gradient vector of the filter tap weights to converge on the optimal wiener solution. With each iteration of the LMS algorithm, the filter tap weights of the adaptive filter are updated according to the following formula (Farhang-Boroujeny 1999, p. 141).

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

Here $\mathbf{x}(n)$ is the input vector of time delayed input values, $\mathbf{x}(n) = [x(n) \ x(n-1) \ x(n-2) \ \dots \ x(n-N+1)]^T$. The vector $\mathbf{w}(n) = [w_0(n) \ w_1(n) \ w_2(n) \ \dots \ w_{N-1}(n)]^T$ represents the coefficients of the adaptive FIR filter tap weight vector at time n . The parameter μ is known as the step size parameter and is a small positive constant. This step size parameter controls the influence of the updating factor. Selection of a suitable value for μ is imperative to the performance of the LMS algorithm, if the value is too small the time the adaptive filter takes to converge on the optimal solution will be too long; if μ is too large the adaptive filter becomes unstable and its output diverges.

For each iteration the LMS algorithm requires $2N$ additions and $2N+1$ multiplications (N for calculating the output, $y(n)$, one for $2\mu e(n)$ and an additional N for the scalar by vector multiplication).

B. Normalised Least Mean Square (NLMS) Algorithm

The recursion formula for the NLMS algorithm is

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

The output of the adaptive filter is calculated as

$$y(n) = \sum_{j=0}^{N-1} w_j(n)x_j(n-1) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (3)$$

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

$$\mathbf{e}(n) = \mathbf{d}(n) - y(n) \quad (4)$$

The step size value for the input vector is calculated as

$$\mu(n) = \frac{1}{(\mathbf{x}(n)\mathbf{x}(n)^T)} \quad (5)$$

The filter tap weights are updated in preparation for the next iteration.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{e}(n)\mathbf{x}(n) \quad (6)$$

Each iteration of the NLMS algorithm requires $3N+1$ multiplications, this is only N more than the standard LMS algorithm this is an acceptable increase considering the gains in stability and echo attenuation achieved.

C. Variable Stepsize Least Mean Square (VSSLMS) Algorithm

The NLMS algorithm exhibits a good balance between computational cost and performance. However, a very serious problem associated with both the LMS and NLMS algorithms is the choice of the step-size (μ) parameters. A small step size (small compared to the reciprocal of the input signal strength) will ensure small mis-adjustments in the steady state, but the algorithms will converge slowly and may not track the non-stationary behavior of the operating environment very well. On the other hand a large step size will in general provide faster convergence and better tracking capabilities at the cost of higher misadjustment. Any selection of the step-size must therefore be a trade-off between the steady-state misadjustment and the speed of adaptation. VSSLMS algorithm overcomes the problem of convergence speed and estimation accuracy in real time environment. The signal to noise (SNR) ratio is defined as the ratio of the average power of the original signal to that of the noise signal. The main aim of proposing this algorithm is that with the help of SNR, the step size adjustment can be controlled. It is efficient to have lesser value of SNR because such a value gives the maximized step size that provides faster tracking. At the same time, the larger value of SNR results in minimized step size producing smaller mis-adjustment.

In the Variable Step Size Least Mean Square (VSSLMS) algorithm the step size for each iteration is expressed as a vector, $\mu(n)$. Each element of the vector $\mu(n)$ is a different step size value corresponding to an element of the filter tap weight vector, $\mathbf{w}(n)$.

The output of the adaptive filter is calculated as

$$y(n) = \sum_{j=0}^{N-1} w_j(n)x_j(n-1) = \mathbf{w}^T(n)\mathbf{x}(n) \quad (7)$$

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

$$\mathbf{e}(n) = \mathbf{d}(n) - y(n) \quad (8)$$

The gradient, step size and filter tap weight vectors are updated as

$$\mathbf{w}_i(n+1) = \mathbf{w}_i(n) + \mu_i(n)\mathbf{e}(n)\mathbf{x}(n) \quad (9)$$

For $i = 0, 1, 2, 3, \dots, N-1$.

Where if $\mu_i(n) > \mu_{max}(n)$, $\mu_i(n) = \mu_{max}(n)$
 $\mu_i(n) < \mu_{min}(n)$, $\mu_i(n) = \mu_{min}(n)$

D. Modified Variable Stepsize Least Mean Square (VSSLMS) Algorithm

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.

The output of the adaptive filter is calculated as

$$y(n) = \sum_{j=0}^{N-1} w(n)x(n-1) = w^T(n)x(n) \quad (10)$$

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

$$e(n) = d(n) - y(n) \quad (11)$$

The gradient, step size and filter tap weight vectors are updated using the following equations in preparation for the next iteration.

For $i=0,1,2,3,\dots,N-1$.

$$\begin{aligned} g_i(n) &= e(n)x(n-i) \\ g(n) &= e(n)x(n) \\ \mu_i(n) &= \mu_i(n-1) + \rho g_i(n)g_i(n-1) \end{aligned} \quad (12)$$

$$\mu_{max}(n) = \frac{1}{(2x(n)x(n)^T)} \quad (13)$$

If $\mu_i(n) > \mu_{max}(n)$, $\mu_i(n) = \mu_{max}(n)$

If $\mu_i(n) < \mu_{min}(n)$, $\mu_i(n) = \mu_{min}(n)$

$$w_i(n+1) = w_i(n) + 2\mu_i(n)g_i(n) \quad (14)$$

ρ is an optional constant the same as is the VSLMS algorithm. With $\rho=1$, each iteration of the VSNLMS algorithm requires $5N+1$ multiplication operations.

IV. PROPOSED ALGORITHM

Different types of adaptive filtering algorithms have been analyzed in the above section. In LMS algorithm, signal to noise ratio (SNR) is good in lower orders until the signal power is moderate. If the desired signal is having high power the excess mean square error of the adaptive filter is increased linearly with signal power. This results in the decrease in SNR value of the desired signal. To overcome this problem NLMS algorithm was proposed But in NLMS algorithm, selection of step size and filter length of adaptive filter for different type of noise with different noise level (dB) that gives maximum SNR is difficult. This needs various trials of step size and filter length to get optimum solution. For that reason VSSLMS algorithm was proposed.

In this algorithm step size parameter is change in accordance with signal to noise ratio. Minimum step size gives least mean square error but the rate of convergence is very low. If the step size is chosen large, it gives better

convergence rate of adoption but results in high mean square errors.

To overcome this problem we proposed a modified variable step size LMS algorithm by using the benefits of both NLMS and VSSLMS algorithms, and also proposed a new algorithm(COMBINED ALGORITHM) by combining all the above four algorithms to find out the suitable algorithm by the requirements of the user needed. This algorithm helps to choose the right algorithm for the right time. That can be explained in detail as below

Command window results:

Enter the filter order: 128

| parameter | LMS | NLMS | VSSLMS | VSSNLMS |
|------------|--------|--------|---------|----------|
| SNR | 70.229 | 73.180 | 70.2254 | 73.2018 |
| DISTORTION | -17.75 | -19.36 | -17.658 | -19.3632 |
| MSE | 0.0048 | 0.0154 | 0.0046 | 0.0154 |
| RMS | 0.1309 | 0.1076 | 0.1309 | 0.1076 |

Maximum SNR in VSSNLMS=73.2018

Minimum DISTORTION in VSSLMS=-17.658

Minimum MSE in VSSLMS=0.0046

Maximum RMS in LMS=0.1309

From the above table we observed that keeping all other parameters constant, maximum SNR value is observed in VSSNLMS algorithm and minimum mean square error in VSSLMS algorithm. That means depends on the requirement of the user (weather required maximum SNR OR minimum distortion OR minimum mean square error) he can choose the appropriate algorithm. One more important thing to observe is the overall execution time for this program is less compared to the sum of the individual time required to execute each program. The results of the proposed algorithm is shown in the simulation section.

V. SIMULATION RESULTS

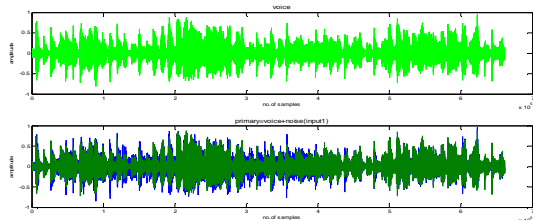
SPECIFICATIONS:

- Voice signal: song (15 sec length).
No. of samples in voice signal (N): 661504.
Voice signal size: (661504 X 2 double).
- Noise signal: applause noise.
No. of samples in noise signal (M): 456457.
Noise signal size: (661504 X 2 double).
- Step size parameter (μ): 0.1.
- Initial weight vector (w): zeros of vector size (128 X 1).
- Primary signal = voice signal+ noise signal.
Primary signal size: (661504 X 2 double).

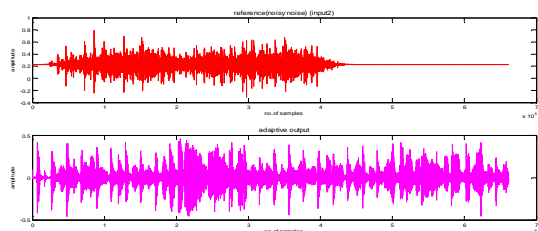
6. Reference signal= noise signal + 0.25*random noise.
Reference signal size: (661504 X 2 double).
7. No. of iterations =N – order of the system.
=661504-128 =331372

RESULTS:

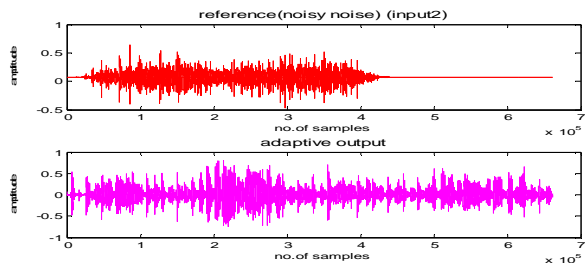
1. Input voice signal and primary signal



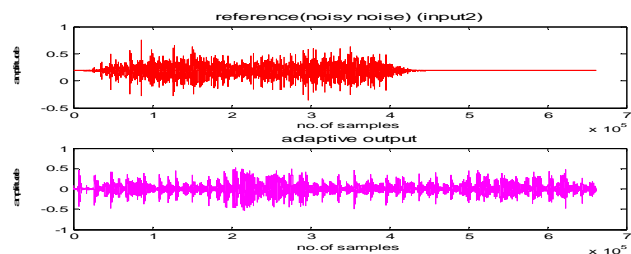
2. Reference noise and desired output(lms)



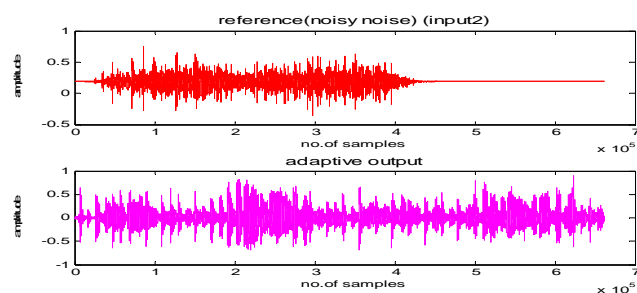
3. Nlms output



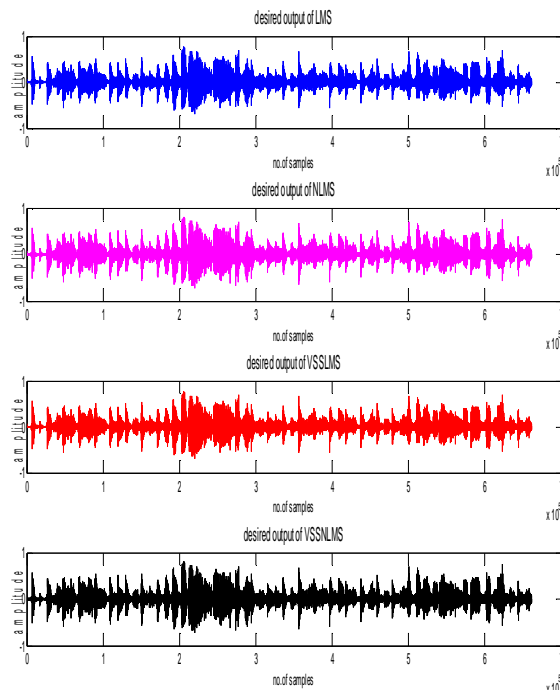
4. Vsslms output



5. Vssnlms output



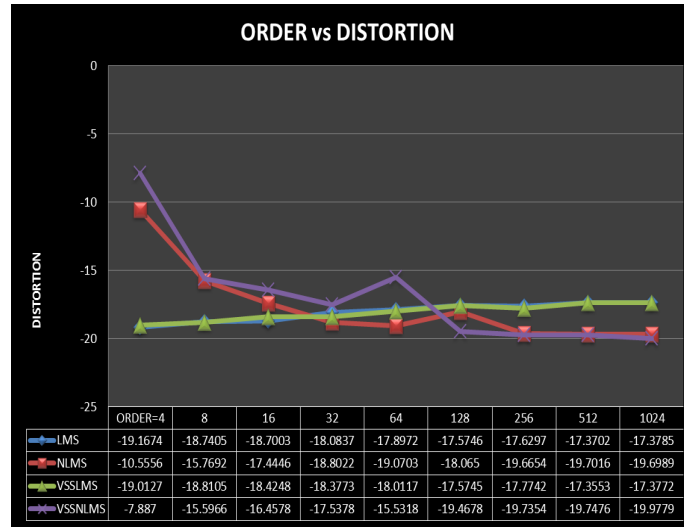
VI. COMPARISON OF ALL ALGORITHMS



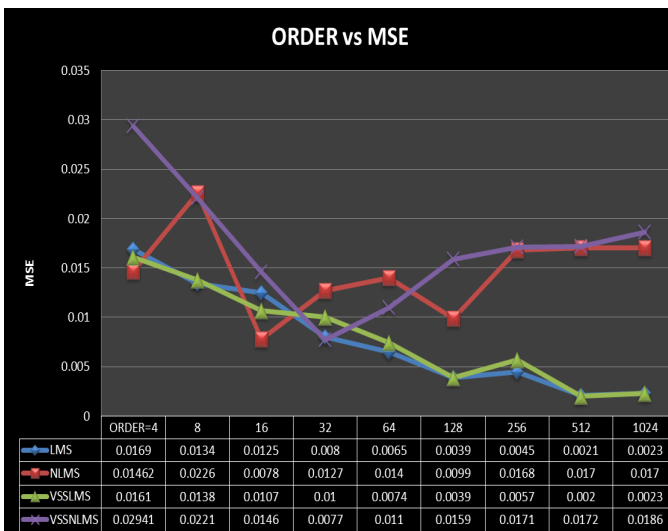
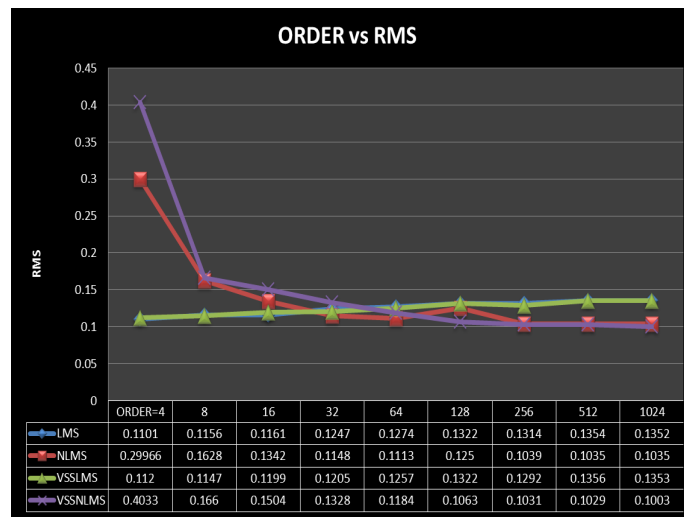
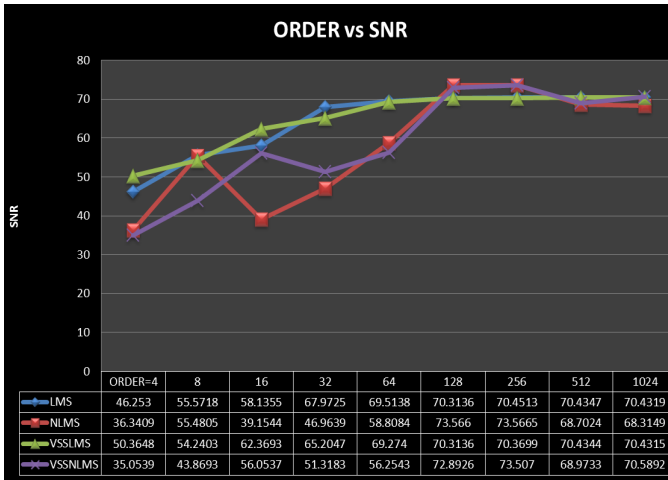
TABULAR

| ORDER | PARAMETERS | LMS | NLMS | VSSLMS | VSSNLMS |
|------------------|------------|----------|----------|----------|----------|
| 4 th | MSE | 0.0169 | 0.01462 | 0.0161 | 0.02941 |
| | SNR | 46.253 | 36.3409 | 50.3648 | 35.0539 |
| | DISTORTION | -19.1674 | -10.5556 | -19.0127 | -7.887 |
| | RMS | 0.1101 | 0.29966 | 0.112 | 0.4033 |
| 8 th | TIME | 7.4347 | 13.6162 | 35.6726 | 47.7774 |
| | MSE | 0.0134 | 0.0226 | 0.0138 | 0.0221 |
| | SNR | 55.5718 | 55.4805 | 54.2403 | 43.8693 |
| | DISTORTION | -18.7405 | -15.7692 | -18.8105 | -15.5966 |
| 16 th | RMS | 0.1156 | 0.1628 | 0.1147 | 0.166 |
| | TIME | 7.6599 | 12.6236 | 35.9202 | 44.04486 |
| | MSE | 0.0125 | 0.0078 | 0.0107 | 0.0146 |
| | SNR | 58.1355 | 39.1544 | 62.3693 | 56.0537 |
| 32 nd | DISTORTION | -18.7003 | -17.4446 | -18.4248 | -16.4578 |
| | RMS | 0.1161 | 0.1342 | 0.1199 | 0.1504 |
| | TIME | 8.5621 | 12.8467 | 37.5956 | 43.75348 |
| | MSE | 0.008 | 0.0127 | 0.01 | 0.0077 |
| 64 th | SNR | 67.9725 | 46.9639 | 65.2047 | 51.3183 |
| | DISTORTION | -18.0837 | -18.8022 | -18.3773 | -17.5378 |
| | RMS | 0.1247 | 0.1148 | 0.1205 | 0.1328 |
| | TIME | 8.49358 | 13.36711 | 37.6875 | 44.67674 |
| 64 th | MSE | 0.0065 | 0.014 | 0.0074 | 0.011 |
| | SNR | 69.5138 | 58.8084 | 69.274 | 56.2543 |
| | DISTORTION | -17.8972 | -19.0703 | -18.0117 | -15.5318 |
| | RMS | 0.1274 | 0.1113 | 0.1257 | 0.1184 |
| 64 th | TIME | 8.69776 | 13.924 | 37.3666 | 44.29301 |

| | | | | | |
|--------------------|------------|----------|----------|-----------|----------|
| 128 th | MSE | 0.0039 | 0.0099 | 0.0039 | 0.0159 |
| | SNR | 70.3136 | 73.566 | 70.3136 | 72.8926 |
| | DISTORTION | -17.5746 | -18.065 | -17.5745 | -19.4678 |
| | RMS | 0.1322 | 0.125 | 0.1322 | 0.1063 |
| | TIME | 10.68516 | 14.85598 | 37.8868 | 46.69061 |
| 256 th | MSE | 0.0045 | 0.0168 | 0.0057 | 0.0171 |
| | SNR | 70.4513 | 73.5665 | 70.3699 | 73.507 |
| | DISTORTION | -17.6297 | -19.6654 | -17.7742 | -19.7354 |
| | RMS | 0.1314 | 0.1039 | 0.1292 | 0.1031 |
| | TIME | 12.4547 | 17.1742 | 42.338 | 48.05387 |
| 512 th | MSE | 0.0021 | 0.017 | 0.002 | 0.0172 |
| | SNR | 70.4347 | 68.7024 | 70.4344 | 68.9733 |
| | DISTORTION | -17.3702 | -19.7016 | -17.3553 | -19.7476 |
| | RMS | 0.1354 | 0.1035 | 0.1356 | 0.1029 |
| | TIME | 16.30845 | 22.38059 | 44.35075 | 52.19673 |
| 1024 th | MSE | 0.0023 | 0.017 | 0.0023 | 0.0186 |
| | SNR | 70.4319 | 68.3149 | 70.4315 | 70.5892 |
| | DISTORTION | -17.3785 | -19.6989 | -17.3772 | -19.9779 |
| | RMS | 0.1352 | 0.1035 | 0.1353 | 0.1003 |
| | TIME | 24.02205 | 29.5997 | 55.023967 | 61.23476 |



Graphs:



VI. CONCLUSION

In this paper an COMBINED LMS ALGORITHM along with the improved VSSLMS algorithm based on step size, filter order and signal to noise ratio (SNR) of speech and reference noise signal for updating weights of adaptive filter is proposed. Proposed algorithm shows improved performance. From rigorous experimental analysis and testing we conclude that proposed algorithm outperforms LMS NLMS and VSSLMS algorithms in terms of SNR, MSE and distortion.

REFERENCES

- [1] Mohammad Shams EsfandAbdadi, Ali Mahlooji Far, “ Unified framework for Adaptive filter algorithm with variable step size”, Science Direct. Computers and electrical Engineering, vol 34 pp. 232-249, 2008.
- [2] Hsu-Chang Huang and JhungsiLee, ”A new variable step size NLMS Algorithm and its performance

- analysis”, IEEE Transa.Signal Process., vol 60,no 4, pp.2055-2060,Apr 2012.
- [3] Jeronimo Arenas-Garcia, AnibalR.Figueiras-Vidal,” Adaptive Combination of proportionate Filters for Sparse Echo Cancellation”, IEEE Transaction on Audio,Speech and Language Processing” ,Vol 17,No.6, 2009.
- [4] Jafar Mohammad, Muhammad shafi, “An Efficient AdaptiveNoise Cancellation Scheme using ALE and NLMS Filters”, IJECE,vol.2, No 3, pp.325-332.
- [5] D.L.Duttweiler,”Proportionate normalized least mean squares adaption in echo cancelers”, IEEE Transaction.Signal Processing”, vol 8,pp 508-518, 2008.
- [6] Bernard widrow, John Glover, “Adaptive Noise Cancelling: Principles and Applications”, IEEE proceeding, Vol. 63 No 12,1975.
- [7] Monson H. Hayes, “Statistical digital signal processing and modelling”,wiley, 2009
- [8] J.M.Gorritz, Javier Ramirez, S.Cruces-Alvarez, Carlos G.Puntonet, ”A novel LMS Algorithm applied to adaptive cancellation ”, IEEE Signal Process. letters, vol 16,no 1, pp.34-37, Jun 2009.
- [9] R.H Kwong, E.W.Johnston, “A variable step size LMS algorithm”,IEEETrans.SignalProcessing,Vol 40,No.7,PP 1633- 1642,1992.
- [10] D.P.Mandic, “ A generalized normalized gradient descent algorithm”, IEEE SignalProcess.lett,Vol 11, No 2,PP 115-118,2004.
- [11] Hsu-Chang Huang and JhunghsiLee,”A new variable step size NLMS Algorithm and its performance analysis”, IEEE Transa.Signal Process., vol 60,no 4, pp.2055-2060,Apr 2012.
- [12] D.L.Duttweiler,”Proportionate normalized least mean squares adaption in echo cancelers”, IEEE Transaction. Signal Processing”, vol 8,pp 508-518, 2008.
- [13] Jeronimo Arenas-Garcia, AnibalR.Figueiras-Vidal,” Adaptive Combination of proportionate Filters for Sparse Echo Cancellation”, IEEE Transaction on Audio,Speech and Language Processing” ,Vol 17,No.6, 2009.
- [14] K.Ozeki,TUmeda, “ An Adaptive filtering algorithm using an orthogonal projection to an affine subspace and its properties”, Electron.Commun.Japan,vol 67-A,PP 19-27,1984.
- [15] Gay S.L, S.Tavathia,”The fast Affine projection algorithm”, Proc of international conference on Acoustics, Speech and Signal Processing (ICASSP’95),pp 3023-3029,1995.
- [16] Kim,S.-E,S.-J,Kong and W.-J,song ,”An Affine Projection Algorithm with Evolving order”,Signal Processing ,16(11), pp 937-940,2009