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RESEARCH ARTICLE

Electrica 2020; 20(2): 116-123

Investigating the Effectiveness of Adaptive Step Size LMS Algorithms for the Use with VOIP Applications

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Cite this article as: Hameed AA, Ajlouni N, Orman Z, Özyavaş A. Investigating the Effectiveness of Adaptive Step Size LMS Algorithms for the Use with VOIP Applications. *Electrica,* 2020; 20(2): 116-123.

ABSTRACT

Adaptive algorithms play a vital role in Digital Signal Processing (DSP) and Communication. Quality of Voice over IP (VoIP) Service is an important issue as VoIP service is an affordable alternative to conventional communication methods. The Least Mean Square (LMS) algorithm is one of the most popular adaptive filters. LMS is the core of many active noise control applications. This paper presents a performance comparison between three modified versions of the LMS algorithms for online noise cancellation problem for VoIP applications. The three modified algorithms are all concerned with modifications of the step-size of the algorithm since the step-size has a direct relation to the convergence speed of the algorithm. The algorithms investigated in this paper are the Normalized LMS (NLMS), the Variable Step Size LMS (VSSLMS), the Variable Leaky LMS (VLLMS), and the Variable Step Size LMS (VSSLMS) algorithms. The comparison is based on various performance indices including convergence speed, Mean Square Error (MSE), Signal to Noise Ratio (SNR). The simulation test results show that the VSSLMS algorithm is the most suitable algorithm for this type of application.
Keywords: Adaptive filters, convergence behavior, misadjustment, VoIP, VSSLMS algorithms

Introduction

The Quality of Service (QoS) of the VoIP network is measured based on delay, jitter, delay variation, and packet loss. Hence it is imperative to reach a high-quality level of service by VoIP. In recent years, many researchers have addressed the problem of designing an echo cancellation system for VoIP signals. Radecki et al. [1] presented a general solution to the problem of echo cancellation in IP networks. In [2], the authors proposed a synthetic stereo acoustic echo cancellation structure for multiple participants of VoIP conferences, [3] proposed an acoustic echo cancellation for synthetic surround sound. [4] presented a solution to the problem of echo target determination using acoustic round trip delay for VoIP conferences. [5] discussed the adaptation scheme in the NLMS algorithm for echo cancellation. [6] proposed an efficient multichannel line echo-cancelling algorithm for PSTN and VoIP/VoDSL applications. Meanwhile, many variations of variable step-size adaptive filters have been proposed by many authors [7-16], the effectiveness of these modified algorithms are well tested for improved algorithm convergence rate. Their effectiveness in solving VOIP problems have not yet been evaluated or dealt with. In this work, it is intended to evaluate such adaptive algorithms and their effectiveness to solve some of the inherent problems of VoIP.

LMS Algorithm

Adaptive filtering is used to overcome the limitations of the conventional static filters. In this sense, the adaptive filter deals with unknown time-varying input signals in numerous noise reduction and cancellation environments [18], including channel equalization, identification [19], and acoustic echo cancellation [7]. Filter output signals utilize weight coefficient vectors to adjust itself iteratively with time to minimize the error between filter output and desired output. Figure 1 and 2 show the main block diagram of a system identification and noise cancellation, respectively. From Figure 1 and 2 it can be seen that the noise is reduced using

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Received: 29.03.2019

Accepted: 19.07.2019

DOI: 10.5152/electrica.2020.19080

adaptive filters, where y*(n)* is the filter output, *d(n)* is the desired response and *e(n)* is the estimation error of the adaptive filter for time iteration *n*.

LMS adaptive fitters are a modified version of the static filter. As shown in Figure 1 and 2 the linear weighted sum of input signal x*(n)* and the coefficient w*(n)* make the output signal *y(n)*, the difference between the desired signal *d(n)* and *y(n)* is the error *e(n)*.

In this paper, we will be utilizing two different adaptive filter configurations. The first is used to identify the system of unknown input source, as shown in Figure 1, while the second deals with the problem of noise cancellation in the case of having prior knowledge about the source of noise, shown in Figure 2.

The output equation of the filter is given by

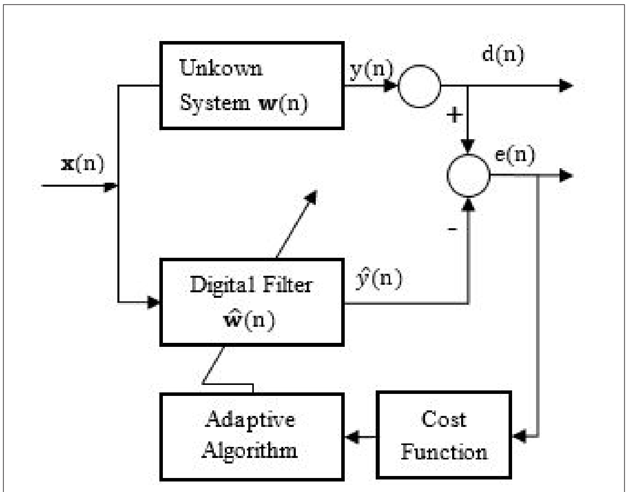

Figure 1. Block diagram of system identification

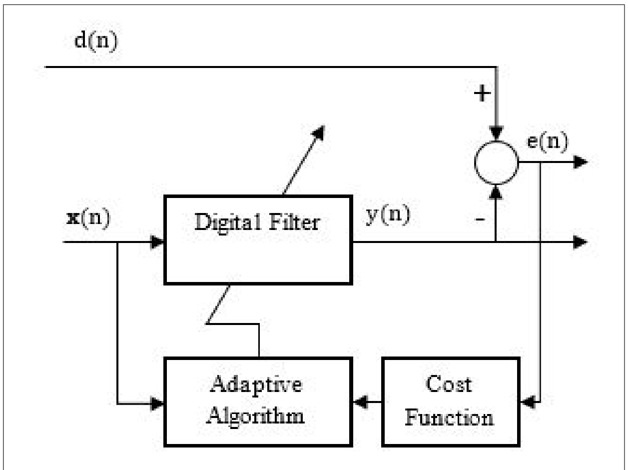

Figure 2. Block diagram of noise cancellation

$$y(n) = \sum_{i=1}^{N} \mathbf{w}_i(n)\mathbf{x}_i(n) = \mathbf{w}(n)^T\mathbf{x}(n) \tag{1}$$

In this case the filters $\mathbf{w}_{opt}$ *(n)* are obtained through minimum mean square error $E\,|e_n^2|$ *min* which is highly dependent on the value of **w***(n)*, this is given as

$$e(n) = d(n) - y(n) = d(n) - \mathbf{w}^T(n)\mathbf{x}(n) \tag{2}$$

The gradient formula of the LMS algorithm is expressed as

$$\hat{\nabla}(n) = \nabla[e^2(n)] = \left[\frac{\partial e^2(n)}{\partial \mathbf{w}_0}\ \frac{\partial e^2(n)}{\partial \mathbf{w}_1} \dots \frac{\partial e^2(n)}{\partial \mathbf{w}_N}\right] \tag{3}$$

The iterative weight equation of the LMS filter is obtained using equation (2) and equation (3), this given as

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \mu\hat{\nabla}(n) = \mathbf{w}(n) + 2\mu e(n)\mathbf{x}(n) \tag{4}$$

In this case the mean square error $E[e^2(n)]$ decreases as the value of *n* increases. When n → ∞, $E[e^2(n)]$ is minimum and the filter achieves its optimal performance.

Equation (4) uses an adaption error and a fixed size μ to update the filter coefficients.

Therefore, it can be seen that the choice of the step size μ is the main factor in achieving convergence and stability as well as the stability margin of the LMS algorithm. Equation (4) shows that the stability of the convergence of the LMS requires μ to be within $0 \le \mu \le \frac{1}{tr(R)} \le \frac{1}{\lambda_{max}}$ where *tr(R)* is the trace of *R* and *R* is the autocorrelation matrix of *x*, and λ_{max} is the maximum eigenvalue of *R* [14]. The relation between the step size and the convergence is summarized as the smaller the step size the smaller the steady-state misadjustment (SSM) but also slower convergence rate. While a large step size results in faster convergence rate but large SSM. Hence the performance of the LMS filter very much dependent on the correct choice of the step-size. As a result, researchers over the decades have developed different variations of the LMS filter. The majority of the modifications were on the improvement of the filter convergence through varying the value of the filter step-size in an efficient and adaptive manner. In all of these cases, the step-size changed its value based on the current conditions of the filter. To increase the convergence speed of the LMS algorithm researchers proposed many modified algorithms in which they proposed a different method for choosing the value of the adaptively varied step-size to be used during the filtering process.

In this paper, a number of these algorithms are investigated against their suitability for use with VoIP applications. However, it must be highlighted that the VoIP may not always require the best convergence or the minimum mean square error since filtering time is very short. Therefore the study will try to investigate and compare the algorithms based on various performance indices including convergence speed, Mean Square Error (MSE), Signal to Noise Ratio (SNR). The algorithms which are investigated in this work are the Normalized LMS (NLMS), the Variable Step Size LMS (VSSLMS), and the Variable Leaky LMS (VLLMS) algorithms,

Normalized Least-Mean-Square (NLMS) Algorithm

In the Normalized LMS, the idea of improving the LMS was very simple. It set the step size as a function of the power of the input signal. This LMS adaptive algorithm is based on the gradient descent method of the cost function ($f(n) = e_n^2$). The weight update equation of the LMS algorithm is derived as,

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{x}(n)e_n \tag{5}$$

where μ is the step-size, that controls the convergence rate and the stability of the algorithm.

The LMS algorithm adjusts the tap weights vector in a recursive manner until obtaining the optimum weights vector to access minimum error on the required signal using (2). The step size is constant in the range of,

$$0 < \mu < \frac{2}{\lambda_{max}} \tag{6}$$

where λ_{max} is the input autocorrelation matrix **R** with the largest eigenvalue, used to guarantee stability. The trace of **R** (sum of the eigenvalues) is used instead of λ_{max}. Therefore, the value of step-size is within $0 < \mu < \frac{2}{tr\,(\mathbf{R})}$. The tr (**R**)=$||x(n)||^2$ is related to the power of the *x(n)*. The well-known step size is obtained as;

$$0 < \mu < \frac{2}{\|\mathbf{x}(n)\|^2} \tag{7}$$

In this case, the step-size μ is inversely proportional to the power of the input signal. Accordingly, when the power of the input is high, the step size is imposed to a small value, on the other hand, when the power of the input is low the step size becomes large. This relationship enables normalizing the step-size of the LMS algorithm according to the input signal power. The normalized step-size provides a useful LMS-type algorithm, commonly known as normalized LMS (NLMS) algorithm [21].

The NLMS algorithm with normalized step-size term updates the weights vector as,

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \frac{\mu}{\mathbf{x}^T(n)\mathbf{x}(n) + \epsilon}\mathbf{x}(n)e_n \tag{8}$$

where the step-size is in the range 0.2. The importance of normalizing the step size is improving the convergence behaviour in the NLMS algorithm. So the algorithm becomes more powerful in non-stationary applications like speech recognition. In addition, the speed of convergence is improved to achieve the minimum steady-state MSE in fewer iterations [22].

Variable Leaky LMS Filter

The leaky LMS adaptive filter is a variant of the conventional LMS adaptive filter [20, 22], the leaky LMS was introduced to minimize the instantaneous objective function

$$J(n) = e^2(n) + \gamma\mathbf{w}^T(n)\mathbf{w}(n) \tag{9}$$

where *w(n)* is the N x 1 coefficient weight vector of the adaptive algorithm and γ is the leakage factor and $\gamma > 0$. The objective function has a unique minimum which is found recursively using the gradient method.

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{\mu}{2}\frac{\partial J}{\partial \mathbf{W}} = (1-\mu\gamma)\mathbf{w}(n) + \mu e(n)\mathbf{x}(n) \tag{10}$$

where μ is the stepsize. The input signal autocorrelation matrix is given by

$$R = Q \wedge Q^T \tag{11}$$

where $\wedge$ = *diag{λ_1,λ_2,…,λ_N}* is matrix eigenvalues and $0<\lambda_1 \leq \lambda_2 \leq \ldots \leq \lambda_N$ and Q is the matrix of the eigenvectors of *R*. The error is given by

$$e(n) = d(n) - \mathbf{w}(n)^T\mathbf{w}(n) \tag{12}$$

where $\mathbf{w}(n)=[\mathbf{w}_{(0,n)}\ \mathbf{w}_{(1,n)} \ldots \mathbf{w}_{L-1,n}]^T$ is the L-dimensional coefficient vector, $\mathbf{X}_n=[\mathbf{x}_n \ldots \mathbf{x}_{n-L+1}]^T$ is the input signal vector, *d(n)* is desired response, *e(n)* is the error, μ is the step size, and γ is the leakage parameter. When $\gamma = 0$ the above will represent the conventional LMS adaptive filter.

Variable Step Size LMS Algorithm

The adaptive problem, in this case, is to adjust the filter weights to obtain an acceptable desired signal. The aim is to use an adaptively varying step size [7]. In this case, the LMS algorithm is a gradient search algorithm which computes the weights *w(n)* required to minimize the Mean square error *e(n)*. The equations representing the algorithm are given by

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)\mathbf{x}(n)e(n) \tag{13}$$

where

$$e(n) = d(n) - x(n)^T\mathbf{w}(n) \tag{14}$$

where *μ(n)* is the step size. In this case, *μ(n)* is time-varying and its value is determined by the number of sign changes of the error surface gradient estimate [8] given by

Table 1. Test results for signal corrupted with office noise using system identification filter configuration

Algorithms/ Indices	NLMS algorithm	VLLMS algorithm	VSSLMS algorithm
μ	0.05	0.05	0.99
γ	-	0.00005	0.00005
α	-	-	0.5
MSE (31750)	0.0079	0.0008	0.0003
MSE	0.0004	0.00041	0.00035
SNR	24.3973	20.0557	29.2884

$$\mu'(n+1) = \alpha\mu(n) + \gamma e_n^2 \tag{15}$$

With 0< α<1, γ>0 and

$$\mu(n+1) = \begin{cases} \mu_{max} & if\ \mu'(n+1) > \mu_{max} \\ \mu_{min} & if\ \mu'(n+1) < \mu_{min} \\ \mu'(n+1) & otherwise \end{cases} \tag{16}$$

where 0 < μ_{min} <μ_{max}. In this scenario the initial step size μ_0 is usually taken as μ_{max}, however, the algorithm is not affected by the choice. It is clear that the step size $\mu(n)$ is positive and is controlled by the predicted error value and the parameters α and γ. The constant μ_{max} is usually selected to ensure that the MSE is bounded, this is usually within

$$\mu_{max} \leq \frac{2}{3tr\,(\mathbf{R})} \tag{17}$$

μ_{min} is chosen to guarantee a minimum tracking ability.

Experimental Results

Filtering Test of Signal Corrupted with Office Noise

In this section, we evaluate the performance of each algorithm in noise cancellation as shown in Figure 1 Test results for signal corrupted with office noise using system identification filter configuration. The original signal used in the test is corrupted with office noise as given in Figure 3, while Figure 4 shows the decoded signal. The number of iteration was set to 200 for all the tests carried in this section. The signal is then processed as in Figure 1. The order of the filter M =16. Table 1, present the algorithm parameters including the step size which is calculated using the algorithms relevant equation, Figure 5 shows the filtered signal of all three algorithms against the original signal. The error behavior of the three algorithms is given in Figure 6 for all three algorithms.

The results of this work show that the VSSLMS obtained the best performance in term of the test indices, where the VSSLMS results are (SNR=29.2884, MSE=0.00035), this compared to the worst results obtained by the VLLMS (SNR =20.0557, MSE=0.00041).

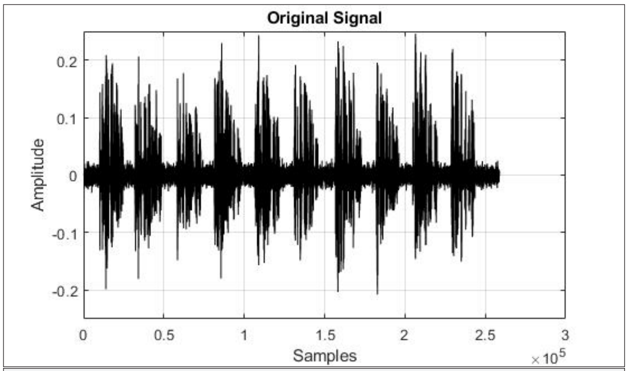

Figure 3. Original signal

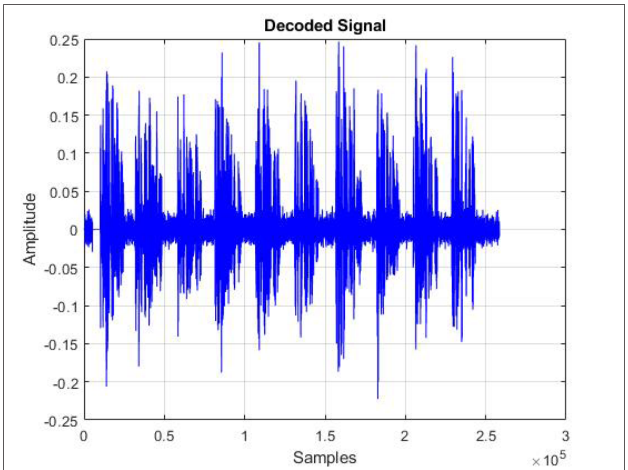

Figure 4. Decoded signal

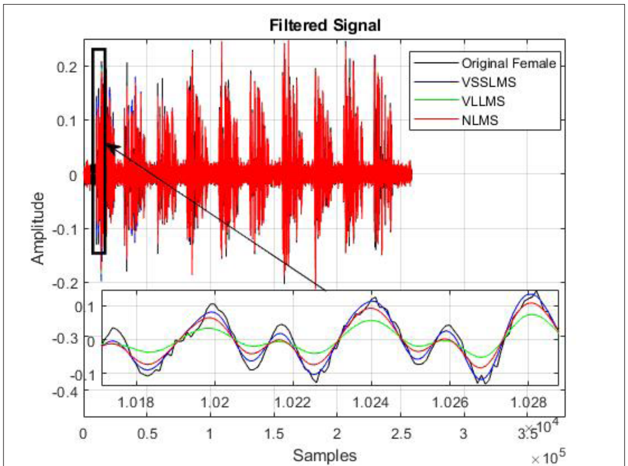

Figure 5. Filtered Signal of NMLS, VLLMS, and VSSLMS algorithms

Figure 5 filtered output signal of all three algorithms, it can be seen that the VSSLMS algorithm has outperformed the other

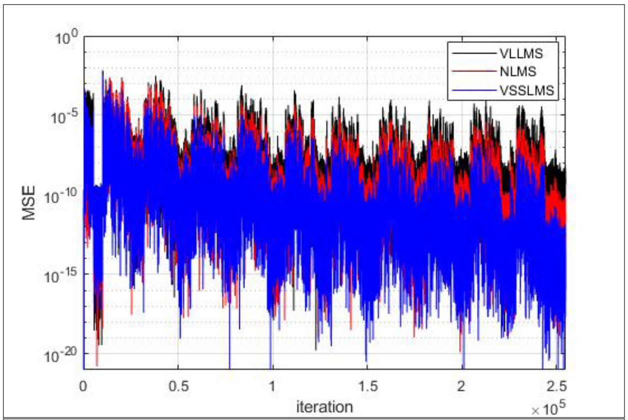

Figure 6. Noise convergence for NLMS, VLLMS, and VSSLMS algorithms

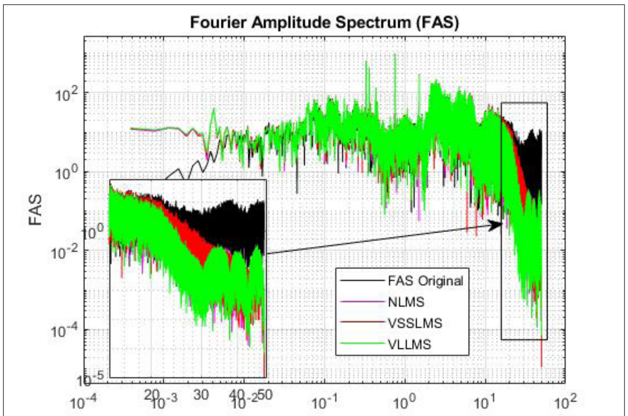

Figure 7. Amplitude spectrum of NLMS, VLLMS, and VSSLMS algorithms

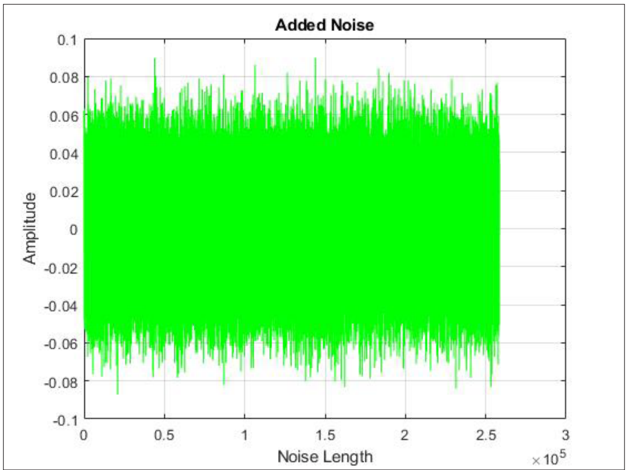

Figure 8. Additive void gaussian noise

algorithms, as it managed to converge much faster and track the original signal within 1.018e^{+04} samples in comparison to the NLMS algorithms which started to track the original signal after 1.023e^{+04} samples, while the VLLMS algorithm continued to have difficulty tracking the original signal.

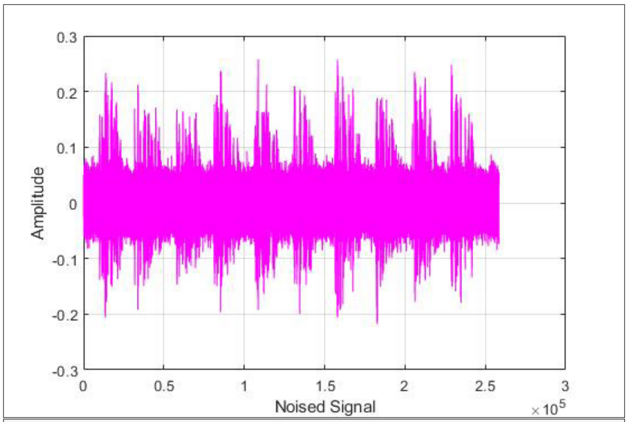

Figure 9. Original signal plus noise (c)

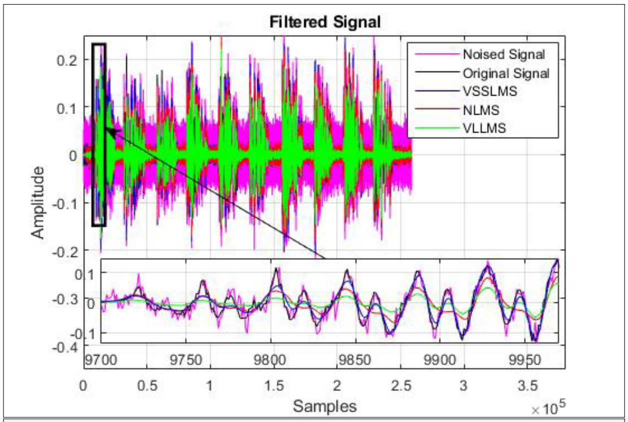

Figure 10. Filtered Signal of NMLS, VLLMS, and VSSLMS algorithms against noise injected signal

Figure 6 confirms the results obtained in Figure 5, as it shows that the VSSLMS algorithm achieved steady-state error at 1.576e + 04 sample, while the NLMS algorithm achieved the steady-state error at 4.076e + 04 sample. However, it can also be seen from Figure 6 that the VLLMS algorithm struggled to achieve the steady-state error.

Figure 7, the Fourier Amplitude spectrum of the out signals of the filters, concludes that the VSSLMS algorithm output at both the low and high frequency (cutoff region) is very close to the original signal while the VLLMS output is the furthest away from the original signal.

Filtering Test of Signal Injected with additive void gaussian noise

In this test, we evaluate the performance of each algorithm in noise cancellation as shown in Figure 2. The original test signal is injected with an additive void gaussian noise σ^2=0.02, Figure 8 shows the noise signal and Figure 9 depicts the output noise injected signal, this noise is used in addition to the office noise. The number of iterations was set to 200 for all the tests carried out in this section. The order of the filter M = 16. Table 2 presents the algorithm parameters including the

Table 2. Test results for signal Injected with noise using noise cancellation

Algorithms/ Indices	NLMS algorithm	VLLMS algorithm	VSSLMS algorithm
μ	0.0005	0.05	0.9
γ	-	0.002	0.8
α	-	-	0.9
MSE (31750)	2.421e-08	2.879e-08	9.363e-11
MSE	7.596e-14	3.25e-10	3.651e-15
SNR	2.9626	0.5184	3.7739

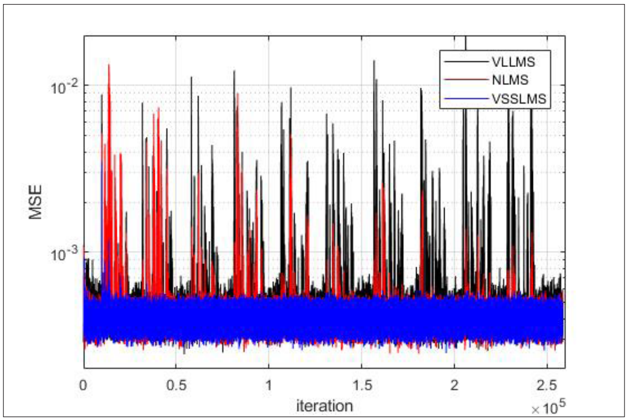

Figure 11. Error convergence behavior

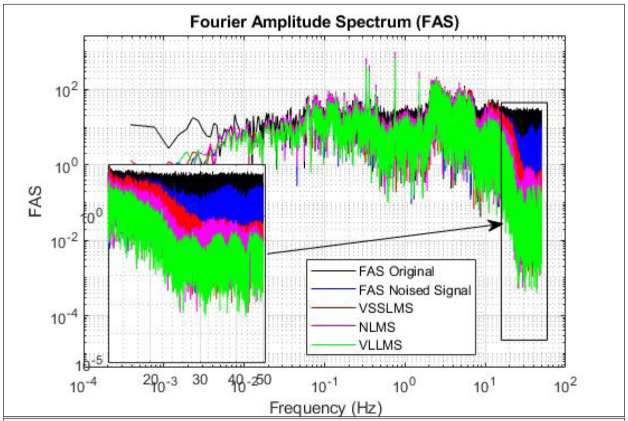

Figure 12. Amplitude spectrum of NLMS, VLLMS, and VSSLMS algorithms

step size μ_k which is calculated using the algorithm relevant equation. The order of the filter M =16. Table 2, present the algorithm parameters including the step size *μ(n)* which is calculated using the algorithms relevant equation, Figure 10 shows the filtered signal of all three algorithms against the original signal. The algorithms error behavior of the three algorithms is as given in Figure 11.

The results obtained in this work show that the VSSLMS obtained the best performance in terms of test indices where the VSSLMS results are (SNR=3.7739,MSE=3.651e-15), this compared to the worst results obtained by the VLLMS (SNR=0.5184,MSE=3.25e-10).

From Figure 10 filtered output signal of all thee algorithms, it can be seen that the VSSLMS algorithm has outperformed the other algorithms, as it managed to converge much faster and track the original signal within samples in comparison to the NLMS algorithms which started to track the original signal after samples, while the VLLMS algorithm continued to have difficulty tracking the original signal

Figure 11 confirms the results obtained from Figure 5 as it shows that the VSSLMS algorithm achieved steady-state error at 2.243e+04 sample, while the NLMS algorithm achieved the steady-state error at 1.849e+05 sample. However, it can also be seen from Figure 6 that the VLLMS algorithm struggled to achieve the steady-state error.

From Figure 12, the Fourier Amplitude spectrum of the out signals of the filters, it confirms the results obtained in the first test with low noise input signal, where the VSSLMS algorithm output at both the low and high frequency (cutoff region) is very close to the original signal while the VLLMS output is the furthest away from the original signal.

Conclusion

In this paper, a family of variable step-size LMS adaptive algorithms effectiveness in VOIP applications was investigated. It is clear that convergence time (number of iterations) and MSE are of high importance in this type of application, in some cases a compromise between the requirement the two-parameter is taken into consideration when choosing a suitable algorithm as the delay (number of iteration) is the main factor in this case. The results showed that the VSSLMS outperformed the other algorithms as it managed to track the original signal and produced the minimum MSE and the least number of iteration. The step size equation used in this algorithm resulted in an MSE of 0.00035 for signal with office noise and MSE of 3.651e-15 for the test with additive noise. The results show that the VSSLMS has better convergence with lower computational complexity.

Peer-review: Externally peer-reviewed.

Conflict of Interest: The authors have no conflicts of interest to declare.

Financial Disclosure: The authors declared that this study has received no financial support.

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