University of Baghdad
College of Engineering
JOURNAL OF ENGINEERING

**Journal of Engineering**
journal homepage: www.jcoeng.edu.iq
Number 5 Volume 24 May 2018

***Electrical, Electronics and communications, and Computer Engineering***

# Performance enhancement of Echo Cancellation Using a Combination of Partial Update ( PU) Methods and New Variable Length LMS (NVLLMS) Algorithm

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## ABSTRACT

In this paper, several combination algorithms between Partial Update LMS (PU LMS) methods and previously proposed algorithm (New Variable Length LMS (NVLLMS)) have been developed. Then, the new sets of proposed algorithms were applied to an Acoustic Echo Cancellation system (AEC) in order to decrease the filter coefficients, decrease the convergence time, and enhance its performance in terms of Mean Square Error (MSE) and Echo Return Loss Enhancement (ERLE). These proposed algorithms will use the Echo Return Loss Enhancement (ERLE) to control the operation of filter's coefficient length variation. In addition, the time-varying step size is used.The total number of coefficients required was reduced by about 18% , 10% , 6%, and 16% using Periodic, Sequential, Stochastic, and M-max PU NVLLMS algorithms respectively, compared to that used by a full update method which is very important, especially in the application of mobile communication since the power consumption must be considered. In addition, the average ERLE and average Mean Square Error (MSE) for M-max PU NVLLMS are better than other proposed algorithms.

**Keywords**: Partial Update, LMS, Echo Cancellation, Variable Length, Variable Step Size, Echo Return Loss Enhancement (ERLE).

# تحسين أداء منظومة الغاء الصدى باستخدام مجموعة من الخوارزميات المدمجة بين خوارزميات التعديل الجزئي مع خوارزمية اقل معدل للتربيع متغيرة الطول

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## الخلاصة

يتناول هذا البحث اقتراح مجموعة من الخوارزميات التي تدمج مابين خوارزميات التعديل الجزئي للمعاملات مع خوارزمية اقل معدل للتربيع ذات الطول المتغير والتي سبق وان تم اقتراحها. عند تطبيق هذه الخوارزميات على منظومة الغاء الصدى المتكيفة تم الحصول على تحسين في اداء المنظومة من حيث تقليل عدد المعاملات ( طول المعاملات ) المستخدمة و زيادة سرعة تقارب عمل

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Peer review under the responsibility of University of Baghdad.
https://doi.org/10.31026/j.eng.2018.05.05

المنظومة وتقليل معدل مربع اشارة الخطاء وكذلك زيادة في خسارة اشارة الصدى . أن تقليل طول ( عدد) المعاملات المستخدمة في عملية التحديث سيسهم في تقليل القدرة المستهلكة والتي تعتبر عامل مهم جدا في التطبيقات الحديثة وخاصة في اجهزة الاتصال المتنقلة . اثبتت نتائج المحاكاة ان نسبة تقليل عدد المعاملات تراوحت مابين 6% الى 18% باستخدام الخوارزميات المقترحة كذلك اثبتت النتائج ان أداء الخوارزمية المقترحة المسماة بالـ ( M-max PU NVLLMS) افضل من بقية الخوارزميات المقترحة من حيث اقل معدل لمربع اشارة الخطاء وكذلك نسبة خسارة اشارة الصدى.

**الكلمات الرئيسية:** التحسين الجزئي، الغاء الصدى، الطول المتغير، سعة الخطوة المتغيرة، تحسين خسارة رجوع الصدى، LMS

## 1. INTRODUCTION

Several adaptive filtering applications like an adaptive echo cancellation and channel equalization require huge taps length (or weight coefficient numbers) which leads to increase of power consumption, memory, and computation. Moreover, it is sometimes impractical for mobile units, **Mahesh and Alfred, 2005**.

Two methods are used to reduce the computation of adaptive filter; the first one is the Partial-Update (PU) adaptive filtering method which updates part of the coefficient vector instead of updating the entire filter vector, **Bei, and Tamal, 2010.** The PU methods like periodic, sequential, stochastic and M-max can be applied to the Least Mean Square (LMS) algorithm which generate so-called PU LMS algorithm, **Bei and Tamal, 2010.**

There is another method used when reducing the power in the adaptive filter core is needed or dealing with the limitation on hardware, **Santillo, et al., 2009.** This method is the Variable Length VL with LMS algorithm (VLLMS) which is used to decrease the total length of adaptive filter when the system is heavily constrained in power, memory and computation requirements for use in mobile wireless applications **Santillo, et al., 2009.**

In this work, the PU LMS methods (periodic, sequential, stochastic and M-max) and our previously proposed algorithm "New Variable Length LMS NVLLMS" **Jamel and Hamood, 2016,** are combined to get a new set of proposed algorithms.Such that we will get Periodic PU NVLLMS, Sequential PU NVLLMS, Stochastic PU NVLLMS, and M-max PU NVLLMS algorithms. Each proposed algorithm updates both the total length of the adaptive filter (N) and the PU coefficients (M; the number of coefficients to be updated at each iteration). These algorithms are implemented using Echo Return Loss Enhancement (ERLE) to control the operation of variation. The total number of coefficients required was reduced compared to that used by the full update method.

## 2. ACOUSTIC ECHO CANCELLATION ( AEC)

**Fig.1** shows an acoustic echo canceller, which tries to model the path of the loudspeaker to the microphone by an adaptive FIR filter. As a result, the AEC to be effective, it has the task of estimating the echo path and keeping track of changes in this path, **Stefan**, **et al., 2002**, **Dogancay, 2008.** As shown in this figure, the input signal $x(k)$ is the far end signal that played over the loud speaker, $d(k)$ is the microphone signal which is consists of the near end signal $v(k)$, the echo signal $y(k)$ and $r(k)$ which stands for the noise signal. Then the microphone signal is expressed as, **Khong, at el., 2008**:

$$d\,(k) = y(k) + v(k) + r(k) \tag{1}$$

Where $k$ is the time index . The echo estimate signal will be

$$y^{\wedge}(k) = \widehat{\boldsymbol{h}}^T(k)\, x(k) \tag{2}$$

The microphone signal is subtracted from the echo estimate signal $\hat{y}(k)$ which is produced by the adaptive filter with a finite impulse response $\boldsymbol{h}(k)$, the result of the subtraction is the desired speech signal $e(k)$ **, Zhixin 2011.**
Only near-end signal is enhanced when the echo signal is canceled successfully and the output signal will be the echo-canceled signal, **Mark and Ho, 2002.** The echo-cancelled outgoing signal is:

$$e(k) = d(k) - y^{\wedge}(k) \tag{3}$$

Where $e(k)$ is the output signal for the AEC scheme that is used for adapting the weights or impulse response of the FIR filter by suitable adaptive algorithm. One of the important parameters of AEC is called Echo Return Loss Enhancement (ERLE) which is a measure of the effectiveness of an echo cancellation system, it can be calculated by taking the ratio between echo power before and after echo cancellation. It can be calculated by **Oyerinde and Mneney, 2009 , Nguyen, 2007 , and Patrick and Andy , 2004** :

$$ERLE = 10log\left(\frac{E[y^2(k)]}{E[e^2(k)]}\right) dB \tag{4}$$

## 3. PARTIAL UPDATING ALGORITHM CONCEPT

The PU is very suitable for applications like echo cancellation and channel equalization since it needs a long filter. **Fig.2** shows an adaptive filter operating under a resource constraint arising from the availability of a limited number of hardware multipliers for the adaptation process (i.e. It's the concept of PU method), **Mahesh and Alfred, 2005, Bei and Tamal, 2010, and Dogancay, 2008**. As shown in this figure the symbol M represents the number of partial update coefficients to be updated each iteration. While the symbol N represents the full band filter length.
This adaptive filter **Fig.2** used LMS algorithm which has the following updating weight coefficients:-

$$\boldsymbol{w}(k+1) = \boldsymbol{w}(k) + \mu\, e(k)x(k), \quad k = 0,1,2,\ldots \tag{5}$$

Where $\boldsymbol{w}(k)$ and $\boldsymbol{w}(k+1)$ represent current and next weight vector coefficients respectively, and μ is fixed step size .
PU adaptive filter usually updates $M \times 1$ coefficients instead of updating all the $N \times 1$ coefficients , where $N > M$. This can be accommodated by modifying the adaptation algorithm in the equation (5) to

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\, e(k)\boldsymbol{I}_M(k)\mathbf{x}(k), \quad k = 0,1,2,\ldots \tag{6}$$

where $\boldsymbol{I_M}(k)$ is a diagonal matrix with $M$ ones and $N-M$ zeros on its diagonal indicating which M coefficients are to be updated at iteration $M$ , **Mahesh and Alfred, 2005, Bei and Tamal, 2010, and Dogancay, 2008:**

$$\boldsymbol{I}_M = \begin{bmatrix} i_1(k) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & i_N(k) \end{bmatrix}, \sum_{j=1}^{N} i_j(k) = M \quad , \quad i_j(k) \in \{0,1\} \tag{7}$$

If $i_j(k) = 1,\ j = 1, \ldots, N,$ then the coefficient $w_j(k)$ gets an update at iteration k, otherwise it remains unchanged, **Huicui, et al. , 2011**.

In this paper, the PU methods are considered which including Periodic PU, Sequential PU, Stochastic PU, and M-Max update. Periodic PU is updating all the filter coefficients every S$^{th}$ iteration instead of every iteration. Sequential PU updates filter coefficient subsets. The (M-max) is another tap selection update in which the largest magnitude elements of the regression vector are updated at each iteration. The last method presented in this work is the Stochastic PU which chooses coefficients subsets randomly**, Bei and Tamal, 2010, and Stefan**, **2002**.The basic concept of these pure PU methods and more details can be found in, **Dogancay, 2008.**

## 4. PROPOSED COMBINATION ALGORITHMS BETWEEN PU LMS METHODS AND NVLLMS ALGORITHM

A New Variable Length LMS ( NVLLMS) algorithm was proposed previously by, **Jamel and Hamood, 2016,** therefore, the concept of NVLLMS algorithm will not be presented here. This NVLLMS will be combined with PU LMS methods and take the following aspects into consideration:-

1) Different length of PU coefficients (variable M).
2) Different adaptive filter length (variable N) taking into consideration, such that the value of N must not exceed twice of the initial value which represents the number of tabs for the response $\boldsymbol{h}(k)$.
3) The step size will be varied as follows, **Jamel and Hamood, 2016:-**

$\mu_l(k+1) = \frac{\mu N_o}{N_l(k+1)},\ l = 1,2$ , Where $N_0$ is the initial filter length, $N_1, and\ N_2$ are the initial filter length of filter 1, and 2 respectively. $\mu$ is the step size parameter of filter1.

The new design of NVLLMS will be applied to AEC as shown in **Fig.3.**

The decision of the NVLLMS algorithm of changing the filter length will depend on ERLE. The system can work normally according to the following assumption:

1) When filter 1 and filter 2 produce the same value of ERLE, this means the length of filter 2 reached the optimum value, so there is no need to increase the length anymore.
2) It is possible to make use of three successive values of ERLE produced by filter 2 to control the length of the filter and this is shown in the following equations.

$$N_1(k+1) = N_1(k) + 1 \quad if\ ERLE_2(k) > ERLE_2(k-1) > ERLE_2(k-2)$$
$$and\ ERLE_2(k) - ERLE_1(k) > thr \tag{8}$$

Where the $thr$ value is set to an optimum value by trial and error method.

$$N_1(k+1) = N_1(k) - 1 \quad if\ ERLE_2(k) < ERLE_2(k-1) < ERLE_2(k-2) \tag{9}$$

$$N_1(k+1) = N_1(k) \quad otherwise \tag{10}$$

Then the other filter length variation $N$ is done after counting $N_1$ as follows:

$$N_2(k+1) = N_1(k+1) + 1, \tag{11}$$

While the value of M is updated when the system fails to converge or becomes unstable, and that happens when the value of average error for a block is greater than the previous block **Jamel and Hamood, 2016** .

$$M(k+1) = \begin{cases} M(k) + \text{update size}, & if \text{ system fail to converge or unstable} \\ M_0 & if \quad M(k) = N - \text{update size} \\ M(k), & otherwise \end{cases} \tag{12}$$

Where $M_0$ is the initial value of .

In order to explain the main idea of the proposed algorithm, **Fig.4** shows the ERLE curves of filter 1 and 2 in NVLLMS configuration and explains how to make use of this curve to control the length of the filter based on previous equations.

It is possible to increase the system speed by choosing a specific number of iterations to make the comparison (i.e. The comparison is done for each block and not for each iteration) the block size can be set by the user. It's worse to mention that increasing the number of iterations on each block size will increase the accuracy, but it will slow the system down. On the other hand, choosing a large block size will speed the system up but decrease the accuracy, so the block size has to be chosen carefully.

## 5. SIMULATION METHODOLOGY

The computer simulation of normal PU LMS and NVLLMS algorithms, based on the adaptive echo cancellation structure shown in **Fig.1** will be shown in this section. The filter length (number of tabs) is equal to 400 ( i.e. 0.05 Sec duration), because the impulse response of the room (the echo path $\boldsymbol{h}(k)$) which is shown in **Fig.5** is strongly decayed after iteration equal to 400, and also to make the simulation simpler. The far-end speech signal x used as the input of the adaptive FIR filter shown in **Fig.6a**, this signal sampled with 8 kHz. The far-end speech signal convolved with h to produce the far-end echoed speech signal as shown in **Fig.6b.** The summation of the near- end speech signal v shown in **Fig.6.c** and the far-end speech signal produce the microphone signal d which is shown in **Fig.6d.** Both the far-end and near-end speech signals were 30 Sec in duration. The step size was taken equal to 0.32. The signal (near end signal) to the Echo signal (far end and echo signal) is equal to -2.1926 dB for all simulation results. Noise signal r(k) is white Gaussian noise with zero mean and variance one. Echo path is 2th order low pass digital Chebyshev filter.

## 5.1. Results of NVLLMS With Full Update LMS

The simulation results of AEC for the case of the full update are shown in **Fig.7** which shows that the performance of NVLLMS is close to that of the normal full update LMS, but with fewer of filter coefficients ( 278 taps length) as shown in **Fig.8,** which corresponding to 31% reduction of total length.

**Fig.8** shows that the final filter length is 278 which is less than the case of full update (400) and that represented a benefit since the optimal length will reduce the consumed power. Moreover, the curve also shows that the variation happens only when there is an echo.

The ERLE for both cases full update and NVLLMS algorithms is shown in **Fig.9** which shows that the case of NVLLMS is better than the normal LMS as illustrated in **Table 1**. **Fig.10** shows the step size variation in time is same as the variation of the length and the step size is variable when there is an echo.

## 5.2. Results of New Sets of Propose Algorithms

The simulation of combination of NVLLMS and pure PU LMS methods will be presented in this section. The number of updates coefficients will be taken as follows: Periodic PU S= 4, Sequential PU M=100, Stochastic PU M=100, M-max PU M=100.

### 5.2.1 Periodic PU NVLLMS algorithm

**Fig. 11** and **Fig.12** show the outputs of AEC and the ERLE for pure Periodic PU LMS and the Periodic PU NVLLMS respectively. It is clear that the performance of Periodic PU NVLLMS is better than the pure Periodic PU LMS algorithm. Also, the number of total tabs required was 325 rather than 400, which corresponding to 18% reduction. Thus, better results were obtained using fewer tabs. **Fig.13** shows the filter length variation with time of Periodic PU NVLLMS.

### 5.2.2 Sequential PU NVLLMS algorithm

**Fig.14** shows the performance of AEC for pure Sequential PU LMS and the Sequential PU NVLLMS algorithms. The ERLE for both methods is shown in **Fig.15.**

**Fig.14, Fig.15,** and **Fig.16** show that the results of the new algorithm are better than pure Sequential PU LMS algorithm and the proposed algorithm will need only 360 tabs, which corresponding to 10% reduction of full band filter coefficients length (400). The AEC in this method shows that it is able to remove the echo earlier than the pure Sequential PU LMS algorithm, but the ERLE for this method is lower than the Periodic NVLLMS.

### 5.2.3 Stochastic PU NVLLMS algorithm

**Fig.17** shows the AEC output for pure Stochastic PU LMS and Stochastic PU NVLLMS. **Fig.18** shows the ERLE of both the cases. The results in this case for Stochastic PU NVLLMS are better than pure Stochastic PU LMS, but this method used 375 tabs as shown in **Fig.19** which corresponding to about 6% reduction of full band filter coefficients length.

### 5.2.4 M-max PU NVLLMS algorithm

Finally, the output of AEC for pure M-max PU LMS and M-max PU NVLLMS algorithms for M=100 are presented in **Fig.20.** The ERLE for both cases is shown in **Fig.21,** which shows that the new algorithm is better in this case and the number of tabs used in M-max PU NVLLMS algorithm is 338 tabs **Fig.22**, which corresponding to 16% reduction of full band filter coefficients length.

The average of MSE and ERLE for all the algorithms are illustrated in **Table 1.**
**Table 1** shows that the best method for echo cancellation is the M-max PU NVLLMS since it produces higher ERLE and lower MSE compared with the other algorithms mentioned in **Table 1** when using M=100 but in other hands, this algorithm has 16% reduction in filter coefficients length.

## 6. CONCLUSIONS

The new sets of proposed algorithms have the advantage of reducing the total number of coefficients, by finding the optimum taps number, and at the same time, the system update part the total coefficients. The arrangement of proposed new algorithms for best reduction full-band filter coefficients length is NVLLMS ( 31%) Periodic PU NVLLMS (18%), M-max PU NVLLMS (18%), Sequential PU NVLLMS (10%), and the last one is Stochastic PU NVLLMS (6%).
In other hands, these proposed algorithms still have better performance compared with its correspond pure PU LMS algorithms in terms of filter length reduction, average ERLE, and MSE. The average ERLE and average Mean Square Error (MSE) for M-max PU NVLLMS are better than other proposed algorithms.

## 7. REFERENCES


- Bei. X. and Tamal B. 2010, *Partial Update EDS Algorithms for Adaptive Filtering*, IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), March, pp. 3750 - 3755.
- Dogancay K. 2008, *Partial-Update Adaptive Signal Processing*, Elsevier Academic Press, Burlington.
- Huicui L., Xiaoping Li. and Lining G., 2011, *Variable Length LMS Adaptive Filter for Carrier Phase Multipath Mitigation*, GPS Solutions January 2011, Volume 15, Issue 1, pp 29–38.
- Jamel and Hamood. 2016, *A New Variable Length LMS Algorithm for Partial Update Adaptive Filtering Driven by Cyclostaionary Signal*, in International Journal of Computing and Digital Systems ( IJCDS), Vol. 5, Sep. issue 5,pp 411-419
- Khong A. W. H., Gan W.-S. and Naylor P. A. 2008, *A Low Complexity Fast Converging Partial Update Adaptive Algorithm Employing Variable Step-Size for Acoustic Echo Cancellation*, IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Vol. 5, April, pp. 237 - 240.
- Mahesh G. and Alfred O. H. 2005, *Partial Update LMS Algorithms*", IEEE Transactions on Signal Processing, Vol. 53, July, No. 7, pp. 2382 - 2399.

- Mark R. and Ho K.C. 2002, *Limits on Echo Return Loss Enhancement on a Voice Codes Speech Signal*, IEEE Midwest Symposium on Circuits and Systems, August, Vol. 2, pp. II-152 – II-155.
- Nguyen T, Leis T., John W. and Xiang W. 2007, *An improved error estimation algorithm for stereophonic acoustic echo cancellation systems.* In: ICSPCS 2007: 1st International Conference on Signal Processing and Communication Systems, 17-19 Dec, Gold Coast, Australia.
- Oyerinde O. O. and Mneney S. H. 2009, *Variable Step Size Algorithm for Network Echo Cancellation*, Electronic and Computer Engineering, University of KwaZulu-Natal, South Africa, UbiCC Journal, August, Vol. 4.
- Patrick A. N. and Andy W.H. K., 2004, *Affine Projection and Recursive Least Squares Adaptive Filters Employing Partial Updates*", IEEE Conference of the Signals, Systems, and Computers, November, Vol. 1, pp. 950 – 954.
- Santillo M. A., Amato A. M. D. and Berstein D. S. 2009, *System Identification using a Retrospective Correction Filter for Adaptive Feedback Model Updating*, IEEE American Control Conference (ACC '09), June, pp. 4392 - 4397.
- Stefan G. F., Rainer M. and Peter J. 2002, *A Psychoacoustic Approach to Combined Acoustic Echo Cancellation and Noise Reduction*, IEEE Transaction on Speech and Audio Processing, Vol. 10, July, pp. 245 - 256.
- Zhixin Ch. 2011, *Design and Implementation on a Sub-Band based Acoustic Echo Cancellation Approach*, IJACSA, Vol. 2, No. 6, pp. 43 - 48.

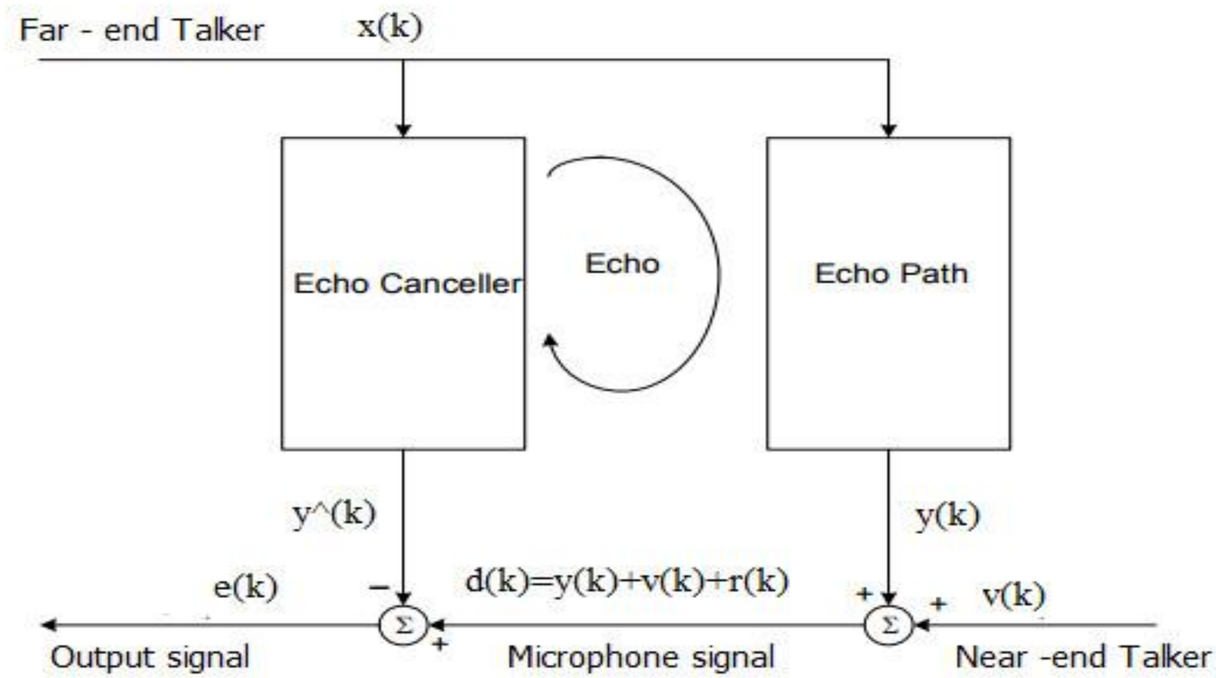


**Figure 1.** A Basic Echo Canceller**.**

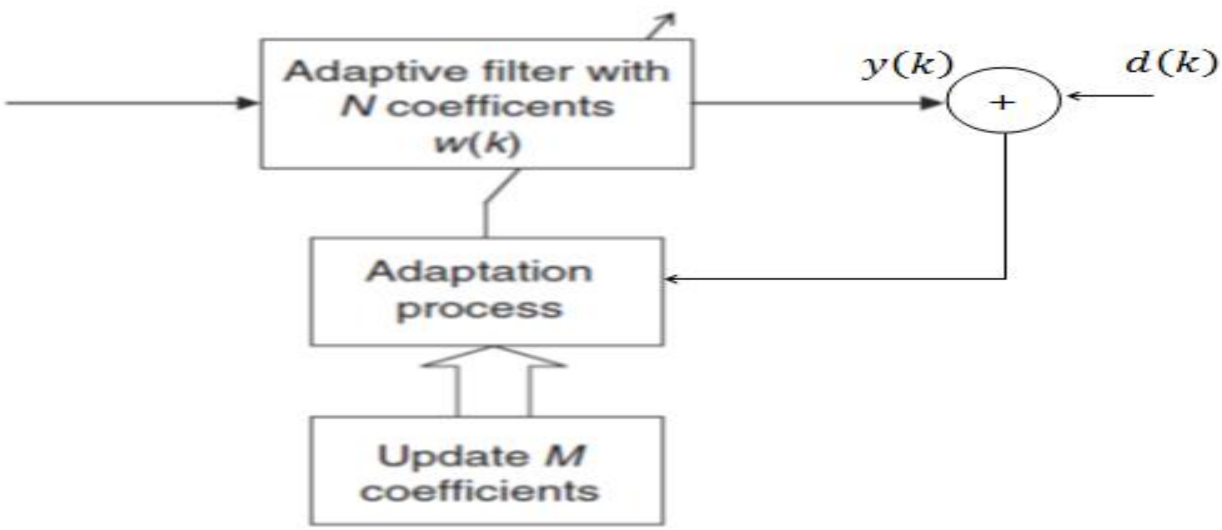


**Figure 2.** An adaptive filter with a limited number of coefficients to be updated, **Dogancay, 2008**.

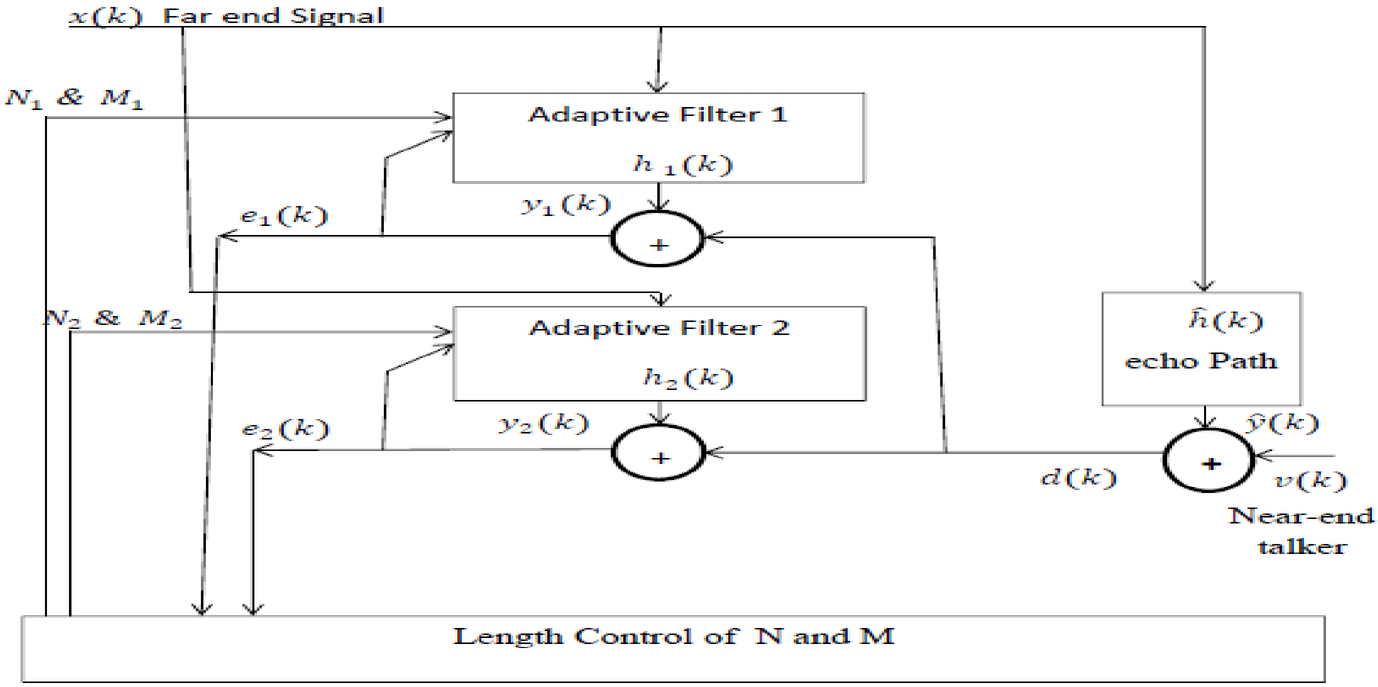


**Figure 3.**The NVLLMS filter configuration for echo cancellation with variable N and M.

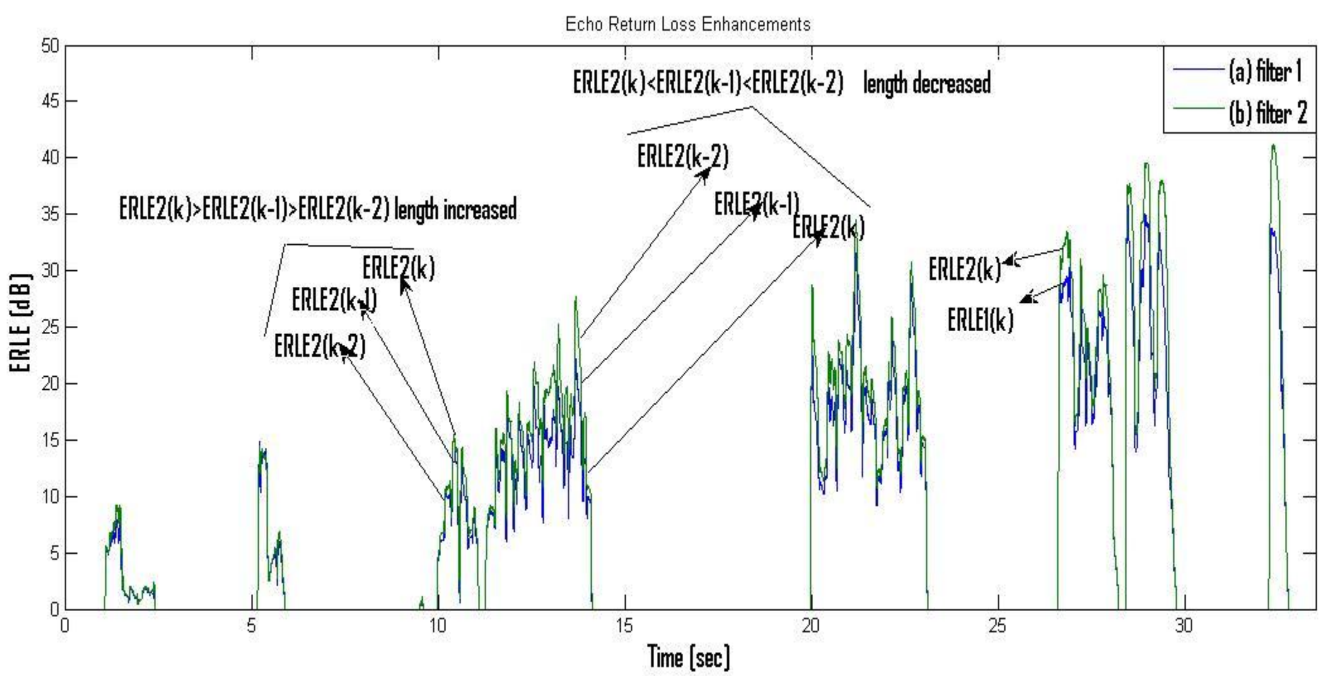


**Figure 4.** ERLE of filter 1 and 2 and the operation of length control.

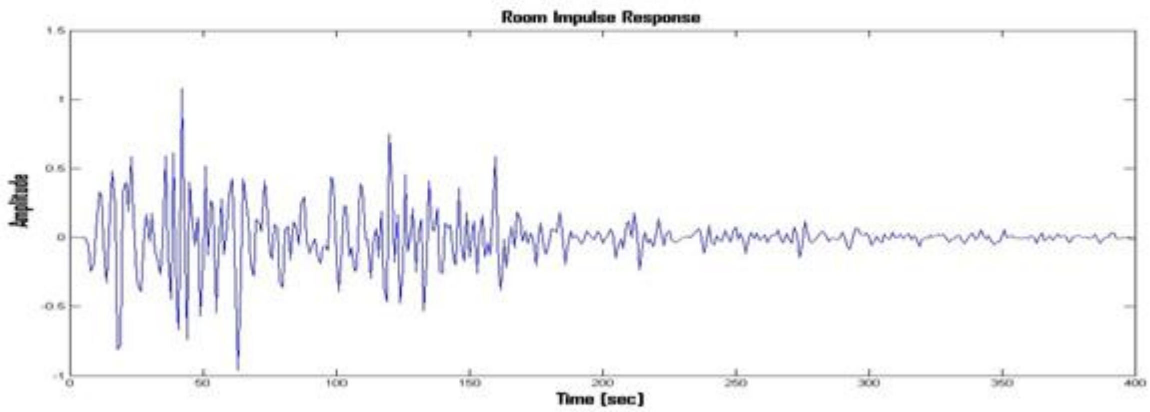


**Figure 5.** The impulse response of the room ( $\boldsymbol{h}(k)$).

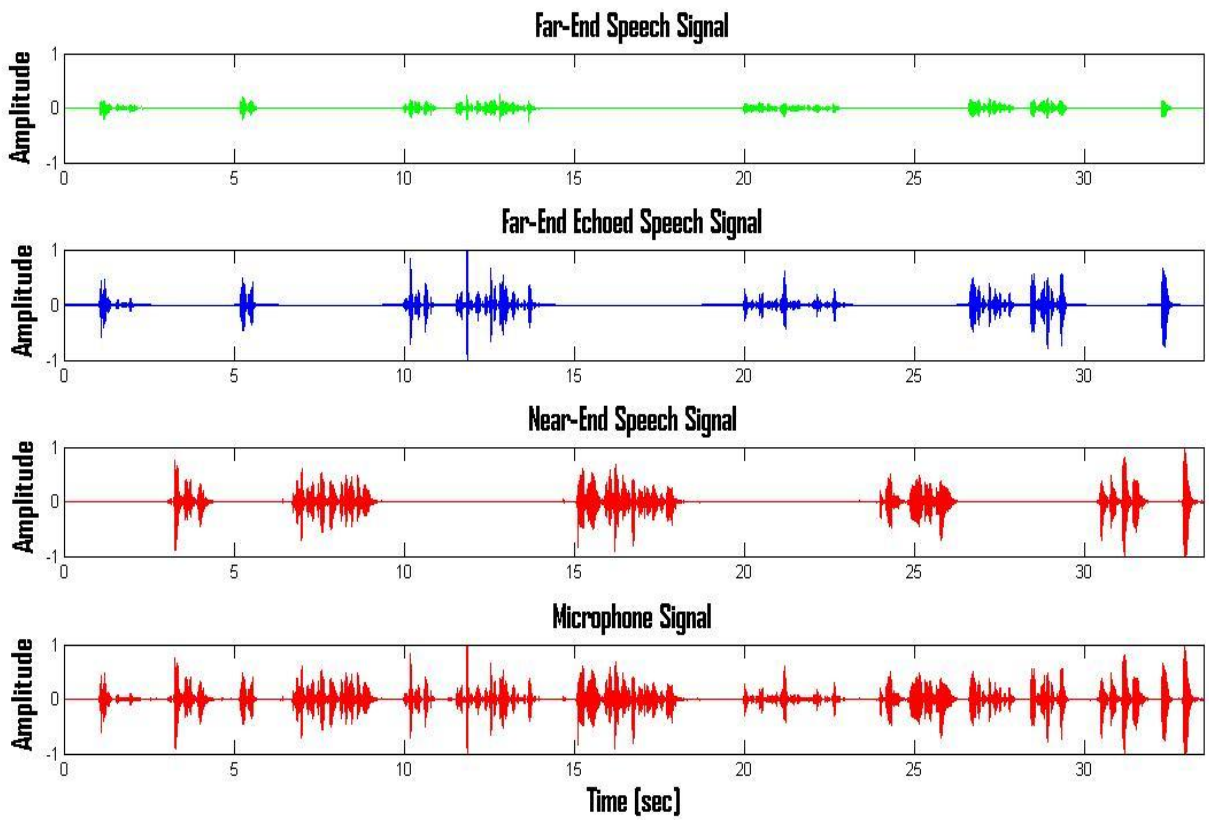


**Figure 6.** a: Far end speech signal; b: Far end echoed speech signal; c: Near end speech signal; d: Microphone signal.

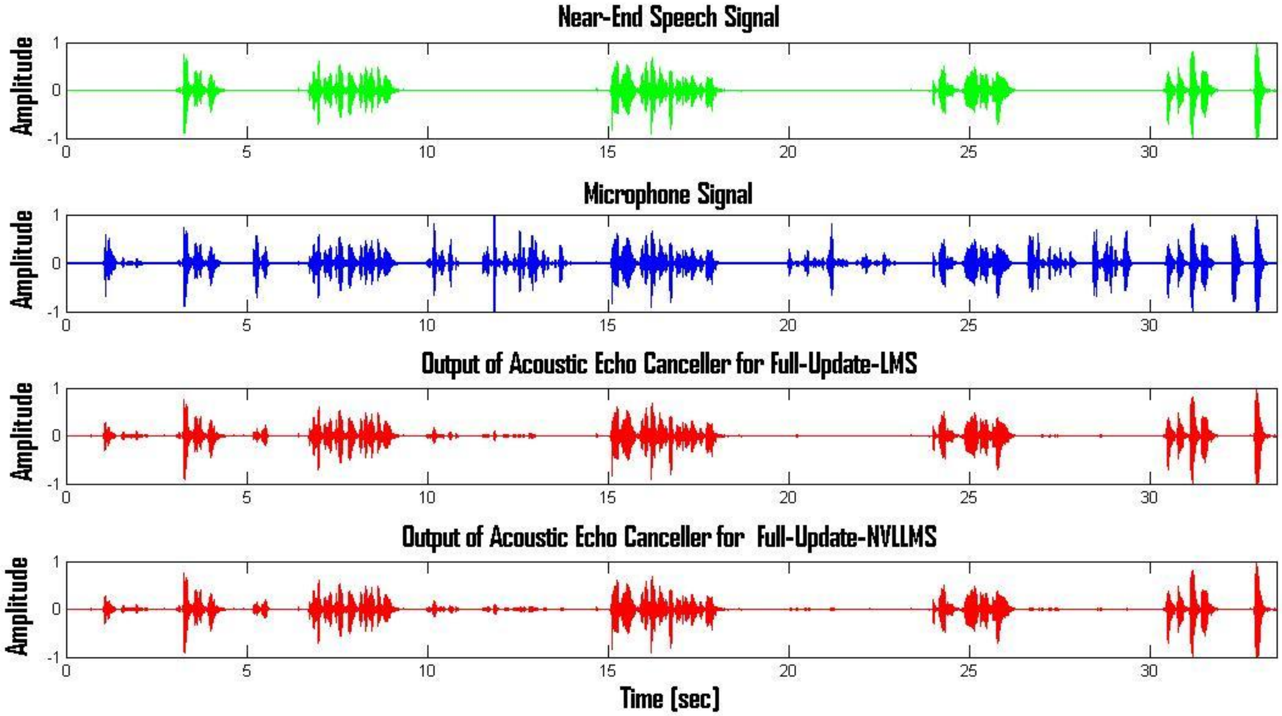


**Figure 7.** AEC of NVLLMS and full update LMS.

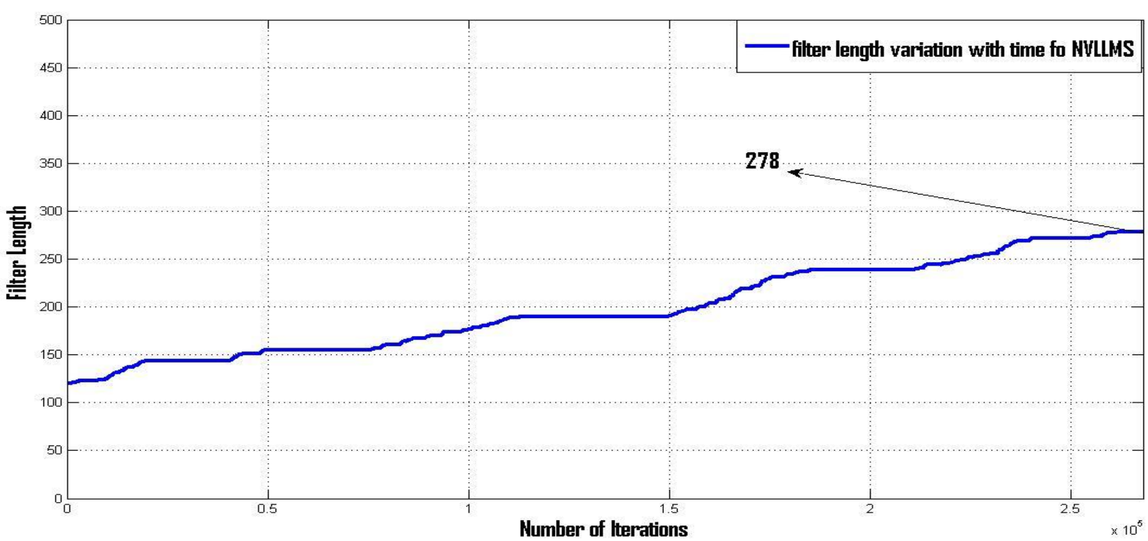


**Figure 8.** Filter length variation with time using NVLLMS algorithm

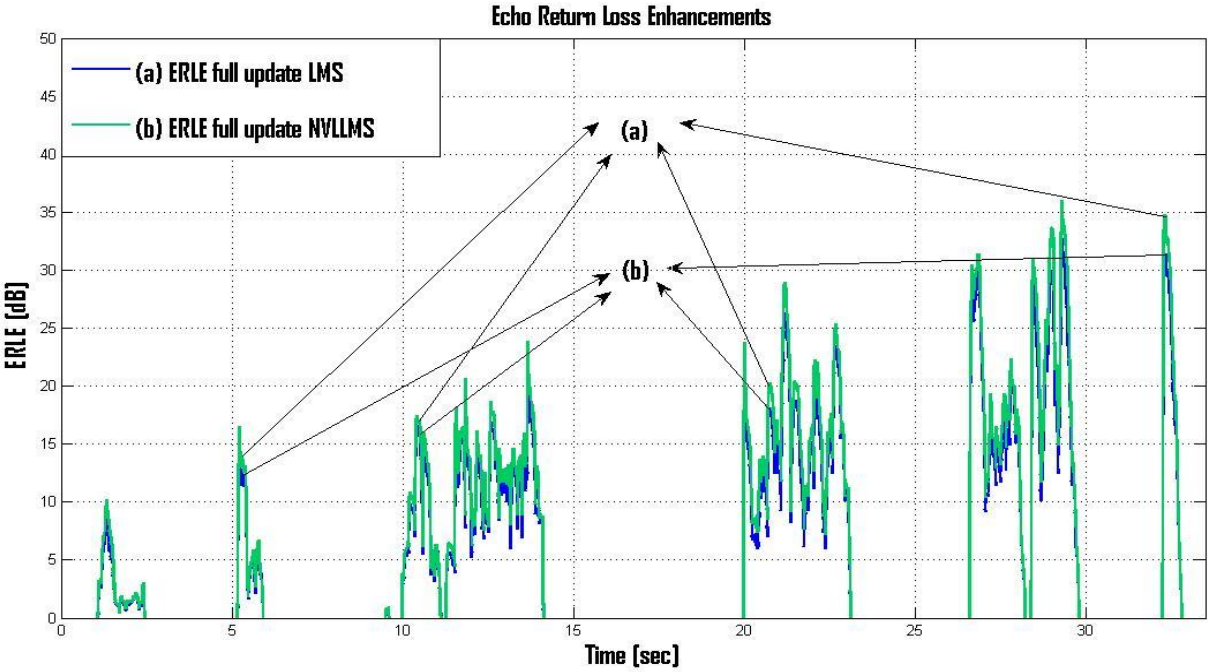


**Figure 9.** ERLE of full update LMS and NVLLMS.

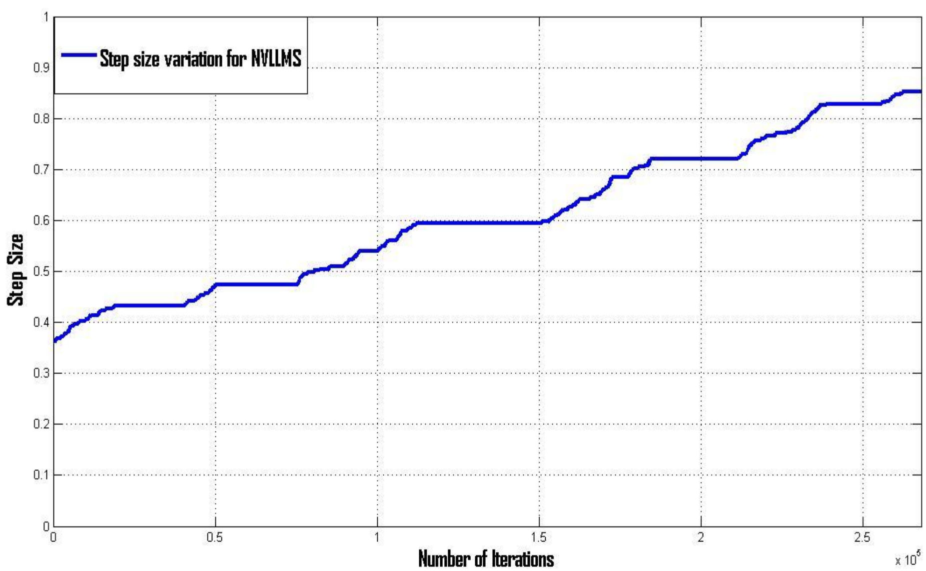


**Figure 10.** Step size variation with time of NVLLMS algorithm.

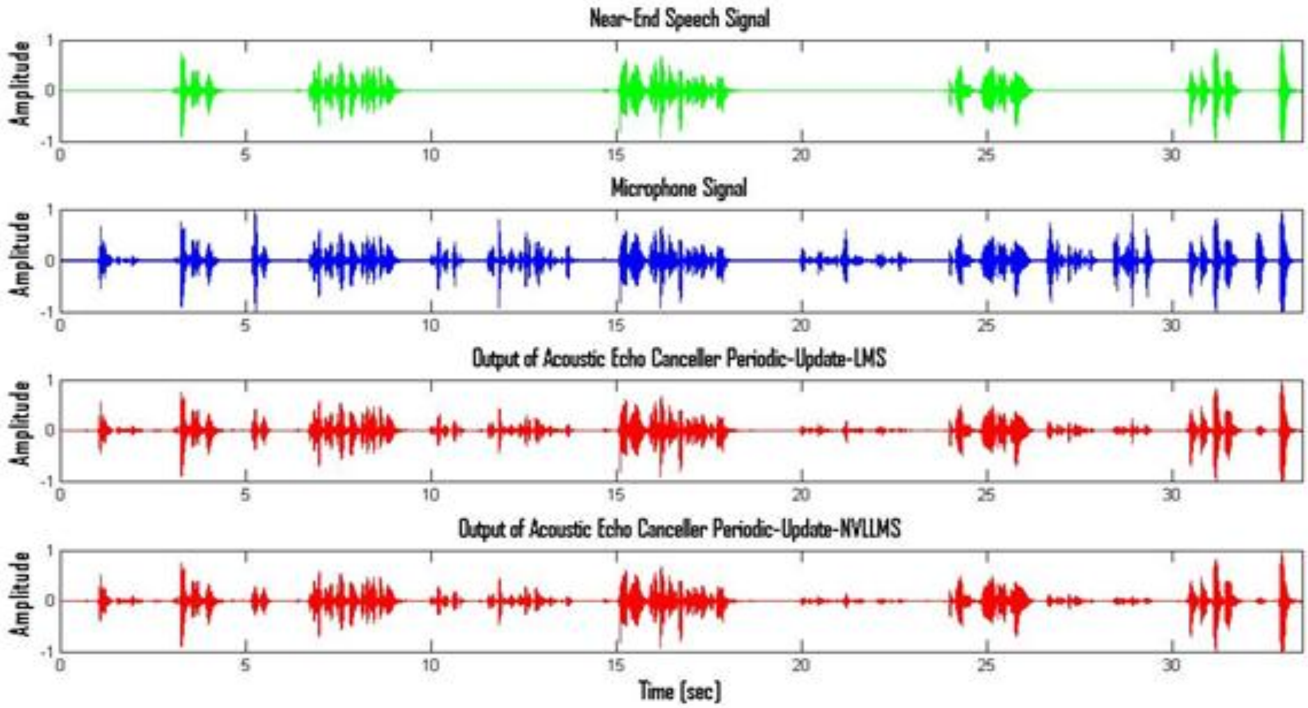


**Figure 11.** AEC of Periodic PU NVLLMS and pure Periodic PU LMS.

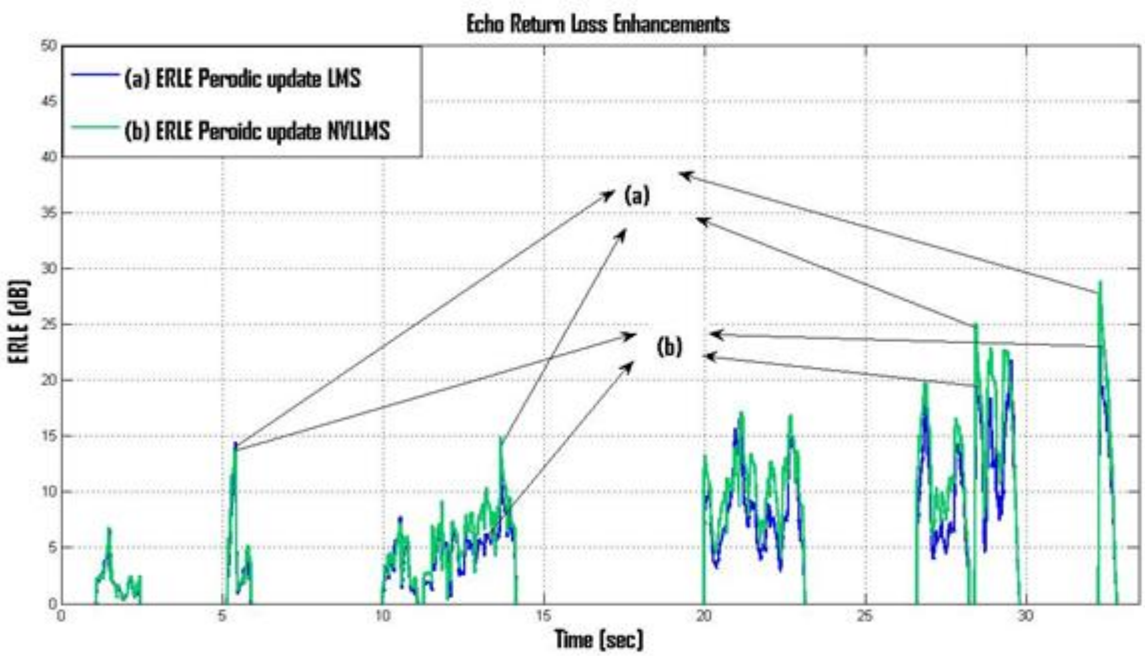


**Figure 12.** ERLE of pure Periodic PU LMS and Periodic PU NVLLMS algorithms.

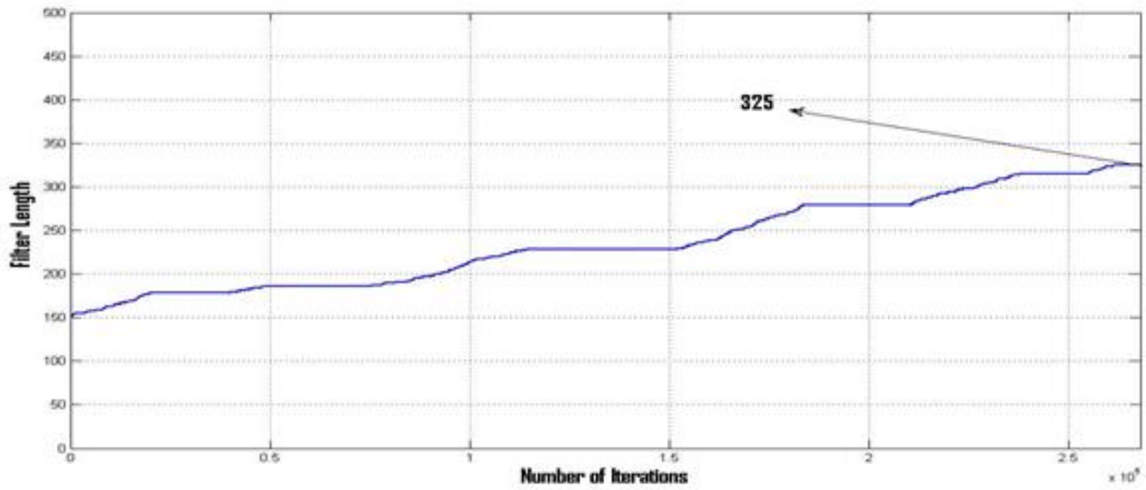


**Figure 13.** Filter length variation with time for Periodic PU NVLLMS.

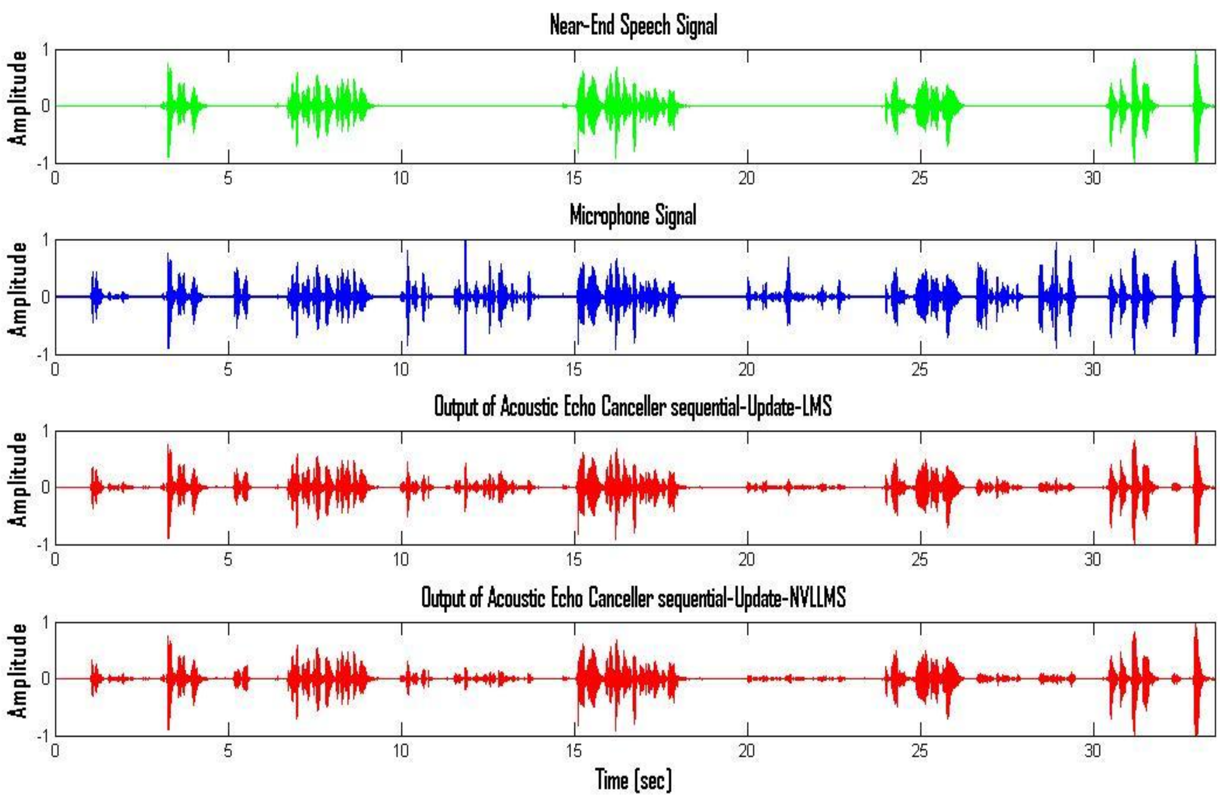


**Figure 14.** AEC of Sequential PU NVLLMS and pure Sequential PU LMS.

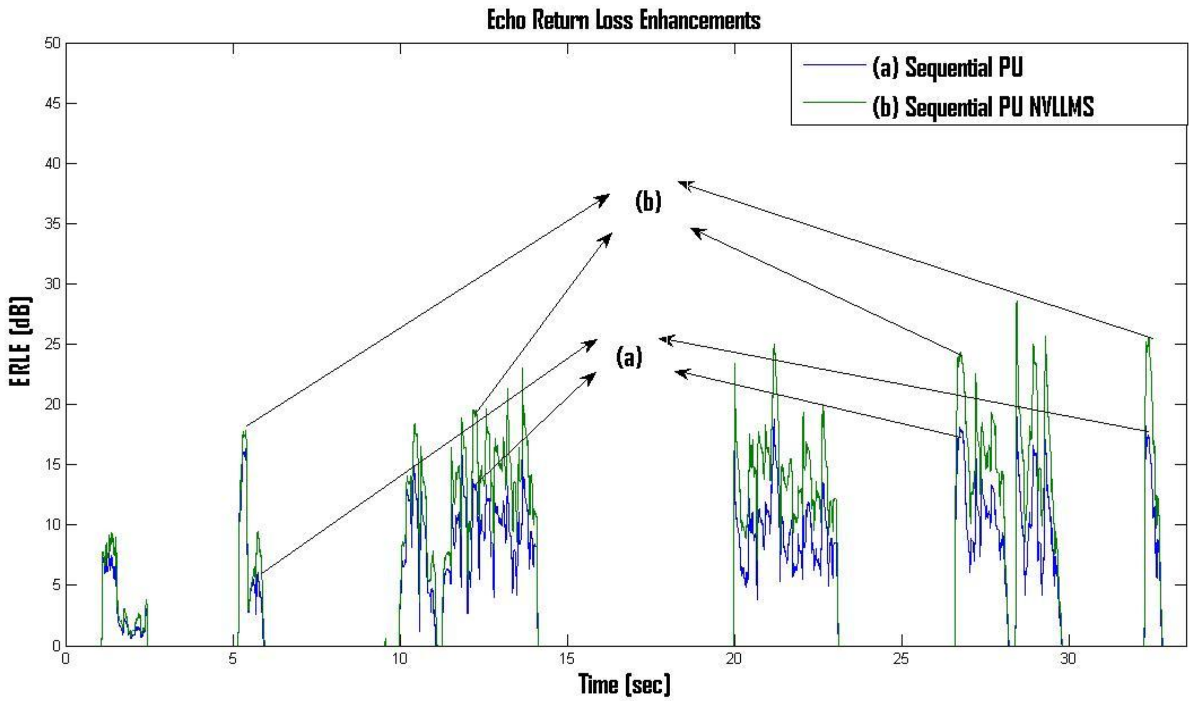


**Figure 15.** ERLE of pure Sequential PU LMS and Sequential PU NVLLMS algorithms.

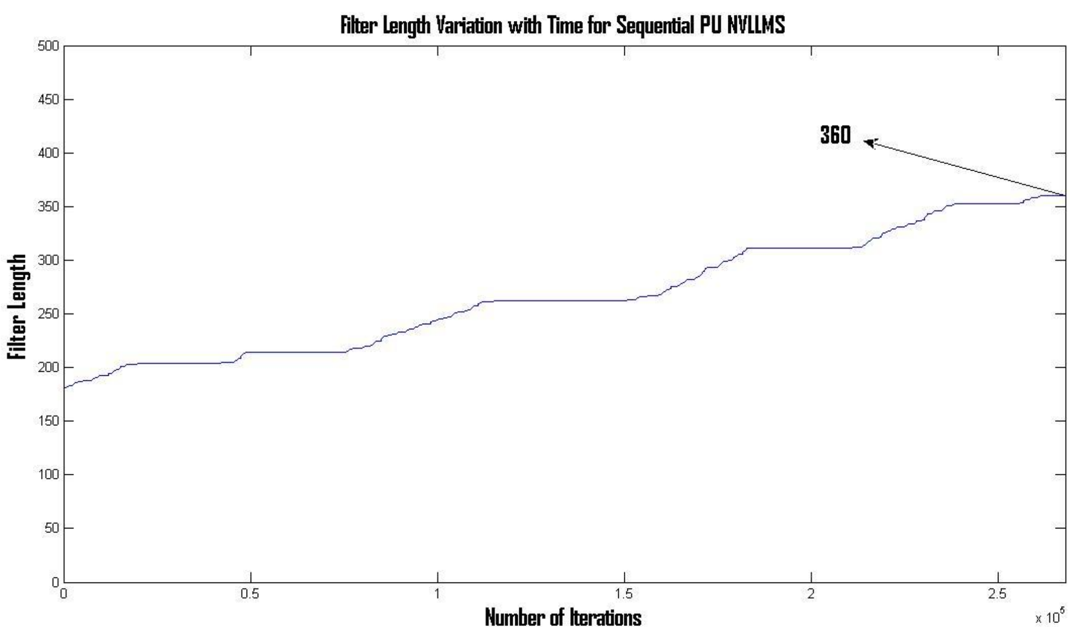


**Figure 16.** Filter length variation with time for Sequential NVLLMS.

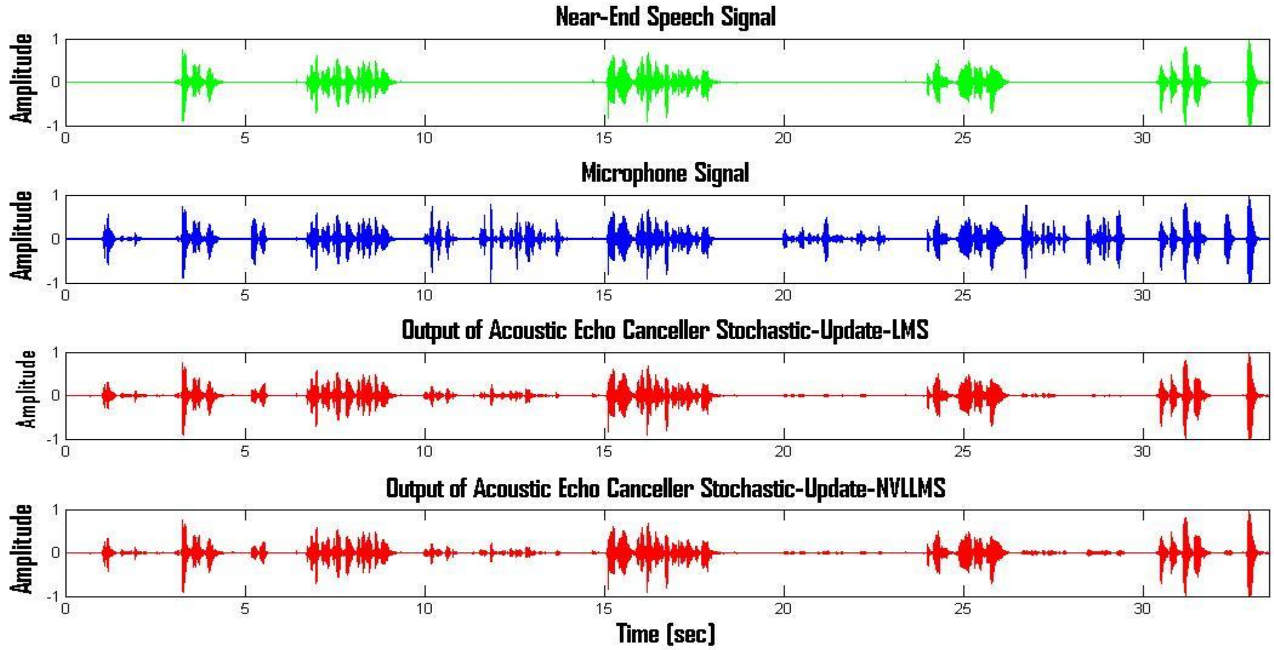


**Figure 17.** AEC of Stochastic PU NVLLMS and pure Stochastic PU LMS algorithms.

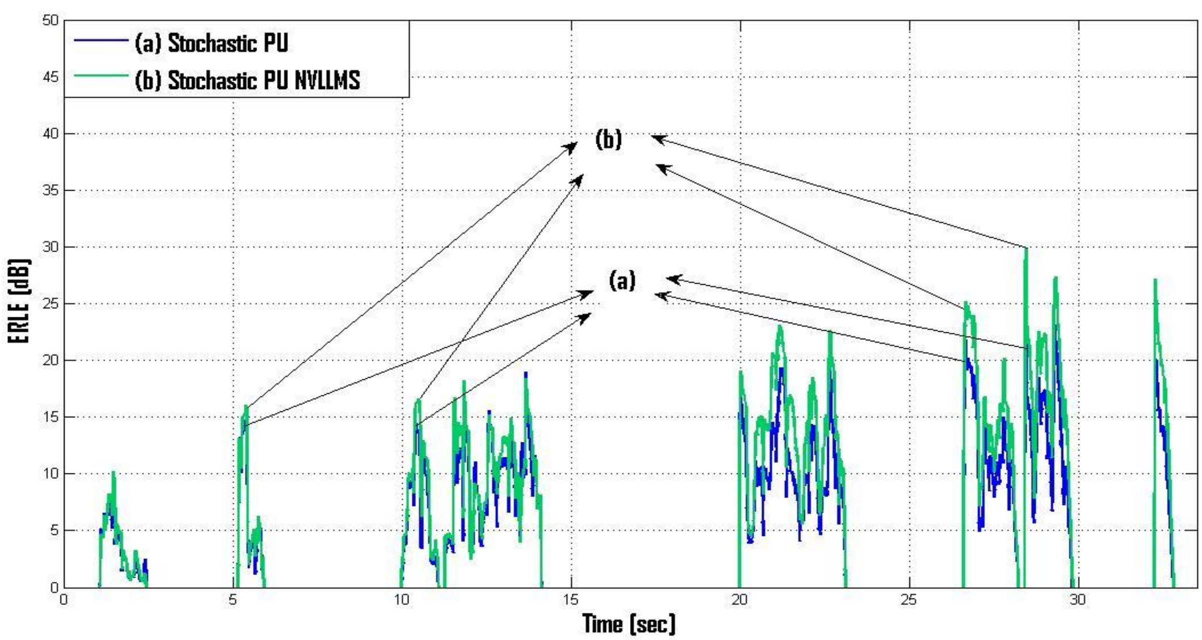


**Figure 18.** ERLE of pure Stochastic PU LMS and Stochastic PU NVLLMS algorithms.

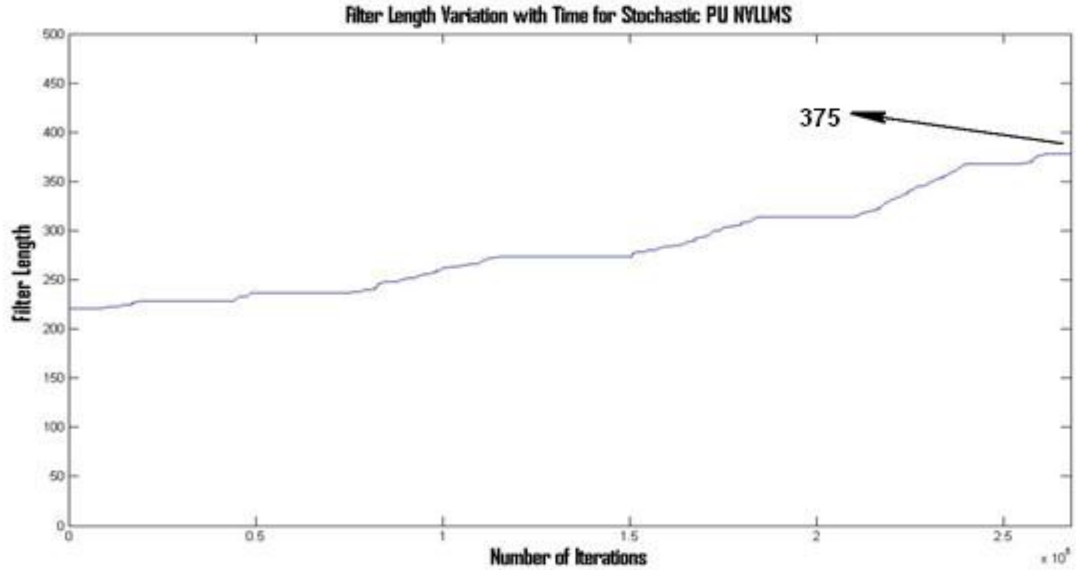


**Figure 19.** Filter length variation with time for Stochastic PU NVLLMS.

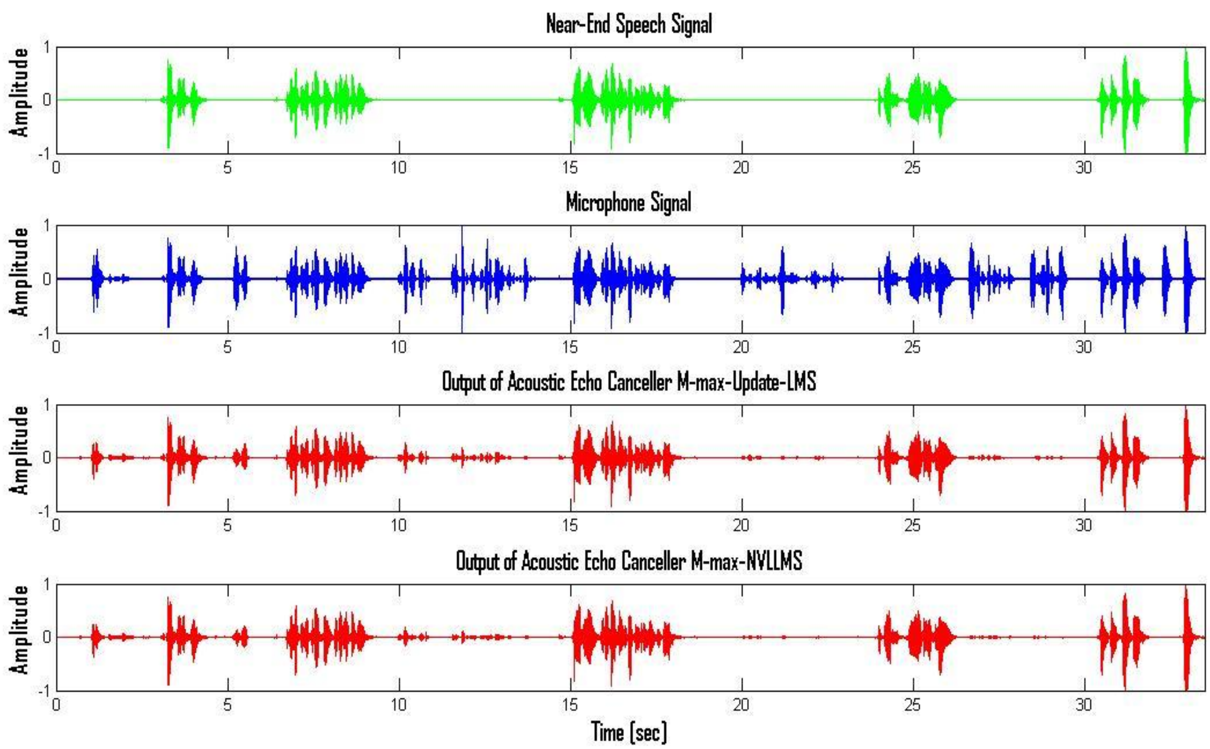


**Figure 20.** AEC of M-max PU NVLLMS and pure M-max PU LMS algorithms.

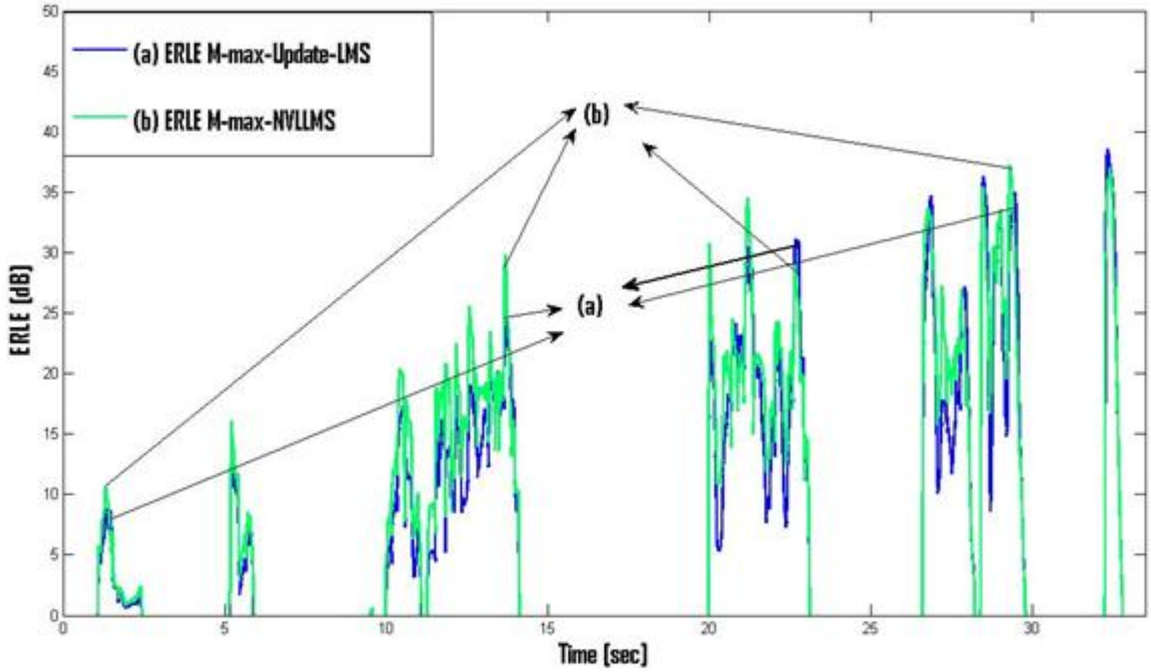


**Figure 21.** ERLE of pure M-max PU LMS and M-max PU NVLLMS algorithms.

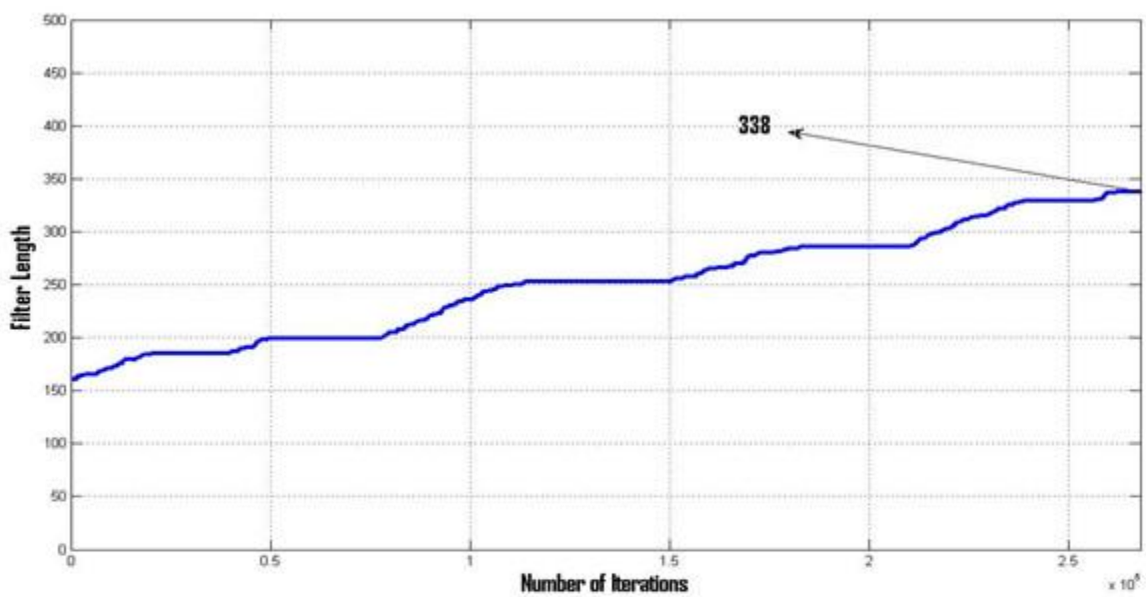


**Figure 22.** Filter length variation with time for M-max PU NVLLMS.

**Table 1.** Average MSE and ERLE for the pure PU LMS and PU NVLLMS Methods.

| Method | Average ERLE NVLLMS (dB) | Average ERLE PU LMS (dB) | Average MSE NVLLMS | Average MSE PU LMS |
|---|---|---|---|---|
| Full update | 18.02 | 16.38 | 0.004297 | 0.004302 |
| Periodic S= 4 | 14.45 | 11.72 | 0.00449 | 0.00458 |
| Sequential M=100 | 12.42 | 10.19 | 0.00436 | 0.00455 |
| Stochastic M=100 | 14.96 | 11.92 | 0.00438 | 0.00457 |
| M-max M=100 | 19.285 | 18.64 | 0.00426 | 0.004331 |