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VEHICLE CABIN NOISE CANCELLATION MODEL USING PRE-FILTER FOR IMPROVED CONVERGENCE RATE AND BETTER STABILITY

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Resume

Adaptive algorithms are used in updating the filter coefficients for active noise cancellation applications in reduction of vehicle cabin noise. The performance of the adaptive algorithms in low-frequency noise cancellation depends on how efficiently it alters the filter coefficient to minimize the difference between the approximated signal and the original one. Here is proposed an active noise cancellation model, using the low pass fixed coefficient filter before the adaptive filter, in order to improve the performance of the adaptive algorithm. Convergence rate, SNR and error vector magnitude are analysed for of adaptive algorithm in support of our research results.

Article info

Received 17 March 2022
Accepted 11 October 2022
Online 9 November 2022

Keywords:

active noise cancellation
adaptive algorithms
adaptive filtering
noise signal
convergence rate
SNR

Available online: https://doi.org/10.26552/com.C.2023.003

ISSN 1335-4205 (print version)
ISSN 2585-7878 (online version)

1 Introduction

Cabin noise in a moving vehicle is quite disturbing for the driver and co-passengers, long term exposure to this noise may increase stress level of the driver, increase fatigue and thus may lead to accidents. Conventional passive noise control techniques involve use of heavier insulating material for the low frequency noise reduction in cabin. This approach increases the overall cabin weight, thus resulting in decreased fuel efficiency [1]. Digital signal processing finds a solution to this problem by active noise cancellation techniques. Active noise cancellation methods use adaptive filters to estimate the noise and cancel it. Adaptive filters are based on algorithms, which are a set of mathematical formulations used to update the co-efficient of adaptive filters according to the variation of the input noise signal so that the adaptive filter approximates the noise signal. This approximated noise signal cancels the noise from original signal through destructive interference. The property of the adaptive algorithm to adapt with the time-varying input signal also finds application in echo cancellers, linear predictive coding, active noise cancellation systems for communication, creating spatial silence zones etc. Many algorithms, such as least mean square (LMS), recursive least mean square (RLS), filtered-x least mean square (FXLMS), normalized least mean square (NLMS) have been developed for optimizing the adaptive filter coefficients so that it may efficiently predict the variation in incoming noise. Major challenges involved in application of active noise cancellation system to vehicle cabin includes sensitivity of vehicles to the low acoustic excitation resulting from the low frequency vibrations caused by road surface [2]. Acoustics inside vehicle cabin depends on multiple noise factors, such as vehicle engine noise, outside traffic, wind flow, acceleration and inside sound of vehicle audio system, passenger noise etc. [3]. Impulsive noise produced inside vehicle cabin due to road bumps is of non-Gaussian nature, thus poses a major challenge

Table 1 Notations

Notation used	Description
n	Present time index
$s[n]$	Audio signal
$r[n]$	Noise signal
$w[n]$	Filter weights
$e[n]$	Difference between estimated signal and desired signal
$x[n]$	Input signal sample vector
$g[n]$	Gain vector
$d[n]$	Desired signal response
α	Leakage factor (0 to 1)
$s[n]$	Covariance matrix
μ	Step size
$Q[n]$	Filtered output
γ^{-1}	Exponential weighting factor
ϵ	Small positive constant

for active noise cancellation system [4]. Acoustic field complexity inside the vehicle geometry, convergence rate, stability, non-causality, inadequate spatial coverage, reflections, absorptions and high implementation cost often hinders the application of active noise cancellation system in the vehicle cabin [5]. A lot of research has been done in adaptive filtering, but the stated challenges are still the deciding factor in the implementation of adaptive filter design techniques to reduce the noise in moving vehicles. Many noise cancellation models using different adaptive algorithms, that are published in the literature have been tested to achieve higher stability, higher convergence rate and more accurate prediction, as well as cancellation. Cheer et al. [6] investigated the application of feedback controllers in attenuation of cabin noise in moving vehicles. Chen et al. [7] proposed the use of integrated loudspeakers in cancelling the noise field within area around the front seat passenger in a car cabin. An active head rest system model for reducing the road noise around passenger's ear in the vehicle cabin have been discussed by Jung et al. [8]. A comparative study of performance of different active noise cancellation algorithms have been done in [9] and an optimised weight filtered-x LMS algorithm for noise cancellation have been proposed for moving vehicles. This paper presents a noise cancellation model with a fixed coefficient pre-filter. Performance of the proposed model is analyzed by applying four different algorithms namely the least mean square (LMS), normalized least mean square (NLMS), sign-error least mean square (SELMS) and sign-sign least mean square (SSLMS) for the same input noise signal [10]. Higher computational complexity, convergence speed and poor numerical properties are the main factors associated with adaptive algorithms [11]. Martin et al. [12] proposed an inverter structure to reduce the computational load in the active noise control. Chiou et al. [13] presents a noise cancellation model to split the error signal by frequency separation so that adaptive algorithm needs to adapt the filter weights for same frequency component at a time. The purpose of this research work is to propose an active noise cancellation model by analysing the shortcoming of adaptive algorithms, tested against each other so that adaptive algorithms with better stability, high convergence rate with low mathematical complexity may be designed for application of active noise cancellation techniques in vehicle cabin noise reduction. The algorithms applied for analysis are the least mean square (LMS), normalized least mean square (NLMS), sign-error least mean square (SELMS), sign-sign least mean square (SSLMS) algorithms [14-16]. The detailed analysis of the algorithms used as given is presented in the following.:

1.1 Least mean square (LMS) algorithm

This is the basic and simplest adaptive algorithm used for active noise cancellation application. It is based on the principle of estimating the filter weights to minimize the mean square error between the filter output signal and the desired signal. Table 1 describes the notations used in computation Equations (1)-(8) of adaptive algorithms.

$$x[n] = s[n] + r[n], \tag{1}$$

$$y[n] = w^T[n-1]x[n], \tag{2}$$

$$e[n] = d[n] - y[n], \tag{3}$$

$$w[n] = w[n-1]\alpha + f(e[n]x[n]\mu), \tag{4}$$

$$f(e[n]x[n]\mu) = x^*[n]\mu e[n]. \tag{5}$$

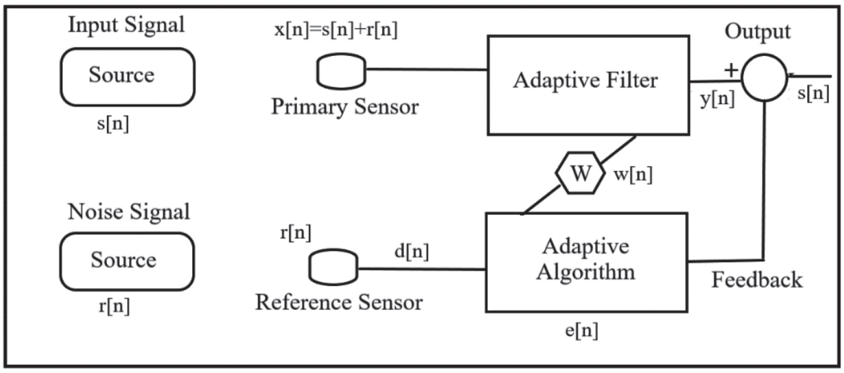

Figure 1 *Basic active noise cancellation model*

1.2 Normalised least mean (NLMS) algorithm

It is an advanced version of the LMS algorithm, it employs a variable step size as shown in:

$$f(e[n]x[n]\mu) = \mu[n]\frac{x^*[n]}{\epsilon + x^H[n]x[n]}. \quad (6)$$

1.3 Sign-error least mean square (SELMS)

It is more advanced form of LMS algorithm, it has added sign(e[n]) function for higher convergence rate, it has increased mathematical complexity with respect to the LMS algorithm as described in:

$$f(e[n]x[n]\mu) = \mu sign(e[n]x)*[n]. \quad (7)$$

1.4 Sign- sign least mean square (SSLMS)

This algorithm is also like the SELMS algorithm defined except for the two sign functions as shown in:

$$f(e[n]x[n]\mu) = \mu sign(e[n])sign(x[n]). \quad (8)$$

Figure 1 shows the basic active noise cancellation model. It consists of the input signal source, which is the primary signal or the signal of significance. The input signal is a pre-recorded 44100 Hz, 128 kbps mono audio human speech signal. The noise signal is also pre-recorded 44100 Hz, 128 kbps mono audio noise, generated by the vehicle engine. The primary sensor and reference sensors are input signal microphones for the desired audio signal and noise signal. The adaptive filter block consists of a combination of an adaptive filter and adaptive algorithm for updating the filter coefficients in response to the input noise signal. Filter weights w[n] determine the output characteristics of the adaptive filter, these filter weights also termed as filter coefficients are continuously updated by the adaptive algorithm based on the time varying noise signal, the adaptive algorithms tend to adjust filter weights in response to feedback signal until noise cancellation is achieved. Adaptive algorithm adjusts the filter weights to minimize the mean square error as defined as error vector magnitude between the desired response and the actual one [17]. In the case of multiple noise sources, the multiple channel reference signal is required for efficient active noise cancellation [18]. Variable step size adaptive algorithms are more robust, simple and offer better performance, as compared to conventional fixed step size algorithm [19]. Finite impulse response (FIR) digital filters are non-recursive, as compared to recursive nature of Infinite impulse response (IIR) digital filters; recursive IIR filters require shorter filter length [20]. Several hundred coefficients are required in cancellation of the low frequency road noise inside moving vehicle, resulting in the low convergence rate [21]. Convergence rate is thus an important factor of concern in performance of an adaptive algorithm. This paper covers all the major factors stated above and proposes a new approach of noise cancellation in the vehicle cabin aimed at achieving better cancellation without increasing algorithm complexity.

2 Proposed noise cancellation model

Simulink tool from MathWorks has been used for modelling and simulation work. Figure 2 shows the active noise cancellation model without the pre-filter. It consists of the input audio signal source, which is the primary signal as well as the signal of significance, the noise signal, an adder; noise signal is also used as a reference signal, adaptive filter and adaptive algorithm block. Figure 3 shows the proposed active noise cancellation model with an additional pre-filter block. The additional pre-filter is a direct form II, low pass IIR Butterworth filter. The filter order is 9, filter attenuation at the cut-off frequency is fixed at 3 dB, which is half the passband power. The application of the pre filter is to cut-off the undesired frequency components present in the noise corrupted signal at an earlier stage. This pre filter assists the adaptive filter in noise cancellation process. Figure 4 (a-d) shows the time domain plots of the input audio signal, noise signal, noise corrupted signal and the pre filter output signal. The reference microphone captures the noise signal,

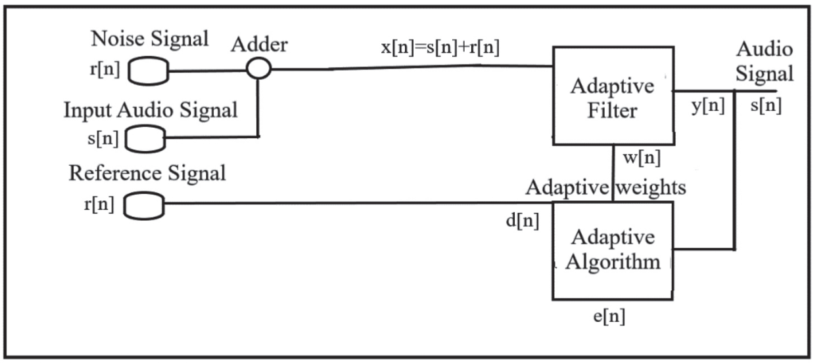

Figure 2 *Active noise cancellation model without the pre-filter*

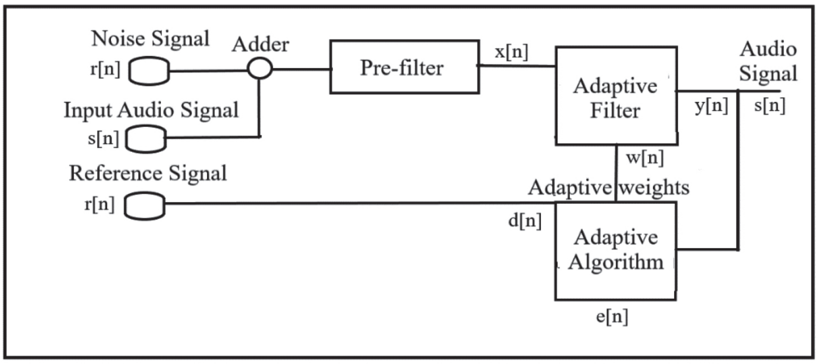

Figure 3 *Proposed Active noise cancellation model with the pre-filter*

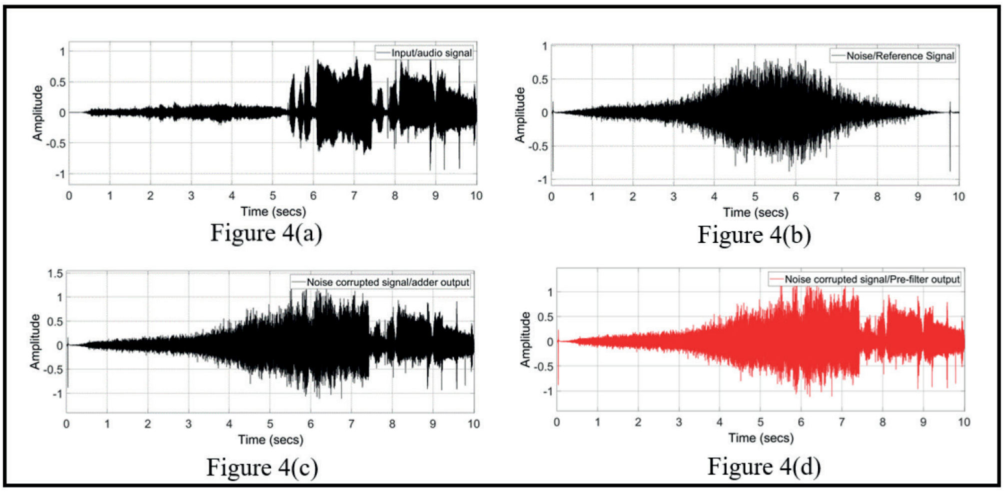

Figure 4 *Input audio signal, noise/reference signal, noise corrupted signal and the pre filter output signal*

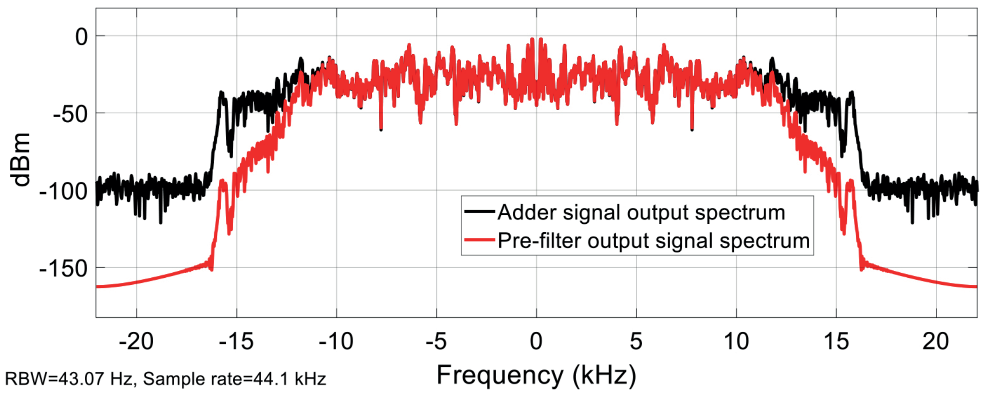

Figure 5 *Spectrogram of the noise corrupted audio signal with and without the pre filter.*

which is to be approximated and cancelled, thus, the input from the reference microphone is the same as the noise signal, denoted by r[n]. The spectrogram given in Figure 5 shows the frequency spectrum of the noise corrupted signal without pre filtering and compared with the pre filtered noise corrupted signal.

3 Results and discussion

The simulation results given in Figure 6 (a-b) show the time domain plot and frequency spectrum of the input audio signal, recovered signal using the pre filter and signal recovered without the pre filter. The effect of use of pre filter can be clearly observed in Figure 6, both in the time domain, as well as in the frequency spectrum. The recovered signal with the pre filter more closely overlaps the input audio signal both in terms of magnitude and frequency, whereas the signal recovered without using the pre filter is quite different from the desired input audio signal. Thus, it proves that the proposed model using the pre filter recovers the input audio signal from the noise corrupted signal more efficiently as compared to the conventional model. Sections 3.1- 3.4 show the effect of step size on convergence rate of adaptive filter for the Least mean square (LMS), Normalised least mean (NLMS), Sign-error least mean square (SELMS) and Sign- sign least mean square (SSLMS) algorithms. Figure 7-10 gives the array plot of magnitude of filter coefficients with respect to time. The filter coefficients amplitude varies in the range of -1 to 1 along the y-axis. The magnitude of adaptive filter coefficients tends to approach zero based on the feedback signal. The faster the filter coefficients approach zero, the higher is the convergence rate of the adaptive algorithm. The convergence rate of different algorithms is analysed for variable step size $\mu = 0.01$, $\mu = 0.001$ and $\mu = 0.00001$.

3.1 Least mean square (LMS) algorithm

The variation of filter coefficients generated by LMS algorithm with respect to time for different values of step size $\mu = 0.01$; 0.001 and μ=0.00001 is given in Figure 7. It is observed that the best convergence rate and stability is achieved by LMS algorithm for step size $\mu = 0.00001$ and lowest convergence rate is obtained for the step size $\mu = 0.01$.

3.2 Normalised least mean (NLMS) algorithm

The variation of filter coefficients generated by NLMS algorithm with respect to time for different values of the step size is given in Figure 8. It is observed

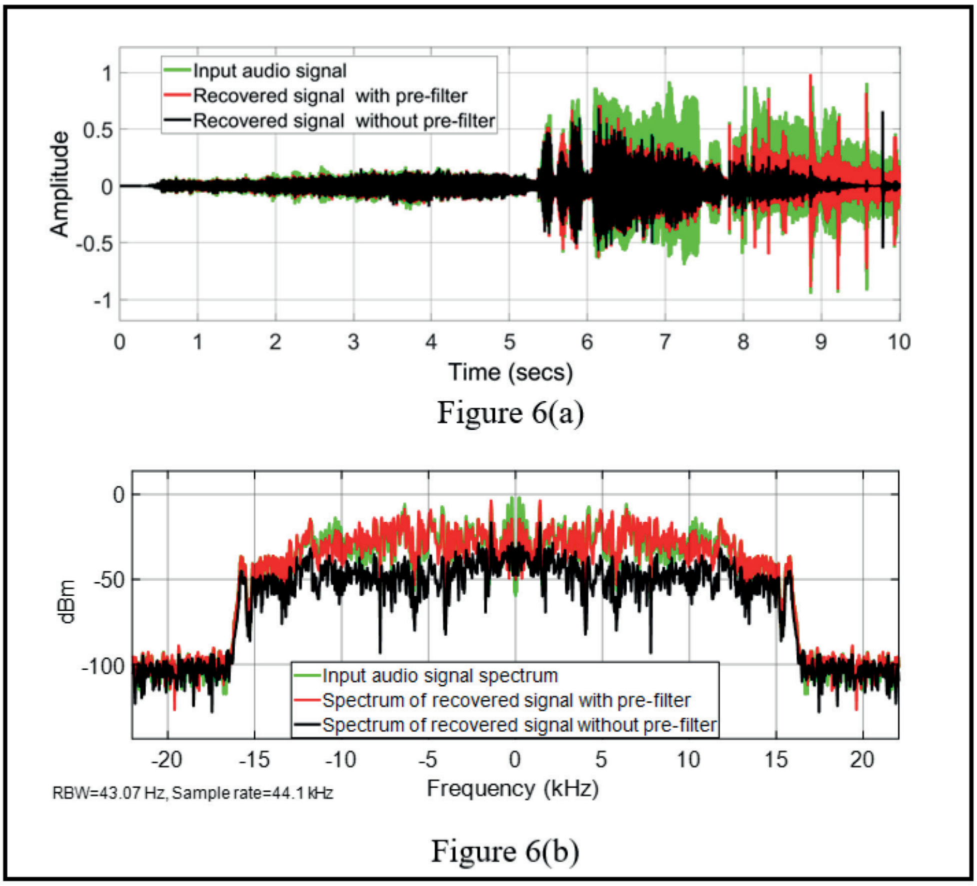

Figure 6 *Time domain plot and frequency spectrum of the signal recovered through the proposed model using the pre filter and without pre filter compared to the input audio signal*

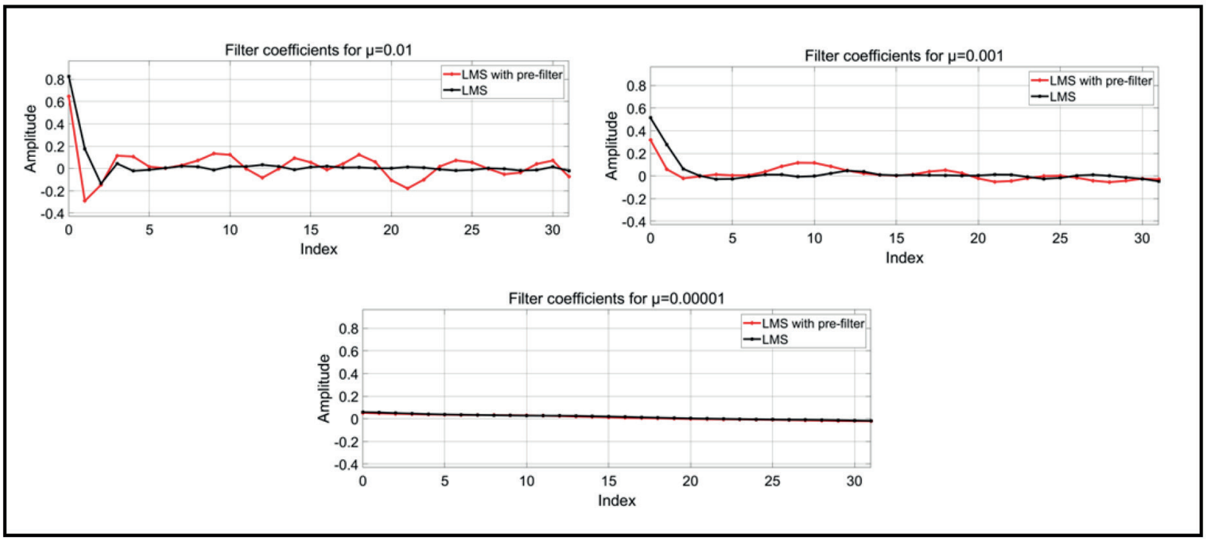

Figure 7 *Array plot of filter coefficients generated by the LMS algorithm for different values of step size*

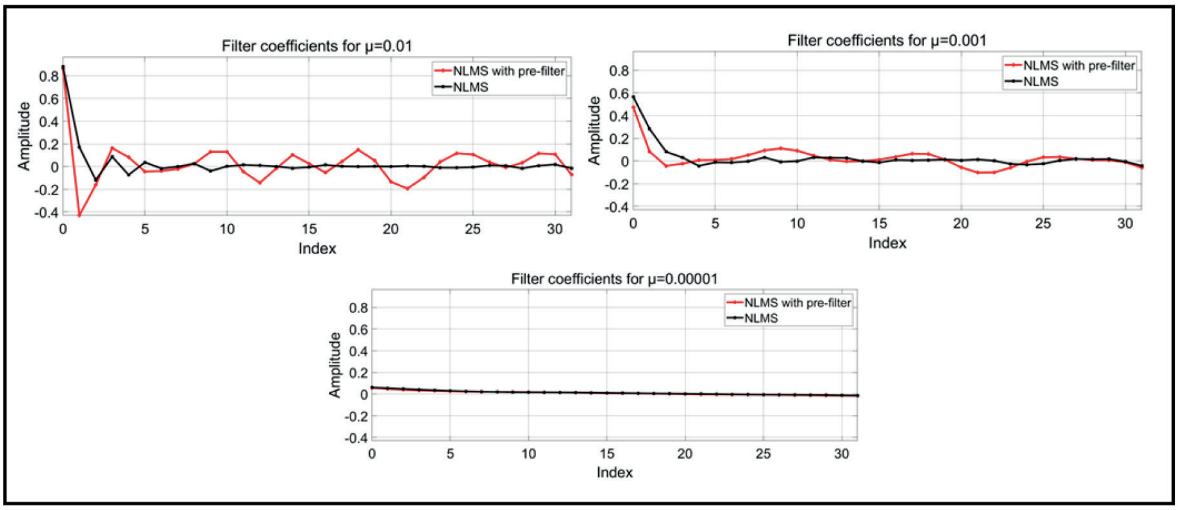

Figure 8 *Array plot of filter coefficients generated by the NLMS algorithm for different values of the step size*

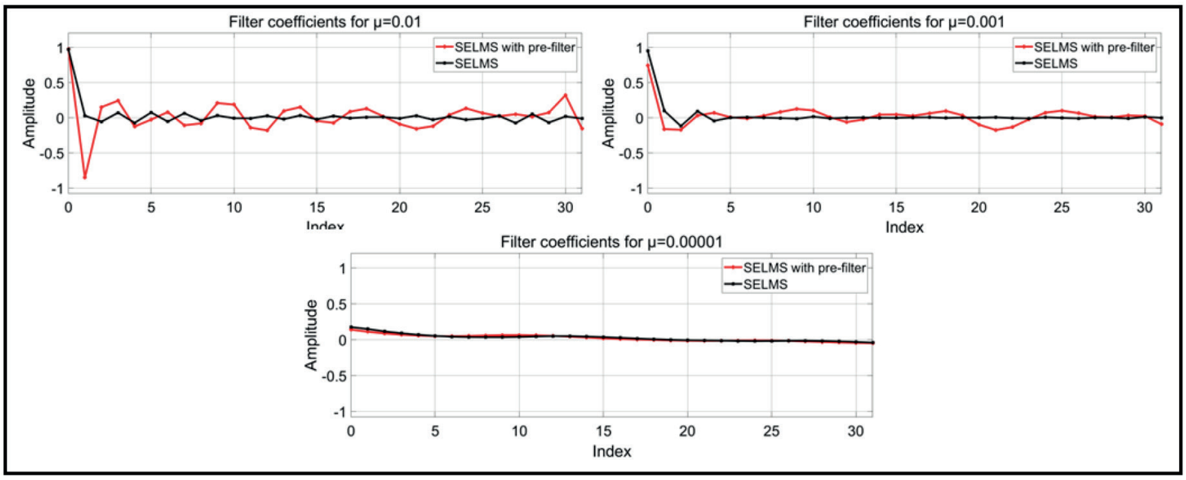

Figure 9 *Array plot of filter coefficients generated by the SELMS algorithm for different values of the step size*

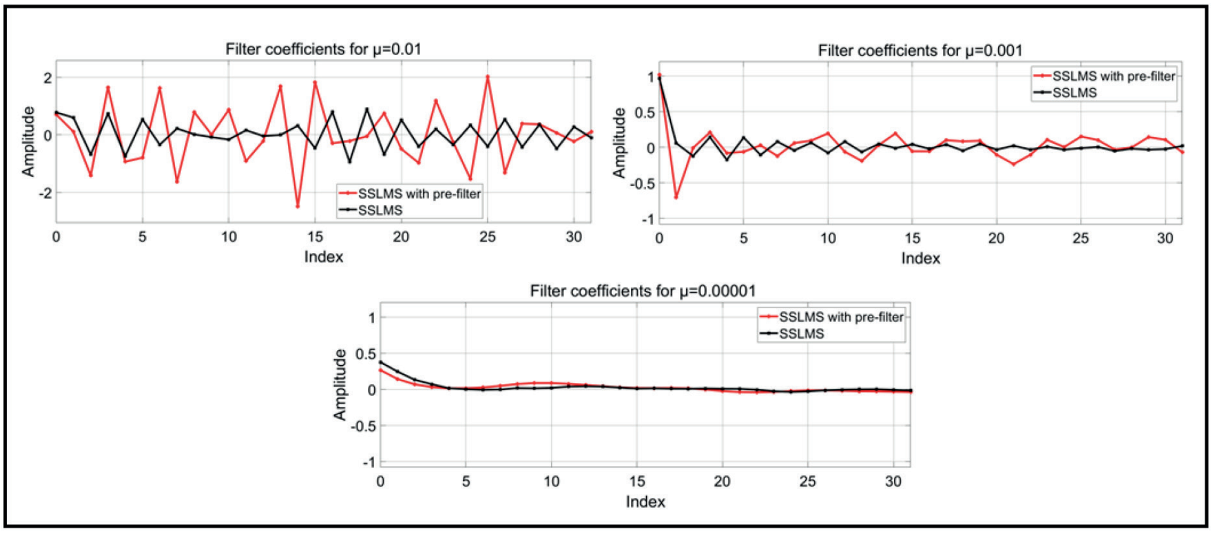

Figure 10 *Array plot of filter coefficients generated by the SSLMS algorithm for different values of the step size*

that the best convergence rate and stability is achieved by NLMS algorithm for step size μ = 0.00001 and lowest convergence rate is obtained for step size μ = 0.01.

3.3 Sign- error least mean square (SELMS)

The variation of filter coefficients generated by SELMS algorithm with respect to time for different values of the step size is given in Figure 9. It is observed that the best convergence rate and stability is achieved by SELMS algorithm for the step size μ = 0.00001 and lowest convergence rate is for step size μ = 0.01.

3.4 Sign- sign least mean square (SSLMS)

The variation of filter coefficients generated by SSLMS algorithm with respect to time for different values of step size is given in Figure 10. it is observed that the best convergence rate and stability is achieved by the SSLMS algorithm for the step size μ = 0.00001 and lowest convergence rate is for step size μ = 0.01.

Literature review states that improving the convergence rate of the adaptive algorithm has been a major factor of research in the concerned area of adaptive filtering. Many methods have been adopted for increasing the convergence rate and most of them adopted focus on modification of the adaptive algorithm [22]. This approach of modifying the adaptive algorithm suffers from the drawback of increased mathematical complexity of the adaptive algorithm. The increased complexity hurdles the practical applicability of the algorithm in noisy and highly unpredictable acoustic environment in a moving vehicle cabin, as it is learned from the previous studies that advanced adaptive algorithms, having high convergence rates, are much more mathematically complex as compared to basic LMS algorithms having low convergence. This paper presents an approach to increase the convergence rate, without modifying the basic algorithms, thus, achieving a higher convergence rate without increasing the mathematical complexity of basic adaptive algorithms. The proposed approach is to pre-filter the noise signal before adaptive filtering. The pre-filter used is a fixed coefficient Butterworth low pass IIR filter, the filter order is 9. The convergence rate of the adaptive algorithms, obtained after pre-filtering the noise signal, is compared to the convergence rate without pre-filtering. The comparative analysis is based on values of the filter coefficients generated by different adaptive algorithms to minimize the mean square error between the predicted signal and the actual signal. Filter coefficients are updated continuously to attain estimation, the faster they attain minimal values, the higher is the convergence rate. The lower range of variation results in higher stability [23-30]. Based on this criterion, Table 2 shows the values of the filter coefficients generated by the least mean square (LMS), normalized least mean square (NLMS), sign-error least mean square (SELMS), sign-sign least mean square (SSLMS) algorithms to cancel the noise signal. The values of filter coefficients are obtained for the step sizes μ = 0.01, \0.001 and 0. 00001. The range of variation of filter coefficients is considered to be from 0 to 0.008. Comparison of values of the filter coefficients values, generated after the pre-filtering on noise signal, depicts that an average number of 16 filter coefficient have magnitude greater than 0.002 for the pre filter LMS. This number is 21.3 for LMS without the pre filtering; similarly for NLMS with pre filter it is 15.3, NLMS without pre filter it is 20, for SELMS with pre filter it is 16.3; for SELMS without pre filter it is 16.3, for SSLMS with pre filter it is 17.6, for SSLMS without pre filter it is 17.3. Similar results are obtained for amplitude range greater than 0.006 and 0.008. From Table 2 is also observed that number of filter coefficients with amplitude greater than zero for all three-step size are 48 in case of LMS with pre filter, 62 in LMS without prefilter. This number is 50 in NLMS with pre-filter, 61 in NLMS without pre-filter. It is 51 in case of SELM with pre-filter and 53 without pre-filter. For SSLM with pre-filter this is 50 and for SSLMS without pre-filter it is 53. From these results is thus observed that the filter coefficients generated by adaptive algorithms for estimation of pre filtered noise is less in all the cases as compared to number of filter coefficients generated for estimation of noise without pre filtering thus these results prove that pre-filtering has increased convergence rate. The range of variation in amplitude of filter coefficients is also obtained to be less in case of pre-filtering than without pre-filtering this result shows improved stability of the adaptive algorithm for pre-filtered noise signal. Thus, simulation results prove that filter coefficients tend to converge at a faster rate and show a low fluctuation range in the case of the proposed pre-filter model as compared to the conventional non-pre filter model. Table 2 gives the mathematical values of filter coefficients shown in Figures 7 to 10. A comparative analysis is done for the values generated after pre-filtering of noise signal and the values obtained without use of the proposed pre-filter, moreover performance of various adaptive algorithms is also compared. Further, Error Vector Magnitude (EVM) and Signal to Noise Ratio of the recovered signal with respect to the input audio signal is calculated for different adaptive algorithms, which are applied with the pre-filter and without the pre-filter. These values are given in Table 3, which shows the error vector magnitude between the input audio signal, signal recovered after pre-filtering and that recovered without prefiltering. Numerical results clearly depicts that the error percentage is higher in case of signal recovered without pre filtering, which means the proposed model with pre filter is more efficient in approximating and cancelling the noise signal as compared to conventional model. Another parameter calculated for comparative analysis is the signal to noise ratio (SNR) of the recovered signal. SNR values of the recovered signals are higher in case of pre filter output justifying the fact further that the proposed model with pre filter cancels the noise more effectively. Figures 11(a-c) show the comparative histogram chart of the error vector magnitude and Figures 12(a-c) show the signal to noise ratio values obtained for variable step size applied to the four adaptive algorithms. Results show that the least error vector magnitude percentage of 26.01% for

Table 2 *Filter coefficients generated for the step size μ = 0.01, 0.001 and 0.00001 by different adaptive algorithms with and without the pre-filter*

Algorithm	Filter Coefficient, μ											
	0.01				0.001				0.00001			
	> 0.002	> 0.006	> 0.008	> 0	> 0.002	> 0.006	> 0.008	> 0	> 0.002	> 0.006	> 0.008	> 0
LMS	19	15	15	19	21	19	17	21	21	20	19	22
LMS with Pre-filter	15	14	14	14	16	16	16	16	17	15	14	18
NLMS	17	16	14	17	21	17	16	21	22	19	17	23
NLMS with Pre-filter	13	13	13	13	17	15	15	19	16	14	13	18
SELMS	17	15	15	19	13	12	11	13	19	18	18	19
SELMS with Pre-filter	16	15	15	16	18	18	18	18	15	14	14	17
SSLMS	16	16	16	15	15	15	15	16	21	21	20	22
SSLMS with Pre-filter	18	18	18	16	20	19	19	19	15	15	14	15

Table 3 *Error vector magnitude (EVM) and Signal to Noise Ratio of recovered signal with respect to the input audio signal calculated for the step sizes μ = 0.01, 0.001 and 0.00001 for different adaptive algorithms with pre-filter and without pre-filter*

Algorithm	EVM %			SNR in dB		
	μ = 0.01	μ = 0.001	μ = 0.00001	μ = 0.01	μ = 0.001	μ = 0.00001
LMS	92.48	80.13	37.75	0.6791	1.924	8.462
LMS with Pre-filter	62.44	58.91	33.08	4.091	4.596	9.609
NLMS	98.38	89.11	29.8	0.1421	1.002	10.52
NLMS with Pre-filter	69.15	68.37	26.01	3.205	3.302	11.7
SELMS	100	99.84	66.47	-0.0034	0.014	3.548
SELMS with Pre-filter	65.15	70.57	59.12	3.721	3.028	4.5666
SSLMS	103.2	100.2	80.57	-0.2743	-0.015	1.876
SSLMS with Pre-filter	91.38	70.92	66.05	0.7828	2.984	3.602

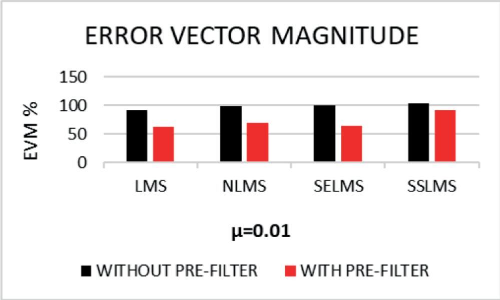

Figure 11(a)

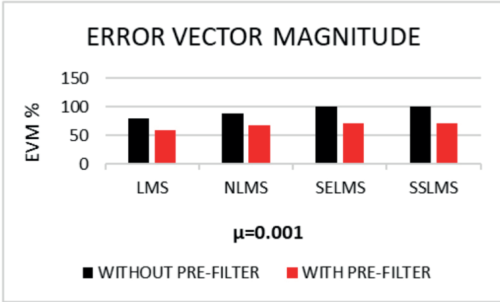

Figure 11(b)

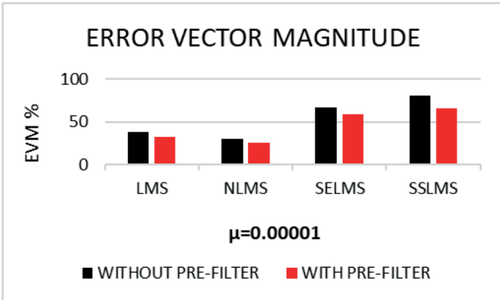

Figure 11(c)

Figure 11 *Error vector magnitude of recovered signal*

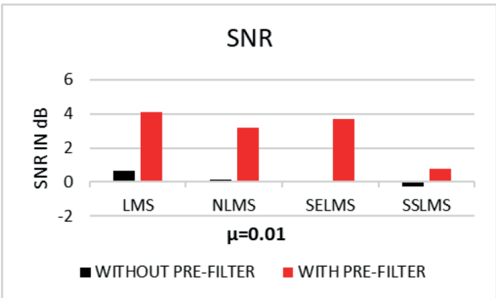

Figure 12(a)

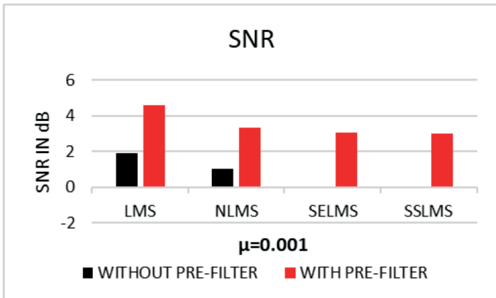

Figure 12(b)

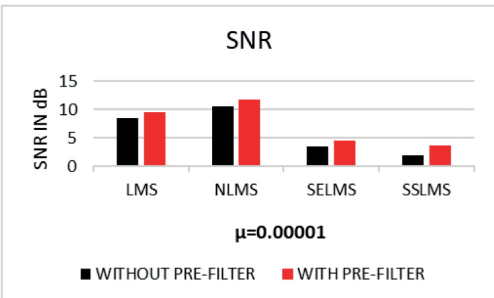

Figure 12(c)

Figure 12 *SNR of recovered signal*

the NLMS algorithm for the step size μ = 0.00001. The highest signal to noise ratio (SNR) obtained is 9.609 dB by least mean square (LMS) algorithm for the step size μ = 0.00001. Given results thus prove that the proposed model has better convergence rate, higher signal to noise ratio, lower error vector magnitude and better audio signal recovery in presence of noise. These results are achieved without increasing the complexity of the adaptive algorithm.

4 Conclusions

This study develops an approach of pre-filtering the input noise corrupted signal before the adaptive filtering, so that many low frequencies noise components are pre-filtered and adaptive algorithms do not tend to adapt to these frequencies, thus increasing the convergence rate without increasing the mathematical complexity of the algorithm. The convergence time is inversely proportional to convergence rate. Increased convergence rate obtained in proposed model through quantitative analysis of filter weights, proves significant decrease in convergence time of adaptive algorithm in cancellation of engine noise inside the vehicle cabin. Precise calculation of convergence time is left for further research and may be covered in authors' next publication in near future. Based on the simulation results for four different algorithms on the proposed model, it is concluded that the increased convergence rate of adaptive algorithm, higher signal to noise ratio and lower error vector magnitude of the recovered signal can be achieved without increasing the complexity of the basic adaptive algorithm. Less complexity leads to practicability of the noise cancellation system for the vehicle cabin noise cancellation. Overall, results show better convergence rate and increased stability of adaptive algorithms in the proposed model. Higher stability and faster convergence rate lead to the more effective cancellation of cabin noise in moving vehicle.

Grants and funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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