A Novel Adaptive ANC Algorithm for Removal of Background Noise in Speech Applications

Vinothkumar.G
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Ramapuram Campus, India
vinothkg@srmist.edu.in

Manoj Kumar.D
Department of Electronics and Communication Engineering
SRM Institute of Science and Technology
Ramapuram Campus, India
manojkud1@srmist.edu.in

Abstract: *Noise is an unsafe mechanical toxin that causes serious hearing misfortune in the working environment of every nation. The working people in the military, mining, development, printing, and saw factories tend to lose their hearing performance due to the adverse effects of noise generated by the machines. They undergo elevated levels of noise, with various machinery producing greater levels of noise measured in decibels. These sounds may cause major health problems that may not allow the person to work in such conditions. Algorithms like Least Mean Square (LMS), Normalized Least Mean Squared (NLMS), Filtered-x Least Mean Squared (FxLMS) and Filtered-x Normalized Least Mean Squared (FxNLMS) are frequently being used for noise cancellation. Moreover, these filters have instability and poor noise reduction; slow convergence also requires a greater number of filter taps and less performance to identify the unknown system in the Active Noise Canceller (ANC). In this paper, a Précised FxNLMS (P-FxNLMS) algorithm is introduced for an ANC. This algorithm consists of dual adaptive filters, an updated Variable Step Size (VSS), a delay in the primary path, a slight improvement in the on-line secondary path, and a modified filter step size when compared to an existing ANC system, with the purpose of minimizing the demerits of existing algorithms. Initially, the P-FxNLMS algorithm was tested with Additive White Gaussian Noise (AWGN) and later tested with real noises from the NOISEUS dataset to check the noise reduction performance. The increase in Signal to Noise Ratio (SNR) segmentation for P-FxNLMS is around 1.45 dB to 4.07 dB and 38.46 % to 73.68 % of the Mean Square Error (MSE) as compared to the algorithms available for different sounds with different SNR input levels. From the performance results of MSE and SNR improvement (SNRi), we found improvements compared with existing algorithms*.

Keywords: *ANC, FxNLMS, NIHL, speech enhancement, background noise cancellation, MSE, SNRi, PESQ and STOI*.

Received February 15, 2024; accepted June 30, 2024
https://doi.org/10.34028/iajit/21/4/4

1. Introduction

Military personnel may be subjected to a high intensity noise of different forms at some point. Small arms fire to anti-armour guns are both sources of noise in the military, with peak pressures ranging from 145 to 200 dB [3]. Most people can handle a maximum sound level of 120 decibels, with levels exceeding 140 decibels. As a result of their noise exposure, some people can experience hearing loss, particularly for high-frequency noises, or tinnitus (ringing in the ears), or both. Small arms fire is the most obvious source of NIHL in the military. This results in sound levels exceeding 100 decibels [21]. The phenomenon of acoustic damage, which is the acute loss of hearing following a single exposure to hazardous noise [4], and Noise-Induced Hearing Loss (NIHL), which most typically occurs from repeated exposures to hazardous noise over a period of several years.

Noise and interference of signals have become a major side effect in the audio signal processing field. It is important for engineers to inset frameworks, processors, and tools for video applications. The sound noise decrease framework is acclimated in such a way to remove the noise from the sound sign. Sound noise decrease frameworks are ordered into two fundamental procedures. Going to the essential procedure is that the corresponding sort that includes compacting the sound sign in a very much characterized way before it's recorded. The second method is that the complete or incomplete type that uses techniques to reduce the range of audio that is already embedded within the content of the feed, is the only playback program for noise reduction. Noise reduction is a way to remove noise from the signal. All analogue or digital recording devices have features that make them vulnerable to sound. The hearing loss can be seen developing mostly in occupational workers due to high-intensity noises above 85dB. Noise exposure for 8 hours and more in this environment, may lead to permanent hearing loss in humans.

In today's scenario where communication plays a vital role, suppression of noise in audio signals will lead to enhancement of the signals that will provide better communication facilities among individuals. Generally, passive noise reduction techniques are not efficient for the lower frequencies, whereas the active noise reduction method is helpful for lower frequencies such as in microphones, earphones. In this paper, we propose the novel Active Noise Canceller (ANC) system model to enhance the signal from background noise. From this model, we can achieve good background noise suppression results from the original signal. Finally, we demonstrate the proposed model achieving results than the existing models by evaluating Mean Square Error (MSE), sign to noise proportion.

To minimise noise from a noisy speech tone, Active Noise Cancellers (ANCs) [2, 5, 6, 7, 9, 10, 12, 14, 15, 19, 20, 22, 23, 25, 26, 27, 30, 32] have been commonly used. The Least Mean Square (LMS), Normalized Least Mean Square (NLMS), and Filtered-x NLMS (FxNLMS) algorithms, on the other hand, do not perform well in the ANC from the speech signal you want. There is a negative effect on the merging ratio and the static fluctuations of these algorithms. A noise reduction filter and dynamic step-size LMS are used in the Modified-FxLMS (MFxLMS) algorithm [18]. It's present in the secondary path to minimise noise by adjusting the phase size according to the residual error's capacity.

In the modeling filter, the step-size is varied in accordance with the power of the residual error signal (the desired response for the modeling filter). The Variable Step Size (VSS) LMS algorithm is different from the Normalized-LMS (NLMS) algorithm, where the step-size is varied with the power of reference signal power. Initially a larger step-size is first chosen for quick convergence and then a small number is eventually employed for misadjustment accordingly. The motivation behind the suggested VSS method is that the modelling filter's desired response is tainted by a noise that is decreasing in nature and gradually converges to zero. In fact, this interference might be so great such that online secondary-path modelling would be significantly slower than offline modelling. In contrast to the current VSS algorithms, the suggested VSS algorithm starts with a small step-size and gradually increases to obtain the convergence

The existing filtering algorithms has required a large number of filter taps Instability, Slow convergence speed, increased Mean Squared Error (MSE) and less performance to identify the unknown system of the filter. To overcome these demerits, the proposed algorithm, suggest a Forward path delay to minimize the filter taps. The VSS with support of White Gaussian Noise (WGN) to maintain stability and improve the convergence speed of the filter and a dummy weighted filter with support of an estimated input signal to improve to recognize the unknown system and reduce the system output error has been discussed in below section.

2. ANC System

2.1. Existing FxNLMS Algorithm

Nowadays, the majority of ANC systems are built using either LMS or NLMS algorithms [16]. For maintaining the convergence of speed in effective manner NLMS algorithm is more desirable for noise reduction while compare with LMS algorithm and also it solves the matter of instability within the power of the reference signal.

When a secondary path is present, the gradient-based algorithm Filtered-x Normalized Least Mean Squared (FxNLMS) can be used to identify an unknown system, such as a desired ANC controller. Although the FxNLMS technique is computationally straightforward and incorporates secondary path effects, its convergence rate tends to be slow. System identification is done using an adaptive filter called the FxNLMS filter. The output of the filter would be such that the error signal fed to its input would gradually decrease. The discrepancy between the desired response and the FxNLMS filter's output would be the error signal.

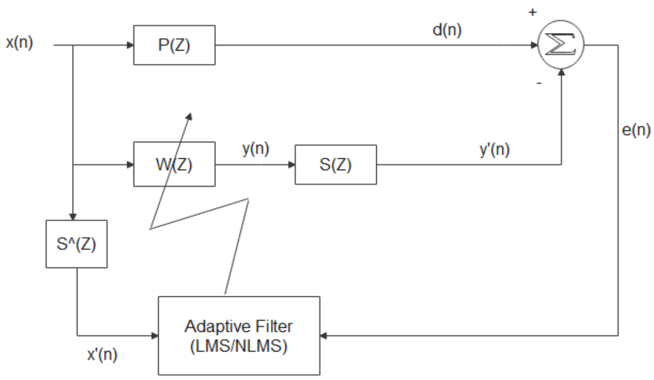


Figure 1. FxNLMS block diagram.

Figure 1 depicts the block diagram of the FxNLMS algorithm. It consists of online secondary path [24] with an estimation of it. The prediction error formula for the FxNLMS is given in the Equation (1),

$$e(n) = d(n) - w^{T}(n) * x'(n) \quad (1)$$

The FxNLMS algorithm updates the filter coefficients [13] that work using a recurring formula is given in the weighted vector matrix Equation (2),

$$w(n+1) = w(n) + \mu\, e(n)\, x'(n) \quad (2)$$

Where, μ is the step-size of the filter $x'(n)$ is an estimation of a secondary path filtering of input signal.

Active noise cancellation can be achieved using the FxNLMS filter. The noise to be cancelled will be referenced by the Reference input. The noise signal close to the error microphone and the acoustic addition of anti-noise make up the error (residual signal) input. The reference signal that has undergone secondary path filtering is known as the Filtered Reference. Where the transfer function of the secondary path is the route from the FxNLMS filter output to the FxNLMS error input.

2.2. Proposed P-FxNLMS Algorithm for ANC

In order to minimize the demerits of existing algorithms the proposed work introduce the novel algorithm to minimize the filter taps by maintaining the stability with improvement in the convergence speed also to minimize the MSE and to identify the unknown system of the filter. Also the proposed algorithm will be more suitable for real noise reduction in various speech application. The proposed algorithm consists of three parts has shown in Figure 2. The first Part proposes a forward path delay with internal and external filter to minimize the filter taps and a Secondary path filter with an actual weighted filter. The second part discussed about a Variable Step Size (VSS) filter with support of WGN and online secondary path to maintain stability and improve the convergence speed of the filter. The time varying secondary direction eliminates the noise from loud speech with VSS. The third part has a dummy weighted filter and an estimated input signal to improve to recognize the unknown system and reduce the system output error.

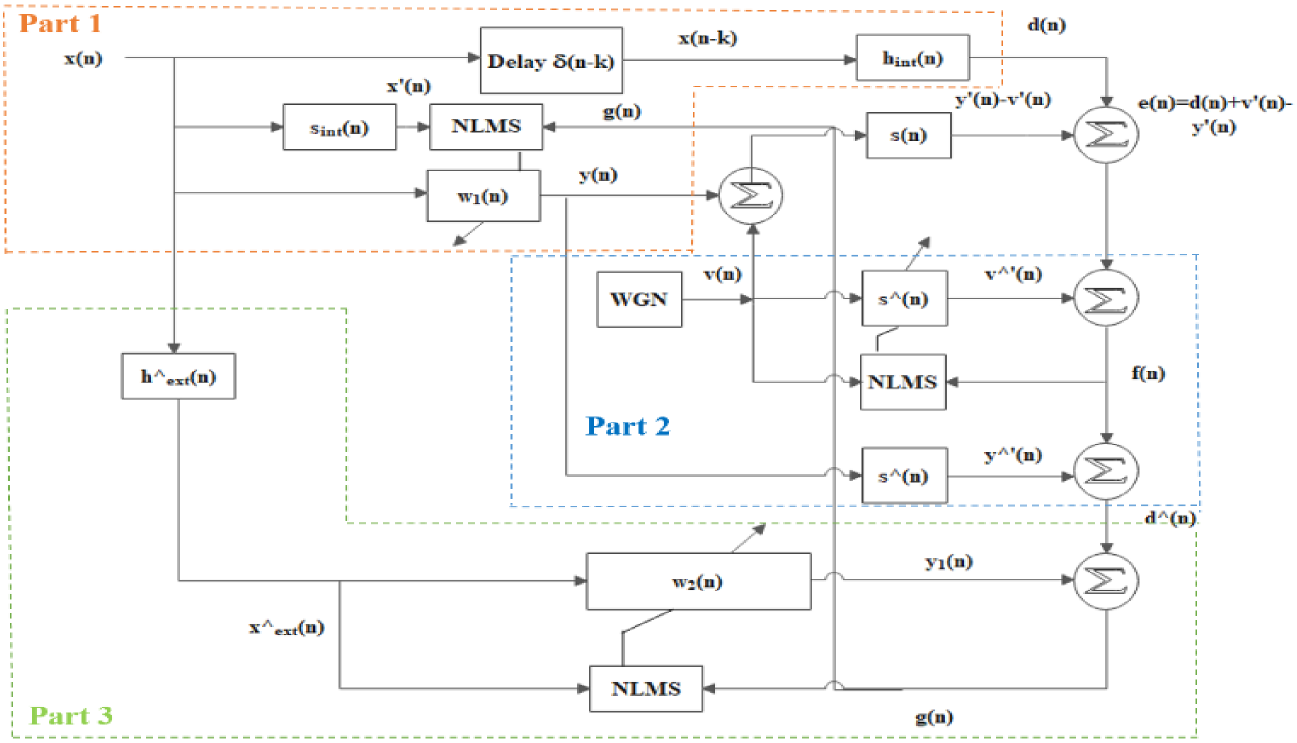


Figure 2. P-FxNLMS block diagram.

The desired impulse response $h_{ext}(n)$ is externally filtered (pre-filtered) before going through the equalisation filter due to distance and room acoustics. The aim of $s(n)$ is to indemnify for the secondary way $s(n)$ that exists betwixt the control filter output and the error microphone output. We know that if increases the filter taps it increases an accuracy of the adaptive process and decreases the convergence rate of the filter. To maintain the speed of convergence while retaining accuracy, a proposed system offered an online secondary route. In order to improve wise, the FXNLMS algorithm in this proposed work added few blocks. The functionality and important of block has been discussed in below headings.

2.2.1. An On-Line Secondary Path Filter

The FxNLMS algorithm is effective in reducing errors between the secondary path and filter model. However, its noise reduction performance is moderate, especially under less than ideal conditions. This effect may compromise the stability of the filter and its ability to maintain noise reduction performance as the secondary path changes over time. Consequently, the proposed work has introduced an online secondary path in the algorithm to maintain the stability of the filter and to prevent adaptation using the FxNLMS algorithm. An additional control filter is also used. The upper bound for the step size parameter is bigger than that for FxNLMS algorithm since the control filter is modified using simple NLMS technique. Faster convergence is possible due to larger step size. As a result, to adjust $W_2(z)$ in the suggested technique, the proposed work employs the P-FxNLMS algorithm [28].

The desired signal $\hat{d}(n)$ for an on-line secondary path is given as

$$\hat{d}(n) = f(n) + \hat{y}'(n) \tag{3}$$

Filter output of on-line secondary path $\hat{y}'(n)$ is given in the Equation (4),

$$\hat{y}'(n) = \hat{s}(n)y(n) \tag{4}$$

Output of updated VSS $\hat{v}'(n)$ defined as,

$$\hat{v}'(n) = \hat{s}(n)v(n) \tag{5}$$

An error signal of Control filter $f(n)$ derived as,

$$f(n) = e(n) - \hat{v}'(n) = e(n) - \hat{s}(n)v(n) \tag{6}$$

2.2.2. VSS Algorithm

The motivation behind the suggested VSS method is that the modelling filter's desired response is tainted by a noise that is decreasing in nature and gradually converges to zero. In fact, this interference might be so great such that online secondary-path modelling would be significantly slower than offline modelling. In contrast to the current VSS algorithms, the suggested VSS algorithm starts with a small step-size and gradually increases to obtain the convergence.

The phase size in the viewing channel (modeling filter) is modified according to the power of the leftover error signal. The NLMS calculation, in which the phase size is changed with the power of the reference signal power, is not the same as this variable step size LMS calculation (algorithm). It's also not the same as the other VSS calculations [13, 28], in which a larger step-size is chosen at first for quick convergence and then a small value is used for little non-adjustable to preserve stability.

The purpose of the $H\hat{}_{ext}(Z)$ model filter is to counterbalance for the secondary way S(Z) exists betwixt the error microphone and that of control filter. The revised step size can be found in the proposed drawing,

$$\hat{s}(n+1) = \hat{s}(n)\mu_s(n)f(n)v(n) \tag{7}$$

A primary path error is,

$$e(n) = d(n) + v'(n) - y'(n) \tag{8}$$

To minimize the error and also maintain the stability of the algorithm to vary the step-size of online secondary path filter, it can define as,

$$\rho(n) = \frac{P_{f(n)}}{P_{e(n)}} \tag{9}$$

Where $P_{e(n)}$ is the power spectra of the error signal in $e(n)$ and $P_{f(n)}$ is the power spectra of the modeling error signal $f(n)$. These attributes can be evaluated using the following pass-through characters, which can be written as,

$$P_{e(n)} = P_{d(n)-y'(n)}P_{v'(n)} \tag{10}$$

Similarly, $P_{f(n)}$ can be expressed as

$$P_{f(n)}P_{d(n)-y'(n)}P_{v(n)\hat{v}'(n)} \tag{11}$$

Since $\hat{v}'(n)$is an estimation of $v(n)$, therefore $P_{f(n)}\approx P_{d(n)-y(n)}$ substitute Equations (10) and (11) in Equation (9) therefore $\rho(n)$can be stated as,

$$\rho(n) \approx \frac{P_{d(n)-y'(n)} + P_{v(n)-\hat{v}'(n)}}{P_{d(n)-y'(n)} + P_{y'(n)}} \tag{12}$$

The injected Additive WGN $v(n)$ is a low-level constant power signal in comparison to the reference noise; hence, at first, $\Rightarrow P_{d(n)-v'(n)} \gg P_{v'(n)}$, $\rho(n)\approx 1$. As $n\rightarrow\infty$, $P_{d(n)-v'(n)} \ll P_{v'(n)}$, $\Rightarrow \rho(n)\approx 1$.

This approach leads to a very straightforward method for determining the size of the steps in the modeling process:

$$\mu_s(n) = [\rho(n)]\mu_{min}(n) + [1-\rho(n)]\mu_{max}(n) \tag{13}$$

Where $\mu_{min}(n)$ represents the step-size lower bounds and $\mu_{min}(n)$ represents the step-size upper bounds determined experimentally.

2.2.3. Delay in a Primary Path

Because of the way that desired signal, may contain the extra deferral because of the space (distance) and an area (room) acoustics put away in the ideal desired reaction [31], the required number of filter taps for the adjustment filter can be enormous. As larger filter taps increase the precision of the adaptive process by closely following the desired signal, they also decrease the convergence rate, so we suggest a P-FxNLMS, as shown in Figure 2. The adaptive filter's secondary path including an extra filter and a forward delay is often known in the critical way with regard to the secondary path's general deferral (A/D, D/A, handling).

A delayed version of input $x(n+k)$ defined as,

$$x(n+k) = x(n) * \delta(n-k) \tag{14}$$

Primary desired signal $d(n)$ derived as,

$$d(n) = p(n) * x(n-k) \tag{15}$$

The adaptive filters proposed system output $y(n)$ is given as,

$$y(n) = w_1^T(n)x'(n) \tag{16}$$

2.2.4. Updated NLMS Step Size

In the previous LMS procedures, the step-size μ is fixed dependent on the insights of the info signal which causes moderate convergence. By and large, in the boisterous climate, the insights of the info signal are obscure. To reduce the adaptive filter's MSE, the NLMS step size parameter was modified.

In the NLMS calculation, the scale of the enhanced signal is modified because of the standard (norm) ‖..‖ value [17]. The computation of step size calculation is used to reduce the MSE performance that modifies the step size. The modification step size μ_m for this proposed P-FxNLMS is portrayed as,

$$\mu_m = \frac{2\alpha}{N(\beta + x(n)x^T(n))} \tag{17}$$

α, β, γ-Selection factor

$0<\alpha<1$, $0<\beta<2$, $0.5<\gamma<1.5$

N-Order of the filter

2.2.5. Two Updated Filter Co-Efficient

In general, most of the adaptive algorithms having one weighted filter for reduce the noise information. But the results are not up to the level. In order to improve the performance, the proposed P-FxNLMS algorithm consists of two adaptive filters aimed to spot to improve to recognize the unknown system and mainly reduce the system output error.

Updated weights of actual and dummy filters are,

$$w_1(n+1) = w_1(n) + \mu x'(n)g(n) \quad (18)$$

and

$$w_2(n+1) = w_2(n) + \mu \hat{x}'(n)g(n) \quad (19)$$

A secondary path output is defined as follow:

$$y_1(1+n) = w_2(n) + \hat{x}_{ext}(n) \quad (20)$$

A secondary path desired input is defined as follow:

$$\hat{d}(n) = f(n) + \hat{y}'(n) \quad (21)$$

From proposed algorithm block diagram we can get an overall error of the system $g(n)$ is derived as,

$$g(n) = y_1(n) + \hat{d}(n) \quad (22)$$

- Parameters for the proposed method's simulation

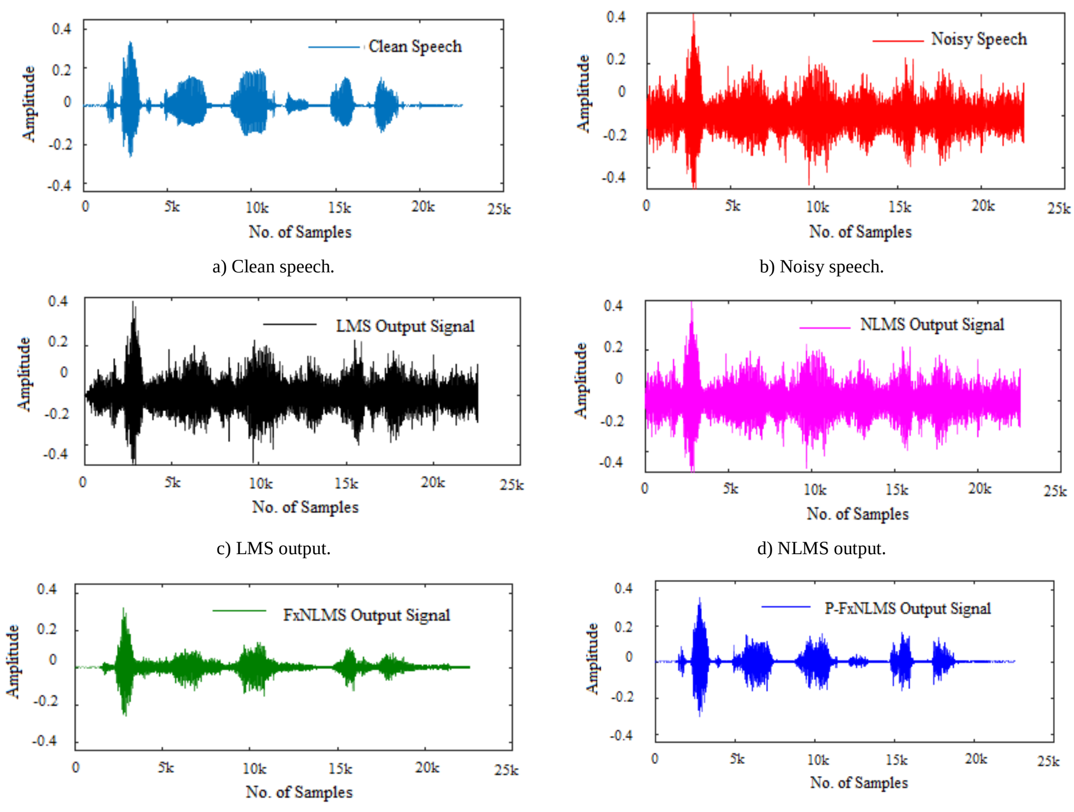
The following parameters have been assumed on the basis of an optimized filter performance for the proposed system.

α_1=Selection factor for $W_1(z)$=0.50
α_2=Selection factor for $W_2(z)$=0.60
β_1=Selection factor for $W_1(z)$=1.25
β_2=Selection factor for $W_2(z)$=1.45
γ_1=Selection factor for $W_1(z)$=1.30
γ_2=Selection factor for $W_2(z)$=0.85
$\mu_{min}(n)=2\times10^{-3}$
$\mu_{max}(n)=6\times10^{-3}$

3. Simulation Result

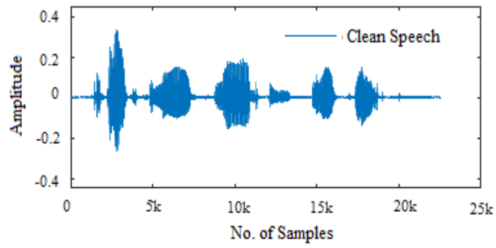
The rationale behind the selection of our proposed algorithm throw insights for better understanding about MSE, improved SNR, subjective speech metrics such as MOS, Perceptional Evaluation Speech Quality (PESQ) and Short Term Objective Intelligibility (STOI) under specific applications or noise conditions. The various existing ANC algorithms are LMS, sign-data, sign-error, sign-sign, NLMS, PNLMS, IPNLMS, MPNLMS and SS-MPNLMS out of these, in [30, 29] the algorithms are compared and the proposed ANC algorithm (P-FxNLMS) justifies better background noise removal. Hence the proposed P-FxNLMS also has been compared with the existing for back ground noise removal to achieve better results. The proposed algorithm can be referred as a base algorithm for many speech applications such as speech enhancement, speech recognition, Background noise removal in telecommunication, Speaker identification, Speech to Text conversion, etc., [1, 8].

The noisy database consists of eight different real-world noises at various SNRs that has 30 distorted IEEE keywords (by three male and female speakers). The noise contains babble, vehicle, exhibition hall, restaurant, street, airport, train and train station sounds and was collected from the NOIZEUS database [11]. At SNRs of 0 dB, 5 dB, 10 dB, and 15 dB, the noise signals were combined with the speech signals accordingly to ensure that the proposed algorithm performs well across different noise level.

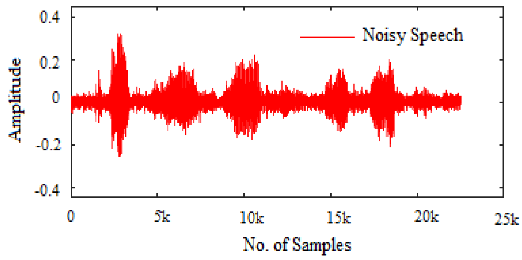


a) Clean speech. b) Noisy speech.
c) LMS output. d) NLMS output.
e) FxNLMS output. f) P-FxNLMS output.

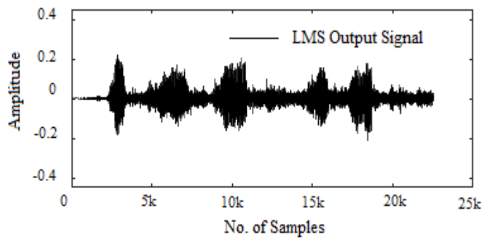
Figure 3. The algorithm performance of babble noise with 0dB SNR input.



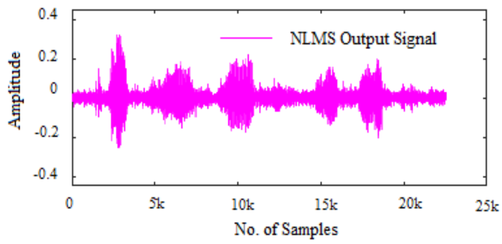
a) Clean speech.



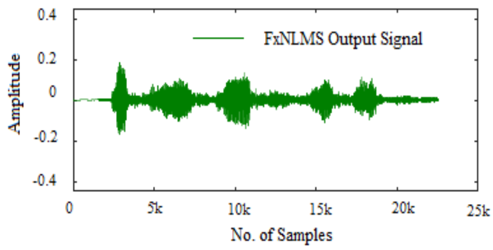
b) Noisy speech.



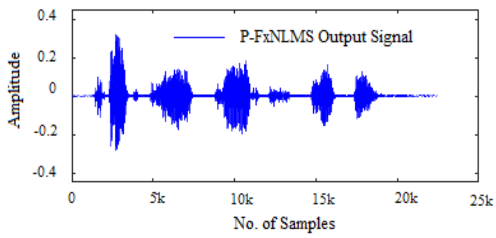
c) LMS output.



d) NLMS output.

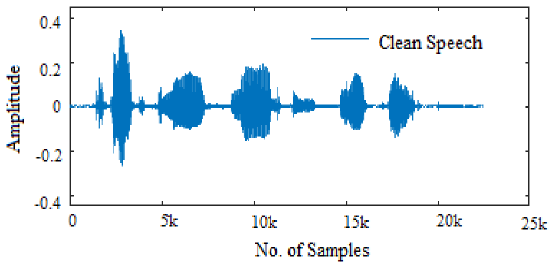


e) FxNLMS output.

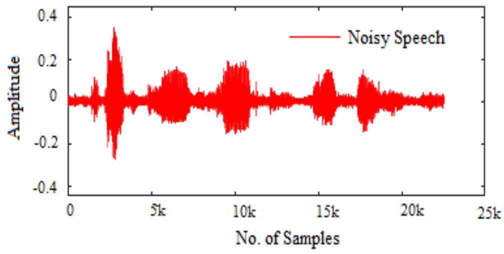


f) P-FxNLMS output.

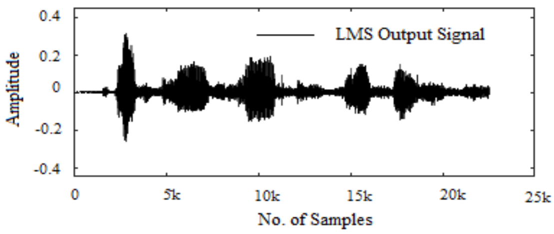
Figure 4. The algorithm performance of babble noise with 5dB SNR input.



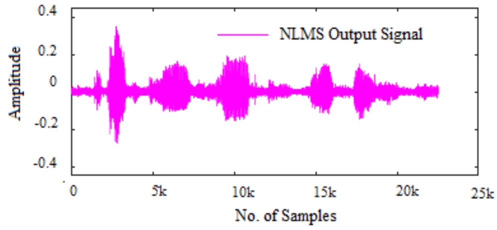
a) Clean speech.



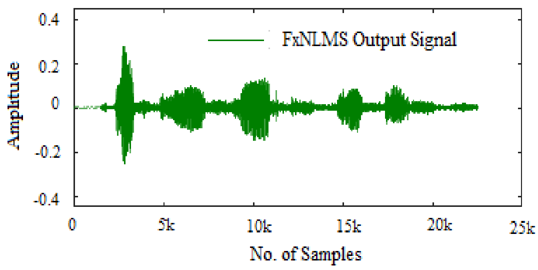
b) Noisy speech.



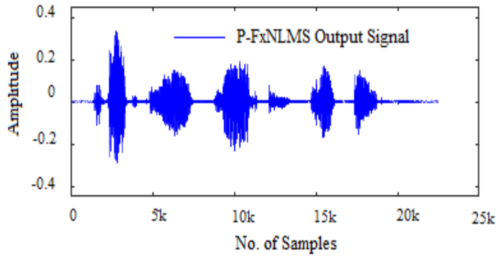
c) LMS output.



d) NLMS output.

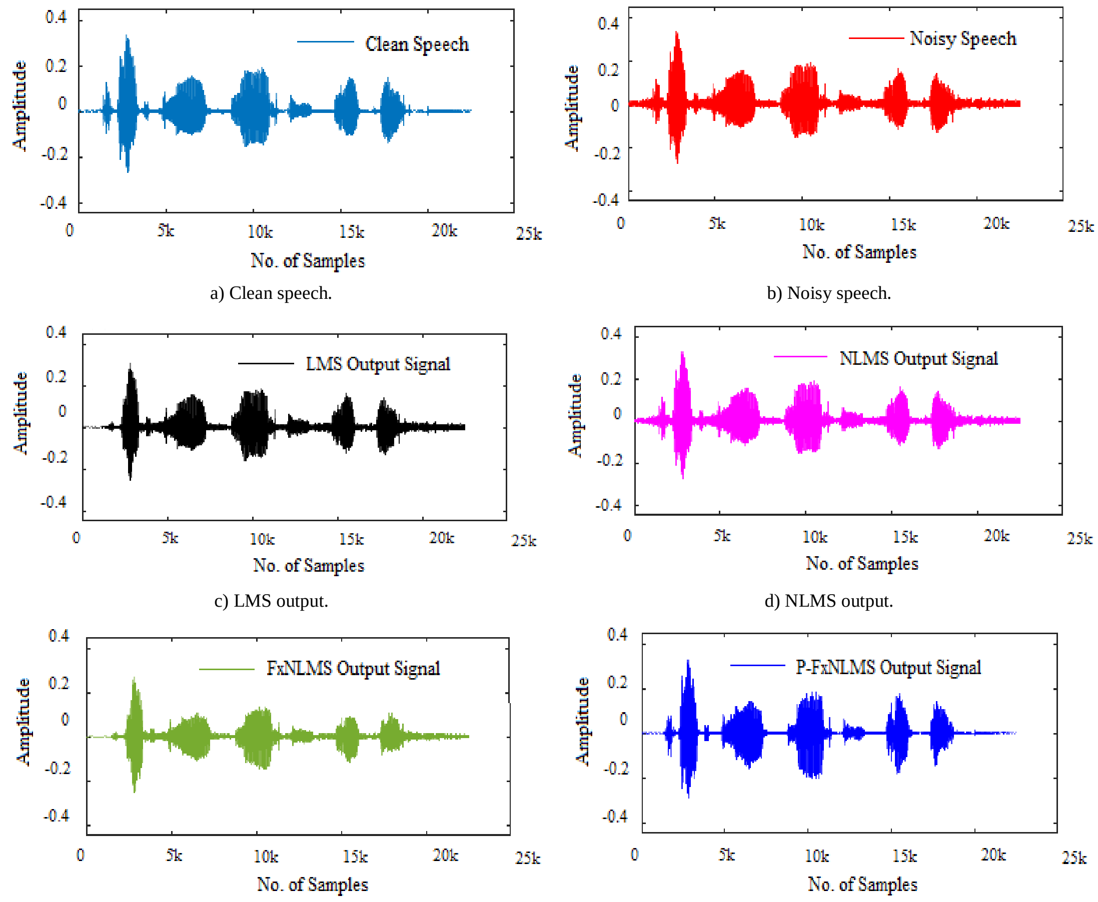


e) FxNLMS output.



f) P-FxNLMS output.

Figure 5. The algorithm performance of babble noise with 10dB SNR input.



a) Clean speech. b) Noisy speech.

c) LMS output. d) NLMS output.

e) FxNLMS output. f) P-FxNLMS output.

Figure 6. The algorithm performance of babble noise with 15dB SNR input.

These signal phrases were down sampled from the original 25 kHz sample rate to 8 kHz. The noise signals were added to the speech signals at various SNRs to evaluate the filter performance. From the analysis of P-FxNLMS algorithm with existing LMS, NLMS and FxNLMS algorithms, it is observed that P-FxNLMS algorithm provides a better result over others. It can observe that convergence speed is high, minimize the error, reduce the filter taps and maintaining the stability compare with all the other algorithms. The time-domain plot shown in Figure 3 is comparison between the algorithm's performance a noisy speech of babble noise with 0 dB SNR input. It having clean speech and a noisy signal with the filter output performance of LMS, NLMS, FxNLMS and P-FxNLMS. Likewise, the time-domain plot shown in Figure 4 is comparison between the algorithm's performance a noisy speech of babble noise with 5 dB SNR input. The time-domain plot shown in Figure 5 is comparison between the algorithm's performance a noisy speech of babble noise with 10 dB SNR input. The time-domain plot shown in Figure 6 is comparison between the algorithm's performance a noisy speech of babble noise with 15 dB SNR input. P-FxNLMS performance appears to be nearly identical to clean expression. In addition, as compared to current speech signal quality, it provides better speech signal quality that is similar to the initial clean speech.

The Jacobi method of convergence is the iterative method. The steady state of existing algorithms is reached after 80 to 100 adaption cycles. It is feasible to directly compare the algorithms with their unique parameters in terms of the other performance criteria based on the information as show in Figure 7. The proposed algorithm achieves stable state before 40th cycles of adaptation.

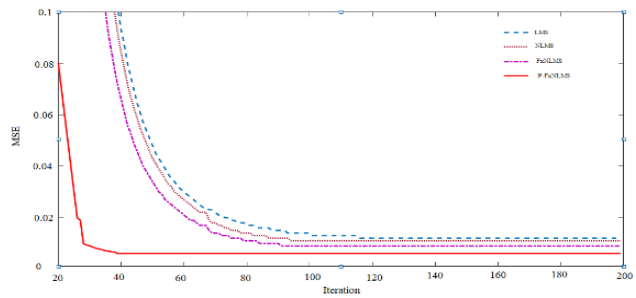


Figure 7. Performance of the proposed and current algorithms in terms of MSE with 0dB input SNR of babble noise.

The MSE Performance of the suggested and existing algorithms is shown in Figure 7 with 0dB input SNR of babble noise. We can observe that P-FxNLMS algorithm reaching the minimum MSE compared to others that also very minimal iteration that means fast convergence speed compare to other algorithms. Since, as the size of the main steps will decrease, the dynamic filter orders increase. Figure 8 shows the proposed algorithm with various input SNRs of babble noise (0dB, 5dB, 10dB, and 5dB) and Figure 9 shows the various noises from the NOIZEUS database, respectively.

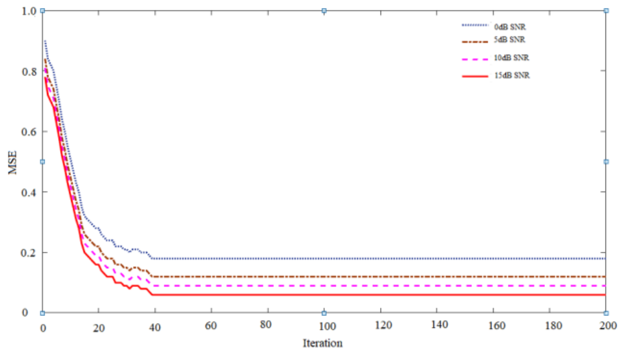


Figure 8. Performance of the proposed algorithms in terms of MSE with different input SNR of babble noise.

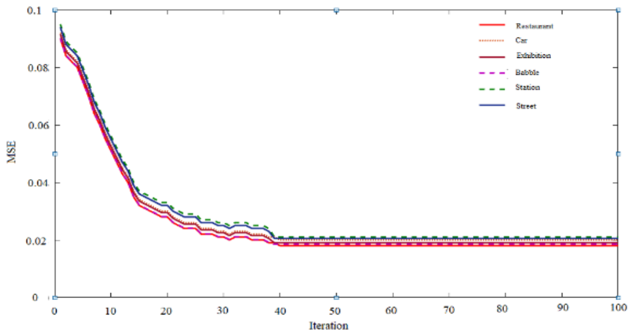


Figure 9. Performance of the proposed algorithms in terms of MSE with various noise type.

The SNR output performance of the suggested and existing algorithms is shown in Figure 10 with 0dB to 15 dB input SNR of babble noise. We can observe that P-FxNLMS algorithm reaching the Maximum SNR output compared to others that also around 1.45 dB to 4.07 dB compare to other algorithms

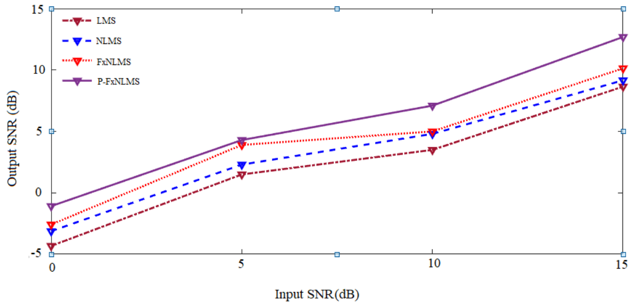


Figure 10. Performance of the proposed and current algorithms in terms of SNR with 0dB to 15 dB input SNR of babble noise.

3.1. Results and Discussion

The Table 1 shows the performance of existing to that of proposed filter with order of N=10 to N=50. It is clearly seen that the proposed filter value gradually decreases when the order of filter is increased in same time producing less MSE value when compare to the existing filter.

Table 1. MSE vs filter order performance of the existing and proposed algorithm.

Filter Order (N)	Existing Filter MSE–FxNLMS	Proposed Filter MSE–P-FxNLMS
10	0.0612	0.0478
15	0.0585	0.0312
20	0.0540	0.0306
25	0.0498	0.0303
30	0.0475	0.0292
35	0.0425	0.0269
40	0.0380	0.0125
45	0.0310	0.0095
50	**0.0125**	**0.0080**

Table 2 compares the MSE of existing and proposed ANC systems for various noises at various input SNR levels. According to the results of these checks, the P-FxNLMS algorithm reduces the MSE by 42% to 73.68%, 48.4% to 72.22% and 38.46% to 58.33% when compared to the LMS, NLMS, and FxNLMS algorithms, respectively.

Table 2. MSE comparison of current and proposed ANC systems for different noises at various input SNR levels.

ANC Algorithms	**LMS**				**NLMS**				**FxNLMS**				**P-FxNLMS**			
SNR in dB	0	5	10	15	0	5	10	15	0	5	10	15	0	5	10	15
Babble	0.041	0.033	0.029	0.021	0.029	0.022	0.018	0.012	0.027	0.020	0.015	0.010	**0.020**	**0.014**	**0.011**	**0.008**
Car	0.038	0.029	0.021	0.015	0.028	0.020	0.014	0.011	0.025	0.017	0.014	0.011	**0.018**	**0.015**	**0.010**	**0.009**
Exhibition	0.043	0.035	0.024	0.019	0.031	0.027	0.021	0.018	0.026	0.019	0.015	0.012	**0.016**	**0.012**	**0.009**	**0.005**
Restaurant	0.040	0.033	0.024	0.018	0.027	0.024	0.019	0.017	0.023	0.017	0.016	0.014	**0.018**	**0.013**	**0.010**	**0.007**
Station	0.042	0.034	0.029	0.021	0.033	0.030	0.024	0.019	0.022	0.019	0.015	0.013	**0.019**	**0.014**	**0.011**	**0.008**
Street	0.044	0.037	0.028	0.019	0.028	0.025	0.022	0.016	0.026	0.020	0.016	0.013	**0.021**	**0.019**	**0.016**	**0.011**

Table 3. SNRi comparison of current and proposed ANC systems for different noises at various input SNR levels.

ANC Algorithms	**LMS**				**NLMS**				**FxNLMS**				**P-FxNLMS**			
SNR in dB	0	5	10	15	0	5	10	15	0	5	10	15	**0**	**5**	**10**	**15**
Babble	-4.32	1.50	3.50	8.65	-3.12	2.30	4.80	9.16	-2.58	3.90	5.00	10.14	**-1.08**	**4.30**	**7.10**	**12.69**
Car	-4.51	-0.23	3.99	8.41	-3.22	0.77	5.02	8.88	-2.95	1.19	5.65	9.87	**-1.35**	**3.29**	**7.69**	**12.16**
Exhibition	-4.36	0.18	1.30	8.76	-3.04	1.20	5.48	9.31	-2.45	1.90	6.08	10.26	**-1.03**	**3.57**	**8.07**	**12.71**
Restaurant	-4.35	0.07	4.08	8.55	-3.13	0.99	5.25	9.07	-2.62	1.71	5.69	9.99	**1.11**	**3.48**	**7.99**	**12.64**
Station	-4.42	0.05	4.06	8.51	-3.19	0.91	5.18	9.09	-2.70	1.68	5.65	9.97	**-1.14**	**3.44**	**7.91**	**12.58**
Street	-4.25	0.13	4.26	8.78	-3.06	1.15	5.39	9.22	-2.51	1.84	5.99	10.19	**-1.06**	**3.57**	**8.09**	**12.76**

The Maximum SNR output reaches around 1.45 dB to 4.07 dB compared to other existing algorithms and

Table 3 shows the SNR improvement (SNRi) performance in the dB for reducing various noises such as babble, exhibition, station, car, restaurant and street noise with various SNR input levels that are used to test current and proposed algorithms. From these test results, it is evident that the proposed algorithm increases 3.19 dB to 4.07dB, 2.04 dB to 3.53 dB and 1.45 dB to 2.57 dB of SNRi compared with LMS, NLMS and FxNLMS algorithms exist respectively.

In Figure 7 displays the MSE Performance of the proposed and current techniques with a 0dB input SNR of babbling noise. The existing algorithms reach their minimum MSE value after 80-100 adaptation cycles, but the proposed algorithm will reach the minimum MSE value before the 30-40 adaption cycle, the suggested approach produces minimal error with stable output. In comparison to other algorithms, it can be seen that the P-FxNLMS algorithm achieves the smallest MSE. This demonstrates that, in comparison to other algorithms, it requires very few iterations and converges quickly.

The advantages of the proposed system can be better understood by comparing with existing algorithms to reduce filter taps, the suggested algorithm recommends adding a forward route delay. The MSE for the L=50 filter tap using the current FxNLMS algorithm was approximately 0.0125, but the identical filter tap using the suggested P-FxNLMS strategy yielded 0.008. Similarly, using the L=40 filter tab, the suggested procedure yielded the 0.0125 MSE. Because the suggested approach introduces forward path delay, the reduction filter provides low MSE and less filter tap.

To maintain the system stability, the proposed system also utilizes VSS aided by WGN to enhance stability in various level of noise with different type of noises. Due to large disturbance [note that initially cancelling signal $y'(n)$ is zero the convergence of the modeling filter is degraded, and in worst case it may be unstable. As $n \rightarrow \infty$, $y'(n)$ would converge to $d(n)$ and thus (ideally) $[d(n)-y'(n)+v(n)]$ converges to zero. Based on these observations, we can increase the step size later on when the disturbance signal $[d(n)-y'(n)+v(n)]$ is zero. Initially, we should set the step size parameter μs to a small value. Since prior algorithms did not have access to this disturbance signal, we suggest an indirect method to change the step size $\mu_s(n)$.

The VSS NLMS technique will aid in boosting convergence as well. In order to account for the decline in $[d(n)-y'(n)+v(n)]$ one should first choose a small step size and increase it to the maximum amount. The step size may remain small for an extended period if $w_1(n)$ reduces $[d(n)-y'(n)+v(n)]$ slowly. This would slow down the convergence in current algorithms. Because it is adapting using a modified error signal, the control filter $w_1(n)$ will converge quickly. Consequently, this enhances the functionality of the modeling filter based on VSS NLMS.

Additionally, employing a dummy weighted filter $w_2(n)$ with an estimated input signal $g(n)$ helps it recognize unknown systems and reduce system $y_1(n)$ output errors as represented in Equation (20).

Table 4. Speech quality metric table.

ANC Algorithms	PESQ				STOI				MOS			
	0 dB	5 dB	10 dB	15 dB	0 dB	5 dB	10 dB	15 dB	0 dB	5 dB	10 dB	15 dB
LMS	3.35	3.44	3.61	3.69	0.48	0.53	0.58	0.65	3.06	3.23	3.45	3.67
NLMS	3.41	3.52	3.69	3.75	0.54	0.59	0.63	0.71	3.24	3.43	3.62	3.85
FxNLMS	3.54	3.66	3.78	3.83	0.62	0.64	0.69	0.78	3.51	3.63	3.83	4.07
P-FxNLMS	**3.62**	**3.84**	**3.98**	**4.10**	**0.71**	**0.75**	**0.78**	**0.89**	**3.78**	**4.01**	**4.16**	**4.50**

Table 5. Sample Calculation for MOS based on PESQ and STOI (15dB).

ANC Algorithms	PESQ for 15 dB babble noise	% PESQ for 4.5 scale	STOI for 15 dB babble noise	% STOI for 1 scale	Avg. % of PESQ and STOI	MOS (5 scale point)
LMS	3.69	82	0.65	65	73.5	3.675
NLMS	3.75	83.33	0.71	71	77	3.85
FxNLMS	3.83	85.11	0.78	78	81.55	4.077
P-FxNLMS	4.1	91.11	0.89	89	90.05	4.502

Table 4 shows the speech quality metric that finds Mean Opinion Score (MOS) for babble noise of different input SNR. The MOS was found by taking the average of PESQ and STOI for various ANC Algorithms.

Table 5 shows the sample calculation for 15 dB SNR MOS based on PESQ with 4.5-point scale and STOI with 1-point scale of clean speech. The calculation clearly justifies that proposed algorithm excels in removing background noise of MOS with the scale value of above 4 as excellent, 3.5 to 4 as very good, 3 to 3.5 as good, 2.5 to 3 as bad and less than 2.5 as poor. The proposed algorithm removes the background noise with excellent scale value compared with existing ANC algorithms.

4. Conclusions

This paper, a P-FxNLMS algorithm is proposed to improve a speech signal quality in the presence of background noise. For the proposed and current algorithms, simulations are conducted using a variety of sounds with various input levels (0dB, 5dB, 10dB, and 15dB), vicelike babble, exhibition, car, exhibition, station, restaurant, and street noises. The increase in SNR segmentation for P-FxNLMS is around 1.45 dB to 4.07 dB similarly 38.46 % to 73.68 % of the MSE and 6 to 16% improvement in speech quality metric (PESQ, STOI and MOS) as compared to the algorithms available for different sounds with different SNR input levels. According to the findings, the proposed algorithm maintains consistency, produces very little error, has a faster convergence rate, and needs fewer filter taps than existing methods. Furthermore, the improved speech signal is free of speech interference and residual noise.

The proposed algorithm adapts the dual adaptive filters, an updated VSS, a delay in the primary path, a slight improvement in the on-line secondary path, and a modified filter step size that maintains consistency, produces very little error, has a faster convergence rate, and needs fewer filter taps than existing methods can be noted as an advantage. The limitation of the proposed work is it uses background noise removal alone and does not concentrate on speech enhancement through machine learning to improve speech quality.

The computational complexity of the existing algorithm has lowest convergence due to the highest tap length in the filter has been overcome by the proposed algorithm for simulated environment. Few challenges present in the creation of any ANC system can be High accuracy, Low latency, easily to adapt existing processor, flexible deployment and scalability for the simulated environment. The real time practical implementation can be taken into consideration for future work to study about computational complexity as well as the challenges faced by the algorithm.

References

[1] Abbas N. and Kabudian J., "Speech Scrambling Based on Independent Component Analysis and Particle Swarm Optimization," *The International Arab Journal of Information Technology*, vol. 14, no. 4, pp. 521-527, 2017. https://www.iajit.org/upload/files/Speech-Scrambling-based-on-Independent-Component-Analysis-and-Particle-Swarm-Optimization.pdf

[2] Belyi V. and Gan W., "A Combined Bilateral and Binaural Active Noise Control Algorithm for Closed-Back Headphones," *Applied Acoustics*, vol. 160, pp. 107129, 2020. https://doi.org/10.1016/j.apacoust.2019.107129

[3] Chavalitsakulcha P. and Shahnavaz H., "The Need for a Participatory Conservation Programme for the Reduction of Noise Exposure to Thai Female Workers," *Asia Pacific Journal of Public Health*, vol. 3, no. 4, pp. 310-314, 1989. DOI:10.1177/101053958900300412

[4] Chen G. and Liu Y., "Mechanisms of Noise-Induced Hearing Loss Potentiation by Hypoxia," *Hearing Research*, vol. 200, no. 1-2, pp. 1-9, 2005. https://doi.org/10.1016/j.heares.2004.08.016

[5] Elliott S. and Nelson P., "Active Noise Control," *IEEE Signal Processing Magazine*, vol. 10, no. 4, pp. 12-35, 1993. DOI:10.1109/79.248551

[6] Elliott S., *Signal Processing for Active Control*, Academic Press, 2001. https://books.google.jo/books?id=GklDOTI6ZLIC&printsec=copyright&hl=ar#v=onepage&q&f=false

[7] Fang Y., Zhu X., Liu H., and Gao Z., "Hybrid Fx-NLMS Algorithm for Active Vibration Control of Flexible Beam with Piezoelectric Stack Actuator," *in Proceedings of the International Conference on Life System Modeling and Simulation, and International Conference on Intelligent Computing for Sustainable Energy and Environment*, Nanjing, pp. 273-281, 2017. https://doi.org/10.1007/978-981-10-6370-1_27

[8] Fekri-Ershad S., Fakhrahmad S., and Tajeripour F., "Impulse Noise Reduction for Texture Images Using Real Word Spelling Correction Algorithm and Local Binary Patterns," *The International Arab Journal of Information Technology*, vol. 15, no. 6, pp. 1024-1030, 2018. https://iajit.org/portal/PDF/November%202018,%20No.%206/10939.pdf

[9] Fuller C., Elliott S., and Nelson P., "*Active Control of Vibration*, Academic Press, 1996. https://www.sciencedirect.com/book/9780122694400/active-control-of-vibration

[10] Hansen C. and Snyder S., *Active Control of Noise and Vibration*, E and FN Spon, 1997. https://m.ciop.pl/CIOPPortalWAR/appmanager/ciop/mobi?_nfpb=true&_pageLabel=P42601713191498050635882&html_tresc_root_id=300007675&html_tresc_id=300007719&html_klucz=300007675&html_klucz_spis=

[11] Hu Y. and Loizou P., "Subjective Evaluation and Comparison of Speech Enhancement Algorithms," *Speech Communication*, vol. 49, no. 7-8, pp. 588-601, 2007. https://doi.org/10.1016/j.specom.2006.12.006

[12] Kim D., Lee M., and Park P., "A Robust Online Secondary-Path Filter Active Noise Control System for Noisy Inputs and Impulsive Noises in Sparse Systems," *in Proceedings of the IEEE Asia Pacific Conference on Circuits and Systems*, Bangkok, pp. 281-284, 2019. DOI:10.1109/APCCAS47518.2019.8953121

[13] Koike S., "A Class of Adaptive Step-Size Control Algorithms for Adaptive Filters," *IEEE Transactions on Signal Processing*, vol. 50, no. 6, pp. 1315-1326, 2002. DOI:10.1109/TSP.2002.1003057

[14] Kuo S. and Morgan D., "Active Noise Control: A Tutorial Review," *Proceeding of the IEEE*, vol. 87, no. 6, pp. 943-973, 1999. DOI:10.1109/5.763310

[15] Kuo S. and Morgan D., *Active Noise Control Systems-Algorithms and DSP Implementations*, John Wiley, 1996. https://dl.acm.org/doi/book/10.5555/553072

[16] Kwong R. and Johnston E., "A Variable Step Size

LMS Algorithm," *IEEE Transactions on Signal Processing*, vol. 40, no. 7, pp. 1633-1642, 1992. DOI:10.1109/78.143435

[17] Luo Z., Shi D., and Gan W., "A Hybrid SFANC-FxNLMS Algorithm for Active Noise Control Based on Deep Learning," *IEEE Signal Processing Letters*, vol. 29, pp. 1102-1106, 2022. DOI:10.1109/LSP.2022.3169428

[18] Luo Z., Shi D., Gan W., Huang Q., and Zhang L., "Performance Evaluation of Selective Fixed-Filter Active Noise Control Based on Different Convolutional Neural Networks," *in Proceedings of the INTER-NOISE and NOISE-CON Congress*, Glasgow, pp. 999-1999, 2022. https://doi.org/10.3397/IN_2022_0228

[19] Meng H. and Chen S., "A Modified Adaptive Weight-Constrained FxLMS Algorithm for Feedforward Active Noise Control Systems," *Applied Acoustics*, vol. 164, pp. 107227, 2020. https://doi.org/10.1016/j.apacoust.2020.107227

[20] Nelson P. and Elliott S., *Active Control of Sound*, Academic Press, 1992. https://www.amazon.com/Active-Control-Sound-P-Nelson/dp/0125154267

[21] Okpala N., "Knowledge and Attitude of Infantry Soldiers to Hearing Conservation," *Military Medicine*, vol. 172, no. 5, pp. 520-522, 2007. https://doi.org/10.7205/MILMED.172.5.520.

[22] Park T., Kim D., and Park P., "A Filtered-x VSS-NSAF Active Noise Control Algorithm Robust to Impulsive Noise through the Application of Step-Size Scaler," *in Proceedings of the 15th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, Chiang Rai, pp. 744-747, 2018. DOI:10.1109/ECTICon.2018.8619925

[23] Ravinchandra K., Fei T., and Yong L., "Active Noise Reduction Using LMS and FxLMS Algorithms," *in Proceedings of the International Conference on Computer Vision and Machine Learning*, Andhra Pradesh, 2018. DOI:10.1088/1742-6596/1228/1/012064

[24] Saito N. and Sone T., "Influence of Modeling Error on Noise Reduction Performance of Active Noise Control Systems Using Filtered-x LMS Algorithm," *Journal of the Acoustical Society of Japan (E)*, vol. 17, no. 4, pp. 195-202, 1996. https://doi.org/10.1250/ast.17.195

[25] Shi D., Gan W., Lam B., and Shi C., "Two-Gradient Direction FXLMS: An Adaptive Active Noise Control Algorithm with Output Constraint," *Mechanical Systems and Signal Processing*, vol. 116, pp. 651-667, 2019. https://doi.org/10.1016/j.ymssp.2018.06.062

[26] Song P. and Zhao H., "Filtered-x Least Mean Square/Fourth Algorithm for Active Noise Control," *Mechanical Systems and Signal Processing*, vol. 120, pp. 69-82, 2019. https://doi.org/10.1016/j.ymssp.2018.10.009

[27] Tokhi O. and Veres S., *Active Sound and Vibration Control: Theory and Applications*, Institute of Electrical Engineers, 2002. http://eprints.soton.ac.uk/id/eprint/22542

[28] Vazquez A., Avalos J., Sanchez G., Sanchez J., and Perez H., "A Comparative Survey of Convex Combination of Adaptive Filters," *IETE Journal of Research*, vol. 69, no. 2, pp. 940-950, 2020. https://doi.org/10.1080/03772063.2020.1844075

[29] Vinothkumar G. and Manoj Kumar D., "Speech Enhancement with Background Noise Suppression in Various Data Corpus Using Bi-LSTM Algorithm," *International Journal of Electrical and Electronics Research*, vol. 12, no. 1, pp. 322-328, 2024. https://doi.org/10.37391/IJEER.120144

[30] Vinothkumar G. and Phani Kumar Polasi P. "Filter Performance of Sparse Noise for Controlling the Occurrence of Noise-Induced Hearing Loss Using Hybrid Algorithm," *in Proceedings of the 12th National Conference on Recent Advancements in Biomedical Engineering*, Chennai, pp. 030013, 2020. https://doi.org/10.1063/5.0072454

[31] Wang X., Ou S., and Pang Y., "Adaptive Combination of Filtered-X NLMS and Affine Projection Algorithms for Active Noise Control," *in Proceedings of the Artificial Intelligence: 2nd CAAI International Conference*, Beijing, pp. 15-25, 2022. https://doi.org/10.1007/978-3-031-20503-3_2

[32] Zhao T., Liang J., Zou L., and Zhang L., "A New FXLMS Algorithm with Offline and Online Secondary-Path Modeling Scheme for Active Noise Control of Power Transformers," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 8, pp. 6432-6442, 2017. DOI:10.1109/TIE.2017.2682043

Vinothkumar.G is a research scholar in the Department of ECE, SRM Institute of science and Technology, Ramapuram Campus, Chennai. He is currently pursuing his Ph.D from SRM Institute of science and Technology Chennai. His areas of interests are Signal Processing, Biomedical Engineering and Communication Systems.

Manoj Kumar.D obtained his Ph.D in Electronics and Communication Engineering under the area of specialization in VLSI-Cryptography from Bharath Institute of Higher Education and Research, Chennai, India during the year 2019. He did his M.Tech in Applied Electronics from St. Peter's Institute of Higher Education and Research, Chennai during 2012. He had his B.E in Electronics and Communication Engineering from Jerusalem College of Engineering, Chennai during 2010. He has 8 years of teaching experience including 4 years of Research experience. He has published more than 8 papers both in International Conference and Journals to his credit.