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Active Noise Control Using Modified FsLMS and Hybrid PSOFF Algorithm

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Featured Application: Military, aerospace and industrial applications.

Abstract: Active noise control is an efficient technique for noise cancellation of the system, which has been defined in this paper with the aid of Modified Filtered-s Least Mean Square (MFsLMS) algorithm. The Hybrid Particle Swarm Optimization and Firefly (HPSOFF) algorithm are used to identify the stability factor of the MFsLMS algorithm. The computational difficulty of the modified algorithm is reduced when compared with the original Filtered-s Least Mean Square (FsLMS) algorithm. The noise sources are removed from the signal and it is compared with the existing FsLMS algorithm. The performance of the system is established with the normalized mean square error for two different types of noises. The proposed method has also been compared with the existing algorithms for the same purposes.

Keywords: active noise elimination; MFsLMS algorithm; multichannel ANC; HPSOFF

1. Introduction

The Active Noise Control (ANC) system has been growing rapidly in recent years because of the failure of the conventional noise mitigation systems in the diminution of the error noise over the applications. The level of the residual noise is controlled by Least Mean Square (LMS) adaptive filters [1]. Narrowband and wideband noise sources are destructed by an ANC system based on the principle of destructive interference between the primary and secondary noise sources. Basic applications of the acoustic noise sources are fans, blowers, transformers, and engines. The ANC scheme diminishes the low-frequency noise, and the magnitude in response path can be determined by the performance of the ANC system [2].

The adaptation algorithms are used for the active noise and vibration control [3]. The multiple harmonics are reduced by the extension of noise sources. The signals are sampled at the beginning, and then, processed by a digital signal processing system; in which anti-noise is generated by the loudspeakers [4]. The FxLMS algorithm is used to compute the acoustic delay and transducer transfer function. As per the radiation impedance, the global sound control is achieved [5].

Any ANC system does not reduce the original amplitude of sounds because of the presence of low noise in the system. Due to the involvement of digital signal processing, the performance of ANC can be improved [6,7]. The filtered error structure is exhibited to reduce the non-linear ANC with the linear secondary path. The statistical properties of the system provide robustness and reduce computational complexity [8].

The fast affine projection algorithm creates a trade-off between the speed and complexity of the method. The reduction of error can create the minimization of filter coefficients. The adaptive filters are used to cancel the noise present in the system. The acoustic plants are derived from removing the poles, and Recursive Least Mean Square (RLMS) algorithm has been adapted as an attenuation system. It converges with random noise signal and narrowband input signals [9,10].

To control the generator noise of real-time experiments, Adaptive Feedback Active Noise Control (AFANC) algorithm is used. The primary noise will be cancelled out according to the superposition principle. Thus, the anti-noise is generated with equal amplitude and phase to remove the original noise [11]. The harmonics and the noise are reduced to the level of blade passing frequency, at different flow rates. Turbulent and rotational blade passing noise is present in the system of the fan. The recursive least square algorithm makes the ANC scheme effective [12].

The controller coefficients are varied by the feedforward and feedback control. Due to the control of blade passing noise, the centrifugal noise is reduced. Undesirable noise is calibrated at the output of the system [13]. To digital ANC system, the analog feedback loop is added to reduce fluctuation in the system. The narrowband and wideband noise can be reduced by a hybrid headset system, and the stability of the FxLMS algorithm can be improved [14]. Any active noise can be controlled by modeling the secondary path online and offline, with faster convergence and high accuracy. Low residue noise and zero mean error can be achieved effectively [15].

The transfer function of the secondary path can be estimated between the secondary source and the error microphone; in which a primary noise exhibits non-linear distortion at the cancellation point. The secondary source can be created by using the FxLMS algorithm [16]. Noise cancellation occurs due to the reintroduction of noise at the position of the field. Primary noise propagates in the duct with high sound pressure. The non-minimum phase response is exhibited between the error phone and speaker [17]. The filter generates the zero error. Thus, the error signal appears with no delay. The gain value can control the speed of the adaptive filter [18]. The use of the FxLMS algorithm sometimes causes high pressure in the primary noise, chaotic behavior in the noise and causality constraint violation. To overcome these problems, the Volterra Filtered-x LMS (VFxLMS) algorithm has been developed [19].

In the broadband feedforward noise measurement, it has been measured directly from the reference sensor, but in the narrowband feedforward system, noise is generated from the information provided by the reference sensor [20]. The primary application of the LMS algorithms is the minimization of the error in the original signal generated by the primary source [21]. The FsLMS algorithm is better than the FxLMS algorithm to eliminate the noise source presented in the system; which can be observed from the reduction of computational complexity [22].

Optimization algorithms are also used in the design of ANC systems. The non-linear approach to noise elimination is the efficient one when compared to the linear approach of ANC [23]. The widely used optimization algorithm is a Genetic Algorithm (GA). It has the advantage that it does not require the information about the secondary path. In recent days, the Particle Swarm Optimization (PSO) algorithm is also used for ANC systems to get the coefficient of the filter bank while tuning [24,25].

2. Contribution

The several techniques were developed and used for the design of the ANC system with reduced noise. In this paper, the MFsLMS algorithm is proposed for the design of the ANC system, and the HPSOFF algorithm for the identification of stability factor.

- The MFsLMS algorithm reduces the computational complexity of the FsLMS algorithm.
- The McLaurin series relaxes the functional expansion of the MFsLMS algorithm.
- The stability of the proposed ANC system is evaluated via HPSOFF, by the stability factor.

3. Related Works

The Recent Works Related to the Proposed Method Are Given Below

For single and multichannel systems, a combined approach of adaptive filters for ANC had been proposed [26]. For the proposed work, in between the adaptive filter output and the error sensor signal output, the secondary path is considered. Although that work provided excellent performance in convergence and minimization of error, it had a drawback of higher computational time.

The method in Ref. [27] analyzed the stability condition of the ANC with two methods; the modified filtered-x structure associated with modified filtered-x affine projection (MFxAP) algorithm and conventional filtered-x structure related to conventional filtered-x affine projection (CFxAP) algorithm. The second one is the main contribution of the proposed work. From the simulation results, it was proved that the proposed method provided an excellent analysis of steady-state performance.

A Variable Step-Size (VSS)-FxLMS algorithm with variable step-size had been implemented for the typical narrowband system [28]. The convergence rate of the proposed method was significantly faster than the existing methods. The FxLMS and filtered-x recursive least square (FxRLS) algorithms were used to compare the superior performance of the proposed work regarding convergence and computational complexity.

The cancellation performance of the ANC system was deteriorated by the acoustic feedback of the conventional FxLMS algorithm and non-linearities. A novel filtered-s LMS algorithm based on the ANC system had been developed [29] for improving the performance of the ANC system. The Functional Link Artificial Neural Network (FLANN) and the adaptive Infinite Impulse Response (IIR) filter based on combined approach were used for enhancing the performance of the ANC system.

Bounded-Input and Bounded-Output (BIBO) stability condition and trigonometric expansions for the recursive FLANN filter was developed [30]. The recursive FLANN filter was studied within the framework of a feedforward scheme for non-linear ANC. The innovation of the proposed approach was enhanced by simultaneous consideration of a secondary path (non-linear) and acoustic feedback between the reference microphone and the loudspeaker. For the elements of the non-linear filters, a Filtered-U normalized LMS adaptation algorithm was derived and applied to the recursive FLANN filter.

4. Proposed Method

In the ANC, the noise will be attenuated by generating another noise known as anti-noise; having an equal amplitude and opposite in phase with the original noise. The work developed in this paper is the novel ANC to reduce the noise. This noise control is done through the MFsLMS algorithm. The stability of this system has been improved through the HPSOFF algorithm. For the proposed mechanism, a multichannel ANC system is considered. Generally, in a single channel system, a reference microphone, of one in number, is used with a loudspeaker and an error microphone. In contrast, multichannel ANC system uses 'L' number of reference microphones, 'N' number of error microphones and 'M' number of loudspeakers.

Figure 1 shows the schematic of the multichannel ANC system that has been designed by using the MFsLMS algorithm. Here, the modification of FsLMS algorithm is given through the HPSOFF algorithm by changing the functional expansion.

4.1. MFsLMS Algorithm

The secondary path is filtered by the non-linear expansion of each element in the FsLMS algorithm. The computational complexity of the FsLMS algorithm is lower due to the reduced non-linearity. Therefore, it is effectively utilized in the ANC system. The works developed recently are done with the help of the FsLMS algorithm, mostly. The FsLMS algorithm is viewed as a non-linear controller, and its input noise becomes non-linear that is produced from a disorganized source.

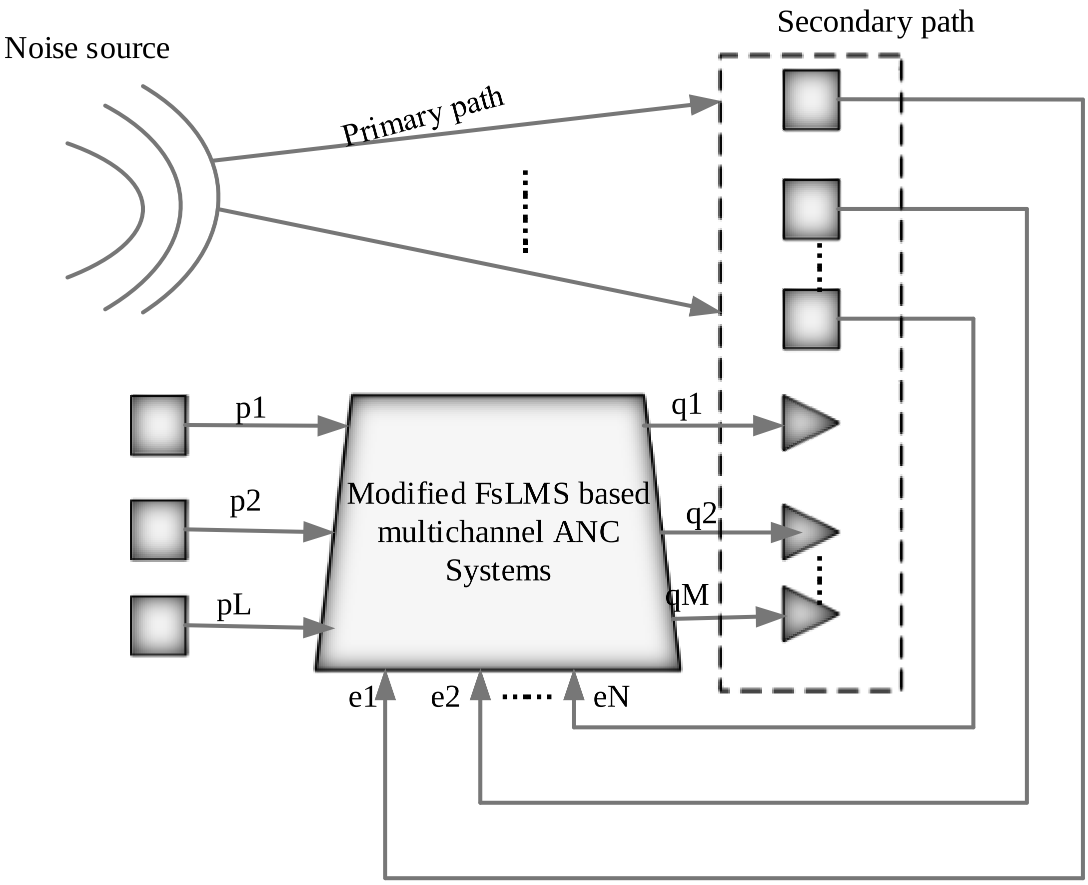


Figure 1. Schematic of MFsLMS based on multichannel ANC.

This algorithm is derived with $p1, p2, \ldots\ldots.., pL$ reference microphones, $q1, q2, \ldots\ldots, qM$ loudspeakers and $e1, e2, \ldots\ldots.., eN$ error microphones. In the present approach, the following terms are considered

$p_l(n)$ is the signal used as input at the l-th reference microphone at the instant n; $1 < l < L$.

$q_m(n)$ is defined as the output signal at the loudspeaker m at the instant n; $1 < m < M$.

$w_{l,n}(n)$ is the adjustable weight vector, which connects l-th reference microphone to n-th error microphone.

$s_i(n)$ is the signal vector, which is functionally expansion of the input signal $p_l(n)$.

$e(n)$ is the noise or the error signal sensed by the reference microphone.

$f(n)$ is the primary noise signal at the n-th error microphone.

$a(n)$ is the impulse response.

$$e(n) = f(n) + a(n) * q_m(n). \tag{1}$$

Equation (1) shows the expression of error signal.

This modified algorithm aims to reduce the noise at the output of the system. For that, the function of cost is defined as

$$\chi = \sum_{n=1}^{N} {e_n}^2(n). \tag{2}$$

The above function is needed to be reduced for the effective design of the ANC systems.

The output signal is estimated as expressed by

$$q_m(n) = \sum_{l=1}^{L} w_{l,n}(n) * s_i(n) \tag{3}$$

where '*' is the convolution operator. The adjustable weight vector $w_{l,n}(n)$ can be computed through the successive relation

$$w_{l,n}(n+1) = w_{l,n}(n) - \frac{\mu}{2}\overset{\wedge}{\nabla}(n). \tag{4}$$

where μ is the stability factor; which is also used for denoting the convergence of the algorithm. If the stability factor holds a small value, it denotes the considerable enhancement in stability but the reduction in convergence. If the stability factor has a larger value, it means faster convergence with reduced stability. $\overset{\wedge}{\nabla}$ is the estimation (instantaneous) of the gradient of χ with respect to the weight vector $w_{l,n}(n)$.

The Maclaurin series is employed for the functional expansion of $s_i(n)$. The series expansion according to the modified algorithm is expressed by

$$s_i(n) = \left\{ \begin{array}{l} x_i(n), \frac{h}{1!}x_i{}'(n), \frac{h^2}{2!}x_i{}''(n), \ldots\ldots x_i(n-1), \frac{h}{1!}x_i{}'(n-1), \\ \frac{h}{2!}x_i{}''(n-1), \ldots\ldots x_i(n-m+1), \frac{h}{1!}x_i{}'(n-m+1), \frac{h}{2!}x''(n-m+1) \end{array} \right\}. \tag{5}$$

The series expansion term is utilized to evaluate the computational cost of the proposed system. The modification is given through the functional expansion term; which reduces the computational complexity of the algorithm. Figure 2 shows the ANC with the MFsLMS algorithm.

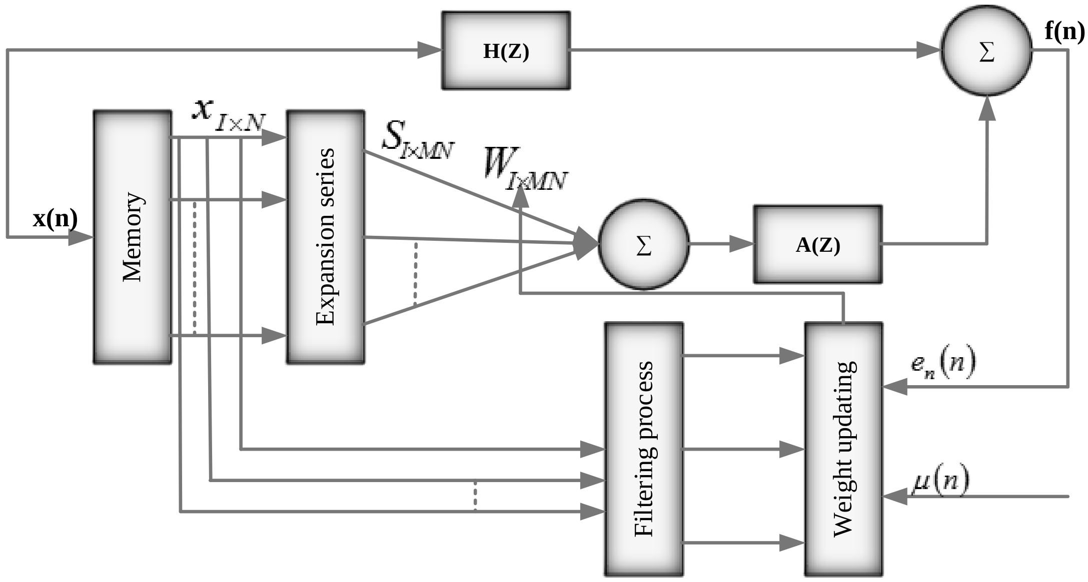


Figure 2. Active noise control with modified FsLMS.

4.2. Hybrid PSOFF Algorithm

A population-based refutable algorithm, developed by Kennedy and Eberhart, is Particle Swarm Optimization [31]. This algorithm is developed based on the inspiration of the blocking behavior of birds or the schooling behavior of fish. This efficient algorithm hybridized with Firefly algorithm is used here for the stability enhancement of the ANC system that has been designed based on the MFsLMS algorithm. In PSO, each particle is moved with a particular velocity and position. The velocity and position of each particle are ameliorated according to the objective function, and sometimes this change depends on the behavior of neighboring particles.

The parameters must be initialized are number of particles = 4; dimension of the problem = 2; upper bound = 2; lower bound = 0; $x_1 = 0.7$; $x_2 = 0.7$; $y_1 = 0.5$; and $y_2 = 0.5$.

The velocity of the particle D_n is defined by

$$D_n = D_0 + (x_1 * y_1 * best\,1 \cdot Z_{ii}) + (x_2 * y_2 * best\,2 \cdot Z_{ii}). \tag{6}$$

In Equation (6), D_0 is the old velocity; *best*1 and *best*2 are the local and global best, respectively. Z_{ii} is the position of a particle. The variables x_1 and x_2 are positive constants; which holds some value depending on convenience. Likewise, y_1 and y_2 are random variables in the range (0, 1).

One of the fastest optimization techniques is Firefly (FF) algorithm [32]. It was developed by Yang [33], who developed this algorithm by taking flashing behavior of fireflies as inspiration. The PSO algorithm is hybridized with the FF algorithm to enhance the stability of the ANC system. The hybridizing of these two algorithms is achieved through the position updating of the particles via the movement of fireflies.

The target function (Fitness Function) of the algorithm is

$$Fitness = \frac{1}{[5 * (2N + 1) * P_r]} \tag{7}$$

where N is the number of error microphones (N = 4) and P_r is the probability of the error noise (0.2).

The movement of fireflies or position of particles will be decided by

$$Z_{ii} = Z_{ii-1} + D_{new}e^{-\gamma r^2} + \alpha\varepsilon \tag{8}$$

where γ is the light absorption coefficient (holds the value 1); r is the relative distance of fireflies; α is the randomization parameter (α = 0.2); ε is a random number between 0 and 1 (ε = 0.1).

5. Reduction of Computational Difficulty of MFsLMS

The computational complexity of the MFsLMS Algorithm is calculated with the proposed ANC system, with reference microphone (L = 1); loudspeaker (M = 2); error microphone (N = 4); memory size (m = 10); filters (n = 3); and order of expansion (P = 1), parameters (assumed). In the MFsLMS, there is no reason to evaluate the trigonometric terms. The multiplication and addition, of the proposed MFsLMS algorithm and available FsLMS algorithm [34], have been presented in Table 1. The original contribution of the proposed topology says that the reduction of computational complexity by a number of multiplication and the additional blocks. These are reduced when compared with the previous MFsLMS algorithm. Thus, the computational complexity is reduced.

Table 1. Computational complexity.

Algorithm	**FsLMS**		**MFsLMS**	
Length of Secondary Path (V)	**Multiplication**	**Addition**	**Multiplication**	**Addition**
2	852	634	316	154
4	950	781	332	202
6	1024	948	348	250
8	1095	1012	364	298

6. Result and Discussion

The multichannel ANC system, with L reference microphones, M loudspeakers and N error microphones, have been analyzed. By modifying the original algorithm with a Maclaurin series part. The computational complexity of the proposed system has been reduced. The functional expansion used in every previously defined algorithm was the trigonometric expansion. However, in this work, the functional expansion is given by the simple computation of the Maclaurin series. When comparing with the FsLMS algorithm, the functioning of the MFsLMS algorithm is verified. The computer simulations are used to analyze the strength of the defined work with two different noise signals. The normalized mean square error value is plotted with the number of iterations for the performance evaluation. The successive relations are used for evaluating the values of the normalized mean square error

$$NMSE = 10\log_{10}\left(\frac{E(e^2(n))}{\sigma_d{}^2}\right) \tag{9}$$

where $\sigma_d{}^2$ is the variance of the primary noise (at cancellation point) and $e^2(n)$ is the square value of the error function.

Case 1: A logistic chaotic primary noise signal [20] is created by using a recursive equation

$$x(n+1) = \eta\, x(n)\,[1 - x(n)]. \tag{10}$$

Figure 3 denotes the noise signal for the considered logistic chaotic noise. In the above noise signal, $\eta = 0.01$ and $x(0) = 0.9$. The non-linear noise is normalized to a signal value of one. The primary and secondary path transfer functions used in the simulation are

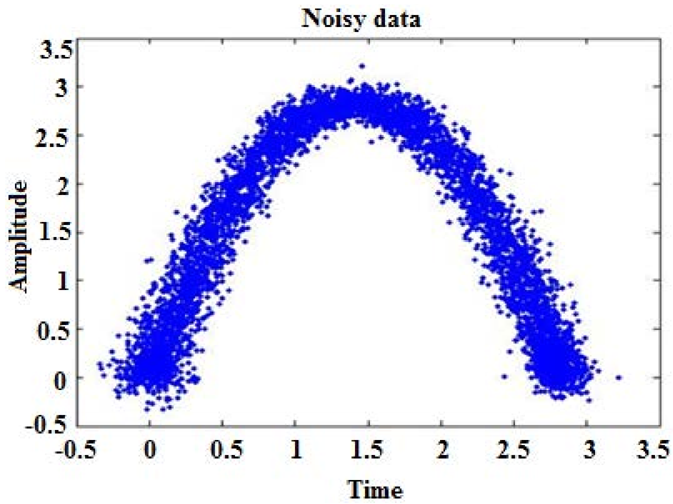
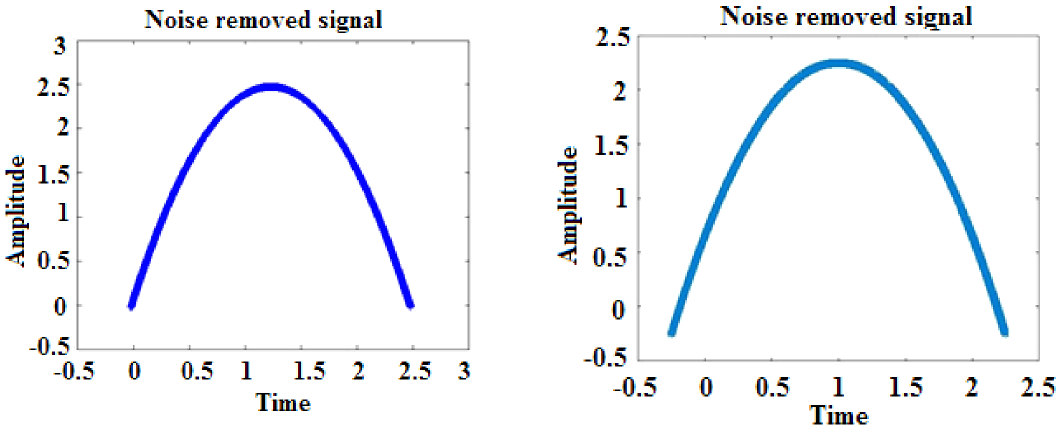


Figure 3. Logistic chaotic noise.

$$\begin{aligned}
H_{(1,1)}(z) &= z^{-5} - 0.3z^{-6} + 0.2z^{-7},\\
H_{(1,2)}(z) &= z^{-5} - 0.2z^{-6} + 0.1z^{-7},\\
H_{(1,3)}(z) &= z^{-5} - 0.3z^{-6} + 0.1z^{-7},\\
H_{(1,4)}(z) &= z^{-5} - 0.2z^{-6} + 0.2z^{-7}.\\
A_{(1,1)}(z) &= z^{-2} - 1.5z^{-3} + 0.2z^{-4},\\
A_{(1,2)}(z) &= z^{-2} - 1.7z^{-3} - z^{-4},\\
A_{(1,3)}(z) &= z^{-2} - 1.8z^{-3} - z^{-4},\\
A_{(1,4)}(z) &= z^{-2} + 1.9z^{-3} - z^{-4},\\
A_{(2,1)}(z) &= z^{-2} + 1.5z^{-3} - z^{-4},\\
A_{(2,2)}(z) &= z^{-2} + 1.2z^{-3} - z^{-4},\\
A_{(2,3)}(z) &= z^{-2} + 1.1z^{-3} - z^{-4},\\
A_{(2,4)}(z) &= z^{-2} + z^{-3} - z^{-4}.
\end{aligned}$$

Figure 4a,b are the expected outcome of the noise-cancelled signal. It is evident that a better noise cancellation is provided through the defined work, as compared to the existing method. The noise cancellation performance yields a reduced normalized mean square error value.

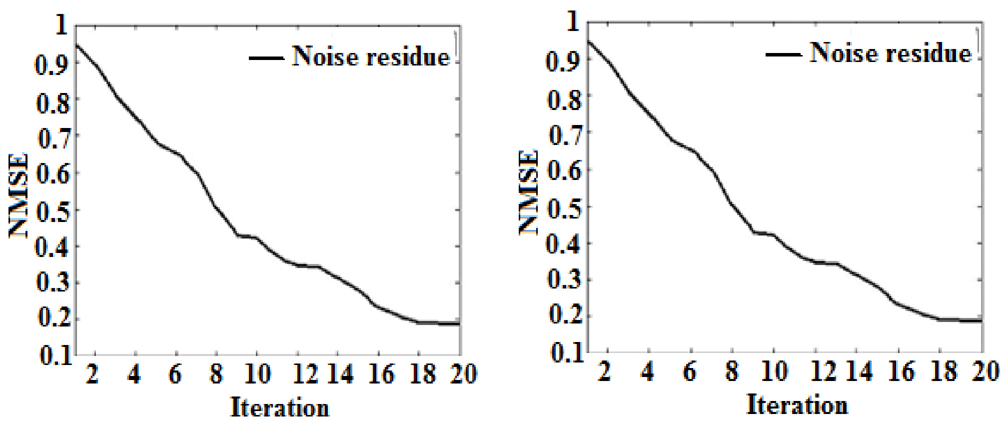


(**a**) (**b**)

Figure 4. Noise removed signal. (**a**) Proposed method; (**b**) Existing method.

The parameters chosen for the simulation are L = 1; M = 2; N = 4 and, the memory size, m = 10. The step size or learning rate used for FsLMS is $\mu = 0.1$ and, for FsLMS, μ is 0.000097.

Figure 5a,b is the representation of the error cancellation performance of the proposed and existing methodology. The minimum value of the normalized mean square error, for the proposed work, is **0.187 dB**. When it is compared with conventional noise reduction techniques, the proposed work provides significant noise reduction. The minimum value of the normalized mean square error, of the existing technique, is **0.257 dB**.



(**a**) (**b**)

Figure 5. Number of iterations versus normalized mean square error. (**a**) Proposed method; (**b**) Existing method.

The reduction of the normalized mean square error enhances the performance of the ANC system, without the addition of any of the specialized noise control devices. The optimal outputs with the reduced computational time is obtained through the proposed algorithm.

Case 2: The following noise signal is considered to be generated at the cancelling point, and it is a third order polynomial model expressed by

$$f(n) = g(n-2) + 0.08g^2(n-2) - 0.04g^3(n-1) \tag{11}$$

Figure 6, shows the Gaussian noise signal. In this noise signal, the expression for $g(n)$ is considered as the convolution of $x(n)$ and the impulse response of the transfer function $B(z) = z^{-3} - 0.3z^{-4} + 0.2z^{-5}$, denoted as $b(n)$. $x(n)$ is the reference signal defined as in Case 1. For the comparison of the performance, the existing method FsLMS and the proposed modified technique are considered. The results are plotted with the comparison of iteration and the normalized mean square error. The parameters for Case 2 were taken as in Case 1.

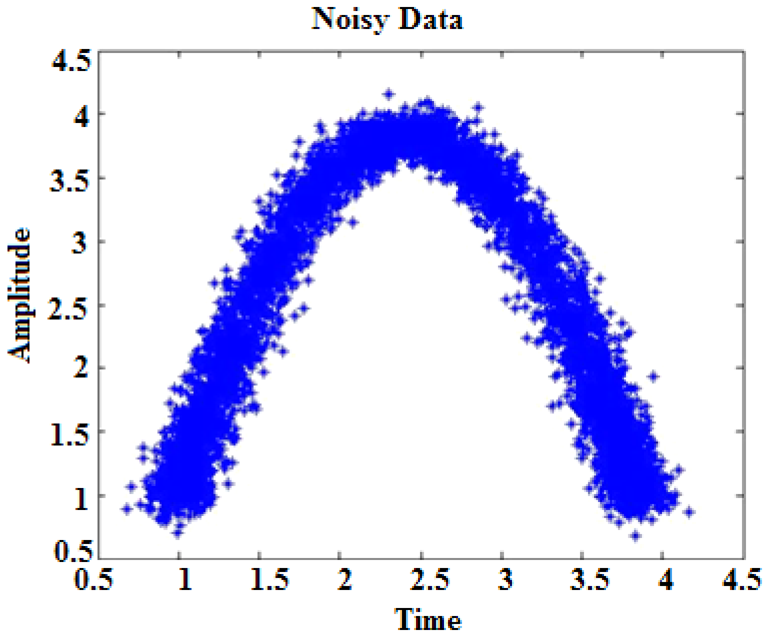


Figure 6. Gaussian noise.

Figure 7a,b provide the noise-removed signal obtained by the proposed and existing techniques, respectively. This is the reduced noise signal from the Gaussian noise signal. It represents the significance of the proposed technique in noise removal.

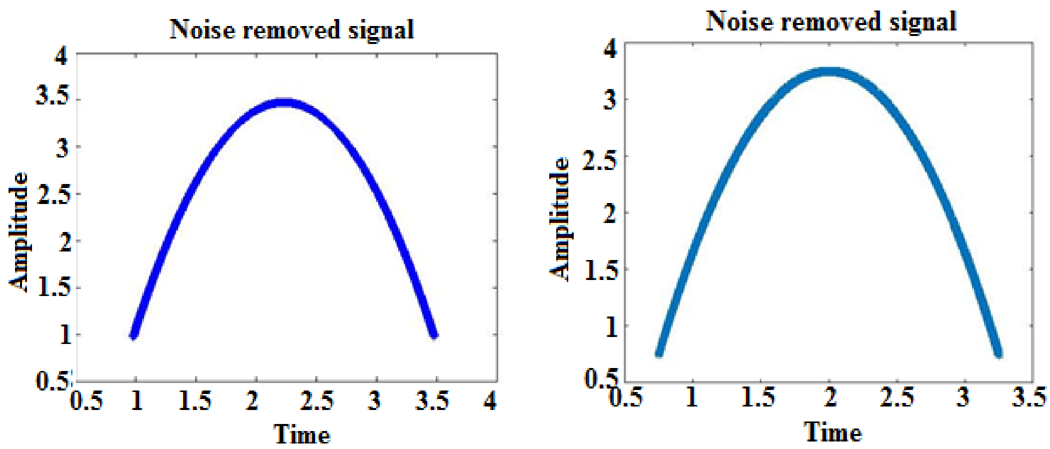
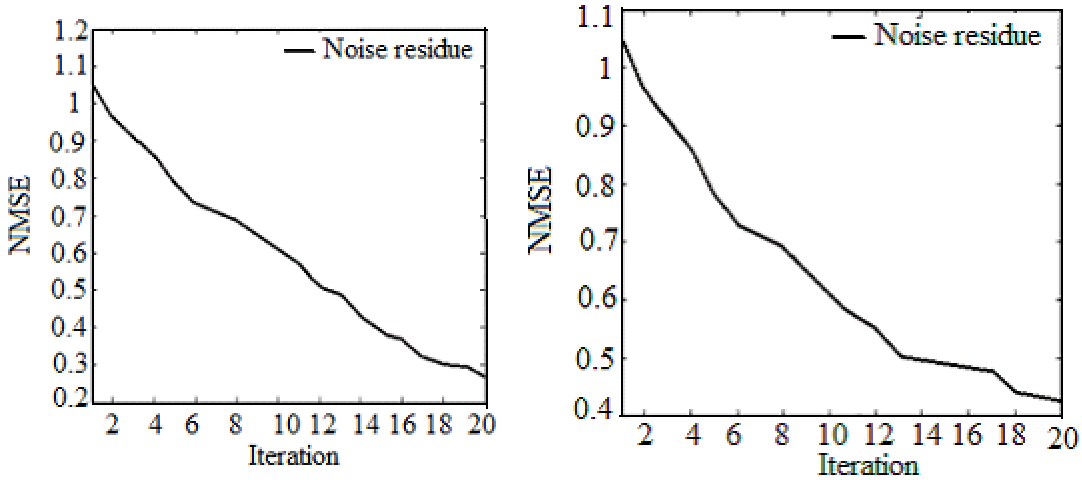


Figure 7. Noise removed signal. (**a**) Proposed method; (**b**) Existing method (FsLMS).

The normalized mean square error is used for the comparison of defined work with the existing FsLMS algorithm. The mean square error (reduced in the proposed case), and existing works are shown in Figure 8a,b. From the result, it is evident that the MFsLMS algorithm dictates the ultimate noise removal in the signal. The minimum value of NMSE in the proposed case is **0.265 dB** and for the existing case is **0.425 dB**.



(**a**) (**b**)

Figure 8. Number of iterations versus normalized mean square error (**a**) Proposed method; (**b**) Existing method (FsLMS).

Table 2 shows the comparison of the proposed method with hybrid PSO-ABC (Particle Swarm Optimization-Artificial Bee Colony) and hybrid PSO-GA (Particle Swarm Optimization-Genetic Algorithm). The enhanced performance of the proposed method, along with other two as mentioned above, is shown in Figure 9 (as a comparison chart). The NMSE value (in dB) has been reduced by **0.187 dB** with the time consumption of about **0.385 s**; in the proposed method.

Table 2. Comparison of the proposed method with other hybrid algorithms.

S.no	Method	NMSE (dB)	Computational Time (s)
1	Proposed Method	0.187	0.385
2	Hybrid PSO—ABC	0.300	0.524
3	Hybrid PSO—GA	0.428	0.628

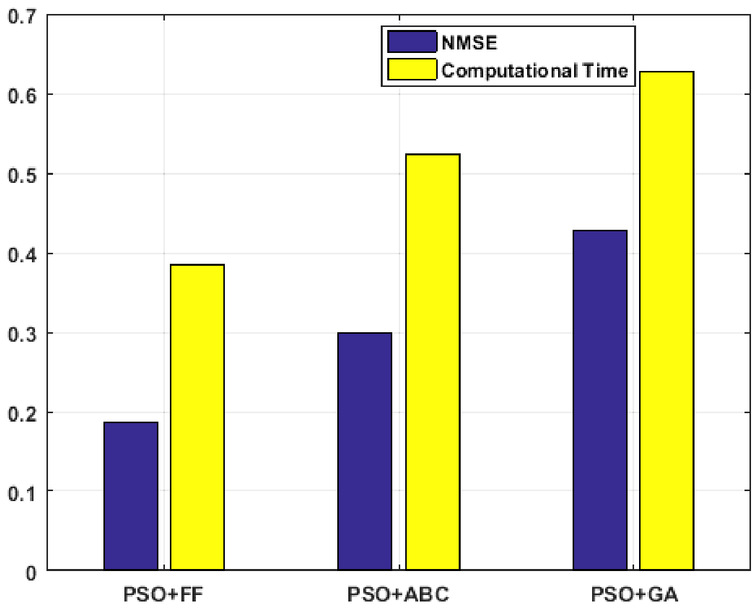
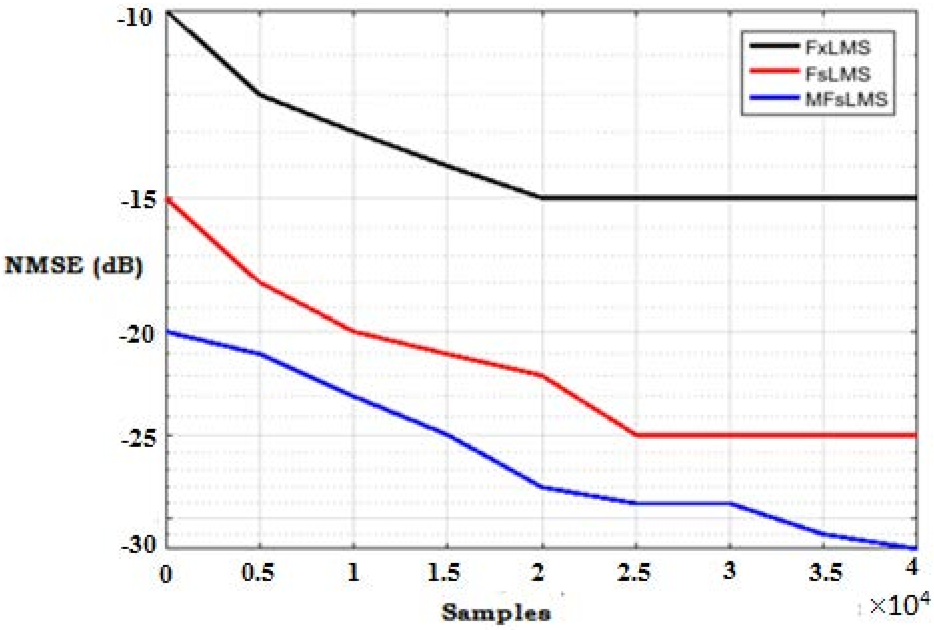
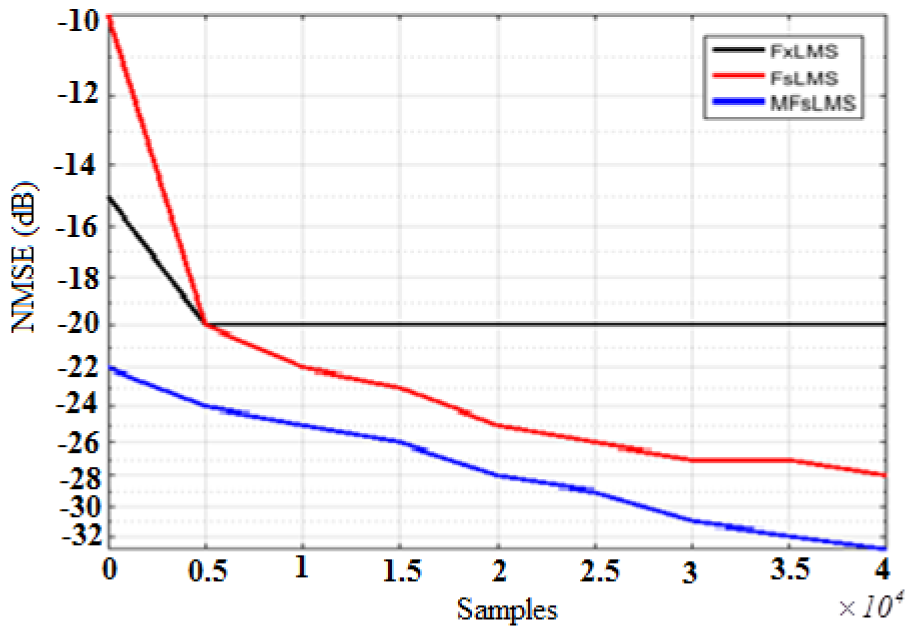


Figure 9. Performance evaluation of the proposed method.

Figure 10a,b shows the performance of the proposed MFsLMS algorithm with the existing FxLMS and FsLMS algorithms regarding the NMSE (in dB) for Case 1 and Case 2 respectively.



(**a**)



(**b**)

Figure 10. Performance evaluation of proposed method in terms of NMSE (**a**) Case 1; (**b**) Case 2.

In summary, this work explains the noise removal in multichannel active noise control system via the MFsLMS and HPSOFF algorithm. From the resulting discussion, it has been proved that the proposed work eliminates the noise well when compared to the existing techniques. The capability of noise removal has been achieved with a minimum computational time and reduced complexity. Thus, the system poses a higher efficiency, so the proposed method is better for noise removal from the multichannel ANC. The stability of the proposed system has been evaluated through the HPSOFF algorithm.

7. Conclusions

In this work, the ANC has been considered as the primary objective. To achieve this goal, the work got assistance from the combined signal processing and optimization fields. The target has been done through the MFsLMS algorithm and the hybrid optimization algorithm HPSOFF. The stability factor of the MFsLMS algorithm has been derived through the hybrid optimization work. The stability is the primary factor to achieve a reliable system. When selecting an appropriate value, the system convergence has been made. The noise cancellation is performed using the MFsLMS algorithm; in which the computational complexity has been reduced by using the functional expansion. The Maclaurin series was used for the functional expansion. The comparative analysis of the proposed work has been carried out with the existing FsLMS algorithm. For this performance comparison, the normalized mean square error is used. The proposed work was compared with existing works and with other optimization algorithms such as PSO-ABC and PSO-GA. The comparative outcomes show a better noise cancellation performance achieved with the proposed work. The presence of approximate algorithm for weight updating improves the stability factor in the future.

Author Contributions: The Problem formulation, code development, implementation of code and manuscript preparation had been carried out by the first author under the supervision of the second author.

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