Complex Frequency Block Domain Analysis and Efficient Implementation for Computational Active Noise Control

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Article Info
Page Number: 1808 - 1824
Publication Issue:
Vol 71 No. 4 (2022)

Article History
***Article Received**: 25 March 2022*
***Revised**: 30 April 2022*
***Accepted**: 15 June 2022*
***Publication**: 19 August 2022*

Abstract

This paper provides a detailed description of active noise control (ANC) algorithms using the frequency-domain filtered-x least mean-square (FDFxLMS). In the ANC system, the traditional FXLMS algorithm is offered inefficient performance where a large number of filter coefficients are used by the secondary path estimate and the adaptive controller. In this paper, a filtered complex least mean square (FBFXCLMS) dependent frequency domain block solution is proposed to reduce the ANC system's computational complexity for higher control filter order coefficients and enhance the convergence performance.It is implemented using an overlap-save technique based on convolution and correlation operations, which offers substantial computational improvements for higher-order adaptive filters as compared to the time domain FxLMS algorithm.The complex adaptive filter algorithm is guided inversely proportional to that bin's signal power, individual step size for each frequency bin.Systematic computer simulations are conducted to demonstrate the precision relative to the time domain FXLMS algorithm for the proposed frequency-domain block FXCLMS algorithm.The proposed solution findings, in comparison to the time domain FxLMS algorithm, have provided fast convergence and stability.

1. Introduction

The acoustic noise problems are becoming more apparent in the current scenario as increased noise-related sound sources are generated from factories (fans, blowers, exhaust pipes, engines), household machinery, cars, and public spaces. Another similar form of noise is mechanical vibration, which is typically created issues in the fields of transport and production [4-5]. Most people prefer to live internationally with ease and composure, but with the advent of new technologies, acoustic pressures (sound) fill the atmosphere. Human life has been affected as a result, and it faces several health concerns.In the conventional approach to acoustic noise control, passive strategies like enclosures, obstacles, and silencers are used to reduce unwanted noise.These passive silencers are valued for their high attenuation over a broad frequency range, but they are disproportionately massive, costly, and inadequate at low frequencies.

ANC [1-3] is an electro-acoustic or electromechanical system that cancels the background noise produced from different noise fields. It is carried out based on destructive interaction(superposition) between two acoustic waves. The unwanted noise is based on the superposition principle; precisely, an anti-noise of equal amplitude and opposite phase is produced and coupled with the unwanted noise, resulting in both the noises being canceled as shown in Fig.1.The ANC system effectively attenuates the low-frequency noise where passive solutions are either ineffective or tend to be very expensive and bulky. The ANC has been an eminent research topic because it allows advances in noise reduction in various field applications and often with potential advantages in weight, volume, and expense.In general, the ANC implementation is graded into feedforward and feedback structures. The feedforward structure can be applied in the digital domain, and feedback can be constructed on both digital and analog strategies.

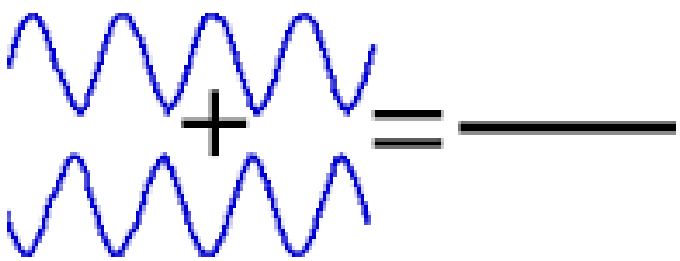

Fig 1: Physical principle of ANC

Lueg first introduced an acoustic ANC idea in 1936 [6], which involved using a microphone and an electronically controlled speaker system to produce a canceling noise. Since the time varies between the characteristics of the acoustic background noise and the environment, the frequency, amplitude, phase, and sound velocity of the unwanted noise are non-stationary.As a result, the ANC system must be adaptive to comply with these variations. The adaptive filters are updated their coefficients to reduce an error signal and be recognized as transversal, recursive, lattice, and transform domain filters [7-15].

The FxLMSalgorithm is frequently used in ANC systems to update the adaptive filter coefficients. In several ANC implementations, the adaptive filters seem to be several thousand, and then the FxLMS algorithm complexity gradually increased with the higher filter length. Therefore, the algorithm FxLMS has been implanted in other time-domain approaches, such as filtered-x affine projection (FxAP), which are also too complicated and unfeasible for real-time systems [16-18].The frequency-domain adaptive filter (FDAF) [19-24] has been effectively used throughout the applications of echo cancellation [25-27], acoustic feedback cancellation [28], and beamforming [29] due to its high convergence behavior and low complexity. Implementations of the ANC were extended to block LMS (BLMS), and the corresponding implementation of the frequency domain was provided.

In this paper, we study and evaluate the efficacy of the functional feedforward ANC duct using FxLMS algorithm. An adaptive FBFxCLMS is proposed to address the FxLMS algorithm shortcomings in ANC system. In addition, several experiments were performed and the efficacy of ANC duct system is discussed using proposed and traditional algorithms.

2. Description of ANC System

The ANC is an electro-acoustic device that generates a control signal (anti-noise) to interact in a destructive way with the unwanted noise. The ANC system implementation is generally divided into feedback and feedforward systems to achieve efficient noise attenuation. In analog as well as digital domains, the feedback system can be modeled. Inside the ANC feedback, the residual error signal can synthesize the initial noise to boost periodic noise signals. However, the ANC feedforward systems placed the primary microphone upstream to detect the reference signal, and the error microphone is placed downstream to sense the residual signal. It can only be applied in the digital domain and is useful in reducing broadband noise.

2.1 Realization of Feedforward ANC using FxLMS algorithm

The ANC implantation is mostly preferred to a famous traditional control algorithm, FxLMS, for noise reduction due to its simplicity. The adaptive filters dependent on the Least Mean Square (LMS) are typically used for system identification and acoustic echo cancellation applications. The feedforward ANC system with adaptive algorithms of LMS and FxLMS are shown in Fig 2 and Fig 3. In that, the reference, control, and error signals are denoted as $x(\mathrm{n})$, $\mathrm{y(n)}$ and $\mathrm{e(n)}$ respectively. The primary path $p(\mathrm{z})$ is determined between the reference and error sensor signal; the adaptive filter $w(\mathrm{z})$ is evaluated in the form of online operation in the tuning $p(\mathrm{z})$. The adaptive filter $w(\mathrm{z})$ response correlated with the unknown system output, i.e., desired response to produce a residual error signal $\mathrm{e(n)}$. The error $\mathrm{e(n)}$ is used while the adaptive filter is revised using the standard LMS algorithm. Whereas the ANC in noise reduction, the adaptive filter response $\mathrm{y(n)}$ is passed through an electro-acoustic path., termed a secondary path $s(\mathrm{z})$ (between the adaptive filter output to the error sensor). This electro-acoustic path propagation introduces a non-negligible phase delay and frequency distortions. Since the ANC becomes unstable and offers a prolonged convergence performance. The secondary path model was, therefore, initially assessed before the ANC operation was carried out. Compared with the primary path response referred to as the desired nose, the secondary path output generates an error $\mathrm{e(n)}$. Using an offline or online modeling technique to estimate the secondary path $\hat{s}(z)$. The obtained error e(n) and the filtered reference signal (reference signal passed through them $\hat{s}(z)$) are used to tune the online adaptive filter coefficients. In order to update the filter coefficients of the adaptive algorithm, the $x(n)$ signal is filtered through an estimated $\hat{s}(z)$, hence called the Filtered x LMS algorithm. It is an effective method compared to other solutions, and designs the filters $w(z)$ and $s(z)$ uses an FIR filter to make the system more stable. In the ANC system, the efficiency of the FxLMS depends on an accurate estimation of the secondary path, which can be obtained by an online or offline modeling process.

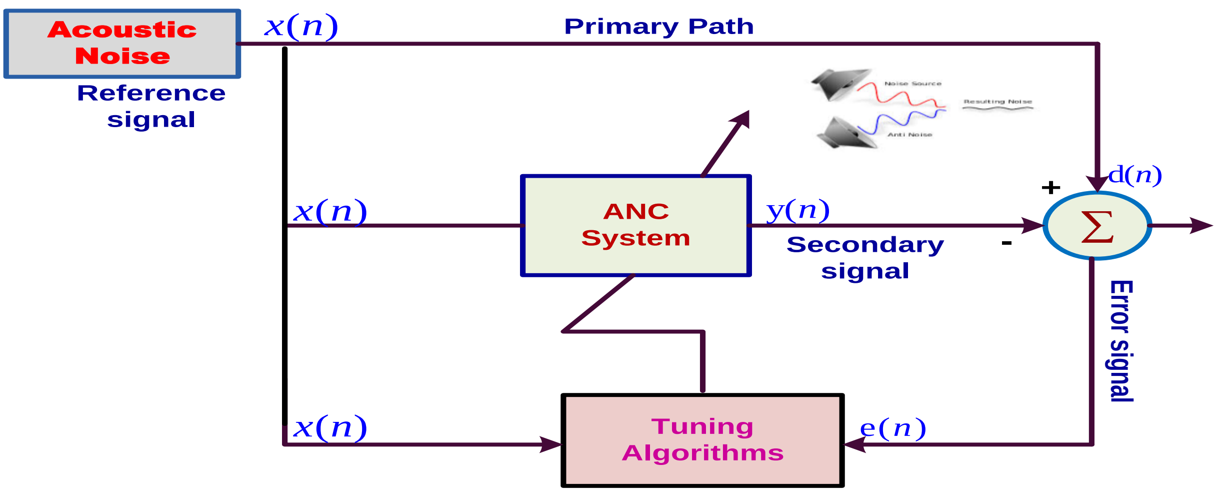

Fig 2. Feedforward ANC system

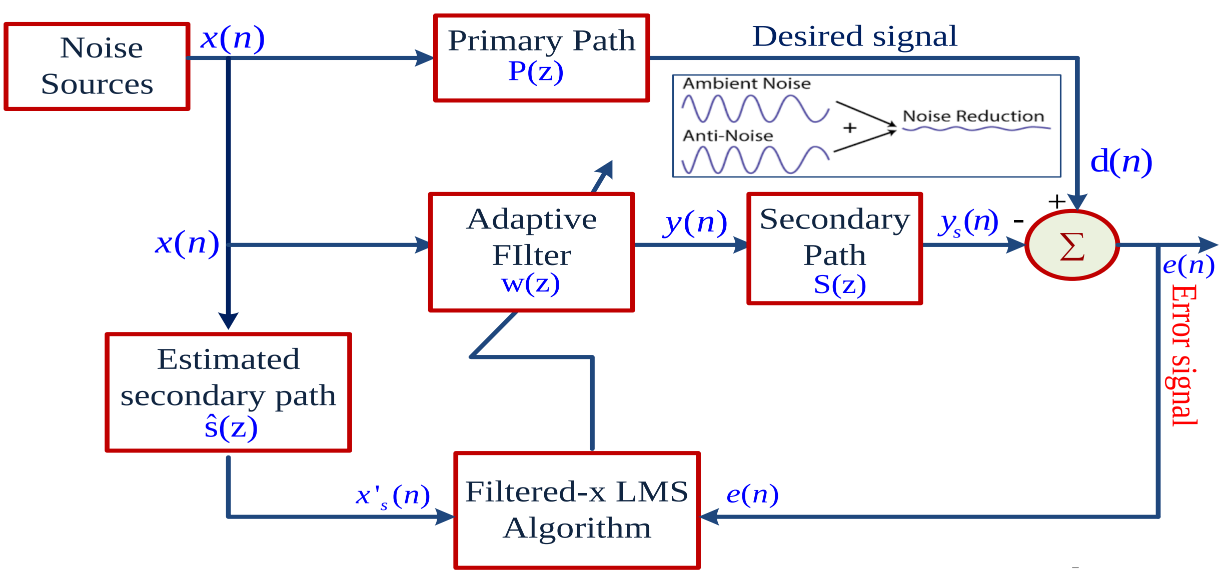

Fig 3Feedforward ANC single-channel system with FxLMS

From Fig 3, we define the mathematical computations of the FxLMS-based ANC system.

The residual signal $e(\mathrm{n})$ is defined as

$$e(\mathrm{n}) = \mathrm{d}(\mathrm{n}) - \mathrm{y}(\mathrm{n}), \tag{1}$$

$$\mathrm{d}(\mathrm{n}) = \mathrm{p}^T(\mathrm{n})\,\mathrm{x}(\mathrm{n}), \tag{2}$$

$$\mathrm{y}'(\mathrm{n}) = s^T(\mathrm{n})\,\mathrm{y}(\mathrm{n}), \tag{3}$$

$$\mathrm{y}(\mathrm{n}) = w^T(\mathrm{n})\,\mathrm{x}(\mathrm{n}), \tag{4}$$

where $\mathrm{p}(\mathrm{n})$ and $\mathrm{s}(\mathrm{n})$ are the impulse response of $\mathrm{p}(\mathrm{z})$ and $\mathrm{s}(\mathrm{z})$ respectively at time n

, and $\mathrm{h}(\mathrm{n})$ is the impulse response of $\mathrm{H}(\mathrm{z})$ at time n.

The aim of the control filter is to minimize the instantaneous square error in the ANC system.

$$\xi(\mathrm{n}) = \mathrm{e}^2(\mathrm{n}). \tag{5}$$

The filter weights are updated usingstochastic gradient Eq (6)

$$\mathrm{w}(\mathrm{n}+1) = w(\mathrm{n}) - \frac{\mu}{2}\nabla\hat{\xi}(\mathrm{n}), \tag{6}$$

where $\nabla\hat{\xi}(\mathrm{n})$ is the estimated MSE gradient instantaneous square at time n, expressed as

$$\nabla\hat{\xi}(\mathrm{n}) = -2x'(\mathrm{n})\,\mathrm{e}(\mathrm{n}), \tag{7}$$

$$\mathrm{x}'(\mathrm{n}) = \hat{s}(\mathrm{n}) * \mathrm{x}(\mathrm{n}) \tag{8}$$

From Eqs (6) & (7), the weight updating FxLMS algorithm expressed as

$$\mathrm{w}(\mathrm{n}+1) = w(\mathrm{n}) + \mu e(\mathrm{n})\,\mathrm{x}'(\mathrm{n}). \tag{9}$$

From the error signal, the optimal weights of the control filter are expressed in z domain as $e \to 0$

$$E(\mathrm{z}) = D(\mathrm{z}) - Y'(\mathrm{z}), \tag{10}$$

$$E(\mathrm{z}) = P(\mathrm{z})\,\mathrm{X}(\mathrm{z}) - H(\mathrm{z})\,\mathrm{X}(\mathrm{Z})\,\mathrm{S}(\mathrm{z})$$
$$H^{o}(\mathrm{z}) = \frac{P(\mathrm{z})}{S(\mathrm{z})} \quad , \tag{11}$$

The secondary path estimation filter order is very high in a realistic situation and increases with an increase in sampling frequency. The increased sampling frequency is necessary to control components of higher frequency noise.

The traditional FXLMS algorithm has become high computational complexity when a large number of filter coefficients are utilized in the secondary path estimation and the adaptive controller. In the past, numerous studies have been conducted to minimize such large measurements. The fast implementation of active noise control in the time domain is documented to achieve around 25percent in terms of computing savings compared to traditional algorithms.

3. Implementation of ANC using the proposed FDBFxCLMS algorithm

The ANC implementation using the FxLMS algorithm has suffered from reasonably slow convergence performance issues with the extensive range of eigenvalues of the autocorrelation matrix from the reference signal. To minimize such restriction, suggested an adaptive frequency-domain method [2] [16-18]. It was noted from section 2.1 that the ANC with FxLMS algorithm comprises three major operations: (a) The linear convolution of the reference signal vector $x(\mathrm{n})$ and control filter coefficients $w(\mathrm{n})$; (b) The reference signal $x(\mathrm{n})$ is convolved with linear filtering of estimated secondary path impulse response coefficients $\hat{s}(\mathrm{n})$; (c) The control filter weights are updated by palcing a cross correlation between error signal $\mathrm{e}(\mathrm{n})$ and filtered reference signal $x_s(\mathrm{n})$. In summary, the process of the ANC system has involved two convolution and one cross-correlation operations. The suggested FDBFxLMS algorithm includes convolution and correlation operations based on the N-point Fast Fourier Transform (FFT) using the adaptive filter length. The signals $x(\mathrm{n})$ & $\mathrm{e}(\mathrm{n})$ are transformed into a frequency domain using an N-point FFT and then processed with an adaptive algorithm. It improves the convergence performance based on applying a unique step size for each frequency bin, which is an inverse ratio to that bin's signal power. It has offered some advantages compared to time-domain adaptive filters in terms of: reducing the computational complexity using FFT; estimating the gradient more accurately (based on the mean of whole block data); applying normalized step size for each bin for obtaining rapid convergence.

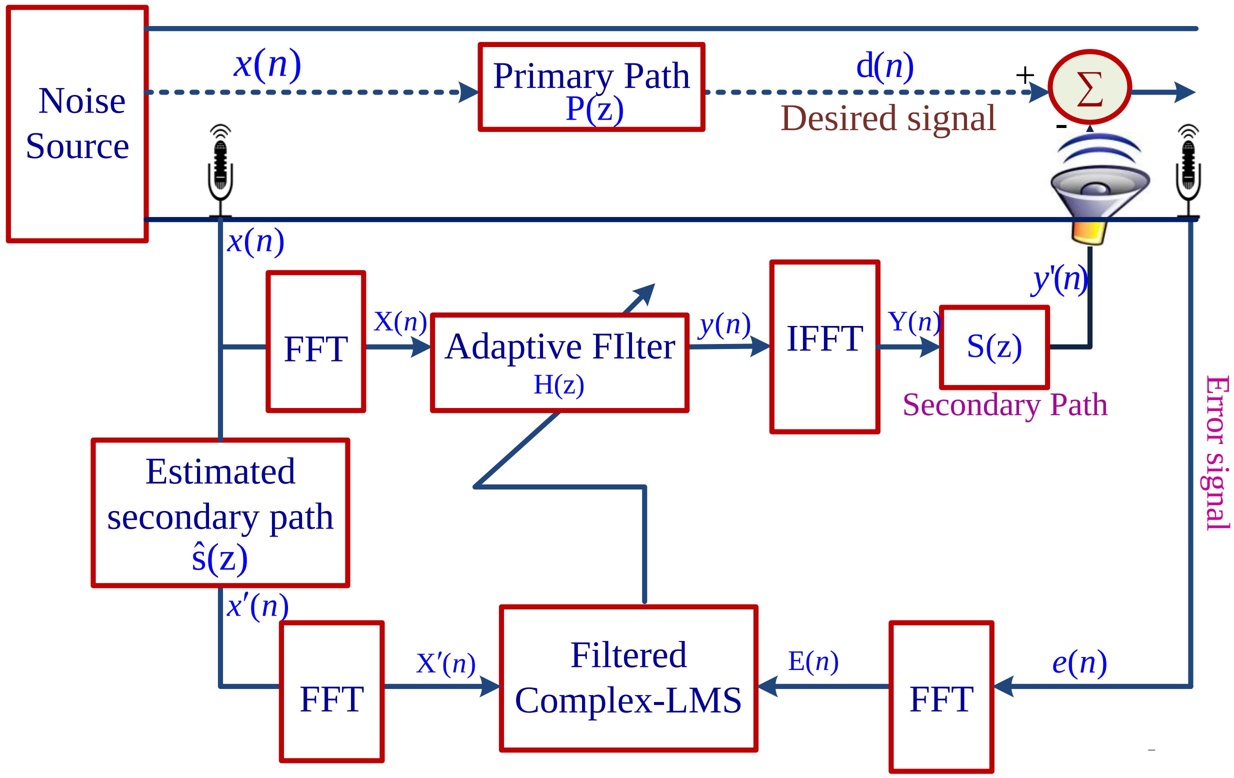

Fig 4: Implementation of ANC using Frequency domain approach

The implementation of the ANC system with frequency domain FxLMS algorithm is depicted in Fig 4. In that, using FFT, the reference signal $x(\mathrm{n})$ is transformed into a frequency domain $X(\mathrm{n})$ with an L data buffer length, which is processed in an adaptive filter that produces a signal $\mathrm{Y}(\omega)$. The vector $\mathrm{Y(n)}$ is again switching from FFT to IFFT to generate a time-domain $\mathrm{y(n)}$ control signal. We measure the $e(\mathrm{n})$ signal between the time domain signals of the desired and the control. Then the measured signal $\mathrm{e(n)}$ and the filtered reference signal $x'(\mathrm{n})$ are transformed into the frequency domain using an N-point FFT as in the form of $\mathrm{E(n)}$ and $\mathrm{X'(n)}$. The control filter weights are updated using FxCNLMS with power estimation of the filtered signal. From Fig 5, the mathematical computations can be expressed as,

Initially, the reference and error signal can be stored as M- point data buffer and transformed into the frequency domain with an N-point FFT expressed as

$$x(\mathrm{n}) = [\mathrm{x(n)\ x(n-1).....x(n-}M+1)]^T, \tag{16}$$

$$X(\mathrm{n}) = \mathrm{FFT[x(n)]} = [\mathrm{X_0(n)}\ X_1(\mathrm{n})........\mathrm{X}_{M-1}(\mathrm{n})]\mathrm{T}, \tag{17}$$

$$\mathrm{e(n)} = [\mathrm{e(n)}\ e(\mathrm{n}-1).....\mathrm{e}(\mathrm{n}-M+1)]^T, \tag{18}$$

$$\mathrm{E(n)} = \mathrm{FFT}[\mathrm{e(n)}] = [\mathrm{E}_0(\mathrm{n})\ E_1(\mathrm{n}) .... \mathrm{E}_{M-1}(\mathrm{n})]\mathrm{T}. \tag{19}$$

The frequency and time domain of the control signal is expressed as

$$Y_m(\mathrm{n}) = H_m(\mathrm{n})\,\mathrm{X}_m(\mathrm{n}), \quad \mathrm{m} = 0,1,......\mathrm{M}-1 \tag{20}$$

$$y(\mathrm{n}) = IFFT[\mathrm{Y(n)}] = [\mathrm{y(n)}\ \mathrm{y(n-1)}\ ......\ \mathrm{y(n-M+1)}]. \tag{21}$$

The error signal $e(\mathrm{n})$ is

$$e(\mathrm{n}) = \mathrm{d(n)} - \mathrm{y}'(\mathrm{n}), \tag{22}$$

$$y'(\mathrm{n}) = \mathrm{s(n)} * \mathrm{y(n)}. \tag{23}$$

where the symbol * represents linear convolution.

The frequency-domain representation of the $x_s'(\mathrm{n})$ signal is expressed by

$$\begin{gathered} x_s'(\mathrm{n}) = [\mathrm{x}'(\mathrm{n})\ \mathrm{x}'(\mathrm{n}-1).....\mathrm{x}'(\mathrm{n}-M+1)]^T \\ X_s'(\mathrm{n}) = [\mathrm{X}_0'(\mathrm{n})\ \mathrm{X}_1'(\mathrm{n})\ ......\mathrm{X}_{M-1}'(\mathrm{n})]^T = FFT(\mathrm{x}'(\mathrm{n})) \end{gathered}. \tag{24}$$

The weight update of the FDBFxCLMS algorithm is evaluated by

$$w_m(\mathrm{n}+M) = w_m(\mathrm{n}) + \mu_m(\mathrm{n})\,\mathrm{E}_m(\mathrm{n})\,\mathrm{conj}(\mathrm{X}_m'(\mathrm{n})) \quad \mathrm{m} = 0,1,......\mathrm{M}-1 \tag{25}$$

where $\mu_m(\mathrm{n})$ is normalized step size at frequency bin m, defined as

$$\mu_m(\mathrm{n}) = \frac{\mu}{\hat{p}_m(\mathrm{n})}, \tag{26}$$

$$\hat{p}_m(\mathrm{n}-\mathrm{M}) = (1-gama)\,\mathrm{abs}(\mathrm{X}_m^2(\mathrm{n})) + gama * \hat{p}_m(\mathrm{n}), \tag{27}$$

where $\hat{p}_m(\mathrm{n})$ is the power estimation updated for each block of M samples.

4. Results and Discussions

4.1 Computer Simulations:

The performance of the ANC with can be evaluated with conventional FxLMS algorithm,and the suggested FDBFxCLMS algorithm has been analyzed under various noise environments in order to measure the error and to know the noise reduction performance. Here, the transfer function of the primary and secondary paths can be modelled as an FIR filter with a length of 128 based on the offline system identification procedure. The coefficients of the adaptive filter $w(\mathrm{n})$ can be estimated from $p(\mathrm{z})$ during the system's online operation. Here, we performed some simulation experiments using Random noise, Impulse noise and Fan noise to measure the error and Noise reduction.

The metric Noise Reduction (NR) performance can be evaluated as

$$\mathrm{NR(n)}_{\mathrm{dB}} = -10\log 10\left\{\frac{\sum\left(e^{2}(\mathrm{n})\right)}{\sum\left(d^{2}(\mathrm{n})\right)}\right\}. \tag{28}$$

Case 1: The unwanted signal is a 0.2 variance of random noise; the length of the filter is 128

A zero-mean and 0.2 variance of the white noise is used as the noise source in this case. The suggested FDBFxCLMS and traditional FxLMS algorithms have been used, and the performance findings of the control signal are seen in Figs 5 & 6. Compared with the traditional FxLMS algorithm, the proposed FDBFxCLMS algorithm has achieved the least error signal magnitude. In addition, over an average of more than 200 independent runs, the convergence curve performance of the mean square error (MSE) for ANC was determined, and the associated learning curve is shown in Fig 7. The suggested FDBFxCLMSalgorithm has achieved faster convergence and less MSE (-42.89dB) than the traditional FxLMS.

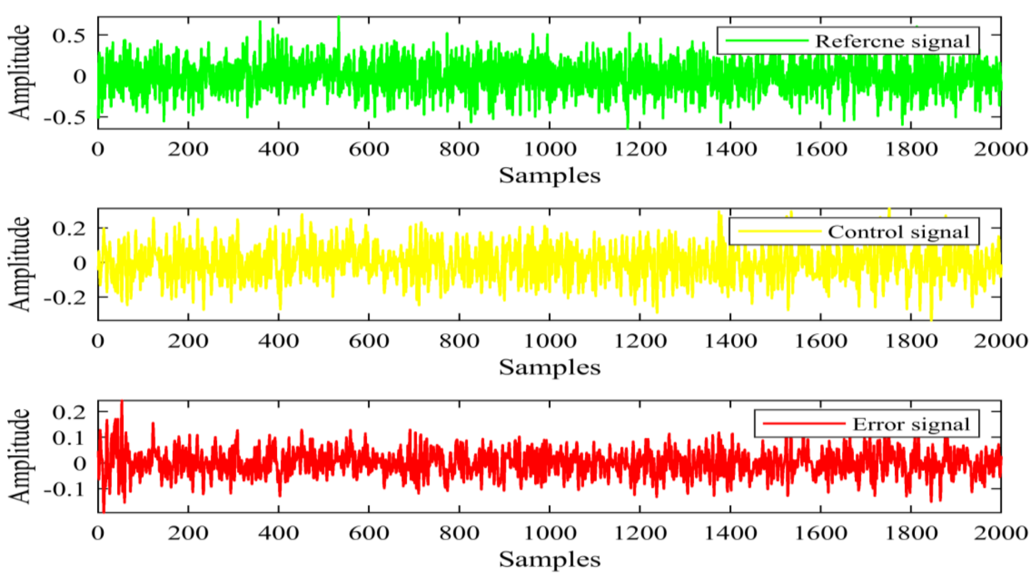

Fig 5: Error Performance of ANC with FxLMSfor random noise

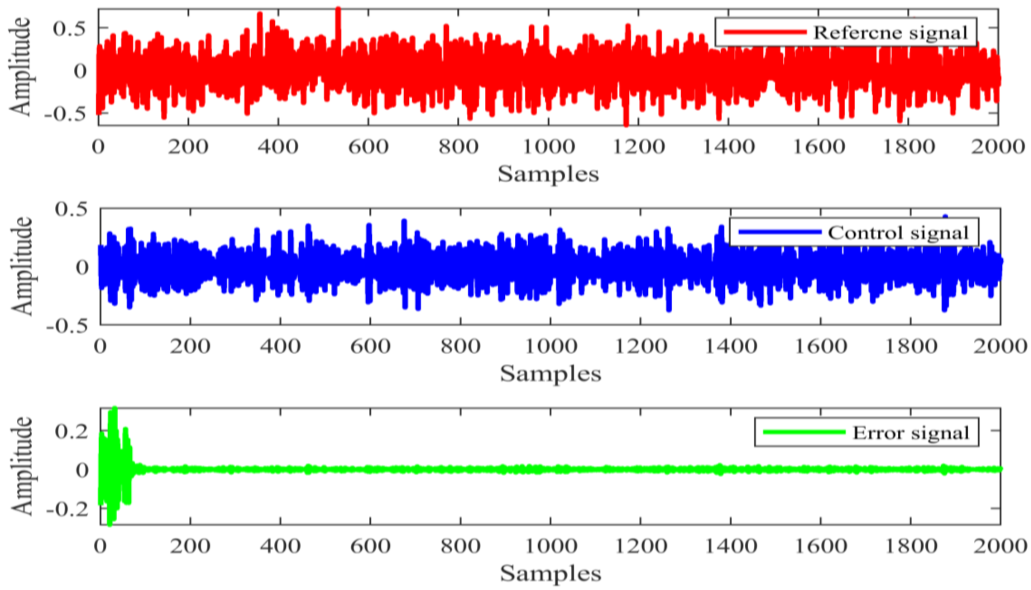

Fig 6: Error Performance of ANC with FDBFxCLMS algorithm for random noise

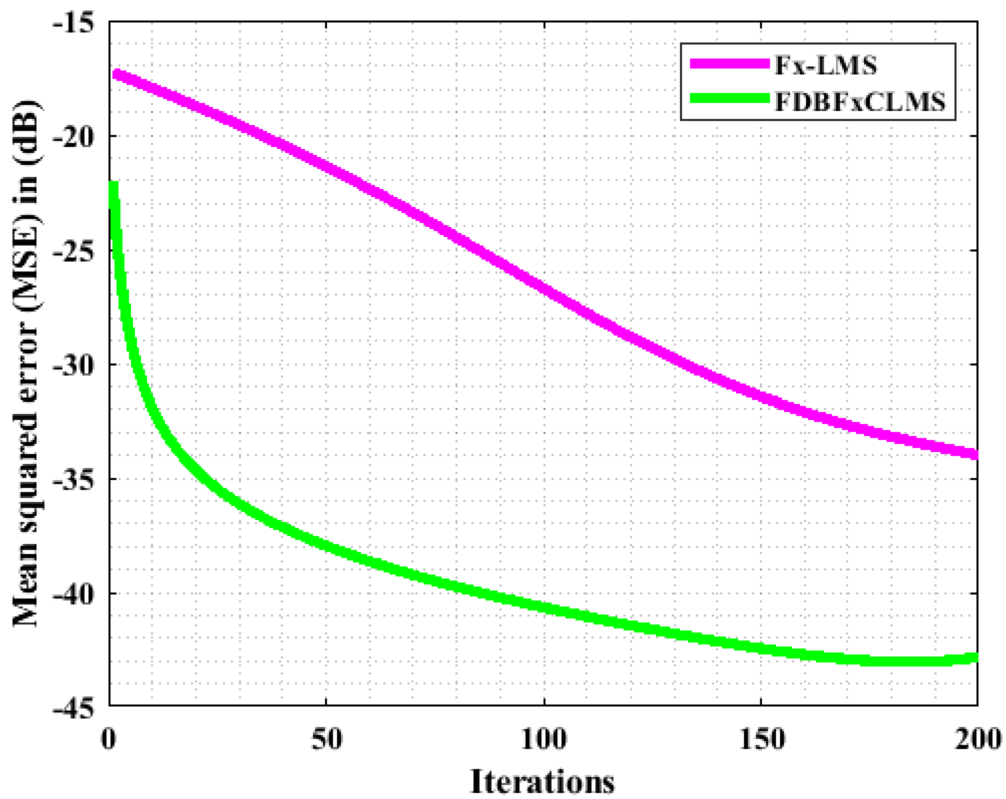

Fig 7: Learning Curve analysis of ANC using different appraoches

Case 2: The unwanted signal is impulse noise, and the control filter length is 128.

The impulse noise α=1.5 is used as the basis of the noise source used in this case. The control signal performance of the proposed FDBFxCLMS and standard FxLMS algorithms are shown in Figs 8and 9. The recommended FDBFxCLMS algorithm has attained minimal error signal strength compared to the traditional FxLMS algorithm. The convergence curve analysis of the mean square error (MSE) for ANC was defined over an average of more than 200 independent runs, and the related learning curve is illustrated in Fig 10. In that, the proposed FDBFxCLMSalgorithm indeed achieved faster convergence and lowered MSE (-22.32dB) than the standard FxLMS.

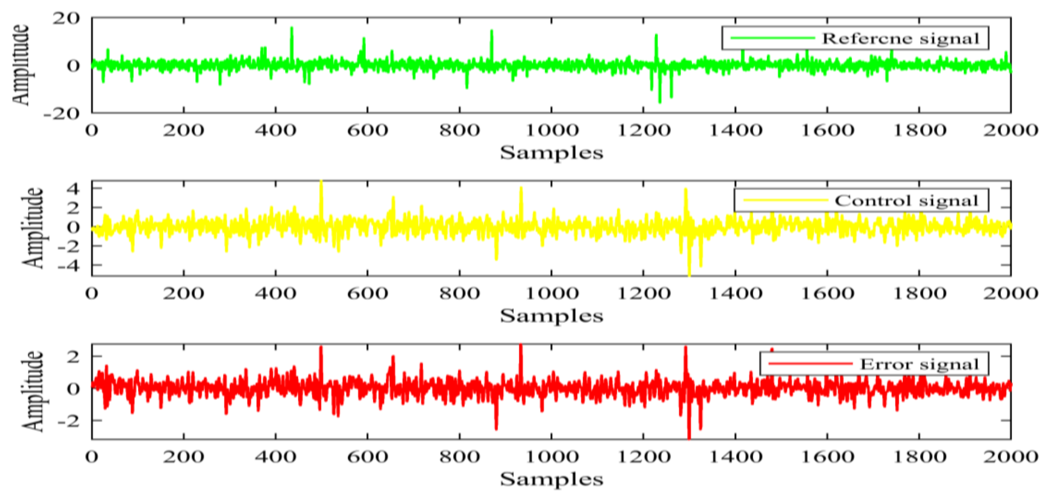

Fig 8: Control Performance of ANC using conventional FxLMS algorithm

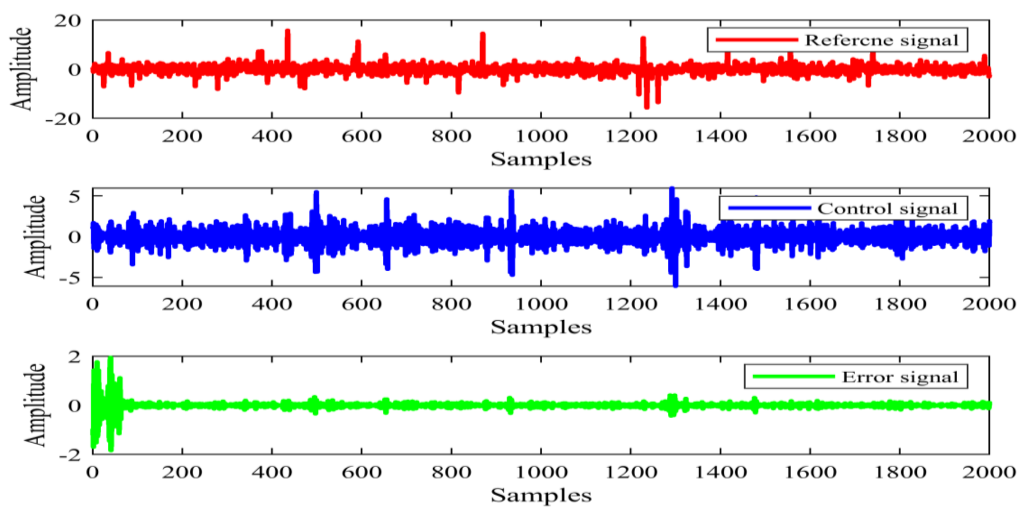

Fig 9: Control Performance of ANC using the proposed FDBFxCLMS algorithm

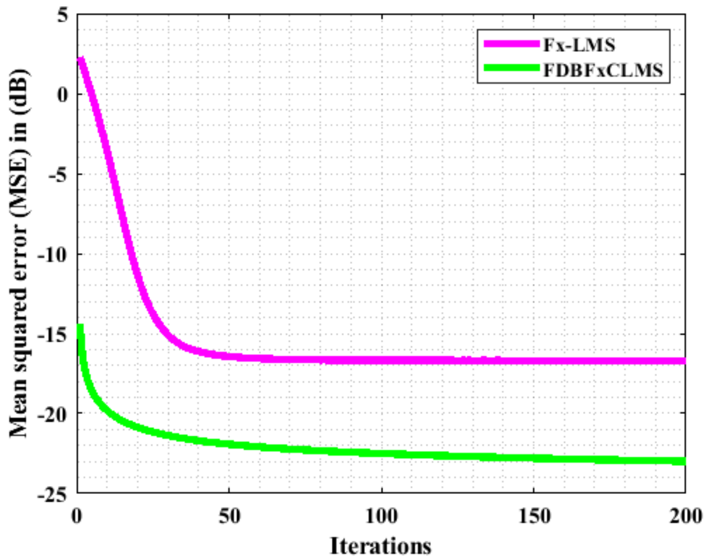

Fig 10: Comparisons of Leatning Curve performance of the ANC system

Case 3: The recorded fan noise and order of the control filter is 128.

In this case,the efficacy of the control ANC performance with the algorithms of conventional and the proposed FDBFxCLMSfor the recorded fan noise – the findings are plotted in Figs 11 & 12. In that the compared to time-domain FxLMS, the FDBFxCLMS algorithm has secured minimum residual signal. In an average of more than 200 independent runs, the MSE of the ANC was evaluated, and the corresponding learning curve is shown in Fig 13. In particular, thealgorithm FDBFxCLMS has achieved faster convergence and low MSE (-34.86dB) compared to the time domain FxLMS.

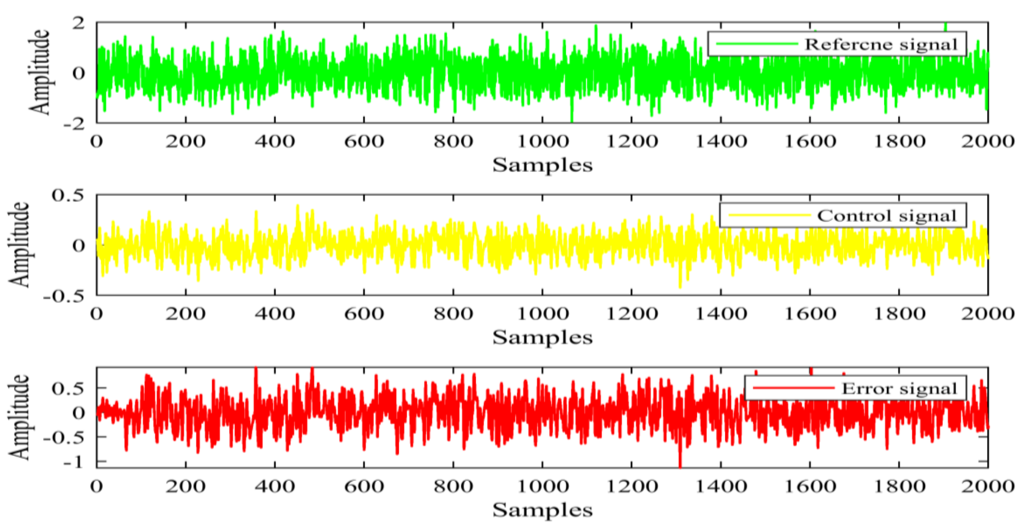

Fig 11: ANC control performance with FxLMS for Fan noise

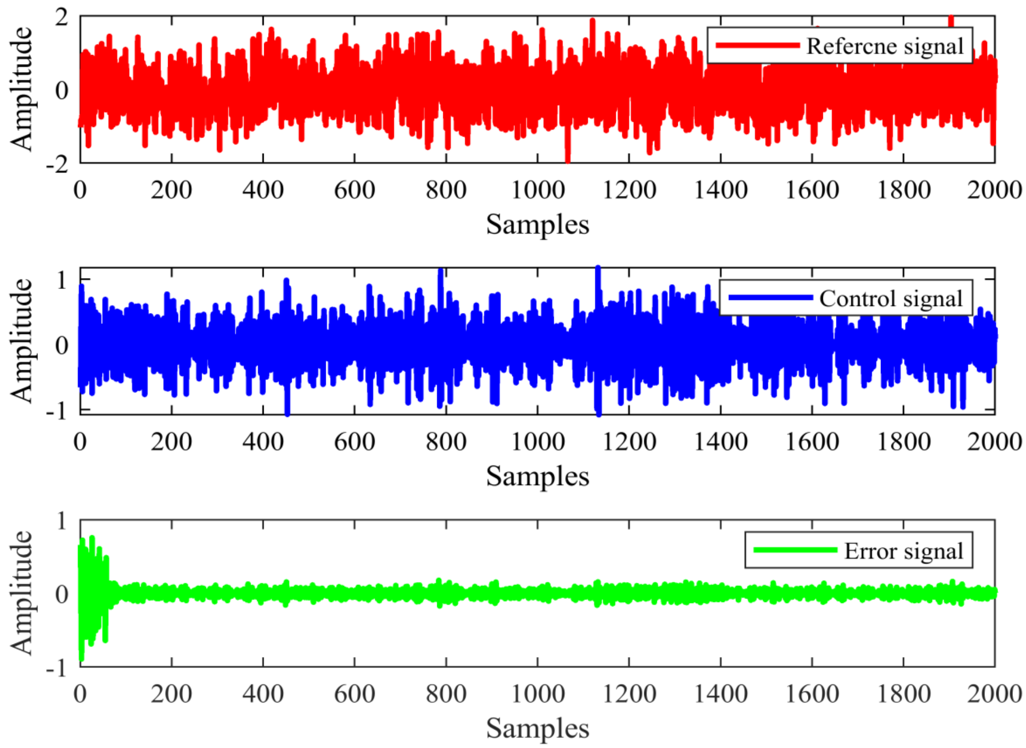

Fig 12: ANC control performance with FDBFxCLMS algorithm for Fan noise

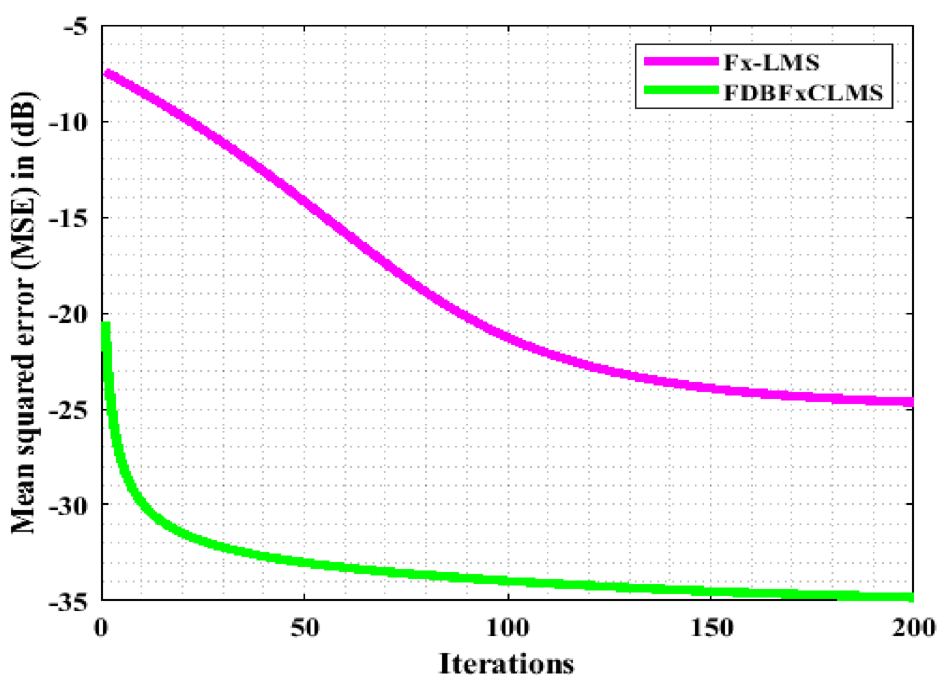

Fig 13. Learning Curve performance ANC with different approaches

For different step size parameter values, the MSE was evaluated for the proposed FDBFxCLMS over a number of iteration changes and also illustrated in Fig 14 for a case 1 noise. It is observed that the step sizes 0.005 to 0.009 the peroformance ANC has shown good convergence perfroamnce and achieved stable ANC. Fig 14 shows that with the increases in the step size below 0.009 and above (more than 0.001), the ANC has attained poor convergence performance and high MSE values.

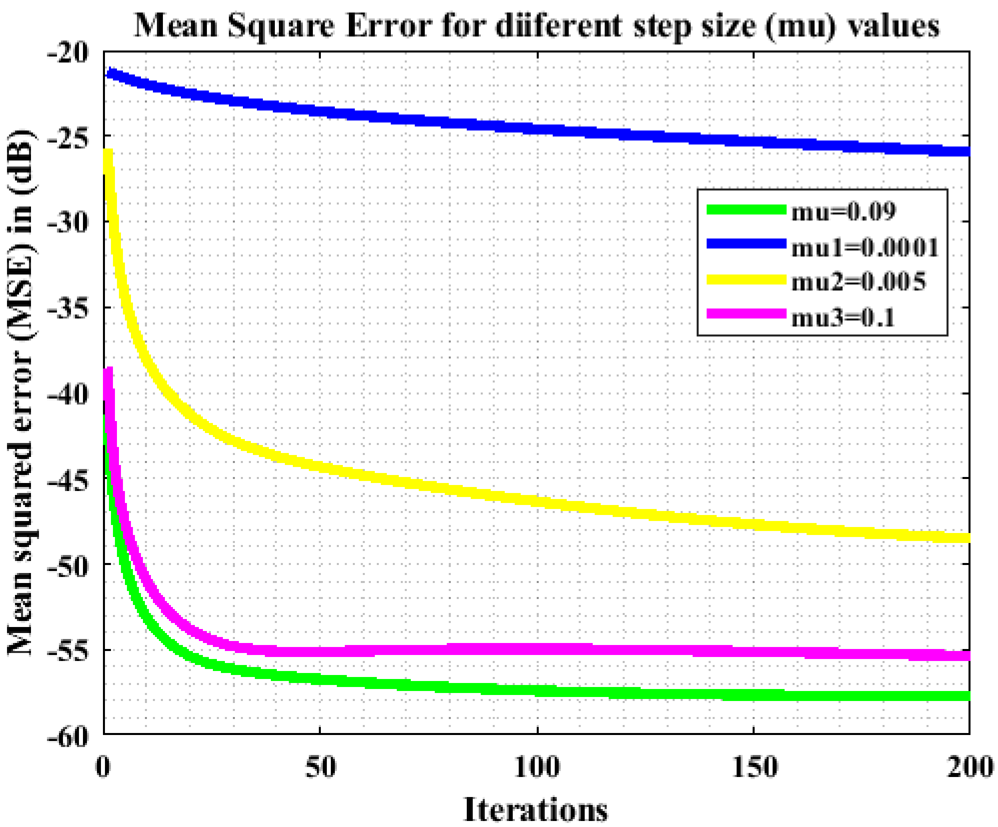

Fig 14 Mean Square Error performance of ANC for different step size values

Conclusions

In this paper, A Frequency Domain Block Filtered Complex algorithm (FDBFxCLMS) was proposed in the ANC system. The typical time-domain FXLMS takes immense computational complexity with a large number of filter coefficients used in adaptive control filters and secondary path estimation.The feedforward ANC performance was tested with conventional time-domain FxLMS and the proposed FDBFxCLMS algorithms, and the results are demonstrated with computer simulation. The simulation findings showed that the FDBFxCLMS had better convergence speed, minimal MSE, good noise reduction effectiveness, and consistent performance compared to the conventional time-domain FxLMS algorithm. The frequency-domain approached algorithm has reduced ANC system computational cost, especially for the large filter length coefficients.

Acknowledgements

I would like to express my deep gratitude to my research supervisor, Professor VenkatanarayanaMoram, for their patient support, constructive support, and valuable evaluation of this research study. I would also like to extend my thanks to the Digital Signal Processing Laboratory at G.Pullaiah College of Engineering and Technology (Autonomous), Kurnool, A.P, for providing me with the resources to run the program.

References

1 P. A. Nelson and S. J. Elliott, Active Control of Sound. San Diego, CA: Academic, 1992.
2 S. M. Kuo and D. R. Morgan, Active Noise Control Systems—Algorithms and DSP Implementations. New York: Wiley, 1996.
3 C. R. Fuller, S. J. Elliott, and P. A. Nelson, Active Control of Vibration. San Diego, CA: Academic, 1996.
4 C. M. Harris, Handbook of Acoustical Measurements and Noise Control, 3rd ed. New York: McGraw-Hill, 1991.
5 L. L. Beranek and I. L. Ver, Noise and Vibration Control Engineering: Principles and Applications. New York: Wiley, 1992
6 P. Lueg, "Process of silencing sound oscillations," U.S. Patent 2 043 416, June 9, 1936.
7 G. C. Goodwin and K. S. Sin, Adaptive Filtering Prediction and Control. Englewood Cliffs, NJ: Prentice-Hall, 1984.
8 B. Widrow and S. D. Stearns, Adaptive Signal Processing. Englewood Cliffs, NJ: Prentice-Hall, 1985.
9 C. F. N. Cowan and P. M. Grant, Adaptive Filters. Englewood Cliffs, NJ: Prentice-Hall, 1985.
10 M. L. Honig and D. G. Messerschmitt, Adaptive Filters: Structures, Algorithms, and Applications. Boston, MA: Kluwer, 1986.
11 S. T. Alexander, Adaptive Signal Processing. New York: Springer-Verlag, 1986.
12 J. R. Treichler, C. R. Johnson, Jr., and M. G. Larimore, Theory and Design of Adaptive Filters. New York: Wiley, 1987.
13 M. Bellanger, Adaptive Digital Filters and Signal Analysis. New York: Marcel Dekker, 1987.
14 S. Haykin, Adaptive Filter Theory, 2nd ed. Englewood Cliffs, NJ: Prentice-Hall, 1991.
15 P. M. Clarkson, Optimal and Adaptive Signal Processing. Boca Raton, FL: CRC Press, 1993..

16 Albu, F.; Bouchard, M.; Zakharov, Y. Pseudo-affine projection algorithms for multichannel active noise control. IEEE Trans. Audio Speech Lang. Process. 2007, 15, 1044–1052.
17 Yang, F.; Wu, M.; Yang, J.; Kuang, Z. A fast exact filtering approach to a family of affine projection-type algorithms. Signal Process. 2014, 101, 1–10
18 Ferrer, M.; Gonzalez, A.; de Diego, M.; Piñero, G. Fast affine projection algorithms for filtered-x multichannel active noise control. IEEE Trans. Audio Speech Lang. Process. 2008, 16, 1396–1408.
19 Farhang-Boroujeny, B. Adaptive Filters: Theory and Applications; John Wiley: Hoboken, NJ, USA, 2013.
20 Clark, G.A.; Mitra, S.K.; Parker, S.R. Block implementation of adaptive digital filters. IEEE Trans. Acoust. Speech. Signal Process. 1981, 28, 584–592. [CrossRef]
21 Ferrara, E.R. Fast implementation of LMS adaptive filters. IEEE Trans. Acoust. Speech Signal Process. 1980, 28, 474–475. [CrossRef]
22 Mansour, D.; Gray, A. Unconstrained frequency-domain adaptive filter. IEEE Trans. Acoust. Speech Signal Process. 1982, 30, 726–734. [CrossRef]
23 Soo, J.S.; Pang, K.K. Multidelay block frequency-domain adaptive filter. IEEE Trans. Acoust. Speech Signal Process. 1990, 38, 373–376. [CrossRef]
24 Merched, R.; Sayed, A.H. An embedding approach to frequency domain and subband adaptive filtering. IEEE Trans. Signal Process. 2000, 48, 2607–2619.
25 Enzner, G.; Vary, P. Frequency-domain adaptive Kalman filter for acoustic echo control in hands-free telephones. Signal Process. 2006, 86, 1140–1156. [CrossRef]
26 Yang, F.; Enzner, G.; Yang, J. Frequency-domain adaptive Kalman filter with fast recovery of abrupt echo-path changes. IEEE Signal Process. Lett. 2017, 24, 1778–1782.
27 Yang, F.; Enzner, G.; Yang, J. Statistical convergence analysis for optimal control of DFT-domain adaptive echo canceler. IEEE/ACM Trans. Audio Speech Lang. Process. 2017, 25, 1095–1106. [CrossRef] .
28 Lu, C.; Yang, F.; Yang, J. A Frequency-domain Adaptive feedback cancellation algorithm based on convex combination. In Proceedings of the Asia-Pacific Signal and Information Processing Association, Annual Summit and Conference (APSIPA ASC), Kuala Lumpur, Malaysia, 12–15 December 2017; pp. 474–477.
29 Herbordt, W.; Kellermann, W. Computationally efficient frequency-domain robust generalized sidelobe canceller. In Proceedings of the International Workshop on Acoustic Echo and Noise Control (IWAENC), Tel-Aviv, Israel, 30 August–2 September 2010; pp. 51–54.

Bibliography

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