STM JOURNALS

International Journal of
Radio Frequency Innovations

Volume 2, Issue 2, 2024
July–December
DOI (Journal): 10.37591/IJRFI

https://journals.stmjournals.com/ijrfi

Review IJRFI

The Role of Adaptive Filters in Enhancing Acoustic Echo Cancellation Efficiency in Noisy Environments

Preeti Manker[1,] *, Poonam Sinha[2], Priyesh Jaiswal[3]

Abstract

The novel approach that this work discusses is a DCD-based iterative learning filter approach improved with deep learning methodologies, designed to improve the efficiency of acoustic echo cancellation. The proposed system can really manage both linear and nonlinear echo scenarios, dynamically adapting to fluctuating acoustic environments. The above comparative evaluations with standard filters, the standard RLS filter, indicate that the mean square error, and the standard deviation of the and the correlation coefficients show the performance of the proposed method is better. The filter delivers robust echo cancellation with reduced computational complexity and thus is best suited for real-time applications such as hands-free devices, teleconferencing, and VoIP systems. This work sets up a new standard in AEC, showing the efficacy of adaptive filtering integration with machine learning towards the support of modern communication technologies development.

Keywords: Acoustic echo cancellation (AEC), DCD-based iterative filter, deep learning, adaptive filtering, nonlinear echo, Mean Square Error (MSE), real-time communication, VoIP, teleconferencing

INTRODUCTION

Acoustic echo must be kept in control to maintain clear and uninterrupted conversations within modern audio communication systems. One of the solutions to the challenge of echo caused by feedback between loudspeakers and microphones is Acoustic Echo Cancellation, most particularly through the mechanism whereby the voice of the far-end speaker picked up by the microphone is transmitted back as a disruptive echo. Such problems are mostly encountered with handsfree communication, teleconferencing, and applications in VoIP wherein echo causes serious degradation in speech quality [1]. AEC removes this problem by using advanced signal processing techniques to predict and subtract the echo from a microphone signal.

AEC employs adaptive filtering. Acoustic echo cancellation shown in Figure 1. The overall system is dynamic in its response to the changes in the environment, such as moving or altering the echo paths due to movement or changes in room acoustics. Also, more aggressive noise and reverberant environments will call for a strategy to noise reduction and dereverberation to be an important part of any advanced systems. Key metrics of system performance include some key ERLE values and perceptual speech quality evaluation [2]. With the inclusion of machine learning and deep learning technologies, AEC solutions process complex and nonlinear echo scenarios with increased precision for flawless communication across a very broad spectrum of devices and applications.

***Author for Correspondence**
Preeti Manker
E-mail: Mankarpreeti8@gmail.com

[1]M. Tech scholar, Department of Digital Communications, Barkatullah University Institute of Technology, Bhopal, Madhya Pradesh, India
[2]HOD, Department of Digital Communications, Barkatullah University Institute of Technology, Bhopal, Madhya Pradesh, India
[3]Assistant Professor, Department of Digital Communications, Barkatullah University Institute of Technology, Bhopal, Madhya Pradesh, India

Received Date: 19th Nov. 2024
Accepted Date: 10th Dec. 2024
Published Date: 20th Dec.2024

Citation: Preeti Manker, Poonam Sinha, Priyesh Jaiswal. The Role of Adaptive Filters in Enhancing Acoustic Echo Cancellation Efficiency in Noisy Environments. International Journal of Radio Frequency Innovations. 2024; 2(2): 9–24p.

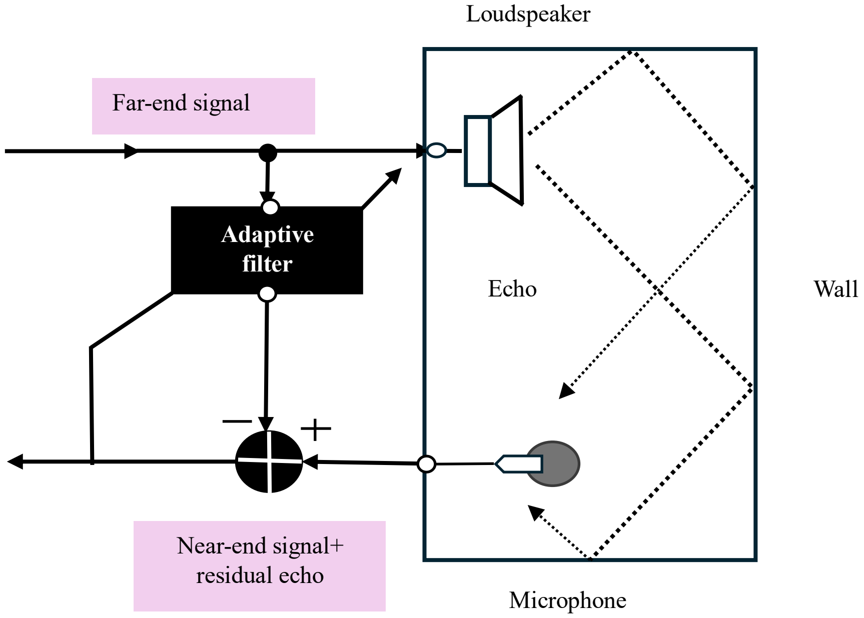

Figure 1. Acoustic echo cancellation.

The massive adoption of handsfree devices, video conferencing systems, VoIP applications, and even smart assistants has made Acoustic Echo Cancellation necessary in today's world of communication technologies. These systems operate in environments characterized by all sorts of acoustic challenges such as sound reflections and feedback loops that lead to severe disruptive echo [3]. Such problems do not only distort speech but also introduce delays and distractions that prevent effective communication. Persistent echoes are frequent, especially in environments that involve teleconferencing where they interrupt the flow of conversation altogether, thereby reducing efficiency and poor user experience as well. If communication remains unclear and jumbles up in a professional or even personal scenario, it is likely to hamper productivity and satisfaction high [4]. It addresses these challenges by way of AEC experience seamless audio transmission without the interruption of an echo. This ensures that AEC eliminates acoustic interference, hence ensuring high-quality audio performance required in modern communication systems [5]. Whether it is a corporate meeting, remote collaboration, or interaction with smart devices, AEC plays an important part in making the reliability and usability of these technologies possible, ensuring effective and break-free communication across all types of applications.

The acoustic echo in a communication system primarily arises due to sound feedback between the loudspeaker and microphone. Feedback primarily occurs via acoustic feedback. Normally it happens when sound from a loudspeaker is captured through a nearby microphone and resent back to the far-end listener. This happens usually when a microphone and speaker are placed close to each other; more often it happens in hands-free devices, teleconferencing systems, and VoIP applications [6]. Another important source is line or hybrid echo, developed in telephony systems due to impedance mismatching of the network, introducing signal reflections. Network or packet echo, developed due to delay in packet-switched networks, can also intensify echo effects developed in modern communication systems. This has an unmistakable effect on speech in that it drowns out clarity and creates distractions for the user. Echo may hinder the comprehension of a conversation, which in turn may cause frustration in understanding the message successfully communicated [7]. Such becomes highly causing disruptions whenever, for example, teleconferences are involved since delays can cause continuity flow interruptions and lower productivity in professional settings. Even in informal discussions, an echo reduces the overall experience of having a more natural conversation and enjoyment. Metrics like Mean Opinion Score (MOS) and Echo Return Loss Enhancement (ERLE) can measure the degradation of speech quality due to echoes [8]. Such quantitative metrics measure the effect of echo on the listener in terms of the quality perceived. If real-time communication is concerned with a high-quality communication system, then the echo sources must be treated using Acoustic Echo Cancellation (AEC) technology. Effective management and suppression of echo sources help provide clear, uninterrupted audio, thereby creating a more satisfied and engaging user.

Challenges in Noisy Environments

Acoustic echo cancellation suffers in noisy environments because the background noise distracts it from being able to identify and suppress the echo accurately. General environmental noises, such as traffic, machinery, or other people talking, mask the echo signal and overwhelm the AEC system so that it cannot distinguish between desired speech and unwanted signals [9]. This interference complicates the working of echo suppression algorithms, thereby making them less efficient and thus resulting in poor communication quality. This aggravates the same problem of overlapping speech, where two or more participants speak at the same time, posing increased complexity for the AEC system to work with.

Dynamic and time-varying acoustics in noise make things even tougher. Time-varying noise, time-varying echo paths, and time-varying room acoustics demand that an AEC system adapt dynamically and actively in real-time to maintain performance [10]. These pose challenges about the reliability of adaptive filtering techniques where the accuracy of signal estimation is paramount. To counter these problems, modern AEC solutions bring noise reduction and dereverberation technologies to bear, coordinated with adaptive filters so as to augment the robustness of such solutions. Such an integrated design helps ensure clear and uninterrupted communication in hostile noisy environments.

Role of Adaptive Filters

Adaptive filters fall into the class of signal processing algorithms that adjust their parameters to adapt the modification generated against changing input conditions. Unlike fixed filters, which base their performance purely on the original preset values, adaptive filters vary their behavior in accordance with changes in the input signal or environment. Their ability makes them very useful for noise cancellation, acoustic echo suppression, and signals. These are known to work by minimizing an error signal, the difference between desired and actual outputs, which they do through techniques like Least Mean Squares (LMS), Normalized LMS (NLMS), and Recursive Least Squares (RLS) [11]. Because of their ability to learn in real-time and adapt, they form a cornerstone in signal processing.

Adaptive filters are very effective in dynamic environments because conditions like noise levels, echo paths, or signal characteristics change much with adaptive filters. In these kinds of conditions, fixed filters suffer as they are applied for specific circumstances and do not work well when that condition varies. Adaptive filters, however, continue changing their coefficients, so they continue working well even in fluctuating scenarios. For instance, the acoustic echo cancellation may have adjustable filters to counteract the varying paths due to movement or changes in environmental conditions [12]. Adaptability ensures more robust and efficient signal processing. It makes adaptive filters suitable for real-time communication systems, teleconferencing, and hands-free devices where there are dynamic acoustic conditions.

LITERATURE REVIEW

Motiei, M. et al. (2024) [13] stated that the adoption of a circular economy (CE) in the building sector was challenging, primarily due to the complexity associated with the design process and the dynamic interactions that occurred among architects, engineers, and construction (AEC) stakeholders. The standard and typical design process and construction methods raise concerns about building life cycles. Buildings should not only fulfill current needs, but one also needs to consider how they will function in the future and throughout their lifetime. To address these complexities, early planning is required to guide designers in holistically applying systems thinking to deliver CE outcomes. This paper outlines a critical review of CE implementation in buildings, with a proposed trifecta of approaches that significantly contribute to the development of circular buildings (CBs). The findings outline a proposed visualized framework with a conceptual formula that integrates CE design strategies to simplify and enhance AEC stakeholders' perception of the circularity sequence in buildings. By strategically integrating loop-based strategies with the value retention process (VRP) and design for X (DFX) strategies, along with efficient assessment tools and technologies, it becomes feasible to embrace a CE during the design phase. The outcome of this review informs AEC stakeholders to systematically and strategically integrate the critical dimensions of a CE throughout the building life cycle, striking a balance between environmental concern, economic value, and future needs.

Agbobli, D., & Mo, Y. (2024) [14] explained about Extended reality (XR) is transforming architecture, engineering, and construction (AEC) education and occupant behavior (OB)-related building energy use analysis. This study conducts a systematic review using the PRISMA framework to explore the latest XR applications in these domains. The Visualization of Similarities (VOS) and network mapping analysis were used to explore research trends. A critical examination of existing research revealed that XR in AEC education primarily enhances educational methods, data management, and simulation techniques. In OB-related building energy use analysis, XR focuses on building data management, control systems, and performance simulations. The review indicates a predominant use of Virtual Reality (VR) and Augmented Reality (AR), with Mixed Reality (MR) remaining underexploited. Given the overlap in educational and analytical applications, a unified approach that uses XR to educate AEC professionals and promote energy-efficient behaviors among building occupants is proposed. This integrated approach promises to leverage XR to educate and promote energy-saving energy use behavior. Finally, the review proposes that future research in XR in AEC education focusing on occupant behavior-related building energy use should focus on comparative and benchmarking studies to explore longitudinal research in the XR modalities, especially MR, which remains underexploited.

Alshahrani, M. H., & Maashi, M. S. (2024) [15] focused on the systematic literature review (SLR) explores the topic of Facial Expression and Lip Movement Synchronization of an Audio Track in the context of Automatic Dubbing. This SLR aims to gain insights into the advancements, trends, and limitations of technologies related to this topic. The review protocol was well-defined, and we formulated specific research questions to guide the review process. A comprehensive search strategy included reputable electronic databases and relevant keywords. The study selection process followed inclusion and exclusion criteria, including 32 relevant studies published from 1995 to 2024. We systematically performed data extraction to gather critical information from the selected studies. The findings of this SLR contribute to understanding the current state-of-the-art technologies, identifying research gaps, and informing further advancements in this field.

Velmurugan, S. (2023) [16] explained in this study to identify current research on noise canceling methods applied to hearing screening tests. Investigations are also being conducted into audiometry issues and solutions related to real-time noise reduction techniques. Background noise levels at testing locations are reduced below the threshold specified by the American National Standards Institute (ANSI) using soundproof studios. The test must be performed in an environment where ambient noise levels are less than the maximum permitted noise levels to avoid false positive screening findings. Excessive ambient noise is a major problem for hearing screening since it masks pure tone stimuli, particularly at frequencies below 500 Hz. As a result, false findings are produced. Ambient noise might make it difficult for those with hearing loss to understand what is being said. In audio-metric testing, noise reduction strategies have been addressed in a variety of ways over the years. This is a survey of journals in the field of noise canceling techniques in hearing screening, with the most recent articles highlighted.

Kim, H. et al. (2022) [17] focused on this study aims to investigate how human and artificial intelligence (AI) speakers interact and to examine the interactions based on three types of communication failures: system, semantic, and effectiveness. We divided service failures using AI speaker user data provided by the top telecommunication service providers in South Korea and investigated the means to increase the continuity of product use for each type. We proved the occurrence of failure due to system error (H1) and negative results on sustainable use of the AI speaker due to not understanding the meaning (H2). It was observed that the number of users increases as the effectiveness failure rate increases. For single-person households constituted by people in their 30s and 70s or older, the continued use of AI speakers was significant. We found that it alleviated loneliness and that human-machine interaction using AI speakers could reach a high level through a high degree of meaning transfer. We also expect AI speakers to play a positive role in single-person households, especially in cases of the elderly, which has become a tough challenge in recent times.

METHODOLOGY

The adaptive echo-canceling algorithm employs the microphone input signal to the hearing aid, and it duplicates this as the echo signal through an adaptive filter. The loudspeaker output is accessed and then subtracted from the estimated echo so that the echo is diminished. The key idea here is that $x(n)$ should approximate the echo channel so that the predicted echo signal $y(n)$ approximates the actual echo signal. This is achieved by iteratively adjusting the coefficients of the adaptive filter, $w(n)$.

Machine Learning Modified RLS Approach for Echo Cancellation in Descent Coordinate Iterations Domain

Deep learning adaptive methods are very important in the field of voice enhancement, especially in echo cancellation. They provide effective robustness in dynamic environments. In this research paper, a two-layer NN architecture combined with a DCI-modified RLS adaptive filter is proposed to be used in solving both linear and nonlinear echo scenarios. Thus, the NN is trained in the frequency domain to predict the moment mask for target speech, exploiting its capability in noise reduction and echo suppression. Fast convergence, however, does not imply low computational complexity; rather, classical RLS algorithms are notorious for large processing depth despite having good convergence rates, especially for larger filter lengths. Approach to Solve System of Equations shown in Table 1. This approaches the problem by decomposing the standard equation into supplementary problems that are solved iteratively, significantly reducing the need for computational burdens. The approach hangs on recursive updates approximating the solution in terms of the residue vectors and the previously calculated values, which simplifies the operations without compromising the accuracy. Therefore, the hybrid approach combining NN with DCI-modified RLS permits an effective, low-complexity reconstruction of echo signals as well as optimal acoustic performance.

Table 1. Approach to Solve System of Equations.

Step	Equation
	Initialization: r(-1)=0,β(-1)=0, h(-1)=0
	For i=0, 1, 2…
1	Determination of $\Delta Q(i)$ and $\Delta\beta(i)$
2	$\beta_0(\mathrm{i})=\mathrm{r}(\mathrm{i}-1)+\Delta\beta(i)-\Delta Q(i)\hat{h}(i-1)$
3	Solve for $Q(i)\Delta\mathrm{h}(\mathrm{i})=\beta_0(\mathrm{i}) \Rightarrow \Delta\mathrm{h}(\mathrm{i}),\mathrm{r}(\mathrm{i})$
4	$\hat{h}(i)=\hat{h}(i-1)+\Delta\hat{h}(i)$

The proposed approach addresses incremental updates of filter weights $h(i)$ through the solution to an ancillary problem sensitive to previous precision and variability in increments rather than directly solving the original system. DCI method with cyclic runs across N elements of h shown in Table 2. A solution to the incremental system then represents a true solution to the original problem. It reduces the computational complexity itself by using the solution from the previous time step, thus achieving the same accuracy with fewer iterations. It also improves the cyclic Descent Coordinate Iteration (DCI) algorithm in processing that uses N multiplications, $(N + 1)$ additions and one division per update without further complex matrix-vector multiplications. By selecting orientations cyclically, such as for Gauss-Seidel iterations, the algorithm minimizes complexity down to $O(N)$, greatly saving computing power compared with normal methods.

Table 2. DCI method with cyclic runs across N elements of H.

Step	DCD equations	+
	Initialization: $\Delta\hat{h}(i) = 0, r(i) = \beta_0(i), \propto = H/2$, m=1	
	For k=1…………………N_u	
1	$n = \arg\max_{p=1,\ldots\ldots N}\{\lvert r_p(i)\rvert\}$, goto step 4	N-1
2	m=m+1, $\propto = \propto/2$	0
3	If $m>M_b$, the iteration stops	0
4	If $\lvert r_n(i)\rvert \leq (\propto/2)Q_{n,n}(i)$, goto step 2	1
5	$\Delta\hat{h}_n(i) = \Delta\hat{h}_n(i) + sign\,[r_n(i)] \propto$	1
6	$r(i)=r(i)-sign\,[r_n(i)] \propto Q_{:,n}(i)$	N
Total	$\leq(2N+1)N_u + M_b$ add	

Because the DCI algorithm provides the solution $h(i)$ with such impressive efficiency, it can be well-appreciated for use in adaptive threshold problems, like some modifications of RLS filtering techniques, including exponential smoothing and moving windows.

Machine Learning Optimistic Approach

A quasi-adaptive algorithm, using deep learning, could be trained with the aim of setting control parameters to a minimum or zero level for echo signals by representing the quasi-echo path as a linear strong space. This would mean generating a training set of noisy input examples and filter responses by models, optimized for the filter's correlation and confidence. This training strategy, shown in Figure 2, can effectively improve echo cancellation using the DCI-modified RLS filter.

The proposed filter design, combining DCI with RLS, effectively suppresses linear echo caused by multi-path reflections but struggles with residual echo from nonlinearities introduced by components like speakers or microphones. To address this, a Recurrent Neural Network (RNN)-based residual echo suppression system is developed, utilizing a deep learning architecture for data processing. This structure integrates raw vibration detection, echo estimation, and cancellation, effectively computing and minimizing leftover echo after noise removal.

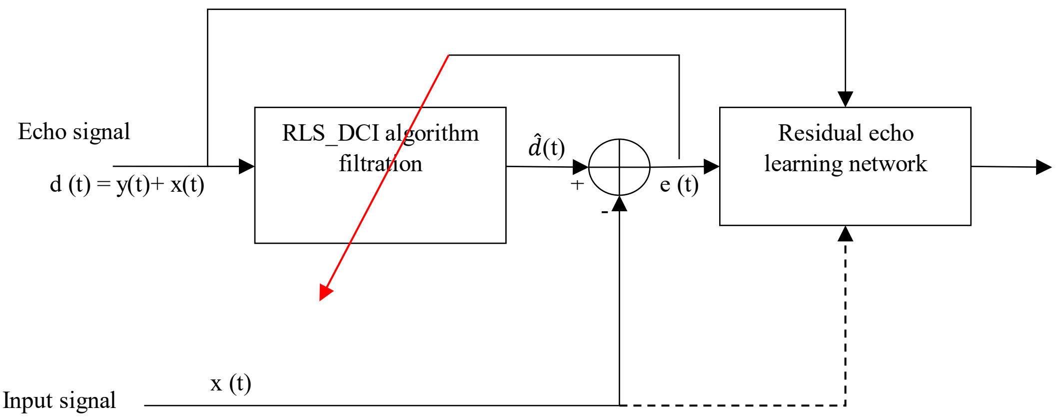

Figure 2. Operation of proposed scheme.

Structure of Implementation

Proposed echo cancellation uses supervised neural computation with annotation on complex spectral signals processed in the STFT domain. The echo error signal $d(t)$, consisting of speech signal $x(t)$ and acoustic echo $y(t)$, is utilized for adaptive filtering with the Composable Least Squares and DCI update rule to predict the acoustic pathway for each frequency bin. Using adaptive RLS-DCI, and deep learning of the estimated near-end signal, this technique keeps the spectral error between the actual and the predicted echoes to a minimum. Neural model application in the filter shown in Figure 3. It employs logarithmic spectral properties of the voice, echo, and error signals using a densely integrated neural network to predict and restore the original voice with high accuracy in the frequency domain.

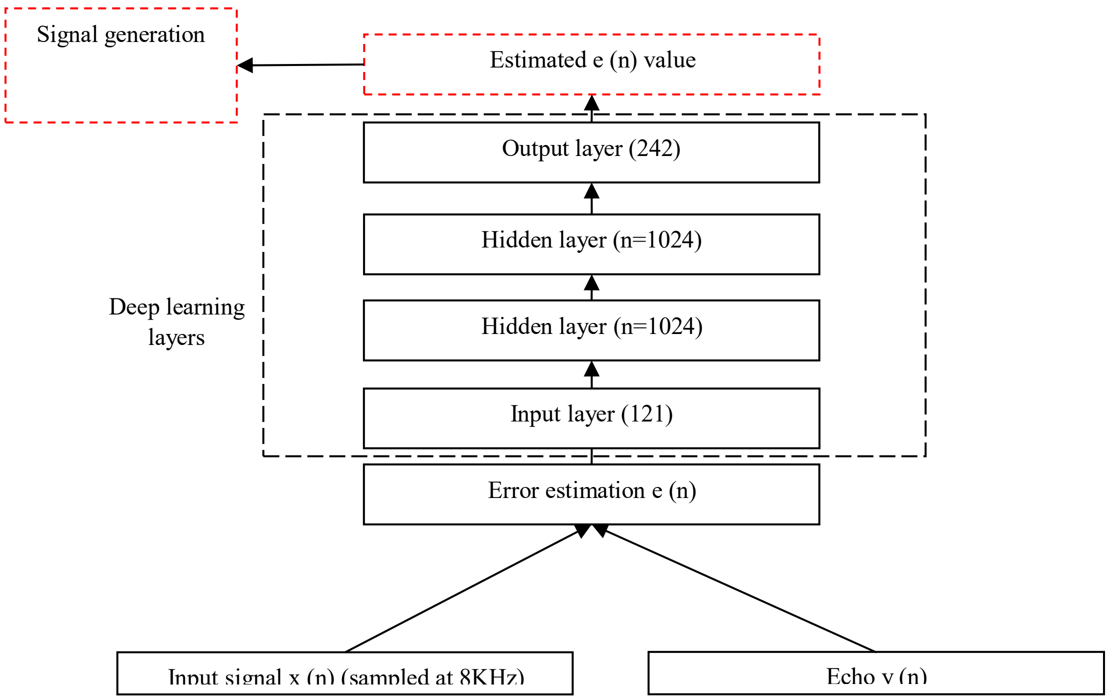

Figure 3. Neural model application in the filter.

The denoising network described uses fully connected layers where every neuron connects to all activations from the previous layer. Inputs of size 129-by-8 passed through two fully connected layers of 1024 neurons, each followed up by ReLU activation layers to introduce non-linearity. Outputs standardized with the batch normalization layers and finally added with a fully connected layer of 129 neurons followed by regression layers for predictions at output. This configuration efficiently extracts the features and denoises the signals input.

RESULTS AND DISCUSSION

The proposed denoising network is constructed by fully connected layers, where all neurons are connected to all activations in the previous layer. The input data size of 129-by-8 follows features and segments, then two fully connected layers of 1024 neurons. With input, it performs multiplication over a weight matrix and adds the bias vector. The number of parameters is determined by the number of neurons and activations. To introduce non-linearity, each fully connected layer in this paper is followed with a Rectified Linear Unit, which enables the network to effectively learn complex mappings and features. The input reference signal taken as input to the filters and Signal with echo to be processed for filtering shown in Figure 4 and Figure 5.

To stabilize and efficiently learn, batch normalization layers are added after the fully connected layers, by normalizing the standard deviation of outputs. The last layer of the network is a fully connected layer with 129 neurons to be able to match the size of the desired output followed by a regression layer for the prediction task. This architecture is optimized for denoising: systematically extracting and refining features while still maintaining structure suitable for input signal processing and clean, noise-free output.

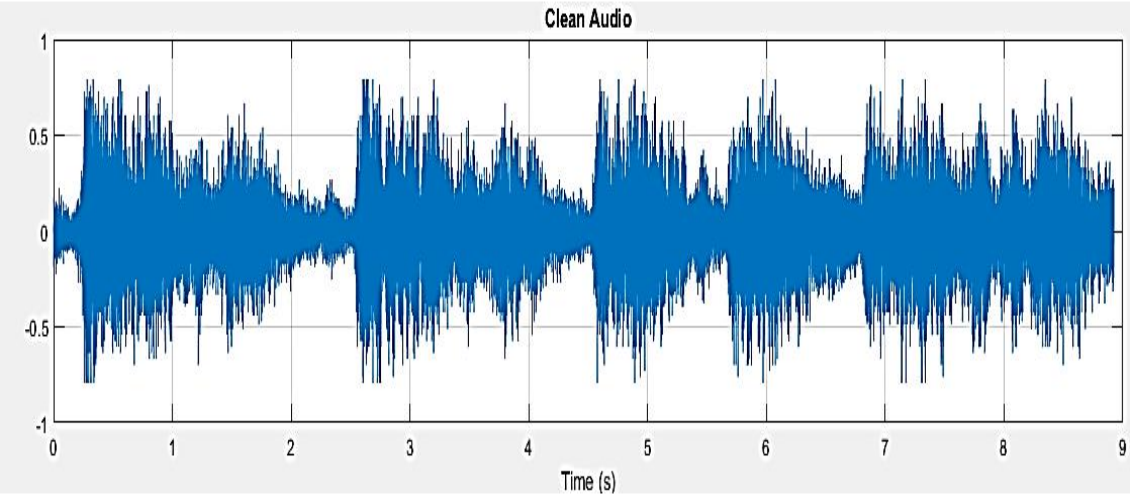

Figure 4. The input reference signal taken as input to the filters.

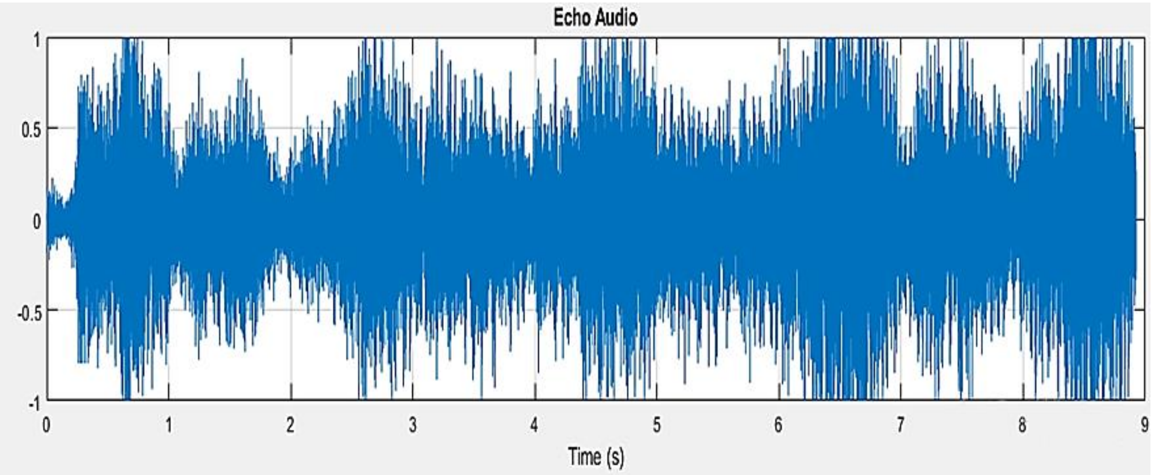

Figure 5. Signal with echo to be processed for filtering.

Variation in forgetting factors

Perform an analysis of performance of proposed filter for varying values of the forgetting factor (ff) from $(ff = 0 \cdot 8)$. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.8 shown in Table 3. Use MATLAB-based GUI for visualization purposes. Evaluate a few metrics such as Mean Square Error (MSE), standard deviation, and correlation values. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.9 shown in Table 4. The output signal quality was highly improved for both values of MSE and standard error evaluated for the value $(ff = 0 \cdot 8)$ as 0.0367 and 0.2451, respectively. Autocorrelation of 0.7131 indicated that the proposed approach based on DCD did well in comparison with the standard RLS filter. Graphical outputs represented in Figures 6 and Figure 7 validated the same.

Figure 8 analysis was carried on to $(ff = 0 \cdot 9)$ and the GUI results obtained are shown for further comparison. The proposed filter was able to outperform the classical RLS filter, showing a better result of signal processing capabilities. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.95 shown in Table 5. The improved performance metrics and graphical representations thus point at the superiority of this customized RLS filter, especially at lower values of forgetting factors, and hence more efficient for use in adaptive filtering applications. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.99 shown in Table 6.

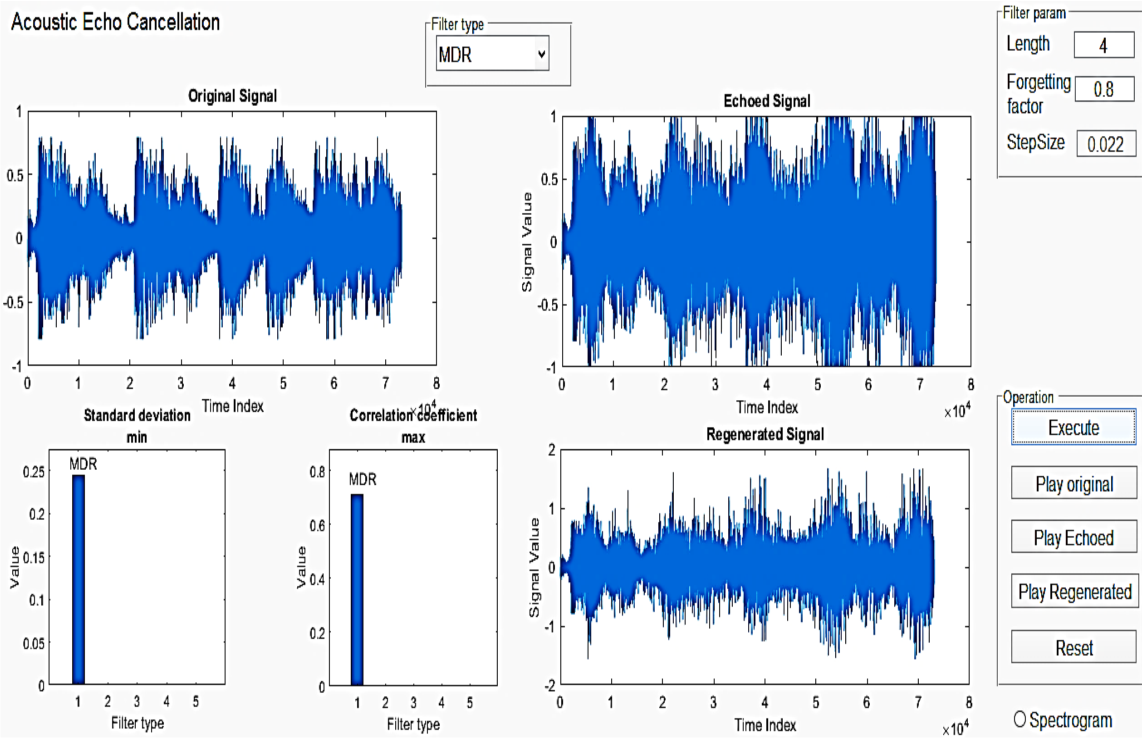

Figure 6. MATLAB/GUI representation of proposed MDR output with ff=0.8.

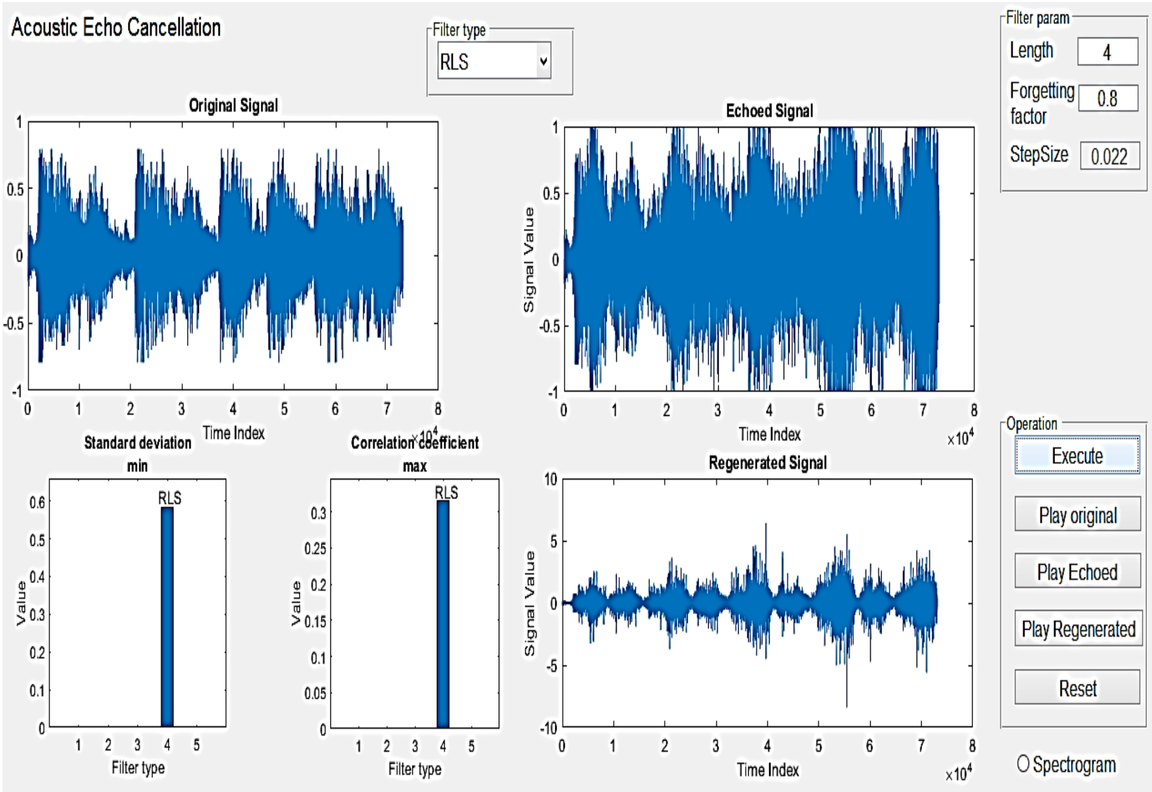

Figure 7. MATLAB/GUI representation of proposed RLS filter output with ff=0.8.

Table 3. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.8

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2451	0.7131	0.0367
RLS	0.5827	0.3148	0.3493

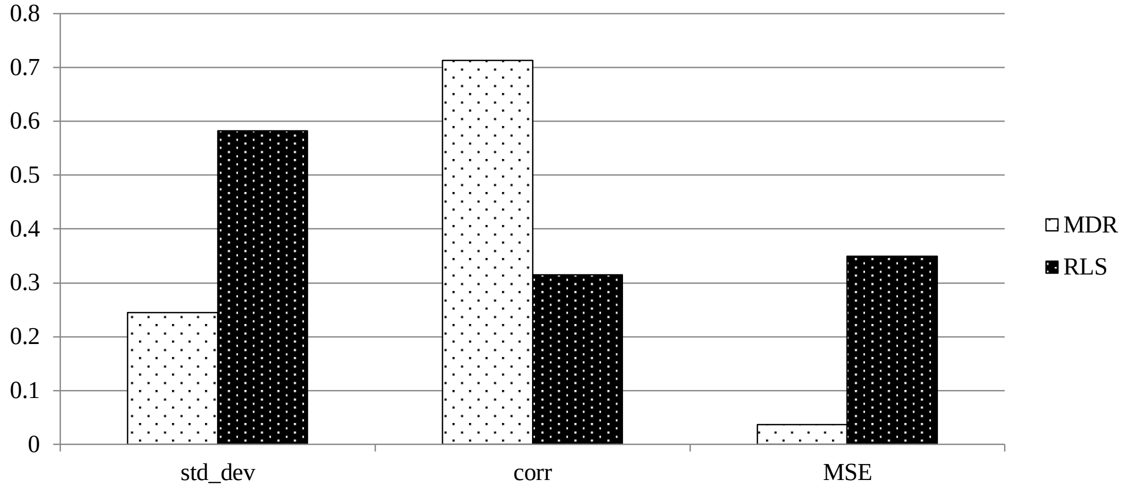

Figure 8. Comparison of outputs from the MDR and RLS filter for ff=0.8.

Table 4. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.9

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2337	0.7845	0.0237
RLS	0.4694	0.3778	0.0.2250

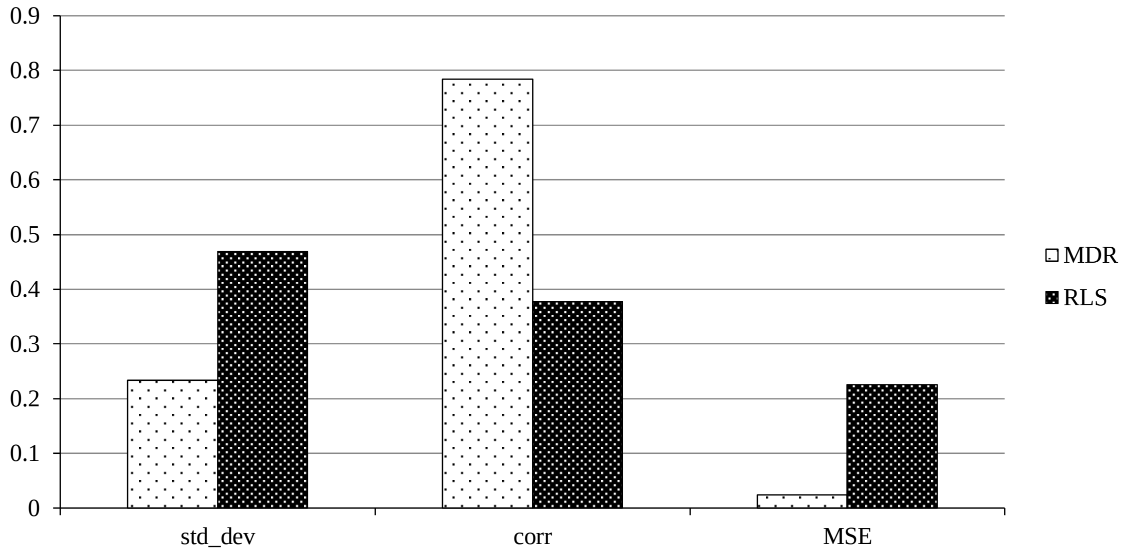

Figure 9. Comparison of outputs from the MDR and RLS filter for ff=0.9.

A proposed DCD-based filter outperformed the standard RLS algorithm with the achieved reduced standard error equals to 0.2337, MSE equals to 0.0237, and improved correlation coefficient equals to 0.7845 Figure 9 at forgetting factor equaling to 0.9, with further analysis planned for $(ff = 0 \cdot 95)$.

Table 5. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.95.

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2304	0.8380	0.0161
RLS	0.3828	0.4526	0.1439

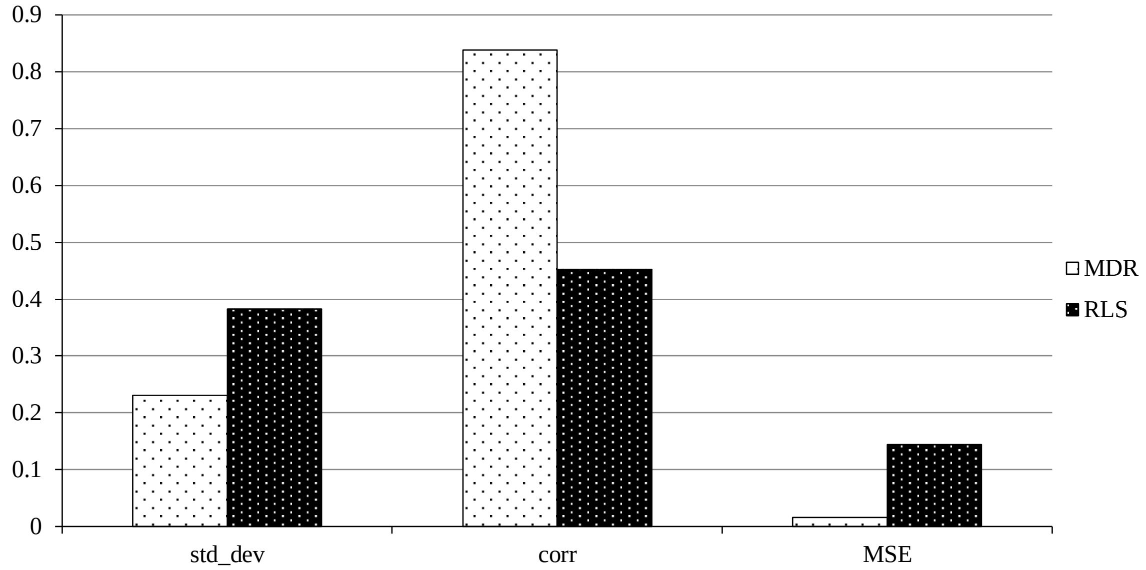

Figure 10. Comparison of outputs from the MDR and RLS filter for ff=0.95

The proposed DCD-based filter acted as outperformer of the standard RLS filter, which also resulted in the lower standard error (0.2304), MSE (0.0161) and much higher correlation coefficient (0.8380, Figure 10) at a forgetting factor of 0.95 and hence further evaluation was carried with ff = 0.99 to check its performance at the new conditions. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=1 shown in Table 7.

Table 6. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=0.99.

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2352	0.9287	0.060×10^{-1}
RLS	0.2722	0.6706	0.456×10^{-1}

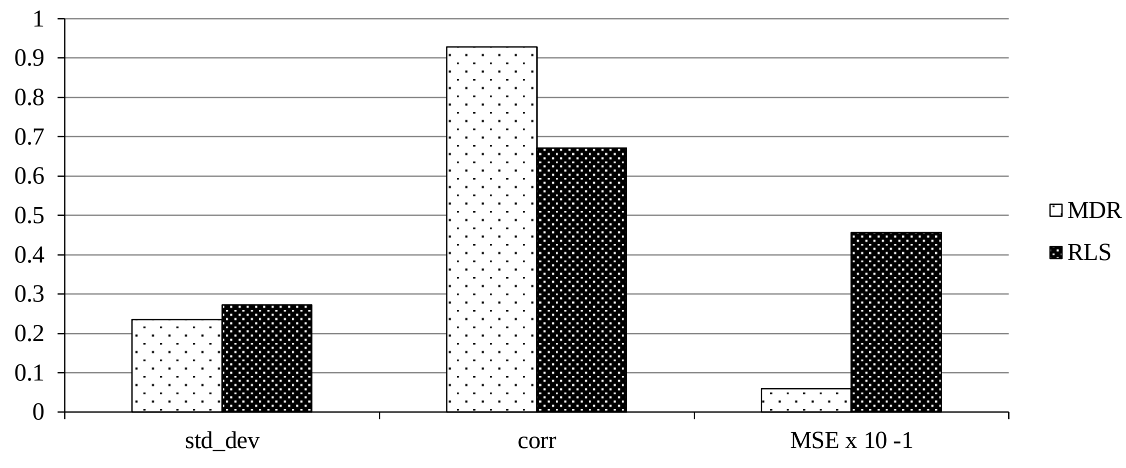

Figure 11. Comparison of outputs from the MDR and RLS filter for ff=0.99.

The proposed DCD-based filter demonstrated superior performance over the standard RLS filter, achieving a reduced standard error (0.2352), MSE (0.0060), and a higher Pearson correlation (0.9287, as shown in Figure 11) at a forgetting factor of 0.99, with further evaluation planned for (ff = 1) to assess its performance. Comparison of outputs from the MDR and RLS filter for ff=1 shown in Figure 12.

Table 7. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at ff=1.

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2437	0.9995	0.5×10^{-4}
RLS	0.2439	0.9969	2.47×10^{-4}

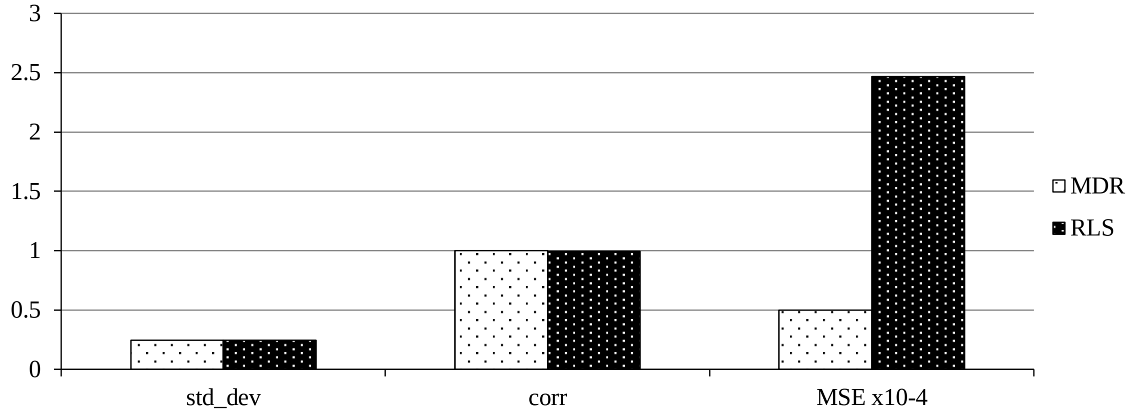

Figure 12. Comparison of outputs from the MDR and RLS filter for ff=1.

Analysis of Effects on the Two Filters by Varying the Filter Lengths

This section deals with the effect on the key parameters such as MSE, standard deviation and most important the correlation factor of the two filters when their lengths are being manipulated. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at L=4 shown in Table 8.

Table 7. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at L=2.

Algorithms	Standard deviation	Correlation coefficient	MSE
MDR	0.2437	0.9997	0.39×10^{-4}
RLS	0.2439	0.9969	2.4×10^{-4}

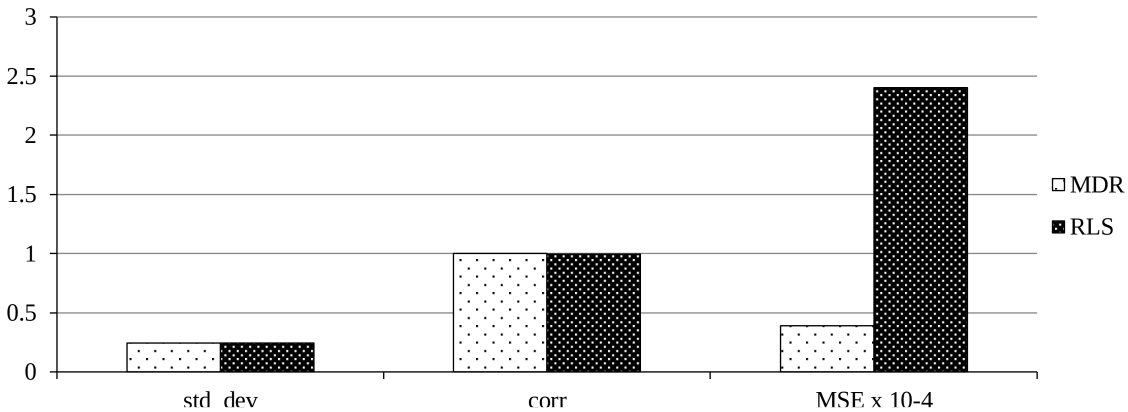

Figure 13. Comparison of outputs from the proposed MDR filter with RLS for length 2.

From Figure 13, proposed the DCD-based filter outperforms a standard RLS filter having the lower standard error of 0.2437 and MSE of 0.000039 and higher correlation factor of 0.9997. In section 4, proposed filter has shown superior efficiency with the best connection performance for a forgetting factor of 1.

Table 8. Performance analysis of the proposed machine learning DCD adaptive RLS with standard RLS algorithm at L=4.

Algorithms	**Standard deviation**	**Correlation coefficient**	**MSE**
MDR	0.2437	0.9995	0.5×10^{-4}
RLS	0.2439	0.9969	2.47×10^{-4}

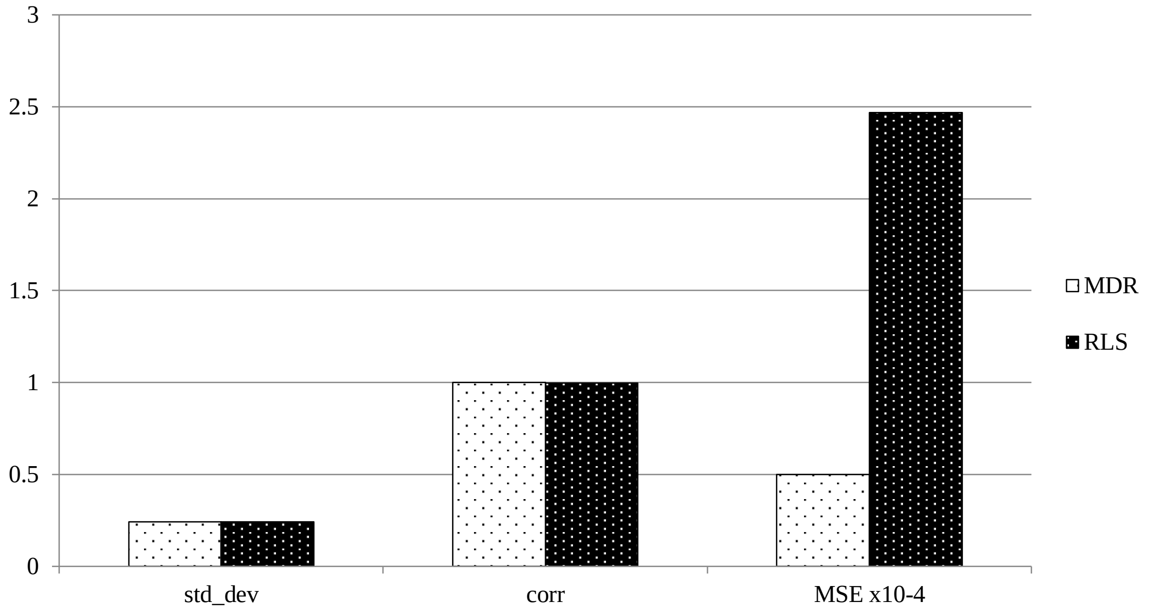

Figure 14. Comparison of outputs from the proposed MDR filter with RLS for length 4.

Figure 14 describes better performances of the proposed DCD-based filter as demonstrated by a lower MSE 0.00005, reduced standard error 0.2437, and higher correlation factor, as demonstrated in Table 8 0.9995 in comparison to conventional RLS filter 0.9969. Switching the filter height to 6 with sampling frequency to 4 also proved that the new version of the RLS filter has efficiency and correlation power significantly higher than that of the standard RLS filter. Standard deviation recorded for filter length 4 keeping shown in Table 9.

Comparative Analysis of MDR Algorithm with Four Traditional Filters

The proposed filter is compared with the other five filters using a length of 4. As seen in Figure 15, the best filter for the removal of the echo is the proposed one, as it provides the lowest deviation 0.2437. The correlation factors are presented in Table 10.

Table 9. Standard deviation recorded for filter length 4 keeping.

Filters	**Standard deviation**
MDR	0.2437
LMS	0.2905
NLMS	0.2586
AAF	0.2860
RLS	0.2439

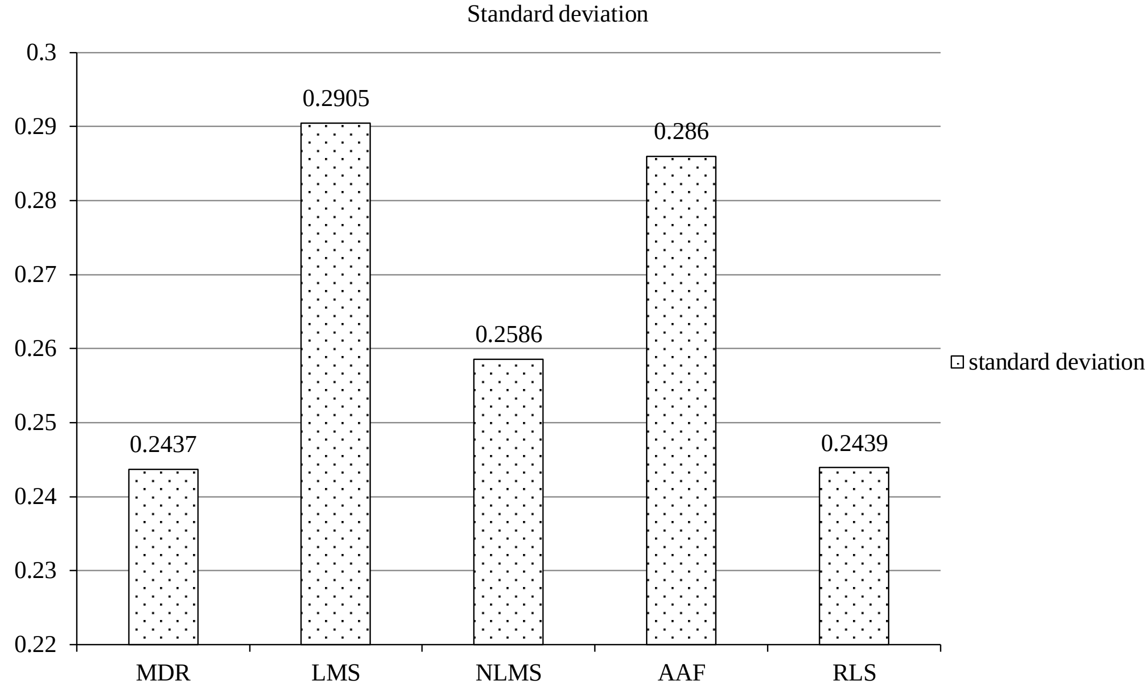

Figure 15. Comparative representation of standard deviation calculated with filter length 4.

Table 10. Correlation coefficient recorded for filter length 4 keeping.

Filters	Correlation coefficient
MDR	0.9995
LMS	0.8311
NLMS	0.9192
AAF	0.8434
RLS	0.9964

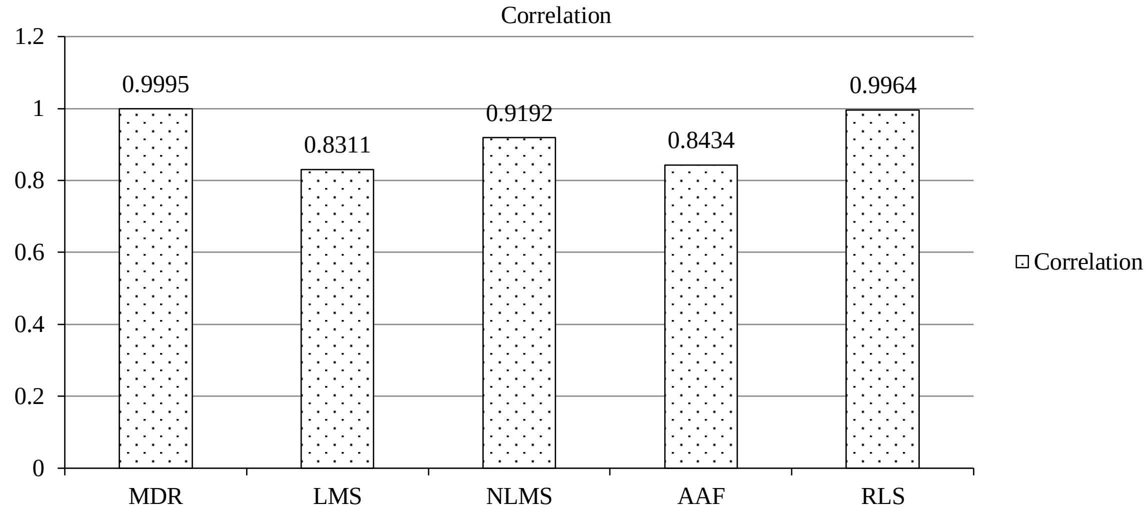

Figure 16. Comparative representation of correlation factors calculated with filter length 4.

The five filters that were compared include the proposed deep learning-based filter, which has a filter length of 4. Figure 16 indicates that the proposed filter has performed better than the rest, with a correlation factor as high as 0.9995, while the LMS filter has the lowest correlation factor, which is 0.8311. Table 11 gives the MSE output for the different filters.

Table 11. MSE recorded for filter length 4 keeping.

Filters	MSE
MDR	0.5×10^{-4}
LMS	0.0257
NLMS	0.0079
AAF	0.0231
RLS	2.4×10^{-4}

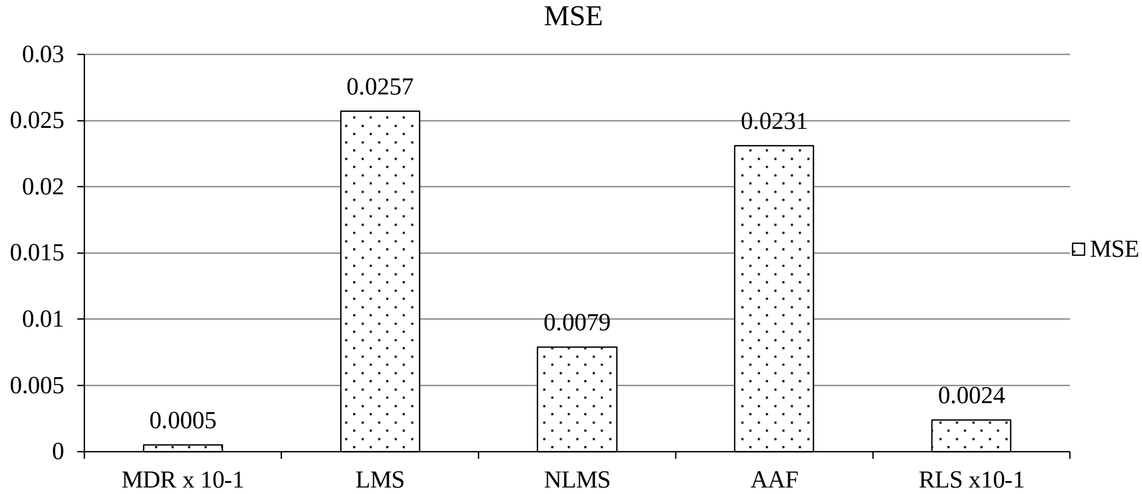

Figure 17. Comparative representation of MSE calculated with filter length 4.

The MSE over the five filters is shown, and from Figure 17, it is evident that the proposed iterative deep learning filter DCD achieved an error of 0.00005 at a filter length of 4; therefore, this one is the most effective to reduce echo. Further analysis was carried out by letting the length of the filters vary between 4 and 6. MATLAB was used for recording parameter variations pertaining to all five filters.

CONCLUSION

A wide variety of scenarios and filter lengths demonstrated that the proposed DCD-based ILF significantly outperforms the traditional filters, such as the RLS filter, by achieving a lower MSE, reduced standard deviation, and higher correlation coefficient values. Utilizing adaptive deep learning techniques, the filter takes care of both linear and nonlinear cases of echo. It dynamically adjusts to a wide range of acoustic conditions, thereby guaranteeing robust echo cancellation, even in noisy complex environments. Its high advanced architecture promises accurate signal processing with reduced complexity, so it is highly efficient for real-time applications: hands-free devices, teleconferencing, and VoIP systems. This research hints at potential revolution by the filter in acoustic echo cancellation by delivering superior performance and high reliability, thereby marking a new benchmark in audio signal processing of modern communication systems.

REFERENCES

1. Venkatesh, A., Kumar, N., & Sathisha, S. B. (2024). Collaborative Edge Computing In IOT: Audio Signal Processing With Low-Power VLSI Implementation. *Library Progress International*, *44*(3), 19270-19282.
2. Weng, C., Gu, X., & Jin, H. (2024). Coded Excitation for Ultrasonic Testing: A Review. *Sensors*, *24*(7), 2167. https://doi.org/10.3390/s24072167
3. Folgado, F. J., Calderón, D., González, I., & Calderón, A. J. (2024). Review of Industry 4.0 from the perspective of automation and supervision systems: Definitions, architectures and recent trends. *Electronics*, *13*(4), 782. https://doi.org/10.3390/electronics13040782

4. Chaccour, C., Saad, W., Debbah, M., Han, Z., & Poor, H. V. (2024). Less data, more knowledge: Building next generation semantic communication networks. *IEEE Communications Surveys & Tutorials*. https://doi.org/10.1109/COMST.2024.3412852
5. Getu, T. M., Kaddoum, G., & Bennis, M. (2024). A survey on goal-oriented semantic communication: Techniques, challenges, and future directions. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3381967
6. Mienye, I. D., Swart, T. G., & Obaido, G. (2024). Recurrent neural networks: A comprehensive review of architectures, variants, and applications. *Information*, *15*(9), 517. https://doi.org/10.3390/info15090517
7. Hojnik, J., Ruzzier, M., Ruzzier, M. K., Sučić, B., Soltwisch, B., & Rus, M. (2024). Review of EU projects with a focus on environmental quality: innovation, eco-innovation, and circular-economy elements. *International Journal of Innovation Studies*, *8*(1), 1-12. https://doi.org/10.1016/j.ijis.2023.10.001
8. Mahmoudi, A., Jemielniak, D., & Ciechanowski, L. (2024). Echo Chambers in Online Social Networks: a Systematic Literature Review. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3353054
9. Orikpete, O. F., Dennis, N. M., Kikanme, K. N., & Ewim, D. R. E. (2024). Advancing noise management in aviation: Strategic approaches for preventing noise-induced hearing loss. *Journal of Environmental Management*, *363*, 121413. https://doi.org/10.1016/j.jenvman.2024.121413
10. Ziegler, L., & Soutullo, A. (2024). Anthropogenic noise in terrestrial Antarctica: a short review of background information, challenges and opportunities. *Polar Research*, *43*. https://doi.org/10.33265/polar.v43.9859
11. Pandey, P., Farach-Colton, M., Dayan, N., & Zhang, H. (2024, June). Beyond Bloom: A Tutorial on Future Feature-Rich Filters. In *SIGMOD Conference Companion* (pp. 636-644).
12. Liu, Y., & Lei, Z. (2024). Review of Advances in Active Impulsive Noise Control with Focus on Adaptive Algorithms. *Applied Sciences*, *14*(3), 1218. https://doi.org/10.3390/app14031218
13. Motiei, M., Iyer-Raniga, U., Andamon, M. M., & Khodabakhshian, A. (2024). Advancing Circular Buildings: A Review of Building Strategies for AEC Stakeholders. *Buildings*, *14*(9), 2594. https://doi.org/10.3390/buildings14092594
14. Agbobli, D., & Mo, Y. (2024). Leveraging XR in AEC education focusing on occupant behavior-related building energy use: A systematic review. *Energy and Buildings*, 114821. https://doi.org/10.1016/j.enbuild.2024.114821
15. Alshahrani, M. H., & Maashi, M. S. (2024). A Systematic Literature Review: Facial Expression and Lip Movement Synchronization of an Audio Track. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3404056
16. Velmurugan, S. (2023). A literature review on noise cancellation techniques in audiometry testing. *IJSA*, *4*(2), 19-22.
17. Kim, H., Hwang, S., Kim, J., & Lee, Z. (2022). Toward Smart Communication Components: Recent Advances in Human and AI Speaker Interaction. *Electronics*, *11*(10), 1533. https://doi.org/10.3390/electronics11101533

