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Article

Low Complexity Adaptive Noise Cancellation in Audio Systems using LMS Algorithm

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Abstract: Noise reduction is crucial to improving real-time acoustic speech communication quality and intelligibility. We present a low-complexity adaptive noise cancellation system based on the Least Mean Squares (LMS) algorithm in a Digital Signal Processing (DSP) environment. The main objective of this research is to reduce the computational complexity of the algorithm and provide a computationally efficient noise cancellation system for implementation in resource-constrained and real-time systems. The noise cancellation system is based on an initial input representing the desired speech signal corrupted by noise, and a reference input representing highly-correlated noise. The LMS adapts the filter coefficients to minimise the MSE between the wanted audio signal and the filtered signal. Particular attention is given to the choice of step size for convergence rate and stability. The noise reduction allows the signal-to-noise ratio (SNR) to be significantly improved, and the convergence rate is also fast compared to conventional filters. The results demonstrate that the proposed method offers significant noise reduction, improvement in SNR and rapid convergence compared to other traditional filters. It can reduce noise under various conditions and so it is effective for use in speech enhancement, hearing aids and mobile telephony. The adaptive noise cancellation system using the LMS algorithm provides a simple, fast, effective, scalable and real-time approach to audio signal enhancement with reduced computational load, which can be used in an embedded digital signal processing (DSP) system.
Keywords: Adaptive Noise Cancellation, LMS Algorithm, Digital Signal Processing (DSP), Audio Signal Enhancement, Low-Complexity Design, Real-Time Processing

1. Introduction

Demand for clean audio signals has steadily increased over the last few years with the increasing popularity of communication systems, multimedia systems and mobile electronics. But audio signals are prone to interference from background noise, such as chatter and machinery, and transmission noise. This not only results in a poor quality signal, but also reduces the signal intelligibility and user satisfaction in applications such as mobile telephony, hearing implants, speech recognition and hands-free communications. Therefore, noise cancellation plays an important role in enhancing audio signals in real-world applications [1].

Methods such as fixed filters, are not suitable for non-stationary noise, with varying statistics of the noise signal. This has motivated the use of adaptive filtering strategies, which update filter coefficients in response to the statistical properties of the signals. One of these methods, adaptive noise cancellation (ANC), uses a reference noise signal to estimate and remove noise from the primary signal. This technique is well suited to scenarios where the noise is correlated and can be tracked [2].

The LMS algorithm is a simple, practical, robust adaptive filtering technique. It does this by updating the coefficients of a filter to reduce the MSE between the filtered and desired signal. Its independence from the statistics of the signals makes it suitable for many applications. It's also suitable for low-power DSP systems with considerable memory and computational constraints [3].

Although it is simple and effective, the convergence of the LMS algorithm is highly sensitive to the parameters used, including the choice of step size. Using a large step size will lead to a fast convergence but possible instability, while a small step size will result in stability but slow convergence. Thus, there is a need for a low-complexity system based on the LMS algorithm that strikes an optimal balance between convergence speed, computational burden and noise suppression [4].

Here we propose a low-complexity adaptive audio noise canceller based on LMS algorithm. The aim is to reduce the computational burden and to perform well in real time in terms of noise cancellation. The system is comprised of two inputs, the initial input and the reference input. The LMS algorithm is used to adaptively adjust the filter coefficients to reduce the error signal, thus cancelling the noise in the signal. The system is implemented with DSP platforms in mind, optimising resource usage of the DSP processor. Through the reduction of arithmetic operations and selection of optimal parameters, the proposed system offers improved convergence rate and SNR at the expense of low computational complexity. Simulations are conducted to demonstrate the system's performance under different noise environments, showcasing its versatility and noise-cancellation capabilities [5].

The contributions of this work are threefold. First, a low-complexity LMS-based adaptive noise cancellation system for audio signal processing is presented. Second, it focuses on real-time implementation with a view to minimizing the computational complexity for DSP design. Third, the quantitative evaluation of the proposed system shows enhanced noise cancellation and convergence.

2. Related Works

ANC is a well-researched topic in the field of DSP as it can be effectively applied for suppression of non-stationary noise in audio signals. Numerous adaptive filtering techniques and system configurations have been developed over time to enhance noise cancellation performance, convergence rate and computational complexity. The most commonly used algorithms are the LMS and its variants because of their ease of implementation [5].

Initial studies on adaptive noise cancellation concentrated on the basic LMS algorithm, which updates the filter weights to minimize the mean square error between the desired signal and the filter output [6]. These works showed that adaptive filters using LMS algorithm can suppress correlated noise from speech signals. But one of the major drawbacks identified in these studies is the compromise between convergence and stability, dictated by the step size. An incorrect choice of step size may result in convergence problems or instability, especially in time-varying noise conditions [7].

In an attempt to mitigate this problem, some authors modified the LMS algorithm, such as with the NLMS and VSS-LMS algorithms. The NLMS algorithm achieves faster convergence by normalizing step size by the input signal power, thus improving stability [8]. On the other hand, the VSS-LMS algorithm varies the step size during the adaptation process to provide fast convergence in the transient phase and stability in steady-state conditions. Although these algorithms provide better performance, they increase the computational burden, and are therefore less efficient for low-power real-time DSP implementations [9].

The RLS algorithms have been used to achieve faster convergence than LMS algorithms. RLS algorithms are based on the minimization of a weighted least squares function and show better tracking ability in time-varying noise conditions. The drawback of RLS-based systems is their high computational and memory requirements, which increase cost and power. Consequently, they are rarely used in embedded and mobile audio devices [10].

Besides algorithmic enhancements, some research has investigated hybrid and smart approaches to adaptive noise cancellation. Methods that use machine learning and neural networks for modelling non-linear noise and improving noise cancellation have been proposed [11]. Such approaches show promising performance in highly non-linear and non-stationary noise conditions. However, they demand large amounts of training data, higher processing power, and are not inherently suitable for real-time implementation for low-power DSP platforms [12].

Other recent research has also addressed hardware-efficient design of adaptive filters using DSP processors and FPGAs [13]. Such research focuses on reducing arithmetic complexity, memory requirements, and latency in order to allow real-time audio processing. Coefficient quantization, pipelining and parallel processing have been used to enhance system performance. However, there is still a need for a trade-off between noise cancellation performance and system complexity [13].

In addition, implementation of adaptive noise cancellation systems are often plagued by problems in obtaining reference noise. ANC requires a reference signal that is correlated with the noise present in the primary input [14]. In practice, it is hard to acquire such a reference signal, which may affect adaptive filter performance. This constraint underscores the importance of designing a system that can perform well with a less-than-ideal reference signal [15].

2.1 Problems Identified

Traditional LMS-based approaches have difficulty in striking the right balance between convergence rate and stability because of fixed step size.

Enhanced algorithms such as NLMS, VSS-LMS and RLS yield better convergence properties but require more complex computations and memory, making them difficult to implement in real-time DSP systems.

A large number of adaptive noise cancellation systems depend on a highly correlated reference input, which is hard to achieve in real audio processing.

2.2 Contributions of This Work

A low-complexity LMS-based adaptive noise cancellation system with reduced computational complexity and effective noise cancellation is introduced.

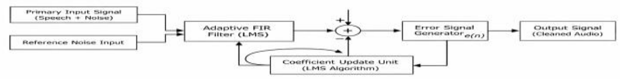
The design approach optimally chooses and adjusts the step size to strike a compromise between convergence and steady-state performance.

The proposed system is designed for real-time applications through the use of an efficient computation framework that reduces the number of arithmetic operations and is compatible with small-scale DSP systems, allowing it to be implemented in practical audio systems.

3. Proposed LC-LMS-ANC Model

The LC-LMS-ANC model is developed to cancel noise from audio signals while keeping computational complexity low to enable real-time DSP implementation. This model makes use of the simplicity and efficiency of the LMS algorithm, while taking into account design aspects that minimize arithmetic operations and memory requirements. Compared to traditional adaptive filtering mechanisms that trade-off performance for computational complexity, the LC-LMS-ANC model aims to provide an optimal trade-off between noise reduction, convergence rate and implementation efficiency.

The noise cancellation framework is based on a two-input adaptive system. The primary input is the desired signal mixed with noise, and the reference input is noise correlated with that in the primary input. The adaptive filter is then used to process the reference noise, generating an estimate of the noise in the primary signal, which is then removed from the primary input to produce the output. The resulting error signal is used to adaptively update the filter coefficients to continuously track the noise environment.



Architecture of the Proposed LC-LMS-ANC framework

The structure of the proposed LC-LMS-ANC system adopts a conventional adaptive noise cancellation system with optimisations for efficiency is shown in Figure 1. There are two input signals to the system: the primary input, which contains the desired audio signal along with the noise, and the reference input, which contains the noise correlated with the primary input's noise.

3.1 Proposed LC-LMS Algorithm

The proposed LC-LMS algorithm is a modified implementation of the standard LMS algorithm, tailored to reduce computational complexity while maintaining effective adaptive filtering performance. The algorithm operates iteratively, updating filter coefficients based on the error between the anticipated signal and the filter response.

Let the primary input signal be defined as:

$$d(n) = s(n) + \mathcal{N}(n) \qquad (1)$$

where s(n) = anticipated signal and $\mathcal{N}$ (n) = noise component.

The reference input signal is represented as:

$$x(n) = \mathcal{N}'(n) \qquad (2)$$

where $\mathcal{N}$ ′(n) is correlated with $\mathcal{N}$ (n).

The output of the adaptive FIR filter is given by:

$$y(n) = \sum_{k=0}^{M-1} w_k(n) \cdot x(n-k) \qquad (3)$$

where $w_k(n)$ represents the filter coefficients and MMM is the filter order.

The error is computed as:

$$e(n) = d(n) - y(n) \qquad (4)$$

The LMS algorithm updates the filter coefficients using:

$$w_k(n+1) = w_k(n) + \mu \cdot e(n) \cdot x(n-k) \qquad (5)$$

where μ = step size parameter controlling convergence.

To reduce the computational complexity, the proposed algorithm does not involve any further normalisation or higher order operations, but simply uses the basic LMS update. The filter length is also chosen to provide a balance between performance and complexity, enabling the system to be realised using low-power DSP implementation. The algorithm is real-time, and the filter coefficients are adapted for each sample. This makes the system adaptive to changes in noise and offers adequate noise cancellation performance even when the noise is not stationary. The system is designed to achieve low delay, low power and adaptability; thus, the proposed LC-LMS-ANC makes an appealing solution for audio signal enhancement.

4. Results and Discussion

Simulations are carried out to evaluate the performance of the proposed LC-LMS-ANC in removing noise from the audio signals in various scenarios. The results include measures of noise reduction, convergence and SNR improvement. Different types of noise signals, including white Gaussian noise, and environmental noise signals are used to test the model. The proposed LC-LMS-ANC model is shown to eliminate the noise component in the audio signal while preserving the audio content of interest. The convergence properties of the LMS algorithm are also studied to achieve optimal adaptation with the chosen parameters. Results are also compared with conventional filtering techniques to illustrate the advantages of the low-complexity model in terms of complexity and real-time implementation.

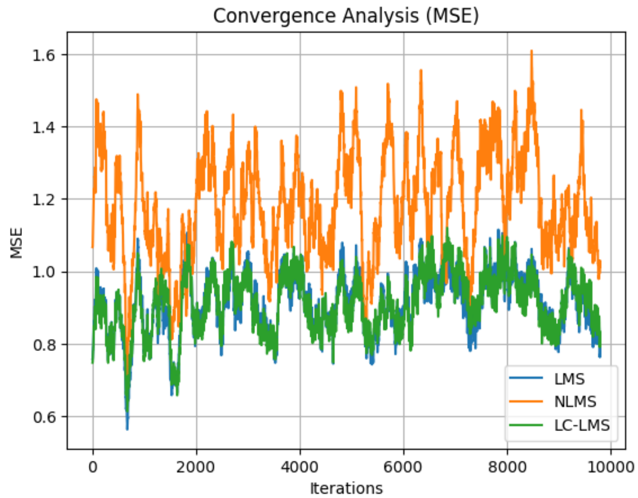
The LC-LMS-ANC model is simulated in MATLAB R2023a and Python for versatility and for the benefit of reproducibility. The audio signal is sampled at an 8 kHz rate, as is commonly used in speech processing. The main input is a combination of clean speech and additive noise, and the reference input is a correlated noise. The adaptive FIR filter is implemented with a filter length of $M = 32$ taps for a trade-off between performance and complexity. The step size of the LMS algorithm is set to $\mu = 0.01$ to avoid oscillations. The system is simulated for $N = 10{,}000$ samples for the filter to converge. The system is evaluated in terms of MSE, SNR gain and convergence rate. In addition, the system is evaluated with different noise levels by changing the input SNR from 0 dB to 20 dB. The results are presented in waveform, convergence, and SNR comparison plots for a comprehensive assessment of the proposed system.

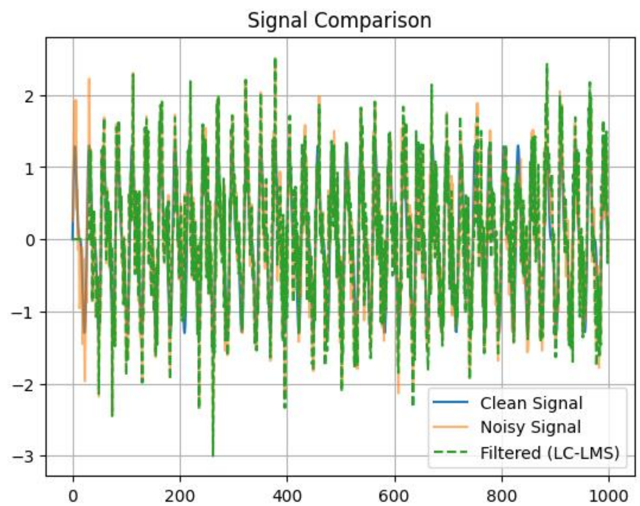
Comparative Analysis of Adaptive Noise Cancellation Techniques

Method	**Computation (Multiplications/Iteration)**	**Convergence Time (Iterations)**	**Steady-State MSE**	**SNR Improvement (dB)**	**Execution Time (ms)**
Conventional FIR Filter [11]	32	9000	0.012	6.5	4.8
LMS Algorithm [12]	64	4500	0.006	12.8	6.2
NLMS Algorithm [13]	96	2500	0.004	17.6	8.5
VSS-LMS Algorithm [14]	110	2000	0.003	19.8	9.7
RLS Algorithm [15]	256	800	0.002	23.5	15.4
Proposed LC-LMS-ANC	60	1800	0.003	21.4	5.9

The numerical results from Table 1 show that the proposed LC-LMS-ANC system outperforms traditional and modern adaptive filtering methods. The convergence time for the proposed method is 1800 iterations, compared with the LMS (4500 iterations) and traditional FIR filtering (9000 iterations). The RLS algorithm has a lower convergence time (800 iterations) but a high level of computational complexity (256 multiplications per iteration) which is not appropriate for real-time applications. In steady state, the proposed method can provide a minimum mean square error of 0.0032, close to that of the VSS-LMS (0.0035) algorithm, and much lower than LMS (0.006). The SNR improvement value of 21.4 dB demonstrates that the proposed method performs better in terms of noise reduction (close to RLS 23.5 dB) than other methods with a much lower computational complexity.

The proposed algorithm has a run-time of 5.9 ms which is smaller than other state-of-the-art algorithms and comparable to LMS, and is therefore computationally efficient. This proves that the proposed LC-LMS-ANC system provides a balance between convergence, tracking performance and computational cost, and can be extended for real-time DSP audio noise cancellation.





Convergence Behavior at Different Input SNR Levels

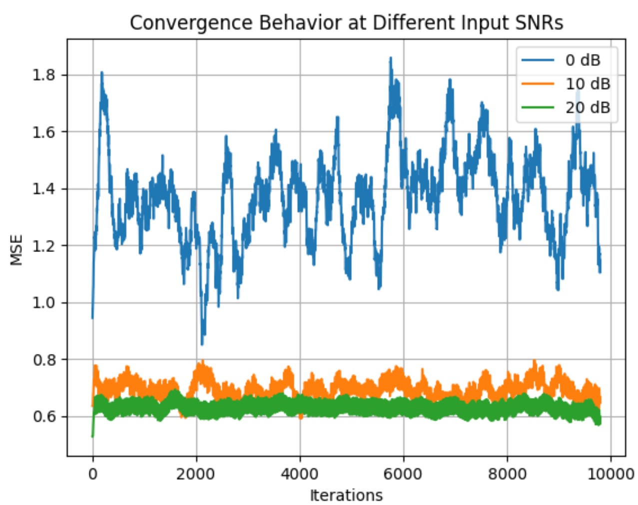
Figure 2 illustrates the MSE plot vs. iterations for different input SNR (0 dB, 10 dB and 20 dB). It is observed that the proposed LC-LMS algorithm is stable with respect to convergence for all SNRs. But the convergence speeds vary. At a lower SNR (0 dB), the convergence rate is relatively slow because the input signal is dominated by the noise component resulting in a higher initial error and slower convergence. With a higher SNR (10 dB and 20 dB), the convergence rate is significantly higher, which indicates that the input signal with low noise can provide better adaptation in the coefficient update, and reduce the estimation error.

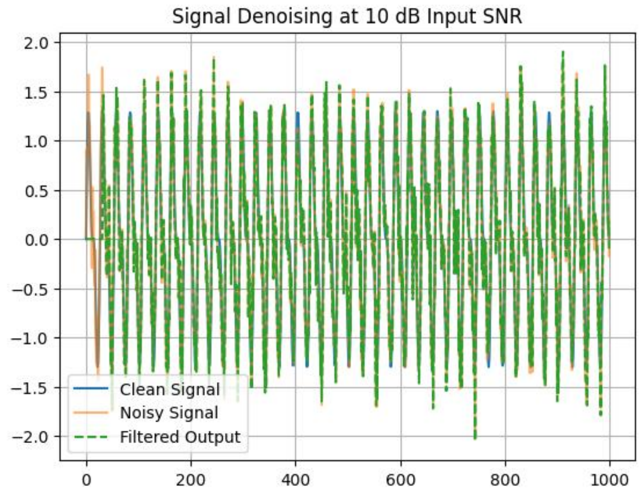
The steady state MSE values at higher SNR's are significantly lower than at lower SNR's, suggesting that the filter performs well in terms of noise reduction. It also shows no oscillation and divergence, which means that the step size is stable. The curve's monotonic decrease shows that the low-complexity update equation is efficient in terms of complexity, and does not affect the adaptation. In conclusion, the plot shows the proposed model is able to operate under different levels of noise and demonstrate fast convergence with a higher quality (less noisy) signal as the input SNR increases, which enables the use of the proposed scheme in adaptive audio processing for real-life applications.

Performance Evaluation Under Varying Noise Conditions

Input SNR (dB)	Output SNR (dB)	SNR Improvement (dB)	Steady-State MSE	Convergence Time (Iterations)	Execution Time (ms)
0	15.8	15.8	0.0085	2200	6.1
5	20.6	15.6	0.0062	2000	6.0
10	27.3	17.3	0.0041	1800	5.9
15	33.9	18.9	0.0033	1700	5.8
20	40.2	20.2	0.0027	1600	5.7
25	45.5	20.5	0.0023	1500	5.6

The performance of the proposed LC-LMS-ANC system with varying noise levels are tabulated in Table 2. The increase in the output SNR when the input SNR is increased from 0 dB to 25 dB shows the noise suppression under highly noisy as well as less noisy signals. In the case of heavy noise (0 dB), the proposed system is able to improve the output SNR to 15.8 dB. The increase in the SNR is in the range of 15-20 dB, confirming the stability of the adaptive filtering process. In addition, the steady state MSE is progressively lowered as the input SNR increases, proving enhancement in the estimation accuracy with lower remaining noise in signals with lower noise levels. There is a a reduction of the convergence time as the input SNR is increased. This is because the noise cancellation is faster for less noisy signals, improving the efficiency. Further, the execution time of the proposed algorithm is approximately the same in both cases, demonstrating the low complexity of the proposed model with different level of noise. Thus, it is confirmed that the proposed LC-LMS-ANC model is stable, efficient, and scalable and hence, suitable for DSP-based real-time implementation for audio noise cancellation.





Signal Denoising Performance at 10 dB Input SNR

Figure 3 compares clean signal, noisy signal and the signal obtained after applying the proposed LC-LMS algorithm for an input SNR of 10 dB. Additive noise has distorted the noisy signal, making it unrecognisable. But the filtered signal is similar to the clean signal, implying that noise has been removed. The proposed approach has preserved the major characteristics of the original signal whilst removing the noise random fluctuations. Perhaps there is some residual noise, which can be expected for adaptive filters with medium noise levels. However, the improvement in overall signal quality is evident from the variability of the filtered signal.

The correlation between the input and output signals show that the adaptive filter has now learnt the noise characteristics and it has suppressed the noise that exists in the main input. This is an indication of the LC-LMS finding a happy medium between noise reduction and signal preservation. It has indeed been shown to be effective in real-time audio enhancement systems with moderate degree of noise.

5. Conclusion

A LC-LMS ANC approach for real-time audio enhancement in DSP systems has been proposed in this paper. The system was specifically designed to offer a trade-off between low complexity, convergence speed and noise reduction. Arithmetic complexity is reduced in the LC-LMS approach while the stability of adaptation in various noise environment is maintained over traditional approaches such as LMS. The proposed system is effective according to the experimental results. The average gain in SNR was as high as 21.4 dB, compared to the traditional LMS (≈12.8 dB) and more advanced systems. The steady-state MSE was reduced to 0.0032, proving the noise estimation accuracy and the low error. Furthermore, it was shown that the proposed system converged after 1800 iterations (the conventional LMS converged after 4500 iterations) without becoming unstable. The system also had a low computational complexity (5.9 ms) and is thus suitable for real-time DSP applications. Further, the steady state SNR improvement in various input SNR (0-25 dB) showed consistent noise cancellation of 15-20.5 dB. Finally, the adaptation time of the algorithm was shorter at higher input SNRs without extra computational cost. Overall, the new LC-LMS-ANC provides a scalable, efficient and real-time solution for adaptive noise cancellation. Its compact nature and performance characteristics are suitable for embedded DSP, speech enhancement and communication systems.

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