**ECHO CANCELLATION USING LMS, NLMS, RLS AND SUBBAND ADAPTIVE FILTER.**

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**Abstract:** An adaptive filter modifies its transfer function autonomously, guided by an optimization algorithm that uses an error signal for adjustments. Such filters are crucial in various applications including echo cancellation and system identification. This paper reviews several adaptive filtering techniques such as LMS, NLMS, RLS, and SAF, specifically for the purpose of echo cancellation. The objective of this study is to identify the most effective algorithm for removing echo from speech signals. This analysis includes evaluations based on cross-correlation, Echo Return Loss Enhancement (ERLE), and spectrogram assessments. The paper concludes by identifying the superior adaptive filtering method for echo cancellation, with conclusions supported through subjective analysis.

1. INTRODUCTION

FIR and IIR digital filters are typically employed in scenarios where the desired filter coefficients remain fixed. However, in various digital signal processing tasks like echo and noise cancellation, filter coefficients are variable and cannot be predetermined. The only method to achieve variable filter coefficients is using an equalizer with adjustable coefficients, optimized to reduce distortion based on the known characteristics of the channel. This type of filter is known as an Adaptive Filter. Specifically, adaptive filters are utilized in acoustic echo cancellation, as depicted in figure 1. Acoustic echo represents a basic type of acoustic modeling issue, occurring when a signal undergoes multipath propagation, illustrated in figure 2. In this scenario, a direct sound first reaches the listener, followed by several reflections that also arrive at the listener with time delays, known as echoes. These echoes are generated when the direct signal encounters obstacles within a space and is reflected. Eliminating or minimizing these echo signals is crucial for improving the quality of perceived sound.

**A diagram of a machine

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Figure 1: Adaptive Echo cancellation

**A diagram of a reflection diagram

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Figure 2: Acoustic echo phenomenon

Within the realm of adaptive filters, a variety of adaptive algorithms are employed, among which the LMS (Least Mean Square), NLMS (Normalized Least Mean Square), RLS (Recursive Least Square) and SAF Algorithms stand out due to their prominence and widespread adoption in handling various signal processing challenges. An adaptive filter is typically divided into two main components. The first component is dedicated to filtering out the echo signals, effectively reducing noise and improving clarity. The second component involves an adaptive algorithm whose role is crucial as it continuously updates the filter's coefficients in real-time to adapt to changes in the signal's properties. This dynamic adjustment helps maintain the effectiveness of the filter across different acoustic environments [3].

1. HISTORY OF ADAPTIVE FILTER

The fundamental concept of the adaptive filter originated at AT&T Bell Labs. Over the years, numerous adaptive filter algorithms have been developed and refined. Among these, the LMS (Least Mean Square), NLMS (Normalized Least Mean Square), RLS (Recursive Least Square) and SAF (Subband Adaptive Filter) algorithms are noteworthy. The LMS adaptive filter, a significant advancement in this field, was developed in 1960 by Bernard Widrow, a professor at Stanford University, and his first Ph.D. student, Ted Hoff. Their pioneering work was part of their research into pattern recognition [4].

III. THEORY EXPLANATION

A. Adaptive Digital Filters

Adaptive filters are dynamic systems that adjust their structure based on input signal characteristics, functioning as either FIR or IIR filters tailored to their operational environment. This environment is characterized by the input signal x(n) and the desired signal d(n), enabling the filters to regulate and track changes autonomously. Adaptive filters are vital in a variety of applications including Echo Cancellation, Noise Cancellation, System Identification, and more. Several adaptive filter algorithms are elaborated on below:

1. LMS (Least Mean Square) Algorithm - The LMS algorithm is the most prevalent algorithm used in adaptive filtering. It belongs to the category of stochastic gradient-based algorithms, which use the gradient vector of the filter tap weights to approximate the optimal Wiener solution. During each iteration of the algorithm, the filter's tap weights are updated according to Equation (3), where w(n) denotes the adaptive filter weight vector at time n, x(n) represents time-delayed input signal samples, e(n) indicates the error signal that needs to be minimized, and µ is the step size or convergence factor.

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LMS Block Diagram

Output, y (n) = 𝑤^h x (n) (1)

Error, e (n) = d (n) – y (n) (2)

Weight, w (n + 1) = w (n) + µx (n) e (n) (3)

The step size parameter, µ, is critical in determining the update dynamics of the algorithm. A very small µ results in slow convergence, while a larger µ can cause the algorithm to converge more quickly but risks instability and divergence from the minimum error value.

2. NLMS (Normalized Least Mean Square) Algorithm – A notable limitation of the LMS algorithm is its fixed step size parameter, which does not adjust based on the signal conditions. In the LMS algorithm, the weight adjustment is proportional to the amplitude of the input vector samples. Consequently, when the input vector x(n) is large, the algorithm may experience a gradient noise amplification issue. The NLMS algorithm addresses this by normalizing the weight adjustment at each iteration. It calculates the step size µ(n) based on the inverse of the total expected energy of the instantaneous values of the input vector x(n), which is equivalent to the dot product of the input vector with itself and the trace of the input vector’s auto-correlation matrix, R. This normalization helps stabilize the update process, making the NLMS an improvement over the traditional LMS by adjusting the step size dynamically to suit the varying signal conditions in each iteration.A diagram of a flowchart

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NLMS Block Diagram

Output, y (n) = 𝑤^ℎ x (n) (4)

Error, e (n) = d (n) – y (n) (5)

Weight, w (n + 1) = w (n) + 1/(1+ 𝑥 ^𝑇(𝑛)𝑥(𝑛)) e (n) x (n)

here, µ = 1 / (1+ 𝑥 ^𝑇(𝑛)𝑥(𝑛)) (6)

3. RLS (Recursive Least Square) Algorithm - Traditional least square algorithms necessitate access to all previous samples of both the input signal and the desired output for each iteration. The RLS filter, however, is an adaptive update of the Weiner filter, suited particularly for adaptive scenarios. It effectively tracks changes in non-stationary signals, while its performance in stationary signals mirrors that of the Weiner filter. The aim of these algorithms is to minimize the cost function detailed in Equation (7). Equation (7) specifies that k 1 is the initiation time for the RLS algorithm and λ is a small positive constant, slightly less than 1. By prioritizing more recent input samples, the algorithm focuses more on new observations and less on historical data.A diagram of a computer

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RLS Block Diagram

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Relative to the LMS algorithm, the RLS algorithm achieves quicker convergence and maintains a lower error rate at steady state. However, the RLS algorithm is significantly more complex in terms of computation. If not designed and implemented correctly, the RLS algorithm can become unstable and diverge, leading to unreliable performance.

4. Subband Adaptive Filter (SAF)

Subband Adaptive Filter (SAF) - Subband adaptive filtering methods segment the input signal into multiple frequency bands, each handled by its own adaptive filter. This segmentation significantly lowers the computational burden, particularly with wideband signals. The bands are usually created using a filter bank that divides the signal, enabling each adaptive filter to manage a narrower, band-limited segment of the signal. This often results in better convergence properties compared to processing the entire bandwidth, as each filter focuses on a segment potentially closer to stationary behavior. After filtering, the outputs from each band are merged back together to form the complete processed signal. SAF proves highly effective in cases where the signal's different frequency components behave distinctly. Nevertheless, the performance of subband adaptive filters critically depends on the design of the filter bank and how well aliasing between the bands is controlled. As with other adaptive filters, SAF aims to minimize a cost function, usually an error signal, within each subband.

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Block Diagram of SAF

B. Echo

Echoes are simply generated by delay units. The direct sound and a single echo appearing after R sampling periods later can be generated by the FIR filter as shown in Fig. 3.

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Figure 3: Echo Filter

The transfer function of the echo filter is given by Equation (8).

H (Z) = 1 + α 𝑍 −𝑅, |α| < 1 (8)

In the above transfer function, the delay parameter R denotes the time the sound wave takes to travel from the sound source to the listener after bouncing back from the reflecting wall, whereas the parameter, α with |α| < 1, represents the signal loss caused by propagation and reflection.

C. Echo Cancellation Echo cancellation is the process of removing echo signals from a voice communication system to achieve quality audio perception. The development of echo reduction began in the late 1950s and continues today as new integrated landline and wireless cellular networks put additional requirement on the performance of echo cancellers. Echo cancellation involves first recognizing the originally transmitted signal that re-appears, with some delay, in the transmitted or received signal. Once the echo is recognized, it is removed by 'subtracting' it from the transmitted or received signal. This technique is usually implemented on DSP’s using adaptive filters.

IV. PERFORMANCE MEASURES

The choice of best algorithms is measured using performance measurement parameters like ERLE, SNR and Cross correlation.

A. Echo Return Loss Enhancement (ERLE) The ERLE is defined as the ratio of send-in power (Pd) and the power of a residual error signal immediately after the cancellation (Pe), and it is measured in db. The ERLE measures the amount of loss introduced by the adaptive filter alone. ERLE depends on the size of the adaptive filter and the algorithm design. The higher the value of ERLE, the better the echo canceller. ERLE is a measure of the echo suppression achieved and given by

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B. Signal to Noise Ratio (SNR) is calculated as the ratio of the power of the signal to the power of the noise that interferes with it. SNR is a key metric for assessing the quality of a signal. A high SNR indicates a high-quality signal with minimal distortion.

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C. Cross-Correlation

Correlation calculates a measure of how similar two input signals are as they are shifted relative to each other. The peak of the correlation output indicates the point at which the two signals---- align most closely. This technique is commonly used to identify the time-shift between two signals.

** (11)**

V.) Implementation Procedure

STAGE 1:

1) The experiment begins with a speech signal that does not contain any echo elements, serving as the desired or ideal signal. 2) An Echo Model is constructed using Simulink, with the decay factor set consistently at 0.001 and the delay value (R) fixed at 2 samples. The filter order is maintained at 1024. This configuration produces an echoed version of the initial signal. 3) Both the original desired signal and the signal combined with the echo are fed into an LMS Echo Canceller. 4) The simulation is conducted over a span of 10 seconds, with the LMS block’s output port delivering the signal from which the echo has been removed. The error port of the LMS block provides the discrepancy between the desired signal and the output from the LMS. 5) The desired signal, signal combined with echo, output signal, and error signal are all stored in the workspace for subsequent analysis. 6) Spectrogram plots are generated for both the desired and output signals using the SPECTROGRAM function. 7) This process is repeated using NLMS, RLS and SAF Echo Canceller Algorithms for comparative analysis.

STAGE 2:

1) The efficacy of echo cancellation is evaluated using the concept of ERLE (Echo Return Loss Estimation), defined as the ratio of the power of the desired signal to the power of the residual signal. The formula for calculating ERLE is outlined in the given equation.**A black text with a black line

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2) It is a smoothed measure of the amount (in dB) that the echo has been attenuated. ERLE should stabilize in the interval [-40dB, 30dB] for a good performance.

STAGE 3:

1)To determine the amount of time shift between desired and echo cancelled signal, we use the concept of cross-correlation. 2) Cross correlation is calculated between desired signal and echo cancelled output obtained from LMS, NLMS, RLS and SAF adaptive filter algorithms. 3) Ideally, the time shift between desired and echo cancelled signal should be minimal; and the amplitude of time shifted signal should be very less for better audio perception.

VI). MATLAB IMPLEMENTATION

A. Digital Implementation using Algorithms.

To evaluate various adaptive echo cancellation algorithms, we utilized a .wav file. This speech signal has a sampling frequency of 22050Hz and lasts for 4 seconds. We generated an echo from this clean speech, which was then used as input for the adaptive algorithms, and the outcomes were subsequently analyzed.

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Figure 4: Real Signal and its Spectrogram

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Figure 5: Echo Signal and its Spectrogram

1. LMS Algorithm

An FIR filter with adaptive LMS algorithm with a step size of 0.005 and filter coefficient of 1024 has been used for simulation experiment.

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Figure 6: LMS output and its Spectrogram

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Figure 7: True and estimated output of LMS

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Figure 8: Actual weights and the estimated weights of LMS

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Figure 9: ERLE (Echo Return Loss Enhancement) of LMS

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Figure 10: Cross correlation between desired and LMS output signal

2. NLMS Algorithm

Below figure shows the NLMS algorithm output which was simulated using MATLAB. Here the adaptive FIR filter is of the order of 1024.

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Figure 11: NLMS output and its spectrogram

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Figure 12: True and estimated output of NLMS

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Figure 13: Actual weights and the estimated weights of NLMS

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Figure 14: ERLE (Echo Return Loss Enhancement) of NLMS

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Figure 15: Cross correlation between desired and NLMS output signal

3. RLS Algorithm

The coefficients of the adaptive FIR filter are adjusted using the RLS algorithm. The settings for λ and the filter length are configured at 0.99 and 5, respectively.

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Figure 16: RLS output and its spectrogram

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Figure 17: True and estimated output of RLS

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Figure 18: Actual weights and the estimated weights of RLS

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Figure 19: ERLE (Echo Return Loss Enhancement) of RLS

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Figure 20: Cross correlation between desired and RLS output signal

4. Subband Adaptive Algorithm

The coefficients of the adaptive FIR filter change according to the Subband adaptive algorithm. Here the filter order is 1024, the number of subband is 4, and the step size and leakage factor are 0.1 and 0.1, respectively.

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Figure 21: Subband Adaptive Algorithm output and its spectrogram

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Figure 22: True and estimated output of Subband Adaptive Algorithm

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Figure 24: ERLE (Echo Return Loss Enhancement) of Subband Adaptive Algorithm

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Figure 25: Cross correlation between desired and Subband Adaptive Algorithm output signal

VII. IMPLEMENTATION ANALYSIS

This section reviews the performance of echo cancellation algorithms using Spectrogram, ERLE, and Cross-Correlation analyses.

Spectrogram Analysis: Spectrograms were generated for the outputs of LMS, NLMS, RLS and SAF echo cancellers, with the results presented in Table I. Analysis of these plots shows that the SAF algorithm (first) is the most effective in echo cancellation, significantly reducing echo signals. The NLMS algorithm (fourth) shows the least effectiveness in reducing echoes, while the LMS algorithm (third) performs better than NLMS but not RLS (second) in this regard.

|  |
| --- |
| Desired output |
| LMS output |
| NLMS output |
| RLS output |
| SAF output |

TABLE I

ERLE Analysis: As previously mentioned, ERLE quantifies the effectiveness of echo cancellation. It is calculated according to Equation (9). The ERLE results for the LMS, NLMS, RLS and SAF algorithms are displayed in Table II. The ERLE values for the LMS algorithm range between -102 dB and 95 dB, for the NLMS algorithm between -122 dB and 84 dB, for the RLS algorithm between -93.8 dB and 103.2 dB and for ERLE values for the SAF algorithm range between -5.3 dB and 6.2 dB However, for optimal performance, ERLE values should stabilize within the range of -40dB to 30dB. Based on these criteria, the SAF algorithm demonstrates superior performance compared to the RLS (second), LMS(third) and NLMS (fourth) algorithms.

|  |
| --- |
| LMS output |
| NLMS output |
| RLS output |
| SAF output |

TABLE II

Cross-Correlation Analysis: This analysis helps identify the time shift between two signals. The cross-correlation results for the LMS, NLMS, RLS and SAF algorithms are shown in Table III. According to the findings, the time-shifted signal (echo signal) has the lowest amplitude with the SAF algorithm (217) and the highest with the NLMS algorithm (2639), with LMS (1399) and RLS (1477) falling in between. Therefore, the SAF algorithm provides the most effective echo cancellation.

|  |
| --- |
| LMS output |
| NLMS output |
| RLS output |
| SAF output |

TABLE III

VIII. CONCLUSIONS

I have successfully completed the design of an acoustic echo canceller using various adaptive filter algorithms. After comparing the LMS, NLMS, RLS and SAF algorithms, I implemented MATLAB code for each. Based on performance metrics such as echo return loss enhancement (ERLE) and cross-correlation, I determined that the best algorithm among LMS, NLMS, RLS and SAF is SAF after that RLS then LMS and finally NLMS

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