Hybrid Noise Reduction And Enhancement Of Audio Quality Using Deep Learning

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***Abstract*—Good voice communication has become a top requirement in today's rapidly growing world. Noise from the surroundings affects the quality of voice and audio signals in acoustic applications. The original voice signal that was broadcast can occasionally no longer be recovered. Acoustic Noise Cancellation (ANC) is a method for improving the quality of speech and audio signals by removing noise in the voice signal. The adaptive filter, a crucial component of the ANC, reduces noise without first knowing the difference between the signal and the noise. Conventional filters would cause the desired voice stream to be distorted. So, when speech and noise signals are random, adaptive filters are appropriate. A primary input with a damaged signal and a reference input with noise that is unknowably associated with the noise in the primary input make up the ANC's two inputs. The reference input is adaptively filtered and subtracted from the primary input to get the clean speech signal estimation. The performance of the LMS and NLMS algorithms is significantly impacted by the step size and filter length M. Smaller mean square errors lead to longer convergence times (MSE). When it is large, the algorithm diverges, which reduces the adaptive filter's efficacy. The trade-off between convergence time and MSE must thus be balanced when deciding on a step size, which is a difficult problem. Another practical difficulty is presented by selecting the filter's tap length M. As filter length M rises, so do the filter's convergence time and MSE. Consequently, a shorter-length filter is required. Unfortunately, deciding on the number of filter taps is mostly a matter of experience and trial and error. In LMS and NLMS algorithms, it can be challenging to choose the step size of the algorithm and the length of the adaptive filter M to provide the most excellent possible noise cancellation.**

Keywords— Acoustic Noise Cancellation (ANC), Subband Adaptive Filtering (SAF), Normalised Least Mean Fourth (NLMF), Least Mean Fourth (LMF), and Acoustic Echo Cancellation (AEC).

I. INTRODUCTION

For humans, a fundamental way to convey information is through speech. It is one of the essential carriers of information and conveys the emotions of a human voice along with the information and has a bandwidth of 4 kHz. Although for humans, the perceptible range of frequencies is from 20 Hz to 20 kHz, the primary frequency components of speech exist only upto 4 kHz. The speech signal is one-dimensional, with time as its independent variable. It is non-stationary and random [1].

Noise is an unwanted signal which causes a disturbance during communication. If the speech signal is corrupted by noise, the listener finds it annoying and sometimes may lose intelligibility. In speech processing, the most critical task is to reduce 1 the interfering noise, which may mask the speech signal. Due to the rapid growth in technology, the usage of ventilation types of equipment, engines, heavy machinery, transport, etc., has dramatically increased, and noise problems have become more pronounced. To add to this, traffic, crowds and other noise sources also contribute to the noise in the environment. Noise reduction is a significant but difficult task and has gained importance as a subject of research in recent years [2]

To control the noise, passive techniques can be used. It is a sound suppression method that uses noise-isolating materials such as insulation, sound-absorbing tiles and mufflers. These techniques are effective over a broad range of frequencies. But they must be more light, practical ,and expensive at lower frequencies. Passive techniques are limited to fixed structures and are impractical where space is at a premium. The limitations of passive methods for noise cancellation have led to research and finding alternative methods [3].

II. RELEATED WORK

The chapter covers the acoustic noise cancellation literature. The two types of ANC systems are addressed in Section (A) The chapter concludes with section (C) after section (B) discusses the various adaptive filter algorithms for acoustic noise cancellation proposed to date by various researchers.

A. Acoustic Noise Cancellation (ANC) System:

Based on the number of microphones utilised, ANC systems are divided into two categories: dual-microphone ANC systems and single-microphone ANC systems [1]. Two microphones are utilised in dual microphone ANC systems. Microphones pick up both the noisy speech signal and the noise signal. A single microphone in a single-microphone ANC system captures the loud speech signal. There is no accessible microphone to record the noise independently.

Block schematic of the dual input ANC with a primary and reference microphone is shown in Fig. 1 The fundamental concept is to subtract the noisy signal d(n) from the noisy signal x(n), which tends to reduce the noise while maintaining the signal's integrity. This method does not need a statistical understanding of signal or noise characteristics [1].

A main microphone records a speech signal (s(n)) and a noise (x′(n)) that are unrelated to each other (n). The main input to the ANC is the combined signal s(n) + x ′ (n). The second microphone picks up a noise x(n), unrelated to the signal s(n), but connected to the noise x ′ in some manner (n). The canceller receives a reference input from this microphone. Filtering the noise x(n) results in an output y(n) that closely approximates x ′. (n).

The ava is crucial to the adaptive noise canceller's efficient operation.

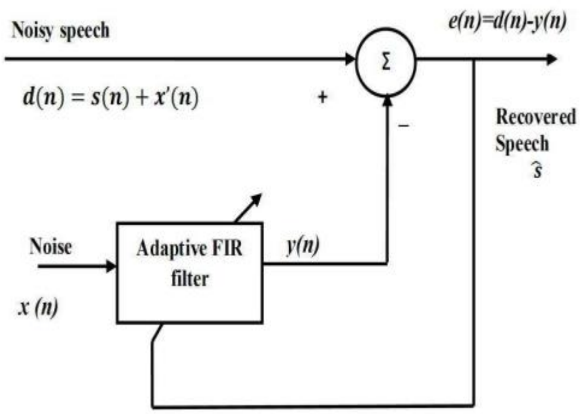

Fig.1: Acoustic noise cancellation system with a reference signal.

A single microphone ANC system is seen in Fig. 2. The noisy speech signal d is delayed in this system to provide a reference signal (n). If x(n) is a broadband process and s(n) is a narrow band process, then the delayed signal d(n n0) is associated with the speech signal s and uncorrelated with the noise x(n) in the speech signal (n). As shown in Fig. 2. the speech signal s(n) is estimated using the delayed signal d(nn0) as a reference signal. Note that the adaptive filter in Fig. 2 yields an estimate of the s(n), in contrast to the ANC system in Fig. 1 and that the 11 error signal e(n) corresponds to an estimate of the noise x(n)[2].

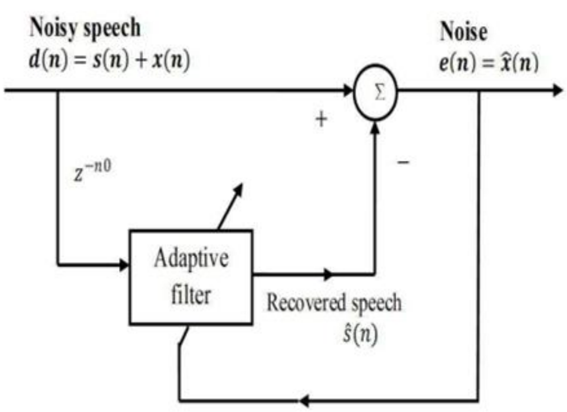

Fig.2: Acoustic noise cancellation system without a reference signal.

Since the reference signal is not used in this system, noise cancellation does not perform well. For more excellent noise cancellation, two microphone systems are often utilised in hearing aids, video conferencing, mobile phones, and other devices. This inspires the study team to utilise a two-microphone ANC system [2].

B. Review of Adaptive Filter algorithms:

Adaptive filters have drawn interest from academics recently because of their self-adjusting characteristics and minimal computing complexity. They are crucial in the process of acoustic noise cancelling. The review of adaptive filter algorithms put out by scholars over the past few decades is presented in this part.

The frequency and time domain techniques are the two primary methods for acoustic noise cancelling. The domain utilized to analyze the signal provides the basis for the categorization [2].

a. Frequency domain and Subband filtering Approach:

The adaptive filter weights are updated in the time domain in both conventional and normalised LMS algorithms. It is equally possible to make the filter parameter adaptation in the frequency domain since, as we know, the Fourier transform maps the time domain signal into the frequency domain, and the Inverse Fourier transform translates the frequency domain signal back to the time domain. The frequency domain has also seen the implementation of ANC systems. This method uses an N point FFT and first stores the reference signal in the N point buffer. The frequency domain is then created from it.

After multiplying the FFT spectrum by the appropriate adaptive filter weights, the output is produced in the frequency domain, which is then converted back into the time domain via the inverse FFT. This method's main flaw is that it processes the data block by block rather than sample by sample. As a result, N samples have a processing delay [5]. This delay may be tolerated when there is low-frequency noise, but broadband noise is a concern. The computational complexity of this method is high. As a result, frequency domain techniques are rarely applied in ANC applications.

Subband adaptive filtering is a different category of adaptive filtering (SAF). Band-partitioning the input signal in SAF uses strong stop band rejection filters, which may increase convergence compared to frequency domain adaptive filtering. As a result, SAF provides an appealing substitute for the frequency domain filtering method.

b. Time domain Approach for Acoustic Noise Cancellation

The stochastic gradient algorithms are classified into two classes as non mean square and mean square algorithms [6]

- Non mean square Adaptive algorithms

The non-mean square adaptive method is the normalised least mean fourth (NLMF). The non-quadratic least mean fourth cost function is used in this approach. The NLMF algorithm optimises filters using the steepest descent technique. The method has stability difficulties, as pointed out by Eugene Walach and Bernard Widrow [11].

The Least Mean Fourth (LMF) algorithm's stability issues have a solution, according to Eweda Eweda [12]. The adaptive filter's input noise power and the weight vector's starting values affect the LMF method's stability. In contrast, the LMS algorithm's stability solely depends on the filter's capacity to reduce input noise. The weight vector update term is normalised by the fourth order in the regressor and the second order in the estimated error in the study to address the stability issues. The algorithm is demonstrated to be stable for any values between 0 and 2. The suggested approach is shown to be computationally exhaustive. Experimentation was done with = 0.1, 1, 1.9, and M = 64.

V´ıtor H. Nascimento, Jos´e Carlos M. Bermudez, et.al [13] showed that the algorithm is sensitive to an impulse type of noise. If by chance larger step size is taken, then the LMS algorithm attains reasonably stable behaviour on the other hand LMF algorithm becomes completely unstable.

- Mean square adaptive algorithms

Utilizing the mean square error cost function are the LMS and NLMS algorithms. The step size in the traditional LMS filter is a scalar parameter. The designer has control over the first variable, the weight vector of the filter, and the second variable, the input noise vector.

As a result, when the input vector is significant, the method suffers from increased gradient noise and delayed convergence. As a result, the method has been changed, and other LMS algorithm versions, including NLMS and Filtered xLMS, have been proposed.

The Filtered X Least Mean Square (FxLMS) method is a noise-cancelling variation of the LMS algorithm. The study on the FxLMS algorithm and its proposed variations, such as lattice ANC, frequency domain ANC, and delay-less subband ANC, are documented in the literature [19–20]. The lattice construction gives suboptimal convergence in the presence of wideband noise. Even though transform domain and subband processing offer higher convergence than time domain processing, these methods are more difficult due to the additional calculations they need.

Researchers have presented fixed step size FxLMS algorithms but need help choosing the right step size to meet a range of settings. Another problem is the choice of the filter's tap count, which is uncertain and varies depending on the environment. Fixed filter length is a problem that has been addressed by Dah Chung Chang [18], who also created a variable tap length and step size FxLMS method to solve the issue. It is noted that the computational complexity of the provided algorithm is greater.

- Variable Step Size (VSS) Adaptive Filter Algorithms

The tradeoff between the rate of convergence and excess MSE determines the choice of the LMS algorithm. To quickly advance the weight vector to the desired solution when the weights are initially far from the optimum solution, they should ideally be big. The surplus MSE should be minimised when the filter converges to the steady-state solution. The researchers suggest variable step-size techniques to meet this need.

Numerous parameters must be modified for improved performance in most variable step size algorithms. Real-time tuning of these parameters is challenging. Using the estimated system noise and the mean square error, Hsu-Chang Huang and Jhunghsi Lee [17] have developed a non-parametric variable step size NLMS method. The authors have examined how well adaptive filters work to cancel echo. The parameter adds design freedom and regulates the algorithm's erroneous adjustment.

The algorithm is evaluated using M = 64, 128, 256 and = 5, 15, 30, 50, 75, and 100 values. The input is the white Gaussian process. For those aged 15 to 30, the algorithm shows a shorter convergence time and minimal misadjustment. It should be noted that although this approach is non-parametric, it still employs a parameter which limits the designer's freedom.

c. Algorithms based on Variable Tap Length of the Filter:

The tap length of a filter is a crucial factor in determining how well the ANC performs, along with the. According to the literature, shorter filters converge more rapidly than longer ones, even if more extended filters are required to mimic natural systems.

The filter's convergence time grows with the length of the filter. Most research, it is discovered, focuses on calculating an algorithm's step size rather than choosing the length of the filter.

To describe the system's impulse response, Christian Schuldt et al. addressed the issue of choosing the number of taps for the acoustic echo cancellation (AEC) filter. The filter length is critical since the echo canceller must function in a range of acoustic conditions.

The author's approach uses an assessment of the mean square deviation to choose the filter length adaptively. Analyses are done on the impact of too-short and too-lengthy filters. M = 500 and 1500 were the chosen filter lengths for the simulation. According to the findings, the suggested method is more reliable and has better tuning than the fractional tap (FT-NLMS) technique.

- Use of Adaptive FIR and IIR filters for Acoustic Noise Cancellation Use

Different structures or realisations can be used to build adaptive filters. The computational complexity of the procedure is influenced by the structure chosen. Filter realisations may be divided into two main categories: finite impulse response (FIR) filters and infinite impulse response (IIR) filters. You may construct an adaptive filter using an IIR or FIR filter. Only forward routes are used in constructing FIR filters, which are also fundamentally stable and have a linear phase response.

The discrepancy between the actual and desired responses is reduced using the minor p th design technique. There is experimentation with different filter orders. It has been demonstrated that the stop band ripples decreased when the filter order was raised.

The author also used the p th norm while designing the filter, and they saw that ripple content vanished and a smooth response was obtained in the stop band. The findings indicate that the FIR filter's implementation costs are lower than those of the IIR filter.

III. Methodology

People are paying more attention to speech signal quality as communication technology advances. If the speaker is in a noisy setting, background noise has always been an issue while speaking on a cell phone. The development of adaptive filter algorithms for noise cancellation has recently been the focus of research and is a challenging research area. Effective noise cancellation systems are needed in mobile phones to suppress the background noise and pass only speech signals to Sthe other end, as shown in Fig. 3

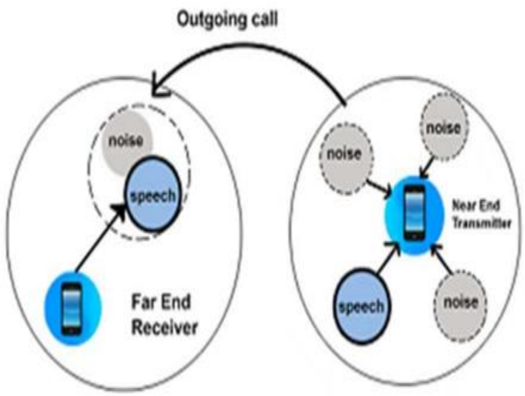

Fig.3: Noise Cancellation system.

A. Research gaps Identified:

There is room for improvement in the problems outlined in chapter 2. Numerous studies on the ANC have been conducted and are continuously being conducted. The goal of improving ANC performance has served as the foundation for several adaptive filter techniques proposed thus far. Even though academics have proposed other methods in the literature, the NLMS algorithm is the most frequently used.

The NLMS algorithm must be appropriately modified to satisfy the following conditions.

- The issue of selection of the initial value of µ is required to be handled intelligently as this parameter is under designer's control. The difficult task of choosing µ requires many trials of the simulation. There is a need to propose an algorithm with the self tuning ability which significantly reduces the task of selection of µ. The performance of the algorithm needs to be validated for all types of real world noisy environments.
- There is a small positive number ϙ in the normalization term of the weight update equation. A small variation in ϙ causes the significant change in the ANC output. Therefore the attempts will have to be made to eliminate this term.
- The comparison of the experimental outcome in the literature needs to be done on common grounds. There is a requirement to use the standard database for the comparison. The algorithms can also be tested for actually recorded noisy environments.
- The problem of the NLMS algorithm pointed out by the researchers is the convergence time that is significantly more than that of the RLS algorithm. There is a need to develop the algorithm in which convergence time is reduced and is comparable with the RLS algorithm.
- Some researchers have worked on misadjustment and showed improvement in it. Although the improvement in terms of misadustment is evident, other parameters are not addressed in detail. Therefore it necessitates the development of an algorithm which exhibits the superior performance in terms of all performance measures like PSNR, MSE, misadjustment and convergence time.
- The hardware implementation point of view, computational complexity of the proposed algorithm needs to be minimized.

The issues above are recognised as contributing to the difficulty in the development of adaptive filter algorithms for the ANC in mobile phones and serve as the impetus for the proposal of an adaptive filter algorithm that outperforms existing stochastic gradient algorithms in terms of PSNR, MSE, convergence time, misadjustment, and computational complexity with the self-tuning feature.

B. Problem Solution strategy:

The current stochastic gradient technique and the least square estimate approach must be tested. The improve the performance of the ANC while overcoming the restrictions above, efforts will be made to analyse the implemented techniques that have already been used and recommend relevant modifications to the current NLMS algorithm.

The thesis focuses mainly on FIR transversal filters due to their inherent stability and simplicity. For the testing of algo rithms, NOIZEUS database and actual recorded database will be used. The validation of the approaches used will have to be confirmed on the basis of the theoretical background and the experimental work performed

The proposed research strategy will be as follows:

- The study of existing adaptive filter algorithms for ANC system.
- Investigating the performance of ANC system for different adaptive filter lengths M and step size µ. The study is carried out for varied noise conditions.
- Research will also involve the study of refined adaptive filter algorithms for correlated and uncorrelated noise components

V. CONCLUSION

The research focuses on an acoustic noise cancellation in a speech signal. There are various adaptive algorithms suggested for the noise cancellation in the literature. Every algorithm has its own advantages and limitations, but the aim is always to achieve maximum PSNR, minimum misadjustment and fast convergence with minimum computational complexity. The LMS, NLMS and RLS are popular algorithms used in ANC application. Due to the fixed step size LMS algorithm cannot handle the trade off between convergence time and MSE. The NLMS algorithm uses a time varying step size, but the convergence time is more than RLS algorithm. The study proved that the RLS algorithm which is a deterministic approach, offers superior performance than all stochastic gradient algorithms at the cost of computational complexity. This leads to suggest refinement in the existing NLMS algorithm so that the its performance is enhanced. The experimental analysis showed that the selection of step size is required to be handled intelligently as this parameter is under designer's control and requires many trials of the simulation. The study revealed that the filter length is a crucial parameter that affects the performance of the ANC and it is difficult to choose this parameter to fit a variety of noisy environments.

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