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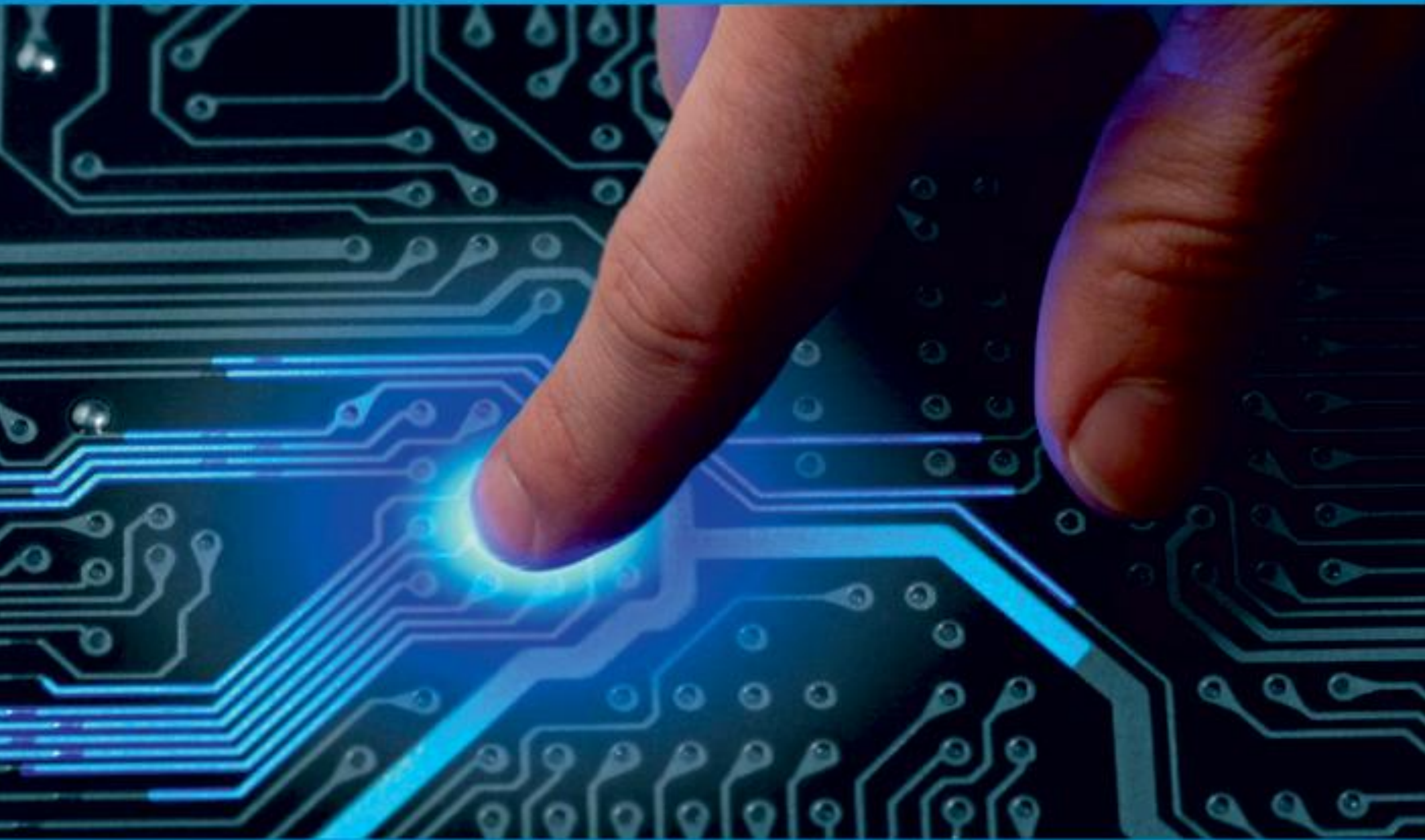

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Adaptive Filter using Multi-Rate Approach for Acoustic Noise Cancellation: A Review

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ABSTRACT: In this thesis, a number of adaptive filtering techniques for noise reduction and acoustic echo cancellation is developed. These algorithms can be integrated with the goal of improving the quality of the desired speech signal and robustness of hands-free speech communication systems. Background noise, far-end acoustic echo, and room reverberation dramatically degrade the performance of many hands-free speech communication systems, in practical environments. For example, for automatic speech recognition system, noises result in the mismatch between the training and testing conditions, further degrading the performance of recognition system in real-world conditions. For hands-free speech communication systems, background noise and far-end acoustic echo signals degrade the quality and intelligibility of received speech signal. Therefore, noise reduction and acoustic echo cancellation has been a fundamental enabling technology and indispensable components for these applications that must recognize or transmit speech in noisy environments.

KEYWORDS: - Finite Impulse Response (FIR), Look Up Table (LUT), Adaptive Filter, Narrow Band Filter

I. INTRODUCTION

In Hands-free communication systems, a microphone often picks up reverberation, background noise, and acoustic echoes together with a speaker's voice which is desired speech signal. Reverberation is due to reflective acoustic environments and leads to degrade the auditory quality of speech signal. This can be remedied by using dereverberation techniques. Dereverberation consists of recovering a desired speech signal from observed reverberant signals. Several dereverberation approaches have been proposed [1-4]. Generally, the research on methods of background noise reduction is being done by the two approaches. One of these is by making use of the single microphone speech enhancement techniques, and the other one is the multi-microphone techniques. Beamforming microphone arrays are very effective since suppress background noise by spatio-temporal filtering without distorting the desired speech signal. Thus the later techniques are preferred to single-microphone techniques. With full-duplex communication, echoes of the loudspeaker signals will join background noise to corrupt the desired speech signal. However, beamforming does not exploit the available loudspeaker signals as reference information for suppressing the acoustic echoes. This is accomplished by acoustic echo cancellation algorithms. In this research work, algorithms will be developed for techniques that allow for removing background noise and acoustic echo from the speech signal before further processing it.

In order to suppress echo, several conventional acoustic echo cancellation techniques can be applied [5]. These techniques are based on adaptive filtering techniques [6]. Adaptive filters are a powerful signal processing tool which can be used to model the unknown system and track possible system variations. A large set of adaptive filtering techniques has been developed during the last decades, differing in terms of performance (such as convergence speed, tracking, delay, complexity, and stability). In acoustic echo cancellation, the far-end echo path has to be modeled by the adaptive filter. The echo path is acoustic impulse response from the far-end signal emitted by loudspeaker to the microphone(s). Since this acoustic impulse response can be quite long and highly time varying, the adaptive filter will require several hundreds or thousands of filter coefficients and high-performance (fast convergence rate), but low complexity adaptive filtering algorithms are desirable. Moreover, the delay introduced by the algorithm cannot be too large. For acoustic applications, cheap algorithms, such as the least mean squares (LMS) and normalized LMS (NLMS) algorithm [7], are typically used. However, these algorithms exhibit a slow convergence behavior, especially for colored signals such as speech. Therefore, the affine projection algorithm (APA) and its variants [8], have been investigated. These algorithms have a better convergence behavior than NLMS algorithms but at a cost of higher

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computational complexity. Another class of acoustic echo cancellation based on advanced adaptive algorithms, such as recursive least squares (RLS) algorithm, has been paid more attention in recent years [9]. Traditionally, noise reduction and echo cancellation have been addressed independently, either by first canceling the echo components in all microphone signals and then performing multi-microphone noise reduction, or vice-versa, by first performing multimicrophone noise reduction, followed by a single-channel echo canceller. Both schemes have their own advantages and disadvantages with respect to performance and complexity. Recently, it has been recognized that both problems are better solved using a combined approach, certainly when using multiple microphones. Initial results indicate that a combined approach yields a better performance at a lower complexity [10].

II. LITERATURE REVIEW

Dandan Wei et al. [1], the block-scanty standardized least mean square (BS-NLMS) calculation which exploits sparsity, effectively shows quick assembly in versatile block-meager framework distinguishing proof, versatile control, and other modern informatics applications. In acoustic processing, where a long impulse response, high correlation, and sparse echo path are encountered, it is also appealing. However, BS-NLMS's main drawback is primarily its computational complexity. This paper proposes an original particular fractional update block-inadequate standardized least mean square (SPU-BS-NLMS) calculation. The proposed elective partial-update block-sparse NLMS algorithm uses partial-update blocks scheme, which is determined by the smallest squared Euclidean-norm at each iteration, rather than whole block coefficients to save computations when identifying block-sparse systems. Researchers use computational complexity analysis to help them choose the right parameters for real-world implementations and applications. The proposed algorithm's effectiveness and results are confirmed through computer simulations of acoustic echo cancellation.

H. A. Mohamed-Kazim et al. [2], a Modified Absolute Weighted Input using Log function (MAWILOG) for the NLMS algorithm is proposed to effectively reduce the impact of the trade-off between the quality of identifying a system and the convergence rate, as well as to increase the algorithm's robustness against unknown sparsity levels. The basic idea of the proposed algorithm is to assign a variable stepsize to each individual adaptive filter coefficient based on a Log-term that takes into account the input power and signal underlying each filter coefficient and adjusts to the gradient value of each coefficient magnitude. Without directly introducing a sparse-aware constraint, the proposed method outperforms the proportionate NLMS (PNLMS) family at any sparsity level by utilizing the gradient of each coefficient to allocate large stepsize values for high gradient coefficients. In addition, the (PNLMS) family's high steady-state mean square deviation and high computational complexity can be circumvented using this method. The proposed algorithm's simulation results are compared to those of comparable algorithms like the NLMS, PNLMS, improved PNLMS, block-sparse PNLMS, and block-sparse IPNLMS. According to the findings, the proposed algorithm performs better than others in achieving a rapid convergence rate and maintaining the lowest steady-state mean-square-deviation across a variety of systems.

Q. Ling et al. [3], streamlining by definition is the activity of making best or the best utilization of an asset or circumstance and that is required practically in each field of designing. Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are used to improve the Least Mean Square (LMS) algorithm in this study. The combination of Swarm Intelligence SI (ACO, PSO) and a gradient-based (LMS) algorithm has been investigated to determine its benefits and drawbacks. The application of adaptive filtering to a system with a multi-model error surface, which is still a gray area, will be made easier with the assistance of this LMS algorithm optimization. Because the current version of the LMS algorithm, which is based on gradients and plays an important role in adaptive filtering, gets stuck at the local minima of a system with a multi-model error surface and treats them as global minima, resulting in an unoptimized convergence. The problem of a system with a multimodal error surface has been profoundly addressed by the proposed method. The performance has improved significantly, and rather than remaining stuck at local minima, the results show a rapid rate of convergence. The LMS algorithm can be used in conjunction with either of the SI techniques for adaptive filtering, each with its own advantages. This enhancement of LMS calculation will additionally assist with settling serious impedance and commotion issues and holds a vital application in the field of biomedical science.

M. Salah et al. [4], in terms of convergence speed, mean square error (MSE), and improvement in signal-to-noise ratio (SNR), variable step-size-based algorithms have outperformed conventional least mean square (LMS) and normalized LMS (NLMS) algorithms in adaptive filters. Due to their speed and adaptability, adaptive filters have recently been suggested for use in field programmable gate array (FPGA) devices. In order to evaluate the proposed design following implementation, recent research has focused not only on the algorithm's performance measures but also on the required

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area, operating frequency, and power consumed. Through a comparison, this paper first demonstrates that the regularized square root absolute error LMS (R-SRAE-LMS) outperforms other variable step size algorithms for acoustic noise cancellation. The R-SRAE-LMS algorithm's steady state and transient analyses are also discussed. Then, at that point, a nitty gritty plan of the R-SRAE-LMS versatile channel is proposed in this paper. There are two feedback paths and a forward path in the design. Following the completion of the FPGA implementation process, the utilization of the device, operating frequency, and power consumption are also presented. When compared to other acoustic noise cancellation algorithms, the results demonstrate that R-SRAE-LMS has a stable and high SNR improvement curve. In addition, when compared to other variable step size adaptive filter designs, the proposed design achieves remarkable implementation results. Performance metrics for the implemented proposed filter design are very similar to those of the fixed-point case.

M. W. Munir et al. [5], at the location of an error microphone, the conventional adaptive noise control algorithms create a quiet zone. In order to introduce a more adaptable positioning of the zone of quiet, a number of virtual active noise control (ANC) algorithms have been suggested in the literature. By taking into account the characteristics of the auditory system, the primary objective of the proposed ANC system in our study is to reduce the amount of noise that disturbs human hearing. In our ANC modeling, we have included the human perception of acoustic disturbances. A novel strategy to reduce acoustic noise in a region away from the error microphone location is presented in this paper. It is based on a remote ANC algorithm that is psychoacoustically enabled. Modeling the transfer function between the error microphone and the remote quiet zone is necessary for this strategy. An FPGA real-time module was used to implement the developed model, and its performance has been verified at four distinct remote locations. In order to observe the psychoacoustic characteristics of the proposed model, noise-weighting filters are incorporated. The proposed algorithm's noise reduction properties are measured by monitoring the acoustic noise at both the physical and remote locations in the experimental setup. Both the simulation and the experiments have shown that the noise level has been reduced by 15 to 18 decibels, which is an improvement of 5-8 decibels on average over the standard ANC model.

G. Li et al. [6], by applying the first-order Taylor series expansion to the sigmoidal active function of CSS-APSA, which has a symmetric independent variable, we propose a simplified CSS-APSA (SCSS-APSA) to further enhance the poor tracking capability and filtering performance of the conventional combined step-size affine projection sign algorithm (CSS-APSA) in system identification. SCSS-APSA's filtering performance is comparable to or even better than CSS-APSA's, and its computational complexity is lower. Additionally, we suggest altering the sigmoidal active function. A variation of the conventional scaling transformation is the modified sigmoidal active function. We can obtain the modified CSS-APSA (MCSS-APSA) by applying the modified function to the CSS-APSA. In addition, CSS-APSA's accelerated convergence rate is made possible by the additional parameter of MCSS-APSA. The computational complexity of MCSS-APSA can be reduced as a result of the simplification operations performed by SCSS-APSA. As a result, the SMCSS-APSA (simplified MCSS-APSA) is what we get. The results of our simulations show that the system identification convergence speed of our proposed algorithms is faster.

V. Tejaswi et al. [7], the unwanted signal that affects the desired signal is known as noise. During the transmission of information, this noise has been a serious issue that is affecting the signals. Speech signal and ECG signal are the two types of noisy signals that are taken into consideration in this project. The ECG signals come from the Physio Net ECG database, and the speech signals come from the NOIZEUS database. Baseline wander, electrode motion, power line interference, and muscle artefact noises are the most significant noises that affect the ECG signal. The baseline wander noise, which occurs when the patient moves, breathes, and the electrode does not touch the skin, the electrode motion noise, which occurs when the electrode moves away from the skin and causes impedance changes, which result in variations in the ECG, and the muscle artefact noise, which occurs when other muscles, other than the heart, contract. The noise from noisy signals can be reduced using the Simulink model. The RLS algorithm is the adaptive algorithm of choice because it has a faster rate of convergence than other algorithms like LMS, NLMS, and RLS. The performance of the Simulink model can be observed from the mean square error that is obtained after it is tested for various scenarios.

K. Fan et al. [8], under non-negativity constraints, conventional non-negative algorithms restrict the weight coefficient vector to satisfy several system-specific inherent characteristics. However, conventional non-negative algorithms perform less well when impulsive noise is present. A robust step-size scaler-based non-negative least mean square (R-NNLMS) algorithm is proposed in this context. In order to avoid being influenced by impulsive noise, the proposed algorithm makes use of a step-size scaler. The step-size scaler is able to adjust the algorithm's step size in response to a variety of outliers, thereby eliminating the significant error brought on by impulsive noise. In addition, the inversely proportional R-NNLMS (IP-RNNLMS) algorithm is proposed to boost the proposed algorithm's efficiency in sparse

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system identification. The simulation results show that the R-NNLMS algorithm has a fast convergence rate and low steady-state error under other noises while removing impulsive noise. In addition, in a sparse system, the IP-RNNLMS algorithm has a faster rate of convergence than the R-NNLMS algorithm.

J. kapoor et al. [9], versatile calculations offer a wide area of exploration in the field of computerized signal handling. Since noise is a random signal, it requires an adaptive approach to analysis and presents a large research opportunity if the received signal changes over time, as does noise, necessitating adaptive predictive algorithms. The least mean square (LMS) algorithm, the recursive least square (RLS) algorithm, and other adaptive algorithms with their use in active noise cancellation are all the subject of a fundamental comparative study in this paper. This paper aims to provide an understanding of the initial components of an adaptive algorithm for use in the creation of more complex algorithms.

H. Ullah et al. [10], de-noising techniques like mean filtering, median filtering, total variation, and filtered variation, among others, can be used to remove noise from signals and images. One of the most common methods for removing noise is wavelet-based de-noising. In the first section of our work, a logarithmic shrinkage technique based on the wavelet transform is used to remove noise from images that have been affected by noise (during frequency domain undersampling). The Shepp–Logan Phantom image is under-sampled and subjected to the logarithmic shrinkage method. According to the findings of the experiments, the logarithmic shrinkage method outperforms the conventional methods in terms of PSNR values by 7 to 10%. Using the four thresholding methods, we de-noise the noisy, under-sampled phantom image with salt and pepper, Gaussian, speckle, and Poisson noises and compute their correlations with the original image in the second part of our work. They provide correlation coefficients that are close to the noisy image. We achieve 30–35% better results than when we apply the thresholding techniques one at a time when we apply the median or wiener filter simultaneously. So, in the second part, we use shrinkage functions and median or wiener filtering to recover and de-noise the sparse under-sampled images.

III. MULTIRATE APPROACH

The process of converting a signal from a given rate to a different rate is called sampling rate conversion. The systems which employ multiple sampling rates in the processing of digital signal are called multi-rate signal processing [5].
Decimation is the processes of lowering the word rate of a digitally encoded signal, which is sampled at high frequencies much above the nyquist rate. It is usually carried out to increase the resolution of an oversampled signal and to remove the out-of-band noise. In a sigma-delta ADC, oversampling the analog input signal by the modulator alone does not lower the quantization noise; the ADC should employ an averaging filter, which works as a decimator to remove the noise and to achieve higher resolutions. A basic block diagrammatic representation of the decimator is shown in Figure 1.The decimator is a combination of a low pass filter and a down sampler. In Figure 1 the transfer function, H(z) is representative of performing both the operations. The output word rate of the decimator is down sampled by the factor M, where M is the oversampling ratio [6]. The function of low pass filtering and down sampling can be carried out using an averaging circuit. The transfer function of the averaging circuit is given by equation (1.1). It establishes a relation between the input and output functions (1.1)

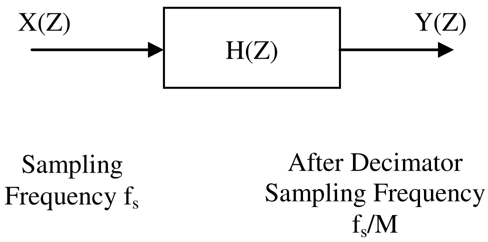

Figure 1: Block Diagram of Decimator

$$H(Z) = \frac{X(Z)}{Y(Z)} = \frac{1}{M}\sum_{x=0}^{M-1} Z^{-x} \qquad (1)$$

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"Up sampling" is the process of inserting zero-valued samples between original samples to increase the sampling rate. (This is called "zero-stuffing".) Up sampling adds to the original signal undesired spectral images which are centered on multiples [7] of the original sampling rate.
"Interpolation", in the DSP sense, is the process of up-sampling followed by filtering. (The filtering removes the undesired spectral images.) As a linear process, the DSP sense of interpolation is somewhat different from the "math" sense of interpolation, but the result is conceptually similar: to create "in-between" samples from the original samples.

IV. PROPOSED METHODOLOGY

It depends on the filter coefficients required to achieve the desired frequency response of the filter. The narrowband filter may be implemented directly or using the multi-rate method. Here we have estimated the required filter coefficients for both these methods to find the complexity of the narrow band filter.

- Specification of the narrowband filter:

Sampling frequency,	$F_s = 250Hz$
Pass band ripple,	$\delta_p = 0.08dB$
Stop band ripple,	$\delta_s = 42dB$
Pass band frequency,	$f_p = .825Hz$
Stop band frequency,	$f_s = 4.15Hz$

- Direct Approach

Block diagram for implementation of narrow band filter is shown in Figure 2.

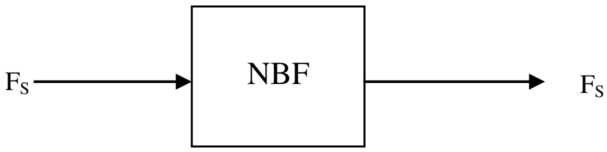

Figure 2: General diagram of narrow band filter

Transition width,

$$\Delta f\,(normalized)\,freq. = \frac{f_s - f_p}{F_S} \qquad (2)$$

Filter order N Filter order by Kaiser Formulation

$$N = -20\log\sqrt{\frac{\delta_s\delta_p - 13}{14.6\Delta f}} \qquad (3)$$

Filter order $$N = 150$$

- **Multi-rate Approach**

The block diagram of multi-rate approach for implementation of narrowband filter is shown in Figure 3.

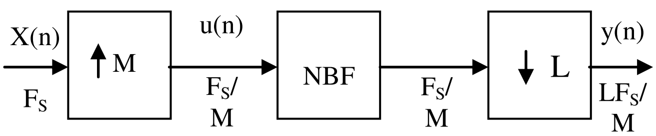

Figure 3: Diagram of the multistage for designing level

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Suppose the sampling frequency of the narrowband filter is 125 Hz.

Down sampling factor M=2, Calculation of filter order of the decimator:

Specification of decimator:

$$\Delta f\,(normalized) = {(f_{s1} - f_p)}\big/{F_s}$$

$$f_{s1} = F_s - {F_s}\big/{2M}$$

$$\Delta f = .2467\,Hz$$

$$FilterOrderN1 = 9$$

V. CONCLUSION

The narrowband filter is realized in FIR filter. Based on the direct approach, the filter requires 150 filter coefficients to meet the desired frequency response. To implement such a large order FIR filter in hardware involves large resources and sometime difficult to implement in resource constrained application. Keeping this in view, we have used Multi-rate approach to design the narrowband filter. We have used down sampling factor 2 and 4 for this purpose and found that, down sampling factor 4 requires significantly less filter constants than 2. To implement the narrowband filter, we therefore chosen down sampling factor 4 and designed the decimator, interpolator and narrowband filter.

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