Acoustic Echo Reduction Using Adaptive Filter: A Literature Review

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ABSTRACT

I. INTRODUCTION

The word filter is used for any hardware or software that can be applied to a set of noisy data to extract the information about the prescribed quantity of interest. So a filter can be considered as a device which manipulates its input into desired output [1] [2]. The linear filter problem is to design a linear filter in such a way that for noisy data as input effect of noise can removed or suppressed at the output [2]. In statistical approach to solve the linear filtering problem, the availability of certain statistical parameter (i.e. means and covariance) of the useful signals and unwanted additive noise is assumed. The error is suppressed according to the statistical criterion. The useful criterion is minimization of the means square value of the error signal the resulting solution is known as Wiener filter [1], [2] which is said to be optimum in means square sense. Wiener filter is not much popular in practical applications. For practical applications adaptive filters are used more realistic approach of gradient based adaption. The filter of this type is more generally used in time domain in tapped delay line form and the least means square algorithm are used to obtain the filter parameter.

Echo cancellation is a signal processing technique for removing unwanted signals from speech and audio. The goal is to improve signal clarity. The human hearing system (ear+brain) has a form of echo cancellation which is built into our audio perception system. It allows us to ignore our own voice during a conversation; consequently we are able to hear other speakers or sounds while talking. Our brain uses a perceptual trick that allows it to focus on other sounds while our ears are barraged by the sound of our own voice. Unfortunately, this biological echo canceller system is tuned for a short and very specific transport delay i.e. the direct path from our mouth to our ears [8].

Classical methods rely on a studio environment or employ voice controlled switches in order to reduce the effect of acoustic echo. In studio environment speakers are not allowed to move freely. In addition reflections can be prevented by using sound absorbing materials. Acoustic Echo Supressor (AES), or voice switching techniques, are the first introduced solutions to deal with acoustic echoes. In the voice controlled switching, echo is suppressed by inserting loss devices between the receiving and the transmitting circuit of the communication system according to the direction of conversation. However, echo suppression is not practicable because of following deficiencies:
I. The attenuation of the acoustic path from loudspeaker to microphone is not high.
II. Only half duplex communication is possible when voice controlled switching is employed.

Several echo suppression methods such as frequency shift, center-clipping, comb filtering, microphone arrays etc. have not been very effective in controlling acoustic echo [4]. Increased network delay render echo suppressor technology ineffective and encouraged the development of echo cancellation equipment.

In late 1960’s echo canceller was invented by J.L. Kelly and B.F. Logan, presented in a paper by M.M. Sondhi. This device adaptively estimates the echo path transfer function and subtracts an estimated echo from the returning signal.

II. ACOUSTIC ECHO REDUCTION AND ADAPTIVE ECHO CANCELLATION

Long distance telephone circuits have generally been impaired by echo effects. Echo suppressors developed at the Bell Laboratories have been perfected during past decades. Conventional echo suppression techniques were not very successful with satellite
communication where international calls have echoes of long time delay. Earlier echo suppressors were used in half duplex mode. To permit simultaneous two way transmission (full duplex mode of communication) of voice and data, adaptive echo cancellers are found to be better replacements for echo suppressors.

Echo cancellation was developed in the early 1960s by AT&T Bell Labs and later by COMSAT Tele-Systems. The adaptive echo canceller tries to overcome the deficiencies of the classical methods. Adaptive echo cancellation is achieved by synthesizing the effect of echo path on voice or data and subtracting it from the echo path output. The synthesized echo is generated by passing the loudspeaker signal through a filter whose impulse response matches with the impulse response of the acoustic channel. As echo path is time varying, an algorithm is needed which can adapt the filter to these acoustic channel impulse response changes. To realize adaptive echo canceller, different possible filter structures and a variety of adaptive algorithms are available. A brief description of the adaptive filter, adaptive filter structure and adaptive algorithms are given in the subsequent subsections respectively.

III. ADAPTIVE FILTER

Adaptive filtering constitutes one of the core technologies in digital signal processing and finds numerous applications including echo cancellation, channel equalization, adaptive noise cancellation. Adaptive filter consists of a digital filter and adaptive algorithm. The ability of an adaptive filter to operate suitably in an unknown environment and track time variation of input statistics make the adaptive filter a powerful device for signal processing and control application. Adaptive filters enable the system to adjust in a changing environment or statistical condition. So arrangements are to be made for adjusting the filter parameter to suit the changing need. The adaptive filter estimates the echo signal and the estimated signal is subtracted from the observed signal generating an error signal $e(t)$. This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize the cost function. In case of echo cancellation, the optimal output of the adaptive filter is equal to the unwanted echoed signal.

A. Adaptive Filter Structure

The adaptive filters can be implemented in a number of different structures or realizations. The choice of the structure and also the necessary number of iterations to achieve a desired performance level. Basically, there are two major classes of adaptive digital filter realizations, distinguished by the form of the impulse response, namely the FIR filter and the Infinite-duration Impulse Response (IIR) filters. FIR filters are usually implemented with non-recursive structures, whereas IIR filters utilize recursive realizations. FIR filter is preferred for AEC applications for its stability during adaptation [9]. IIR can normally achieve similar performance as FIR, with smaller amount of coefficients and less computation. However, as the complexity of the filter grows, the order of the IIR filter increases a lot and the computational advantage is less dominant. Also, IIR suffers from the instability problem.

B. Adaptive Algorithms

The algorithm is the procedure used to adjust the adaptive filter coefficients in order to minimize a prescribed criterion. The performance of an adaptive filter is critically dependent not only on its internal structure, but also on the algorithm used to recursively updates the filter weights that define the structure. There are many recursive algorithms for the adaptation of linear adaptive filtering. The choice of algorithm is determined by the performances like rate of convergence, mis-adjustment, tracking, robustness, computational complexity, structure. Adaptive algorithms are broadly classified as sample-by-sample adaptive and block adaptive algorithms.

In the sample-by-sample adaptive algorithms the adaptation can take place both in time domain as well as in frequency domain. Therefore, sample-by-sample adaptive algorithm will further divided into two classes of algorithms. One class includes filter that are updated in time domain sample-by-sample, called time domain sample-by-sample adaptive algorithm. Algorithms belonging to this category are Least Mean Square (LMS) and Recursive Least mean Square (RLS) which are popular due to number of advantages [6]. Other class includes filters that are updated in frequency domain and are known as Frequency Domain Adaptive Filter (FDAF). In FDAF the adaptation of the filter can be performed in frequency domain sample-by-sample in order to exploit the advantage of Fast Fourier Transform (FFT). The use of FFT reduces the computational complexity of FDAF.

The common algorithm belonging to this category is frequency domain adaptive algorithm based on Discrete Fourier Transform (DFT), frequency sampling methods, and sub-band technique. Sub-band technique has the advantage that it can achieve fast convergence at reduced computational complexity [5]. But the sub-band solution exists if and only if sub-band signals obtained are alias-free. This requires band pass filters with infinite stop band attenuations which are not realizable. Although, in this approach the reduced computational complexity is achieved but the price to be paid is a delay introduced into the signal path by the analysis and synthesis banks.

Similarly the block adaptive algorithm further divided into two classes. One class include filter that are updated in time domain, block-by-block, and is called time domain block adaptive algorithm. The basic principle for time domain block adaptive algorithm is that a number (says $B$ sample) input signal are collected before computing a block of output signals using convolution. Thus the filter is only adapted once every $B$th sampling instant, resulting poor tracking performance. In order to make use of FFT the filter adaptation has to be performed in the frequency domain. Thus the multiplication replaces convolution in the adaptive filter, leading to reduction in the computational complexity. These results another class of adaptive algorithm in which filters are updated in frequency domain and are called as block-by-block frequency domain block adaptive algorithm [26].
We will discuss only the time domain sample-by-sample adaptive algorithm and frequency domain block adaptive algorithm in the subsequent subsections respectively.

### C. Time Domain Adaptive Algorithms

#### 1. Recursive Least Square Algorithm

Recursive Least square (RLS) algorithm is based on the minimization of the weighted squared error sum. In the RLS algorithm initialization of the inverse of the autocorrelation matrix and the choice of forgetting factor are important. The RLS algorithm must be provided with suitable initial values. The choice of the forgetting factor also influences the convergence and tracking behavior. The RLS algorithm has computational and storage complexity \( O(L^2) \), where \( L \) is the length of the filter. It appears quite appropriate to choose RLS algorithm for AEC application due to its high convergence speed. But RLS algorithm has high computational complexity, thus not preferred in AEC applications [5], [9].

#### 2. LMS Algorithm

LMS estimation algorithm was first proposed by Widrow and Hoff in 1960 through their studies of pattern recognition. The LMS algorithm is most commonly used algorithm for adaptive filtering applications, due to its simplicity and low implementation cost. The algorithm is defined by the equations:

\[
e(n) = d(n) - W^T(n)X(n)
\]

\[
W(n+1) = W(n) + \mu X(n)e(n)
\]

where \( \mu \) is adaptive step size parameter. If \( \mu \) is too large then the algorithm will not be convergent in a mean square algorithm. On the other hand, if \( \mu \) is small then the convergence of the algorithm will be slow. It can be shown that the LMS algorithm is stable for \( 0 < \mu < \frac{2}{\lambda_{\text{max}}} \) where \( \lambda_{\text{max}} \) is the largest eigenvalue of the correlation matrix of the input data.

The LMS algorithm is a most popular algorithm due to number of advantages. But it is noticed that the convergence speed is slow when LMS algorithm is used for adaptation especially for longer filter length. Furthermore, the adaptive filter convergence is slow due to step size restriction which depends on the characteristics of the input signal [5], [9]. Some methods like; pre-whitening of inputs signal etc. have therefore been explored to improve the convergence speed of the LMS algorithm. Although, these methods attempt to improve convergence speed of the LMS algorithm but add some computational complexity.

There are more common variant of LMS algorithm like; Normalized LMS (NLMS) [6], Proportionate NLMS (PNLMS) [5], Affine Projection Algorithm (APA) [6]. These have their relative advantages and disadvantages when used for the long length adaptive filter adaptation.

NLMS is defined as,

\[ e(n) = d(n) - W^T(n)X(n) \]

\[ W(n+1) = W(n) + \frac{\mu}{\delta + \|X(n)\|^2} X(n)e(n) \]

where \( \delta \) is the controlling factor which prohibits the weight updation equation to go into infinite when \( \|X(n)\|^2 \) is equals to zero. The stability and convergence properties of NLMS are determined by the step-size parameter \( \mu \). The NLMS algorithm is stable for \( 0 < \mu < 2 \) and the stability of NLMS is thereby independent of the properties of the input signal. Furthermore, NLMS exhibits faster convergence compared to LMS for both correlated and uncorrelated data. Both the LMS and NLMS algorithm are computationally efficient and having computational complexity \( O(L) \). Although, the computational complexity of both the LMS and NLMS are same, but NLMS require extra computation for obtaining the input vector norm and further used normalization of the adaptation step size.

Since last several decades, there has been a great deal of interest in the study of adaptive signal processing. An adaptive filter is defined as a self-designing system that relies for its operation on a recursive algorithm, which makes it possible for the filter to perform satisfactorily in an environment where knowledge of the relevant statistics is not available. At present time most celebrated adaptive algorithm is LMS algorithm due to their simplicity and robustness, led to their wide use in variety of applications. Very important independence assumption, impractical in the case of adaptive filtering, is avoided [3]. The error in LMS decreases over time as sum of exponential whose time constants are inversely proportional to eigenvalues of the autocorrelation matrix of filter input. But we know that the main disadvantage of LMS algorithms is slow rate of convergence. This draw back can overcome with the new normalized adaptive algorithm, give certain computationally efficient, rapidly converging adaptive filtering algorithm has been independently discovered many times and performance of algorithm very well in acoustic echo cancellation application. The most common algorithms used for echo cancellation are the normalized least-mean-square (NLMS) and the Affine Projection (AP). Letter presents a class of variable step-size NLMS and AP algorithms, which are designed to recover the near-end signal from the error of the adaptive filter. The NPVSS adaptive algorithm that uses the power estimate of the background noise in order to control its step-size parameter and the step size of the proposed algorithm is adjusted according to the square of a time-averaging estimate of the autocorrelation of a priori and a posteriori error. Also, the Affine Projection Algorithm (APA) and its some version were found very attractive choices for echo cancellation. However there is still need to improve the performance of these algorithm for echo cancellation More importantly, it is necessary to find some way to increase the convergence rate and tracking of the algorithms since it is known that the performance of both NLMS and APA are limited for high length adaptive filters. This can be partially overcome the exploiting the character of system to identify the path of echo.
3. Frequency Domain Adaptive Algorithm

Frequency domain techniques are implemented in order to handle the long impulse response system. Transformation from time to frequency and vice-versa had brought a revolution in the field of communication. Frequency domain adaptation is published earlier for adaptive equalization. In 1978 Dentino et al. published a paper describing the concept of adaptive filtering in frequency domain. A number of papers subsequently appeared which served to develop further the theory of frequency domain adaptation. The use of Discrete Fourier Transform (DFT) in an adaptive filter has been reported by many researchers to accomplish an improvement in convergence rate when the input signal is colored noise. Unfortunately, the DFT is a complex transform; a practical implementation requires the use of complex arithmetic in real time. In practical applications such as echo cancelation and channel equalization, where the signals are all real-valued, it is undesirable to introduce complex arithmetic for the sake of introducing DFT. Moreover, in applications where the adaptive filter is implemented in real-time with a programmable DSP chip real values signals are preferred. The desire to avoid complex arithmetic, motivates a search for real-valued orthogonal transforms, which provide the same type of improved convergence rates as the DFT. It was soon learned that there exist other orthogonal transforms that can form the basis of efficient adaptive filtering algorithms [42],[43]. It should be noted here that the use of a fixed-parameter orthogonal transform will not result in optimal convergence rates for all types of input signals. So the convergence rate will depend upon the ability of the transforms to process the input signals to achieve optimal convergence rate. Combination of these transforms with LMS are known as Discrete Fourier Transform LMS (DFT-LMS), Discrete Sine Transform LMS (DST-LMS), Discrete Cosine Transform (DCT-LMS) and Discrete Wavelet Transform LMS (DWT-LMS). Their performances are studied partially by many authors. Further the improvements in convergence rate are suggested by partially update or modified step size.

An approach to reduce computation complexity of large adaptive FIR filter is to incorporate block updating strategies. In this method, blocks of input samples are transformed and processed in frequency domain using Fast Fourier Transform (FFT). This method reduces the computational complexity at the expense of delay [9]. The delay problem can be alleviated by partitioning the filter vector. A small filter length results in large number of parallel branches and vice versa. Obtaining too many branches of small length increases the steady state error but using less number of branches with large block length reduces the convergence speed. From the above discussion, it can be seen that based on the performance criteria, LMS is suitable for AEC application.

4. Multiple Sub Filter and Partial Update Techniques

There are number of methods available in literature to alleviate the slow convergence limitation [10], [11], [15]. One such method is variable step size approach as suggested in [15]. Another way to mitigate the slowly convergent adaptive filter problem in time domain is to use decomposition to get multiple sub-filter (MSF) parallel structure [6] instead of using single long filter (SLF) [11]. The long length impulse response of acoustic echo channel is realized by lower order parallel sub-filters. The decomposition is done by partitioning the SLF into N smaller MSF. The idea of decomposing the input signal vector and the weight vector into sub vectors was presented in [11]. The parallel structure distributes the load of adjusting a long adaptive filter by one adaptive algorithm into lower order MSF updated individually by LMS adaptive algorithm [10]. For MSF structure different adaptive algorithms are constructed depending upon the how the error signal is generated. The error signal used for weight update of adaptive filter can be obtained at each stage of the sub-filter or it can be a common error obtained at the last stage named different error and common error respectfully. In different error algorithm convergence improves but the steady state error also increases as the number of sub-filter increases. But the common error adaptation algorithm for MSF can be able to overcome the high steady state error problem with little sacrifice in convergence speed due to coupling of each weight update equation. Computational complexity can be reduced by introducing partial update of filter coefficients. It is also seen that low complexity with fast convergence can be achieved by partial update with Variable Step Size (VSS).

This convergence and computational complexity problem further can be reduced by proposing new algorithm containing both MSF structure and partial update with variable step size. As M-max partial update is well known method for reducing computational complexity, M-max partial update is an example of data dependent approach. Data dependent approaches results in sluggish convergence when the input is a sample function of white random process, but works well for highly correlated. So we studied a low complexity M-max partial filter coefficients update variable step size normalized least mean square (M-max VSS NLMS) algorithm for MSF structure to achieve fast convergence. The presented simulation results shows that the proposed MSF structure for M-max VSS NLMS algorithm achieves higher rate of convergence compared to normalized least mean square (NLMS) [2], variable step size normalized least mean square (VSS NLMS) [15], and M-max variable step size normalized least mean square (M-max VSS NLMS) [16] with single long filter (SLF) for both uncorrelated and correlated inputs.

5. Acoustic Echo Cancellation Performance Metrics

Algorithm performance is normally measured in terms of the time evolution and asymptotic behavior of measures such as the output Mean Square Error (MSE), the Echo Return Loss Enhancement (ERLE).

6. Mean Square Error

Convergence time is the time taken to reach an acceptable level of steady state residual echo. The convergence test can be done by varying the adaptation step size and examining the effect on filter coefficients and the plot of the Mean Square Error (MSE)
signal. It is mathematically expressed as the expectation of the norm of the square error.

\[
MSE = 10 \log_{10} E \left[ \|e(n)\|^2 \right] (dB)
\]

MSE shows the adaptation curves of the algorithm which is a common measure for examining the performance of EC.

7. **Echo Return Loss Enhancement (ERLE)**

ERLE, a measure of quality of echo cancellation algorithm is defined as the ratio of the instantaneous power of the signal \(d(n)\), and the instantaneous power of the residual error signal, \(e(n)\), immediately after cancellation. Mathematically it can be expressed as

\[
ERLE = -10 \log_{10} \left( \frac{\frac{\partial^2}{\partial d^2}}{\frac{\partial^2}{\partial d^2}} \right) = -10 \log_{10} \left( \frac{E[e(n)^2]}{E[d(n)^2]} \right)
\]

It is a measure of how successful the canceller has been in reducing the echo.

**IV. CONCLUSION**

A conclusion of the performance of the LMS adaptive filtering algorithm is expressed by it’s simplicity to implement, and its stability when the step size parameter is selected appropriately. This proves quite satisfactory in simulating a medium to large size room. There are many possibilities for further development in this work. Other techniques such as infinite impulse response (IIR) or lattice filtering may prove to be more effective in an echo cancellation application, but with more hardware complications and need more than one FPGA chip to implement.

**REFERENCES**


