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Literature Review on a Class of Different Sparse Adaptive Algorithms for Echo Cancellation

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Abstract:-- **Echo is the repetition of a waveform due to reflection from points where the characteristics of the medium through which the wave propagates changes. Echo is usefully employed in sonar and radar for detection and exploration purposes. In telecommunication, echo can degrade the quality of service, and echo cancellation is an important part of communication systems. In hands-free telephony and in teleconference systems, the main aim is to provide a good free voice quality when two or more people communicate from different places. The problem often arises during the conversation is the creation of acoustic echo. This problem will cause the bad quality of voice signal and thus talkers could not hear clearly the content of the conversation, even thought lost the important information. This acoustic echo is actually the noise which is created by the reflection of sound waves by the wall of the room and the other things exist in the room. The main objective for engineers is the cancellation of this acoustic echo and provides an echo free environment for speakers during conversation. For this purpose, scientists design different adaptive filter algorithms. In the context of acoustic echo cancellation (AEC), it is shown that the level of sparseness in acoustic impulse responses can vary greatly in a mobile environment. When the response is strongly sparse, convergence of conventional approaches is poor. we propose a class of AEC algorithms that can not only work well in both sparse and dispersive circumstances, but also adapt dynamically to the level of sparseness using a new sparseness-controlled approach. The proposed algorithms achieve these improvements with only a modest increase in computational complexity.**

Keywords: **Echo cancellation, Noise, Adaptive filter, Adaptive algorithm, AEC.**

I. INTRODUCTION

In the context of echo cancellation, it is shown that the level of sparseness in acoustic impulse responses can vary greatly in a mobile environment. When the response is strongly sparse, convergence of conventional approaches is poor[1]. We have presented echo cancellation algorithms to work for sparse responses ,to adapt dynamically with the level of sparseness using a new sparseness-controlled approach.

The echo response in system is typically of length 64–128 ms and is characterized by a bulk delay dependant on network loading, encoding, and jitter buffer delays[1] . This results in an active region in the range of 8–12 ms duration and consequently, the impulse response is dominated by inactive regions where coefficient magnitudes are close to zero, making the impulse response sparse[1]. The echo canceller must be robust to this sparseness.

Traditionally, adaptive filters have been deployed to achieve echo cancellation by estimating the echo response using algorithms such as the normalized least-mean-square algorithm[15]. Various sparse adaptive algorithms have been developed specifically to address the performance of adaptive filters in sparse system identification.

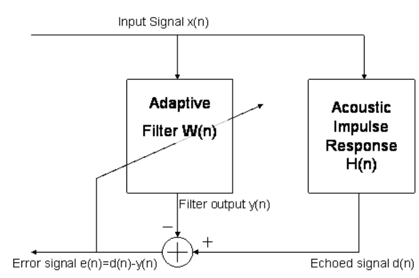

Fig 1. Adaptive echo Cancellation system

Figure 1 shows a block diagram of the adaptive echo cancellation system. Here the filter H (n) represents the impulse response of the acoustic environment, W(n)

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represents the adaptive filter used to cancel the echo signal. The adaptive filter aims to equate its output y(n) to the desired output d(n) (the signal reverberated within the acoustic environment). At each iteration the error signal, e (n) =d (n)-y (n), is fed back into the filter, where the filter characteristics are altered accordingly. The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function. In the case acoustic echo cancellation, the optimal output of the adaptive filter is equal in value to the unwanted echoed signal. When the adaptive filter output is equal to desired signal the error signal goes to zero.

A. *ECHO and TYPES OF ECHO*

An echo is said to occur when delayed and possibly distorted versions of a signal are reflected back to the source of that signal.
There are two types of echo

1. Acoustic echo

It is a type of echo which is produced by poor voice coupling between the earpiece and microphone in handsets and hands-free devices. As shown in figure sound signal from a loudspeaker is heard by a listener, as intended[1]. However, this same sound also is picked up by the microphone, both directly and indirectly, after bouncing off the wall. The result of this reflection is the creation of echo which is transmitted back to the far end and is heard by the talker as echo.

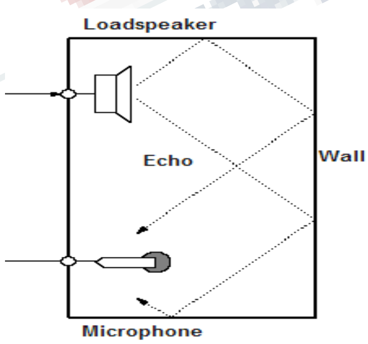

Fig 2. Example of Acoustic echo

2. Hybrid echo

It is the other type of echo generated in the public-switched telephone network (PSTN) due to the impedance mismatch in the hybrid transformers. As illustrated in figure 3 , when voice signals pass from the four-wire to the two-wire portion of the network, the energy in the four-wire section is reflected back to the speaker and create the echoed speech. The network echo response in such systems is typically of length 64-128 ms, characterised by an unknown bulk delay dependant on network loading, encoding and jitter buffer delays[1].

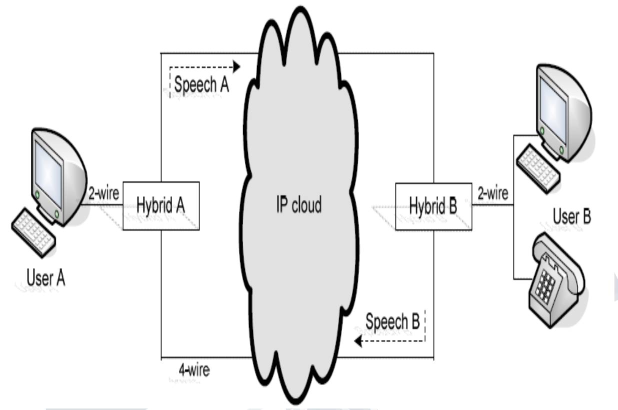

Fig. 3 Example of Hybrid echo

This results in an 'active' region in the range of 8-12 ms duration and consequently, the impulse response is dominated by 'inactive' regions where coefficient magnitudes are close to zero, making the impulse response sparse.

B. Adaptive Filter

Adaptive filter is the most important component of acoustic echo canceller and it plays a key role in acoustic echo cancellation. It performs the work of estimating the echo path of the room for getting a replica of echo signal. It requires an adaptive update to adapt to the environmental change. Another important thing is the convergence rate of the adaptive filter which measures that how fast the filter converges for best estimation of the room acoustic path.

One of the first sparse adaptive filtering algorithms for is proportionate NLMS (PNLMS) [2] in which each filter coefficient is updated with an independent step-size that is linearly proportional to the magnitude of that estimated filter coefficient.

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Traditionally, echo cancellers are realized by a Finite impulse response (FIR) structure to achieve echo cancellation using algorithms such as the NLMS algorithm. For sparse systems such as encountered in NEC, the NLMS algorithm suffers from slow convergence[1] and therefore new algorithms have been proposed for sparse adaptive filtering. Sparse adaptive algorithms have been derived from NLMS to improve the performance in sparse system identification. One of the first sparse adaptive filtering algorithms for NEC is PNLMS [14] in which each filter coefficient is updated with an independent step-size that is linearly proportional to the magnitude of that estimated filter coefficient. It is well known that PNLMS has very fast initial convergence for sparse impulse responses after which its convergence rate reduces significantly, sometimes resulting in a slower overall convergence than NLMS. In addition, PNLMS suffers from slow convergence when estimating dispersive impulse responses[14]. To address the latter problem, subsequent improved versions, such as IPNLMS, were proposed. The IPNLMS algorithm achieves improved convergence by alternating between NLMS and PNLMS for each sample period., the IPNLMS algorithm only performs best in the cases when the impulse response is sparse or highly dispersive. In order to address the problem of slow convergence in PNLMS for dispersive AIR, we require the step-size control elements to be robust to the sparseness of the impulse response. For this purpose the SC-PNLMS algorithm has been proposed for sparseness control[17].

II. Block diagram

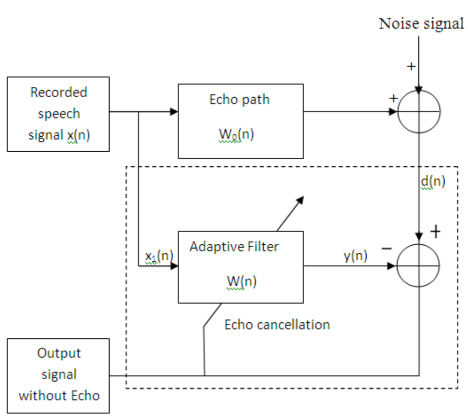

Fig 4. Block Diagram Of Echo Cancellation

Where

$x(n)$ is the input recorded signal
$W_0(n)$ is the echo signal
$x_1(n)$ is the reference input signal
$d(n)=W_0(n)$ +Noise signal
$y(n)$ is the filter output
$e(n)$ is the error signal.
$e(n)=d(n)-y(n)$

Adaptive filters are dynamic filters which iteratively alter their characteristics in order to achieve an optimal desired output. An adaptive filter algorithmically alters its parameters in order to minimize a function of the difference between the desired output d (n) and its actual output y (n). This function is known as the cost function of the adaptive algorithm. Here, W(n) represents the adaptive filter used to cancel the echo signal. The adaptive filter aims to equate its output y(n) to the desired output d(n). At each iteration the error signal, e (n) =d (n)-y (n), is fed back into the filter, where the filter characteristics are altered accordingly[15].

The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function.

In the case of acoustic echo cancellation, the optimal output of the adaptive filter is equal in value to the unwanted echoed signal. When the adaptive filter output is equal to desired signal the error signal goes to zero. In this situation the echoed signal would be completely cancelled and the far user would not hear any of their original speech returned to them.

Thus We are proposing a class of sparseness-controlled algorithms which will achieve improved convergence compared to normalized least-mean-square algorithm and typical sparse adaptive filtering algorithm such as Proportionate normalized least-mean-square algorithm .

We are going to incorporate the sparseness measure into sparse adaptive filtering algorithm to achieve fast convergence that is robust to the level of sparseness encountered in the impulse response of the

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echo path. In the proposed work after comparing algorithms, the algorithm which is robust to variations in the level of sparseness will be selected. Throughout our simulations, algorithm will be tested using a White Gaussian noise and a recorded speech signal as the input.

III. IMPLEMENTATION

A. IMPLEMENTATION STEPS

1. Recorded speech signal (.Wave file) will be considered as
   the input[6].
2. Echo signal will be added to the input signal & output of
   this is corrupted with the noise signal.
3. The output signal of adaptive filter is subtracted from d(n)
   where d(n)= Echo signal +Noise signal.
4. The coefficient of the adaptive filter are updated until the
   error is minimised. The error signal is given by
   e(n)= d(n)-y(n).
5. These all steps will be simulated in MATLAB.
6. The comparision of NLMS & PNLMS algorithms will be
   based on the performance parameters such as no of additions, multiplications, Logarithm & Sparseness measure.

B. ADAPTIVE FILTERING METHODS

The method used to cancel the echo signal is known as adaptive filtering.

Methods of adaptive filtering

1. LMS
2. NLMS
3. PNLMS
4. IPNLMS
5. SCPNLMS

The above algorithms have been implemented in Matlab. As the step size parameter is chosen based on the current input values [6]. The above algorithms are an extension of the standard LMS algorithm and the practical implementation of these algorithms is very similar to that of the LMS algorithm.

IV.REVIEW OF ALGORITHMS FOR ECHO CANCELLATION

A. LEAST MEAN SQUARE (LMS) ALGORITHM

This algorithm is used widely for different application such as channel equalization and echo cancellation. This algorithm adjusts the coefficients of $w(n)$ of a filter in order to reduce the mean square error between the desired signal and output of the filter[15]. This algorithm is basically the type of adaptive filter known as stochastic gradient-based. The equation below is LMS algorithm for updating the tap weights of the adaptive filter for each iteration.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e(n)\mathbf{x}^*(n) \qquad (1)$$

Where,

• $\mathbf{x}(n)$: input vector of time delayed input values.
• $\mathbf{w}(n)$: weight vector at time n .

In order to converge on the optimal Wiener solution, this algorithm use the gradient vector of the filter tap weights. This algorithm is also used due to its computational simplicity. μ is a step-size parameter and it controls the immediate change of the updating factor.

It shows a great impact on the performance of the LMS algorithm in order to change its value. If the value of μ is so small then the adaptive filter takes long time to converge on the optimal solution and in case of large value the adaptive filter will be diverge and become unstable.

As the step size parameter is chosen based on the current input values, the NLMS algorithm shows far greater stability with unknown signals [6].

B.NORMALISED LEAST MEAN SQUARE (NLMS) ALGORITHM

As the NLMS is an extension of the standard LMS algorithm, the NLMS algorithms practical implementation is very similar to that of the LMS algorithm[12]. Each iteration of the NLMS algorithm requires these steps in the following order.

1. The output of the adaptive filter is calculated.

$$y(n) = \sum_{i=0}^{N-1} w(n)x(n-i) = \mathbf{w}^T(n)\mathbf{x}(n)$$

(2)

2. An error signal is calculated as the difference between the desired signal and the filter output

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$e(n)= d(n)-y(n)$ (3)

3. The step size value for the input vector is calculated

$$\mu(n) = \frac{1}{\mathbf{x}^{T}(n)\mathbf{x}(n)} \quad (4)$$

4. The filter tap weights are updated in preparation for the next iteration

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu(n)e(n)\mathbf{x}(n) \quad (5)$$

One of the main drawbacks of the NLMS algorithm is that its convergence rate reduces significantly when the impulse response is sparse, such as often occurs in NEC. The poor performance has been addressed by several sparse adaptive algorithms such as those described below that have been developed specifically to identify sparse impulse responses in NEC applications.

C. PROPORTIONATE NORMALISED LEAST MEAN SQUARE (PNLMS) ALGORITHM

For sparse echo systems, the NLMS algorithm suffers from Slow Convergence[1]. One of the first sparse adaptive filtering algorithms for NEC is proportionate NLMS (PNLMS) [2] in which each filter coefficient is updated with an independent step-size that is linearly proportional to the magnitude of that estimated filter coefficient. It is well known that PNLMS has very fast initial convergence for sparse impulse responses after which its convergence rate reduces significantly, sometimes resulting in a slower overall convergence than NLMS. In addition, PNLMS suffers from slow convergence when estimating dispersive impulse responses. The proportionate normalized least mean square (PNLMS) [5] and improved proportionate normalized least mean square (IPNLMS) [6] algorithms have been proposed for network echo cancellation where the impulse response of the system is sparse. The PNLMS algorithm [7] assigns higher step-sizes for coefficients with higher magnitude using a control matrix **Q**(n). Elements of this control matrix for PNLMS can be expressed as

$$q_l(n) = \frac{\kappa_l(n)}{\sum_{i=0}^{L-1} \kappa_i(n)}, \quad (6)$$

$$\kappa_l(n) = \max\Big\{\rho \times \max\{\gamma, |\hat{h}_0(n)| \ldots |\hat{h}_{L-1}(n)|\}, |\hat{h}_l(n)|\Big\} \quad (7)$$

with l = 0, 1, . . ., L − 1 being the tap-indices. The parameter γ, with a typical value of 0.01, prevents ˆhl(n) from stalling during initialization stage where ˆ**h**(0) = **0**L×1 while ρ prevents coefficients from stalling when they are much smaller than the largest coefficient. PNLMS employs larger step-sizes for 'active' coefficients than for 'inactive' coefficients and consequently achieves faster convergence than NLMS for sparse impulse responses. However, it is found that PNLMS achieves fast initial convergence followed by a slower second phase convergence.

D. IMPROVED PROPORTIONATE NORMALIZED LEAST MEAN SQUARE (IPNLMS) ALGORITHM

An enhancement of PNLMS is the IPNLMS algorithm [11]
which is a combination of PNLMS and NLMS with the relative significance of each controlled by a factor α. Elements
of the control matrix **Q**(n) for IPNLMS are given by

$$q_l(n) = \frac{1-\alpha}{2L} + \frac{(1+\alpha)|\hat{h}_l(n)|}{2\|\hat{\mathbf{h}}(n)\|_1 + \epsilon}, \quad l = 0, \ldots, L-1, \quad (8)$$

where ε is a small value and It can be seen from the second term of (8) that the magnitude of the estimated taps are normalized by the l1-norm of h[14]. This shows that the weighting on the step-size for IPNLMS is dependent only on the relative scaling of the filter coefficients as oppose to their absolute values.

E. SPARSENESS CONTROLLED PNLMS(SC-PNLMS) ALGORITHM

In the proposed SC-PNLMS algorithm in order to address the problem of slow convergence in PNLMS for dispersive AIR, we require the step-size control elements *ql(n)* to be robust to the sparseness of the impulse response. We now propose to incorporate the computation of ρ for PNLMS. We consider two example functions

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$$\rho(n) = (\tilde{\varepsilon} - 1)\hat{\xi}(n) + 1, \quad (9)$$

$$\rho(n) = e^{-\lambda \hat{\xi}(n)}, \quad \lambda \in \mathbb{R}^+, \quad (10)$$

As a consequence, the performance of SC-PNLMS is reduced when the AIR is dispersive[16].

V. PERFORMANCE MEASURES

The choice of one algorithm over the wide variety of others needs to be addressed to differentiate it from the rest, so that one can pick a right algorithm for his particular application. The following three measures deal with different concepts in applications akin to echo cancellation.

A. MEAN SQUARE ERROR (MSE)

MSE is one of the ways to define an objective unction that satisfies the optimality and non-negativity properties[16]. It is the expected value of the square of the error and can be seen from following equation that the lower MSE value is favourable.

$$MSE(n) = E\{e\ (n)\} \quad (11)$$

B. ECHO RETURN LOSSLESS ENHANCEMENT (ERLE)

It measures the attenuation of the echo signals in an Acoustic Echo Cancellation system. It can be witnessed from following equation that a higher ERLE corresponds to higher reduction in echo.

$$\mathrm{ERLE}(n) = 10 \times \log_{10} \frac{y^2(n)}{e^2(n)}\,\mathrm{dB} \quad (12)$$

C. NORMALISED PROJECTION MISALIGNMENT (NPM)

The normalized projection misalignment measures the closeness of the estimated impulse response (hˆ(n)) to that of the unknown impulse response (h(n)) [16].

$$\mathrm{NPM}(n) = 20 \times \log_{10}\left(\frac{1}{\|\mathbf{h}\|}\left\|\mathbf{h} - \frac{\mathbf{h}^T\hat{\mathbf{h}}(n)}{\hat{\mathbf{h}}^T(n)\hat{\mathbf{h}}(n)}\hat{\mathbf{h}}(n)\right\|\right)\mathrm{dB} \quad (13)$$

where the denominator is defined as the squared l2-norm operator. To achieve a good performance, the misalignment must be close to zero, which is the case when the length of unknown filter (LR) is close to that of adaptive filter (L). It is interesting to note that when the filter has only one tap the term inside the logarithm becomes zero and therefore yields negative infinity for NPM.

VI. COMPUTATIONAL COMPLEXITY

The relative complexity of LMS, NLMS, PNLMS, SC-PNLMS in terms of the total number of additions (A), multiplications (M), logarithm (Log) and comparisons (C) per iteration is assessed[17]. The additional complexity of the proposed sparseness-controlled algorithms, on top of their conventional method, arises from the computation of the sparseness measure $\xi(n)$.

VII. CONCLUSION

In this paper we have reviewed a family of algorithms developed in the last years for improving the convergence of adaptive filters when modeling sparse impulse responses. The first proposed approach, the PNLMS algorithm, was shown to produce fast initial convergence for sparse impulse responses, followed by a significant reduction after the fast initial period. Also, its performance was poor for non sparse impulse responses.

The NLMS algorithm achieves good convergence in dispersive AIRs, whereas PNLMS performs well in sparse impulse response. We have also reviewed that the sparse ness measure into NLMS, PNLMS for AEC to achieve fast convergence that is robust to the level of sparseness encountered in the impulse response of the echo path. The resulting SC-PNLMS algorithms take into account the sparseness measure via a modified coefficient update function.

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