ACOUSTIC ECHO CANCELLATION BY USING NPVSS NLMS-UM CASE

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ABSTRACT

In this paper we, present a new approach to acoustic echo cancellation in today's telecommunication system. This approach is a combination of distribution free and variable step size algorithm in under modeling case general. In Under modeling case algorithm doesn't required any prior information from acoustic environment so, we can differentiate new approach with conventional approach in the terms of the computational complexity and convergence rate, so this is suitable candidate for real world application.

Keywords: Acoustic Echo Cancellation, Adaptive Filtering, Variable Step Size , Distribution Free, Double Talk Detection, White Gaussian Noise, Loudspeaker

I. INTRODUCTION

Acoustic echo cancellation is one of the most popular applications of adaptive filter [1]. The role of the adaptive filter is to identify the acoustic echo path between the terminals loudspeaker and microphone.

Even though many interesting adaptive filtering algorithm have been developed and are applicable for acoustic echo cancellation [2], an application with limited precision and processing power, the least means-square (NLMS) algorithm [3] (e.g., frequency domain or subband versions [1]) are usually applied.

The standard least means square (LMS) algorithm is considered to be one of the simplest algorithms for adaptive filtering, but it is sensitive to the scaling of its input when choosing a step-size parameter to guarantee stability [2],[3].

The NLMS algorithms solve this problem by normalizing with the power of the input. For both algorithms, the parameter of step-size governs the convergence speed and the steady-state excess mean-square error. To better tradeoff the conflicting requirement of fast convergence rate and low misadjustment, various schemes for adjusting the step-size have been reported [4], [5], [6], [7],. To meet these conflicting requirements, the step size needs to be controlled. Thus, a number of variable step size NLMS (VSS-NLMS) algorithms have been proposed [8], [9] and references therein. In [5], elaborated and distribution free VSS-NLMS (DFVSS-NLMS) is proposed. This algorithm is gives the good performance in the context of acoustic echo cancelation [AEC].

1.1 Basic Concepts of Echo Cancellation

In acoustic echo cancelation, the estimates of the near-end echo path response is computed which is used to generate an estimate of echo. The estimate of echo is subtracted from the near-end microphone output to subtract the actual echo.

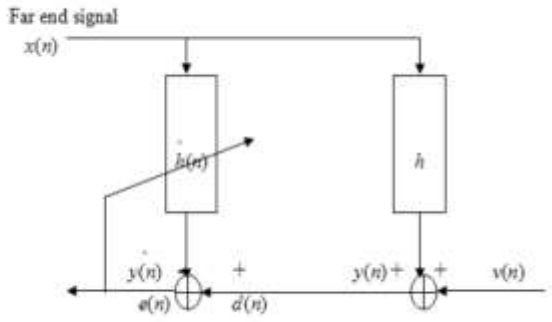

Fig1. Block Diagram of the Echo Canceller

Where,

x (n) Far-end signal

v (n) Near-end signal

d(n) Echo or desired signal

The problem then reduces to similar to the room echo path response h by an impulse response $\hat{h}(n)$ of the adaptive filter. So that feeding a same input to the adaptive filter the estimate of actual echo, $\hat{y}(n)$ is obtained. The use of adaptive filter in the echo cancellation is necessary because the path of echo's are highly time varying, so that the use of fixed filter is not suitable.

II. BASIC PROBLEM

In hand free telephony, the objective is to permit two or more people, sitting in two different rooms, two converge with each other. In simple configuration, there are two separate rooms one is far end room and another is near end room. Each room contains a microphone and a loudspeaker pair which is used by one speaker to converge with other..

The far-end signal broadcast to the near end signal x(n) is broadcast to the near end room. The near end room has a microphone which is for the use of near end speaker but this
near end speaker also receives a delayed and distorted version of the far end signal x(n) as an echo d(n) due to the room.

(a) System Identification

System identification refers to the ability of an adaptive system to find the FIR filter that best reproduces the response of another system, whose frequency response is apriori unknown. System identification is mostly used in divergence application, setup is given below Fig2.

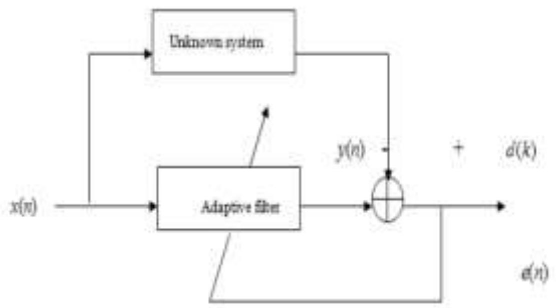

Fig2. System Identification

The FIR filter reproduces the behavior of the 'unknown system'. This works perfectly when the system to be identified has got a frequency response that matches with that of a certain FIR filter.

But if the unknown system is an all-pole filter, then the FIR filter will try its best. It will never be able to give zero output but it may reduce it by converging to an optimum weights vector. The frequency response of the FIR filter will not be exactly equal to that of the 'unknown system' but it will certainly be the best approximation to it.

Let us consider that the unknown filter is a time invariant, which indicate that the coefficient of the impulse response are constant and of finite extent (FIR). Therefore,

$$d(n) = \sum_{k=0}^{N-1} h_k x(n-k)$$

The output of the adaptive filter with the same number of the coefficient N, is given by,

$$y(n) = \sum_{k=0}^{N-1} w_k x(n-k)$$

These two systems to be equal, the difference between e(n) = d(n) - y(n) must be equal to zero. Under these conditions, the two set of the coefficients are also equal. It is the method of adaptive filtering that will enable us to produce an error, e(n) approximately equal to zero and therefore will identify that. $w_k \approx h_k$.

III. DESCRIPTION OF PROPOSED ALGORITHM

Acoustic echo cancellation is one of the most popular application of adaptive filter [1]. The role of the adaptive filter is to identify the acoustic echo path between the terminals loudspeaker and microphone.

Even though many interesting adaptive filtering algorithm have been developed and are applicable for acoustic echo cancellation [2], an application with limited precision and processing power, the least means-square (NLMS) algorithm [3] (e.g., frequency domain or subband versions [1]) are usually applied.

Setup shown in fig 3. The main purpose of this setup is that the near end speech signal $v(t)$ is to be picked up by the microphone M and propagated to the far-end room while far-end speech is to be emitted by the loudspeaker L in to the near – end room. During single talk, which are the cases only when the far-end or speech signal present means $v(t) = 0$.

$$y(t) = h^T x(t) + w(t) \qquad (1)$$

During doubletalk, which is the case when both near-end and far-end speech is present, the near-end speech in the microphone signal $y(t)$ is corrupted by the echo of the far-end speech signal $x(t)$ that is propagated in the near-end room from the loudspeaker L to the microphone M .

Therefore, during doubletalk, the resulting microphone signal $y(t)$ consists of near-end speech mixed with far-end speech

filtered by the near-end room impulse response h from the loudspeaker to the microphone

$$y(t) = h^T x(t) + v(t) + w(t) \qquad (2)$$

Where n is the order of the room impulse response modeled as FIR filter.

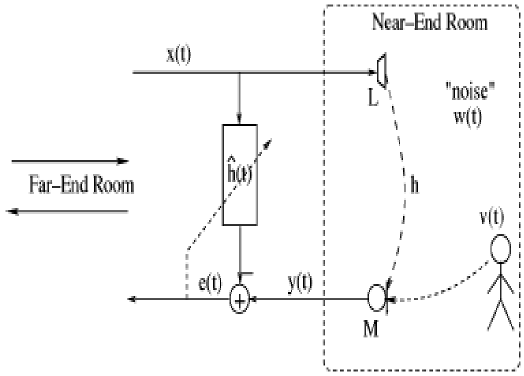

Fig.3. AEC setup

$$h = [h_0 h_1 ....h_{n-1}]^T \qquad (3)$$

The room impulse response is varying with time since movements (e.g., people moving around) may occur in the room. Thus, usually in order to remove the undesired echo an adaptive filter estimate $\hat{h}(t)$ of h is used to predict the far-end speech contribution $h^T x(t)$ and subtract it from the microphone signal $y(t)$. Thereby, we get the error signal,

$$e(t) = y(t) - \hat{h}^T(t) x(t)$$

$$e(t) = v(t) + h^T x(t) - \hat{h}^T(t) x(t) + w(t) \qquad (4)$$

$E\{.\}$ is mathematical expectation and $\sigma_v^2 = E\{v^2(n)\}$ is the power of system noise. Using approximation $x^T(n)x(n) = LQ\sigma_x^2 = LE\{x^2(n)\}$, for $L \succ\succ 1$, where σ_x^2 is power of input signal and we also known that $\mu(n)$ is deterministic nature.

$$E\{\varepsilon^2(n)\} = \left[1 - \mu(n)LQ\sigma_x^2\right]\sigma_e^2(n)$$

$$= \sigma_v^2$$

where $E\{\varepsilon^2(n)\} = E\{e^2(n)\}$ is power of error signal from (33) obtained a quadratic equation,

$$\mu^2(n) - \frac{2}{L\sigma_x^2}\mu(n) + \frac{1}{(LQ\sigma_x^2)^2}\left[1 - \frac{\sigma_v^2}{\sigma_e^2(n)}\right] = 0$$

The step size parameter of a proposed nonparametric VSS-NLMS algorithm is given by:

$$\mu_{NPVSS-NLMS-UM}(n) = \frac{1}{x^T(n)x(n) + Q}\left[1 - \frac{\sigma_v}{\sigma_e(n)}\right]$$

$$= \mu_{NLMS}(n)\alpha(n)$$

Where $\alpha(n)$ is normalized step size, range is given $0 \le \alpha(n) \le 1$. The NPVSS-NLMS-UM algorithm is,

$$\hat{h}(n) = \hat{h}(n-1) + \mu_{NPVSS-UM}(n)x(n)e(n)$$

We conclude that if $\sigma_e(n) \succ \sigma_v$ then the $\mu_{NPVSS-NLMS-UM}(n) \approx \mu_{NLMS}(n)$. When the algorithm starts to converge to true value, $\sigma_e(n) \approx \sigma_v$ and $\mu_{NPVSS-NLMS-UM}(n) \approx 0$. This exactly what we desired to have good convergence and low misadjustment.

NPVSS-NLMS algorithm written in terms of misalignment,

$$m(n) = m(n-1) - \mu_{NP-VSSNLMS-UM}(n)x(n)e(n)$$

It is understandable that $\sigma_e(n) \ge \sigma_v \mu_{NPVSS-NLMS-UM}(n)$, which imply that $\mu_{NPVSS-NLMS-UM}(n) \ge 0$. The quantity $\sigma_e^2(n)$ is estimated as follows:

$$\hat{\sigma}_e^2(n) = \lambda \hat{\sigma}_e^2(n-1) + (1-\lambda)e^2(n)$$

Where λ is an exponential window.This estimation could result in a lower magnitude than σ_v^2, which would make $\mu_{NPVSS}(n)$ negative. To overcome this problem, when its occurs is to set $\mu_{NPVSS}(n) = 0$.

Table- NP VSS-NLMS-UM ALGORITHM

Initialization:	$\hat{h}(0) = 0$ $\hat{\sigma}_e^2(0) = 0$
Parameters:	$\lambda = 1 - \frac{1}{KL}$, exponentialwindow with $K \ge 2$ σ_v^2, noise power known or estimated δ = constant. σ_x^2, regularizatio $\varepsilon \succ 0$, very small nuber to avoid division by zero
Error	$e(n) = y(n) - \hat{h}(n-1)x(n)$
Update:	$\hat{\sigma}_e^2(n) = \lambda \hat{\sigma}_e^2(n-1) + (1-\lambda)e^2(n)$ $\beta(n) = \left[\delta + x^T(n)x(n)\right]^{-1}\left[1 - \frac{\sigma_v}{\varepsilon + \hat{\sigma}_e(n)}\right]$ $\mu_{NPVSS}(n) = \begin{cases} & \text{if } \hat{\sigma}_e(n) \ge \sigma_v \\ 0 & \text{otherwise} \end{cases}$ $\hat{h}(n) = \hat{h}(n-1) + \mu_{NPVSS}(n)x(n)e(n)$

IV. SIMULATION

The input signal applied to the unknown system is either a white Gaussian noise or speech signal. The output of the plant is mixed with noise such that the signal to noise ratio remain 20-dB. This signal is a desired signal for adaptive filter. The error vector obtained as the difference of desired and output vector is used to update output of adaptive filter. The initial weights of are initially set to zero. The simulation study has been carried out for

NLMS, NPVSS-NLMS-UM

(a) NLMS And NPVSS-NLMS-UM

The acoustic coupling between microphone and microphone in hand free telephones generates echoes .To remove this echo, we need to identify impulse response of unknown system. Simulation results, input signal are consider as white Gaussian signal or speech signal. An independent white Gaussian noise signal is added to the output of unknown system at 30-dB. We also assume that power of noise signal is known. Parameters setting for simulations are $\hat{\sigma}_e^2(0) = 0$, $\delta = 20\sigma_x^2$ and $\lambda = 1 - \frac{1}{KL}$ and $K = 2$ for white Gaussian noise signal. The performance of algorithm measured in terms of the normalized misalignment in (dB).

$$Misalignment\left(\hat{h}(t)\right) = 20\log\left(\frac{\left\|\hat{h}(t) - h\right\|}{\left\|h\right\|^2}\right)$$

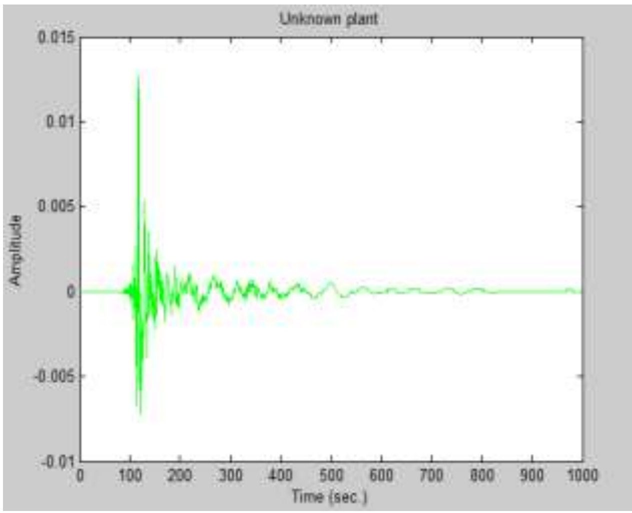

Fig4. Unknown plant

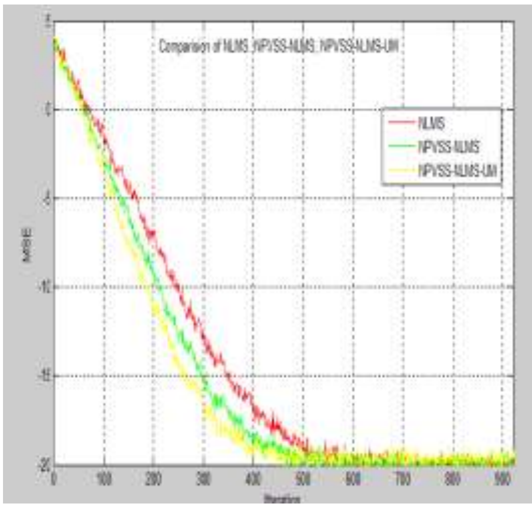

Fig 5

Fig.5. Misalignment of The NLMS Algorithm At $\left[\delta + X^T(n)X(n)\right]^{-1}$**, And The npvss-NLMS-UM And NLMS Algorithm. The Input Signal Is White Gaussian Noise,** $L = 500$ **,**

$\lambda = 1 - \frac{1}{1-(2L)}$**, And** SNR **= 20 Db.**

The simulation results show that NPVSS algorithm is better than NLMS and DFVSS-NLMS algorithm. We have compared NPVSS and NLMS and DF-VSS-NLMS. The plot has been taken between numbers of iterations and corresponding MSE. The iteration range varied from 0 to 950 where as MSE value varies from 0 dB to 5 dB. It is clear from the above plot, fig.5 that proposed algorithm converges in 20 dB signal to noise ratio, which is lesser than NLMS algorithm.

Tracking is a very important issue in adaptive algorithms. In applications like acoustic echo cancellation, it is essential that an adaptive filter tracks fast since impulse responses are not very stationary. Fig. shows that, when the impulse response has changed NLMS algorithm provides more erroneous results than the previous one, where as DFVSS-NLMS algorithm shows the same results with more efficiency compare to NLMS and NPVSS algorithm.

V. SIMULATION

In AEC, the acoustic echo paths are extremely long. The main property of the algorithm doesn't require any priori information about acoustic environment. It can be deduced from above figures that distribution free variable step size normalized least means square adaptive algorithm perform better than the other two algorithms, NLMS and NPVSS in the context of echo cancellation. In NLMS algorithm, we need to find a compromise between fast convergence and low final misadjustment. In many applications, this compromise may not be satisfactory so a DFVSS-NLMS algorithm is required. It should be noted that the idea of proposed algorithm can be used in coincidence with other NLMS-based algorithms This improves the convergence rate and reduced the computational complexity. So it is suitable for real world application.

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