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Implementation of NLMS Algorithm and its Performance Evaluation with Double Talk Detection Using Acoustic Echo Cancellation Systems

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Abstract: The objective of this Paper work is to analyze the algorithms and concepts behind the working of time and frequency domain based Acoustic Echo Cancellation algorithms. To understand the performance of the sub-band filtering based Acoustic Echo Cancellation (AEC) algorithm and propose a novel sub-band based AEC algorithm with Double talk detector (DTD). Which has better convergence time, higher value of Echo Return Loss Enhancement (ERLE) and Normalized Squared Coefficient Error (NSCE)? the Estimate the echo path response is a critical component for acoustic echo suppression (AES) and acoustic echo Cancellation (AEC) operation Most of the traditional acoustic echo suppression (AES) algorithms and Echo Cancellation are based on an adaptive finite impulse response (FIR) filter for estimating the echo path response. The FIR filter in turn is based on normalized least-mean-square (NLMS) and Implementation version of New Variable Step Size NLMS (NVSSNLMS) in the time domain, Hence in our research work reliable echo detection and cancellation algorithms are developed, with stationary background noise using Matlab tool .

***Key words**:* LMS, NLMS, VSSLMS, NVSSNLMS, DTD.

1. INTRODUCTION

Traditional approaches to acoustic echo cancellation have used filtering algorithms which try to Estimate the impulse response of the acoustic path and filter the incoming signal from the far-end by loud speaker and near-end input from a microphone.

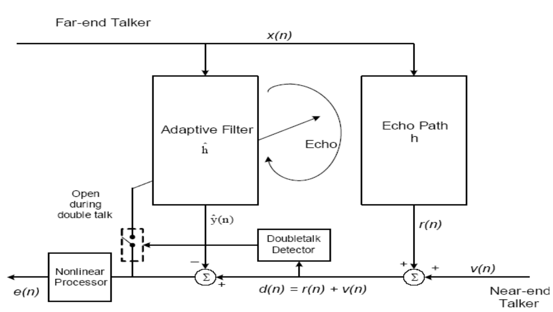

Figure 1: Basic Echo Canceller

The far-end sound is convolved with the estimated, and subtracted from before being sent to the far-end as shown in figure1. The estimate is refined by updating the filter according to its output. A common

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approach for estimating is the Least Mean Square (LMS) algorithm. Most echo cancellation algorithms attempt to explicitly detect double-talk [1] conditions and then react by freezing the coefficients of the adaptive filter. Reliable double-talk detection is a difficult problem and sometimes it is not clear what should be considered as double-talk, especially in an acoustic echo cancellation context with stationary background noise. In a modified approach [2] to make echo cancellation more robust to double-talk. A continuous learning rate is used. The learning rate depends on a misalignment estimate, which is obtained through a linear regression. Valin [6] proposed an approach where the misalignment is estimated in closed-loop based on a gradient adaptive approach. This closed-loop technique is applied to the block frequency domain (MDF) adaptive filter [3] and shows a significant improvement over previous approaches. the NLMS [7] performs well. But the human speech has more energy in low frequencies than in high frequencies. Therefore, a NLMS gives good echo cancellation for low frequencies and poor echo cancellation for high frequencies. There are conflicting objectives between fast convergence and low excess MSE and NSCE for NLMS with fixed regularization parameter. In the past two decades, many variable step-size NLMS (VSS-NMS) algorithms [8] have been proposed to solve this dilemma of the conventional NLMS. These VSS-NLMS algorithms have been presented and have claimed that they have good convergence and tracking properties.

2. ADAPTIVE ALGORITHM ANALYSIS

2.1. Implementation of the 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. each iteration is.

1. The output of the adaptive filter is calculated.

$$\mathrm{Y(n)}=\sum_{i=0}^{N-1} w(n)x(n-i) = w^T(\mathrm{n})\mathrm{x(n)} \tag{2.1}$$

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

$$\mathrm{e(n)=d(n)-y(n)} \tag{2.2}$$

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

$$\mathrm{W\ (n+1) = w(n)}+\mu(n)e(n)X(n) \tag{2.3}$$

Each iteration of the NLMS algorithm requires 3N+1 multiplications, this is only N more than the standard LMS algorithm and this is an acceptable increase considering the gains in stability and echo attenuation achieved as shown in Table 1.

Tabe 1

Necessary steps for the NLMS algorithm

Initial Condition	$0< \mu_n \leq 2$ $x(0) = w(0) = [0,\dots 0]^T$
For each instant of time, k = 1,2,….,compute	
Filter output:	$y(k) = x(k)^T w(k)$
Estimation Error	$e(k) = d(k) - \hat{y}(k)$
Tap-weight Adaptation	$w(k+1)=w(k) + \dfrac{2\mu_n}{\gamma + X^T(K)X(K)} e(k)X(k)$

Table 1 shows the necessary steps for the NLMS algorithm

2.2. VSS-NLMS Based ECHO Canceller Implementation

Given the input vector X*k*, the Euclidean norm of the input vector $IX_k I^2$, the NLMS algorithm with fixed step size, μ, for adjusting the adaptive echo canceller's coefficients at time instant k is defined as follows:

$$w_{k+1} = w_k + \mu_k e_k \frac{x_k}{||x_k||^2} \tag{2.4}$$

In this work, the fixed step size μ in (1) is made variable and is updated according to the following recursion:

$$\mu_k = \mu_{k-1} + \rho e_k e_{k-1} \frac{x_k^T x_{k-1}}{||x_{k-1}||^2} \tag{2.5}$$

2.3. New Time Varying Step Size NLMS Algorithm (NVSS NLMS)

The **NVSSNLMS** algorithm is tested with real speech input signal and the result shows that it has fast convergence time, low level of maladjustments, and high Echo Return Loss Enhancement (ERLE) compared with NLMS and VSSNLMS

$$\mu(n+1) = \mu(n)(1 - Abs(mean(e(n)) * \delta) \tag{2.6}$$

Where $0 < \delta < 1$, and mean(e (n))= $\frac{\sum_{k=0}^{L-1} e(n-k)}{L}$

i.e. *mean(e(n)* is the mean value of previous and current estimation values of error

signal as shown in Table belw.

Table 2

(NVSSNLMS)

Initial Conditions	$X(0)=H(0)=[0.0,\ldots0]^T$ Assign values for, U_{MAX}, U_{MIN}, and δ
For each instant of time index n=1,,2,…..iteration, compute	
Adaptive FIR Filter output	$\hat{y}(n) = \hat{H}^T X(n)$
Output Estimation Error	$E(n)=d(n) - \hat{y}$
Step Size Adaptation	$\mu(n+1) = \mu(n)(1 - Abs(mean(e(n))\delta)$
Check the Upper and Lower bound of the $\mu(n+1)$	$\mu(n+1) = \mu_{MAX}$ if $> \mu(n+1) > \mu_{MAX}$ Or $\mu(n+1) = \mu_{min}$ if $< \mu(n+1) < \mu_{min}$ Otherwise $\mu(n+1) = \mu(n+1)$
Weights Adaptation	$H(n+1)=H(n)+2\mu(n)e(n)X(n)$

Table 2 shows the necessary steps for the proposed algorithm (NVSSNLMS)

3. EXPERIMENTAL PROCEDURE

3.1. Correlation Coefficient (CC)

A number between +1 and −1 calculated so as to represent the linear interdependence of two variables or sets of data. The correlation coefficient takes on values ranging between +1 and -1. and 0 indicates no linear relationship.

3.2. Log Spectral Distance (LSD)

The log-spectral distance between spectra $P(\omega)$ and $\widehat{\boldsymbol{P}}(\omega)$ is defined as:

$$D_{LS}=\sqrt{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left[10\,log_{10}\frac{P(\omega)}{\widehat{P(\omega)}}\right]^2\ d\omega},$$

3.3. Segmental SNR (SSNR)

The well known Segmental SNR (SSNR) is defined as the average of SNR values over segments with speech activity.

$$\text{SSNR}=\frac{1}{K}\sum_{i=0}^{L-1}\left(10log\frac{\sum_{n=0}^{M-1}si^2}{\sum_{n=0}^{M-1}\ n_{i[n]}^2}.\text{VAD}\right)$$

where K is the number of Segment

4. RESULTS

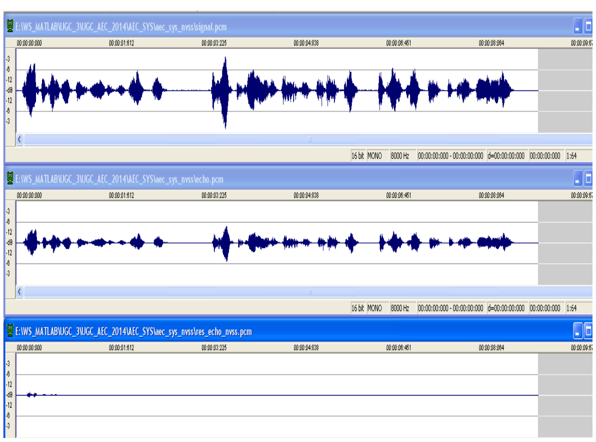

Figure 2: Output of the AEC (Single Talk)

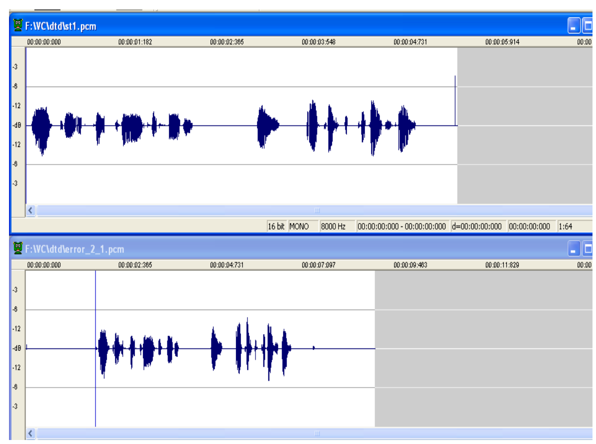

Figure 3: Output of the AEC (Double Talk)

Comparison Performance Matrices Table for of all algorithms

Table 3
Comparison Table for Performance Matrices

AEC Algorithm vs Performance Metrics	*Correlation Coefficient CC*	*Segmental SNR (SSNR)*	*Log Spectral Distance (LSD)*	*Processing Time on MATLAB*
NLMS	0.99811	282.8128	0.047545	47.4437
VSS-NLMS	0.99857	288.9965	0.041096	58.4242
NVSSNLMS	0.99857	289.2659	0.041081	57.2733

5. PERFORMANCE METRICS

Performance Results for Echo Return Loss Enhancement (ERLE)

1. **NLMS Method**

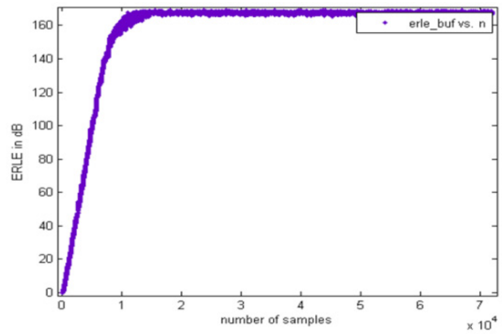

Figure 6: NLMS value reaches 139.9 dB at 9,672 samples, the time to reach Maximum ERLE is 1.3

2. VSSLMS Method

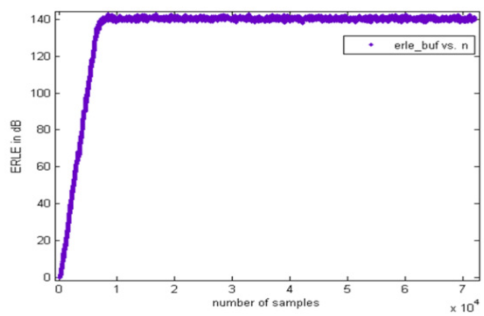

Figure 7: VSSLMS value reaches 166.8 dB at 13,636 Samples, the time to reach Maximum ERLE is 1.2

3. VSSNLMS Method

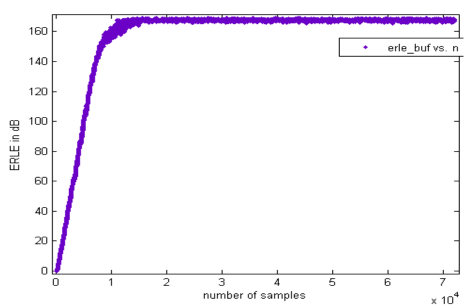

Figure 8: The maximum ERLE for NVSS-LMS method is 169.3 dB at 8,160 samples and time taken is 1.02 seconds.

Performance Results for Normalized Squared Coefficient Error [NSCE]

1. NLMS Method

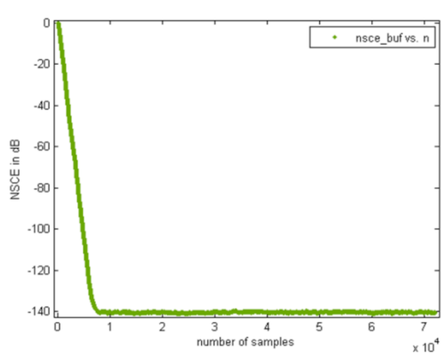

Figure 9:The minimum NSCE for NLMS is -140.49 dB at 10,606 samples and taken is 2.89 Seconds

2. VSSLMS Method

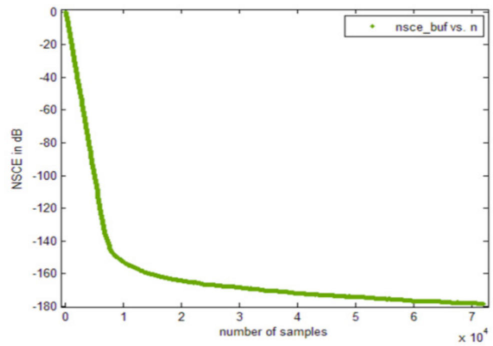

Figure 10: The minimum NSCE for VSS LMS method is 166dB at 23,153 samples and time taken is 1.32 seconds.

3. NVSSNLMS Method

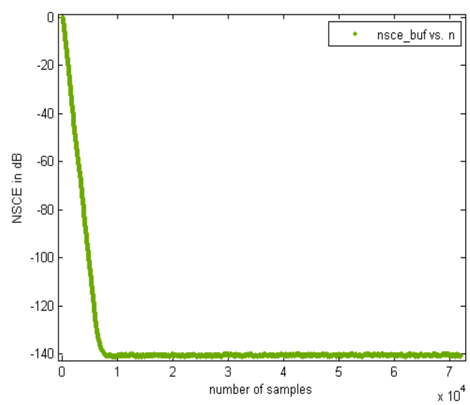

Figure 11: The minimum NSCE for NVSS-LMS method is -166 dB at 23,153 samples and time taken is 2.89 seconds

7. CONCLUSION

Implementation of Acoustic Echo Canceller Systems based on NLMS, VSS-NLMS, are implemented using MATLB Tool and Implement for Future Enhancement in Real Time Application, the Proposed Algorithm of NVSS-NLMS in Time and Frequency domain algorithms Performance metrics has higher ERLE value and lower NSCE value. Time and Frequency domain based AEC system to be designed and this work simulation results are obtained using MATLAB and waveforms are observed in WAVOSAUR.

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