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Analysis and Implementation of Time-Varying Least Mean Square Algorithm and Modified Time-Varying LMS for Speech Enhancement

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Abstract: ***This paper aims to investigate performance analysis and enhancements for the adaptive algorithms in speech enhancement and develop refined algorithms. The speech signal may get corrupted due to different types of noise. Hence, it becomes a challenge to maintain its high quality [2]. Noise Cancellation is a technique used for reducing undesired noise signal. Communication has become an integral part of our life. Main challenge in speech enhancement is performance analysis of algorithm in non-stationary environment Analysis of Time-Varying Least Mean Square Algorithm and Modified Time-Varying LMS algorithms and comparison on the basis of various performance indices like MSE, SNR. Objective of Implementing and analyzing the adaptive filter algorithms is to improve convergence behavior, reduce computational requirements and decrease steady state mean square error. The experimental results reveal that the modified TVLMS algorithm outperforms the existing TVLMS algorithm.***

Keywords: LMS, TVLMS, SNR,MSE, Execution Time

1. Introduction

Noise Cancellation is a technique used for reducing undesired noise signal. Communication has become an integral part of our life. Improvements in Network bandwidth, computing speed, digital storage capacities, and techniques of noise reductions are changing our lives. In recent years, with the development of data communication in Internet and Wireless networks, more and more information is frequently transmitted as digital forms including text, image, audio, video and other media. Adaptive filters finds variety of applications in communication which includes noise control, echo cancellation and online machine learning. Adaptive filters are suitable for the systems in which the statistical characteristics of the signals to be filtered are either unknown prior or time variant (non-stationary signal) [3]. Adaptive filters attract great attention because of robustness against noise and low computational complexities. Adaptive filters have received considerable importance over last two decades. Many adaptive filtering algorithms have been proposed by the researchers. There is a need for application specific adaptive filter algorithms. Speech enhancement is the area which deals with the improvement of quality and intelligibility of voice [4]. Speech enhancement finds the application in mobile phones, car communication, Teleconferencing, hearing aids, voice coders and Automatic speech recognition system

2. Literature Review

Set An early work on speech enhancement is done by widrow using LMS algorithm. A study of LMS was done, assuming a decreasing value of μ, convergence in probability of the LMS algorithm was already proved in the context of stochastic approximation.

Further work in the engineering field was done by Sinha and Griscik, followed by Ljung and Eweda and Macchi [7]. The assumption of a decreasing μ (convergence factor) cannot be applied to most applications, since it is desirable for the algorithm to continuously adapt. The earliest work assuming a constant μ was done by Widrow, Lucky and Gersho [10, 17, 18, 19 20] with the use of the independence assumptions; the work of Widrow et al [22] provided many useful results and rules of thumb that are still used today in spite of the independence assumption used; however, later on a precise study was developed in which was possible by assuming Gaussian regresses. Early attempts to get rid of the independence assumptions for the analysis of LMS were done by Daniel [6], obtaining a bound on the mean square deviation assuming ergodicity of second moments, bounded conditional fourth moments, and asymptotic independence of x_k ; those conditions however, could not be applied to Gaussian inputs. Davisson relaxed those conditions to obtain bounds on the steady state MSD assuming it converged to a steady-state value; convergence however, was not demonstrated.

During the late 90's, recent results on the exponential stability of random linear equations were used by Guo et al in an attempt to provide necessary and sufficient conditions for the stability of LMS [10]; their analysis included possibly unbounded, non stationary, and non phase mixing signals, obtaining results that could be applied to a very large class of signals, including those generated from a Gaussian process via a time-varying linear filter.

The work of Dabeer and Masry is the most general to date on the analysis of the LMS algorithm under stationary conditions. For completeness, we mention other studies that have been done on the properties of LMS for particular applications; for example, to implement filter [9][10], for

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adaptive noise canceling, with a tapped delay line with only two weights [9][12], for sinusoidal signals with inputs from cyclo-stationary processes [11] or cyclic sequences, for estimating a wide sense stationary channel [10], and for a tapped-delay with independent identically distributed inputs and large step-size [11][12].

3. Problem Definition

Efficient speech enhancement systems are required in applications like voice recognition system, voice communication products and mobile communication systems. Environment noise significantly degrades the performance of speech based applications. Therefore it is important to incorporate a speech enhancement system as a preprocessing step in these systems. Development of adaptive filter based algorithm and its application for speech enhancement is the focus of research in recent times. The adaptive filter based algorithms is a challenging and complex research area. After analyzing the existing adaptive filer algorithms, there is a need of refinement of the existing algorithms, with the following requirement

1) The adaptive filter algorithm based speech enhancement system should provide improvement in convergence behavior which leads to improvement in the speed of operation.
2) The System should reduce the noise present in the speech signal by improving the SNR.
3) The developed adaptive filter algorithm based speech enhancement system should reduce the Mean Square Error (MSE).

The noise reduction problem considered in this paper is on recovering the desired speech signal (clean speech) $s[n]$,

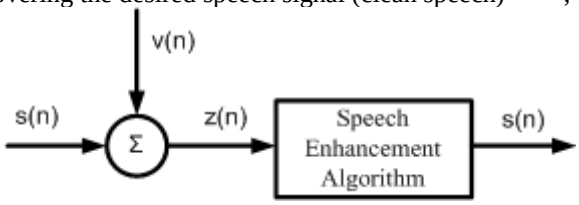


Figure 1.2: Problem Formulations

$$z[n] = s[n] + v[n] \quad (1.1)$$

where $s[n]$ represents speech model, $v[n]$ represents the noise, $z[n]$ represents the observed distorted signal, $\hat{s}[n]$ represents the enhanced, or estimated speech signal, n is the discrete time index of zero mean from the noisy observations(microphone signal)

3.1 Adaptive Filter

Adaptive filters self learn. As the signal into the filter continues, the adaptive filter coefficients adjust themselves to achieve the desired result, such as identifying an unknown filter or canceling noise in the input signal. Figure 3.1 shows block diagram that defines the Inputs and Output of a Generic RLS Adaptive Filter

Figure 3.1 Inputs and Output of a Generic RLS Adaptive Filter

The next figure provides the general adaptive filter setup with inputs and outputs. Figure 3,2 shows block diagram defining General Adaptive Filter Algorithm Inputs and Outputs

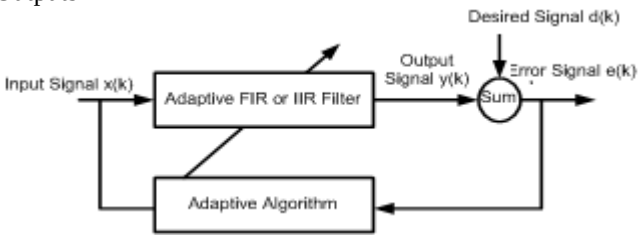


Figure 3.2: General Adaptive Filter Algorithm Inputs and Outputs

An adaptive filter designs itself based on the characteristics of the input signal to the filter and a signal that represents the desired behavior of the filter on its input. Designing the filter does not require any other frequency response information or specification. To define the self-learning process the filter uses, The selection of the adaptive algorithm used to reduce the error between the output signal y(k) and the desired signal d(k) is done.

When the LMS performance criterion for e(k) has achieved its minimum value through the iterations of the adapting algorithm, the adaptive filter has finished its work and its coefficients have converged to a solution. Now the output from the adaptive filter matches closely the desired signal d(k). When there is a change in the input data characteristics, sometimes called the filter environment, the filter adapts to the new environment by generating a new set of coefficients for the new data. Notice that when e(k) goes to zero and remains there you achieve perfect adaptation, the ideal result but not likely in the real world.

3.2 Time Varying LMS (TVLMS) Algorithm

The basic idea of TVLMS algorithm is to utilize the fact that the LMS algorithm need a large convergence parameter value to speed up the convergence of the filter coefficient to their optimal values, the convergence parameter should be small for better accuracy. In other words, the convergence parameter is set to a large value in the initial state in order to speed up the algorithm convergence. As time passes, the parameter will be adjusted to a small value so that the adaptive filter will have a smaller mean squared error.

In all the algorithms discussed above, the convergence factor is kept constant. In this case convergence factor is varied and hence referred to as TVLMS i.e. time varying LMS algorithm. For that purpose one new variable is defined and is called as alpha n. So the value of n can be varied and hence value of TVLMS is also varied. The algorithm for TVLMS is given by following equations,

$$w(n) = w(n-1) + \mu \times e(n) \times x(n) \quad (1.1)$$

Where, $\mu = \alpha_n \times \mu_0$

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$$\alpha_n = C(\frac{1}{1 + a_n b})$$

Where C, a and b are constants.

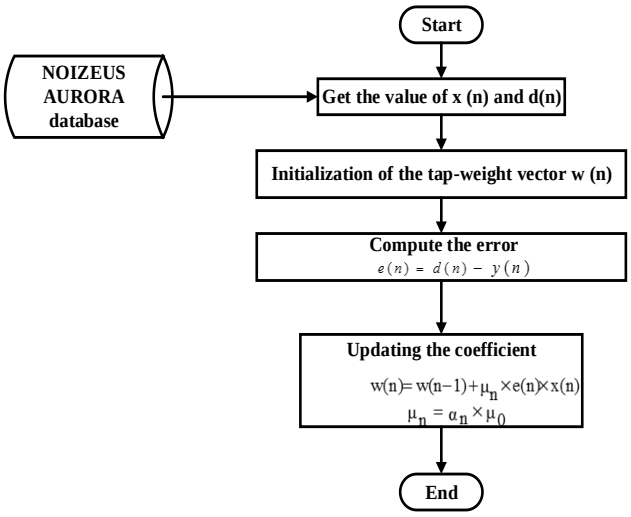


Fig. 3.9 Flow diagram for RLS algorithm

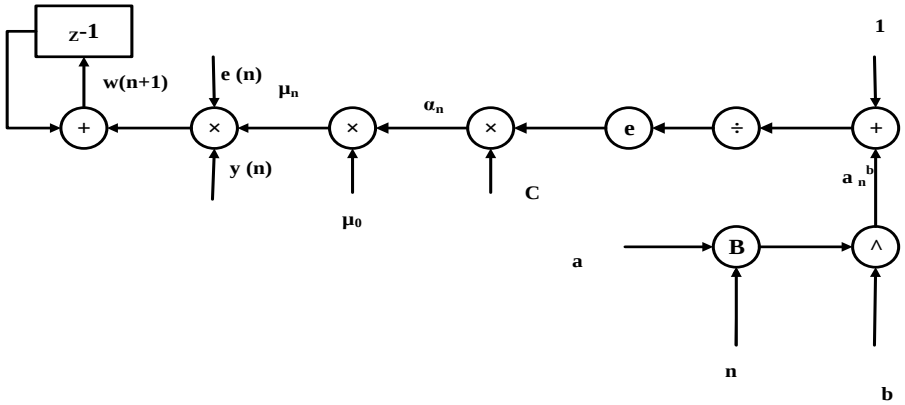


Fig. 3.10 Schematic Flow diagram for TVLMS algorithm

A novel approach for the least-mean-square (LMS) estimation algorithm is proposed. The approach utilizes the conventional LMS algorithm with a time-varying convergence parameter μn rather than a fixed convergence parameter μ. It is shown that the proposed time-varying LMS algorithm (TVLMS) provides reduced mean-squared error and also leads to a faster convergence as compared to the conventional fixed parameter LMS algorithm.

These algorithms have been tested for noise reduction and estimation in single-tone sinusoids and nonlinear narrow-band FM signals corrupted by additive white Gaussian noise. The study shows that the TV-LMS algorithm has a computation time close to conventional LMS algorithm with the advantages of faster convergence time and reduced mean-squared error

3.3 Modified TVLMS Algorithm

The algorithm for Modified TVLMS is given by following equations,

$$w(n) = w(n-1) + \mu \times e(n) \times x(n) \qquad (1.2)$$

Where, $\mu = \alpha_n \times \mu_0$

$$\alpha_n = C(\frac{1}{FsFact + a.n b})^{\frac{1}{fs}}$$

$$C = fs^2$$

$$a = \frac{1}{fs}$$

$$b = \frac{1}{fs}$$

Where fs is sampling frequency of input signal, and FsFact is constant.

3.4 Experimental Conditions

The speech signal with different combinations of noise signal is used for experimentation. The NOIZEUS AURORA database has used. For the implementation and analysis of algorithms, different speech signal data corrupted with three level 0dB, 5dB and 10dB of noise is considered and experimentations are carried out. These signals are collected from NOIZEUS database. The speech signal that we use was sp07 “We find joy in the simplest thing.” Different noise signals include Airport noise, Babble noise, Car Noise, Exhibition Noise, Restaurant Noise, Station Noise, Street Noise and Train Noise with 0dB, 5dB and 10dB values.

4. Results

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Table 1: Performance comparison TVLMS & M-TVLMS for different noise level for SNR

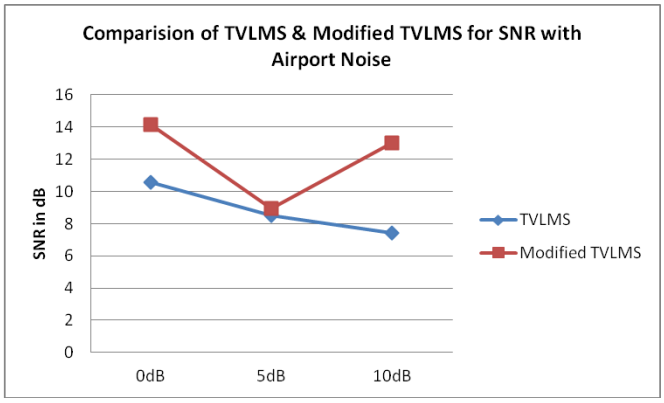
SNR	0dB	5dB	10dB
TVLMS	10.5812	8.5311	7.4149
Modified TVLMS	14.1355	8.9532	12.9926

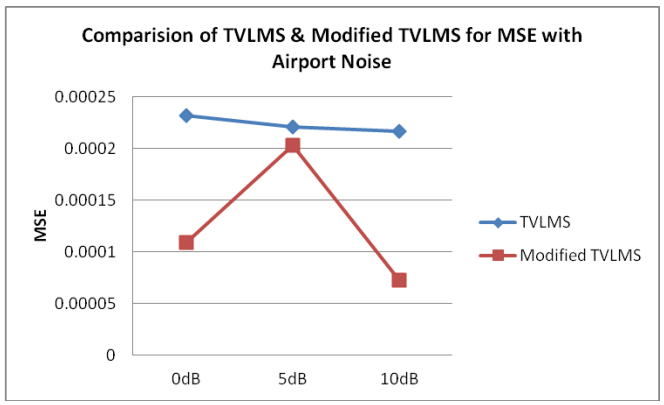
Table 2: Performance comparison TVLMS & M-TVLMS for different noise level for MSE

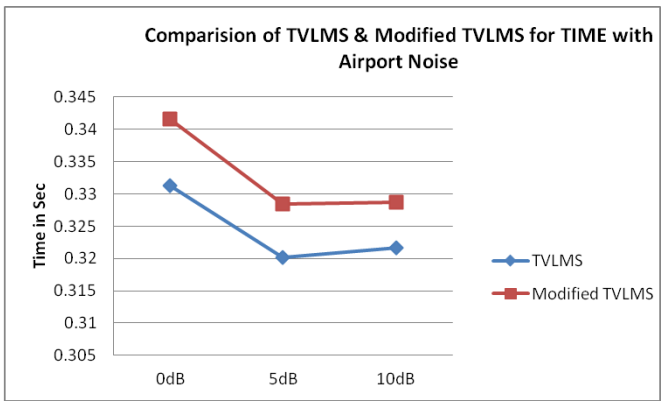
MSE	0dB	5dB	10dB
TVLMS	0.0002322	0.0002209	0.000217
Modified TVLMS	0.0001096	0.0002034	7.25E-05

Table 3: Performance comparison TVLMS & M-TVLMS for different noise level for Execution Time

Execution Time	0dB	5dB	10dB
TVLMS	0.33124	0.32018	0.32168
Modified TVLMS	0.3416	0.32845	0.3287







5. Conclusions

Experimental results reveal that the Modified TVLMS provides a better SNR as compared to existing TVLMS algorithm when the speech is corrupted by airport noise. The test is performed at 0dB, 5dB and 10dB airport noise. The experimentation and validation are carried out for Mean Square Error (MSE) is very less in case of Modified TVLMS as compared with existing TVLMS for low noisy data, medium noisy and highly noisy data. The performance parameter called as execution time is also compared and the experimentation confirms the modified TVLMS algorithm converges fast. The experimentation and validation is carried out for modified TVLMS and is compared with existing methods and it is observed that modified method performs better as compared to existing methods.

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