ANC BASED ON VARIABLE STEP SIZE NORMALIZED DIFFERENTIAL LMS ALGORITHM

G.SUNIL KUMAR1, DR.S.M.RAMESH2

1Research scholar, Department of ECE, Sri Satya Sai University of Technology and Medical Sciences, Sehore, Bhopal, Madhya Pradesh
2Professor, Department of ECE, KPR Institute of Engineering and Technology (Autonomous), Coimbatore

ABSTRACT

Interference noise in speech signals is the most common problem in speech processing. Acoustic sources of disturbance include ventilation devices, traffic crowds, and, more generally, reverberation and echoes. The LMS algorithm is the basic adaptive algorithm, but its main disadvantage is that the excess mean square error increases linearly with the desired signal power. The Variable Step Size Normalized Differential LMS algorithm (VSSNDLMS) was proposed in this paper for filtering speech sounds in the adaptive noise cancellation (ANC) problem. Real-world speech signals with varying levels of noise power were used in simulations. The results show that the proposed VSSNDLMS algorithm is superior, with much lower steady-state excess mean square error.

Keyword: Adaptive noise canceler, least-mean-square (LMS), stability constraint, and speech enhancement.

I. INTRODUCTION

The elimination of background noise from a speech signal is a noise cancellation operation. Special difficulties arise in various processed signal tasks such as voice recognition, speech recognition, speakers’ verification etc. because of background noise and some other noises [1-4]. There are many techniques used to avoid noise caused by a speech signal, such as linear and non-linear filtering, adaptive cancellation of noise and absolute de-noising for variations. Speech improvement helps to increase the voice signal quality by reducing background noise. Clarity, intelligibility and pleasure are an important factor in the quality of speech [5-7]. Including speech recognition, speech synthesis, speech interpretation and speech coding, voice enhancing is a preliminary technique in the field of speech processing. Speaking signals are often damaged by short duration’s noises such as an impulsive noise in the communications systems[8]. These interferences are particularly disagreeable to listeners and should be eliminated so that speech signals are better able and more intelligible. Most algorithms for voice signals processing are supposed to be additive in their design and to obey Gaussian distribution. But the non-Gaussian probability distribution is characteristic for noises, such as impulsive noise. In the presence of impulsive noise, this dramatically reduces the efficiency of the speech processing systems[9 and 10]. This article analyses and compares different speech processing algorithms as LMS, NLMS, VSSNLMS and their disadvantages to the proposed algorithm (NDLMS) which improves the state output of adaptive noise cancelers in speech treatment.

II. LITERATURE REVIEW

Zayed Ramadan and et.al [11] proposed new variable step size LMS algorithms and performance has tested in terms of misadjustment (M) and excess MSE in stationary and nonstationary environment. They demonstrated that the performance of recommended algorithms is better than that of NLMS algorithm.

Paulo A. C. Lopes [12] proposed a Kalman based normalized LMS algorithm for speech enhancement and demonstrated the performance of the algorithm in OFDM equalization system. The algorithm extracts the advantages of both Kalman filter and NLMS algorithm in terms of speed of convergence and stability.
Ching-Ta Lu and et.al [13] reviewed the effect of overestimation and underestimation of the noise during speech enhancement and also proposed a method for development for a minima-controlled-recursive-averaging algorithm for noise estimation. Extending to above many researchers are focused in the area of speech enhancement and proposed different algorithms based on statistical and signal processing methods for improving signal to noise ratio(SNR), intelligibility, reducing musical noise, reducing Mean square error. The next section gives detail study of literature survey based on statistical and signal processing methods.

M.Górriz et al [14] suggested a new LMS algorithm based on minimalizing the Euclidean squared norm of a weight differential vector under a stability limit specified by an a posteriori estimation error. The algorithm performance evaluation is demonstrated using AURORA 2 and 3 speech databases.

Rey Vega L and et.al [15] offered a new robust variable step size NLMS algorithm. The algorithm based on optimization of the square of the posteriori error. They demonstrated the performance of the algorithm using different noise environments for both system identification and noise cancellation along with theoretical model.

Ramsey Faragher [16] presented a review article on Kalman filter and its applications. The author describes computational requirement, recursive properties and using as optimal estimator for one-dimensional system with Gaussian noises.

III. PROBLEM STATEMENT

- LMS Drawback: The LMS is very straightforward in computational terms; however, due to the stochastic and nonlinear design of the filter, its mathematical analysis is extremely complicated.

- The phase size variable It is proposed to use the NLMS algorithm where phase size adjustment is monitored by the SNR estimate which is provided by the ratio between the average power of the original signal and the average noise signal power.

IV. MATERIALS AND METHODS

4.1 Adaptive Algorithms

Adaptive filtering algorithms can be considered as a mechanism in which, by some criteria, the parameters used to process signals change. The estimated average squared error or correlation is usually the criterion. The adaptive filters differ because their parameters change continuously to fulfil the performance needs. A filter that carries out on-line the approximation step can be interpreted in that sense as adaptive filter. Typically a reference signal that is usually concealed during approximation phase of the fixed-filter design must be present for the definition of the criterion of efficiency. Let us look at the Least Medium Squares Algorithm (LMS) in depth. We also evaluate the LMS variants of two other algorithms. They are Normalized lowest mean squares (NLMS) and standardized variable-step size algorithms for minimum mean squares (VSS-NLMS).

4.2 VARIABLE STEP SIZE LMS ALGORITHM

ANC utilizing VSSLMS Procedure is utilized as an Adaptive Filter to eliminate the noise from the discourse signal. For STT change model, noiseless discourse is needed for STT Transformation.

Based on the mistake squared force, planned a less complex VSSLMS algorithm. The mistake power mirrors the intermingling condition of the adaptive channel, where a joining framework has a higher blunder power while the merged framework has a more modest blunder power. In this way, scalar step size increments or diminishes as the squared blunder increments or diminishes, consequently permitting the adaptive channel to follow changes in the framework and produces a more modest consistent state mistake.

ISE in VSSLMS algorithm, the step size variation is constrained by the square of the expectation blunder. A huge expectation blunder will vary step size to increment to give quicker following while a little forecast mistake will bring about a lessening in step size to achieve more modest maladjustment. By considering the adaptive separating or the framework ID issue, a bunch of channel loads is changed so the framework yield tracks an ideal sign. Leave the information vector of the framework alone signified by $X_k$ and the ideal scalar yield is $d_k$. These cycles are connected by the condition.
\[ d_k = X_k^TW_k^* + e_k \]  

Where, \( e_k \) is a zero mean Gaussian autonomous grouping, free of the information interaction \( X_k \). As considered two cases will be:

1. \( W^* \) equals a constant \( W^* \)

2. \( W^* \), is randomly varying according to the equation.

Here the primary case will be alluded to as a fixed framework climate, the second a non-stationary framework or climate.

\[ W_{t+1}^* = aW_t^* + Z_k \]  

Here ‘\( a \)’ is less than but near to 1, and \( Z_k \), is an independent zero mean sequence which is independent of \( X_k \) and \( e_k \) with the covariance \( E\{Z_kZ_k^T\} = \sigma^2 \). The input process \( X_k \), is assumed with covariance \( E\{Z_kZ_k^T\} = R \), a positive definite matrix.

There is a gradient search algorithm as LMS category adaptive algorithm, which totals a set of weights \( W_t \) that seeks to lessen \( E\{d_kX_k^TW_k\}^2 \), and \( \mu_k \), the size of the step. The LMS algorithm is standard. He's constant. He's a constant. In some cases \( \mu_k \), the time varies with the value of an error gradient estimate determined by the number of changes in the signs. In the step algorithm, the step size can be set \( \mu_k \).

\[ W_{k+1} = W_k + \mu_kX_k\epsilon_k \]  

Where,

\[ \epsilon_k = d_k - X_k^TW_k \]  

\[ \mu_{k+1}^* = \alpha\mu_k + \gamma\epsilon_k^2 \]  

\[ 0 < \alpha < 1, \quad \gamma > 0 \]

\[ \mu_{k+1} = \begin{cases} \mu_{max} \ldots \ldots \text{if} \mu_{k+1} > \mu_{max} \\ \mu_{min} \ldots \ldots \text{if} \mu_{k+1} < \mu_{min} \\ \mu_{k+1} \ldots \ldots \text{otherwise} \end{cases} \]  

Where, \( 0 < \mu_{min} > \mu_{max} \). The initial step size \( \mu_0 \), is usually taken to be \( \mu_{max} \), although the algorithm is not sensitive to the choice. From (6), phase 4 can be seen as always positive and the prediction error size and the parameters \( \alpha \) and \( \gamma \) is regulated. The phase size to provide faster monitoring is increased by a significant prevision error. If the preview error declines, the phase size to minimize the maladjustment would be decreased. A constant \( \mu_{max} \) to ensure that the algorithm’s MSE (MSE) remains limited. A condition to ensure MSE is limited

\[ \mu_{max} \leq \frac{2}{\text{str}(R)} \]  

A sufficient level of tracking capacity is chosen. Usually the value of \( u \) that is chosen for the fixed step size algorithm (FSS) is \( \mu_{max} \), and ‘\( a \)’ must be selected in the range (0, 1). The \( y \) parameter is generally small and can be chosen together with the requirements of maladjustment.

### 4.3 NORMALIZED DIFFERENTIAL LMS ALGORITHM

ANC utilizing Normalized Differential LMS Algorithm is utilized as an AF to eliminate the noise from the discourse signal. For STT change model, noiseless discourse needed for STT Transformation.

In NDLMS Algorithm an alternate methodology is considered for weight change. The inspiration is to plan aLMS that can deal with both the solid and the feeble objective signs. Consequently at whatever point the channel data sources and yields vary pretty much, the loads ought to be changed appropriately. Some unfriendly impacts may happen when we utilize aLMS algorithm as portrayed in (1). Under the situation that the weight \( W (k) \) has been
moving toward the ideal worth $W_{opt}$, when $e(k)$ are generally huge for some time, Condition (8) suggests that $W(k)$ will stay away from the ideal load in a moderately huge way. This makes the adaptive loads vary around their ideal qualities for a generally longer period; and it is beyond the realm of imagination to expect to make the consistent state EMSE discretionarily little by diminishing $u$.

LMS algorithm conditions and they suggest the Normalized Differential LMS Algorithm. It is principally utilized for finding the blunder signal and the channel loads. For this situation the algorithm improves the consistent state execution for dropping noise in discourse preparing. NDLMS Algorithm proposes to change the load as per the distinction of the signs, rather than the actual signs. Like the normalized LMS plot, the weight update condition becomes

$$w(n+1) = w(n) + \frac{\mu}{\varepsilon + \nabla x(k)^2} \nabla x(n) \cdot \nabla e(n)$$ (8)

This algorithm is appropriate for discourse handling where the extents of discourse flags for the most part fluctuate gradually. The exhibition model behind this proposition is the MSE distinction measure,

$$J(k) = E[|e(k) - e(k-1)|^2]$$ (9)

If an independent random sequence identified as $\{x(k)\}$ and the elements of $\nabla x(k)$ are identically distributed satiating the subsequent conditions,

$$E\{\nabla x(i)\} = 0 \text{ and } E\{\nabla x(i)\nabla x(j)\} = \sigma_{\nabla x}^2 \delta(i - j)$$

At that point the ideal change acquire is $u = 12$ and the ideal union rate $\text{ist } = 1 - 1/N$. NDLMS algorithm is utilized for both the solid and the frail objective signs, yet the step size $u$ worth isn’t variable, so union rate is low.

V. PROPOSED VARIABLE STEP SIZE NORMALIZED DIFFERENTIAL LMS ALGORITHM

ANC utilizing Variable Step Size Normalized Differential LMS Algorithm is utilized as an AF to eliminate the noise from the discourse signal. For STT change model, noiseless discourse needed for STT Transformation.

The NDLMS and VSSLMS are consolidated together and an improved productive algorithm called Variable Step Size Normalized Differential LMS (VSSNDLMS) algorithm is proposed to upgrade discourse handling. The target of proposing this algorithm is to plan a viable adaptive channel to eliminate the noise and to improve the nature of discourse signals. Figure 3.4 shows the proposed algorithm utilizing VSSNDLMS technique.

The Normalized Differential LMS Algorithm is especially appropriate for gradually changing signals and is less delicate to the craving signal force variety contrasted with the current Algorithms. Additionally, the abundance mistake and maladjustment by NDLMS are substantially less than that of existing Algorithms. VSSLMS Algorithm is utilized to diminish the compromise among maladjustment and following capacity of the fixed step size LMS Algorithm. The VSSLMS likewise diminishes affectability of the maladjustment to the degree of non-fixed. The highlights of NDLMS and VSSLMS are consolidated, VSSNDLMS Algorithm is proposed.

In the event of LMS algorithm under non-fixed climate, blunders happen which prompts deviation of channel loads from the ideal load of the channel. The proposed algorithm fulfills this standard by changing the step size. The VSSLMS algorithm combines quicker and NDLMS algorithm has negligible MSE. By joining the VSS and NDLMS, the VSSNDLMS algorithm combines quickly with MMSE. VSSNDLMS Algorithm are represented in follows as,

Step 1: Input discourse signal in (*.wav) design
Step 2: Select the VSSNDLMS Algorithm
Step 3: Select step size
Step 4: Update weight vector
Step 5: Compute info and yield
Step 6: Compute MSE
Step 7: Check blunder $e(n) = 0$, if off limits to step 3
Step 8: Stop
A normal Adaptive Noise Canceller has two sources of info: 1) an essential information, $d(k)$, made out of the ideal sign, $s(k)$, debased by a sifted added substance noise signal $v(k)$, and 2) a reference input, $X(k)$, which is an alternate channel noise and the contribution to the adaptive channel. $X(k)$ is thought to be connected with $v(k)$ and uncorrelated with $s(k)$. The yield of Adaptive Noise Canceller is $e(k)$, it is the Difference of essential information and the yield of the adaptive channel. The noise signal is addressed by $n(k)$.

The distinction in input $x(k)$ and contrast in yield $e(k)$ is given to VSSNDLMS Algorithm.

![Figure 1: Proposed VSSNDLMS Algorithm](image)

**VI. EXPERIMENTAL RESULT AND DISCUSSION**

In this section we discuss about the performance of the proposed method with variable step size LMS and normalized differential LMS algorithm. Here VSSLMS Algorithm is utilized in Adaptive channels to remove Noise from the Speech signal. Speaker creates the yield of the discourse sign and reproduction results are performed utilizing MATLAB. Figure 2 shows the reproduced MATLAB information, yield and MSE of the discourse signal.

![Figure 2: Input speech signal corrupted with Noise and VSSLMS Output of Speech Signal](image)

The discourse signal is tried with NDLMS Algorithm. Here NDLMS Algorithm is utilized in Adaptive channels to eliminate Noise. The speaker creates the yield of the discourse sign and recreation results are performed utilizing MATLAB, which are examined in the Next Chapter. Figure 3 shows the reproduced MATLAB input yield and MSE of the discourse signal.
Discourse Signal is tried with VSSNDLMS Algorithm. Figure 4 shows the square outline of ANC utilizing Improved Adaptive channel Based Noise cancellation Techniques for discourse signals. Here Proposed VSSNDLMS Algorithm is utilized in Adaptive channels to eliminate Noise from Speech signal. The speaker creates the yield of the discourse sign and reenactment results are performed utilizing MATLAB, which are examined in the Next Chapter. Figure 5 shows the reproduced MATLAB information, yield and MSE of the discourse signal.

**Figure 3:** Input speech signal corrupted with Noise and NDLMS Output of Speech Signal

**Figure 4:** Experimental Setup of Adaptive Filter using VSSNDLMS Algorithm

**Figure 5:** Input speech signal corrupted with Noise and NDLMS Output of Speech Signal
VII. CONCLUSION

The proposed amended VSSNDLMS algorithm has improved performance in Excess MSE, for example. It can be expanded for in-house and non-stationary speech processing applications. In real-time applications such as speech therapy with DSP processors, this proposed algorithm is implemented. For the future work in this field, these algorithms can be implemented using a digital signal processor to compare the speed and the malfunctions of the algorithms. A real-time implementation is also a way to interface a real sound into a processor and to get the output in a filtered version of the input signal that compares performance with speed.

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Mr. G. Sunil Kumar isa research scholar in the Department of Electronics and Communication Engineering in Sri Satya Sai University of Technology and Medical Sciences,Sehore, Bhopal, Madhya Pradesh. He has completed his M.Techin VLSI System Design and B.Tech in ECE from JNTU, Hyderabad.

Dr. S.M. Ramesh is a Professor and currently working in the Department of Electronics & communication engineering in KPR Institute of Engineering and Technology (Autonomous), Coimbatore. His research areas include Signal Processing, VLSI, Embedded Systems and Communications. He has published many journals and also supervising many research scholars from various institutes in India.