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# Adaptive Noise Cancellation for Speech Processing in Real Time Environment

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## Abstract

**The most common problem in speech processing is the interference noise in speech signals. Interference can come from acoustical sources such as ventilation equipment, traffic crowds and commonly reverberation and echoes. The basic adaptive algorithm is the LMS algorithm but its' major drawback is the excess mean square error increase linearly with the desired signal power. We proposed an algorithm for adaptive noise cancellation using normalized differential least mean square NDLMS algorithm in real time environment. In this paper NDLMS algorithm is proposed to deal with situation when the desired signal is strong for example, speech signal. Simulations were carried out using real speech signal with different noise power levels. Results demonstrate the superiority of the proposed NDLMS algorithm over LMS algorithm in achieving much smaller steady state excess mean square error.**

**Keywords***:* ANC, Noise Power, Speech Signal, Step Size , SNR.

## 1. Introduction

Noise cancellation is the process of removing background noise from speech signal. The degradation of speech due to the presence of background noise and several other noises cause difficulties in various signal processing tasks like speech recognition, speaker recognition, speaker verification etc [1]. Many methods have been widely used to eliminate noise from speech signal like linear and nonlinear filtering methods, adaptive noise cancellation, total variation denoising. Speech enhancement aims in improving the quality of the speech signal by reducing the background noise. Quality of speech signal is weighed by its clarity, intelligibility and pleasantness [2]. Speech enhancement is a preliminary procedure in the speech processing area, including speech recognition, speech synthesis, speech analysis and speech coding. In communication systems speech signal is sometimes corrupted with short duration noises like impulsive noise [3]. To listeners, these interferences are highly unpleasant and should be suppressed in order to enhance the quality and intelligibility of speech signal. Most of the speech-signal processing algorithms are based on the assumption that the noise follows Gaussian distribution and is additive in nature. But noises like impulsive noise are characterized by non-Gaussian probability distribution. This will reduce the performance of the speech processing systems drastically, in presence of impulsive noise [3]. In this paper the various speech processing algorithms like LMS, NLMS, VSS NLMS and its drawbacks are analysed and compared with the proposed algorithm (NDLMS) that improves the steady state performance of the adaptive noise cancellers for speech processing.

### 1.1 Adaptive Filtering

Adaptive filtering can be considered as a process in which the parameters used for the processing of signals changes according to some criterion [4]-[6]. Usually the criterion is the estimated mean squared error or the correlation. The adaptive filters are time-varying since their parameters are continually changing in order to meet a performance requirement. In this sense, an adaptive filter can be interpreted as a filter that performs the approximation step on-line. Usually the definition of the performance criterion requires the existence of a reference signal that is usually hidden in the approximation step of fixed-filter design. The general set up of adaptive filtering environment is shown in Figure 1, where k is the iteration number, x(k) denotes the input signal, y(k) is the adaptive filter output, and d(k) defines the desired signal. The error signal e(k) is calculated as d(k)-y(k). The error is then used to form a performance function or objective function that is required by the adaptation algorithm in order to determine the appropriate updating of the filter coefficients. The minimization of the objective function implies that the adaptive filter output signal is matching the desired signal.

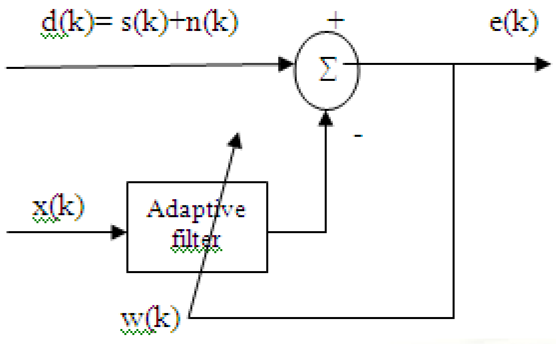


Figure 1: Adaptive Filter as a Noise Canceller

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. By way of contrast, a non-adaptive filter has a static transfer function. Adaptive filters are required for some applications because some parameters of the desired processing operation (for instance, the locations of reflective surfaces in a reverberant space) are not known in advance. The adaptive filter uses feedback in the form of an error signal to refine its transfer function to match the changing parameters. Generally speaking, the adaptive process involves the use of a cost function, which is a criterion for optimum performance of the filter, to feed an algorithm, which determines how to modify filter transfer function to minimize the cost on the next iteration .As the power of digital signal processor has increased, adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment.
Applications of adaptive filter are Noise cancellation, Adaptive feedback, Adaptive feedback cancellation, Echo cancellation. There are various adaptive filter algorithms available. These algorithms when applied through a filter result in adaptive filters. These filters are then used to remove noise from the noise mixed speech in order to enhance the speech.

## 2. Adaptive Algorithms

Adaptive filtering algorithms can be considered as a process in which the parameters used for the processing of signals changes according to some criterion. Usually the criterion is the estimated mean squared error or the correlation. The adaptive filters are time-varying since their parameters are continually changing in order to meet a performance requirement. In this sense, an adaptive filter can be interpreted as a filter that performs the approximation step on-line. Usually the definition of the performance criterion requires the existence of a reference signal that is usually hidden in the approximation step of fixed-filter design. Let us analyse in detail about Least mean Squares (LMS) algorithm. We also analyze two other algorithms which are the variations of LMS. They are Normalized Least Mean Squares (NLMS) and the Variable Step Size Normalizes Least Mean Squares (VSS-NLMS) algorithms.

### 2.1 LMS Algorithm

The LMS algorithm was devised by Widrow and Hoff in 1959 in their study of a pattern-recognition machine known as the adaptive linear element, commonly referred to as the Adeline[7]. The LMS algorithm is a stochastic gradient algorithm in that it iterates each tap weight of the transversal filter in the direction of the instantaneous gradient of the squared error signal with respect to the tap-weighting question.

Let w^(n) denote the tap-weight vector of the LMS filter, computed at iteration (time step) n. The adaptive operation of the filter is completely described by the recursive equation (assuming complex data)

$$\hat{\mathbf{W}}(n+1) = \hat{\mathbf{W}}(n) + \mu\mathbf{u}(n)[d(n)-\hat{W}^H(n)u(n)]^* \qquad (1)$$

The quantity enclosed in square brackets is the error signal. The asterisk denotes complex conjugation, and the superscript H denotes Hermitian transposition. Equation (1) is testimony to the simplicity of the LMS filter. This simplicity, coupled with desirable properties of the LMS filter and practical applications has made the LMS filter and its variants an important part of the adaptive signal processing kit of tools, not just for the past 40 years but for many years to come. Simply put, the LMS filter has withstood the test of time. The stochastic nature of the LMS filter manifests itself in the fact that in a stationary environment, and under the assumption of a small step-size parameter, the filter executes a form of Brownian motion. Specifically, the small step-size theory of the LMS filter is almost exactly described by the discrete-time version of the Langevin equation.

$$\begin{aligned}\Delta v_k(n) &= v_k(n+1)-v_k(n)\\ &= -\mu\lambda_k v_k(n)+\varphi_k(n),\ \ k=1,2,\ldots M \qquad (2)\end{aligned}$$

To illustrate the validity of Equation (2) as the description of small step-size theory of the LMS filter, we present the results of a computer experiment on a classic example of adaptive equalization. The example involves an unknown linear channel, whose impulse response is described by the raised cosine series as,

$$H_n = \begin{cases} \frac{1}{2}\left[1+\cos\left(\frac{2\pi}{w}(n-2)\right)\right] & ,n=1,2,3 \\ 0 & ,otherwise \end{cases} \qquad (3)$$

Where the parameter W controls the amount of amplitude distortion produced by the channel, with the distortion increasing with W. Equivalently, the parameter W controls the Eigen value spread (i.e., the ratio of the largest Eigen value to the smallest Eigen value) of the correlation matrix of the tap inputs of the equalizer, with the Eigen value spread increasing with W. The equalizer has M ¼ 11 taps

**Drawback of LMS:**

Although the LMS filter is very simple in computational terms, its mathematical analysis is profoundly complicated because of its stochastic and nonlinear nature.

### 2.2 NLMS Algorithm

In the standard LMS algorithm, when the convergence factor μ is large, the algorithm experiences a gradient noise amplification problem [8]. In order to solve this difficulty, we can use the NLMS (Normalized Least Mean Square) algorithm. The correction applied to the weight vector w(n) at iteration n+1 is "normalized" with respect to the squared Euclidian norm of the input vector x(n) at iteration n. We may view the NLMS algorithm as a time-varying step-size algorithm, calculating the convergence factor μ as in equation (4).

$$\mu(n) = \frac{\alpha}{c+||x(n)||\text{^}2} \qquad (4)$$

Where α is the NLMS adaption constant, which optimize the convergence rate of the algorithm and should satisfy the condition 0< α<2, and *c* is the constant term for normalization and is always less than 1.The Filter weights are updated by the equation (5).

$$W(n+1)=w(n)+\frac{\alpha}{c+||x(n)||\text{^}2}\, e(n)x(n) \qquad (5)$$

This algorithm has two distinct advantages over the LMSalgorithm.potentially-faster convergence speeds for both correlated and whitened input data. Stable behavior for a known range of parameter values.

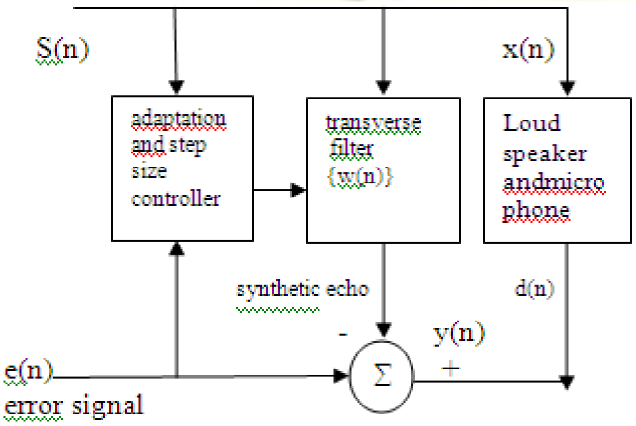


Figure 2: Block Diagram of NLMS

**Drawback of NLMS**:

The NLMS algorithm requires a minimum of one additional multiply, divide, and addition over the LMS algorithm to implement for shift-input data. Even so, the multiplies required for the algorithm update may still be prohibitive in certain high-data-rate applications. In these situations, it is useful to determine modified versions of the NLMS algorithm that retain the fast convergence properties of the algorithm while reducing the amount of computation per iteration.

### 2.3 VSS-NLMS algorithm

The variable step size NLMS algorithm is proposed where the step size adjustment is controlled by the estimation of signal to noise ratio (SNR), which is produced by the ratio of the average power of the original signal to the average power of the noise signal [9]. The motivation is that a small SNR will cause the step size to increase to provide faster tracking while a large SNR will result in a decrease in the step size to yield smaller maladjustment. The ANC (Adaptive noise canceller) using the variable step size NLMS algorithm is shown in Figure 3 and the SNR is found by equation( 6),

$$SNR(n) = 10 \log_{10} P_S(n)/P_n(n) \text{ dB} \qquad (6)$$

Where $P_S(n)$ and $P_n(n)$ are the average power of the speech and noise signal.
The updating of the normalized filter coefficients is given by,

$$W(n+1) = W(n) + \frac{\mu}{X^T(n)X(n)} e(n)X(n) \qquad (7)$$

Where μ is the step size coefficient. The step size μ is controlled by the SNR(n). If SNR(n) is small, the step size μ is set large for fast convergence. Otherwise the step size is set small.

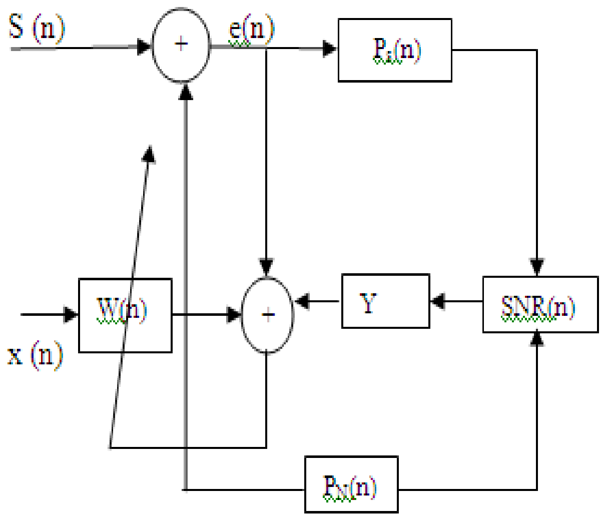


Figure 3: VSS-NLMS Adaptive Filter Setup

**Drawback of VSS-NLMS**:

Its implementation requires 5N±4 multiplications N multiplications for calculating the output , one to obtain $\nabla e(n)$,N+1 for normalization, 2N+2 for estimating the SNR, and N for the scalar-by vector multiplication $[\nabla e(n)]$ $[\nabla X(n)]$ plus 5N-3 additions.

### 2.4 Proposed Algorithm (NDLMS)

Here we consider a different approach for weight adjustment. The motivation is to design an LMS algorithm that can tackle both the strong and the weak target signals. Hence whenever the filter inputs and output fluctuate more or less, the weights should be adjusted accordingly. Some adverse effects may occur for the LMS algorithm described in equation(1).Under the Circumstance that the weight w(n) has been approaching the optimal value. When e(n) is relatively large for a while, equation(1) implies that w(n) will deviate away from the optimal weight in a relatively large manner. This causes the adaptive weights to fluctuate around their optimal values for a relatively longer period; and it is not possible to make the steady-state excess MSE arbitrarily small by reducing f(n) which is given by,

$$f(n) = \frac{\mu}{\left[L\left(\|e(n)\|^2+\mu\|x(n)\|^2\right)\right]} \qquad (8)$$

We proposed to adjust the weight according to the difference of the signals, instead of the signals themselves. Similar to the NLMS scheme, the weight update equation becomes,

$$w(n+1) = w(n) + \frac{\mu}{\varepsilon+\|\Delta x(n)\|^2}\Delta e(n)\Delta x(n) \qquad (9)$$

Where

$$\Delta e(n) = e(n)-e(n-1) \qquad (10)$$

is the first order difference of the ANC output signals and

$$\Delta x(n) = x(n)-x(n-1) \qquad (11)$$

the first order difference of the input ANC input. This adaptive scheme is called the normalized difference LMS (NDLMS) algorithm. It follows from (9) that the weight adjustment is in proportion to the variation of the signal magnitude. Hence, whether the desired signal is strong or not, the degree of the adaptation depends only on how large the signal magnitude varies. This algorithm is very suited for speech processing in the magnitudes of speech signals are generally slowly varied .The performance criterion behind this proposal is the mean square error difference criterion.

$$J(n) = E\{|e(n)-e(n-1)|^2\} \qquad (12)$$

If $\{\Delta x(n)\}$ is an independent random sequence and the elements of $\Delta x(n)$ are independent and identically distributed satisfying the following conditions

$$E\{\Delta x(i)\} = 0 \text{ and} \qquad (13)$$

$$E\{\Delta x(i)\Delta x(j)\} = \sigma^2_{\Delta x}\delta(i-j), \qquad (14)$$

Then the optimal adjustment gain is $\mu^*=1$ and the optimal convergence rate is

$$\eta^* = 1-1/N \qquad (15)$$

## 3. Simulation Results

Extensive simulations were carried out to validate the effectiveness of the proposed adaptive noise cancellation algorithm. Results presented here are for a male speech signal sampled at 44.1KHz .Simulations of the NDLMS algorithm is carried out with the following specifications, Mean Square Error = 0.0090 , Variance = 0.9972 , First order N = 200, Step size μ = 0.1. The number of bits per sample is 8 and the total number of samples is 33000. In all simulations, the values of parameters used are L = 12, N = 200, and P = 2000. The step-size is selected for a tradeoff between small excess MSE and high initial rate of convergence for a wide range of noise variances. The value of u used in the simulation, which is selected as a tradeoff between fast rate of convergence and good tracking capability, is 0.5 for the modified NLMS algorithm and 0.1 for the NLMS and the proposed NDLMS algorithms. The impulse responses of the two IIR low-pass filters that produce the filtered additive noise v(k) and the reference input x(k) are hl = [1 -0.3 -0.1] and h2 = [1 -0.2], respectively.

It is known that the quality of adaptation can be measured by the mis adjustment , M, which is the dimensionless ratio of the EMSE to the MMSE in the steady-state environment [4], [10],[11] .

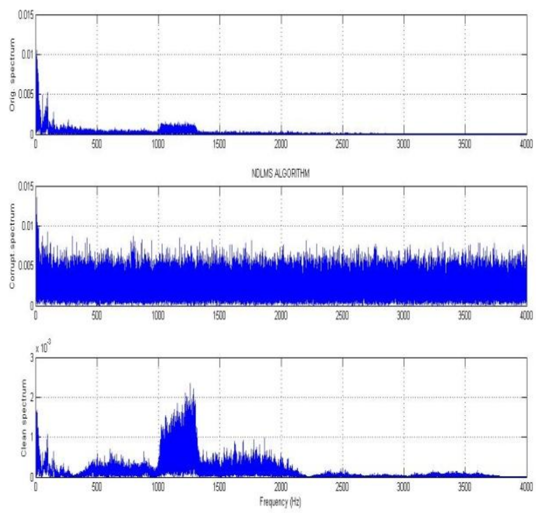


Figure 4 : Clean Speech Signal, Speech Signal Corrupted by Noise,

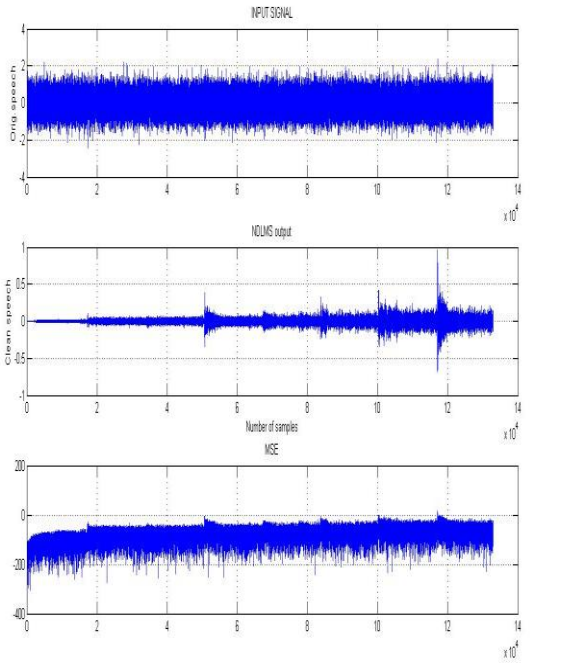


Figure 5: Noise Cancelled Speech Signal by the Proposed Method

## 4. Conclusion

The proposed modified NDLMS algorithm exhibits better performance such as lower level in Excess MSE and mis adjustment. It can be expanded for real time speech processing applications corrupted by stationary and non-stationary noises. The proposed algorithm will be implemented in real time applications like speech therapy using DSP processor. The future work in this field can be trying to implement these algorithms using a digital signal processor so as to compare the algorithms' speed and mal-adjustments. A real-time implementation is also a possibility wherein a real audio speech can be interfaced into a processor and the output can be retrieved in the form of an audio speech which is filtered version of the input signal thus comparing the performance and speed. Simultaneously an FPGA implementation can also be done and the best can be identified .After identifying the best possible implementation, the next step could be a real time implementation and making it market ready.

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