

# Noise Cancellation In Speech Signal Processing Using Adaptive Algorithm

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**Abstract**— Speech has always been one of the most important carriers of information for people it becomes a challenge to maintain its high quality. In many application of noise cancellation, the changes in signal characteristics could be quite fast. This requires the utilization of adaptive algorithms, which converge rapidly. Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) adaptive filters have been used in a wide range of signal processing application because of its simplicity in computation and implementation. The Recursive Least Squares (RLS) algorithm has established itself as the “ultimate” adaptive filtering algorithm in the sense that it is the adaptive filter exhibiting the best convergence behavior. Unfortunately, practical implementations of the algorithm are often associated with high computational complexity and/or poor numerical properties. Recently adaptive filtering was presented, have a nice tradeoff between complexity and the convergence speed. This paper describes a new approach for noise cancellation in speech signal using the new adaptive filtering algorithm named affine projection algorithm for attenuating noise in speech signals. The simulation results demonstrate the good performance of the new algorithm in attenuating the noise

**Keywords**- Adaptive Filter, Least Mean Squares, Normalized Least Mean Squares, Affine Projection, Noise Cancellation, and Speech Enhancement

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## I. INTRODUCTION

It is well known that two of most frequently applied algorithms for noise cancellation [1] are Least Mean Square algorithm and Normalized Least Mean Squares (NLMS) [2-5]. Considering these two algorithms, it is obvious that LMS algorithm has the advantage of low computational complexity. On the contrary, the high computational complexity is the weakest point of NLMS algorithm but it provides a fast adaptation rate. Thus, it is clear that the choice of the adaptive algorithm to be applied is always a tradeoff between computational complexity and fast convergence. The convergence property of the AP algorithms is superior to that of the usual LMS, NLMS and comparable to that of the RLS algorithm. In these algorithms, one of the filter coefficients is updated one or more at each time instant, in order to fulfill a suitable tradeoff between convergences rate and computational complexity. The performance of the proposed algorithms is fully studied through the energy conservation analysis used in adaptive filters and the general expressions for the steady-state mean square error and transient performance analysis were derived in. What we propose in this paper is the use of the AP algorithm in noise cancellation for speech enhancement. We compare the results with classical adaptive filter algorithm such as LMS, NLMS, and AP. Simulation results show the good performance of the AP algorithm in attenuating the noise. In the following we find also the optimum parameter which is used in these algorithms.

The removal of noise from signals is an underlying problem related to several areas of research in signal processing and communications. The introduction of noise between the transmitter and receiver corrupts and distorts the input signal, thus providing an inferior signal quality on the receiving end. Processes to remove this unwanted interference are common

and come in many renditions. The technique of adaptive filtering is one medium by which signal enhancement or noise reduction is accomplished. In a similar adaptive fashion, systems submerged in an unknown environment can be detected with a system identification structure. An adaptive filter is a filter that self-adjusts its transfer function according to an optimizing algorithm. Because of the complexity of the optimizing algorithms, most adaptive filters are digital filters that perform digital signal processing and adapt their performance based on the input signal. By way of contrast, a non-adaptive filter has static filter coefficients (which collectively form the transfer function). For some applications, adaptive coefficients are required since some parameters of the desired processing operation (for instance, the properties of some noise signal) are not known in advance. In these situations it is common to employ an adaptive filter, which uses feedback to refine the values of the filter coefficients and hence its frequency response. An adaptive filter is required when either the fixed specifications are unknown or time invariant filters cannot satisfy the specifications. Strictly speaking an adaptive filter is a nonlinear filter since its characteristics are dependent on the input signal and consequently the homogeneity and additive conditions are not satisfied. Adaptive filters are time-varying since their parameters are continually changing in order to meet a performance requirement. In this sense, we can interpret an adaptive filter as a filter that performs the approximation step on-line. The design of digital filters with fixed coefficients requires well defined prescribed specifications. However, there are situations where the specifications are not available, or area time varying. The solution in these cases is to employ a digital filter with adaptive coefficients, known as adaptive filters. Since no specifications are available, the adaptive algorithm that determines the updating of the filter coefficients requires extra

information that is usually given in the form of a signal. This signal is in general called a desired or reference signal, whose choice is normally a tricky task that depends on the application [1].

Adaptive filters are considered nonlinear systems therefore their behavior analysis is more complicated than for fixed filters. On the other hand, because the adaptive filters are self designing filters, from the practitioner's point of view their design can be considered less involved than in the case of digital filters with fixed coefficients. The general set up of an adaptive filtering environment is illustrated in fig. 1, where,  $k$  is the iteration number.  $x(k)$  denotes the input signal,  $y(k)$  is the adaptive filter output signal, and  $d(k)$  defines the desired signal. The error signal  $e(k)$  is calculated as  $d(k) - y(k)$ . The error signal is then used to form a performance 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 in some sense.

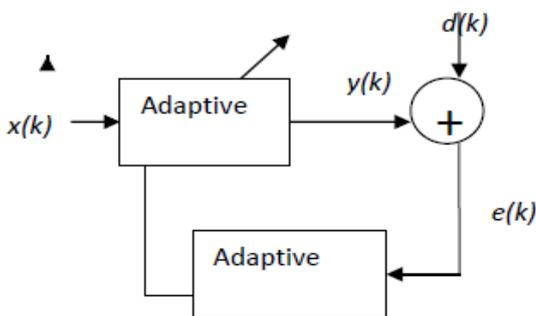


Fig1: Adaptive Filtering

Here, the input signal is the sum of a desired signal  $d(k)$  and interfering noise  $v(k)$  as expressed in (1).

$$x(k) = d(k) + v(k) \quad (1)$$

The error signal  $e(k)$  is difference between the desired and the estimated signal and given in (2).

$$e(k) = d(k) - y(k) \quad (2)$$

The variable filter has a Finite Impulse Response (FIR) structure. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order  $p$  are defined as in the expression (3).

$$w(n) = [w_n(0), w_n(1), \dots, w_n(p)]^T \quad (3)$$

The variable filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is

expressed as in (4) and (5).

$$y(k) = w_n^T x(k) \quad (4)$$

where

$$x(n) = [x(n), x(n-1), \dots, x(n-p)]^T \quad (5)$$

is an input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant as in (6).

$$w_{n+1} = w_n + \Delta w_n \quad (6)$$

where,  $\Delta w_n$  is a correction factor for the filter coefficients in equation (6). The adaptive algorithm generates this correction factor based

on the input and error signals. LMS and RLS define two

different coefficient update algorithms. Some of the applications of the adaptive filters are as follows:

1. Channel equalization
2. Channel identification
3. Signal prediction
4. Adaptive feedback cancellation
5. Noise cancellation

Adaptive Noise Cancellation is used to remove background noise from useful signals. This is an extremely useful technique where a signal is submerged in a very noisy environment. A typical example is inside a jet aircraft. The jet engine can produce a noise over 140dB. Since normal human speech is at a level between 30 and 40 dB, the pilot's communication is impossible in such a environment if there no noise cancellation equipments inside the cockpit. Usually the background noise does not keep steady and it will change from time to time. For example, the noise from the jet engine will be different at various flight states. So the noise cancellation must be an adaptive process. it should be able to work under changing conditions, and be able to adjust itself according to the changing environment. Suppose a hospital is recording a heart beat (an ECG), which is being corrupted by a 50 Hz noise (the frequency coming from the power supply in many countries). One way to remove the noise is to filter the signal with a notch filter at 50 Hz. However, due to slight variations in the power supply to the hospital, the exact frequency of the power supply might (hypothetically) wander between 47 Hz and 53 Hz. A static filter would need to remove all the frequencies between 47 and 53 Hz, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive filter could be used. The adaptive filter would take input both from the patient and from the power supply directly and would thus be able to track the actual frequency of the noise as it fluctuates. Such an adaptive technique generally allows for a filter with a smaller rejection range, which means, in our case, that the quality of the output signal is more accurate for medical diagnoses.

## II ADATIVE NOISE CANCELLATION

The basic idea of an adaptive noise cancellation algorithm is to pass the corrupted signal through a filter that tends to suppress the noise while leaving the signal unchanged. And as we mentioned above, this is an adaptive process, which means it cannot require a priori knowledge of signal or noise characteristics.

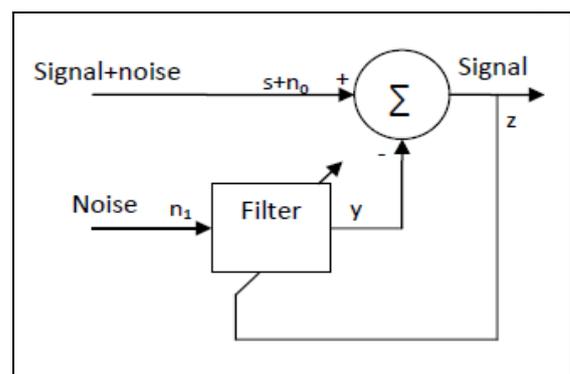


Fig. 2: Adaptive Noise Cancellation

To realize the adaptive noise cancellations please refer the figure where, we use two inputs and an adaptive filter. One input is the signal corrupted by noise (Primary Input, which can be expressed as  $S_{n_0}$ ). The other input contains noise related in some way to that in the main input but does not contain anything related to the signal (Noise Reference Input, expressed as  $n_1$ ). The noise reference input pass through the adaptive filter and a output  $y$  is produced as close a replica as possible of  $n_0$ . The filter readjusts itself continuously to minimize the error between  $n_0$  and  $y$  during this process. Then the output  $y$  is subtracted from the primary input to produce the system output  $z = s + n_0 - y$ , which is the de-noised signal [2]. Assume that  $s$ ,  $n_0$ ,  $n_1$  and  $y$  are statistically stationary and have zero means. Suppose that  $s$  is uncorrelated with  $n_0$  and  $n_1$ ,  $n_1$  is correlated with  $n_0$ . We can get the following equation of expectations in (7).

$$E[z^2] = E[s^2] + E[(n - y)^2] \tag{7}$$

When the filter is adjusted so that  $E[z^2]$  is minimized,  $E[(n - y)^2]$  is also minimized. So the system output  $z$  can serve as the error signal for the adaptive filter.

### III. LEAST MEAN SQUARE ALGORITHM

Several algorithms can be used for the adaptive filter here. The Least Mean Squared (LMS) algorithm is the most widely used and the simplest one. This algorithm tries to minimize the mean square value of the error signal. The adaptive filter coefficients change according to the equation (8). Here  $e(i)$  is error signal and  $\mu$  is step size parameter and  $u$  is the input signal

$$w(n) = w(n-1) + \mu u_1(i)e(i) \tag{8}$$

$\mu$  is the step size which determines the convergence speed of the algorithm and  $w$  is the weight of the filter in (8).

### IV. THE AFFINE PROJECTION ALGORITHM

The affine projection algorithm, in a relaxed and regularized form, is defined as follows:

$$\underline{e}_n = \underline{s}_n - X_n h_{n-1} \tag{9}$$

$$\tag{10}$$

$$\tag{11}$$

The excitation signal matrix,  $X_n$ , is  $L$  by  $N$  and has the structure,

$$X = \begin{bmatrix} x_n & x_{n-1} & \dots & x_{n-(N-1)} \end{bmatrix} \tag{12}$$

Where  $x_n = [x_n, \dots, x_{n-(L+1)}]$

The adaptive tap weight vector is  $h = [h_0, \dots, h_{L-1}]$  where,  $h_i$  is the  $i^{th}$  tap at sample period  $n$ . The vector  $\underline{e}_n$ , is of length  $N$  and consists of background noise and residual echo left uncanceled by the echo canceller's  $L$ -length adaptive tap weight vector,  $h_n$  The  $N$ -length vector,

$\underline{s}_n$  is the system output consisting of the response of the echo path impulse response to the excitation and the additive system noise,  $\underline{v}_n$

The scalar  $\delta$  is the regularization parameter for the sample autocorrelation matrix inverse used in (10) in the calculation

of the  $N$ -length normalized residual echo vector,  $\epsilon$ . Where,  $X_n$  may have eigenvalues close to zero, creating problems for the inverse  $X_n^T X_n + \delta I$  has  $\delta$  as its smallest eigenvalue which, if large enough, yields a well behaved inverse. The step-size parameter,  $m$  is the relaxation factor. As in NLMS, the algorithm is stable for  $0 \leq \mu < 2$ . If  $N$  is set to one, relations (9), (10), and (11) reduce to the familiar NLMS algorithm. Thus, APA is a generalization of NLMS.

### V. EXPERIMENTAL RESULTS

In this section we evaluate the performance of each algorithm in noise cancellation setup as shown in fig. 2. The original, primary, and reference signals are from the reference. The original speech is corrupted with office noise. The Signal to Noise Ratio (SNR) of the primary signal is -10.2180 dB. This signal is then processed as in fig. 3, shows the signals. The order of the filter was set to  $M=8$ . The parameter was set to 0.002 in the LMS and 0.005 in the NLMS. fig. 4, shows the filtered output signal and the mean squared error (learning curve) in the LMS algorithm. The SNR of the filtered signal is calculated for this experiment. The SNR improvement (SNRI) is defined as the final SNR minus the original SNR. The SNRI in the LMS algorithm is 13.5905. fig. 5, fig. 6, shows the results for NLMS and AP algorithms. As we can see the convergence speed in the NLMS and AP algorithms is faster than LMS algorithm. This fact can be seen in both filtered output and learning curve. For the NLMS and AP algorithms the SNRI are respectively 16.8679, 20.0307

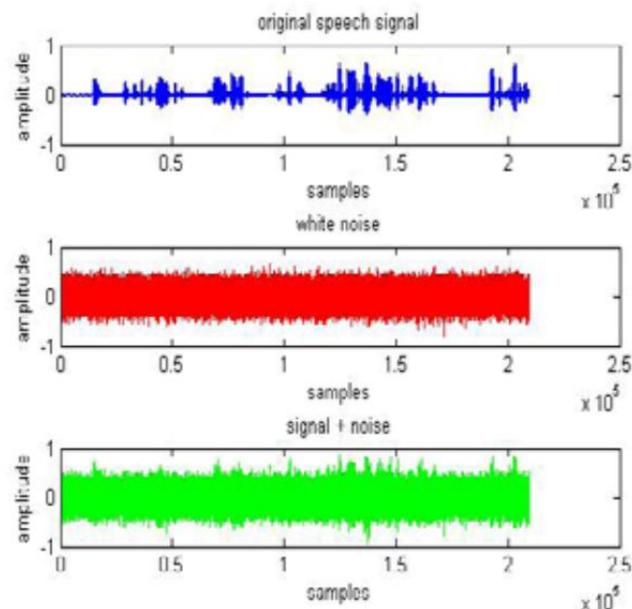


Fig 3: Original Speech Signal Recorded Through Quality Head Set, Noise Signal, Signal Plus Noise

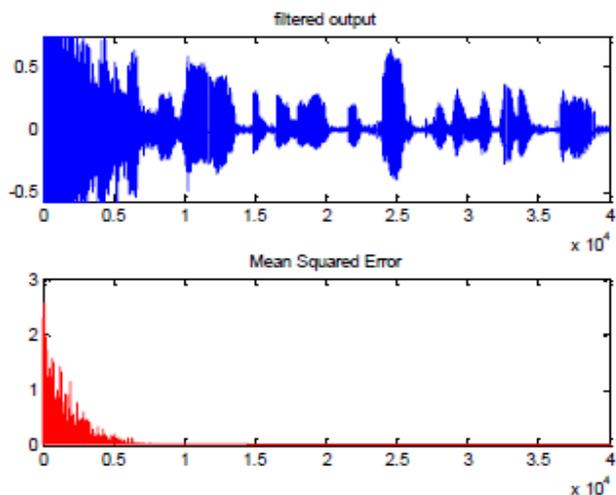


Fig. 4: Filtered Output Signal and MSE Cure of the LMS Algorithm

Affine Projection Algorithm

Table 1: SNR Improvements in db

Algorithm	SNR(db)
LMS	13.5905
NLMS	16.8679
AP	20.0307

VI. CONCLUSIONS AND FUTURE SCOPE

In this paper we have applied AP algorithm on adaptive noise cancellation setup. The simulation results were compared with the classical adaptive filters, such as LMS, NLMS, for attenuating noise in speech signals. In each algorithm the time evolution of filter taps, mean square error, and the output of filter were presented. The simulation results show that the convergence rate of these algorithms is comparable with the RLS algorithm. Also, the optimum values of the AP algorithm were calculated through experiments. In these algorithms, the number of iterations to be performed at each new sample time is a user selected parameter giving rise to attractive and explicit tradeoffs between convergence/ tracking properties and computational complexity. We can efficiently use this Affine Projection algorithm in Sub-Band Adaptive filtering Applications in order to produce optimized response. So, undoubtedly this algorithm has appreciable significance in speech processing.

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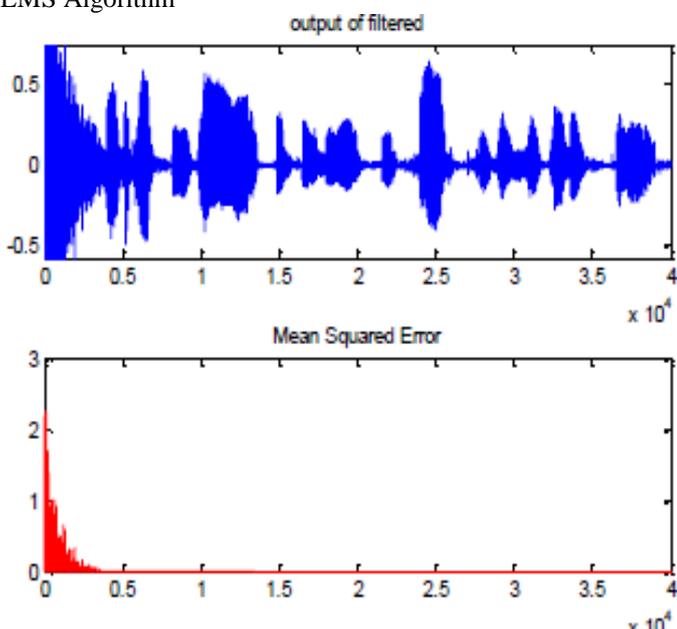


Fig. 5: Filtered Output Signal and MSE Cure of the N LMS Algorithm

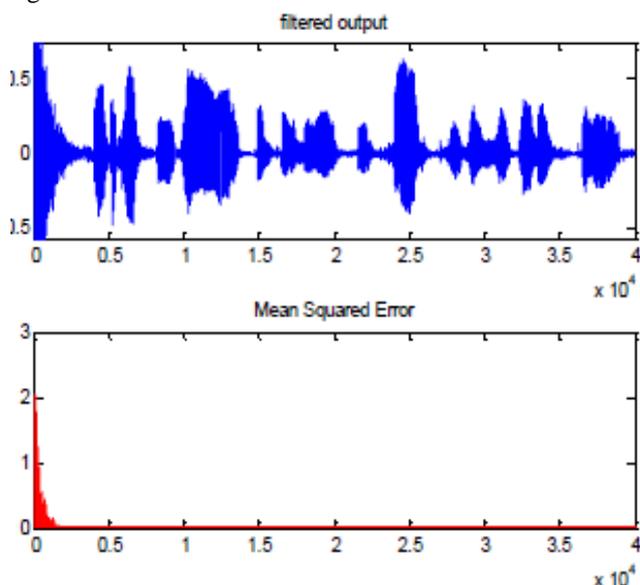


Fig. 6: Filtered Output Signal and MSE Cure of the AP Algorithm