Noise Cancellation using NLMS Adaptive Filter

Ahmed Saeed Obied, Hind Mowafaq Taha

Abstract— This paper presents the simulation of noise canceller system which contains adaptive filter and using adaptive algorithm. The objective of noise cancellation is to produce the estimate of the noise signal and to subtract it from the noisy signal and hence to obtain noise free signal. This work basically focuses on using NLMS filter in noise cancellation. We used Matlab to simulate our adaptive filter.

Index Terms— Noise canceller; adaptive algorithm; NLMS.

I. INTRODUCTION

Liner filtering is required in a variety of applications. A filter will be optimal only if it is designed with some knowledge about input data. If this information is not known, then adaptive filters are used [1]. An adaptive filter is essentially a digital filter with self-adjusting characteristics. It adapts, automatically, to changes in its input signals. In adaptive filtering, the adjustable filter parameters are to be optimized. The criteria arrived at for optimization should consider the filter performance and reliability. Adaptive algorithms are used to adjust the coefficient of the digital filter. Common algorithms that have found widespread applications are the least mean square (LMS), the Normalized Least Mean Square (NLMS), the Recursive Least Squares (RLS) algorithms, and the kalman filter algorithms [2].

II. ADAPTIVE FILTER

A system is said to be adaptive when it tries to adjust its parameters with the aid of meeting some well-defined goal or target that depends upon the state of the system and its surroundings [3]. So thesystem adjusts itself so as to respond to some phenomenon that is taking place in its surroundings. An event related signal could be considered as a process, which can be decomposed into an invariant deterministic signal time locked to a stimulus and an additive noise uncorrelated with the signal. The most common signal processing of this type of bioelectric signal separates the deterministic signal from the noise. Several techniques can be considered of which we are considering the adaptive signal processing technique. Adaptive filters are self-designing filters based on an algorithm which allows the filter to "learn" the initial input statistics and to track them if they are time varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal. The principle of adaptive filter is, as shown in Fig. 1.

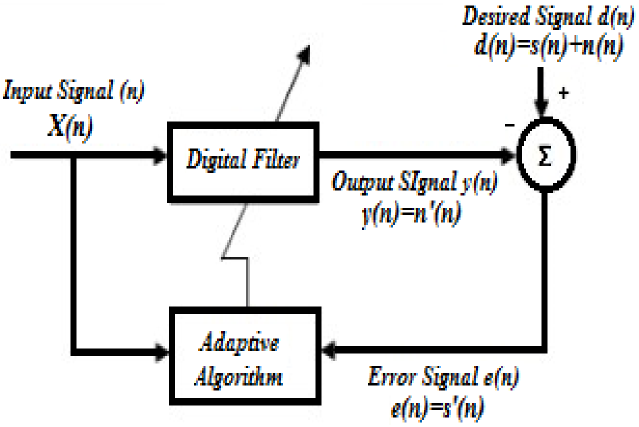

Fig. 1 Principle of Adaptive Filter.

Obtained signal d (n) from sensor contains not only desired signal s (n) but also undesired noise signal n(n). Therefore measured signal from sensor is distorted by noise n (n). At that time, if undesired noise signal n(n) is known, desired signal s(n) can be obtained by subtracting noise signal n(n) from corrupted signal d(n). However entire noise source is difficult to obtain, estimated noise signal n' (n) is used. The estimate noise signal n' (n) is calculated through some filters and measurable noise source X(n) which is linearly related with noise signal n(n). After that, using estimated signal n' (n) and obtained signal d (n), estimated desired signal s' (n) can be obtained. If estimated noise signal n' (n) is more close to real noise signal n (n), then more desired signal is obtained. In the active noise cancellation theory, adaptive filter is used. Adaptive filter is classified into two parts:

1. Adaptive algorithm
2. Digital filter.

Function of adaptive algorithm is making proper filter coefficient. General digital filters use fixed coefficients, but adaptive filter change filter coefficients in consideration of input signal, environment, and output signal characteristics. Using this continuously changed filter coefficient, estimated noise signal n' (n) is made by filtering X(n).

The different types of adaptive filter algorithms can be explained as follows.

A. LMS Algorithm

The LMS algorithm is a method to estimate gradient vector with instantaneous value. It changes the filter tap weights so that e (n) is minimized in the mean-square sense [4]. The conventional LMS algorithm is a stochastic implementation of the steepest descent algorithm. It simply replaces the cost function ξ (n) = E [e2 (n)] by its instantaneous coarse estimate. The error estimation e(n) is

$$e(n) = d(n) - w(n)\,X(n) \tag{1}$$

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Ahmed Saeed Obied, High Education, Al-Mansour University College, Baghdad, Iraq.

Hind Mowafaq Taha, High Education, Al-Mansour University College, Baghdad, Iraq.

Coefficient updating equation is

$$w(n+1) = w(n) + x(n)\,e(n) \quad (2)$$

Where μ is an appropriate step size to be chosen as $0 < \mu < 0.2$ for the convergence of the algorithm.

The larger step sizes make the coefficients to fluctuate wildly and eventually become unstable.

B. Signed-Regressor Algorithm (SRLMS)

The signed regressor algorithm is obtained from the conventional LMS recursion by replacing the tap input vector x (n) with the vector sgn{x(n)}. Consider a signed regressor LMS based adaptive filter that processes an input signal x(n) and generates the output y(n) as per the following:

$$y(n) = W^t(n)\,x(n) \quad (3)$$

where, w(n) = $[w0(n), w1(n), \dots, wL\text{-}1(n)]^t$ is a L-th order adaptive filter. The adaptive filter coefficients are updated by the Signed-regressor LMS algorithm as,

$$w(n+1) = w(n) + \mu\,\mathrm{sgn}\{x(n)\}e(n) \quad (4)$$

Because of the replacement of x(n) by its sign, implementation of this recursion may be cheaper than the conventional LMS recursion, especially in high speed applications such as biotelemetry these types of recursions may be necessary.

C. Sign Algorithm (SLMS)

This algorithm is obtained from conventional LMS recursion by replacing e(n) by its sign [5]. This leads to the following recursion:

$$w(n+1) = w(n) + \mu x(n)\,\mathrm{sgn}\{e(n)\} \quad (5)$$

D. Sign – Sign Algorithm (SSLMS)

This can be obtained by combining signed-regressor and sign recursions, resulting in the following recursion:

$$w(n+1) = w(n) + \mu\,\mathrm{sgn}\{x(n)\}\,\mathrm{sgn}\{e(n)\} \quad (6)$$

Where sgn{.} is well known signum function, e(n)= d(n) – y(n) is the error signal. The sequence d(n) is the so-called desired response available during initial training period. However the sign and sign – sign algorithms are both slower than the LMS algorithm. Their convergence behaviour is also rather peculiar. They converge very slowly at the beginning, but speed up as the MSE level drops.

E. Block LMS (BLMS) Algorithm

To reduce the computational requirements of LMS algorithm, block LMS is introduced. Here the filter coefficients are held constant over each block of L samples, and the filter output y(n) and the error e(n) for each value of n within the block are calculated using the filter coefficients for that block. Then at the end of each block, the coefficients are updated using an average for the L gradients estimates over the block.

F. Normalized LMS (NLMS) Algorithm

In NLMS, the step size takes the form of,

$$\mu(n) = \frac{\beta}{\|X(N)\|^2} \quad (7)$$

Where β is a normalized step size with 0< β<2. When x(n) is large, the LMS experiences a problem with gradient noise amplification. With the normalization of the LMS step size by $\|x(n)\|^2$ in the NLMS, noise amplification problem is diminished [6].

III. SIMULATION AND RESULTS

This section presents the results of simulation using MATLAB to investigate the performance behaviour of NLMS adaptive filter algorithm.

A. Section 1 (two-tap filter case)

It will consider only the two-tap (weights) filter case in this section in order to filter the given distorted signal. Firstly, we will illustrate the performance surface contours for the two-tap filter case, as shown in Fig. 2. The figure shows that the weights converge iteratively to the optimum solution w0, w1 that corresponds to the bottom of the performance surface. We found that the optimal solution for this case is: W0=0.77115, w1=0.42826.

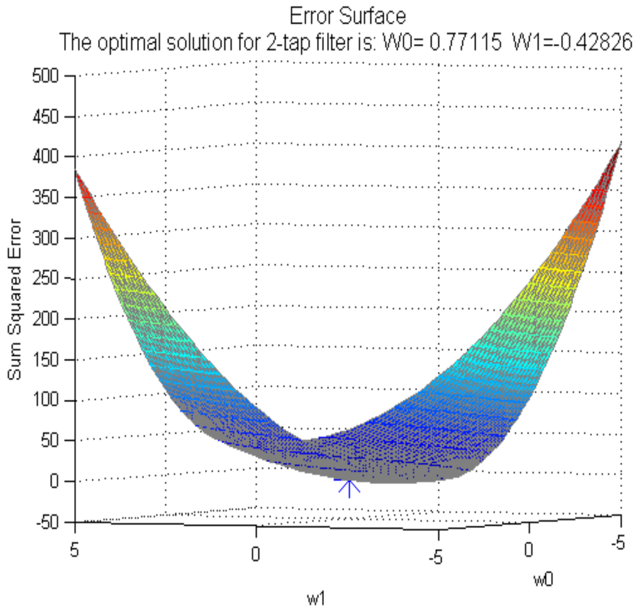

Fig. 2 Performance surface for a 2-tap adaptive FIR filter.

Now, It will use the NLMS Algorithm to achieve 2-tap adaptive NLMS filter. We considered step size value equal to 0.03 (this value gave us a fair convergence speed and a fair accuracy). Fig. 3 shows the weight tracks for this 2-tap NLMS filter. Clearly, as the iteration increases, the filter weights converges to the Wiener weights value (W0=0.77115, w1=0.42826). By plotting of the Mean Squared Error (MSE) across iterations, we can find the learning curve. Fig. 4 shows the learning curve for the 2- tap NLMS adaptive filter (step size equals to 0.03). Clearly, as the iteration increases, the adaptive filter MSE decreases and tries to converge to a value around the steady state value.

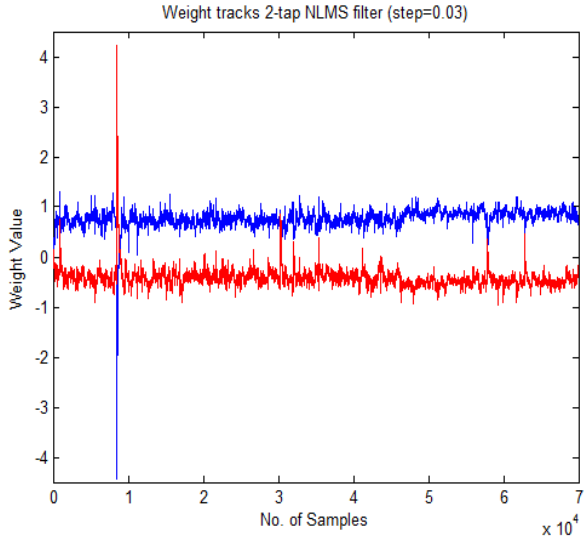

Fig. 3 Weight tacks for 2-tap NLMS adaptive (Step =0.03).

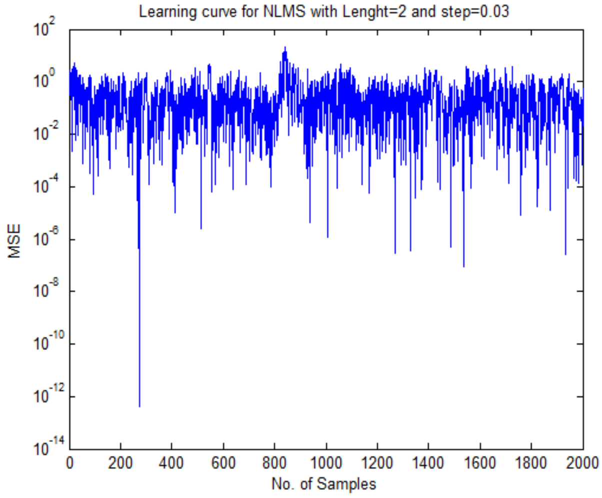

Fig. 4 Learning curve (over 2000 samples) for a two-tap NLMS adaptive filter (at step size=0.03).

Fig. 5 shows the spectrogram (STFT) for the primary (desired) signal and for the error (speech) signal. To Estimate the SNR improvement we found the Echo-Return-Loss Enhancement (ERLE) which is defined as:

$$ERLE = 10\log \{E\,[d^2(n)] \,/\, E\,[e^2(n)]\,\}$$

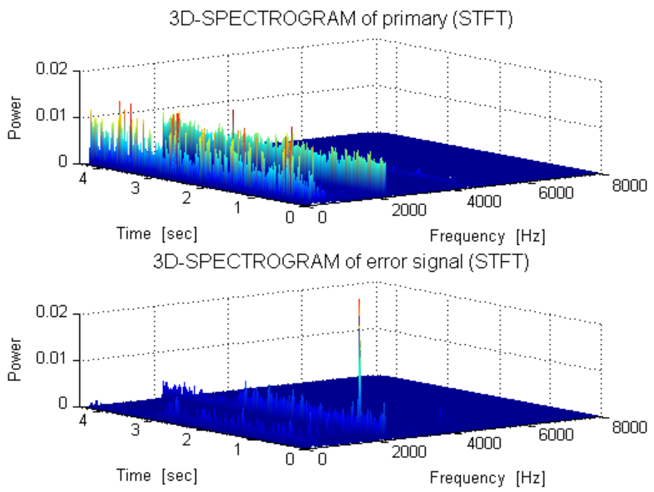

Fig. 5 Spectrogram (STFT) for the primary signal and for the error (speech) signal.

Fig. 6 shows an increasing in ERLE as the iteration increases.

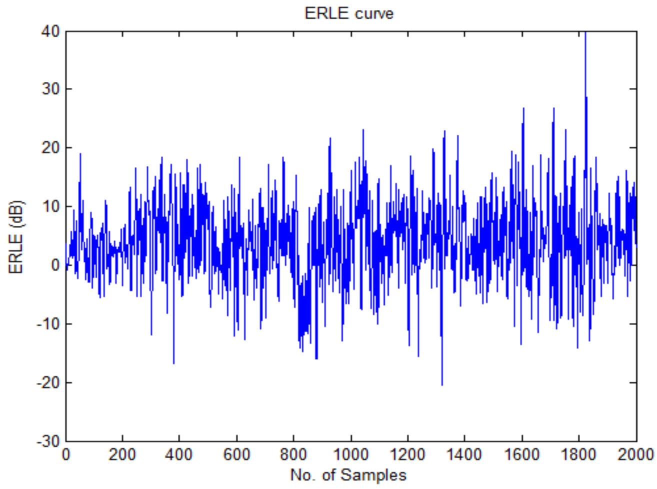

Fig. 6 ERLE [dB] (over 1000 samples) for a two-tap NLMS adaptive F IR filter (at step size=0.03).

B. Section 2 (multiple-tap filter case)

Firstly, we must specify a value for the adaptive filter length. The filter length affects the computational resource requirements, convergence speed, and steady state error of the resulting adaptive filter. As the length of the NLMS filter is increased, the convergence rate and the steady state error decrease but the computational requirements increase. For our study we considered filter length value equal to 64 (this value gave us a fair convergence speed, a fair steady state error and also fair computational requirements). Fig. 7 shows the spectrogram (STFT) for the primary (desired) signal and for the error (speech) signal when using NLMS filter (length=64 and step size=0.07).

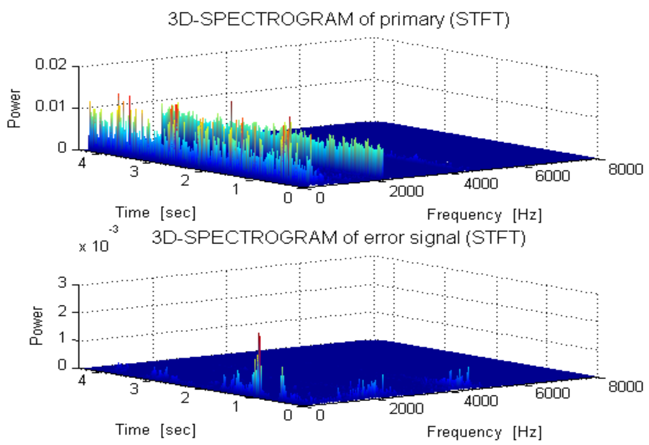

Fig. 7 Spectrogram (STFT) for the primary signal and for the error (speech) signal using 64-tap NLMS filter (step=0.07).

Fig. 8 shows the SNR improvement (ERLE) in dB while Fig. 9 shows the performance of NLMS adaptive filter with different step size values and the same filter length. As shown in the figure as the step size is increased, the speed of convergence increases but also the steady state squared error (MSE) increases. It also estimated the Misadjustment M which is defined as the ratio of the excess MSE in the steady-state and the minimum MSE.

To calculated this value for our case, it was equal to M=0.04121. From the results that we obtained, we can say that NLMS can operate in a stationary or non-stationary environment.

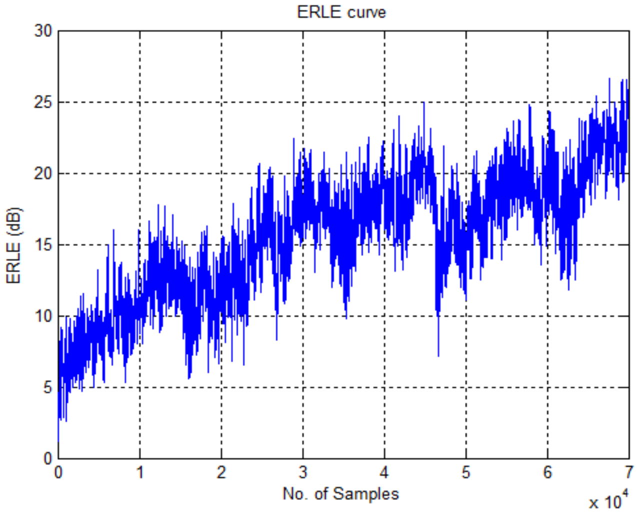

Fig. 8 (ERLE) in dB using 64-tap NLMS filter (step=0.07).

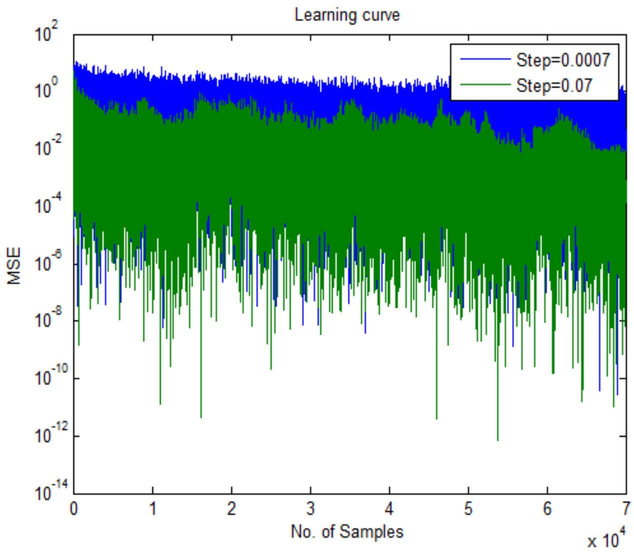

Fig. 9 Performance of NLMS adaptive filter with different step size values (step1=0.0007 and step2=0.07) and the same filter length (filter length=64).

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AUTHORS PROFILE

Ahmed Saeed Obied, was born in Baghdad, Iraq in 1987, received the M.Se of Electrical Engineering (Communication) from University Tun Hussein Onn Malaysia (UTHM), Malaysia in 2014 and BE degree in Computer Engineering and Information Technology from University of Technology, Iraq in 2009. Presently working as Lecturer in Computer Communication Engineering, Al-Mansour University College.

Hind Mowafaq Taha, was born in Baghdad, Iraq in 1988, received the M.Se of Electrical Engineering (Communication) from University Tun Hussein Onn Malaysia (UTHM), Malaysia in 2014 and BE degree in Control and Systems Engineering from University of Technology, Iraq in 2009. Presently working as Lecturer in Computer Communication Engineering, Al-Mansour University College.