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Implementation of Recursive Least Squares (RLS) Adaptive Filter for Noise Cancellation

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***Abstract*: In this paper, we will perform noise cancelling using Recursive Least Square adaptive filtering algorithm in order to clean the noisy speech signal.ASIMULINK model is developed using RLS for noise cancelation.The effects on stability, convergence, speed and computation on choosing the different parameters for RLS and adaptive filter is studied here and in the end we will decide on a system which has the best tradeoffs.**

Keywords-Adaptive Noise Cancellation (ANC), Digital SignalProcessor (DSP), Least mean square (LMS), Recursive Least Square(RLS), Normalized LeastMean Square (NLMS).

I. Introduction

Noise problems in the environment have gained attentiondue to the tremendous growth of technology that has led tonoisy engines, heavy machinery, audio devices and other noise sources. The problem ofcontrolling the noise level has become the focus of a vastamount of research over the years. There is a hardware implementation of adaptive filter for noise cancelation using RLS filter.

There are four main types of adaptive filter configurations: Adaptive system identification, Adaptive noise cancellation, Adaptive linear prediction and Adaptive inverse systems. While they implement the same algorithm, their system configuration differs.

The basic adaptive algorithms which widely used for performing weight updation of an adaptive filter are: the LMS (Least Mean Square), NLMS (Normalized Least Mean Square) and the RLS (Recursive Least Square) algorithm. Among all adaptive algorithms LMS has probably become the most popular for its robustness, good tracking capabilities and simplicity in stationary environment. RLS is best for non-stationary environment with high convergence speed but at the cost of higher complexity. Therefore a trade-offis required in convergence speed and computational complexity, NLMS provides the right solution. 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.**II**. **Theory**

A. Recursive Least Square (RLS) Adaptive Filter

The Recursive Least Squares (RLS) filter is a better filter than the LMS filter, but it is not used as often as it could be because it requires more computational resources. The LMS filter requires 2N+1 operation per filter update, whereas the RLS filter requires $2.5N^2 + 4N$.It has been successfully used in system identification problems and in time series analysis where its real-time performance is not an issue.

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity, and potentially poor tracking performance when the filter to be estimated changes.

In general, the RLS can be used to solve any problem that can be solved by adaptive filters. For example, suppose that a signal d (n) is transmitted over an echoic, noisy channel that causes it to be received as

$$x(n) = \sum_{k=0}^{q} b_n(k) d(n-k) + v(n+1)$$

Where v(n) represents additive noise. We will attempt to recover the desired signal d (n) by use of a p-tap FIR filter,

$$\hat{d}(n) = \sum_{k=0}^{p-1} w_n(k)x(n-k) = \mathbf{w}_n^T \mathbf{x}(n)$$

Where $\mathbf{x}_n = [x(n) \quad x(n-1) \quad \ldots \quad x(n-p+1)]^T$

is the vector containing the p most recent samples of x (n). Our goal is to estimate the parameters of the filter $\mathbf{W}$, and at each time n we refer to the new least squares estimate by $\mathbf{W_n}$. As time evolves, we would like to avoid completely redoing the least squares algorithm to find the new estimate for $\mathbf{W}_{n+1}$, in terms of $\mathbf{W}_n$.

B. Noise Cancellation

Adaptive noise cancellation is often used to extract the desired speech from the given noisy speech. The noise cancellation plays an important role in digital voice communication systems for e.g. Cell phones require adaptive noise cancellation to reduce further degradation of vo-coded speech.

Active noise control (ANC) (also known as noise cancellation, active noise reduction (ANR) or anti-noise) is a method for reducing unwanted sound.

The following figure shows the block diagram of an Active Noise Control (ANC) system. It incorporates an adaptive filter, whose coefficients are updated from the error function, e (n).

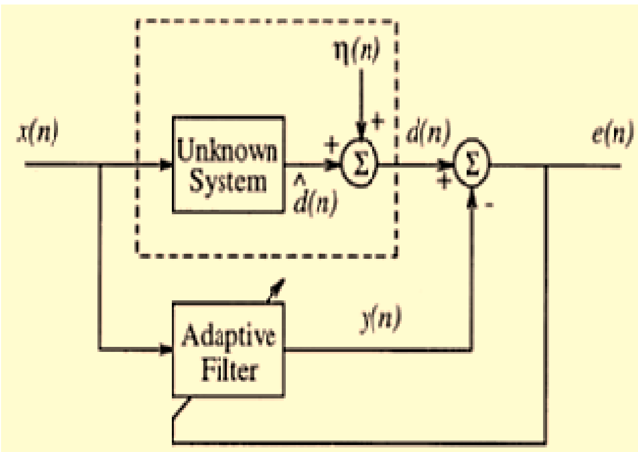

Figure 1.1 Block diagram of an ANC system

III. Methodology

A. MATLAB Simulink Model of RLS Adaptive Filter

The figure 1.2 shows the simulink model of the RLS Adaptive Filter

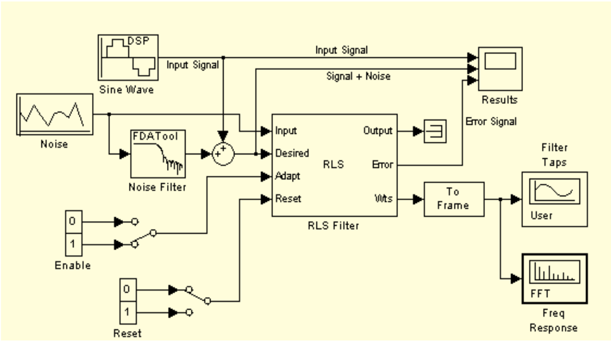

Figure 1.2 Simulink Model of RLS Adaptive Filter

In the simulation the reference input signal x(n) is a white Gaussian noise of power two-dB generated using random function in MATLAB, the desired signal d(n) ,obtained by adding a delayed version of x(n) into clean signal s(n), d(n) = s(n) + x1(n).

The clean speech signal typically exists in a subspace of the input. The speech signal is a sentence that is repeated four times. The distorted Speech & noise signal is fed to input as original wav manually. Then we can choose to enhance or improved results stored in the same directory.

B. Simulation Results

The SNR between original distorted signalsin below diagram is 15.1894. The following Figure 1.3 shows the result of the simulated RLS filter. It shows the input signal, which is a sine wave. Then it shows the input signal with the noise signal. Lastly it shows the error signal.

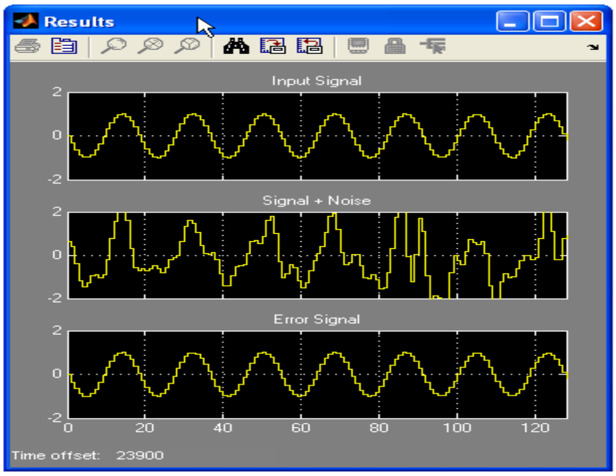

Figure 1.3 Simulation Results

The following figure shows the filter taps in the graph between filter coefficients & samples.

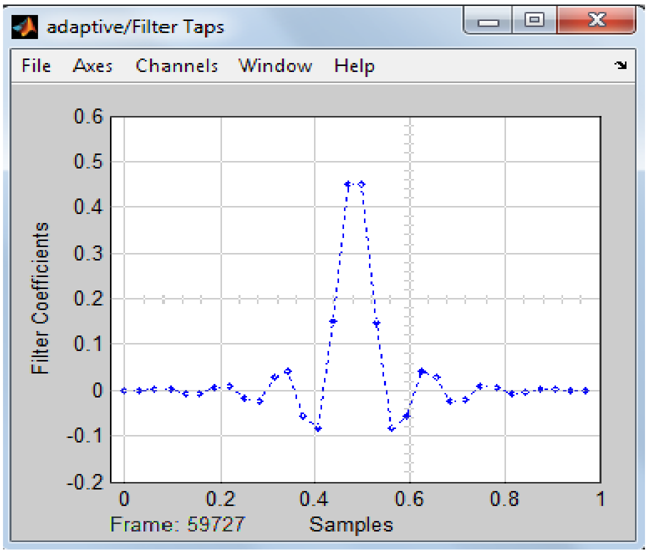

Figure 1.4 Filter taps of RLS filter

The following figure 1.5 represents the frequency response of RLS filter.

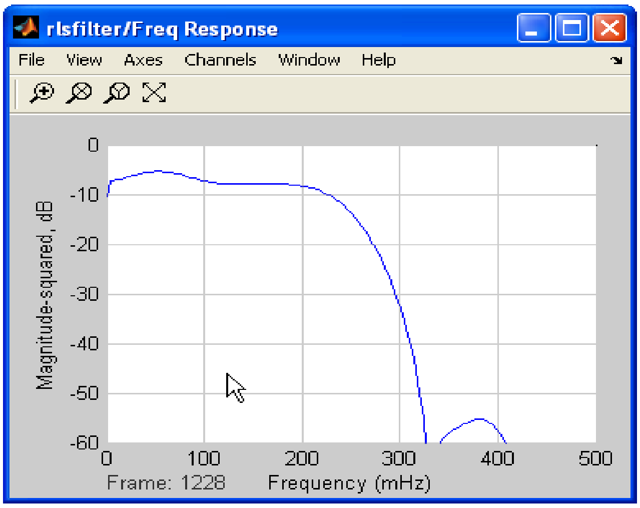

Figure 1.5 Frequency Response of RLS filter

IV. Conclusions

A. RLS Algorithm: Best suited for noise cancellation

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.

B. Future Scope

In the view of noise cancellation, no ‘perfect’ solutions exist yet for multi-channel de-correlation. For speech signals non–linearity’s like half–wave rectifiers are providing good results, but in applications where multichannel audio is involved, these solutions introduce intolerable distortion. This subject clearly requires more research.Another subject for future research would be if this topic could be handled by ’cheaper’ adaptive filtering algorithms, like perhaps APA–based filters. Here the NLMS–algorithm is used to implement unconstrained optimal filtering for multichannel noise cancellation.

V. References

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