

## LMS and RLS Based Interference Cancellation in Uniform Array System

Bhavya H R<sup>1</sup>, Nagaraj P<sup>2</sup>, Channaya<sup>3</sup>, Dr. Siva S Yellampalli<sup>4</sup>

**Abstract:** Array of antennas or sensors is widely used in many applications like communication, Rader, Sonar, Speech Processing and etc. Advantages of such system are higher degree of freedom, Adoption, Redundancy, Flexibility and etc. In real world the signals received by the array not only consist of desired signal but also consists the interferences from the sources in the surrounding environment. It is essential to remove the interfering signal and increase the Signal-to-Interference plus Noise Ratio (SINR) of the desired signal. Interference degrades the performance of the system and reduces the Detection and Estimation of the desired signal in the received signal. The goal of this Paper is to find the behaviour of LMS and RLS for different set of interfering signal, and to find the interference cancellation capability of the algorithms, and Comparison between the algorithms.

**Keywords:** Adaptive filter, Least mean square Algorithm, Recursive least square Algorithm.

### I. Introduction

Over the last few years, there has been an increasing demand for better quality and new value added services on existing wireless mobile communications networks [1]-[2]. This demand has brought technological challenges to service providers. Antennas, so far a neglected component in wireless mobile communications, have gained a renewed interest among researchers. In the form of “smart antennas” or “adaptive array antennas”, they meet the challenging demand and bring many benefits to the wireless communications services [3]. These benefits include the enhancement of coverage and the channel capacity; lower transmitted power, better signal quality, higher data rate, and providing value-added services such as users’ location. An antenna array is a set of individual antennas used for transmitting and/or receiving radio waves, connected together in such a way that their individual currents are in specified amplitude and phase relationship [4]. This allows array to act as a single antenna, generally with improved directional characteristics (thus higher antenna gain) than would be obtained from the individual elements. The resulting array in fact is often referred to and treated as an “antenna”, particularly when the elements are in rigid arrangement with respect to each other, and when the ratio of currents (and their phase relationships) is fixed. On the other hand, a steer able array may be fixed physically but has electronic control over the relationship between those currents, allowing for adjustment of the antenna’s directionality without requiring physical motion [5]. There are two kinds of adaptive algorithm, to cancelling the interference signal from the desired signal. The LMS algorithm introduced by Widrow and Hoff in 1959 [6]. The algorithm uses the estimates of the gradient vector from the available data [7]-[9]. The RLS algorithms have a faster rate of convergence speed and do not exhibit the Eigen value spread problem [10]-[11]. It recursively find the filter coefficients that minimize a weighted linear least square cost function [12].

### II. Linear Arrays

Uniform linear arrays (ULAs) mean that the array elements are same as each other and they are aligned along a straight line with equal element separations. Linear array is uni directional. And the communication tower will also at the same height, Simulation will take less time. A Uniform linear array is as shown in the figure.1 it’s having N number of antenna elements placing at an equal distance d.

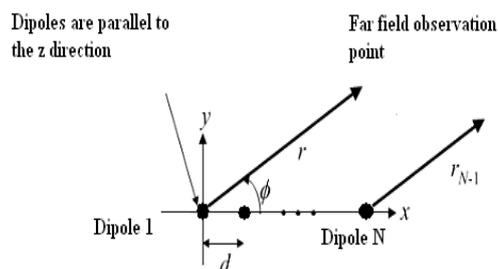


Fig1: Block diagram of linear array [2].

The system having high level of efficiency and power is provided by the smart antenna for the target signal. Smart antennas generate narrow pencil beams, when a big number of antenna elements are used in a high frequency condition. Thus, in the direction of the target signal, the efficiency is significantly high. By using array antenna at the same time the power gain can also produced by suppressing large amount of interference [2].

### III. Adaptive Filter

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 location 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 [3].

An adaptive filter has an adaptation algorithm that is a meant to monitor the environment and vary the filter transfer function based on the actual signals received attempts to find the optimum filter design [4].

The basic operation now involves two processes;

A filtering process, which produces an output signal in response to a given input signal.

An adaptation process, which aims to adjust the filter parameters (filter transfer function) to the (possibly time-varying) environment. Often, the (average) square value of the error signal is used as the optimization criterion.

Interference is the kind of time-varying, unknown signal. This characteristic requires the filter can automatically track the change of signals, and respond to the changes by adjusting the weight coefficient quickly. What is more, this just fits well with the functions of the adaptive filter. Thus the adaptive filter is to be chosen for the interference cancellation. The principle of adaptive filtering interference cancellation is shown in the figure.2 [4].

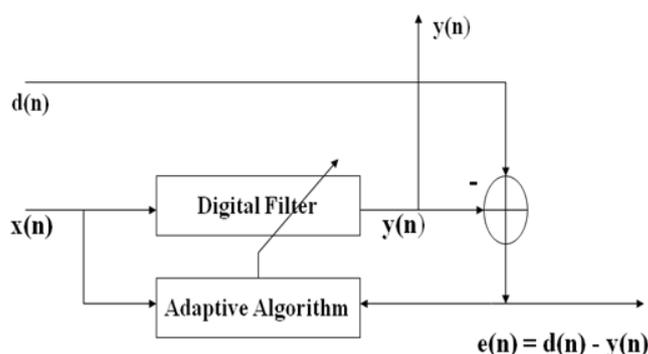


Fig2: Block diagram of Adaptive Filter [4].

It consists of two distinct parts, a FIR filter with adjustable coefficients and an adaptive algorithm, which is used to adjust or modify the coefficients of the filter to a FIR filter  $y(n)$  is the corresponding output. In the figure.2  $x(n)$  is the input signal,  $d(n)$  is the desired input signal to the adaptive filter,  $e(n)$  is the error signal that denotes the difference between  $d(n)$  and  $y(n)$ .

### IV. Lms Algorithm

Least mean squares algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal. LMS algorithm has been widely used according to its advantages, such as simple structure, good stability low computational complexity, proof of convergence in stationary environment, stable behaviour and so on.

In order to use the LMS algorithm, we must determine a filter order and then a good step size [7]. This can be done by trial and error or by finding the autocorrelation of the reference signal and cross correlation between the reference and primary signal.

In the LMS algorithm the weight vector can be calculated by the equation (1) [6].

$$W(n) = w(n-1) + \mu X(n) e^*(n) \quad (1)$$

For  $n=0, 1, 2, \dots$  where  $\mu$  represent the step size,  $w(n)$  is present weight vector,  $w(n-1)$  is previous weight vector,  $x(n)$  is input signal,  $e^*(n)$  is the conjugate of the error signal, it can be calculate from the desired signal and the output signal as shown in the figure.3 [13].

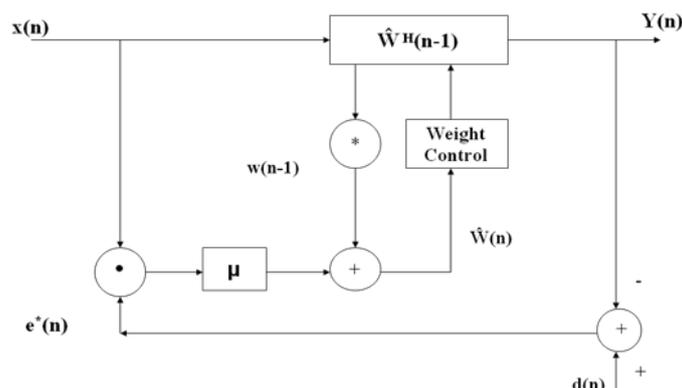


Fig3: Block diagram of LMS Algorithm [13].

### V. Rls Algorithm

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. RLS algorithms are able to track the dynamics of a time-variant fading channel and at the same time to suppress the effect of the received noise on the equalization error.

The important feature of the Recursive Least Mean Square algorithm is that its rate of convergence is typically an order of magnitude faster than that of the LMS filter, due to the fact that the RLS filter whitens the input data by using the inverse correlation matrix of the data, assumed to be zero mean. This improvement in performance is achieved at the expense of an increase in the computational complexity of the RLS filter, as shown in Figure 4 [13].

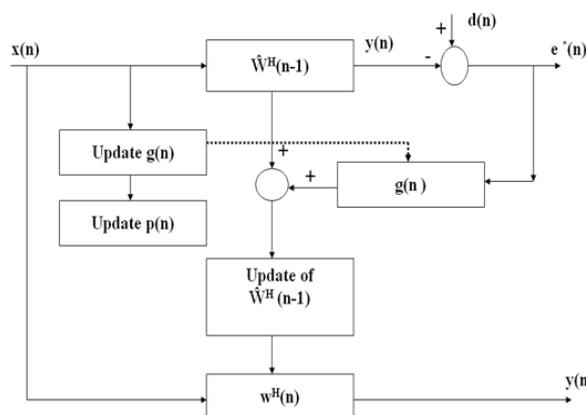


Fig4: Block diagram of RLS Algorithm [13].

RLS algorithms have good tracking ability and noise suppression ability. The forgetting factor is chosen according to an inverse function of the residual power in order to achieve a constant weighted sum of the squares of the posterior errors. In other words, the amount of forgetting at each step corresponds to the amount of new information in the latest measurement, thereby ensuring that the estimation is always based on the same amount of information. The basic concept of the time-varying optimal forgetting factor can be explained as follows [10]. In the case of a near-deterministic system, the posterior estimation error provides information about the state of the estimator. When the initial value is set to unity and the error is small, it may be concluded that the estimator is sensitive enough to adjust the variations of the system parameters. Hence, the estimation error is reduced significantly [11]. The standard RLS algorithm performs the following operation to update the coefficients of an adaptive filter.

1. Calculates the output signal  $y(n)$  of the adaptive filter.
2. Calculates the error signal  $e(n)$  by using the following equation [4]:  $e(n) = d(n) - y(n)$
3. Updates the filter coefficients by using the following equation [10]:

$$W(n) = w(n-1) + g(n) \cdot e^*(n) \quad (2)$$

Where  $w(n)$  is the filter coefficients vector and  $g(n)$  is the Kalman gain vector. It is computed from the auto-correlation matrix, using the following equation [10]:

$$g(n) = p(n-1) x^*(n) / (\mu + x(n) x^T(n) p(n-1)) \quad (3)$$

Initially take  $P(n-1)$  as an identity matrix, then update the value for the Kalman gain vector, then compute  $p(n)$  using the following equation [10]:

$$p(n)=1/\mu[p(n-1)-g(n)x^t(n)p(n-1)] \quad (4)$$

### VI. Performance Analysis

To find the interference cancellation capability of the LMS and RLS algorithm for the system selected number of elements are 20 and number of sample are 100. Distance between two elements is  $d=\lambda/2$ ,  $\lambda=0.1$  and sampling frequency is  $2*10^6$ .

The signal amplitude is 100, signal frequency is  $0.2*10^6$  and signal direction is 20 degree. And the two interference signal having an amplitude 10 frequency  $0.5*10^6$  and  $0.6*10^6$  are coming from the direction 40 degree and -10 degree respectively, this interference degrade the performance of the system by using Matlab the interference capability of the algorithm and error graph of LMS and RLS algorithm is as shown in figure.5, figure.6, and figure.7, respectively. X-axis represents angle in degree and Y-axis represents amplitude in decibels and is given by  $20*\log(\text{number of elements} * \text{amplitude of the signal in particular direction})$ .

At -10 degree and 40 degree have interference in input pattern, but this interference is getting deep null (zero) in the output pattern, this shows the interference cancelling capability of the algorithm. From the figure.5 it's also concluded that RLS algorithm has a faster rate of convergence than the LMS algorithm.

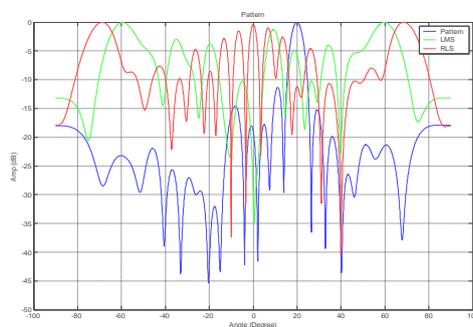


Fig.5 Interference cancellation capability of the LMS and RLS algorithm

From the figure 5, can calculate the SINR of LMS algorithm (20db) is less than the SINR of RLS algorithm (36 db).stability of the RLS algorithm is more comparing to LMS algorithm. From the figure5, RLS algorithm getting optimal weight (deep null at the interference) than the LMS algorithm.

Absolute error of the LMS algorithm has 10 the learning curve become steady state after 25 samples is as shown in the figure6

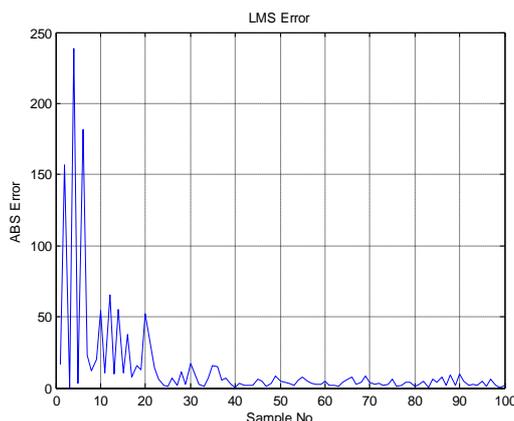


Fig.6 LMS error for number of samples

Absolute error of the RLS algorithm has 5 the learning curve become steady state after 10 samples is as shown in the figure7.

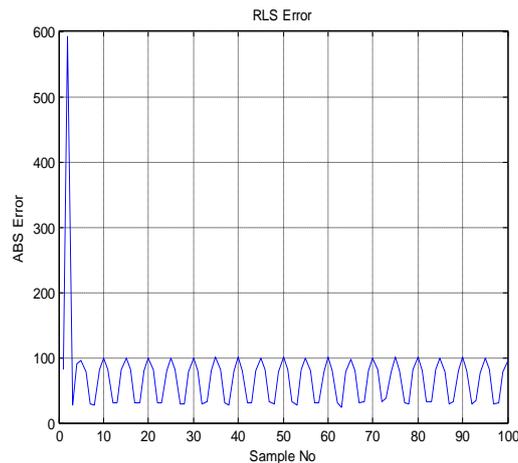


Fig.7. RLS error for number of samples

From the figure 6 and figure 7 can concluded that the RLS algorithm has faster convergence rate (after 5<sup>th</sup> sample the learning curve become steady state) than LMS algorithm (after 10<sup>th</sup> sample the learning curve become steady state).

## VII. Conclusions

LMS algorithm has low computation complexity (no matrix multiplication) than RLS algorithm (matrix multiplication). LMS algorithm has single adjustable parameter ( $\mu$ ), but RLS algorithm has multiple adjustable parameters. SINR of the RLS algorithm is more (figure 5) compare to LMS algorithm, so the stability of the RLS algorithm is more.

From the learning curve (figure6 and figure7) RLS algorithm has a faster rate of convergence than the LMS algorithm and is not sensitive to variation in the Eigen value spread of the correlation matrix of the input vector.

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