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Systematic comparison of performance of different Adaptive beam forming Algorithms for Smart Antenna systems

M.V.S.L. Srikanth[1], P.Santosh Kumar [2], S.Vijay Kumar [3] K.Gowriprasad [4] R.V.Ch.Sekhar Rao [5]
[1,2,3,4] *B.Tech Student,Dept of ECE, Lendi Institute of Engineering and technology, Vizianagaram, Andhra Pradesh, India*
[5]*Assistant Professor, Dept of ECE, Lendi Institute of Engineering and technology, Vizianagaram, Andhra Pradesh, India*

Abstract: *Smart antenna is the most efficient leading innovation for maximum capacity and improved quality and coverage. Efficient utilization of limited radio frequency spectrum is only possible to use smart/adaptive antenna system. Smart antenna radiates not only narrow beam towards desired users exploiting signal processing capability but also places null towards interferers, thus optimizing the signal quality and enhancing capacity. Smart antennas exploit space diversity to help provide high data rates, increased channel capacity, and improved quality of service.*

A systematic comparison of the performance of different Adaptive Algorithms for beam forming for Smart Antenna System has been extensively studied in this research work. Simulation results revealed that training sequence algorithms like Recursive Least Squares (RLS) and Least Mean Squares (LMS) are best for beam forming (to form main lobes) towards desired user but they have limitations towards interference rejection. While Constant Modulus Algorithm (CMA) has satisfactory response towards beam forming and it gives better outcome for interference rejection, but Bit Error Rate (BER) is maximum in case of single antenna element in CMA. The effect of changing step size for LMS algorithm has also been studied.

Index Terms: *Adaptive antenna systems, Constant modulus algorithm, Least mean squares, Smart antenna.*

I. INTRODUCTION

The Smart antenna technology which tracks the mobile user continuously by steering the main beam towards the user and at the same time forming nulls in the directions of the interfering signal. The development of smart antennas includes the design of antenna array and adjusting the incoming signal by changing the weights of the amplitude as well as phase using efficient Digital Signal Processing algorithms[1].The Demand for increased capacity in wireless communications networks has motivated recent research activities toward wireless systems that exploit the concept of smart antenna and space selectivity[2].The deployment of smart antennas at existing cellular base station installations has gained enormous interest because it has the potential to increase cellular system capacity, extend radio coverage, and improve quality of services.

Smart antennas may be used to provide significant advantages and improved performance in almost all wireless communication systems, including time-division multiple-access cellular systems, code-division multiple-access cellular
systems as well as others[9]. One smart antenna implementation strategy uses an adaptive antenna array, whose outputs are adaptively combined through a set of complex weights (signal amplitude and phase adjustments) to form a single output with beam steering [4]. The advent of powerful, low-cost, digital processing components and the development of software based techniques have made smart antenna systems a practical reality for cellular communications systems.

Adaptive Beam forming is a technique in which an array of antennas is exploited to achieve maximum reception in a specified direction by estimating the signal arrival from a desired direction (in the presence of noise) while signals of the same frequency from other directions are rejected. This is achieved by varying the weights of each of the sensors (antennas) used in the array[5]. It basically uses the idea that, though the signals emanating from different transmitters occupy the same frequency channel, they still arrive from different directions. This spatial separation is exploited to separate the desired signal from the interfering signals. In adaptive beam forming the optimum weights are iteratively computed using complex algorithms based upon different criteria[11].

To illustrate different beam forming aspects, let us consider an adaptive beam forming configuration shown below in figure 1[3]. The output of the array y(t) with variable element weights is the weighted sum of the received signals si(t) at the array elements and the noise n(t) the receivers connected to each element. The weights are iteratively computed based on the array output y(t) reference.

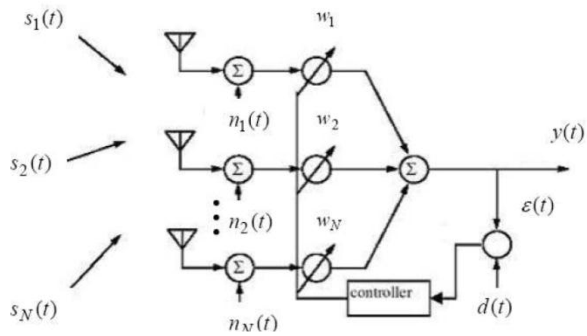

Fig 1: An Adaptive Array System

Signal d(t) that approximates the desired signal, and previous weights. The reference signal is approximated to the desired signal using a training sequence or a spreading code, which is known at the receiver. The format of the reference signal varies and depends upon the system where adaptive beam forming is implemented[3]. The reference signal usually has a good correlation with the desired signal and the degree of correlation influences the accuracy and the convergence of the algorithm. The array output is given by:

$$Y(t) = W^H x(t) \qquad \text{--------------1(a)}$$

In order to compute the optimum weights, the array response vector from the sampled data of the array output has to be known [3]. The array response vector is a function of the incident angle as well as the frequency[12]. The baseband received signal at the N-th antenna is a sum of phase-shifted and attenuated versions of the original signal Si(t).

$$x_N(t) \cong \sum_{i=1}^{N} a_N(\theta_i) s_i(t) e^{-j2\pi f_c \tau_N(\theta_i)} \qquad \text{--------------1(b)}$$

Adaptive arrays those are dynamically able to adapt to the changing traffic requirements. Smart antennas, usually employed at the base station, radiate narrow beams to serve different users. As long as the users are well separated spatially the same frequency can be reused, even if the users are in the same cell[6]. Smart antenna is one of the most promising technologies that will enable a higher capacity in wireless networks by effectively reducing multipath and co channel interference.

This is achieved by focusing the radiation only in the desired direction and adjusting itself to changing traffic conditions or signal environments [4].

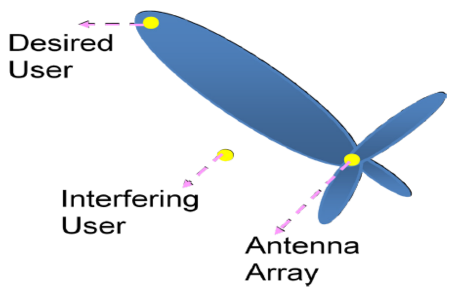

Fig 2: Beam forming Pattern

The process of combining the signals and then focusing the radiation in a particular direction is often referred to as digital beam forming.

II. Least Mean Square Algorithm

The Least Mean Square (LMS) algorithm uses a gradient based method of steepest decent. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error [1]. LMS algorithm is relatively simple, it does not require correlation function calculation nor does it require matrix inversions[1]. A very computationally efficient adaptive algorithm is the least mean squares (LMS) algorithm.

LMS is an iterative solution to solve for the weights which track to the bottom of the performance surface[8]. The LMS algorithm estimates the gradient of the error signal, e(k), by employing the method of steepest descent, which is summarized below.

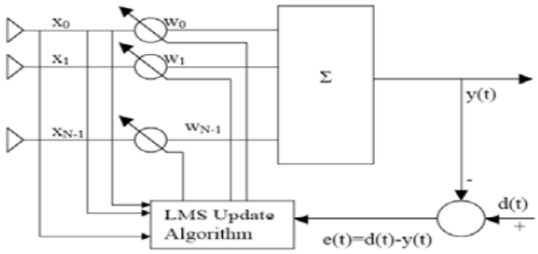

Fig 3: LMS Adaptive Beam forming Network

Let k w represent the Nx1 weight vector at time sample k. The weight vector can be updated at time sample k+1 by offsetting (k w by some small quantity which drives the weight vector one step closer to the bottom of the performance surface. This small quantities the value of the error gradient for time sample k, which is given as:

$$\vec{w}(k+1) = \vec{w}(k) + \mu\left[-\nabla(J(k))\right]$$

$$\vec{w}(k+1) = \vec{w}(k) + 2\mu E\left[\vec{x}(k)d^*(k) - \vec{x}(k)\vec{x}^H(k)\vec{w}(k)\right]$$

$$= \vec{w}(k) + 2\mu E\left[\vec{x}(k)\{d(k) - y(k)\}^*\right]$$

$$\boxed{\vec{w}(k+1) = \vec{w}(k) + 2\mu E\left[\vec{x}(k)e^*(k)\right]}$$

-------------2(a)

where μ is an incremental correction factor known as the step-size parameter or weight convergence parameter[3]. It is a real valued positive constant generally less than one. When a proper step size parameter is chosen and enough iteration is performed then the above result will converge to the optimum weight vector [13]. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. The step size varies from 0 to max, where max is the largest Eigen value of the correlation matrix R. However, as was previously stated obtaining the statistics of the channel and developing an adequate estimate of the received signal are quite difficult. In this case, we can use the LMS algorithm to form an instantaneous estimate of the error signal.

It is apparent that if the step size parameter is decreased, then a slower convergence is achieved. Also note the maladjustment at each iteration. This is Somewhat due to the noise present in the channel, but mostly caused by the gradient search method used to track the weights to the bottom of the performance surface[1]. Below is a plot of the resulting beam pattern for this particular scenario. In the backdrop is a shadow of the beam pattern using the SMI method, which is used as a benchmark. It is clear to see that the two beam patterns are nearly identical. Also, it can be seen from the asterisk marking the interferer arriving at 30^0 that the SMI method provides a deeper null than that using the LMS algorithm.

Consider a Uniform Linear Array (ULA) with N micro strip elements, which forms the integral part of the adaptive beam forming system as shown in the figure. The output of array antenna x (t) is given by equations.

$$x(t) = s(t)a(\theta_0) + \sum_{i=1}^{N_u} u_i(t)a(\theta_i) + n(t)$$

The weights here will be computed using LMS algorithm based on Minimum Squared Error (MSE) criterion. Therefore the weight update can be given by the following equation, where μ is the step-size parameter and controls the convergence characteristics of the LMS algorithm [10]. The initial weight w (0) is assumed as zero. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. The step size varies from 0 to max, where max is the largest Eigen value of the correlation matrix R.

The signal x(t) received by multiple antenna elements is multiplied with the coefficients in a weight vector w (series of amplitude and phase coefficients) which adjusted the phase and the amplitude of the incoming signal accordingly. The weighted signal is summed up, resulted in the array output y(t). An adaptive algorithm is then employed to minimize the error e(t) between a desired signal d(t) and the array output y (t) given by linear combination of the data at the k sensors.

Adaptive beam forming scheme that is least mean square (LMS) is used to control weights adaptively to optimize signal to noise ratio (SNR) of the desired signal in look direction and minimize the mean square error[3]. A smart antenna system are capable of efficiently utilizing the radio spectrum and is a promise for an effective solution to the present wireless systems problems while achieving reliable and robust high speed high data rate transmission. The Smart Antenna incorporates this algorithm in coded form which calculates complex weights according to the signal environment. The performance of LMS algorithm is compared on the basis of normalized array factor and mean square error (MSE) for SA systems. It is observed that an LMS algorithm is converging after 50 iteration.

III. Constant Modulus Algorithm

A typical polar NRZ signal possesses an envelope which is constant, on average. During transmission, corruption from the channel, multipath, MAI, and noise can distort[7].Using the constant modulus algorithm (CMA), the envelope of the adaptive array output, y (k), can be restored to a constant by measuring the variation in the signal's modulus and minimizing it by using the cost function[7]. The constant modulus cost function is a positive definite measure of how much the array Output's envelope varies from the unity modulus used to minimize the result. Setting p=1, q = 2, we can develop a recursive update method to determine the proper weights by Utilizing the method of steepest descent for the above cost function.Taking the gradient of the below equation yields.

If we know that the arriving signals of interest should have a constant modulus[14],we can devise algorithms that restore or equalize the amplitude of the original signal

$$J(k) = E\left[\left||y(k)|^p - 1\right|^q\right] \quad ,p = 1, 2 \text{ or } q = 1, 2$$

3(b)

The p = 1, q = 2 solution is typical because it provides the deepest nulls of the four configurations and provides the best signal to interference noise ratio (SINR). Figure below depicts the convergence curve for the constant modulus algorithm with p =1, q = 2.

The general beam pattern for CM algorithm is represented in the below graph.

From the above equations 2(a) and 3(a),the Lms and CM algorithms can be implemented for maximum beam pattern towards the desired user and nul towards the interferer.

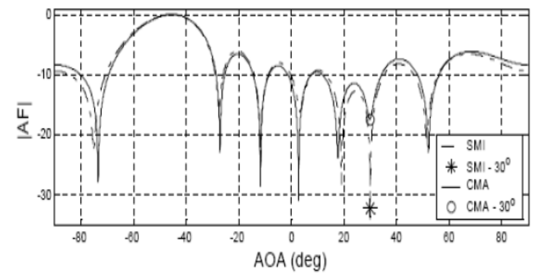

Fig 4: Beam Pattern for CMA

The bit error rate is maximum in the case of CMA, where as best beam forming will be obtained by LMS algorithm.

IV. Recursive Least Square Algorithm

The most inherent capacity of RLS is its high convergence rate, because the error at any point of time is independent of the statistical properties of the signal. The algorithm updates the autocorrelation matrix for the next instant with the aid of the autocorrelation matrix calculated for the present instant. It suffers from the drawback of having high computational complexity [3]. The RLS weight update Equation is the most inherent capacity of RLS is its high convergence rate, because the error at any point of time is independent of the statistical properties of the signal. The algorithm updates the autocorrelation matrix for the next instant with the aid of the autocorrelation matrix calculated for the present instant. It suffers from the drawback of having high computational complexity. The RLS weight update Equation is:

w(n) = w(n-1)+ (n)*g(n) ------ 4(a)

The convergence speed of the LMS algorithm depends on the Eigen values of the array correlation matrix. Contrary to the LMS algorithm, which uses the steepest descent method to determine the complex weight vector, the Recursive Least Squares (RLS) algorithm uses the method of least squares. The weight vector is

updated by minimizing an exponentially weighted cost function consisting of two terms: 1.) sum of weighted error squares and
2.) a regularization term. Together the cost function is given by:

$$\varepsilon(k) = \underbrace{\sum_{i=1}^{k} \lambda^{k-i} \left| e(i) \right|^2}_{\text{Sum of Weighted Error Squares}} + \underbrace{\delta \lambda^k \left\| \bar{w}(k) \right\|^2}_{\text{Regularization term}}$$

------------- 4(b)

where: e(i) is the error function and λ is called the forgetting factor, which is a positive constant close to, but less than one[2]. It emphasizes past data in a Non-stationary environment so that the statistical variations of the data can be tracked. In a stationary environment, λ = 1 corresponds to infinite memory.

V. Simulation Results

LMS algorithm simulation:

The graph is obtained between phase of desired signal and LMS output. Here we see two lines a red and a blue. Red is the phase of desired signal and blue is the phase of LMS output. So in this way we see there is not much difference in the desired and the obtained Output.It is obvious from the above results that by decreasing the value of the step size parameter, a faster convergence is achieved. Likewise, due to the high correlation between the transmitted signal and its multipath component, the null formed at 30^0 is Very shallow compared to that formed by the SMI method.

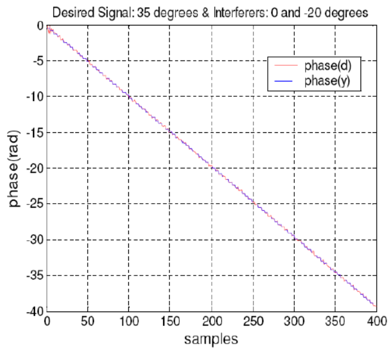

Fig 5: Phase of desired signal and LMS output

This is graph obtained between magnitude of desired signal and LMS output. In the figure we see that the LMS output is a blue line while the desired output shows a little about the LMS output line.

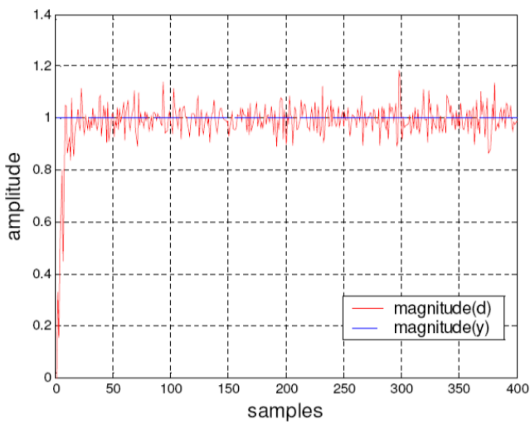

Fig 6: Magnitude of desired signal and LMS output

This is graph obtained between error between desired signal and LMS output.

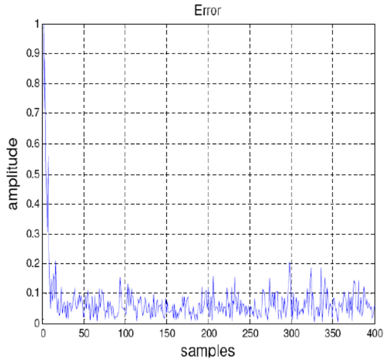

Fig 7: Error between desired signal and LMS output

This is graph is obtained for amplitude response after beam forming. It clearly depicts the plot between angle and magnitude of the L.M.S output.

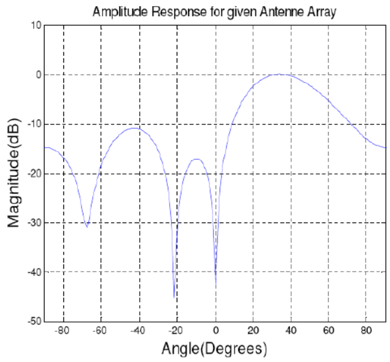

Fig 8: AMPLITUDE RESPONSE

CM algorithm simulation:

The graph is obtained between phases of desired signal and CMA output. Here we see two lines a red and a blue. Red is the phase of desired signal and blue is the phase of CMA output. So in this way we see there is not much difference in the desired and the obtained output.

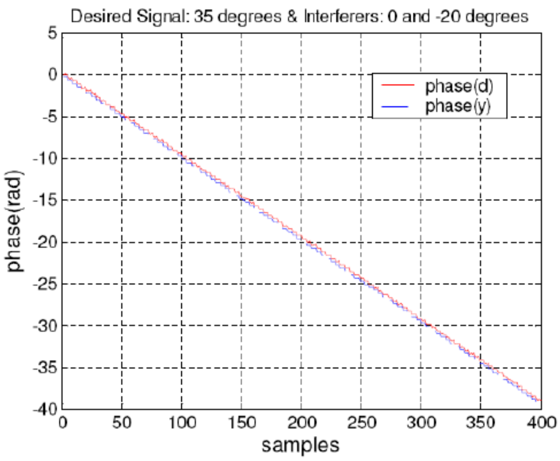

Fig 9: Phase of desired signal and CMA output

This is graph obtained between magnitude of desired signal and CMA output. In the figure we see that the CMA output is a blue line while the desired output shows a little about the Lms output line.

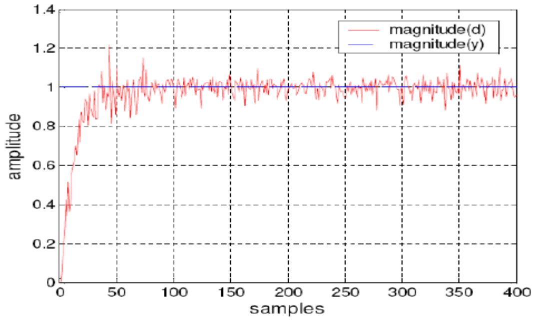

Fig 10: Magnitude of desired signal and CMA output

This is graph obtained between error between desired signal and CMA output.

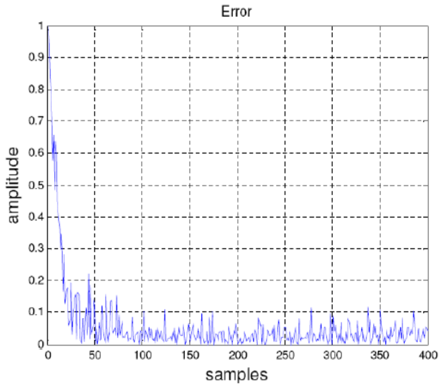

Fig 11:Error between desired signal and CMA output

In the above plot the error between desired signal and CMA output is decreasing. That is CMA output is approaching the desired signal. There will be always a minute error that is less than 0.1 which can be neglected in some cases.

This graph clearly depicts the amplitude response for given antenna array. It is a plot between angle and magnitude (db).

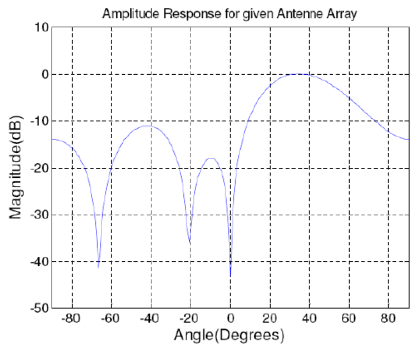

Fig 12: AMPLITUDE RESPONSE

The LMS algorithm continuously adaptive algorithm and has a slow convergence when the Eigen values of the covariance matrix are widespread and hence the convergence takes much more time. The advantage of the RLS algorithm over SMI is that it is no longer necessary to invert a large correlation matrix. The recursive equations allow for easy updates of the inverse of the correlation matrix. The RLS algorithm also converges much more quickly than the LMS algorithm. CMA has slow convergence time which limits the usefulness of the algorithm in dynamic environments where the signal must be captured quickly.CM algorithm converges slower than LMS algorithm. During the efforts to simulate the CM algorithm it was clear that the algorithm is less stable than the LMS algorithm. CM algorithm seems to be more sensitive to gradient constant μ and also for both algorithms, μ can be calculated adaptively.

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