Smart Antenna Algorithms for WCDMA Mobile Communication Systems

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Abstract :
The goal of 3rd generation systems is to integrate a wide variety of communication services such as high speed data, video and multimedia traffic as well as voice signals. WCDMA as the radio access technology for the 3G has many advantages such as highly efficient spectrum utilization and variable user data rates. Smart antenna technologies are very important for the system implementation. Smart Antennas serve different users by radiating narrow beams. The same frequency can be reused even if the users are in the same cell or the users are well separated. Thus the capacity of the system is increased by implementing this additional intra cell reuse. This paper discusses algorithms developed for smart antenna applications to WCDMA. The Direct Matrix Inversion Algorithm and RLS algorithms are the two adaptive beam forming algorithms used in smart antennas.
Simulation results show that convergence is faster in the RLS algorithm than in the DMI algorithm.

Key words: *Wide band CDMA, Direct Matrix Inversion (DMI), Recursive Least Squares (RLS), Adaptive beam forming, smart antenna.*

1. Introduction

Smart Antenna systems continually monitor their coverage areas and adapts to the users direction providing an antenna pattern that tracks the user and provides maximum gain in the direction of the user. Smart Antenna system was adopted by ITU for 3G wireless networks because of its ability to increase the capacity by reducing interference. A smart antenna system combines multiple antenna elements with a signal processing capability to optimize its radiation pattern automatically in response to the signal environment.

The DSP controls radiation parameters of the antenna. The DOA algorithms tracks the signal received from the user. The radiation pattern is adjusted to place nulls in the Direction of Interferers and Maxima in the direction of the desired user.

Various algorithms can be used in DSP that differ in their complexity and convergence. The adaptive algorithm must have low computational complexity and hardware implementation.

The Least Mean Square algorithm is the simplest algorithm but the convergence of the algorithm depends on the eigen value spread of the covariance matrix. When the covariance matrix has large eigen value spread the algorithm has slow convergence. Considering that the CDMA slot is small it is preferable to use algorithms with faster convergence that do not depend on matrix eigen value spread.

This paper discusses the Direct Matrix Inversion (DMI) algorithm and Recursive Least squares algorithms developed for WCDMA systems.

There are many types of adaptive beam forming algorithms. Fig(1) shows the adaptive beam forming system. Most of the beam forming algorithms can be categorized under two classes according to whether the training signal is used or not. These two classes are non-blind adaptive algorithms and blind adaptive algorithms. Non blind adaptive beam forming algorithms uses a training signal d(t) to update its complex weight vector. This training signal is sent by the transmitter to the receiver during the training period. Beam forming in the receiver uses this information to compute new complex weight. LMS, NLMS, RLS and DMI algorithms are categorized as non blind algorithms. Blind algorithms do not require any training sequence to update its complex vector. Constant Modulus Algorithm (CMA), Spectral Self-Coherence RE Storal (SCORE) and Decision Directed (DD) algorithms are examples of blind beam forming algorithms. These algorithms use some of the known properties of the desired signal.

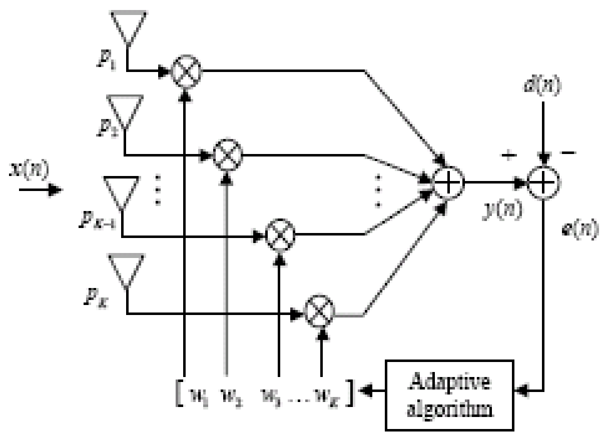

Fig 1. Adaptive Beam forming System

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2. Smart Antenna Processor with WCDMA

The beam forming of adaptive antenna is a computationally intensive process. Beam forming is a process in which each users signal is multiplied by complex weight vectors that adjust the magnitude and phase of the signal from each antenna element. Various algorithms can be applied for DOA estimation and tracking such as blind algorithms that use the temporal constant modulus structure of the signal (without training signal) or algorithms that use the spatial properties of received signals or training signal method.
The training signal method has the advantage of faster convergence rate. This can be applied to 3G communication systems because a pilot signal is presented in the structure of the up link WCDMA frame of UMTS/IMT 2000 physical channel. The reason for a dedicated pilot instead of a common pilot is to support the use of adaptive antenna arrays.

3. Direct Matrix Inversion Algorithm

3.1 Introduction

The co-variance matrix of the input vector x for a finite sample size is defined as the maximum likelihood estimation of matrix R and can be calculated as

$$R(N) = (1/N)\sum_{h=0}^{N-1} x(n)x^H(n) \qquad \text{….(1)}$$

The optimum weight vector that correspond to the estimated matrix R_k for any i^{th} channel is given by
$W_{opt}=R^{-1}r$ ……...(2)
The Direct Matrix Inversion Algorithm provides good performance in a discontinuous traffic when the number of interferers and their positions remain constant during the duration of the block acquisition.
The DMI algorithm employs direct inversion of the co-variance matrix R and therefore it has faster convergence rate.
The equation for co-variance matrix R is given by equation (3)

$$R = E\left[x(t)x^H(t)\right] \qquad \text{…….(3)}$$

The equation for correlation matrix r is given by equation (4)

$$r = E\left[d(t)x(t)\right] \qquad \text{…….(4)}$$

If a prior information about the desired signal and the interfering signals is known, then the optimum weights can be calculated directly by using the wiener solution

$$w^* = R^{-1}r \qquad \text{………(5)}$$

However, in practice signals are not known and the signal environment is highly dynamic. Therefore by estimating the covariance matrix R and the correlation matrix r the optimal weights are computed, by time averaging from the block of input data.
The estimates of the covariance matrix R and correlation matrix r over a block size N_2- N_1 are given by equations (6) and (7)

$$\hat{R} = \sum_{i=N_1}^{N_2} x(i)x^H(i) \qquad \text{……..(6)}$$

$$\hat{r} = \sum_{i=N_1}^{N_2} d^*(i)x^H(i) \qquad \text{………(7)}$$

Where N_1 and N_2 form the lower and the upper limits of the observation interval. This limit is taken to be small to ensure that the effect due to the changes in the signal environment during block acquisition does not effect the performance of the algorithm. Also large limit or block only means more matrix inversions, making the algorithm computationally intensive. The DMI algorithm requires the calculation of the inverse covariance matrix R and this much high computational complexity.
The weigh vector can be estimated by the equation (8)

$$\hat{W} = \hat{R}^{-1}\hat{r} \qquad \text{…….(8)}$$

From above equation the weights will be updated for each incoming block.
Because of the estimation there is a chance to have residual error in the Direct matrix inversion (DMI) algorithm. The error e due to estimation can be computed by the equation (9)

$$e = \hat{R}w^* - \hat{r} \qquad \text{…….(9)}$$

3.2 Weight adaptation techniques

Weight adaptation in the DMI algorithm can be achieved by using block adaptation technique where the adaptation is carried over disjoint intervals of time is the most common type. This block adaptation technique is suitable for mobile communications where the signal environment is highly time varying. The overlapping block adaptation technique is computational intensive as adaptation intervals are not disjoint but overlapping. This technique gives better performance but the number of inversions required are more when compared to block adaptation method. Another block adaptation technique is the block adaptation technique with memory. This method utilizes the matrix estimates computed in the previous blocks. This approach provides faster convergence for spatial channels that are highly time correlated. This technique works better when the signal environment is stationary.

3.3 Simulation Results

For simulation purpose an N element linear array is used with its individual elements spaced at half wave length distance.
The desired signal S(t) arriving at θ_0 is a simple complex sinusoidal phase modulated signal of the form given in equation (10)

$s(t)= e^{j\ \sin(wt)}$ ……..(10)

The interfering signals ui(t) arriving at angles θ_i are also the above form.
By doing so it can be shown in the simulations how interfering signals of the same frequency as the desired signal can be separated to achieve rejection of co-channel interference.
For simplicity sake the reference signal d(t) is considered to be same as the desired signal s(t). The array factor is obtained for the AOA of the desired user is at 30^0 and an interferer at 60^0. The figure (2) shows how the DMI algorithm is able to update the weights block-wise to force deep nulls in the direction of the interferer and maximum in the direction of the desired signal. The optimum weight vector that the algorithm converged is found to be w_1= 1 +3.9489e-018i, w_2=-0.13212 +1.0412i, w_3=-1.0696 + 0.094176i, w4= 0.58623 - 0.73939i, and ,w5= 0.70113 - 0.47576i for the number of elements N = 5.Fig(2) shows the normalized array factor for the number of elements N = 5,8 and 10 with spacing between the elements d = 0.5 lambda. Figures (3) and (4) shows the normalized array factor plots for DMI algorithm for different block lengths.

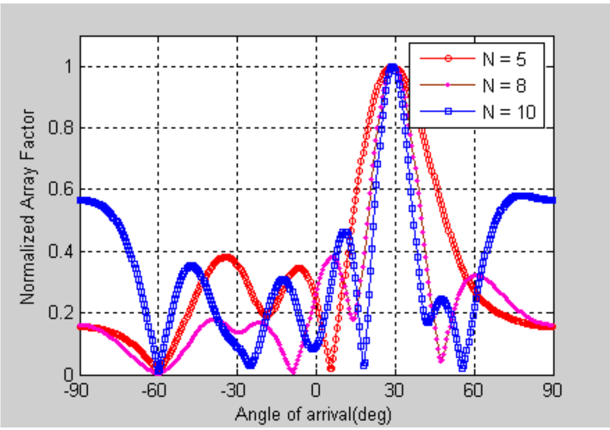


Fig.2. Normalized Array factor plots for DMI algorithm when the AOA of desired user at 30^0 and the interferer at -60^0 (d = 0.5λ), N_s=100; N_b=30

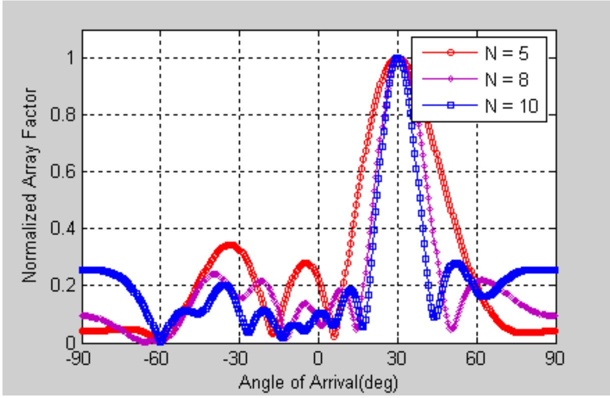


Fig.3. Normalized Array factor plots for DMI algorithm when the AOA of desired user at 30^0 and the interferer at -60^0 (d = 0.5λ), N_s=100; N_b=100

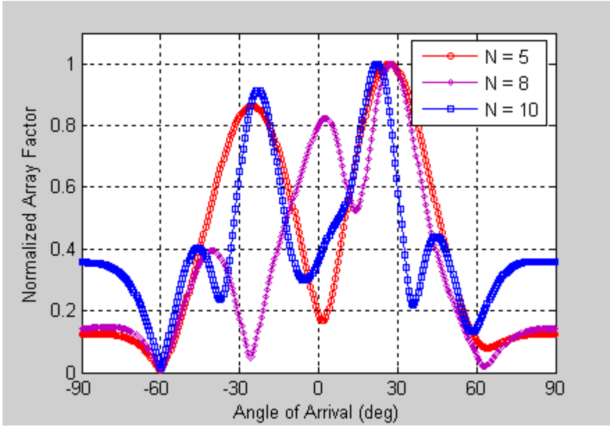


Fig.4. Normalized Array factor plots for DMI algorithm when the AOA of desired user at 30^0 and the interferer at -60^0 (d = 0.5λ), N_s=100; N_b=10

4. RLS Algorithm

4.1 Introduction

In LMS algorithm, the algorithm must go through many iterations before convergence is achieved. In mobile communication environment where the signal characteristics are more dynamic, the LMS algorithm may not allow tracking of the desired signal in a satisfactory manner. The rate of convergence is dictated by eigen value spread of the array correlation matrix. By using DMI algorithm the convergence speed can be achieved. The DMI algorithm, although faster than the LMS algorithm has several drawbacks. The correction matrix may be ill conditioned resulting in errors or singularities when inverted. For large arrays, there is a challenge of inverting large matrices. In RLS algorithm, the recursive equations allow for easy updates of the inverse of the correlation matrix. Thus the RLS algorithm converges faster than the LMS algorithm and it is not necessary to invert large correlation matrix as in DMI algorithm.

4.2 The Recursive Least Squares algorithm (RLS) :

The convergence speed of the LMS algorithm depends on the Eigen values of the array correlation matrix. In an environment yielding an array correlation matrix with large eigen value spread the algorithm converges with a slow speed This problem is solved with the RLS algorithm by replacing the gradient step size μ with a gain matrix $\hat{R}^{-1}(n)$ at the nth iteration, producing the weight update equation

$$\omega(n) = \omega(n-1) - \hat{R}^{-1}(n)x(n)\varepsilon^*(\omega(n-1))$$
…….. (11)

Where $\hat{R}(n)$ is given by

$$\hat{R}(n) = \delta_0 \hat{R}(n-1) + x(n) * x^H(n)$$

$$= \sum_{k=0}^{n} \delta_o^{n-k} x(k).x^H(k)$$
(12)

Where δo denoting a real scalar less than but close to 1. The δo is used for exponential weight of past data and is referred to as the for getting factor as the update equation tends to de-emphasize the old samples. The quantity $\frac{1}{1-\delta_0}$ is normally referred to us the algorithm memory. Thus for δo=0.99 the algorithm memory is close to 100 samples. The RLS algorithm updates the required inverse of using the previous inverse and the present samples as

$$\hat{R}^{-1}(n) = \frac{1}{\delta_0}\left[\hat{R}^{-1}(n-1) - \frac{\hat{R}^{-1}(n-1)x(n)x^H(n)\hat{R}^{-1}(n-1)}{\delta_0 + x^H(n)\hat{R}^{-1}(n-1)x(n)}\right]$$
……… (13)

The matrix is initialized as

$$\hat{R}^{-1}(0) = \frac{1}{\varepsilon_0} I, \varepsilon_0 \succ 0$$ …..(14)

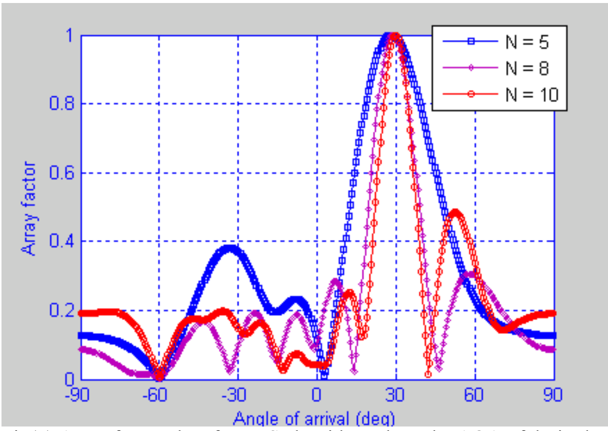
The RLS algorithm minimized the cumulative square error

$$J(n) = \sum_{k=0}^{n} \delta_0^{n-k} |\varepsilon(k)|^2$$ ……(15)

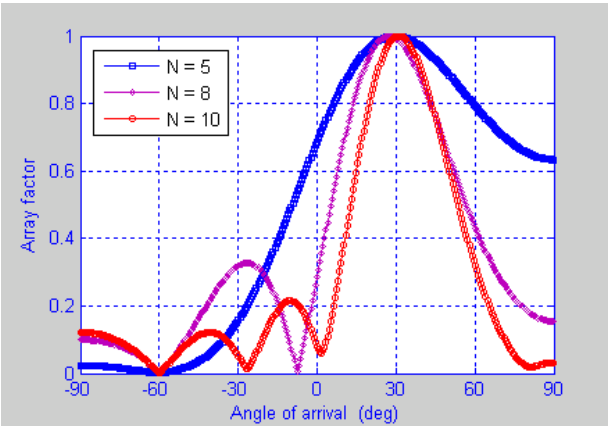
And its convergence is independent of the Eigen values distribution of the correlation matrix.

4.3 Simulation results of RLS algorithm

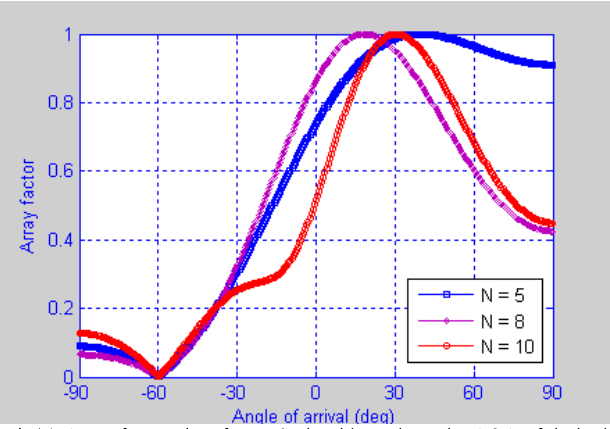
For simulation purpose an N element linear array is used. Fig (5) shows the array factor plots for RLS algorithm when the angle of arrival of the desired user is at 30 deg and interferer at -60 degrees for spacing between the elements equal to half wave length . The RLS algorithm places adaptively the maxima in the direction of desired user and nulls at the AOA of the interferer for various values of N. figures (6) and (7) shows the array factor plots for spacing between the elements equal to quarter wave length and one eigth wave length respectively. From these simulations it is evident that the optimum spacing between the elements is half wave length.



Fig(5) Array factor plots for RLS algorithm when the AOA of desired user at 30 degrees and the interferer at -60 degrees.(d = 0.5λ)



Fig(6) Array factor plots for RLS algorithm when the AOA of desired user at 30 degrees and the interferer at -60 degrees.(d = 0.2λ)



Fig(7) Array factor plots for RLS algorithm when the AOA of desired user at 30 degrees and the interferer at -60 degrees.(d = 0.125λ)

5 CONCLUSIONS:

This paper discussed various adaptive beamforming algorithms like Direct matrix inversion algorithm(DMI) and Recursive Least Square algorithms(RLS)used in smart antennas. The result obtained from the simulations showed that the DMI had poor convergence compared to RLS , and the RLS algorithm is the most efficient algorithm.

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