

Smart Antenna Adaptive Algorithms Development for 3G Cellular Communication with Training Signal

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Abstract

The smart antenna have to optimize reception and radiation patterns dynamically in response to the signal environment and the spatial beamformer has to maximize the signal/interference relation (SIR) continuously for each moving user. There is a growing need for the development of efficient algorithms for real-time optimization. Various algorithms can be applied for Digital Signal Processors (DSP), which differ in their complexity, convergence and so on. In this paper we consider and compare two adaptive algorithms: Sample Matrix Inversion (SMI) and Regularized Sample Inversion Matrix (RSMI) algorithms. Two criteria for comparison of algorithms were applied: convergence to optimal solution and convergence of radiation pattern. The efficient linear complexity RSMI algorithm is proposed.

1. Introduction

Smart array antenna systems continually monitor their coverage areas and the system adapts to the user's motion providing an antenna pattern that tracks the user, achieving the maximum gain in the user's direction. For this purpose smart antenna base station combines an antenna array with a control unit that optimize reception and radiation patterns dynamically in response to the signal environment, i.e. mobile moving about the coverage area [Liberti99], [Godara97].

The control unit of a smart antenna normally realized using a DSP. The DSP controls radiation parameters of the antenna, based on several inputs, in order to optimize the communications link. In smart antennas continuous tracking is achieved by including the Direction of Arrival (DoA) algorithm for the signal received from the user. The radiation pattern is adjusted to null out the interferers to maximize the SIR. It means that the development of efficient algorithms for real-time optimization is a current problem. Various

algorithms can be applied for DSP that differ in their complexity and convergence. It is evidently that adaptive algorithm must be implemented with a number of contradictory demands. This is, fast convergence to optimum solution, since with slow convergence it will be seen the high level of interference at the beginning part of communication between subscribers. Furthermore, the adaptive algorithm must preferably have low computational complexity as well as hardware implementation.

A simpler adaptive algorithm is the Least Mean Square (LMS) that has computational complexity $O(N)$, but when the covariance matrix has large eigenvalue spread the LMS algorithm has a rather slow convergence [Monzingo80]. Taking into account that the training time of a CDMA slot is small it is preferable to use algorithms with faster convergence that do not depend on matrix eigenvalue spread.

In this paper we consider and compare two faster adaptive algorithms to achieve optimal weight vectors: Sample Inversion Matrix (SMI) algorithm and Regularized Sample Inversion Matrix (RSMI) algorithm. We will apply two main criteria for comparison of algorithms: the convergence of SIR to optimal solution and the convergence of radiation pattern. We propose the recursive RSMI algorithm with linear complexity.

2. CDMA Smart Antenna Processor

The adaptive antenna beamforming is a computationally intensive process. Various algorithms can be applied for direction of arrival estimation and tracking problems, 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 [Godara97]. The main advantage of the training signal method is the faster convergence rate. It can be applied to 3G

communication systems because a pilot signal is presented in the structure of the uplink CDMA frame of UMTS/ITM2000 physical channel [Liberti99]. The reason for a dedicated pilot instead of a common pilot is to support the use of adaptive antenna arrays.

The processing of events occurring in 3G smart antenna communication systems could be presented as the following sequence:

- “Snapshot”, or sampling, is taken of the training signals coming from all of the antenna elements.
- DoA estimation. The number of incoming wave fronts and their DoA’s is estimated.
- DoA classification. First, the spatially resolved wave fronts, each incident from an estimated DoA extracted from the input data. Then, user identification decides whether a DoA belongs to a user or to an interfere.
- The optimum weight calculation. The processor calculates the optimum weights to maximize the SIR for each user. A beamforming algorithm forms an antenna pattern with a main beam steered into the direction of the user, while minimizing the influence of the interfering wave fronts.
- Tracking. The user DoA’s are tracked to increase the reliability of the DoA estimates.

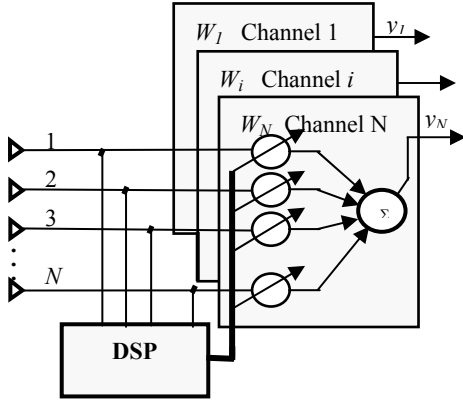


Figure 1. The smart antenna system structure

The system now has the ability to both transmit and receive information on each of the spatial channels making them two-way channels. As the Figure 3 shows, the smart antenna reception part consists of three units: the antenna itself with a radio unit, a beam forming unit, and a signal processing unit.

3. Signal Model and Criteria description

After DoA estimation, the steering vectors that correspond on K active users are available as a matrix

$$V = |V_1, V_2, \dots, V_i, \dots, V_K|, \quad (1)$$

where $V_i = |1, e^{-j\varphi_i}, e^{-j2\varphi_i}, \dots, e^{-j(N-1)\varphi_i}|^T$.

The input signals of N antenna elements from K active users are given by

$$S = |S_1, S_2, \dots, S_i, \dots, S_K|, \quad (2)$$

where $S_i(t) = \sqrt{\rho_i} |1, e^{-j\varphi_i}, e^{-j2\varphi_i}, \dots, e^{-j(N-1)\varphi_i}|^T$ is the signal from the i -th user, $\varphi_i = 2\pi(d/\lambda)\sin\phi_i$, ϕ_i is the angle of the i -th user arrival signal that coincide with estimated DoA’s angles, ρ_i is the power of the i -th user signal.

We present the complex vector in the output of the antenna elements in the form

$$X = \sum_{i=1}^k S_i \chi(t) + n(t), \quad (3)$$

where $n(t)$ is zero-mean thermal noise that is presented at the input of the receiver, $\chi(t)$ is a complex quasi stationary Gaussian process with unit variance .

The output signal of the i -th user adaptive beam former is given by

$$y_i = W_i^H X, \quad (4)$$

where W_i is a n -dimension weight vector of the i -th beamformer, and H denotes complex transpose.

The criteria of SIR maximization (MSIR) will be applied

$$SIR = |W_{i opt}^H S_i|^2 / W_{i opt}^H R W_{i opt} \quad (5)$$

where $R = E\{X X^H\}$ is the $N \times N$ correlation matrix of the total received signal, E denotes expectation and

$$W_{i opt} = R^{-1} V_i. \quad (6)$$

where $W_{i opt}$ is the optimum weight vector.

4. SMI Algorithm Description

The covariance matrix of the input vector X for a finite sample size is defined as the maximum likelihood estimation of matrix R and can be calculate as

$$R_k = (1/k) \sum_{i=1}^k X_i X_i^H \quad (7)$$

The optimum weight vector that correspond to the estimated matrix R_k for any i -th channel is given by

$$W_k = R_k^{-1} V_i, \quad (8)$$

Using these estimation to calculate the weights is known as the SMI algorithm. When one use finite sample size then formula (5) can be rewritten as

$$SIR_k = |W_k^H S_i|^2 / W_k^H R W_k \quad (9)$$

The convergence of the SMI algorithm is $2N-1$ samples and does not depended on eigenvalues distribution [Reed74]. But even with the powerful DSP’s available today it is a very challenging task to perform eq.(8) in

real time because the base operation of this algorithm is *matrix inversion*, with computational complexity $O(N^3)$. The SMI algorithm has other disadvantages. The sample matrix can not be inverted until N samples could be collected, because it rank is not complete. Even if the rank is complete ($k > N$) the ill condition causes calculation errors. Another way to solve eq. (8) in the DSP is by Gaussian elimination with back substitution. This method is both faster and more accurate than calculating the inverse of the covariance matrix, but it has the same computational complexity $O(N^3)$.

5. RSMI Algorithm and Recursive RSMI Algorithm Development

Applying a priori information that the sampled correlation matrix contains non correlative Gaussian noise we present the new sample matrix as

$$R_k = (1/k) \sum_{i=1}^k X_i X_i^H + I\varepsilon \quad (10)$$

where I is the identity matrix and ε is a small constant.

The method of weighting vector calculation applying of eq.(10) is known as the RSMI algorithm [Monzingo80] and it gives some advantage in the computation process, because matrix R_k in this case is better determined, but the computational complexity is $O(N^3)$ which is the same as the SMI algorithm.

Eq. (10) gives the possibility to present the correlation matrix as one rank modified

$$R_k = R_{k-1} + X_k X_k^H, \quad (11)$$

It is well known [Monzingo80] that R_k^{-1} is computed using the matrix inversion lemma.

$$R_k^{-1} = R_{k-1}^{-1} - \frac{R_{k-1}^{-1} X_k X_k^H R_{k-1}^{-1}}{\varepsilon + X_k^H R_{k-1}^{-1} X_k} \quad (12)$$

Calculation of the weight vector can be made by applying eq. (8) and eq. (12). The base operation of this algorithm is *matrix by vector multiplication*, with computational complexity $O(N^2)$ and the (12) can be performed easier in real time processing with the DSP. The computational complexity is still too large.

We present a recursive RSMI vector operations efficient algorithms that apply eq.(12) and has lineal computational complexity $O(N)$. This algorithm does not need to calculate the weight vectors directly. For this reason it has some computational advantages. If X_k is the current sample vector of the antenna array then the output signal is

$$y_k = S R_k^{-1} X_k = S \left(R_{k-1}^{-1} - \frac{R_{k-1}^{-1} X_k X_k^H R_{k-1}^{-1}}{\varepsilon + X_k^H R_{k-1}^{-1} X_k} \right) X_k \quad (13)$$

Making the substitution $\xi_k = R_{k-1}^{-1} X_k$ eq.(13) can be rewritten as

$$y_k = S(\xi_k - \xi_k d_k \xi_k^H X_k) \quad (14)$$

where $d_k = (\varepsilon + \xi_k^H X_k)^{-1}$ is a scalar.

Taking into account that $\xi_1 = \varepsilon^{-1} X_1$, the recursive update formula for vectors ξ_k is given by

$$\xi_k = X_k - \sum_{j=1}^{k-1} \xi_j d_k \xi_j^H X_k \quad (15)$$

As follows from eq.(14) and eq.(15) the calculation of y_k needs $O(N)$ operations because the base operation of this algorithm is *vector by vector multiplication*. Equations (14) and (15) will be called the recursive RSMI algorithm.

6. Simulation Result

To observe the convergence of the SMI and the RSMI algorithms some communication scenario was created. The antenna array consists of $N=12$ linearly arranged elements with $\lambda/2$ spacing. Each user was simulated as a Gaussian distributed process. A perfect power control is assumed with SNR 17dB and azimuth location uniformly distributed between $+60^\circ$ and -60° . Two hundred independent simulations have been averaged. Convergence of the algorithm was evaluated as the number of samples that corresponds to a SIR decreasing not worst than -3db in comparison with the optimum solution. As the simulation results show (figure 2), the convergence of SMI algorithm is $2N-1$ samples and does not depend on the number of interfered users. This result confirms the one obtained in [Reed74]. The convergence of the RSMI algorithm strongly depends on the number of interfered users K and it is approximately equal to 1.5K. The convergence of the radiated pattern is evaluated as the number of samples required to achieve the optimum main lobe form and at the same time the side lobe no exceeding the -13db level (level of first side lobe no adaptive antenna). The result is present in Figures 3,4. As follows from these figures the convergence of radiation pattern for the SMI and the RSMI algorithms are 36 and 6 samples respectively, that corresponds approximately $2N$ for the SMI algorithm and K for the RSMI algorithm. Simulation of other scenarios confirms this result. The choice of the regularization parameter is very important for RSMI algorithm because on one hand the bigger is the regularization parameter the better are the numerical properties of algorithm, but on the other hand, it convergence becomes worse. Figure 5 shows that convergence depends on the regularization parameter but it almost does not change in the range of (0-30)dB. It means that the RSMI algorithm is not critical to regularization parameter changing.

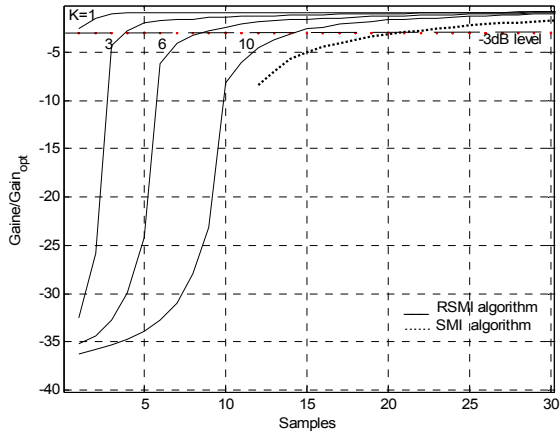


Figure 2. The convergence of the SMI and the RSMI algorithms

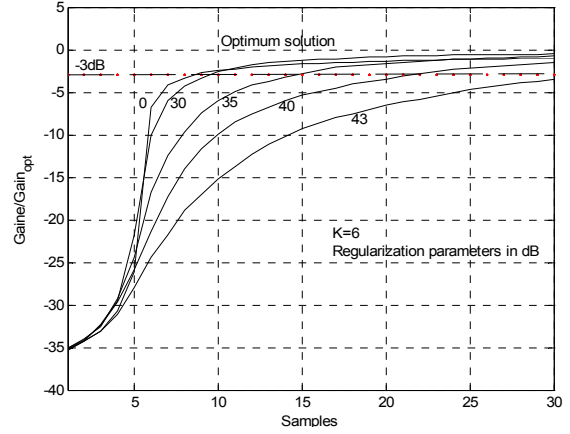


Figure 5. The pattern convergence of the RSMI algorithm vs. regularization parameters

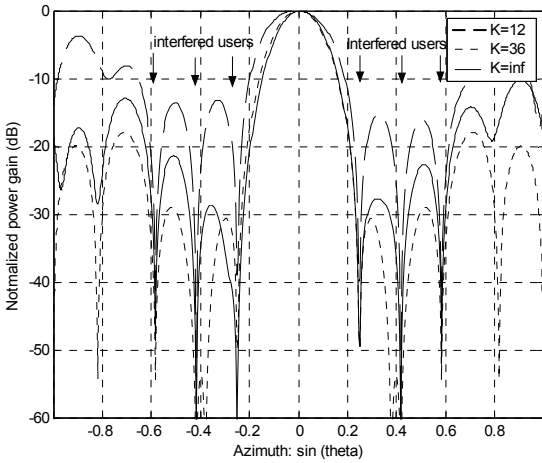


Figure 3. The pattern convergence of the SMI algorithm

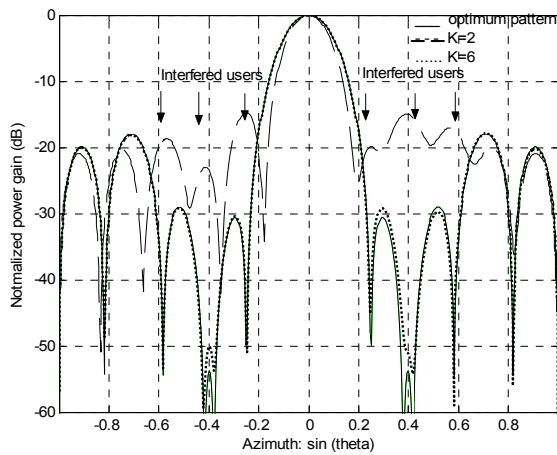


Figure 4. The pattern convergence of the RSMI algorithm

7. Conclusions

Two adaptive algorithms for smart antenna were investigated and compared, namely the Sample Inversion Matrix (SMI) algorithm and the Regularized Sample Inversion Matrix (RSMI) algorithm. We applied two criteria for comparison of algorithms: the convergence of SIR to an optimal solution and the convergence of radiation pattern. The next conclusions can be made:

- The convergence of algorithms depends both on adaptive algorithm type and the communication scenario. The convergence of the SMI algorithm is $2N-1$ but for the RSMI it can be achieved a number of active interfered users (K).
- The pattern convergence for the SMI and the RSMI algorithms are approximately $3N$ for the SMI algorithm and K for the RSMI algorithm.
- For the RSMI algorithm the regularization parameter can be chosen in the range of (0-30)dB in many communication scenarios without changing the convergence rate.
- The RSMI algorithm can be implemented with linear complexity without calculating directly the sampled weight vectors.

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