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Study and Simulation of Smart antenna using SMI and CGM Algorithm

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Abstract: - This paper presents, conjugate gradient method (CGM) and sample matrix inversion method to adapt the weights vector of the smart antenna system. The radiation pattern of the proposed antenna system is adjusted to emphasize the desired signal by orienting the main beam toward it and eliminate the interfering signals perfectly by pointing nulls in their directions. The main aim of the paper is , beam-forming using conjugate gradient method and sample matrix inversion which helps the smart antenna to track mobile targets, communicate directionally with the desired users, suppressing interference and covering a long range with high throughput. RF spectrum is a limited resource and is becoming crowded day by day due to the advent of new technologies. The sources of interference are increasing as well and hence interference is becoming the limiting factor for wireless communication. Smart Antenna adapts its radiation pattern in such a way that it steers its main beam in the DOA (direction of arrival) of the desired user signal and places null along the interference. It refers to a system of antenna arrays with smart signal processing algorithms.

I. INTRODUCTION

The term smart antenna refers to any antenna system that uses an antenna array with an adjustable antenna pattern as required. In wireless applications, Smart antennas have an important benefit such as: improving system capacity, providing robustness to system perturbation, reducing sensitivity to non ideal behaviours, as well as separating the received signals spatially with aid of space division multiple access (SDMA) concept. Recently, smart antenna have wide range of applications includes, but not limited to, wide band code division multiple access (CDMA) systems ,ad-hoc networks , radio frequency identification ,wireless sensor networks , and even radar systems. Smart antenna patterns are controlled via algorithms based upon certain criteria. These criteria could be maximizing the signal-to interference ratio (SIR), minimizing the variance, minimizing the mean square error (MSE), steering toward a signal of interest, nulling the interfering signals, or tracking a moving emitter to name a few. The implementation of these algorithms can be performed electronically through analogue devices but it is generally more easily performed using digital signal processing (Gross n.d.). This digitization can be performed at either IF or baseband frequencies. Since an antenna pattern (or beam) is formed by digital signal processing, this process is often referred to as digital beam forming. When the algorithms used are adaptive algorithms, this process is referred to as adaptive beam forming. Adaptive beam forming is a subcategory under the more general subject of digital beam forming. The chief advantage of digital beam forming is that phase shifting and array weighting can be performed on the digitized data rather than by being implemented in hardware. On reception, the beam is formed in the data processing rather than literally being forming in space. The digital beam forming method cannot be strictly called electronic steering since no effort is made to directly shift the phase of the antenna element currents. Rather, the phase shifting is computationally performed on the digitized signal. If the parameters of operation are changed or the detection criteria are modified, the beam forming can be changed by simply changing an algorithm rather than by replacing hardware. The following figure 1.1 shows the contrast difference between a traditional electronically steered antenna and DBF or smart antenna. Adaptive beam forming is generally the more useful and effective beam forming solution because the digital beam former merely consists of an algorithm which dynamically optimizes the array pattern according to the changing electromagnetic environment. (Boroujeny n.d.) An adaptive array system consists of the antenna array elements terminated in an adaptive processor which is designed to specifically maximize certain criteria. As the emitters move or change, the adaptive array updates and compensates iteratively in order to track the changing environment. This chapter will focus on key areas such as historical developments of the smart antennas, the need of smart antennas in dense and changing environments and different types of smart antennas.

II. ADAPTIVE BEAM FORMING

A. Introduction:

There are two types of beam forming approaches; one is fixed beam forming approach which was used if the angles of arrivals don’t change with time i.e. the user emitting the desired signals is fixed and not moving. As explained in the previous chapters, this type of adaptive technique actually does not steer or scan the beam in the direction of the desired signal. Switched beam employs an antenna array which radiates several overlapping fixed beams covering a designated angular area. The fixed beam forming techniques used are the maximum signal to interference ratio (MSIR), the Maximum likelihood method (ML) and the Minimum Variance method (MV). If the arrival angles are such that they don’t change with time, the optimum array weights won’t need to be adjusted. (Gross n.d.) However, if the desired arrival angles change with time, it is necessary to devise an optimization scheme that operates dynamically according to the changing environment so as to keep recalculating the optimum array weights. The receiver signal processing algorithm then must allow for the continuous adaptation to an ever-changing electromagnetic environment. Thus, if the user emitting the desired signal is continuously moving due to which the angle of arrival

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is changing, this user can be tracked and a continuous beam can be formed towards it by using one of the adaptive beam forming techniques. This is achieved by varying the weights of each of the sensors (antennas) used in the array. 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. (Haykin 1985) The adaptive beam forming algorithms are classified into two types;

1. **Non-blind adaptive algorithms -** These types of algorithms make use of a reference signal to modify the array weights iteratively, so that at the end of each and every iteration, the output of the weights is compared to the reference signal and the generated error signal is used in the algorithms to modify the weights. The examples of this type of algorithm are Least Mean Square Algorithm (LMS), Recursive Least Square algorithm (RLS), Sample Matrix Inversion (SMI) and Conjugate Gradient (CG).
2. **Blind adaptive algorithms** – Unlike the non-blind adaptive algorithms, the blind adaptive algorithms do not make use of the reference signal and hence no array weight calibration is required. The examples of this type of algorithms are Constant Modulus algorithm (CMA) and Least Square Constant Modulus (LS-CMA)

Before we move on to the details and explanation of these algorithms let us have a brief look on the adaptive beam forming problem setup which will lead us a better understanding of the adaptive array algorithms.

B. Adaptive Beam forming Problem Setup:

In order to illustrate the different beam forming techniques, consider the following adaptive array system configuration.

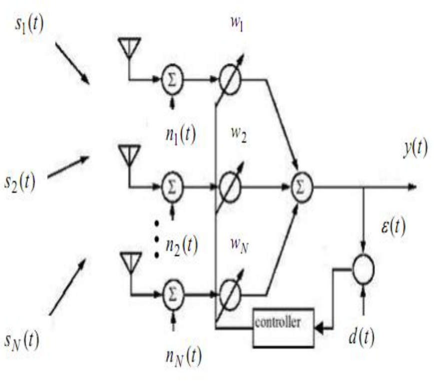

Fig 1 An Adaptive array system (Awan 2008)

In this section we will get to know a class of optimum linear filters known as Wiener filters which forms the basis of the SMI and the concept of Wiener filter is essential and helpful to understand the adaptive filters. The output of the array y (t) with variable element weights is the weighted sum of the received signals s_i (t) at the array elements and the noise at the receiver's n (t) connected to each element. The weights w_m are iteratively computed based on the array output y(t), a reference 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. 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. (Awan 2008)

The array output is given as;

$$y(t) = w^H.x(t) \quad 2.1$$

Where, w^H denotes the complex conjugate transpose of the weight vector w.In order to compute the optimum weights, the array response vector from the sampled data of the array output has to be known. The array response vector is a function of the incident angle as well as the frequency. The baseband received signal at the N^{th} antenna is a sum of phase-shifted and attenuated versions of the original signal $S_i(t)$ [4].

$$x_N(t) = \sum_{i=1}^{N} a_N(\theta_i) s_i(t) e^{-j2\pi f_c \tau_N(\theta_i)} \quad 2.2$$

The $S_i(t)$ signal consists of desired and interference signals;

The $\tau_N(\theta_i)$ is the delay which each signal experiences and f_c is the centre frequency.

$$\text{Now, } A(\theta) = [a(\theta_1)\ a(\theta_2)\ a(\theta_3) \ldots a(\theta_d)]$$
$$S(t) = [s_1(t)\ s_2(t)\ s_3(t) \ldots s_d(t)]^T$$

Therefore the incoming signals along with their array steering vector and noise are given in a matrix form as;

$$x(t) = A(\theta).S(t) + n(t) \quad 2.3$$

To have a better understanding let us rewrite the above equation by separating the desired signal and interference signals. Let s (t) be denoted as the desired user signal arriving at an angle θ_0 and u_i (t) be the N_u number of interference signals arriving at an angle θ_i. The respective angle of arrival can be found using the Direction of Arrival (DOA) algorithms Thus, the output of the antenna array can be written as;

$$y(t) = s(t).a(\theta_0) + \sum_{i=1}^{N_u} u_i(t) a(\theta_i) + n(t) \quad 2.4$$

Where, $a(\theta_i)$ is the array propagation vector of the i^{th} interfering signal $a(\theta_0)$ is the array propagation vector of the desired signal.Once the above information is known then the adaptive algorithms are required to estimate the error difference between the output of the antenna array y(t) and the reference signal d(t). The reference signal is similar to the original signal s (t) and the algorithm should minimize the error difference between the output signal and reference signal so that the output signal is as close to the original signal s (t) and once that is done, a beam can be formed towards the desired signal and the user can be tracked at all times. The output of the array

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approaches the desired signal d (t) as the estimation error e(t) approaches zero and in order to achieve this the parameters of the filter must be chosen appropriately. The most straightforward approach would be to choose an appropriate function of these filter parameters as a cost function and that set of filter parameters must be selected which optimises this cost function in some sense. The cost function or performance function must be mathematically tractable and should have single minima so that the optimum set of filter parameters can be selected easily. (Boroujeny n.d.) In Wiener filters, the performance function is given as;

$$\varepsilon = E[|e(t)|^2] \qquad 2.5$$

Where, E[.] is denoted as statistical expectation.

The performance function ε, which is also called as Mean Square Error Criterion satisfies both the conditions specified above i.e. it can be easily tracked mathematically and has a single global minimum, like a hyperparaboloid (bowl shaped) with a single minimum point which can be easily calculated by using the second-order statistics of the random processes. In the above case, the Mean Square error $(e(n)^2)$ between the beam former output and the reference signal can be given as; (Awan 2008)

$$e(t)^2 = [d(t) - w^{H} \cdot x(t)]^2 \qquad 2.6$$

Taking expectation on both sides of the equation above, we get;

$$E[e(t)^2] = E\{[d(t) - w^{H} \cdot x(t)]^2\}$$
$$E[e(t)^2] = E\{[d(t)]^2\} - 2w^H r + w^H R w$$

Where, r = E[d(t).x(t)] is the cross correlation matrix between the desired signal and the input received signal and, $R = E[x(t).x^H(t)]$ is the autocorrelation matrix of the received signal which is also known as the Covariance matrix. The minimum MSE can be obtained by setting the gradient vector of the above equation with respect to w equal to zero, i.e.

$$\nabla_w (E[e(t)^2]) = -2p + 2Rw = 0;$$

Therefore the optimum solution for the weight is given as;

$$w_{opt} = R^{-1}p \qquad 6.7$$

The above equation is also called as the Wiener-Hopf equation and as we can see from the above equation that the computation of the optimum tap-weight vector w_{opt} requires knowledge of the two quantities:

1. The correlation matrix R of the tap-input vector x(t) and;
2. The cross correlation vector p between the tap-input vector x(t) and the desired signal d(t).

This equation forms the basis of some non-blind algorithms like the Least Mean square (LMS) algorithm and Sample Matrix Inversion (SMI) algorithm.

III. SAMPLE MATRIX INVERSION ALGORITHM

In the previous section we learnt about the basic of SMI algorithm.Sample Matrix Inversion (SMI) which is also known as Block adaptive approach because it invloves block implementation or block processing i.e. a block of samples of the filter input and the desired output are collected and processed together to obtain a block of output samples. Thus, the process involves serial to parallel conversion of the input data, parallel processing of the collected data and parallel to serial conversion of the generated output data. The computational complexity can be further reduced by the elegant parallel processing of the data samples. (Gross n.d.) Thus, we can say that the sample matrix inversion algorithm is a time average estimate of the array correlation matrix using K time samples i.e. dividing the input samples into 'k' number of blocks and each number of blocks are of length K as shown in the figure below. Thus we can sat that in this type of algorithm we are adapting the weights block by block thus increasing the convergence rate of the algorithm and reducing the computational complexity further. (Gross n.d.)

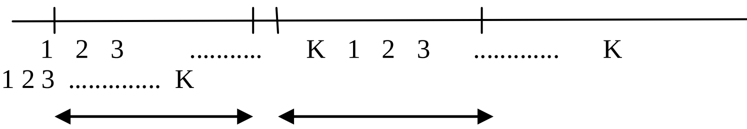

Fig 2

Recalling the earlier equation given by the optimum Weiner solution as;

$$W_{opt} = R^{-1}p$$

Where, p is the cross correlation matrix between the desired signal d (n) and the input samples x(n) ; R is the auto-correlation matrix between the input samples itself.

Since we are using a block adaptive approach, hence, defining a matrix $\bar{X}_K(K)$ as the kth block of $\bar{x}$ vectors ranging over K- data snapshots. Thus,

$$\bar{X}_K(k) = \begin{bmatrix} x_1(1+kK) & x_1(2+kK) & \cdots & x_1(K+kK) \\ x_2(1+kK) & x_2(2+kK) & & \vdots \\ \vdots & & \ddots & \\ x_M(1+kK) & & \cdots & x_M(K+kK) \end{bmatrix}$$

Where, k is the block number and K is the block length as shown in the fig above.

Thus, the estimate of the array correlation matrix is given as;

$$R(k) = \frac{1}{K}\, \bar{X}_K(k).\bar{X}_K^H(k) \qquad 3.1$$

In addition the desired signal vector can be defined as;

$$\bar{d}(k) = [d(1 + kK) \;\; d(2 + kK) \;\ldots\ldots\; d(K + kK)] \qquad 3.2$$

Thus, the estimate of the correlation vector $\bar{p}$ is given as;

$$\bar{p}(k) = \frac{1}{K}\, d^*(k).\bar{X}_K(k) \qquad 3.3$$

Thus, the SMI weights can be calculated for the k^{th} block of length K as;

$$\bar{w}_{SMI}(k) = \bar{R}^{-1}(k).\bar{p}(k) \qquad 3.4$$

The block processing used in this type of algorithm may be faster than the LMS algorithm in terms of convergence rate but it generates certain time delay at the

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system output. It arises because a block of samples of input signals has to be collected before the processing of the data can begin. Thus, the processing delay increases with the block length because the number of input signal to collected and processed are increased.

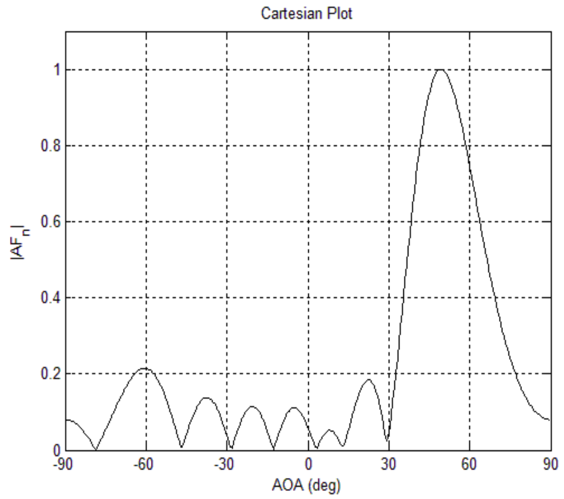

Fig 3. Cartesian plot for 50 degree using SMI

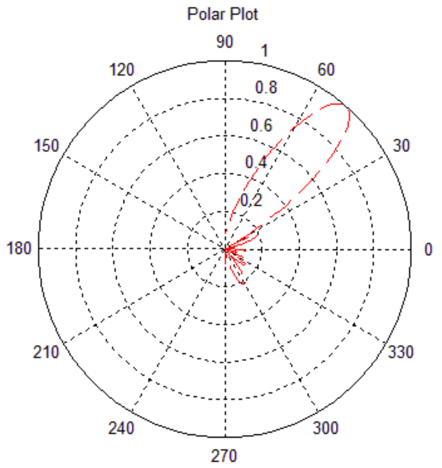

Fig 4. 3Polar plot

IV. CONJUGATE GRADIENT METHOD

The main disadvantage of the steepest descent method and the algorithms depending on it like the LMS, SMI and RLS algorithms is that sensitivity of the rate of convergence to the Eigen value spread of the correlation matrix as greater is the Eigen value spread slower is the convergence rate. This convergence rate can be accelerated using the Conjugate Gradient method (CGM) algorithm which is by far the fastest iterative method to reach the optimum solution by choosing conjugate (perpendicular) paths for each new iteration and the conjugacy in this case is meant to be orthogonal i.e. this method produces orthogonal search directions resulting in the fastest convergence towards the optimum solution which is depicted in the figure below.

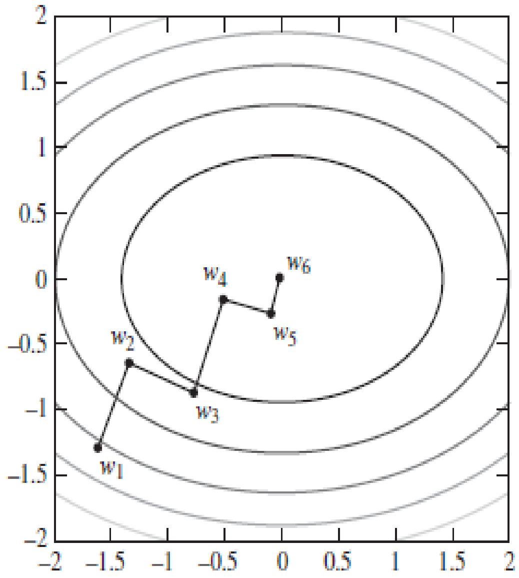

Fig 5 Convergence using Conjugate Gradience

Conjugate gradient uses the equation of the form $A.\bar{w} = \bar{d}$ to obtain value of $\bar{w}$. It produces weights vector at each sample of time, corresponding to the complex conjugate of the optimum weights vector of the smart antenna system. (Mousa Jan 2011)

Therefore, $A\bar{w}^{H} = \bar{d}$ 4.1

Consider A as a K×M matrix of array snapshots, K denotes a specific number of iteration and $\bar{d}$ represents reference signal (same as desired signal) of K snapshots.

$$A = \begin{bmatrix} x_1(1)\ x_2(1) \ldots\ldots x_M(1) \\ x_1(2)\ \ x_2(2) \ldots\ldots\ldots\ldots.. \end{bmatrix}$$

Vector $\bar{e}$ denotes the error between the desired signal and the array output signal at every iteration. (Mousa Jan 2011)

$\bar{e} = \bar{d} - A.\bar{w}^{H}$ 4.2

Thus, CG method starts with an initial guess of the weights vector to obtain the above equation. Then, the direction vector $\bar{D}$ gives the new conjugate direction towards the optimum weights.

$\bar{D} = A^{H}\bar{e}$ 4.3

In order to update the weights the following equation is used;

$w^{H}(n+1) = w^{H}(n) - \mu(n).\bar{D}(n)$ 4.4

Where, μ is the step size of the n^th iteration and once the weight is updated the error function and the direction vector $\bar{D}$ must be updated using the following equations; (Mousa Jan 2011)

$\bar{e}(n+1) = \bar{e}(n) + \mu(n).A.\bar{D}(n)$ 4.5

$\bar{D}(n+1) = A^{H}.e(n+1) - \alpha(n).\bar{D}(n)$ 4.6

Where, α(n) minimizes the error function.

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A. CGM Outputs:-

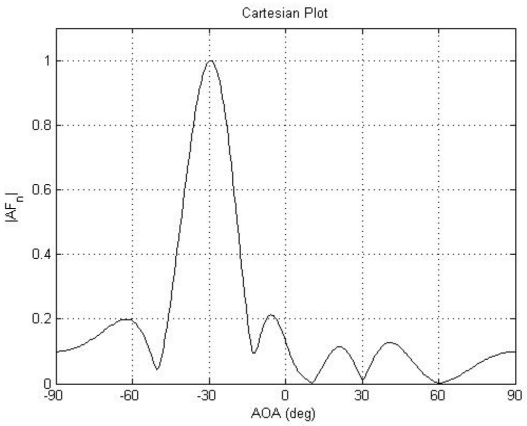

Fig 6 cartesion plot for -30 degree using CGM

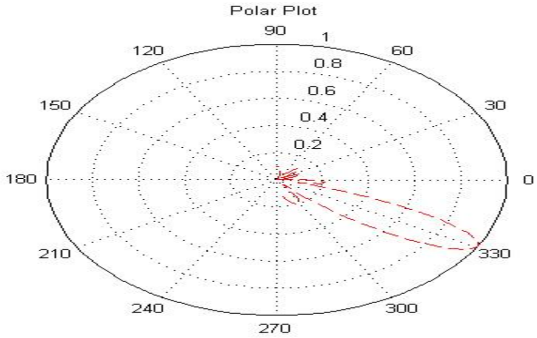

Fig 7 Polar Plot

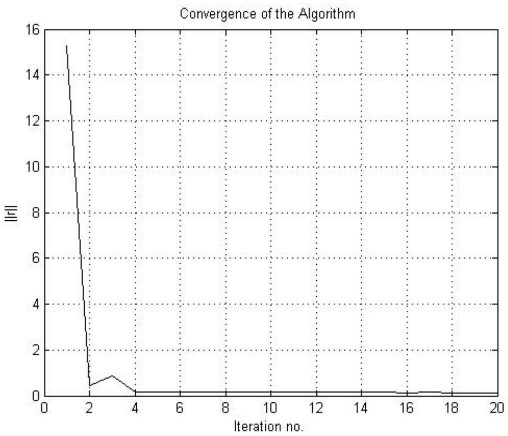

Fig 8 Convergence Plot

The CGM method also has a better resolution as compared to the previous algorithms because the main beam pointing towards the desired user is quite sharp with a high directivity and the side lobes which in this case are very less and have power level very low than what was achieved in the previous algorithms. As we can from the polar plot (Fig 6.23) below the side lobes are hardly visible making this algorithm the most efficient of all the algorithms. The convergence of the algorithm is very quick as we can see from the figure 6.24 below and comparing it with the other algorithms. The CGM algorithm converges in the fourth iteration which if compared to the SMI algorithm is very fast because the SMI algorithm takes around 70 iterations to reach the optimum solution.

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