## Optimization Techniques for Smart Antenna Beamforming

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Abstract---Smart antenna systems processes signals arriving from different directions to detect (estimate) desired signal direction of arrival DOA. Biased on the estimated DOA the beam former optimize antenna elements weights such that the radiation pattern of the antenna array is adjusted to minimize a certain error function or to maximize a certain reward function derived by the adaptive algorithm. In wireless applications the antenna pattern is shaped so as to cancel interfering signals (placing nulls) and produce or steer a strong beam towards the wanted signal according to direction of arrival (DOA). Linear Antenna arrays provide alternative solution to dimensional structure of Antennas. In Linear arrays, the array elements are same as each other, and they are aligned along a straight line with equal element separations. In this paper, an optimization technique known as Particle swarm optimization (PSO) is discussed to determine optimal antenna elements feed that provide null (minimum power) in the directions of the interfering signals while to maximize of radiation in the direction of the useful signal. Due to changing environment, the target goal changes and modification in the algorithm is required to provide optimal solution for varying real time target. The PSO algorithm emerges as a powerful stochastic optimization method inspired by the social behaviour of organisms such as bird flocking or fish schooling, in which individuals have memory and cooperate to move towards a region containing the global or a near-optimal solution.

#### 1.INTRODUCTION

A smart antenna system combines multiple antenna elements with a signal-processing capability to optimize its radiation and/or reception pattern automatically in response to the signal environment. Antennas have been the most neglected of all the components in personal communications systems. Yet, the manner in which energy is distributed into and collected from surrounding space has a profound influence on the efficient use of spectrum, the cost of establishing new networks, and the service quality provided by those networks. A smart antenna is an array of antenna elements connected to a digital signal processor. Such a configuration

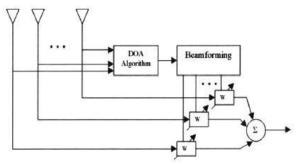
dramatically enhances the capacity of a wireless link through a combination of diversity gain, array gain, and interference suppression. Increased capacity translates to higher data rates for a given number of users or more users for a given data rate per user. Multipath paths of propagation are created by reflections and scattering. Also, interference signals such as that produced by the microwave oven in the picture, are superimposed on the desired signals. Measurements suggest that each path is really a bundle or cluster of paths, resulting from surface roughness or irregularities. The random gain of the bundle is called Multipath fading.

An antenna in a telecommunications system is the port through which radio frequency (RF) energy is coupled from the transmitter to the outside world for transmission purposes, and in reverse, to the receiver from the outside world for reception purposes. To date, antennas have been the most neglected of all the components in personal communications systems. Yet, the manner in which radio frequency energy is distributed into and collected from space has a profound influence upon the efficient use of spectrum, the cost of establishing new personal communications networks and the service quality provided by those networks. The commercial adoption of smart antenna techniques is a great promise to the solution of the aforementioned wireless communications' impairments.

#### 2.BEAMFORMING

Different beamforming algorithms like Side-lobe Cancellors, Linearly Constrained Minimum Variance (LCMV), Least Mean Squares (LMS), Recursive LMS, and Direction of Arrival (DOA) exist in literature. Among the Direction of Arrival (DOA) algorithms, Multiple Signal classification (MUSIC) and Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) play the most important role. These two algorithms were implemented, and their

performances were compared. The algorithms were



simulated for different signal levels and the DOAs were computed for use in next generation wireless. ESPRIT was found to be a better DOA technique for uncorrelated source used in beamforming. The performance of next generation wireless can be greatly improved by using adaptive beamforming algorithms. Beamforming can meet the challenge of increasing spectral efficiency and improving wireless communication system performance by significantly increasing the reception and transmission ranges and reducing the probability of interception of secure transmission. Adaptive Beamforming 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 [1].

## 3.BEAMFORMING SETUP WITH DOA ESTIMATION

Beamforming principles apply to both the transmission and reception of signals. Beamforming is accomplished through the use of an array of sensors such as antenna, hydrophones and so on. In order to proceed with the discussion of beamforming, it is important to note some basic assumptions. First, a signal originating far away from the sensor array can be modelled as a plane wave. Next the signal received by each sensor element is a time-delayed (phase shift) version of the signal received by other sensor elements. Finally, an N-element beamforming system is capable of forming up to N beams. For the beamformer to steer the radiation in a particular direction and to place the nulls in the interfering directions the direction of arrival has to be known beforehand. The Direction of arrival algorithms does exactly the same; they work on the signal received at the output of the array and compute the direction of arrivals of all the incoming signals. Once the angle information is known it is fed into the beamforming network to compute the complex weight vectors required for beam steering [2].

## Beamforming setup with DOA Estimation 1.DOA ESTIMATION ALGORITHMS

#### A. Least Mean Square Algorithm

This algorithm was first developed by Widrow and Hoff in 1960 [3, 4]. The design of this algorithm was stimulated by the Wiener-Hopf equation. By modifying the set of Wiener-Hopf equations with the stochastic gradient approach, a simple adaptive algorithm that can be updated recursively was developed. This algorithm was later on known as the least-mean-square (LMS) algorithm [3, 4].

The algorithm contains three steps in each recursion: the computation of the processed signal with the current set of weights, the generation of the error between the processed signal and the desired signal, and the adjustment of the weights with the new error information. The following equations summarize the above three steps.

$$\hat{d}(n) = w_1^*(n)u_1(n) + w_2^*(n)u_2(n) + \dots + w_t^*(n)u_t(n)$$

The w in the above equations is a vector which contains the whole set of weights

Here, we have taken eight elements, so there are eight u's for each symbol received at time n. A large step-size allows fast settling but causes poor steady state performance. On the other hand, a small step-size decreases the steady state error but compromises the rate of convergence. The current value of this parameter is selected by trying out different values in the algorithm.

### B. RLS Algorithm

The RLS algorithm[3,4] recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals, i.e., given the least squares estimate of the tap weight vector of the filter at iteration (n-1),we compute the updated estimate of the vector at iteration n upon the arrival ofthe new data. This, in contrast to LMS algorithm aims toreduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS, they are considered stochastic. Compared to most of its competitors, the RLS exhibits

extremely fast convergence due to the fact that the RLSfilter whitens the input data by using the inverse correlation matrix of the data, assumed to be of zero mean. However, this benefit comes at the cost of high computational complexity.

The RLS algorithm can be summarized as follows, Initialize the algorithm by

settingw
$$(0) = 0$$
,

$$P(0) = \delta^{-1}I$$
.

and

 $\delta$  = large positive constant for low SNR. small positive constant for high SNR For each instant of time, n = 1, 2 ... compute $\pi$ (n) = P(n -1)u(n),

$$k(n) = \pi (n)$$

$$\frac{\lambda + u^{H} \pi (n)}{\xi (n) = d (n) - w^{\hat{}} H (n - 1) u (n) ,}$$

$$w^{\hat{}} (n) = w^{\hat{}} H (n - 1) + k (n) \xi *$$
(n),and

 $P\left(n\right)=\lambda^{-1}\ p\left(n-1\right)-\lambda^{-1}k\left(n\right)u^{H}\left(n\right)P(n-1)$ 

# $\begin{array}{c} \text{4.RESULTS AND DISCUSSIONS OF LMS AND} \\ \text{RLS ALGORITHMS} \end{array}$

The performance of beamforming algorithms has been studied by means of MATLAB simulation. In this simulation we have considered three cases with different look direction and interference which gives finest beam. For Simulation the following assumptions are considered

Simulation logarithm: LMS, RLSNumber of antenna

elements: 8 Element spacing:

 $0.5\lambda$ 

DOA of desired signal: 10° DOA of interference signal:

20°

Forgetting factor (α) (for RLS):

0.9Number of data samples: 100

In Figure 1, the amplitude responses of the algorithms from -90 degrees to +90 degrees are plotted. It is evident from the figure that in LMS algorithm the interference signal is completely rejected at 20° but with more number of sidelobes rings. Whereas, in RLS algorithms the interference signal is completely rejected at 20° but with less side lobe rings.

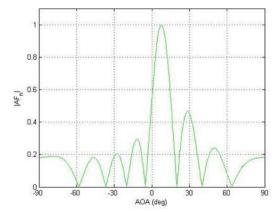


Fig: (1.a). Beam Plot of LMS algorithm

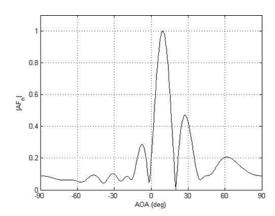


Fig. (1.b) Beam Plot of RLS algorithm

## 5.OPTIMIZATION METHODS

#### A. Particle Swarm Optimization

PSO ( Particle Swarm Optimization ) is applied to determine optimal antenna elements feed that provide null (minimum power) in the directions of the interfering signals while to maximize of radiation in the direction of the useful signal. The problem is formulated and solved by means of the suggested algorithm. Examples are simulated to demonstrate the effectiveness and the design flexibility of PSO in the framework of electromagnetic synthesis of linear arrays.

#### B. Standard PSO Algorithm

The PSO algorithm [5,6] is an evolutionary algorithm capable of solving difficult multidimensional optimization problems in various fields. As an evolutionary algorithm, the PSO algorithm depends on the social interaction between independent particles, during their search for the optimum solution. A population of particles is randomly generated initially.

Each particle represents a potential solution and has a position represented by a position vector. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a velocity vector  $\vec{v}_i$ . Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector  $\vec{P}_i$ . Furthermore, the best position among all the particles obtained so far in the population is kept track of as  $\vec{pg}$ . The particle's velocity update and position update are the main PSO operators, which can be expressed as:

$$\vec{x}_{i} \ \vec{v}_{i}(\tau+1) = w\vec{v}_{i}(\tau) + c_{1}r_{1}(\vec{p}_{i}(\tau) - \vec{x}_{i}(\tau)) + c_{2}r_{2}(\vec{p}_{q}(\tau) - \vec{x}_{i}(\tau))$$

$$i \overline{v} \quad \vec{x}_i \left( \tau + 1 \right) = \vec{x}_i \left( \tau \right) + \vec{v}_i \left( \tau + 1 \right)$$

where c1 and c2 are acceleration constants and r1 and r2 are uniformly distributed random numbers in [0,1]. The term is limited to its bounds. If the velocity violates this limit, it is set to its proper limit. w is the inertia weight factor and in general, it is set according to the following equation:

$$w = w_{ ext{max}} - rac{w_{ ext{max}} - w_{ ext{min}}}{T} \cdot au$$

where wmax and wmin is maximum and minimum value of the weighting factor respectively. T is the maximum number of iterations and  $\tau$  is the current iteration number [5].

$$F(\theta) = 2\sum_{n=1}^{N} a_n \cos\left(\frac{2\pi}{\lambda}d_n \sin\theta\right),\,$$

Simulated annealing (SA) is a random-search technique which exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the search for a minimum in a more general system. It forms the basis of an optimization technique for combinatorial and other problems. Metropolis algorithm simulated the material as a system of particles. The algorithm simulates the cooling process by gradually lowering the temperature of the system until it converges to a steady, frozen state [5,7].

### D. Bacteria Foraging

Bacteria foraging optimization (BFO) is based on the foraging (i.e. searching food) strategy of Escherichia coli bacteria. In BFO, the optimization follows chemotaxis, swarming, reproduction and elimination

and dispersal events to reach global minima. During chemotaxis, the bacteria climb nutrient concentration and avoid noxious substances. During swarming, the bacteria move out from their respective places in ring of cells by moving up to the minimal value. Bacteria usually tumble, followed by another tumble or tumble followed by run or swim. If the cost at present is better than the cost at the previous time or duration then the bacteria takes one more step in that direction. During reproduction, the least healthy bacteria dies and others split into two, which are placed in the same location. This causes the population of bacteria to remain constant. During reproduction the fitness of the bacteria are stored in ascending order. The elimination and dispersal events are based on population level longdistance motile behavior. During elimination and dispersal events, each bacterium is eliminated with a probability.

### E. Biogeography Based Optimization (BBO)

Mathematical models of biogeography describe how species migrate from one island to another, how new species arise, and how species become extinct. Geographical areas that are well suited as residences for biological species (S) are said to have a high habitat suitability index (HSI). HSI can be considered the dependent variable. Habitats with a high HSI tend to have a large number of species, while those with a low HSI have a small number of species. Habitats with a high HSI have many species that emigrate (µ) to nearby habitats. Habitats with a high HSI have a low species immigration rate ( $\lambda$ ) because they are already nearly saturated with species. Therefore, high HSI habitats are more static in their species distribution than low HSI habitats. Habitats with a low HSI have a high species immigration rate because of their sparse populations. Low HSI habitats are more dynamic in their species distribution than high HIS habitats [5,7].

Biogeography-Based Optimization algorithm:

- Initialize the maximum species count Smax and the maximum migration rates, E and I, the maximum mutation rate, mmax, and elitism parameter set of solutions to a problem.
- Compute "fitness" (HSI i.e. is a measure of the goodness of the solution represented by the habitat) for each solution.
- 3. Compute S,  $\lambda$ , and  $\mu$  for each solution.
- 4. Modify habitats (migration) based on  $\lambda$ ,  $\mu$ .

- 5. Update Mutatation based on probability.
- 6. Typically, we implement elitism.
- 7. Go to step 2 for the next iteration if needed.

#### 6.APPLICATION OF PSO

Evolutionary algorithms use the concept of fitness to represent how well an arbitrary solution satisfies the design parameters. Each of the parameters used to calculate the fitness is referred to as a fitness factor. The fitness factors must together quantify the solution. For antenna problems, common fitness factors are directivity, gain, sidelobe level, physical size, and complex weights (both the phase and amplitude) [6]. If the element amplitude is symmetrical about the center of the linear array, the far-field array factor of this array with an even number of isotropic elements (2N) can be written as where an is the amplitude of the nth element, 0 is the angle from broadside, and dn is the distance between the position of the nth element and the array's center. In this paper, where the main aim is null steering, we restricted ourselves to finding an appropriate set of an to place array nulls in any prescribed directions. The following cost function will therefore be minimized by using Particle Swarm Optimization [6,7].

#### 7.CONCLUSION

It is observed that LMS is the simplest and more suitable choice because of its simplicity and a reasonable performance. RLS has fastest convergence at the cost of high computational burden when compared to LMS. Comparing the result of LMS and RLS, RLS have better result with less side lobes and sharp beam. PSO application for solving different numerical problems in smart antenna is illustrated. Improvement is suggested to the algorithm to support the continuous real time varying target problem. Simulation for different scenarios is solved with the aid of PSO. Synthesis of an adaptive Beamforming using the phase only control where target is dynamic over time has been presented. PSO was introduced to solve position-only and position-phase synthesis, which is a bounded searchspace problem.

#### **REFERENCE**

[1] S. Bellofiore , C. Balanis, J. Foutz, and A. Spanias, "Smart-antenna systems for mobile communication

- networks. Part1. Overview andantenna design", IEEE Antennas Propag. Mag., vol. 44, no. 3, 2002, pp. 145–154, Jun.
- [2] Balanis, C.A., "Antenna Theory: analysis and design", New Jerse y:John Wiley & Sons,2005.
- [3] Dimitris G. Manolakis , Vinay K.Ingle, StephenM .Kogon, "Statistical and adaptive signal processing", Mc Graw Hill Publication, 2005.
- [4] Symon Haykin, "Adaptive filter theory", Forth edition, Pearson education asia, Second Indian reprint, 2002.
- [5] W. T. Li, X. W. Shi and Y. Q. Hei, "An Improved Particle Swarm Optimization Algorithm For Pattern Synthesis Of Phased Arrays", Progress In Electromagnetics Research, PIER 82, 2008, pp. 319– 332
- [6] Z. D. Zaharis, K. A. Gotsis, and J. N. Sahalos, "Adaptive Beamforming with Low Side Lobe Level Using Neural Networks Trained by Mutated Boolean PSO", Progress InElectromagnetics Research, Vol. 127, 2012, pp. 139-154.
- [7] K. Guneyand M. Onay, "Amplitude-Only Pattern Nulling of Linear Antenna Arrays with the Use of Bees Algorithm," Progress in Electromagnetics Research, 70, 2007, pp. 21-36.