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# Smart Antenna Optimization Algorithms

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## Abstract

*A smart antenna is actually combination of an array of individual antenna elements and dedicated signal processing algorithm. With this technology, each user's signal is transmitted and received by the base station only in the direction of that particular user. Smart antenna technology attempts to address this problem via advanced signal processing technology called beam-forming. Through adaptive beam-forming, a base station can form narrower beam toward user and nulls toward interfering users. There are adaptive and sample-by-sample algorithms, used to update weights of the smart antenna. The sample-by-sample method updates the weight vector with each sample. Various sample-by-sample methods, attempted in the present study are least mean square (LMS) algorithm, recursive least square (RLS) algorithm. In this paper, it is suggested how the Smart antennas technology would offer a significantly improved solution to reduce interference levels and improve the system capacity using Particle Swarm Optimization (PSO).*

## 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.

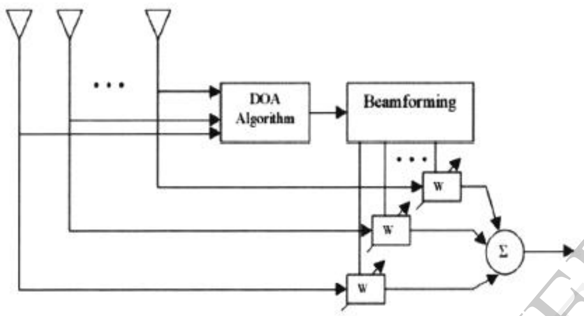
An antenna in a telecommunications system is the port through which radio frequency (RF) energy is coupled from the transmitter to the outside world for transmission purposes, and in reverse, to the receiver from the outside world for reception purposes. To date, antennas have been the most neglected 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**

## 4. 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.

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

The $\boldsymbol{w}$ 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 of the new data. This, in contrast to LMS algorithm aims to reduce 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 RLS filter 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 setting

$\hat{w}(0) = 0$,
$P(0) = \delta^{-1} I$,

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

$$k(n) = \frac{\pi(n)}{\lambda + u^H \pi(n)}$$

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

## 5. Results And Discussions Of LMS And RLS Algorithms

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, RLS
Number of antenna elements: 8
Element spacing: 0.5λ
DOA of desired signal: 10˚
DOA of interference signal: 20˚
Forgetting factor (α) (for RLS): 0.9
Number of data samples: 100

In Figure1, 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.

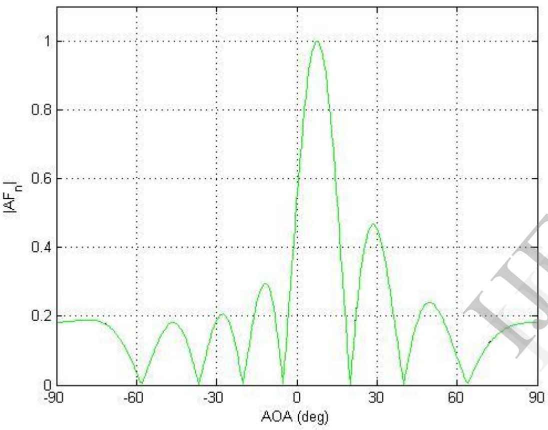



Fig: (1.a). Beam Plot of LMS algorithm

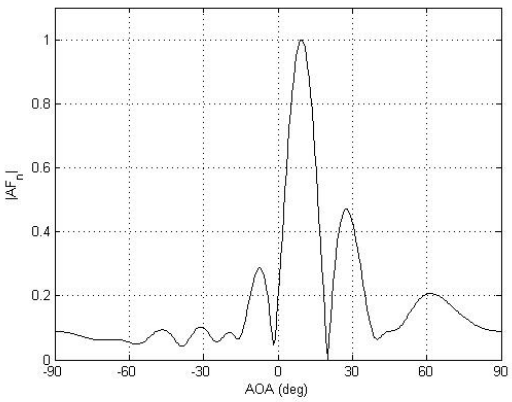



Fig. (1.b) Beam Plot of RLS algorithm

Comparison of LMS and RLS with respect to their desired signal and array output is shown in fig 2.

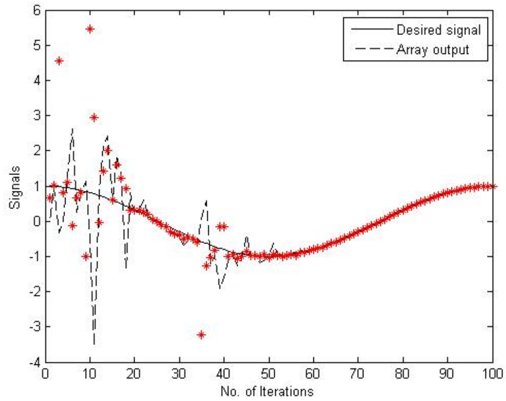



Fig :( 2.a) The simulation results of LMS algorithm with 100 iterations

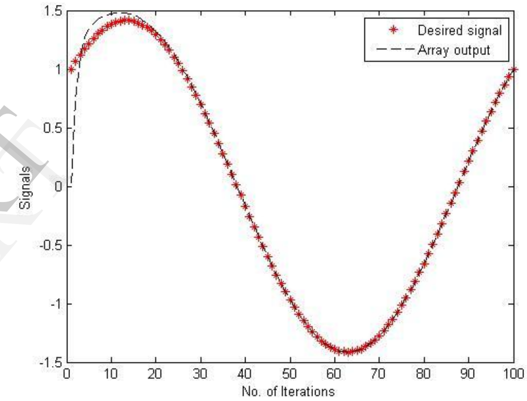



Fig :( 2.b) Simulation results of RLS algorithm with 100 iterations

## 6. Optimization Technique

### *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 proposed 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 $\vec{x}_i$. 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 $\vec{p}_g$. The particle's velocity update and position update are the main PSO operators, which can be expressed as:

$$\vec{v}_i(\tau+1) = w\vec{v}_i(\tau) + c_1 r_1\left(\vec{p}_i(\tau) - \vec{x}_i(\tau)\right) + c_2 r_2\left(\vec{p}_g(\tau) - \vec{x}_i(\tau)\right)$$

$$\vec{x}_i(\tau+1) = \vec{x}_i(\tau) + \vec{v}_i(\tau+1)$$

where $c_1$ and $c_2$ are acceleration constants and $r_1$ and $r_2$ are uniformly distributed random numbers in [0,1]. The term $\vec{v}_i$ '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:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{T} \cdot \tau$$

where $w_{max}$ and $w_{min}$ 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].

## 7. 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

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

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].

## 8. 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 proposed 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 search space problem.

## 9. References

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