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Optimized Detection in Multi-Antenna System using Particle Swarm Algorithm

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***Abstract*—**In this paper we propose a Particle Swarm heuristic optimized Multi-Antenna (MA) system. Efficient MA systems detection is performed using a robust stochastic evolutionary computation algorithm based on movement and intelligence of swarms. This iterative particle swarm optimized (PSO) detector significantly reduces the computational complexity of conventional Maximum Likelihood (ML) detection technique. The simulation results achieved with this proposed MA-PSO detection algorithm show near optimal performance when compared with ML-MA receiver. The performance of proposed detector is convincingly better for higher order modulation schemes and large number of antennas where conventional ML detector becomes non-practical.

***Keywords*—**Multi Antenna (MA), Multi-input Multi-output (MIMO), Particle Swarm Optimization (PSO), ML detection.

I. Introduction

MULTIPLE Antennas based communication systems have shown promise to meet the high bandwidth requirements of multimedia based applications [1-3]. Multi-input Multi-output (MIMO) systems are a natural evolution of so-called *Smart antennas,* a popular technology using antennas arrays for improving wireless transmissions couple of decades back. A MIMO system has the ability to deal with multi-path propagation, by turning it into a benefit for the user. It effectively takes advantage of random fading [1–4] and multipath delay spread [5-6].

A number of architectures have been developed for MIMO systems in the last few years. Maximum Likelihood (ML) detection scheme performs the best, but its complexity increases exponentially when numbers of transmit antennas increase and complex modulation schemes are used [7-8].

The ML detection of the signals transmitted over the MIMO channel is a known NP-complete communications problem. A number of MIMO detectors have been proposed [9-11] to reduce its complexity. Another potential solution is Sphere Decoder (SD) [12-16] with has polynomial computational cost on the average [13]. However when problem dimensions are high its complexity coefficients and variance of computational time becomes large. These drawbacks of SD were tackled in Ordered Sphere Decoding (OSD) [17-19].

The PSO is a population-based search algorithm inspired by the social behavior of animals like birds flocking, bacteria molding and fish schooling [20]. PSO can be understood through an analogy. Consider a flock of birds searching for food in an area. Their goal is to find the best food spot, without any a priori knowledge. The birds start at random locations in the field with random velocities in their hunt for food. Every bird can remember the locations where it found the food and in some way know the place where the others discover food. In a state of perplexity to return to the location where a bird had personally found the food, or exploring the location reported by others, the unsure bird accelerates in both directions. Reminiscence or social pressure influence bird's decision as it changes its trajectory to fly in the resulting direction. During travel to a newer location, a bird might find a place with more food than it had found earlier. A bird may occasionally fly over a place with more food than earlier encountered by any other bird in the flock. The whole flock would now be attracted towards that location as well as their own personal best finding. The birds explore the field in the similar fashion. Flying over locations of greatest concentration of food and then being attracted back towards them. The birds are continually checking the location they fly over against previously encountered places in their endeavor to find the absolute best food concentration. Ultimately, the birds concentrate at the best available food location in the complete field. Kennedy and Eberhart reached an optimizing heuristic in their attempt to model this natural phenomenon.

In this contribution we present a simple but efficient MIMO detector optimized by Particle Swarm algorithm. The paper is organized as follows. The MIMO system model is presented in Section-II. In Section-III, the proposed PSO-MIMO detection scheme is explained and its computational complexity is compared with the ML detection. Followed by Section-IV showing simulation results and comparison of the computational complexity vis-à-vis the systems performance, finally Section-V concludes the paper.

II. MIMO System Model

The Multi-Input Multi-Output system model consists of N transmit antennas and M ($\geq N$) receive antennas. The demultiplexer in the transmitter divides the input data stream

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into N sub-streams, transmitted using N transmit antennas with equal transmit power. The N radiated sub-streams after passing through a scattering wireless channel are collected by M receive antennas. The MIMO model of the received signal vector at each sampling instant can be represented as:

$$\mathrm{r} = \sqrt{\frac{P}{N}}\,\mathrm{H.x} + \mathrm{n} \qquad (1)$$

where $\mathbf{r} = [r_1 \ldots r_m \ldots r_M]^T$ is an $M\times1$ received signal vector, $\mathbf{x} = [x_1 \ldots x_n \ldots x_N]^T$ is an $N\times1$ sub-stream vector, $\mathbf{n} = [n_1 \ldots n_m \ldots n_M]^T$ is an $M\times1$ white complex Gaussian noise vector with elements having zero mean and variance of σ^2. P is the total transmitted energy. The channel impulse response matrix is:

$$H=\begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1N} \\ h_{21} & h_{22} & \cdots & h_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ h_{M1} & h_{M2} & \cdots & h_{MN} \end{bmatrix} \qquad (2)$$

where $h_{m,n}$ denotes the channel impulse response from the n-th transmit antenna to the m-th receive antenna and is assumed to be an independent and identically distributed complex Gaussian random variable with zero-mean and unit-variance. In MIMO the data is transmitted over a *matrix* rather than a vector channel. Each element of x has unit power and is determined from the same set ***S*** comprised of ***C*** constellation points. Perfect channel estimation is assumed at the receiver.

III. Swarm Intelligence Optimized Detection

A. Conventional ML Detection

The optimal ML detector estimates sub-streams $x_1, x_2, \ldots, x_N$ by choosing the symbol combination associated with the minimal distance metric among all possible symbol combinations in the constellation:

$$\hat{x}_{ML} = \arg \min_{\hat{x}} \left\| r - \sqrt{\frac{P}{N}} H.\hat{x} \right\| \qquad (3)$$

As shown in "(3)", the conventional ML detection scheme needs to examine all C^N symbol combinations. Therefore, the computational complexity increases rapidly with C and N. The high speed processing requirements of real time applications and the advanced communication systems demand a comparatively simplified detection scheme. The proposed detection scheme clearly avoids this huge complexity at an affordable performance loss.

B. PSO Algorithm Terminologies

The main PSO terminologies are elaborated below [21]:

1) Particle: One individual in the swarm (birds in our analogy).

2) Swarm: The entire collection of particles, like bird flock.

3) Fitness: It is a unique value representing the goodness of a solution in the solution space. As regards the problem at hand, fitness function is the minimum value of Euclidean distance of the symbol being detected.

4) pbest: Location of the best fitness returned for the specific agent in the parameter space.

5) Gbest: This is the location of the best fitness returned for the entire swarm in parameter space.

6) V_{max}: It is Maximum allowable velocity of a particle in a particular direction.

7) Generations/Iterations: The maximum allowable position updates for each particle. It is the maximum number of times a particle can change its present location to reach *gbest*.

C. The PSO Heuristic

The PSO algorithm is detailed below:

1) *Allocate Solution Space parameters:* The initial step for implementation of the PSO is to select the parameters that need to be optimized.

2) *Fitness Function definition:* The definition of fitness function is crucial since it should precisely represent the goodness of the solution in a single value. The fitness function and the solution space development is optimization problem specific.

3) *Random Swarm Velocities and Location Initialization:* Every particle starts at its own random location to begin searching for the optimal position in the solution space with a velocity that is random both in its magnitude and direction.

4) *Particles Systematically Fly-through the Solution Space:* Each particle must traverse through the solution space parameter. The heuristic is applied on every particle one after another, moving it by a small distance and cycling through the entire swarm. The following steps act individually on each particle Fig. 1.

a) *The Particle's Fitness Evaluation:* The fitness function returns a fitness value for the present location using the coordinates of the particle in solution space. The locations are updated if the fitness value is greater (or smaller, problem dependent) than the value at the respective *pbest* or the *gbest.*

b) *The Particle's Velocity Update:* The particle's velocity is altered according to the relative locations of *pbest* and *gbest.* A Particle is accelerated in the directions of the location of the best fitness according to (4) given below:

$$\mathrm{v_{ij}}(\mathrm{t}+1) = \mathrm{w} * \mathrm{v_{ij}}(\mathrm{t}) + \mathrm{c_1 r_{1j}}(\mathrm{t})[\mathrm{y_{ij}}(\mathrm{t}) - \mathrm{x_{ij}}(\mathrm{t})] + \mathrm{c_2 r_{2j}}(\mathrm{t})[\hat{\mathrm{y}}_{\mathrm{j}}(\mathrm{t}) - \mathrm{x_{ij}}(\mathrm{t})] \qquad (4)$$

Where $y_{ij}(t)$ is the *pbest* for particle i in dimension j, $\hat{y}_j(t)$ is the *gbest.* $v_{ij}(t)$ is the velocity of particle i in dimension j. $x_{ij}(t)$ is the position of particle i in dimension j at a particular time t. C_1 and C_2 are positive acceleration constants used to scale contribution of cognitive and social elements can also be termed as learning factors. r_1 and r_2 are the random number function rand() which returns a number between 0 and 1 randomly. Two independent random numbers are used to stochastically vary the relative pull of

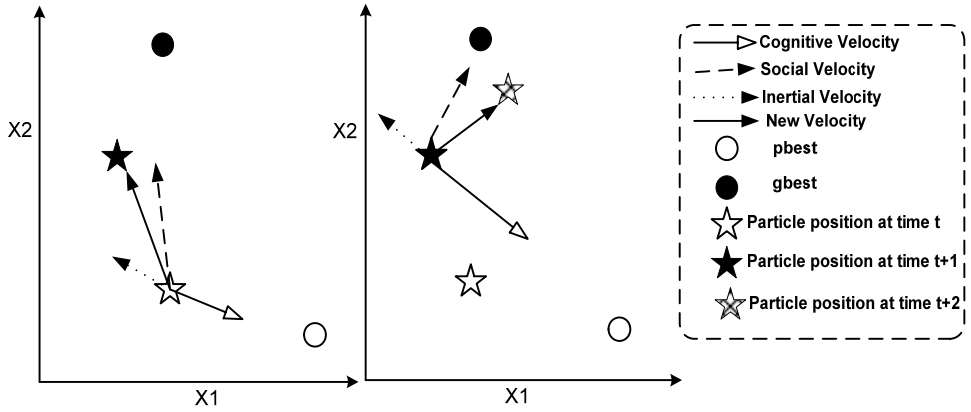

Fig. 1 Particle are pulled towards their gbest and pbest, snap shot at time 't' (left) and time 't+1' (right) in parameter space

gbest and *pbest*. "W" is the inertial weight. A number chosen between 0 and 1, shows the particles resistance to the drag of *pbest* and *gbest.* The particle motion is based on (4). The greatest "pull" from the respective locations is experiences by the particle farthest from *gbest* or *pbest.* Therefore move toward them more rapidly than any nearer particle. The particles accelerate in the direction of the place of greatest fitness until they run over them. Now these will be attracted back in the reverse direction. It is considered that this over running of the local and global maxima is a to the PSOs success [22]. The velocity consists of three components first is 'previous velocity' which is the memory of the previous flight direction (inertia). Secondly a 'Cognitive component' it is the *pbest* for a particle, and last is the 'Social component' that quantifies the influence on particle based on *gbest* and *pbest*. This is depicted in Fig.1, where x(t) is the present and x(t+1) is the new position of particle in the parameter space. y(t) and $\hat{y}(t)$ are *pbest* and *gbest* respectively. A particle at its present position experiences these cognitive, inertial and social velocities and moves in the resultant direction of new velocity to jump to next location.

c) *Particles Movement:* The velocity is applied for a given time-step, and the particle moves to the next position. New coordinate are computed for each of the dimensions in the parameter space based on the following equation:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (5)$$

Where $x_i(t+1)$ and $v_i(t+1)$ is the new position and velocity for i^{th} particle.

5) *Repeat:* This process act on each particle in the swarm; the procedure is repeated starting at Step 4 until the termination criteria met or stopping condition is reached.

D. PSO Parameter Control

The algorithms parameters are required to be tuned to achieve optimal solution. The particles size is typical in the range of 10 to 40. For most of the problems this particle size some times referred as population is large enough to get good results. For our simulations it kept at 32 for most of the results. The range of particles 'Vmax' determines the maximum change one particle can take during iteration. Eberhart and Shi [23] found that without inertial weight (w=1), this maximum allowed velocity 'Vmax' was best set around 10–20% of the dynamic range of each dimension. In our simulations we have chosen this Vmax range between -10 to +10, to avoid particles flying out of meaningful solution space. Inertial weight 'w' is also introduced in [23]. Larger value of this parameter encourages global search more and is lesser influenced by *pbest* and *gbest*, analogous to the phenomenon that it is difficult to diverge heavier objects in their flight trajectory than the lighter ones. Smaller inertial weight encourages the local exploration as the particles are attracted towards pbest and gbest more. In our case w = 1 is assumed. The stopping criteria can be the maximum number of iterations (velocity changes allowed for each particle) or reaching the minimum error threshold.

E. Computational Complexity

The computational complexity of the PSO based detection scheme compared with that of ML detection is discussed here. The computational complexity is taken in terms of the number of transmit antennas, number of receive antennas and the number of bits per symbol *b*. In case of ML detector the Euclidean distance metric calculation for a candidate symbols possible combinations require *M+N-1*additions and *M(N+1)* multiplications respectively. The search space for ML detector (3) is C^N where *C* is the total number of constellation points given by 2^b.If equal weight in terms of complexity is assumed for the above mathematical operations, the computational complexity for ML detector comes out to be:

$$\gamma_{ML} = 2^{b\times N}\,(M(N+2)+N-1) \quad (6)$$

For the proposed detector, first fitness of each particle in initial population (N_{pop}) is calculated which results in PSO detector complexity given by:

$$\gamma_{pso} = N_{pop}\,(M(N+2)+N-1) \quad (7)$$

The velocity updating of each particle requires α_{vel} additions and μ_{vel} multiplications (4). Therefore:

$$\gamma_{pso} = N_{pop}((M(N+2)+N-1)+\alpha_{vel}+\mu_{vel}) \quad (8)$$

The position updating involves α_{pos} additions (5), resulting:

$$\gamma_{pso} = N_{pop}((M(N+2)+N-1)+\alpha_{vel}+\mu_{vel}+\alpha_{pos}) \quad (9)$$

A detailed computational complexity comparison is presented next.

IV. Simulation and Numerical Results

In this section, the performance of the propose PSO based detector is presented. The MIMO System considered in our simulation consists of two transmit antennas (N = 2) and four receive antennas (M = 4). Different modulation schemes including 4-QAM, 16-QAM, 32-QAM and 64-QAM are used with the proposed algorithm. The block size is 1 i.e one symbol from each transmit antenna is under detection. The particle or population size is kept at 32 initially. The simulation results in Fig. 2 demonstrate that the proposed optimized detector generally achieves near-optimum performance. However when the signal strength is high the performance of ML detector outplays that of proposed PSO detector. This is because of the algorithm's inherent limitations. Fig. 2 also show that the proposed detector achieves same BER performance as that of ML detection till 11db Eb/No, but experiences some variations above it.

Fig. 3, compares the performance of proposed and ML detector with different modulation schemes. Simpler modulations achieve optimal results in lesser iterations. The results in Fig. 4 show the performance of PSO detector with varying population (particle) sizes compared with ML detector. There is a gradual increase in BER performance as the population size increase. Both previous results also indicate that the proposed MA-PSO detection converges to optimal performance with the increase in iterations. The computational complexity of the proposed scheme is analyzed using the results from Fig. 3. A comparison of the complexities is drawn in Table I.

TABLE I
Computational Complexity Comparison

Modulation Scheme	Required N_{itr}	γ_{pso}	γ_{ML}	Efficiency Achieved
16-QAM	18	7488	4352	42% (degraded)
32-QAM	20	8320	17408	52% (improved)
64-QAM	24	9984	69632	85% (improved)

The exponential increase in complexity of ML detector with higher order modulation schemes make it unsuitable for practical MIMO systems. The proposed swarm intelligence optimized detector results in drastic improvement in terms of computational efficiency as compared to ML detection especially with higher order modulation schemes. This efficiency improvement with higher order modulation techniques make it useful for high data rate transmission systems. With 32-QAM, Iterative PSO detection improves by 52%, this efficiency improvement reaches 85 % when 64-QAM is used in MIMO systems.

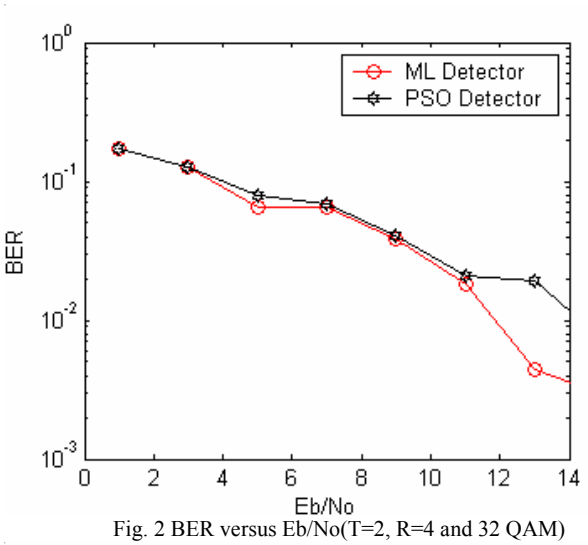

Fig. 2 BER versus Eb/No(T=2, R=4 and 32 QAM)

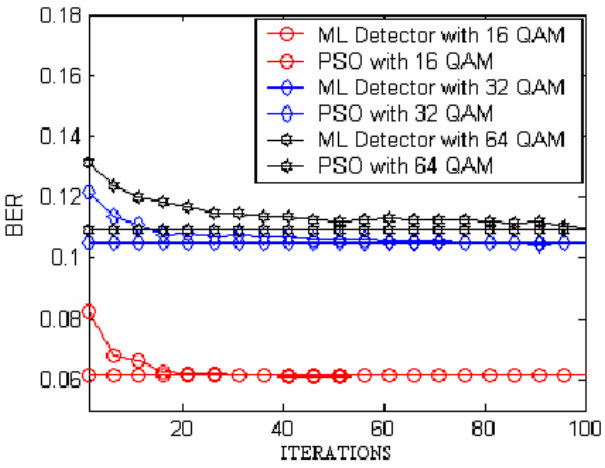

Fig. 3 BER versus modulation complexity

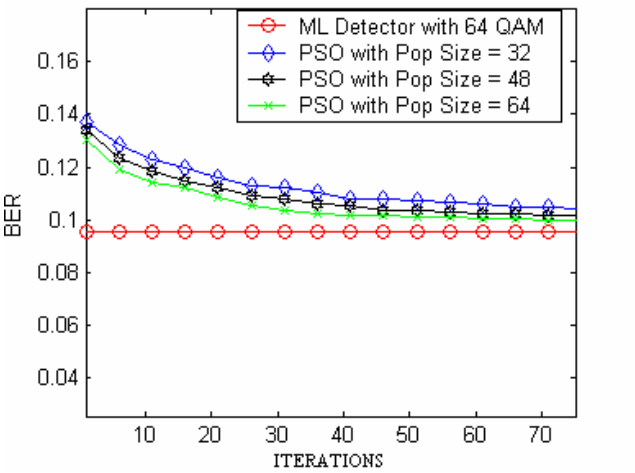

Fig. 4 BER Performance with varying population sizes

V. Conclusion

In this contribution, MA-PSO detection is proposed. This evolutionary computational intelligent algorithm shows promising results when compared with the traditional ML detector. The proposed simple detection mechanism approaches near optimal performance with much reduced complexity especially for higher order modulation schemes and when greater numbers of antennas are used in MIMO system. The results depict that with two transmitters and four receivers, using 64 QAM, this iterative MA-PSO detector achieves near optimal performance at a much lower computational complexity. The proposed algorithm has resulted in 85% increase in the efficiency when compared with ML detection using 64-QAM. This proposed efficient MIMO receiver gives acceptable performance with convincingly reduced receiver complexity, especially with higher order modulation when ML detector is not practical to use. The results show that this intelligent optimization based on natural heuristic performs better for symbol detection in multiple antennas systems than the conventional approach. The performance enhancement increases exponentially with the increase in number of antennas and complexity of modulation schemes.

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