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# Genetical Swarm Optimization-Based Symbol Detection for MIMO Systems

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***Abstract*—A genetical swarm optimization (GSO)-based detector using multiple-input multiple-output (MIMO) spatial multiplexing signaling is proposed. By taking advantage of gene evolution and the collective intelligence of swarms, the proposed detector offers a slightly degraded bit error rate (BER) performance compared with the full-search-based optimum detector does while greatly reducing the computational complexity.**

***Index Terms*—multiple-input multiple-output, genetical swarm optimization, genetic algorithm, particle swarm optimization**

## I. Introduction

Seamless communications are becoming a reality with businesses using 3rd generation cellular communication systems. The success of 3rd generation cellular communications has mainly been associated with a continuous increase in system capacity and quality of service. As bandwidth is a scarce resource, this trend can only be continued by using new technologies that provide higher spectral efficiency and improved link reliability. Multiple-input multiple-output MIMO) communications schemes have been shown to achieve significant increase in spectral efficiency using arrays of transmit and receive antennas with spatial processing [1]. Since MIMO scheme has recently emerged as a key enabling technology for achieving the requirements of high spectral efficiency, it has been standardized as extensions to current wireless communication specifications such as IEEE 802.11, IEEE 802.16, and HSDPA.

The performance improvements resulting from MIMO wireless technology come at the cost of increased computational complexity in the receiver. Maximum-likelihood detection (MLD) is the optimum detection method and minimizes the bit error rate (BER). However, the MLD is a nondeterministic polynomial (NP)-hard problem. It is also regarded as unfeasible since its complexity is high especially for large number of transmit antennas and high-order modulation. To overcome the complexity issue, a variety of suboptimum polynomial time algorithms are suggested in the literature. The linear detectors such as the zero-forcing (ZF) and minimum mean squared error (MMSE) detectors, lower the complexity; however, the performance degradation is serious in comparison with the ML method. There exists nonlinear detection method: the ordered successive interference cancellation which is known as VBLAST [2]. Its implementation is simple and the performance is improved compared to the ZF and MMSE methods. The VBLAST, however, is still unable to be good in comparison with the ML method due to insufficient receive diversity and imperfect interference cancellation.

Genetic algorithms (GAs) and particle swarm optimization (PSO) were proposed as a heuristic approach to solve combinatorial optimization problems. Using intelligent computation techniques seems to be a feasible approach to achieve a BER performance close to that of the MLD while reducing computational complexity for signal detection in MIMO systems. MIMO signal detection based on genetic algorithms (GAs) has been proposed by Bashir *et al.* [3]. The proposal by Liu *et al.* [4] utilized the PSO-based multiuser detection in STBC systems assisted by receive-diversity techniques. In this paper, we present a new low-complexity MIMO signal detection based on a new kind of hybrid heuristic optimization , called genetical swarm optimization (GSO), consisting in a cooperation of GA and PSO. The rest of this paper is organized as follows. Section 2 describes the MIMO system model. Section 3 describes the details of heuristic-approach MIMO signal detection algorithms, including the GA-based, the PSO-based, and the GSO-based MIMO signal detector. In Section 4, we present the performances of three types of heuristic-approach MIMO signal detectors in the context of a 2×2 MIMO with 64 quadrature-amplitude modulation (QAM) signaling and a 4×4 MIMO with 16 QAM signaling. Finally, Section 5 gives the conclusions.

## II. MIMO System Model

In a spatially multiplexed MIMO system as shown in Fig. 1, different data streams are transmitted from different antennas. At the receiver, multiple antennas are used to separate the different data streams. Consider the discrete-time model of a MIMO frequency non-selective fading channel with $n_T$ transmit antennas and $n_R$ receive antennas, the receive signal vector can be represented as follows,

$$\mathbf{r} = \mathbf{H}\mathbf{s} + \mathbf{n} \tag{1}$$

where $\mathbf{s} = [s_1 \quad s_2 \quad \cdots \quad s_{n_T}]^T$ denotes the spatial multiplexing transmission with the complex $n_T \times 1$ transmit signal vector, in which $s_i$ denotes the *M*-ary signaling emitted from the *i*th transmitter antenna. $\mathbf{H}$ is the $n_R \times n_T$ channel matrix where its element $h_{ji}$ denotes the link gain from the *i*th transmitter antenna to the *j*th receiver with an i.i.d. complex Gaussian random variable with zero-mean and unit-variance. $\mathbf{n}$ is a $n_R \times n_T$ white complex Gaussian noise vector.

It is assumed that the receiver has acquired knowledge of the channel $\mathbf{H}$ through a preceding training phase. The optimal ML detection, which solves

$$\hat{\mathbf{s}} = \arg\min_{\mathbf{s}\in\Omega} \left\| \mathbf{r} - \mathbf{Hs} \right\|^2 \quad (2)$$

where $\Omega$ denotes the set of all possible input signal vector. A straightforward approach to solve (2) is an exhaustive search in which the computational complexity grows exponentially with the number of transmitter antennas and the order of the applied modulation.

## III. Heuristic Detection Algorithms

### A. Genetic Algorithm

GA is considered to be the one of the most effective heuristic optimization tool developed until now. Since GA is very efficient at exploring the entire solution space, it is now quite popular to be applied to solve the communication optimization problems [5]-[8]. GA simulates the natural evolution, in terms of survival of the fittest, adopting pseudo-biological operators. The set of parameters that characterizes a specific optimization problem is called an individual which is composed of a list of genes. For each individual of the population, a cost function is therefore evaluated, resulting in a fitness value assigned to the individual. Based on these fitness values, a new population is generated iteratively with each successive population referred to as a generation. The GA uses basically three operators (selection, crossover, and mutation) to manipulate the genetic composition of the population.

Firstly, $P$ legitimate $K$-bit individuals in GA parlance are created randomly, where the $p$th individual is expressed here as $\tilde{\mathbf{s}}_p^{(y)} = [\tilde{s}_{p,1}^{(y)} \quad \tilde{s}_{p,2}^{(y)} \quad \cdots \quad \tilde{s}_{p,K}^{(y)}]^T$, in which $K = \log_2 M \times n_T$ and $y$ denotes the $y$th generation. Each $K$-bit individual is associated with a fitness value denoted as $f(\tilde{\mathbf{s}}_p^{(y)}) = \left\| \mathbf{r} - \mathbf{H}\tilde{\mathbf{s}}_p^{(y)} \right\|^2$. Secondly, individuals having the $T$ highest fitness values in the population are then selected and placed in the so-called mating pool. Two $K$-bit individuals in the mating pool are then selected as parents based on their corresponding figure of merit in $f(\cdot)$ according to a probabilistic function known as sigma scaling [9]. The antipodal bits of the $K$-bit parent vectors are then exchanged using the so-called uniform crossover [10] process, in order to produce two $K$-bit offspring. The selection of $K$-bit parents from the mating pool is repeated, until a new population of $P$ offspring is produced. Finally, the mutation process refers to the alternation of the value of an antipodal bit in the offspring from 1 to −1 or vice versa, with a probability $p_m$. The lowest-merit $K$-bit offspring in the population are identified and replaced with the highest-merit individual from the mating pool. After ($Y$–1) generations, the individual corresponding to the highest scalar fitness value is selected as the solution $\tilde{\mathbf{s}}_{GA}^{(Y)}$.

### B. Particle Swarm Optimization

The PSO is based on swarm and fitness function of each particle's position coordinate vector (PCV). Each particle has PCV and velocity vector (VV). The algorithm is based on social interaction between independent particles. Since its simple concept, easy implementation, and quick convergence, PSO had been applied to various applications in different fields. Considering the MIMO system described in Section II, there $K$ bits needed to be detected in each MIMO symbol. Like the first step used in GA, $Q$ $K$-bit particles in PSO parlance are created randomly, where the PCV of the $q$th particle is expressed here as $\tilde{\mathbf{s}}_q^{(i)} = [\tilde{s}_{q,1}^{(i)} \quad \tilde{s}_{q,2}^{(i)} \quad \cdots \quad \tilde{s}_{q,K}^{(i)}]^T$ in the $i$th time step. Each $K$-bit particle is associated with a fitness value denoted as $f(\tilde{\mathbf{s}}_q^{(i)}) = \left\| \mathbf{r} - \mathbf{H}\tilde{\mathbf{s}}_q^{(i)} \right\|^2$.

Secondly, at each time step $i$, for the $q$th particle and among all of its visited positions up to the present, the position having the highest fitness value is defined as the $q$th particle's best personal position and is abbreviated it as $\mathbf{pb}_q = [pb_{q,1}\ pb_{q,2}\ \cdots\ pb_{q,K}]$ for simplicity. Similarly, at each time step $i$, for the whole swarm and among all the swarm's visited position so far, the position having the highest fitness value is defined as the best global position of the swarm and is abbreviated as $\mathbf{gb} = [gb_1\ gb_2\ \cdots\ gb_K]$. The updating formula of the velocity in the $j$th position of the $q$th particle is as follows,

$$\begin{aligned} V_{q,j}^{(i+1)} &= w \bullet V_{q,j}^{(i)} + c_1 \bullet rand \bullet (pb_{q,j} - p_{q,j}^{(i)}) + \\ &\quad c_2 \bullet rand \bullet (gb_j - p_{q,j}^{(i)}) \end{aligned} \quad (3)$$

where $w$, $c_1$, $c_2$, $rand$, and $p_{j,i}$ denote the inertia weight, step-lengths, random numbers with a uniform distribution, and the position of each particle, respectively.

Finally, each component of each particle's VV, $V_{q,j}^{(i+1)}$, should be transformed into a value on the interval [0, 1] by using a sigmoid function $\mathrm{smd}(\cdot)$. And then, each component of each particle's PCV is updated by the following rule: if rand < $\mathrm{smd}(V_{q,j}^{(i+1)})$, $p_{q,j}^{(i+1)} = 1$ else $p_{q,j}^{(i+1)} = -1$. After ($Y$–1) generations, the particle corresponding to the highest scalar fitness value is selected as the solution $\tilde{\mathbf{s}}_{PSO}^{(Y)}$.

### C. Genetical Swarm Optimization

GSO is a new hybrid approach proposed in [11] consists in a stronger co-operation of GA and PSO. In GSO, the population is divided into two parts which are evolved with the two techniques respectively. The two parts are then recombined in the updated population for the next iteration. After that it is again divided randomly into two parts for the next run, in order to take advantage of both genetic and particle swarm operators. Thus, GSO can achieve an evolutionary process where individuals not only improve their score for natural selection of the fitness or for good-knowledge sharing, but for both of them at the same time. A flowchart of the GSO algorithm is shown in Fig. 2.

The first process of GSO algorithm operator is random generator population and exploits those populations to operation for the GA and PSO algorithm. When those populations operation complete, it will select the best population and particle of the GA and PSO algorithm, then according to the literature [11], the hybridization coefficient ($h_c$) is defined to select the chromosome and position coordinate percentage of the best population and particle of the GA and PSO algorithm. In terms of this percentage, it will make up a new population and put the new population into the next iteration need populations. When $h_c$ = 1 the procedure is a pure GA, $h_c$ = 0 means pure PSO. Fig. 3 shows a example of the $h_c$ = 0.5, when the part of random generator $h_c$ sequence is bit "1", the new next population will select the best GA population chromosome, on the other hand, if the part of $h_c$ sequence is bit "0", the new next population will select the best PSO particle position coordinate. After the new next population is selected, the useless solution of the original population will be replaced with the new next population, until the system setting generation number is achieved.

## IV. Simulation Results

The simulation is based on 16-QAM with four transmit and four receive antennas and 64-QAM with two transmit and receive antennas. The detailed parameters associated with the three heuristic-approach MIMO signal detector are summarized in Table I. Detection algorithms are said to converge when the slope of the convergence curve decreases with an increase in the number of generations.

When the signal-to-noise ratio (SNR) is 15 dB, figures 4 and 5 show the convergence characteristics of the three detectors for the $4 \times 4$ MIMO system with 16-QAM and the $2 \times 2$ MIMO with 64-QAM, respectively. From Fig. 4, the GA-based, the PSO-based, and the GSO-based MIMO signal detectors with population size of 200 achieved convergence after 20 generation for $4 \times 4$ MIMO system with 16-QAM. From Fig. 5, the GA-based, the PSO-based, and the GSO-based MIMO signal detectors with population size of 80 achieved convergence after 20 generation for $2 \times 2$ MIMO system with 64-QAM.

Fig. 6 shows the BER performance of the GSO-based MIMO signal detector with a search stage of 20 against the average SNR $\overline{\gamma}_k$ for $2 \times 2$ MIMO system with 64-QAM. For the sake of comparison, the BERs of a GA-based detector and a PSO-based detector are also shown. As for the BERs of the GA-based and the PSO-based detectors, error floors are observed for the results shown in the figure. This is due to the limitations of the GA and PSO associated with the particular set of individuals and generations values. On the other hand, the BER of the proposed GSO-based signal detector demonstrated a perfect approach similar to that of MLD. Fig. 7 shows the BER performance of the GSO-based MIMO signal detector with a search stage of 70 against the average SNR $\overline{\gamma}_k$ for $4 \times 4$ MIMO system with 16-QAM. The GSO-based signal detector still outperforms the GA-based and the PSO-based signal detectors for $4 \times 4$ MIMO system with 16-QAM.

## V. Conclusions

The formulation of a signal detection problem in MIMO systems is a combinatorial optimization problem with a nonlinear and non-differential objective function. In this paper, a suboptimal GSO-based heuristic approach was proposed to solve the optimum signal detection problem in MIMO systems. The GSO implicitly realizes signal detection by simulating natural evolution using the heuristic operator in GA and the social knowledge exchange in PSO updating rules. Simulation results demonstrate that the GSO-based MIMO signal detection is capable of achieving a near-optimum BER performance with a lower computational complexity compared with that of the MLD.

## REFERENCES


[1] A. Paulraj, R. Nabar, and D. Gore, "Introduction to space-time wireless communications," Cambridge, UK: Cambridge University Press, 2003.

[2] G. J. Foschini, "Layered space-time architecture for wireless communication in a fading environment when using multiple antennas," Bell Labs Technical Journal, vol. 1, pp. 41-59, Aug. 1996.

[3] S. Bashir, A. A. Khan, M. Naeem, and S. I. Shah, "**An Application of GA for Symbol Detection in MIMO Communication Systems," Third International Conference on Natural Computation, ICNC 2007, vol. 2, pp. 404-410, Haikou, China, 24-27 Aug. 2007.**

[4] H. Liu and J. Li, "A particle swarm optimization-based multiuser detection for receive-diversity-aided STBC systems," IEEE Trans. Signal Processing Letter, vol. 15, pp. 29-32, 2008.

[5] F. Grimaccia and M. Mussetta and R. E. Zich, "Genetical Swarm Optimization: Self-Adaptive Hybrid Evolutionary Algorithm for Electromagnetic," *IEEE Trans. Antennas and Propagation*, vol. 55, no. 3, pp.781-785, Mar. 2007.

[6] N. Telzhensky and Y. Leviatan, "Novel method of UWB antenna optimization for specified input signal forms by means of genetic algorithm," IEEE Trans. Antennas and Propagation, vol. 54, no. 8, pp. 2216-2225, Aug. 2006.

[7] C. Ergun and K. Hacioglu, "Multiuser detection using a genetic algorithm in CDMA communications systems," IEEE Trans. Communication, vol. 48, no. 8, pp. 1374-1383, Aug. 2000.

[8] K. Yen and L. Hanzo, "Antenna-diversity-assisted genetic-algorithm-based multiuser detection schemes for synchronous CDMA systems," IEEE Trans. Commun., vol. 51, no. 3, pp. 366-370, Mar. 2003.

[9] M. Mitchell, *An Introduction to Genetic Algorithms*. Cambridge, MA: MIT Press, 1998.

[10] G. Syswerda, "Uniform crossover in genetic algorithms," in *Proc. 3rd Int. Conf. Genetic Algorithms*, J. D. Schaffer, Ed.. San Mateo, CA, 1989, pp. 2–9.

[11] F. Grimaccia and M. Mussetta and R. E. Zich, "Genetical Swarm Optimization: Self-Adaptive Hybrid Evolutionary Algorithm for Electromagnetics," *IEEE Trans. Antennas and Propagation*, Vol. 55, No. 3, Part 1, pp.781-785, Mar. 2007.


**Table I the parameters of MIMO system**

| Algorithm / Mod. \ Parameter | PSO | | GA | | GSO | |
|---|---|---|---|---|---|---|
| | 16QAM | 64QAM | 16QAM | 64QAM | 16QAM | 64QAM |
| Generation | 70 | 20 | 70 | 20 | 70 | 20 |
| Particle | 200 | 80 | | | 100 | 40 |
| Population | | | 200 | 80 | 100 | 40 |
| Mutation Ratio | | | 0.1 | 0.1 | 0.1 | 0.1 |
| Constant c1,c2 | 2 | 2 | | | 2 | 2 |
| Inertia Weight $w$ | 0.9 | 0.9 | | | 0.9 | 0.9 |
| $h_c$ | | | | | 0.3 | 0.3 |

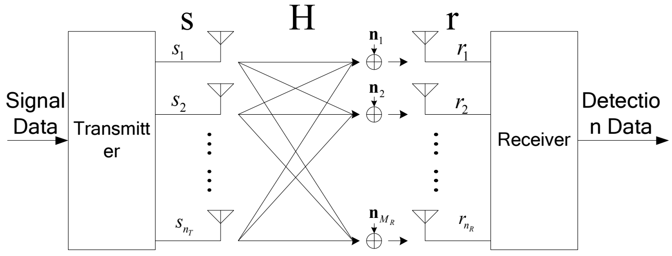


**Fig. 1 MIMO system model with $n_T$ transmit and $n_R$ receive antennas**

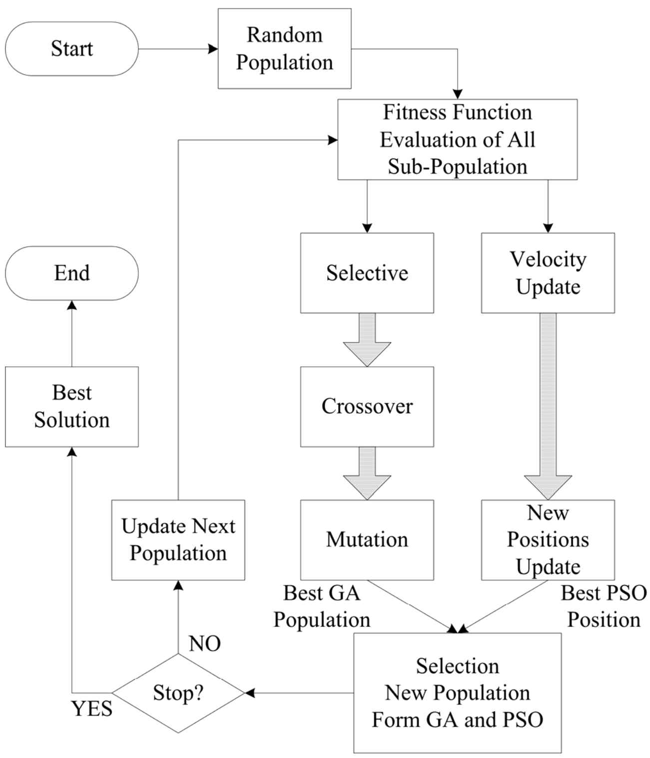


**Fig. 2 The flowchart of GSO algorithm**

Random $hc$ ($hc$=0.5) → [0100 1100 1010 1101]

Best GA Population → [1011 0100 1001 0011]

Best PSO Position → [1010 0001 1011 0010]

New Next Population → [1010 0101 1001 0011]

**Fig. 3 example of the new next population select**

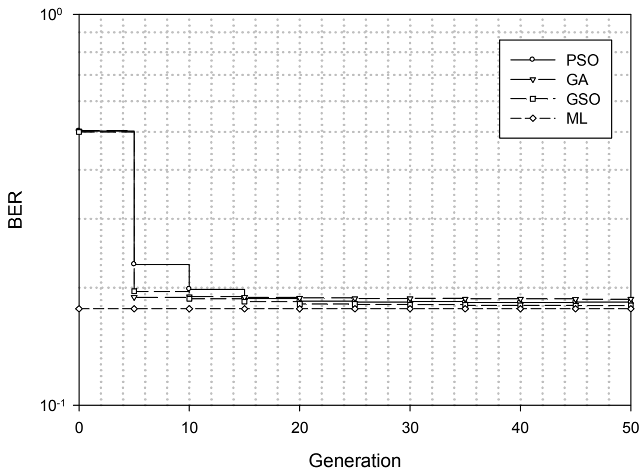


**Fig. 4 the curves of convergence rate for 4x4 16-QAM MIMO signal detection with 15dB**

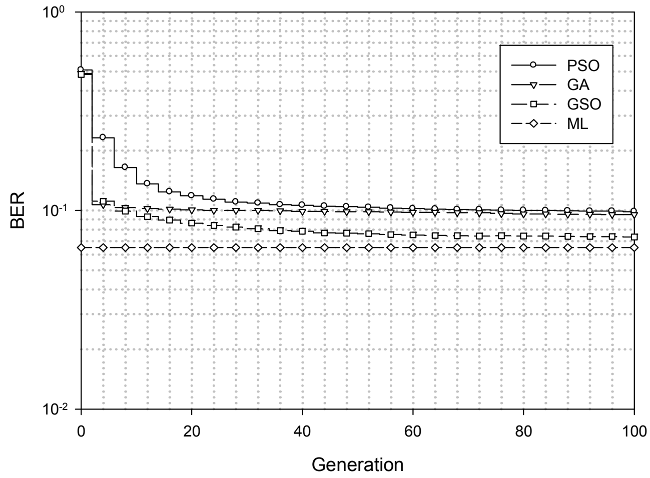


**Fig. 5 the curves of convergence rate for 2x2 64-QAM MIMO signal detection with 15dB**

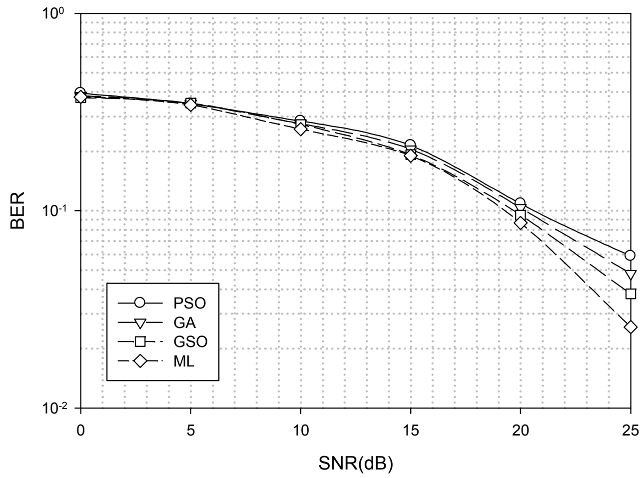


**Fig. 6 BER performance comparison for a 2x2 system using 64-QAM**

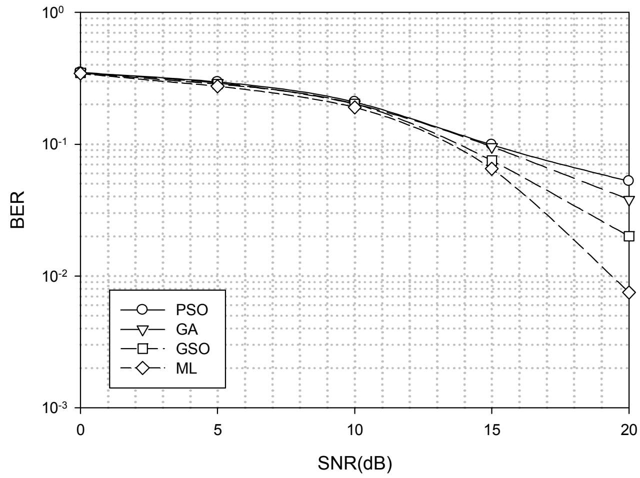


**Fig. 7 BER performance comparison for a 4x4 system using 16-QAM**