

Symbol Detection in MIMO Systems Using PSO GSA Optimization Algorithm

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Abstract:-

We present a PSO GSA based algorithm for symbol detection in multi-input multi-output (MIMO) system. Since symbol detection is an NP-hard problem so PSO GSA is particularly attractive as PSO GSA algorithms are one of the most successful strands of swarm intelligence and are suitable for applications where low complexity and fast convergence is of absolute importance. Maximum Likelihood (ML) detector gives optimal results but it uses exhaustive search technique. We show that PSO GSA based detector can give near-optimal bit error rate (BER) at a much lower complexity level. The simulation results suggest that the proposed detector gives an acceptable performance complexity trade-off in comparison with ML and VBLAST detectors.

1.1 Introduction

Wireless communication systems have made large developments since the first generation (1G) Systems. Frequency Division Multiple Access (FDMA) was the main techniques used at that level. Similarly, Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA) multiple access methods are widely used in today's communication systems. CDMA is also used in the third generation (3G) schemes. Three multiple access schemes are used to allow users to simultaneously share radio spectrum, which is a finite and essential resource of all wireless communications skills.[1] Nowadays, the wireless system designers are facing several challenges: like the limitation of the radio spectrum, the complexity of wireless propagation environment, the increasing demand for better quality of service (QoS) and higher transmission data rate. Traditional wireless communication schemes

have been made more spectrally efficient through the use of complex coding techniques and algorithms.[2]

1.2 Multiple Input Multiple Output (MIMO)

MIMO systems can be defined simply. Given an arbitrary wireless communication system, we consider a link for which the transmitting end as well as the receiving end is equipped with multiple antenna elements.

The idea behind MIMO is that the signals on transmit (Tx) antennas at one end and the receive (Rx) antennas at the other end are "combined" in such a way that the quality (bit-error rate or BER) or the data rate (bits/sec) of the communication for each MIMO user will be improved. Such an advantage can be used to increase both the network's quality of service and the operator's revenues significantly. To multiply throughput of a radio link, multiple antennas (and multiple RF channel accordingly) are put at both the transmitter and the receiver. [3]

A MIMO system with similar count of antennas at both the transmitter and the receiver in a point-to-point (PTP) link is able to multiply the system throughput linearly with every additional antenna. For example, a 3×3 MIMO will double the throughput. [3]

MIMO often employs Spatial Multiplexing (SM) to enable signal (coded and modulated data stream) to be transmitted across different spatial domains. Meanwhile, Mobile WiMAX supports multiple MIMO modes that is using either SM or STC or both to maximize spectral

efficiency (increase throughput) without shrinking the coverage area.

The dynamic switching between these modes based on channel conditions is called Adaptive MIMO Switching (AMS). If combined with AAS (Adaptive Antenna System), MIMO can further boost WiMAX performance.

MIMO is widely used in today wireless communications because all wireless technologies (PAN, LAN, MAN, and WAN) try to add it to increase data rate multiple times to satisfy their bandwidth-hungry broadband users.

that will most likely make 4G reality are MIMO, OFDM MIMO system will deliver multimedia services (VoIP, video, Internet) at high speed (100 Mbps or more) over end-to-end IP network infrastructure and it will enable seamless handoff between mobile wireless WAN and fixed wireless LAN. [4]

1.3 MIMO System model

A MIMO channel with N_t transmitters and N_r receivers is typically represented as a matrix H of dimension $N_r \times N_t$, where each of the coefficients H_{nm} represents the transferfunction from the n th transmitter to the m th receiver. [5]

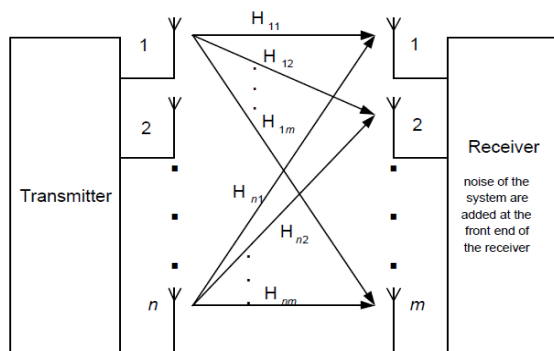


Fig.1.1: Multi-Input Multi-Output system

We denote the signal or symbol transmitted from the n th transmitter x_n . With this notation, the matrix model of the channel is [5]

$$Y = Hx + s$$

Where s a vector of additive noise, and y is a $N_r \times 1$ complex received vector. H is a complex

matrix representing the Rayleigh flat fading channel.

$$\begin{bmatrix} h_{11} & h_{21} & \dots & h_{M1} \\ h_{12} & h_{22} & \dots & h_{M2} \\ \dots & \dots & \dots & \dots \\ h_{1M} & h_{2M} & \dots & h_{MM} \end{bmatrix}$$

Each coefficient h_{nm} shows the complex path gain between the n th transmits and m th receive antenna. [6]

Assuming the presence of a rich scattering environment in which the columns of H are independent and entries h_{nm} are modelled as independent zero mean complex Gaussian random variables with unit variance. x is a $N_t \times 1$ complex transmitted vector. n is an $N_r \times 1$ complex noise vector whose components n_i are modelled as zero mean independent complex Gaussian random variables with variance σ^2 per real dimension [5][7]

1.4 PSO-GSA

a. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is one of the more recently developed evolutionary technique, and it is based on a suitable model of social interaction between independent agents (particles) and it uses social knowledge in order to find the global maximum or minimum of a generic function [8], the improvement in the population fitness is assured by pseudo-biological operators, such as selection, crossover and mutation, the main PSO operator is the velocity update that takes into account the best position explored during the iterations, resulting in a migration of the swarm towards the global optimum.

In the PSO the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories of a set of particles according to a swarm-like set of rules [9]. The position of each particle is used to compute the value of the function to be optimized. Consequently every position is a particular solution of the optimization problem. Individual particles traverse the problem hyper-space and are attracted by both the position of

their best past performance and the position of the global best performance of the whole swarm.

Particles are moved in the domain of the problem with variable speeds and every position they reach represents a particular configuration of the variables set, which is then evaluated in order to get a score.

As for GA, the starting point for PSO is the definition of a random population of particles. In the PSO technique each particle *i*-th is defined by its position vectors X_i in the space of the parameters to be optimized but, differently than GA, such a particle also has a random velocity V_i in the parameter space. At each iteration the particle moves according to its velocity and the cost function to be optimized $f(x)$ is evaluated for each particle in their current position. The value of the cost function is then compared with the best value obtained during the previous iterations. Besides, the best value ever obtained for each particle is stored and the corresponding position P_i is stored too. The velocity of the particle is then stochastically updated following the updating rules based on the attractions of the position P_i of its personal optimum and the position P_g , which is the global optimum. Remembering that the global optimum is the best fitness value ever reached by all the swarm, equation shows the well-known standard PSO updating rule for particles' velocities,

$$V_{i+1} = \omega V_i + \varphi_1 \eta_1 (P_i - X_i) + \varphi_2 \eta_2 (P_g - X_i)$$

where ω is a friction factor that tends to stop the particle and prevents oscillations around the optimal value, effectively speeding up convergence, φ_1 and φ_2 are constants, while η_1 and η_2 are random positive numbers with a uniform distribution between 0 and 1. [10]

The presence of random weights in the pull terms generated by the particle's best position P_i and the global swarm best position P_g , causes wide oscillations and a random search in the entire parameter space.

Such oscillations are precious whereas they broaden the search of each particle but they have some drawbacks since they can produce continuous oscillation around the optimal point. Such oscillation can be dampened, and so the convergence enhanced, via an effective use of the ω parameter.

b. Gravitational Search Algorithm (GSA)

Our optimization algorithm based on the law of gravity [8]. In the proposed algorithm, agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses.

Hence, masses cooperate using a direct form of communication, through gravitational force. The heavy masses which correspond to good solutions – move more slowly than lighter ones, this guarantees the exploitation step of the algorithm. In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass.

The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function. In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, we expect that masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space.[11]

1.5 MIMO Detection Techniques

There are numerous detection techniques available with combination of linear and non-linear detectors. The most common detection techniques are ZF, MMSE and ML detection technique. ML detection technique is compared with the proposed algorithm.

a. Zero Forcing (ZF)

The ZF is a linear estimation technique, which inverse the frequency response of received signal, the inverse is taken for the restoration of signal after the channel. The estimation of strongest transmitted signal is obtained by nulling out the weaker transmit signal. The strongest signal has been subtracted from received signal and proceeds to decode strong signal from the remaining transmitted signal. ZF equalizer ignores the additive noise and may significantly amplify noise for channel. The major advantages of ZF linear equalizer is that it simply eliminates ISI by forcing the overall pulse, which is the convolution of the channel and the equalizer to make a unit-impulse response. Although the noise power and covariance function does not need to be estimated in ZF even than it's perform poor than that of ML. It is because ZF equalizer will further enhance the noise in channel where already deep fading is affecting the channel, which degrades its performance than ML. The channel response is $H(s)$ then the input signal is multiplied by the reciprocal of $H(s)$. The basic Zero force equalizer of 2×2 MIMO channel can be modeled by taking received signal y_1 during first slot at receiver antenna as:

$$y_1 = h_{1,1}x_1 + h_{1,2}x_2 + n_1$$

$$= [h_{1,1} \ h_{1,2}] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + n_1$$

The received signal y_2 at the second slot receiver antenna is:

$$y_2 = h_{2,1}x_1 + h_{2,2}x_2 + n_2$$

$$= [h_{2,1} \ h_{2,2}] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + n_2$$

Where $i = 1,2$ in x_i is the transmitted symbol and $i = 1,2$ and $j = 1,2$ in $h_{i,j}$ is correlated matrix of fading channel, with j represented transmitted antenna and i represented receiver antenna, n_1 and n_2 is the noise of first and second receiver antenna.

b. Maximum Likelihood (ML)

The Maximum Likelihood (ML) detection is a scheme well known to be very robust and well suited for practical implementation whereas linear receiver suffers from numerical

complexity. ML detector is the optimal receiver in terms of bit error rate (detector performance) but it is a nonlinear detector with a high complexity. The ML detection rule is given by

$$R = \operatorname{argmin} \|y - Hx_i\|^2$$

Where element R of are optimized variable and $\|y - Hx_i\|^2$ is objective function, after minimized R , we get

$$R = \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \right\|^2$$

In case of BPSK, the possible value of x_1 and x_2 is +1 or -1, to find the minima from the all combination of x_1 and x_2 . The estimation of the transmitted symbol is done on the basis of the following values

$$R_{+1,+1} = \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{bmatrix} \begin{bmatrix} +1 \\ +1 \end{bmatrix} \right\|^2$$

$$R_{+1,-1} = \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{bmatrix} \begin{bmatrix} +1 \\ -1 \end{bmatrix} \right\|^2$$

$$R_{-1,+1} = \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{bmatrix} \begin{bmatrix} -1 \\ +1 \end{bmatrix} \right\|^2$$

$$R_{-1,-1} = \left\| \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} - \begin{bmatrix} h_{1,1} & h_{1,2} \\ h_{2,1} & h_{2,2} \end{bmatrix} \begin{bmatrix} -1 \\ -1 \end{bmatrix} \right\|^2$$

The estimate of the transmit symbol is chosen based on the minimum value from the above four values with $R_{+1,+1} \gg [1,1]$, $R_{+1,-1} \gg [1,0]$, $R_{-1,+1} \gg [0,1]$, $R_{-1,-1} \gg [0,0]$.

1.6 Results

We consider a MIMO systems designed for an underlying 4-QAM and 4-PSK constellation with up to 4 transmit and 4 receive antennas. We assume a quasi-static Rayleigh fading channel model which is constant over a frame and varies independently between frames. We assume that the channel exhibits a quasi-static frequency flat Rayleigh fading over the frame duration. Thus, it is constant over one frame and varies independently between frames. We consider a frame size of 100 symbols. We assume perfect channel state information (CSI) is available at the receiver. Detection/Decoding

of the received symbols is done via PSO-GSA algorithm. For performance comparison, we consider MIMO system which has specifications same as the system described above, the only difference being in the detection/decoding of the received symbols which is done via maximum likelihood (ML) Viterbi decoder. The following figures from 1.2 to 1.3 demonstrates the BER performance comparison for PSO-GSA based and ML based MIMO detectors using different transmit and different receive antennas and using 4-QAM and 4-PSK modulations separately.

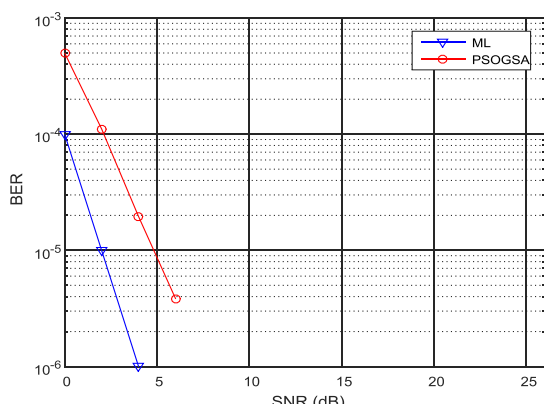


Figure 1.2 BER performance for 4 transmit and 4 receive antenna in case of 4-QAM.

Fig. 1.2 demonstrates the error performance comparison for four transmit and four receive antenna using 4-QAM modulation. It can be seen that with ML system is superior to PSO-GSA system by just about 2.2 dB at the BER of 10^{-4} .

Fig. 1.3 demonstrates the error performance comparison for four transmit and four receive antenna using 4-PSK modulation. It can be seen that with ML system is superior to PSO-GSA system by just about 1.7 dB at the BER of 10^{-3} .

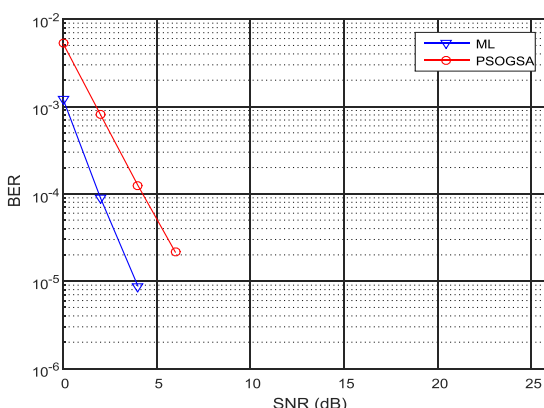


Figure 1.3 BER performance for 4 transmit and 4 receive antenna in case of 4-PSK.

a. Receive Diversity

Here we consider the effect of receive diversity on the bit error rate performance of the system. Performance is evaluated using 2 transmit and 1, 2 and 4 receive antennas and using 4 transmit and 1, 2 and 4 receive antennas.

The underlying system is considered to be a MIMO systems designed for an underlying 4-QAM and 4-PSK. We assume that the channel exhibits a quasi-static frequency flat Rayleigh fading over the frame duration. Thus, it is constant over one frame and varies independently between frames. We consider a frame size of 100 symbols. We assume perfect channel state information (CSI) is available at the receiver. Decoding of the received symbols is done via PSO-GSA algorithm.

The result shows that increasing the number of receive antennas yield a significant performance gain.

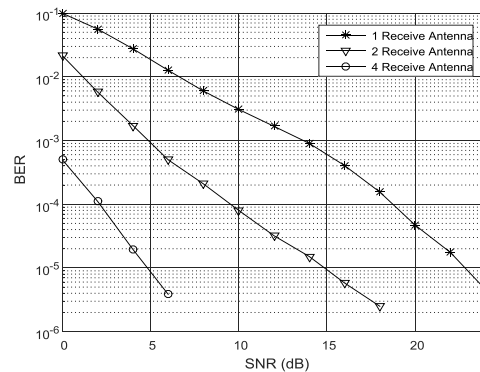


Figure 1.4 BER performance for 4 transmit antennas (4-QAM).

Fig. 1.4 demonstrates the error performance comparison for four transmit and one, two and four receive antennas using 4-QAM modulation. It can be seen that four receive antenna system is superior than two receive antenna system by about 9.1 dB at the BER of 10^{-5} .

Fig. 1.5 demonstrates the error performance comparison for four transmit and one, two and four receive antennas using 4-PSK modulation. It can be seen that four receive antenna system

is superior than two receive antenna system by about 7.9 dB at the BER of 10^{-4} .

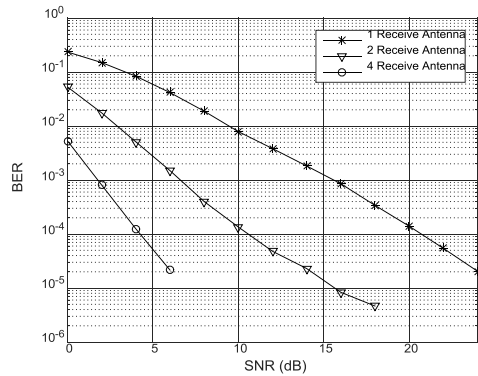


Figure 1.5 BER performance for 4 transmit antennas (4-PSK).

b. Transmit Diversity

Here we consider the effect of transmit diversity on the bit error rate performance of the system. Performance is evaluated using 2 and 4 transmit antennas and 1, 2 and 4 receive antennas. The underlying system is considered to be a MIMO systems designed for an underlying 4-QAM and 4-PSK. We assume that the channel exhibits a quasi-static frequency flat Rayleigh fading over the frame duration. We consider a frame size of 100 symbols. We assume perfect CSI is available at the receiver. Decoding of the received symbols is done via PSO-GSA algorithm.

The result shows that increasing the number of transmit antennas yield a significant performance gain.

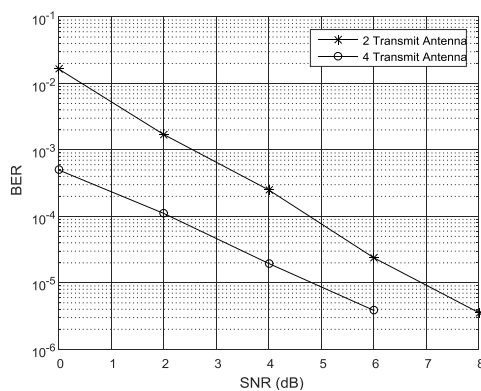


Figure 1.6 BER performance for 4 receive antenna (4-QAM).

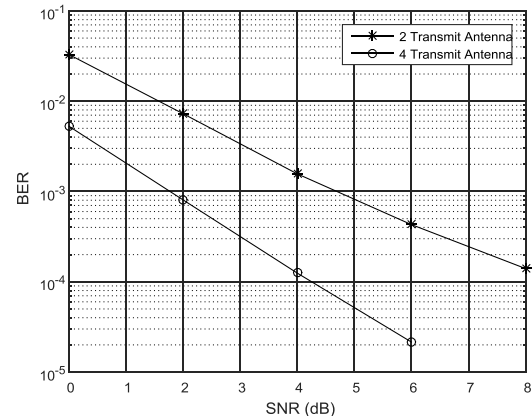


Figure 1.7 BER performance for 4 receive antenna (4-PSK).

Fig. 1.6 demonstrates the error performance comparison for four receive and two and four transmit antennas using 4-QAM modulation. It can be seen that 4 transmit antenna system is superior than two transmit antenna system by just about 2.2 dB at the BER of 10^{-5} .

Fig. 1.7 demonstrates the error performance comparison for four receive and two and four transmit antennas using 4-PSK modulation. It can be seen that four transmit antenna system is superior than two transmit antenna system by just about 2.9 dB at the BER of 10^{-3} .

c. Effect of Modulation

Here we consider the effect of modulation used on the bit error rate performance of the system. Performance is evaluated using 2 and 4 transmit antennas and 1, 2 and 4 receive antennas. The underlying system is considered to be a MIMO systems designed for an underlying 4-QAM and 4-PSK. We assume that the channel exhibits a quasi-static frequency flat Rayleigh fading over the frame duration. We consider a frame size of 100 symbols. We assume perfect CSI is available at the receiver. Decoding of the received symbols is done via PSO-GSA algorithm performs better than all the systems compared with.

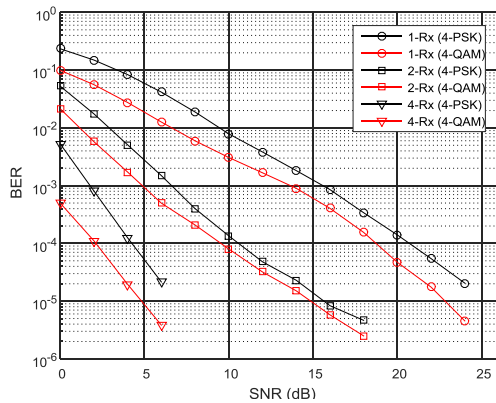


Figure 1.8 BER performance for 4 transmit antennas.

It can be seen that with QAM modulation the system performs better than the one with PSK modulation for same number of transmit and receive antennas.

Fig. 1.8 demonstrates the error performance comparison for two transmit and one, two and four receive antennas using 4-QAM and 4-PSK modulations. It can be seen that with QAM modulation the system performs better than the one with PSK modulation for same number of transmit and receive antennas.

d. Comparison

Fig. 1.9 demonstrates the error performance comparison for various techniques with our proposed system using PSO-GSA algorithm. It can be seen that the proposed system

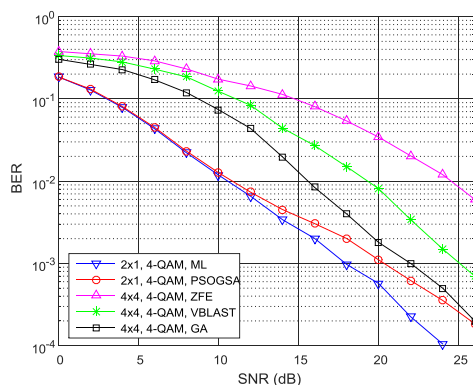


Figure 1.9 BER performance comparison.

e. Summary

From the above results we can deduce that though the PSO-GSA based MIMO decoder is not better than the ML based MIMO decoder,

but provides near optimal results with much lower complexity level as compared to the ML detector. PSO-GSA based MIMO detector uses a simple model and has lesser implementation complexity.

Conclusion In this dissertation, PSO-GSA Optimization assisted symbol detection in a spatial multiplexing system is reported. The resistance to being trapped in local minima, convergence to reasonable solution in fewer iterations and exploratory exploitive search approach makes it a suitable candidate for real-time wireless communications systems. PSO-GSA based MIMO detector uses a simple model and has lesser implementation complexity. For larger number of antennas and higher modulation schemes the proposed detector is expected to give near optimal results with much lower complexity level as compared to the ML detector and VBLAST detectors.

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