

Symbol detection in MIMO systems using SA-BFO optimization algorithm

Ramanpreet Kaur¹, Sonia Goyal²

Electronics and Communication Eng., University College of Engineering, Punjabi University, Patiala, India^{1,2}

Abstract: Multi-Input Multi-output based communication system architecture promises increased capacity and high data rates. Self-adaptive Bacterial Foraging Optimization (SA-BFO), inspired by foraging behaviour of bacteria, is one of the recent technologies in solving optimization problems. In this paper SA-BFO based algorithm for symbol detection in multi-input multi-output system is presented. While an optimal Maximum Likelihood (ML) detection using an exhaustive search method is prohibitively complex, simulation results show that the SA-BFO optimized MIMO detection algorithm results in near optimal Bit Error Rate (BER) performance, with significantly reduced complexity.

Keywords: MIMO (Multi-Input Multi-Output system), BER (Bit Error Rate), SA-BFO (Self-Adaptive Bacterial Foraging Optimization algorithm), ML (Maximum Likelihood)

I. INTRODUCTION

Wireless communication using mimo antenna architecture also referred to as spatial multiplexed system is one of the most significant technological developments of last decade, which promises to play a key role in realizing the tremendous growth in the field of communication. MIMO systems achieve transmit and receive diversity by employing a Multi-Element Antenna (MEA) structures at both the transmitter and receiver [1]. Fading problem is a major impairment of the wireless communication channel. traditional mobile radio channel has always suffered from the detrimental effects of multipath fading. The use of multiple antennae at both ends of the wireless channel has proven to be very effective in combating fading and enhancing the channel's spectral efficiency. By employing spatial multiplexing, Multiple-Input Multiple-Output (MIMO). wireless antenna systems provide increases in capacity without the need for additional spectrum or power[2]. The inter-symbol interference caused by multipath MIMO channels distorts the MIMO transmitted signal which causes bit errors at receiver. [3]

Optimization problems defined by functions for which derivatives are unavailable or available at a prohibitive cost are appearing more and more frequently in computational science and engineering. Increasing complexity in mathematical modelling, higher sophistication of scientific computing, and abundance of legacy codes are some of the reasons why derivative-free optimization is currently an area of great demand.[4]

In order to improve the BFO's searching performance, Self-adaptive Bacterial Foraging Optimization (SA-BFO) is presented in the present paper.[5] Instead of the simple

description of chemotactic behavior in original BFO, SA-BFO also incorporates the adaptive search strategy, which allows each bacterium strikes a good balance between exploration and exploitation during algorithmic execution by tuning its run-length unit self-adaptively.

The paper is organized as follows: Section I, presents brief introduction about MIMO technique. Section II, introduces about MIMO system model. Section III, describes the bit error rate. Section IV, includes the SA-BFO based detector for MIMO systems and section V, discusses simulation results and discussion. Section VI, concludes the results of work.

II. MIMO SYSTEM MODEL

MIMO channel model is assumed to be quasi-static. Consider the MIMO system shown in fig.1 where N different signals are transmitted and arrive at an array of M ($N \leq M$) receivers via a rich-scattering flat-fading environment.[1] The block transmission is assumed to contain one symbol i.e. $L=1$. Baseband equivalent model of received signal vector at each sampling instant can be represented as:

$$\mathbf{r} = \sqrt{P}/N \mathbf{H}\mathbf{x} + \mathbf{n} \quad (1)$$

Where \mathbf{r} is an $M \times 1$ vector of received symbols at each antenna, \mathbf{x} is an $N \times 1$ vector of symbols transmitted by each antenna, and \mathbf{n} is an $M \times 1$ vector of complex Additive White Gaussian Noise (AWGN) random variables seen at each



receive antenna. The channel matrix \mathbf{H} is an $M \times N$ matrix, whose elements h_{ij} represent the complex fading coefficients experienced by a signal transmitted from transmit antenna 'j' to receive antenna 'i'. P is total transmit energy for one transmit antenna system and is normalized for N transmit antenna system.

The receiver is also assumed to have perfect knowledge of the channel coefficients. This is a reasonable assumption when the fading is slow enough to allow estimation of the CSI with negligible error, as in the case of fixed wireless systems.

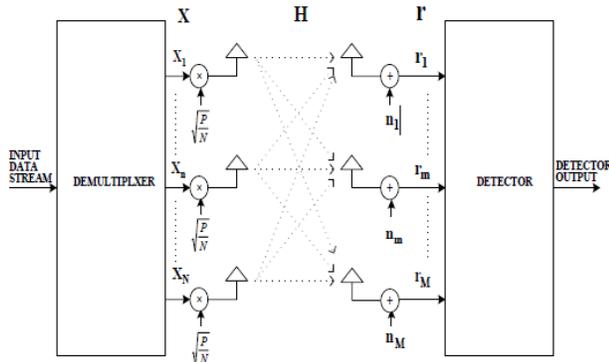


Fig 1. MIMO system model with N transmit and M receive antennas

III. BIT ERROR RATE

The measure of performance of any communication system is usually bit error rate (BER). Bit Error Rate is given as follows

$$\text{BER} = \frac{\text{Errors}}{\text{Total Number of Bits}}$$

With a strong signal and an unperturbed signal path, this number so small as to be insignificant. It becomes significant when we want to maintain an adequate signal-to-noise ratio in the presence of inadequate transmission through electronic circuitry and the medium for propagation.

IV. SA-BFO BASED DETECTION FOR MIMO SYSTEMS

A. Steps for SA-BFOA

1) Chemotaxis:

This process simulates the movement of an E.coli cell through swimming and tumbling via flagella. Suppose $\theta^i(j, k, l)$ represents the i th bacterium at j th chemotactic, k th reproductive, and l th elimination–dispersal step. $C(i)$ is a

scalar and indicates the size of the step taken in the random direction specified by the tumble (run length unit). Then, in computational chemotaxis, the movement of the bacterium may be represented by

$$\Theta^i(j+1, k, l) = \Theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (2)$$

where Δ indicates a unit length vector in the random direction.

2) Swarming:

Interesting group behaviour has been observed for several motile species of bacteria including E.coli and S. typhimurium, where stable spatiotemporal patterns (swarms) are formed in semisolid nutrient medium. A group of E.coli cells arrange themselves in a traveling ring by moving up the nutrient gradient when placed amid a semisolid matrix with a single nutrient chemo-effector. The cells when stimulated by a high level of succinate release an attractant aspartate, which helps them to aggregate into groups and, thus, move as concentric patterns of swarms with high bacterial density.

3) Reproduction:

The least healthy bacteria eventually die while each of the healthier bacteria (those yielding lower value of the objective function) asexually split into two bacteria, which are then placed in the same location. This keeps the swarm size constant.

4) Elimination and Dispersal:

To simulate this phenomenon in BFOA, some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space[3]

B. Step-by step algorithm

- [Step 1]** Initialize parameters $n, S, N_c, N_s, N_{re}, N_{ed}, P_{ed}, C(i)$ ($i=1, 2, \dots, S$), Θ^i . Where,
 - n : Dimension of the search space,
 - S : The number of bacterium,
 - N_c : chemotactic steps,
 - N_s : swim steps,
 - N_{re} : reproductive steps,
 - N_{ed} : elimination and dispersal steps,
 - P_{ed} : probability of elimination,
 - $C(i)$: the run-length unit during each run or tumble.
- [Step 2]** Elimination-dispersal loop: $l = l+1$.
- [Step 3]** Reproduction loop: $k = k+1$.
- [Step 4]** Chemotaxis loop: $j = j+1$.



[substep **a**] For $i = 1, 2, \dots, S$, take a chemotactic step for bacteria i as follows.

[substep **b**] Compute fitness function, $J(i, j, k, l)$.

[substep **c**] Let $J_{last} = J(i, j, k, l)$ to save this value since we may find better value via a run.

[substep **d**] Tumble: Generate a random vector $\Delta(i) \in \mathbb{R}^n$ with each element $\Delta_m(i)$, $m = 1, 2, \dots, S$, a random number on $[-1, 1]$.

[substep **e**] Move: Let

$$\Theta^i(j+1, k, l) = \Theta^i(j, k, l) + C(i) \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (3)$$

This results in a step of size $C(i)$ in the direction of the tumble for bacteria i .

[substep **f**] Compute $J(i, j+1, k, l)$ with $\Theta^i(j+1, k, l)$.

[substep **g**] Swim:

(i) Let $m = 0$ (counter for swim length).

(ii) While $m < N_s$ (if have not climbed down too long)

• Let $m = m + 1$.

• If $J(i, j+1, k, l) < J_{last}$, let $J_{last} = J(i, j+1, k, l)$. then another step of size $C(i)$ in this same direction will be taken as equation (1) and use the new generated $\Theta^i(j+1, k, l)$ to compute the new $J(i, j+1, k, l)$.

• Else let $m = N_s$.

[substep **h**] Go to next bacterium ($i+1$): if $i \neq S$ go to (b) to process the next bacteria.

[Step 5] If $j < N_c$, go to step 3. In this case, continue chemotaxis since the life of the bacteria is not over.

[Step 6] Reproduction:

[substep **a**] For the given k and l , and for each $i = 1, 2, \dots, S$, let J_{health} be the health of the bacteria. Sort bacterium in order of ascending values.

$$J_{health}^i = \sum_{j=1}^{N_c+1} J(i, j, k, l) \quad (4)$$

[substep **b**] The S_r bacteria with the highest J_{health} values die and the other S_r bacteria with the best values split and the copies that are made are placed at the same location as their parent.

[Step 7] If $k < N_{re}$ go to step 2. In this case the number of specified reproduction steps is not reached and start the next generation in the chemotactic loop.

[Step 8] Elimination–dispersal: For $i = 1, 2, \dots, S$, with probability ped , eliminate and disperse each bacteria, which results in keeping the number of bacteria in the population constant. To do this, if a bacterium is eliminated, simply disperse one to a random location on the optimization domain. If $l < N_{ed}$, then go to step 2; otherwise end.

In SA-BFO evolution process, each bacterium displays alternatively two distinct search states:

(1) Exploration state, during which the bacterium employs a large run-length unit to explore the previously unscanned regions in the search space as fast as possible.

(2) Exploitation state, during which the bacterium uses a small run-length unit to exploit the promising regions slowly in its immediate vicinity. Each bacterium in the colony permanently maintains an appropriate balance between Exploration and Exploitation states by varying its own run-length unit adaptively. This is achieved by taking into account two decision indicators: a fitness improvement and no improvement registered lately. The criteria that determine the adjustment of individual run-length unit and the entrance into one of the states are the following:

Criterion-1: if the bacterium discovers a new promising domain, the run-length unit of this bacterium is adapted to another smaller one. Here “discovers a new promising domain” means this bacterium register a fitness improvement beyond a certain precision from the last generation to the current. Following Criterion-1, the bacterium’s behavior will self-adapt into Exploitation state.

Criterion-2: if the bacterium’s current fitness is unchanged for a number K_u (user-defined) of consecutive generations, then augment this bacterium’s run-length unit and this bacterium enters Exploration state. This situation means that the bacterium searches on an un-promising domain or the domain where this bacterium focuses its search has nothing new to offer [4].

V. SIMULATION RESULTS AND DISCUSSION

We consider a MIMO system 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. 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. We show that SABFO based detector gives near optimal results with much lower complexity level as compared to the ML detector.

Fig 2. demonstrates the error performance comparison for two transmit and one receive antenna using 4-QAM modulation. It can be seen that with ML system is superior to SABFO system by just about 2.3 dB at the BER of 10^{-3} .

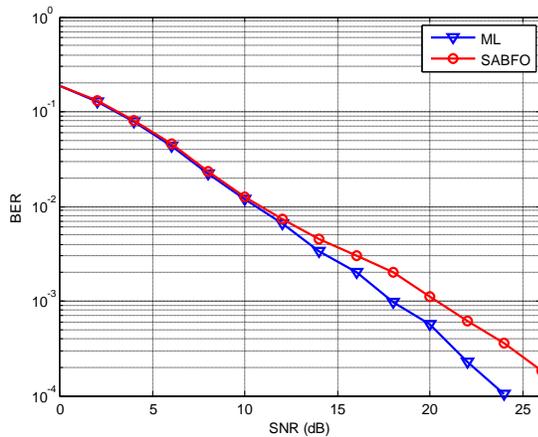


Fig 2. BER performance for 2 transmit and 1 receive antenna in case of 4-QAM.

Fig 3. demonstrates the error performance comparison for two transmit and one receive antenna using 4-PSK modulation. It can be seen that with ML system is superior to SABFO system by just about 0.2 dB at the BER of 10^{-2} .

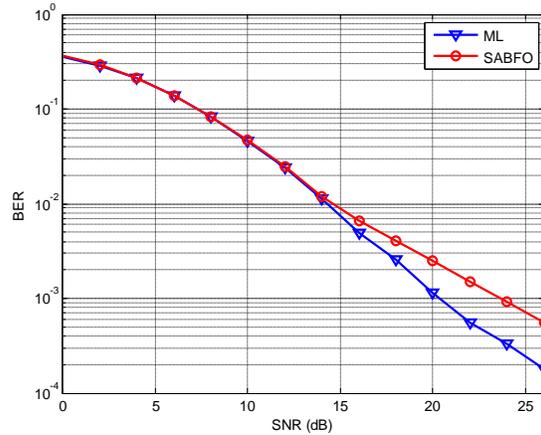


Fig 3. BER performance for 2 transmit and 1 receive antenna in case of 4-PSK.

5.1 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 SABFO algorithm. Fig 4. 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.

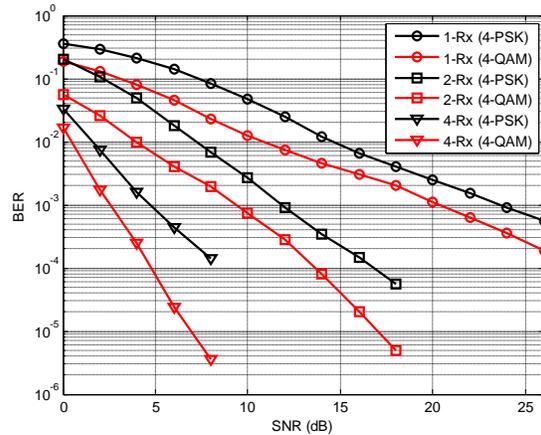


Fig 4. BER performance for 2 transmit antennas.

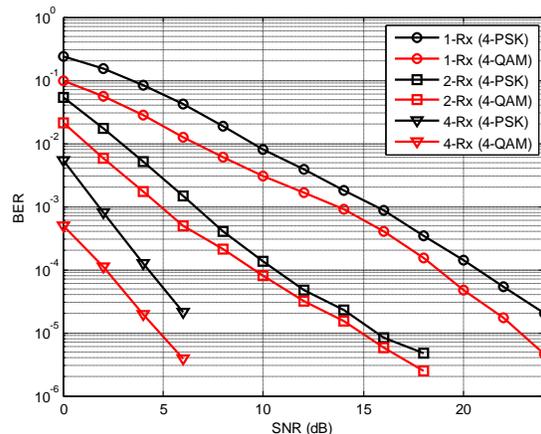


Fig 5. BER performance for 4 transmit antennas.



Fig 5. 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.

VI. CONCLUSION

In this paper, Self-Adaptive Bacterial Foraging Optimization algorithm based symbol detection is presented. SA-BFO based MIMO detector uses a simple model and has lesser implementation complexity. For larger number of antennas and higher modulation schemes, the proposed SA-BFO algorithm is expected to give near optimal results with much lower complexity level as compared to the ML detector.

ACKNOWLEDGMENT

I express my sincere thanks to Er. Sonia Goyal, Assistant Professor, Electronics and Communication Department, UCoE, Punjabi University Patiala for the Technical Assistance.

REFERENCES

- [1] Sajid Bashir, Muhammad Naeem and Syed Ismail Shah, "An Application of GA for symbol detection in MIMO communication Systems", *IEEE*, 2007
- [2] Kiran Khurshid, Safwat Irteza and Adnan Ahmed Khan, "Application of Ant Colony Optimization based algorithm in MIMO Detection", *IEEE*, 2010
- [3] Bhasker Gupta and Davinder S. Saini, "BER analysis of SFBC MIMO-OFDM systems using different Equalizers in quasi-static mobile radio channel", *IEEE*, 2011.
- [4] Nitin Kumar Jhankal and Dipak Adhyaru, "Bacterial Foraging Optimization Algorithm: A Derivative free technique", *IEEE*, 2011.
- [5] Hanning Chen, Yunlong Zhu and Kunyuan Hu, "Self-Adaptation in Bacterial Foraging Optimization Algorithm", *IEEE*, 2008.
- [6] Rafik ZAYANI, Mohamed L. AMMARI, "Neural Network Equalization For Frequency Selective Nonlinear MIMO Channels", *IEEE*, 2012
- [7] Cheng-Yu Hung, Wei-Ho Chung and Chiao-En Chen, "A Monte Carlo MIMO Detection Via Random Noise Generation", *IEEE*, 2012
- [8] Cheng-Yu Hung and Ronald Y. Chang, "A Hybrid MMSE and K-Best Detection Scheme for MIMO systems", *IEEE Vehicular Technology Conference (VTC Fall)*, 2012
- [9] Rong-Rong Chen, Ronghui Peng, "Markov Chain Monte Carlo: Applications to MIMO detection and channel equalization", *IEEE Information Theory and Applications Workshop*, 2009.
- [10] G. D. Forney, "The Viterbi algorithm," *Proceedings of the IEEE*, vol.61, no.3, pp. 268--278, March 1978.