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A low-complexity hybrid algorithm based on particle swarm and ant colony optimization for large-MIMO detection

Manish Mandloi*, Vimal Bhatia

Discipline of Electrical Engineering, Indian Institute of Technology Indore, Indore 453441, India

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ABSTRACT

With rapid increase in demand for higher data rates, multiple-input multiple-output (MIMO) wireless communication systems are getting increased research attention because of their high capacity achieving capability. However, the practical implementation of MIMO systems rely on the computational complexity incurred in detection of the transmitted information symbols. The minimum bit error rate performance (BER) can be achieved by using maximum likelihood (ML) search based detection, but it is computationally impractical when number of transmit antennas increases. In this paper, we present a low-complexity hybrid algorithm (HA) to solve the symbol vector detection problem in large-MIMO systems. The proposed algorithm is inspired from the two well known bio-inspired optimization algorithms namely, particle swarm optimization (PSO) algorithm and ant colony optimization (ACO) algorithm. In the proposed algorithm, we devise a new probabilistic search approach which combines the distance based search of ants in ACO algorithm and the velocity based search of particles in PSO algorithm. The motivation behind using the hybrid of ACO and PSO is to avoid premature convergence to a local solution and to improve the convergence rate. Simulation results show that the proposed algorithm outperforms the popular minimum mean squared error (MMSE) algorithm and the existing ACO algorithms in terms of BER performance while achieve a near ML performance which makes the algorithm suitable for reliable detection in large-MIMO systems. Furthermore, a faster convergence to achieve a target BER is observed which results in reduction in computational efforts.

1. Introduction

Employing multiple-input multiple-output (MIMO) systems in wireless communication provides a linear increase in capacity with minimum number of the transmit and the receive antennas (Foschini & Gans, 1998; Telatar, 1999). Using multiple antennas, several data streams can be transmitted simultaneously which results in a higher spectral efficiency without the need of additional spectrum. Recently, large MIMO systems (i.e. systems with tens to hundreds of antennas) are getting increased research attention (Chockalingam & Rajan, 2014) because of their potential to achieve a higher diversity as well as multiplexing gains. Practical implementation of large-MIMO systems relies on the computational complexity incurred in the reliable detection of the transmitted symbol vector. Minimum bit error rate (BER) performance can be achieved by using maximum likelihood (ML) detector which performs an exhaustive search over all the possible transmit symbol vectors. But the computational complexity of ML detection increases exponentially with increase in the number of transmit antennas. Sphere decoder (SD) is a well known ML detector but it suffers from variable complexity which depends on the received signal to noise ratio (SNR) and is practical only up to certain number of dimensions (Viterbo & Boutros, 1999). Low-complexity sub-optimum detectors for MIMO systems include linear detectors which are zero-forcing (ZF), minimum mean squared error (MMSE) detector and the non-linear detectors like vertical Bell laboratories layered architecture (V-BLAST) detector (Wolniansky, Foschini, Golden, & Valenzuela, 1998). The ZF, MMSE and V-BLAST detectors are low-complexity algorithms but are inferior in performance when compared to ML performance. For this reason they are least selective and are used to get an initial solution in some of the other detection algorithms. Several algorithms for MIMO detection have been proposed in the literature, some of which are based on lattice reduction (LR) (Marinello & Abrão, 2013; Maurer, Matz, & Seethaler, 2007; Seethaler, Matz, & Hlawatsch, 2007) where the detection is carried out into a different space obtained by transforming the channel matrix into an equivalent matrix with near orthogonal column vectors, message passing based detection algorithm

* Corresponding author. Tel.: +91 9584858734.
E-mail addresses: phd1301202006@iiti.ac.in, manishmandloi1@gmail.com (M. Mandloi), vbhatia@iiti.ac.in (V. Bhatia).

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(Som, Datta, Chockalingam, & Rajan, 2010) which utilizes the concept of belief propagation and factor graph, local search algorithm (Vardhan, Mohammed, Chockalingam, & Rajan, 2008) based on the local neighborhood search of an initial solution, mixed Gibbs sampling based detection (Datta, Ashok Kumar, Chockalingam, & Rajan, 2012) which is derived from the Monte-Carlo Markov chain (MCMC) technique, sparse sensing based algorithm (Peng, Wu, Sun, & Liu, 2015) and likelihood ascent search based detection algorithm (Pereira & Sampaio-Neto, 2015). As an alternative in our study, we focus on the application of bio-inspired algorithms in symbol vector detection in MIMO systems. Bio-inspired algorithms are promising in terms of providing better performance with less computational complexity. Further, they involve less mathematics which is another positive aspect of such algorithms.

Recently, there has been a lot of research in developing algorithms which mimics the biological phenomena such as birds flocking, fish schooling and foraging behavior of ants for solving the real world optimization problems which are hard to solve by the conventional techniques. Several algorithms in this regard have been proposed in the literature, some of which include genetic algorithm (GA) (Tang, Man, Kwong, & He, 1996), ant colony optimization (ACO) (Dorigo & Gambardella, 1997), particle swarm optimization (PSO) (Eberhart & Kennedy, 1995), cuckoo optimization algorithm (Rajabioun, 2011) and artificial bee colony (ABC) optimization algorithm (Karaboga, 2005). All these algorithms are useful in terms of finding a sub-optimal solution with lesser computational complexity for a given optimization problem. Some of the applications of these algorithms in engineering involves designing finite impulse response (FIR) filters (Boudjelaba, Ros, & Chikouche, 2014), load balanced clustering in mobile ad-hoc networks (Cheng, Yang, & Cao, 2013), non-linear channel equalization (Das, Pattnaik, & Padhy, 2014), non-linear rational filter modeling (Lin, Chang, & Hsieh, 2008) and material flow problem in manufacturing plant (Alvarado-Iniesta, Garcia-Alcaraz, Rodriguez-Borbon, & Maldonado, 2013). However, the major challenge in using bio-inspired algorithms is to find a suitable initial point and a proper update mechanism which helps in avoiding the premature or early convergence of these algorithms to a local optimal solution. PSO and ACO algorithms (considered in our study) suffer from similar problem of pre-mature convergence which results in convergence to a local minimum solution and thus, a large population size is required for getting a highly reliable solution but it unnecessarily reduces the convergence rate of the algorithms, and also sometimes the local trap cannot be overcome even by a large population of ants or particles. To overcome these drawbacks, there are several hybrid algorithms based on ACO and PSO proposed in the literature (Kaveh & Talatahari, 2009; Kıran, Özceylan, Gündüz, & Paksoy, 2012; Shelokar, Siarry, Jayaraman, & Kulkarni, 2007).

ML detection in MIMO systems is a non-deterministic polynomial (NP) hard problem and becomes impractical for higher number of antennas (large-MIMO systems) and hence, bio-inspired algorithms, because of their low-complexity, serves as a suitable candidate for MIMO detection problem. Several bio-inspired MIMO detection algorithms based on PSO (Khan, Naeem, & Shah, 2007) and ACO (Lain & Chen, 2010; Mandloi & Bhatia, 2015; Marinello & Abrão, 2013) have been proposed in the literature, recently. However, there are some deficiencies associated with these algorithms. For example, the algorithm proposed in Khan et al. (2007) achieves sub-optimal BER performance and requires more number of particles to converge to a near optimum solution. The algorithm proposed in Lain and Chen (2010) requires a large number of ants to achieve a near ML performance which leads to high computational complexity and a slow convergence of the algorithm. Congestion control based ACO algorithm in Mandloi and Bhatia (2015) is another low complexity MIMO detection algorithm however, it is sub-optimal in terms of BER performance which is due to the convergence of the algorithm to a local optimal solution. In Marinello and Abrão (2013), a lattice reduction (LR) aided ACO algorithm is proposed for MIMO detection. But the use of LR increases the computational complexity significantly for higher number of antennas. The convergence rate and trap to a local optima are the two main issues associated with the existing algorithms and thus it motivates us to work further is this direction and improve the convergence rate and escape from the local optima trap in ACO and PSO algorithms.

In this paper, we propose a low-complexity HA which is based on the two well known bio-inspired algorithms, namely PSO and ACO, for large-MIMO detection. In the proposed HA, the symbol vector detection problem in MIMO systems is solved as a traveling salesmen problem (TSP) where a set of artificial particles (N_{part}) are used to finding a solution which minimizes a given cost function. Each transmit antenna is considered as a city and the possible transmit symbols are considered as the available paths to travel the particular city. The problem now reduces to find a path (symbol vector) with minimum distance (ML cost) to travel each city (antenna) exactly once. The motivation behind the HA is that the distance traveled (as in ACO) by each particle gives only the local information about the fitness of a solution, hence to get a global information on the fitness of a solution we use the velocity update rule of each particle which uses the local best and global best solution to update itself (as in PSO). ACO and PSO alone are not suitable because of their early convergence to a local optimum solution due to the unreliable initialization of pheromones in ACO and position of particles in PSO. The proposed HA combines the concept of distance as in ACO with the velocity update rule of PSO in order to avoid the premature convergence to a local optimum solution and improve the convergence speed. In the proposed algorithm, a new probability metric is designed which is a weighted combination of the distance traveled by the particles so far and the velocity of each particle. Simulation results demonstrate that the proposed HA outperforms MMSE and the existing ACO algorithms in terms of BER and achieves a near ML performance. Our contributions in this paper are: 1. A new probability metric is devised using the hybrid of ACO and PSO algorithms, 2. Use of HA for symbol vector detection in MIMO systems is shown and the results are simulated to validate the performance of the proposed HA.

The rest of the paper is organized as follows. In Section 2, we present the general PSO and ACO algorithm. System model and mathematical formulation are given in Section 3. HA based MIMO detection algorithm is discussed in Section 4. In Section 5, we present the simulation results for BER performance versus signal to noise ratio (SNR), convergence analysis curve for BER performance versus number of particles and the complexity curve for number of computations versus the number of particles and the number of antennas respectively. a discussion on the comparison of proposed HA with ACO and PSO is given in Section 6. Section 7 concludes the paper.

2. Proposed hybrid algorithm

In this section, we briefly discuss the proposed HA along with a review of basic PSO algorithm and ACO algorithm.

2.1. Particle swarm optimization algorithm

PSO developed by Eberhart and Kennedy (1995), is a population based probabilistic search approach which is inspired by the social behavior of bird flocking and fish schooling. Fig. 1 shows the flow chart of the basic PSO algorithm. PSO starts with a number of particles and each particle is initialized with random velocity and position. In every iteration of PSO, each particle updates its velocity based on the local best (pbest) solution and the global best (gbest)

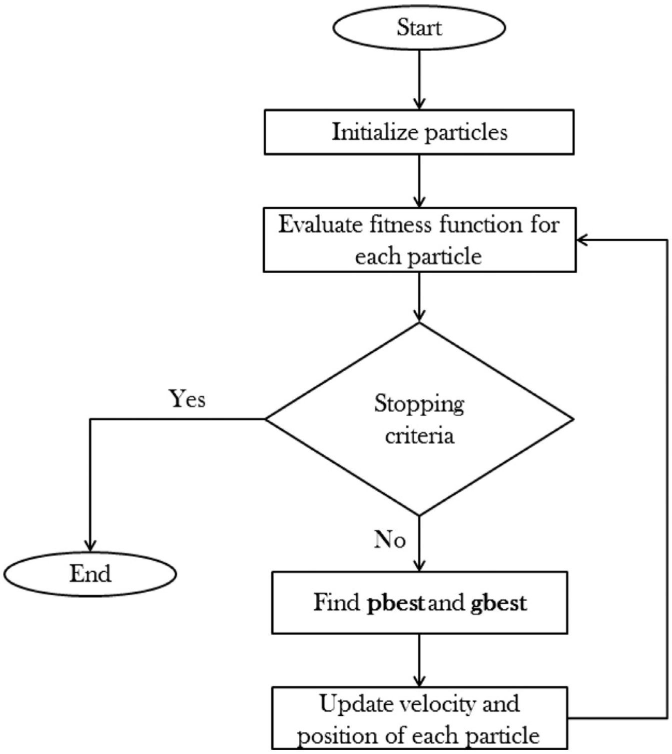

Fig. 1. Flow chart of basic PSO algorithm.

solution obtained in the search process. The 'pbest' solution is the best position obtained by the particle so far. The 'gbest' solution is the best position among all the particles. 'pbest' and 'gbest' are evaluated using a fitness function which is to be optimized using PSO. The velocity update rule is given by Eq. (1).

$$\mathbf{V}^{p}_{new} = w \times \mathbf{V}^{p}_{old} + c1 \times rnd1^{p} \times (\mathbf{pbest}^{p} - \mathbf{X}^{p}_{old}) + c2 \times rnd2^{p} \times (\mathbf{gbest} - \mathbf{X}^{p}_{old}) \quad (1)$$

where $\mathbf{X}^{d}_{old}$ denote the particles' position in previous iteration. $\mathbf{V}^{p}_{new}$ and $\mathbf{V}^{p}_{old}$ denotes the velocity of pth particle in the present and previous iteration respectively. $\mathbf{pbest}^{p}$ is the particle's best position obtained so far and **gbest** is the best position obtained among all the particles. $c1$ and $c2$ are the learning factors and w is the inertia weight. After updating the velocity, each particle update its position using Eq. (2).

$$\mathbf{X}^{p}_{new} = \mathbf{V}^{p}_{new} + \mathbf{X}^{p}_{old} \quad (2)$$

where $\mathbf{X}^{p}_{new}$ is the new position of pth particle. The above steps are repeated for a given number of iteration or until a given termination condition is not met. The basic steps involved in PSO algorithm are shown in Algorithm 1.

Algorithm 1 Particle swarm optimization algorithm.

procedure
  Initialize particles
  while iterations not completed or termination condition not met **do**
    Find local best and global best solution: find 'pbest' and 'gbest'
    Update velocity of each particle: update $\mathbf{V}^{p}_{new}$ as in Eq. (1)
    Update position of each position: update $\mathbf{X}^{p}_{new}$ as in Eq. (2)
  end while
  'gbest' is the final solution
end procedure

2.2. Ant colony optimization algorithm

Inspired by the foraging behavior of natural ants, ant colony optimization (ACO) (Dorigo & Gambardella, 1997) use a number of artificial ants (N_{ants}) to find a shortest path between their nest N and the food location F. Phenomena known as 'stigmery' is used for communication among the ants. Flow chart of ACO is shown in Fig. 2. Each ant deposit a substance called *'pheromone'* on the path they walk. The amount of pheromone dropped depends on the distance of the path and quality of food present. Pheromone concentration on each path decays with time and other ants choose the path with higher pheromone concentration. ACO is an iterative algorithm and in each iteration, ants follow three basic steps which are given in Algorithm 2

Algorithm 2 Ant colony optimization algorithm.

procedure
  Initialize the system parameters
  while iterations not completed or termination condition not met **do**
    Compute distance metric
    Compute probability metric
    Construct ant solutions
    Apply local search
    Update Pheromone Concentration
  end while
end procedure

Compute distance metric: After initialization, ants start walking on the available path. In the first iteration, pheromone concentration on all the paths are kept equal to zero. During this step ants will compute distance of paths on which they walk.

Compute probability metric: The probability metric serves as a guide for stochastic selection of a path. It depends on the distance metric and the pheromone concentration associated with each path.

Construct ant solutions: Each ant use probability metric for selecting a path during their walk on the available paths and construct a solution.

Apply local search: Once the solutions are decided, best solution among the solution found in previous step is selected. This selection of best solution is done based on the value of fitness function.

Update pheromone concentration: In this step, the pheromone concentration associated with the best solution is increased based on the quality of the solution.

2.3. Hybrid algorithm

The proposed HA is inspired from the foraging behavior of ACO and velocity update nature of particles from PSO. We combine the distance metric of ACO with the direction (velocity) metric of PSO and generate a new probability metric. The concept of pheromone update in ACO is replaced with the velocity update from PSO. A sigmoid function is used to convert distance and velocity into heuristic values. These heuristic values are used in the probability metric with different weights (shown in Section 4). The advantages of hybrid algorithm are: (1) in avoiding convergence to a local optima, (2) providing a better solution within few iterations i.e. fast convergence and (3) low computational complexity. Flow chart of the proposed HA is shown in Fig. 3. In HA, we denote the swarm population as particles (as 'ants' in ACO and 'particles' in PSO). Algorithm 3 below provides the basic steps followed in the HA.

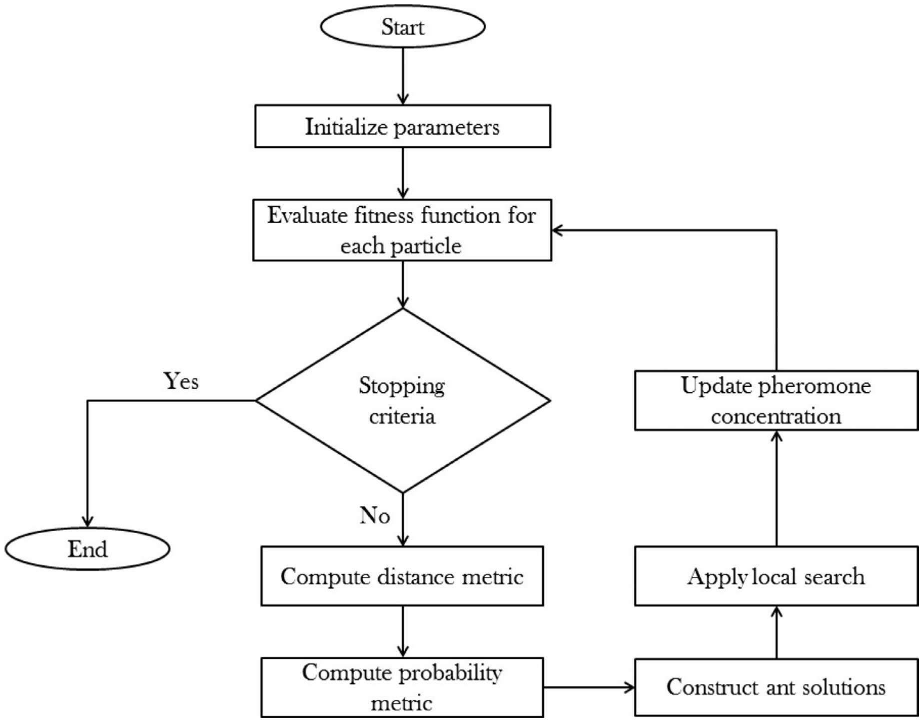

Fig. 2. Flow chart of basic ACO algorithm.

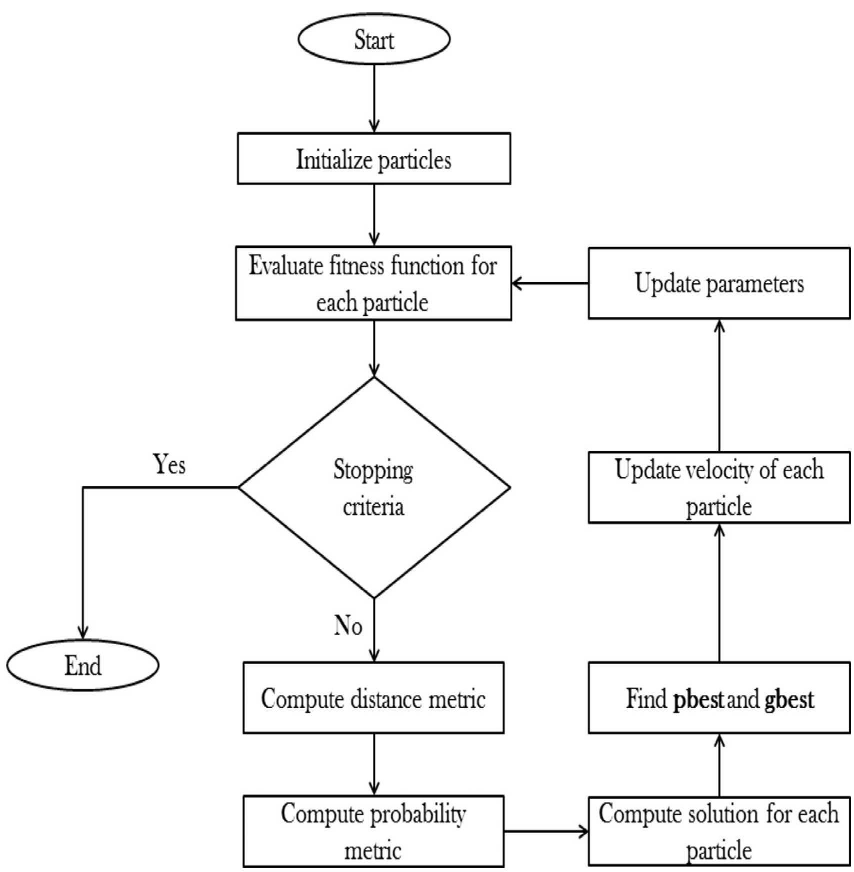

Fig. 3. Flow chart of the proposed HA algorithm for MIMO detection.

Algorithm 3 Proposed hybrid algorithm.

procedure
  Initialize particles
  while iterations not completed or termination condition not met **do**
    Compute distance metric
    Compute probability metric
    Construct solutions
    Find pbest and gbest
    Update velocity of each particle
  end while
end procedure

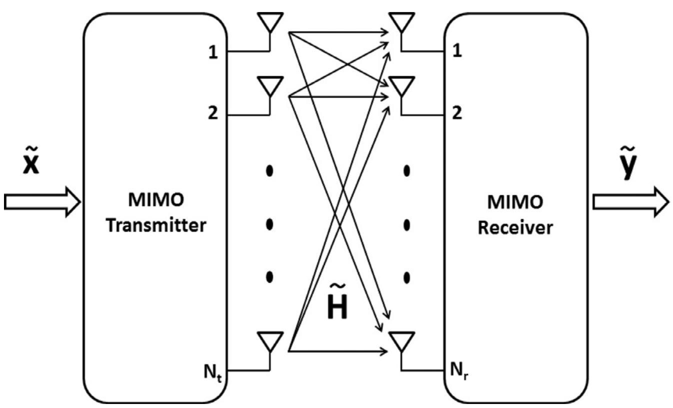

Fig. 4. MIMO system model.

3. System model

We consider a discrete-time MIMO system model with flat fading channel where the transmitter is equipped with N_t transmit antennas and the receiver is equipped with N_r receive antennas as shown in Fig. 4. Let $\tilde{\mathbf{x}}$ be an $N_t \times 1$ transmitted vector in which $\tilde{x}_i$, the ith element of $\tilde{\mathbf{x}}$ denotes the Q-ary modulated symbol transmitted from ith transmit antenna. The $N_r \times 1$ received signal vector $\tilde{\mathbf{y}}$ in MIMO system can be represented as

$$\tilde{\mathbf{y}} = \widetilde{\mathbf{H}}\tilde{\mathbf{x}} + \tilde{\mathbf{n}} \tag{3}$$

where $\widetilde{\mathbf{H}}$ denotes the $N_r \times N_t$ channel matrix with its elements $\left\{\tilde{h}_{j,i}\right\} \sim \mathcal{CN}(0, 1)$. $\left\{\tilde{h}_{j,i}\right\}$ denotes the channel gain between the ith transmit antenna and jth receive antenna. $\tilde{\mathbf{n}}$ is $N_r \times 1$ white complex Gaussian noise vector in which the entries are distributed as $\sim \mathcal{CN}\left(0, \sigma^2\right)$. The average SNR is defined as $10\log_{10}\frac{N_t E_x}{\sigma^2}$ dB, where E_x is the average energy per symbol. The complex-valued received vector $\tilde{\mathbf{y}}$ can be transformed into an equivalent real-valued representation as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{4}$$

where $\mathbf{y} = [\begin{smallmatrix}\Re(\tilde{\mathbf{y}}) \\ \Im(\tilde{\mathbf{y}})\end{smallmatrix}]_{2N_r\times 1}$, $\mathbf{H} = [\begin{smallmatrix}\Re(\widetilde{\mathbf{H}}) & -\Im(\widetilde{\mathbf{H}}) \\ \Im(\widetilde{\mathbf{H}}) & \Re(\widetilde{\mathbf{H}})\end{smallmatrix}]_{2N_r\times 2N_t}$, $\mathbf{x} = [\begin{smallmatrix}\Re(\tilde{\mathbf{x}}) \\ \Im(\tilde{\mathbf{x}})\end{smallmatrix}]_{2N_t\times 1}$, and $\mathbf{n} = [\begin{smallmatrix}\Re(\tilde{\mathbf{n}}) \\ \Im(\tilde{\mathbf{n}})\end{smallmatrix}]_{2N_r\times 1}$. $\Re(.)$ and $\Im(.)$ denote the real and imaginary parts of (.) respectively. When the receiver has the perfect knowledge of the channel state information (CSI) $\mathbf{H}$, the ML solution can be written as

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}\in\mathbb{A}^{2N_t}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 \tag{5}$$

where $\mathbb{A}$ is the set of real-valued entries in the signal constellation, e.g., $\mathbb{A} = \{-1, 1\}$ in 4-QAM signaling and $\mathbb{A} = \{-3, -1, 1, 3\}$ in 16-QAM signaling. The channel state information matrix $\mathbf{H}$ can further be decomposed using $\mathbf{QR}$ decomposition as $\mathbf{H} = \mathbf{QR}$, where $\mathbf{Q}$ is a $2N_r \times 2N_t$ orthogonal matrix and $\mathbf{R}$ is a $2N_t \times 2N_t$ upper triangular matrix (Golub & Van Loan, 2012). Eq. (4) will then be rewritten as

$$\mathbf{y} = \mathbf{QRx} + \mathbf{n} \tag{6}$$

$$\mathbf{Q}^H\mathbf{y} = \mathbf{Q}^H\mathbf{QRx} + \mathbf{Q}^H\mathbf{n} \tag{7}$$

$$\mathbf{Q}^H\mathbf{y} = \mathbf{Rx} + \mathbf{Q}^H\mathbf{n} \tag{8}$$

$$\hat{\mathbf{y}} = \mathbf{Rx} + \hat{\mathbf{n}} \tag{9}$$

where $\hat{\mathbf{y}} = \mathbf{Q}^H\mathbf{y}$, $\hat{\mathbf{n}} = \mathbf{Q}^H\mathbf{n}$, and $(.)^H$ denote the matrix Hermitian transpose.

4. Hybrid algorithm based large-MIMO detection

In this section, we present the application of hybrid algorithm for symbol vector detection in large-MIMO systems. The MIMO detection problem is modeled as path finding problem similar to the ACO based modeling in Lain and Chen (2010). The concept of traveling salesman problem (TSP) is used where the problem is finding a shortest path among all the available paths so that the cost of visiting each city exactly once is minimized. Similar to TSP, in HA based MIMO detection, we assume each antenna as a city and the number of possible symbols are consider as the number of available paths to reach a particular city. The objective function to be minimized is given in Eq. (10) which is the cost incurred in estimating a symbol vector. Using Eq. (9), the cost function of estimating a symbol vector $\mathbf{x}$ is

$$\mathbf{f}(\mathbf{x}) = \|\hat{\mathbf{y}} - \mathbf{Rx}\|^2 \tag{10}$$

We consider N_{part} number of artificial particles to find the solution jointly. There exists M paths to reach a specific city i where M depends on the modulation order i.e. $M = 2$ in 4-QAM and $M = 4$ in 16-QAM and $i = 1, 2, \cdots, 2N_t$. Each path between the cities is represented as x_{ik} where $i = 1, 2, \cdots, 2N_t$ and $k = 1, 2, \cdots, M$. Further expanding Eq. (10) we yield

$$\mathbf{f}(\mathbf{x}) = \sum_{i=1}^{2N_t} \mid \hat{y}_i - \sum_{l=i}^{2N_t} R_{il}x_l \mid \tag{11}$$

Using Eq. (11) we formulate a distance metric d_{ik}^p for the pth particle as

$$d_{ik}^p = \mid \hat{y}_i - \sum_{l=i+1}^{2N_t} R_{il}\tilde{x}_l^p - R_{ii}x_{ik}^p \mid, k = 1, \cdots, M \tag{12}$$

where i should progressively decrease from $2N_t$ to 1. $\tilde{x}_l^p$ are the hard decision of the transmitted symbols x_l^p for $l = i+1, i+2, \ldots, 2N_t$ and $x_{ik}^p \in \mathbb{A}$ denotes all possible transmitted symbols for the ith antenna. A sigmoid function is then used to convert d_{ik}^p into γ_{ik}^p as

$$\gamma_{ik}^p = \frac{1}{1 + \exp\left(d_{ik}^p\right)} \tag{13}$$

The function γ_{ik}^p is used in order to take the distance of the path traveled into account. The path with smaller distance will have higher chances of getting selected by the particle. In each iteration, all the particles walk on the available paths and stochastically selects a path based on the transition probability metric given as

$$p_i^p = \frac{[\gamma_{ik}^p]^\alpha[\phi_{ik}^p]^\beta}{\sum_{k=1}^M[\gamma_{ik}^p]^\alpha[\phi_{ik}^p]^\beta} \tag{14}$$

where ϕ_{ik}^p depends on the velocity of the particle as shown in Eq. (19) (discussed late in this section). α and β are the weights corresponding to γ_{ik}^p and ϕ_{ik}^p respectively. Note that, we the velocity of each particle is initialized with zero and hence, during the 1st iteration, value of ϕ_{ik}^p is 0.5 for all i and k. However, from 2nd iteration onward the updated values (as computed using Eq. (19)) are used.

In each iteration, **gbest** and $\mathbf{pbest}^p$ are computed where $p = 1, 2, \cdots, N_{part}$. $\mathbf{pbest}^p$ is the best solution obtained by pth particle so far as

$$\mathbf{pbest}_{new}^p = \arg \min_{\mathbf{x} \in \{\mathbf{x}^p, \mathbf{pbest}_{old}^p\}} \|\hat{\mathbf{y}} - \mathbf{Rx}\|^2 \tag{15}$$

where $\mathbf{x}^p$ denotes the solution obtained by pth particle in the present iteration. **gbest** is the best solution among all the particles given as

$$\mathbf{gbest} = \arg \min_{\mathbf{x} \in \left\{\mathbf{pbest}_{new}^1, \cdots, \mathbf{pbest}_{new}^{N_{part}}\right\}} \|\hat{\mathbf{y}} - \mathbf{Rx}\|^2 \tag{16}$$

The velocity vector of each particle is then updated as

$$\mathbf{v}_{new}^p = w\mathbf{v}_{old}^p + c1\left(\mathbf{pbest}_{new}^p - \mathbf{x}^p\right) + c2(\mathbf{gbest} - \mathbf{x}^p) \tag{17}$$

where w is the inertia weight i.e. weight corresponding to the velocity in the previous iterations ($\mathbf{v}_{old}^p$). $c1$ and $c2$ are the weights which controls the direction of particle towards the **gbest** and $\mathbf{pbest}^p$. Moderate values of $c1$ and $c2$ are assumed in order to avoid premature convergence to a local minima. Another sigmoid function is used to convert the value of elements of $\mathbf{v}_{new}^p$ into η_i^p as

$$\eta_i^p = \frac{1}{1 + \exp\left(v_i^p\right)} \tag{18}$$

where v_i^p denotes the ith element of the velocity vector $\mathbf{v}_{new}^p$. For the sake of simplicity we assume 4-QAM modulated MIMO systems throughout the paper. This implies that the value of $k = 2$ and the set of possible symbols is $\mathbb{A} = \{-1, +1\}$. The value of η_i^p guides the movement of particles in the direction of the transmitted symbols i.e. if v_i^p is smaller, the particles will choose -1 and if v_i^p is higher than the particles will choose $+1$. In order to incorporate η_i^p in the probability metric we use ϕ_{ik}^p as

$$\phi_{i1}^p = \eta_i^p \quad \text{and} \quad \phi_{i2}^p = \left(1 - \eta_i^p\right) \tag{19}$$

In the proposed HA, we have combined the foraging behavior of ants from ACO with the velocity update rule of particles from PSO. The distance metric from ACO together with the velocity metric (direction metric) from PSO are used to generate a new transition probability metric which shows significant gain in terms of BER performance and faster convergence (discussed in Section 5). Algorithm 4 below gives the listing of HA algorithm for large-MIMO detection.

5. Simulation results

In this section, we present the simulation results of the proposed HA algorithm which include BER performance comparison, convergence rate with respect to the number of particles (N_{part}) and the computational complexity with respect to number of antennas and particles respectively. We used 4-QAM modulated 16 × 16 and 32 × 32 MIMO systems for simulating the results. MATLAB is used for performing the simulations and up to 10^3 errors are counted for averaging.

Simulation results are shown in Figs. 5–10. The value of parameters used are $w = 0.7$, $c1 = 0.4$, $c2 = 0.6$, $\alpha = 2$ and $\beta = 0.4$. In Fig. 5, we computed the BER performance of the proposed HA algorithm for 16 × 16 MIMO systems with 4-QAM modulation and compared it with the BER performance of MMSE detector and

Algorithm 4 Hybrid algorithm for large-MIMO detection.

input: $\mathbf{y}$, $\mathbf{H}$, N_t, N_r, N_{part}, α, $c1$, $c2$, w;
initialize: $\mathbf{v}^p$, $\forall p = 1, 2, \cdots, N_{part}$;
Compute $\hat{\mathbf{y}} = \mathbf{Q}^H\mathbf{y}$ where $\mathbf{H} = \mathbf{QR}$[1];
$\mathbf{x}^{(int)}$: initial solution vector;
for iterations $\leqslant IT$ **do**
  while $j \leqslant N_{part}$ **do**
    for $i \leqslant 2N_t$ **do**
      Compute $\eta_i^j = \frac{1}{1+\exp\left(v_i^j\right)}$ using (18);
      Compute ϕ_{ik}^j using (19);
      Compute $d_{ik}^j = \mid \hat{y}_i - \sum_{l=i+1}^{2N_t} R_{il}\tilde{x}_l^j - R_{ii}x_k^j \mid$;
      $\gamma_{ik}^j = \frac{1}{1+\exp\left(d_{ik}^j\right)}$;
      $p_{ik}^j = \frac{[\gamma_{ik}^j]^\alpha [\phi_{ik}^j]^\beta}{\sum_{k=1}^{M} [\gamma_{ik}^j]^\alpha [\phi_{ik}^j]^\beta} \quad \forall k = 1, 2, \cdots, M$;
      Choose x_i according to the probability p_{ik};
    end for
    Find $\mathbf{pbest}_{new}^j$ using (15);
  end while
  Find **gbest** using (16);
  Update the velocity $\mathbf{v}_{new}^p \quad \forall p = 1, 2, \cdots, N_{part}$ using (17);
end for
output: gbest is output solution vector

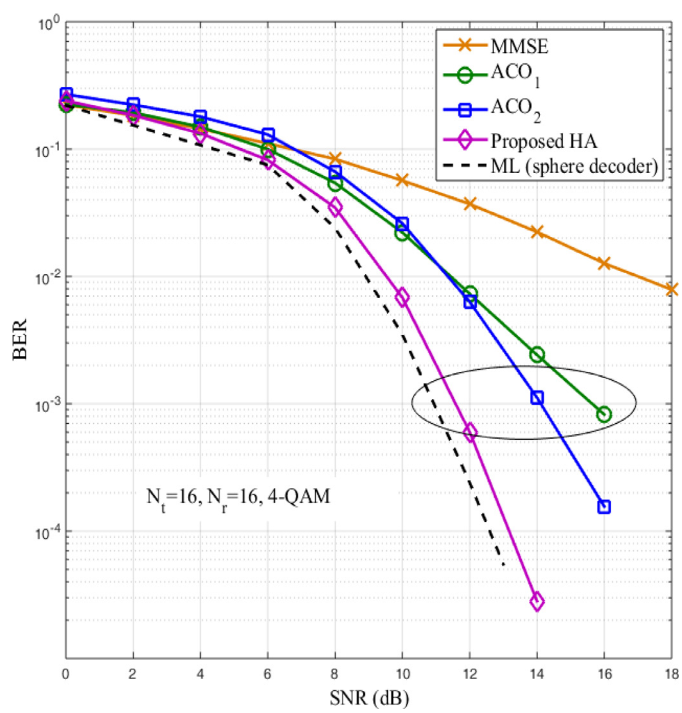

Fig. 5. BER performance comparison for 16 × 16 MIMO system with 4-QAM modulation.

other existing ACO based MIMO detection algorithms (Lain & Chen, 2010; Mandloi & Bhatia, 2015). We named the ACO algorithm proposed in Mandloi and Bhatia (2015) as ACO_1 and that proposed in Lain and Chen (2010) as ACO_2. For fair comparison, the number of ants (N_{ants}) used in ACO_1 and ACO_2 is kept equal to the number of particle times number of iterations in the proposed HA algorithm

[1] For performing QR decomposition of H we have used the log-likelihood ratio (LLR) based sorted QR decomposition (SQRD) algorithm in Lee, Jeon, Choi, Kim, Cha and Lee (2006).

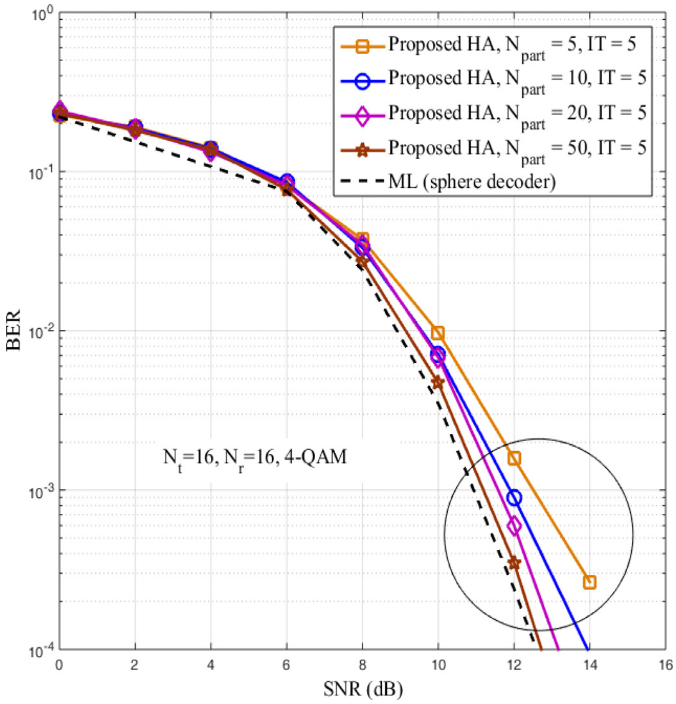

Fig. 6. BER performance of the proposed HA algorithm for 16 × 16 MIMO system with 4-QAM modulation.

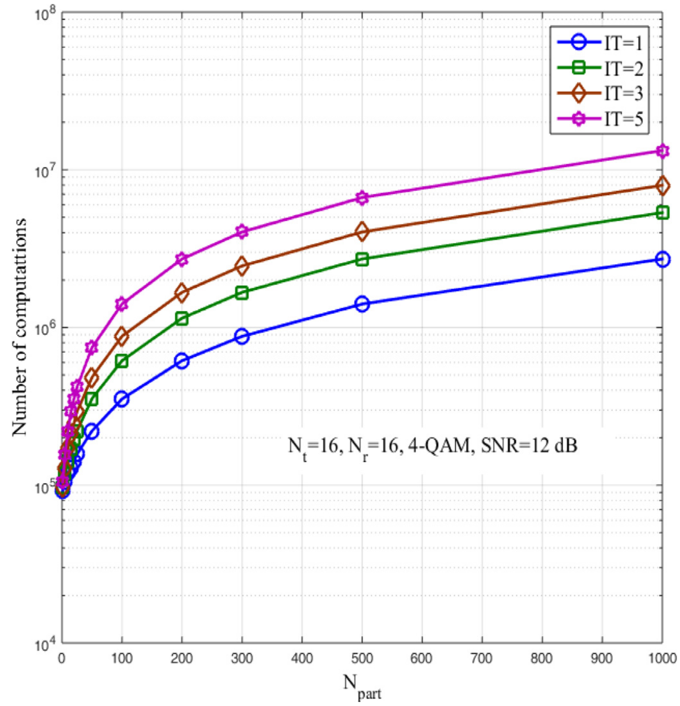

Fig. 8. Computational complexity curve of the proposed HA algorithm with N_{part} for different number of iterations for 16 × 16 MIMO system with 4-QAM modulation at SNR = 12 dB.

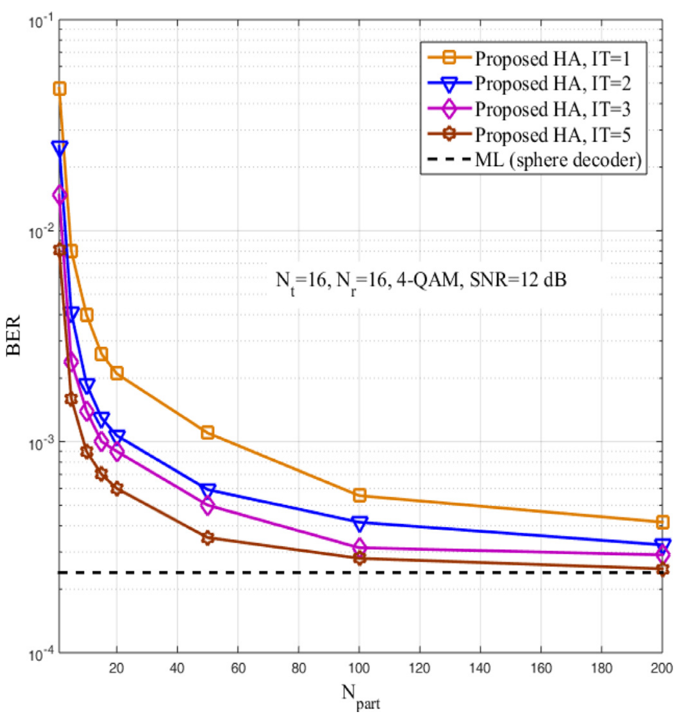

Fig. 7. Convergence curve of the proposed HA algorithm with N_{part} for different number of iterations for 16 × 16 MIMO system with 4-QAM modulation at SNR = 12 dB.

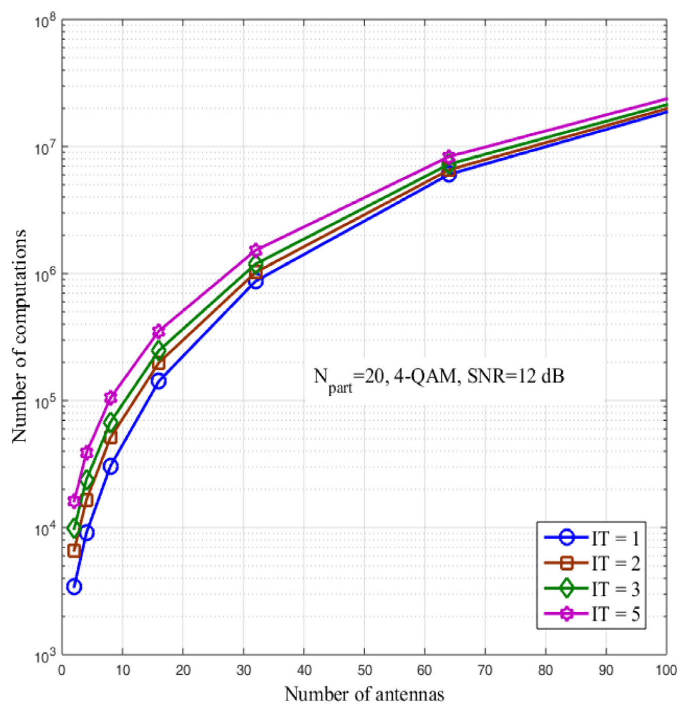

Fig. 9. Computational complexity curve of the proposed HA algorithm with number of antennas for different number of iterations.

(i.e. $N_{ants} = 100$, $N_{part} = 20$ and Iterations = 5). It is observed that the proposed HA outperforms MMSE, ACO_1 and ACO_2 in terms of BER with approximately 4 dB gain over ACO_1 and 2.5 dB gain over ACO_2 for a target BER of 10^{-3}.

In Fig. 6, we present the BER performance plot for different $N_{part} = 5$, 10, 20 and 50 and number of iterations (IT) = 5. Observation reveals that the BER performance of the proposed HA algorithm shift towards the ML performance with increase in N_{part}. This shows that the proposed HA achieves near ML performance with less computational efforts.

Fig. 7 is for convergence rate with respect to N_{part}. We compared the results for different values of IT i.e. IT = 1, 2, 3 and 5. It is observed that, the proposed HA achieves near ML performance with increase in N_{part}. We also observe that, with increase in IT,

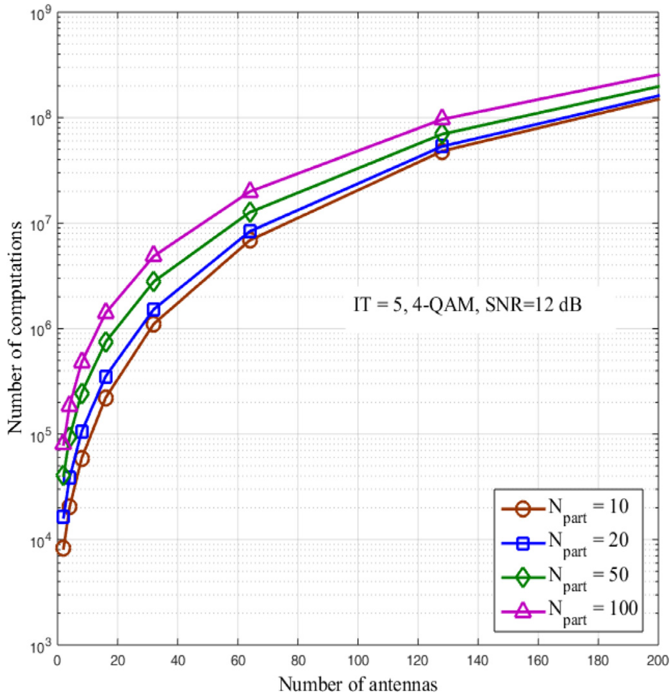

Fig. 10. Computational complexity curve of the proposed HA algorithm with number of antennas for different N_{part}.

N_{part} required to achieve near ML performance decreases and the algorithm converges rapidly. This shows the fast convergence behavior of the proposed HA algorithm.

Figs. 8–10 are the obtained simulation results for the computational complexity of the proposed HA algorithm. In Fig. 8, we plot the number of computations versus N_{part} for different number of iterations for 16×16 MIMO system with 4-QAM at SNR = 12 dB. Observations reveals that the difference between the number of computations for different iterations increases with increase in N_{part} which shows that both N_{part} and number of iterations leads to increase in computational complexity.

In Fig. 9, we plot the number of computations with respect to number of antennas for different number of iterations and $N_{part} = 20$. We observe that the computational complexity becomes nearly equal with increase in number of antennas.

6. Discussion

In this section, we present a discussion on the comparison of ACO, PSO and the proposed HA. ACO and PSO algorithms available in the literature (Khan et al., 2007; Lain & Chen, 2010; Mandloi & Bhatia, 2015; Marinello & Abrão, 2013) for MIMO detection suffers from two major issues which are low convergence rate and premature convergence to a local optimal solution. In ACO, the pheromone concentration on each path in the early iterations have a significant impact on the convergence of the algorithm. If the pheromone concentration accumulates more on sub-optimal paths then there is a high probability of converging to a local optimal solution and get trapped to it. To escape from the local optima trap a large number of ants could be used as a possible solution, however it reduces the speed of convergence which significantly increases the computational complexity of the algorithm. Similarly, in PSO the convergence of the algorithm depends highly on the initial state of each particle. In PSO, random selection of solution for each particle sometimes results in the convergence to a local optima which makes the performance far inferior as compared with the optimal solution. Thus, in the proposed work (in Section 4) we utilize the distance metric of ACO which provides local information about a particular solution and the velocity metric from PSO which provides global information (depends on the present solution as well as on the local best and global best solutions). In ACO, the distance metric plays an important role in selection of a solution whereas, in PSO, it is done by the velocity (direction) of each particle. Both the information together gives an improved probability metric by jointly considering the local and global information about the fitness of a solution and thereby the selection of a path becomes more reliable which results in an improved performance. However, when the number of transmit antennas grow or the modulation order increases the search space grows i.e. number of possible path increases along with the increase in number of cities, and hence, the number of particles required to get a sub-optimal solution needs to be increased which in turn reduces the convergence rate of the algorithm. Thus, there lies a trade-off between the convergence rate and the size of search space.

7. Conclusion

We have proposed a low-complexity HA for symbol vector detection in large-MIMO detection. To improve the convergence rate and escape the local optima trap in PSO and ACO, we presented a hybrid of PSO and ACO which utilizes the concept of distance metric from ant colony optimization (ACO) and the direction (velocity) metric from particle swarm optimization (PSO) algorithm to design a new probability metric. Simulation results reveal that the proposed HA outperforms MMSE and other existing ACO based MIMO detection algorithms in terms of BER performance. The BER performance of the proposed algorithm is near optimal which makes it suitable for large-MIMO detection. We have also observed that the proposed HA converges near to the ML solution within few iterations which means a faster convergence rate. We have also analyzed the computational complexity of the proposed HA algorithm with respect to the number of antennas and number of particles, respectively and observe that the computations depends more significantly on the number of antennas rather that of the number of particles. From observations, we believe that the proposed hybrid algorithm could be effective as an alternative approach to obtain near optimal solution to the MIMO detection problem.

As a future work, techniques could be devised to improve convergence rate of the algorithm for a large search space (i.e. when number of antennas are large or higher modulation order). In such scenarios, convergence to local solution is a major issue and hence, one could think of dividing the whole subspace into smaller subspace and search the solution on each subspace separately. Similarly, multiple restart based strategies could be incorporated to improve the performance in large search space.

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