A Low-Complexity Discrete Gbest-guided Artificial Bee Colony Algorithm for Massive MIMO Detection

Boyang Zou(✉), Weixiao Meng, Lin Li, and Shuai Han

Communications Research Center, Harbin Institute of Technology, Harbin, China
16S005051@stu.hit.edu.cn, wxmeng@hit.edu.cn

Abstract. Massive multi-input multi-output (MIMO) technology is one of the most promising concepts in 5G wireless system. Grounded on the fact that the channel matrix in massive MIMO system is large dimensional, classical MIMO detection algorithms are not appropriate for large scaled antennas. In this paper, a low-complexity discrete gbest-guided artificial bee colony (DGABC) detection algorithm is proposed for massive MIMO uplink, chaotic maps for parameter adaptation is also proposed in order to improve the convergence characteristic of the DGABC algorithm and to prevent the algorithm from getting stuck in local solutions. Experiments show that the proposed DGABC detection algorithm outperforms both the original ABC algorithm and MMSE detection with a relatively low complexity.

Keywords: Massive multiple input multiple output (MIMO) system
Discrete gbest-guided artificial bee colony (DGABC)
Computational complexity · Detection algorithm · Chaotic maps

1 Introduction

Massive MIMO has been a key technology in wireless communication systems with much more antennas at both sides. While many traditional problems have been solved by massive MIMO benefitting from its advantageous properties of increased diversity, there are still some technical problems existing to be explored, one of which is the computational complexity of uplink symbol detection at the base station with large scaled antennas [1].

As antennas increase to a large amount, traditional detection algorithms for MIMO have poor bit error rate (BER) performance and high computational complexity. It is not appropriate for traditional algorithms to be applied directly in the massive MIMO system. Therefore, it is necessary to improve the massive

This work is supported by National Natural Science Foundation of China (61471143) and the Provincial Natural Science Foundation of Heilongjiang, China (No. ZD2-017013).

C. Li and S. Mao (Eds.): WiCON 2017, LNICST 230, pp. 75–84, 2018.
https://doi.org/10.1007/978-3-319-90802-1_7

MIMO detection algorithm for optimum BER performance and low computational complexity. Karaboga proposed the artificial bee colony (ABC) algorithm firstly for numerical optimization problem [2], and it was applied for massive MIMO detection by Li [3]. In this paper, to reduce the computational complexity, we propose a novel initialization approach for DGABC algorithm by virtue of the prior information of matched filter in MMSE. Chaotic maps for parameter adaptation is also employed to improve the convergence characteristic of the algorithm. The proposed algorithm reduces the computational complexity apparently while achieving a near-optimal BER performance compared to the original ABC detection algorithm in [3].

The remainder of this paper is organized as follows. Section 2 describes system model of the massive MIMO uplink as well as some classical massive MIMO detection algorithms. The proposed low-complexity DGABC algorithm is presented in Sect. 3. We present the simulation of the low-complexity DGABC detection algorithm and analysis its computational complexity and BER performance in Sect. 4. Finally, the conclusion is given in Sect. 5.

Notation: Lowercase boldface letter is used to indicate a vector and uppercase boldface letter to indicate a matrix; superscript $(\cdot)^{-1}$ denotes matrix inversion, $(\cdot)^T$ and $(\cdot)^H$ denote transpose and complex conjugate transpose, $\|\cdot\|$ denotes two-norm, statistical expectation is denoted as $E\{\cdot\}$, $\Re(\cdot)$ indicates the real part of a complex number, $\Im(\cdot)$ indicates the imaginary part, $\mathbb{C}$ and $\mathbb{R}$, respectively, denotes the field of complex numbers and field of real numbers.

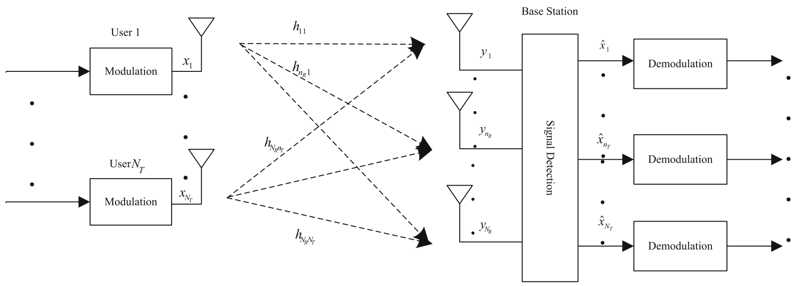

Fig. 1. System model of massive MIMO uplink

2 System Model of Massive MIMO Uplink

2.1 System Model

We consider a massive MIMO uplink consisted of N_T cells with single transmitting antenna and one BS with N_R receiving antennas ($N_R \geq N_T$). At the transmitter, the bit stream generated by users are modulated to transmitted symbols [4]. Modulation alphabet is donated as $\mathbb{S}$, and $\mathbb{R}$ denotes the real part of Modulation alphabet $\mathbb{S}$ as in (1), and M-QAM is adopted. The perfect channel state information is known by the receiver throughput the paper.

$$\mathbb{S} = \mathbb{R} + j\mathbb{R}, \mathbb{R} \in [\pm 1, \pm 3, \cdots, \pm\sqrt{M} - 1]. \tag{1}$$

According to [5], the signal propagation process can be expressed as in (2)

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n}. \tag{2}$$

For a clarity illustration, real-valued system model is adopted in this paper. Vector $\mathbf{y}$ is an $2N_R \times 1$ dimensional real received signal vector, $\mathbf{H}$ is an $2N_R \times 2N_T$ dimensional real Rayleigh fading channel matrix, $\mathbf{x}$ is an $2N_T \times 1$ dimensional transmitted real vector, and $\mathbf{n}$ is an $2N_R \times 1$ dimensional, independent zero-mean additive white Gaussian noise vector and $E\{\mathbf{n}\mathbf{n}^H\} = \sigma^2 \mathbf{I}_{2N_R}$, where $\sigma^2 \in \mathbb{R}$ denotes the average noise variance per receiving antenna. The system model is as shown in Fig. 1.

2.2 Classical Detection Algorithms

Maximum Likelihood (ML) detection algorithm can obtain the optimum BER performance for MIMO [6].

$$\hat{\mathbf{x}}_{\mathrm{ML}} = \arg \min_{\mathrm{x} \in \mathbb{S}} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2. \tag{3}$$

The complexity of ML detection algorithm is exponential in an order of magnitude of $\mathrm{O}(M^{N_T})$, which is extremely high in the case of scaled number of antennas [6]. The hardware implementation of ML is a most critical issue in the BS side.

Minimum mean square error (MMSE) decoder is a widely used linear detection algorithm. The matched-filter output is computed firstly as $\mathbf{y}^{\mathrm{MF}} = \mathbf{H}^H \mathbf{y}$, and the estimated transmitted symbol $\hat{\mathbf{x}}_{\mathrm{MMSE}}$ is achieved as in (4).

$$\hat{\mathbf{x}}_{\mathrm{MMSE}} = \mathbf{A}^{-1} \mathbf{y}^{MF}. \tag{4}$$

The detection results are obtained with hard decision. The computational complexity of MMSE is in an order of magnitude of $\mathrm{O}(N_T^3)$, which is much lower than that of the ML algorithm. However, the BER performance of MMSE is rather poorer compared with ML algorithm. Research on improvement of BER performance of MMSE detection has been extremely attractive.

3 Low-Complexity DGABC Detection Algorithm for Massive MIMO System

The process of searching the optimum solution vector in ML algorithm can be formalized as a nonlinear integer programming problem [7]. The ABC detection algorithm is applied in the process of bees foraging for food and obtains an approximately optimum BER performance [3]. However, per-symbol complexity of the ABC algorithm is still as an order of $O(N_T^2)$. In this paper, a proposed low-complexity DGABC algorithm with a novel initialization and chaotic maps is proposed to reduce the computational complexity with a near-optimum performance.

3.1 ABC Optimization

The ABC algorithm is a heuristic random search algorithm deriving from the Swarm intelligence Optimization. In the ABC algorithm, each feasible solution to the problem is represented by a food source, and the nectar quality of the food source corresponds to the fitness of this feasible solution, which reflects the quality of this solution. The detailed process is introduced in [2].

In [7], discrete gbest-guided ABC (DGABC) detection algorithm was presented to solve the global service composition problem. In this paper, a proposed low-complexity DGABC detection algorithm is applied for massive MIMO detection, which can be recognized as an interger programming problem.

3.2 Proposed Low-Complexity DGABC Algorithm for Massive MIMO System

The solution vector $\hat{\mathrm{x}}$ is calculated as (5) from (2).

$$\hat{\mathbf{x}} = \arg \max_{\mathbf{x} \in \mathbb{S}} (\mathbf{2y}^H \mathbf{H} \hat{\mathbf{x}} - \hat{\mathbf{x}}^H \mathbf{H}^H \mathbf{H} \hat{\mathbf{x}}). \tag{5}$$

The cost function $f(\hat{\mathrm{x}})$ as in (6) is corresponding to the nectar amount in the ABC algorithm [3].

$$f(\hat{\mathbf{x}}) = \mathbf{2y}^{\mathbf{H}} \mathbf{H} \hat{\mathbf{x}} - \hat{\mathbf{x}}^{\mathbf{H}} \mathbf{H}^{\mathbf{H}} \mathbf{H} \hat{\mathbf{x}}. \tag{6}$$

The global optimum solution vector $\hat{\mathrm{x}}_{\mathrm{best}}$ is obtained until maximizing the cost function $f(\hat{x})$ as in (7).

$$\hat{\mathbf{x}}_{\mathrm{best}} = \arg \max_{\mathbf{x} \in \mathbb{S}} f(\mathbf{x}). \tag{7}$$

To speed up the convergence and obtain a better BER, hard decision result of MMSE is employed as the initial solution vector $\hat{\mathrm{x}}^{(0)} = \mathrm{x}_{\mathrm{MMSE}}$ in ABC detection algorithm [3]. However, the complexity of algorithm increases to $O({N_T}^3)$ resulting from the computation of MMSE. Instead, the algorithm proposed in this paper takes advantage of the properties of A^{-1} introduced in Sect. 2 that are applicable in massive MIMO [8]:

(i) A^{-1} is a diagonally dominant matrix.
(ii) All diagonal elements of A^{-1} are positive.

Deriving from the properties above, the sign of the ith element in $\hat{\mathbf{x}}$ is almost the same as that of the ith element in $\mathbf{y}^{MF}$. More precisely:

$$\begin{aligned} &sign(\hat{\mathbf{x}}_{\mathrm{i}}^{(0)}) = sign(\sum_{j=1}^{N} \mathrm{a'}_{\mathrm{ij}}\mathbf{y}_{\mathrm{i}}{}^{MF}) \simeq sign(\mathrm{a'}_{\mathrm{ij}}\mathbf{y}_{\mathrm{i}}{}^{MF}) \\ &= sign(\mathbf{y}_{\mathrm{i}}{}^{MF}). \end{aligned} \tag{8}$$

where $\hat{\mathbf{x}}_{\mathrm{i}}$ and $\mathbf{y}_{\mathrm{i}}{}^{MF}$ are the ith elements of $\hat{\mathbf{x}}$ and $\mathbf{y}^{MF}$ respectively, and a'_{ij} denotes the element of $\mathbf{A}^{-1}$ at the ith row and jth column, $j \in \{1, 2, \cdots 2N\}$. For example, if $sign(\hat{\mathbf{x}}_{\mathrm{i}}) = sign(\mathbf{y}_{\mathrm{i}}{}^{MF}) > 0$, the jth dimension of feasible initial solutions $\hat{x}_j^{(0)}$ is a positive value and generated from the positive part of real modulation alphabet as $[1, 3, \cdots \sqrt{M} - 1]$.

After initialization, the exploitation of all the SN feasible solutions will start. Let the maximum cycle number be $Maxiter$. The behaviors of employed bees, onlooker bees and scout bees are repeated in each cycle.

Algorithm 1. Low-complexity ABC detection algorithm

Require: $\mathbf{y}$,$\mathbf{H}$, σ^2, SN, $limit$,$Maxiter$

intialization of $\hat{\mathbf{x}}_{\mathrm{i}}^{(0)} (i = 1, 2, \cdots, SN)$.
for $i = 0$ to $Maxiter$ **do**
  for $d = 0$ to SN **do**
    $v_d^i \leftarrow \hat{x}_d^i + \lfloor \phi_d^i \times (\hat{x}_d^i - \hat{x}_e^i) \rfloor + \lfloor \varphi_d^i \times (x_{best}{}^i - \hat{x}_d^i) \rfloor$
    if $f(\mathbf{v}_d) > f(\hat{\mathbf{x}}_d)$ **then**
      $\hat{\mathbf{x}}_d \leftarrow \mathbf{v}_d, f(\hat{x}_d) \leftarrow f(v_d)$
    end if
  end for
  for $f = 0$ to SN **do**
    The fth onlooker bee selects jth food source through the wheel selection method.
    $v_f^i \leftarrow \hat{x}_j^i + \lfloor \phi_f^i \times (\hat{x}_j^i - \hat{x}_e^i) \rfloor + \lfloor \varphi_f^i \times (x_{best}{}^i - \hat{x}_f^i) \rfloor$
    if $f(\mathbf{v}_f) > f(\hat{\mathbf{x}}_j)$ **then**
      $\hat{\mathbf{x}}_j \leftarrow \mathbf{v}_f, f(\hat{x}_j) \leftarrow f(v_f)$
    end if
  end for
  if the kth solution $(k = 1, 2, \cdots, SN)$ is not updated after $limit$ iterations **then**
    $x_k^i \leftarrow lb + \lfloor rand(0, 1) \times (ub - lb) \rfloor$
  end if
end for
update $Fitness\_best$ and x_{best} so far

Ensure: $\hat{\mathbf{x}}_{\mathrm{best}}$

Employed Bees Phase. There is one employed bee assigned to each food source. At the beginning of each cycle, the dth food source, of which the corresponding employed bee exploits the neighborhood, is denoted as X_d, where $X_d \in \mathbb{R}^{2N_T \times 1}$, $d \in \{1, 2, \cdots, SN\}$. The local search method is described as in (9)

$$v_d^i = \hat{x}_d^i + \left\lfloor \phi_d^i \times (\hat{x}_d^i - \hat{x}_e^i) \right\rfloor + \left\lfloor \varphi_d^i \times ({x_{best}}^i - \hat{x}_d^i) \right\rfloor. \tag{9}$$

The parameters i and e in (9) are generated randomly as in (10) and (11)

$$i = 1 + \left\lfloor rand(0,1) \times 2N_T \right\rfloor, \tag{10}$$

$$e = 1 + \left\lfloor rand(0,1) \times SN \right\rfloor. \tag{11}$$

The current global optimal composition solution is denoted as x_{best}, where $x_{best} \in \mathbb{R}^{N \times 1}$, and ${x_{best}}^i$ represents the ith element of x_{best}. To escape the local optimum, chaotic map is employed in the proposed algorithm to generate the factor ϕ_d^i and φ_d^i instead of stochastic sequence, while the initial value of the sequence c_0 is generated randomly in $(0, 1)$. The ϕ_d^i and φ_d^i are generated as in (12) and (13), and the c_k is updated as in (15) after each generation of ϕ and φ. Tent map is selected from the chaotic maps for its superior characteristics of convergence

$$\phi_n = 2c_k - 1, \tag{12}$$

$$\varphi_n = 2c_k, \tag{13}$$

$$c_{k+1} = \begin{cases} c_k/0.7 & c_k < 0.7, \\ 10(1 - c_k)/3c_k & otherwise. \end{cases} \tag{14}$$

The rounding down operation $\lfloor \rfloor$ is introduced considering that each element of the v_d^i is an integer. The bound value will be assigned to v_d^i in case it is out of the bound $\lfloor lb, ub \rfloor$, where v_d denotes the location of the new food source attached to dth employed bee. The fitness value $f(v_d^i)$ of the new food source v_d^i will be calculated by cost function as in (6) after it is generated. If the fitness value of the new solution is higher, the original one will be replaced. After the search of the employed bees is finished, new population is updated.

Onlooker Bees Phase. The heuristic factor matrix is denoted as η in (15), which is an $2N_T \times 1$ real vector, each entry η_n of it is a real number reflecting the quality of the nth solution. The calculation of η_n is given in (15).

$$\eta_n = 1/f(\hat{x}_n). \tag{15}$$

The employed bees return to the hive and deliver the pheromone to the onlooker bees. The onlooker bee select the nth solution vector based on the selecting probability denoted as $p(n)$ in (16).

$$p(n) = \frac{\eta_n}{\sum_{j=1}^{SN} \eta_j}. \tag{16}$$

The fth onlooker bee attaches itself to one nectar by Debs method based on selecting probability and exploit its neighborhood. Apparently, the food source with higher fitness value will attract more onlooker bees. The procedure of the exploitation is identical to (9), and the food source position is updated as the process of updating in the scout bees phase.

Scout Bees Phase. If the kth solution ($k = 1, 2, \cdots, SN$) is not updated after *limit* iterations, the attached employed bee will abandon the solution and become a scout bee to sought new nectar randomly through (17).

$$x_k^i = lb + \lfloor rand(0,1) \times (ub - lb) \rfloor . \tag{17}$$

The bound value will be assigned to x_k^i if it is out of the $\lfloor lb, ub \rfloor$. When the whole exploration is finished, the largest fitness value achieved so far is denoted as $Fitness\_best$ and its corresponding nectar position is denoted as x_{best}. Both $Fitness\_best$ and x_{best} will be updated.

The whole iteration will be repeated until the end condition is fulfilled. The global optimum solution vector $\hat{\mathbf{x}}_{\mathrm{best}}$ is obtained and is remapped to the complex domain as the final detection result. The pseudo code of the proposed low-complexity DGABC detection algorithm is as shown in Algorithm 1.

4 Simulation and Numerical Result

In this section, the simulation of computational complexity and BER are stated to illustrate the performance of the low-complexity DGABC algorithm. For comparsions, ML detection, MMSE detection and original ABC detection in [3] are in consideration. The proposed algorithm is simulation in both 64×64 and 128×128 massive MIMO system. The transmitted signals are modulated by 16-QAM. Each antenna transmit 200000 symbols simultaneously.

We denote the average received SNR (dB) per received antenna as $\mathrm{SNR(dB)} = 10\log_{10}((N_R E_a vg)/\sigma^2)$, where $E_a vg = 10$ is the mean symbol energy of the 16-QAM complex alphabet $\mathbb{S}$. The SNR ranges from 0 to 18 dB. Parameters of the algorithm are detailed in Table 1.

Table 1. Algorithm parameters setting

Amount of bee colony	$N = 40$
Number of employed bees	$SN = 20$
Heuristic factor β	0.8
Maximum number of iteration	20

4.1 Computational Complexity Analysis

The evaluation criterion of computational complexity is the order of magnitude of $\mathrm{O}(\cdot)$ with the number of floating point operations. As shown in Table 2, there are three main parts constituting the computational complexity of the low-complexity DGABC detection algorithm. Since a large number of symbols are transmitted during one symbol time, average calculation per symbol is applied to measure the computational complexity. The per-symbol computation complexity of the DGABC algorithm is $\mathrm{O}(N_T)$.

Table 2. Computational complexity of DGABC algorithm

Calculation of initial solution $\hat{\mathbf{x}}^{(0)}$t	$\mathrm{O}(N_T^2)$
Calculation of cost function $F(\hat{\mathbf{x}})$	$\mathrm{O}(N_T^2)$
Calculation of the solution vector searching	$\mathrm{O}(N_T)$
The per-symbol computation complexity	$\mathrm{O}(N_T)$

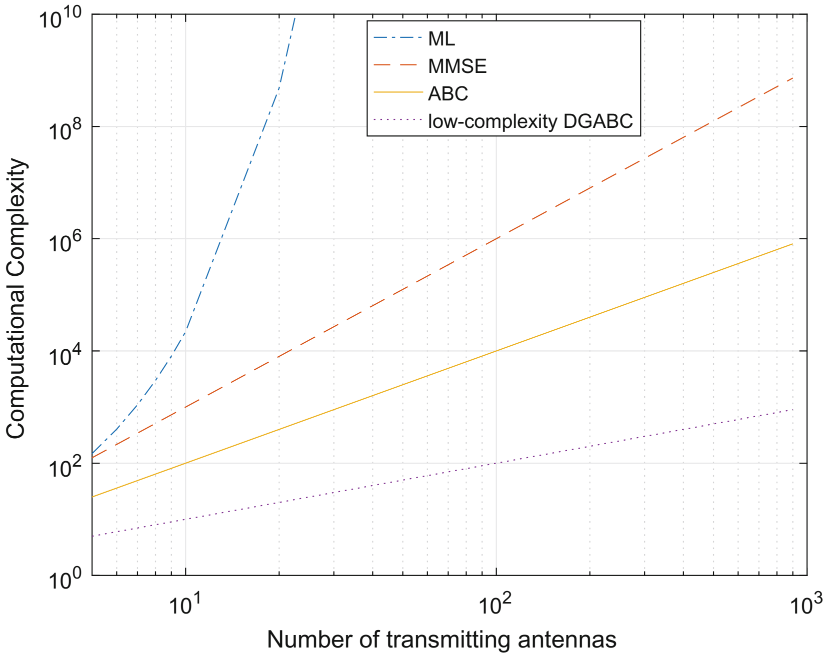

Fig. 2. The bit error (BER) performance of the low-complexity artificial bee colony (DGABC) detection algorithm for massive MIMO system at 16QAM; ABC, original artificial bee colony detection algorithm in [3], AWGN, addictive White Gaussian noise; MMSE, minimum mean square error; SISO, single-in-single-out.

The computational complexity of the proposed low-complexity DGABC detection algorithm is shown as in Fig. 2. With the number of transmitting antennas increasing, the computational complexity of ABC algorithm in [3] increases in two orders polynomial rate, the computational complexity of MMSE increases in three orders polynomial rate and the computational complexity of the proposed low-complexity DGABC algorithm increases in one order polynomial which is much lower than that of the original ABC algorithm. Obviously, the proposed DGABC algorithm lowers the computational complexity effectively.

4.2 BER Performance Simulation

As is introduced in Sect. 3, the optimum BER performance of ML is unable to be simulated in consideration of its exponential computational complexity. Therefore, we use lower bound of ML performance for massive MIMO obtained by the BER performance of the single-in-single-out (SISO) AWGN. The theoretical BER for M-QAM of SISO AWGN is given in [9] as (18).

$$P_{theory} = a \cdot Q(\sqrt{b \cdot (SNR/\log_2(M)}). \tag{18}$$

where $a = 2(1 - 1/\sqrt{M}/\log_2(\sqrt{M}))$, $b = (6\log 2(\sqrt{M})/(M-1))$, $Q(x)$ signifies a function of x, where $Q(x) = \frac{1}{2}erfc(\frac{x}{\sqrt{2}})$ and $erfc(\cdot)$ denotes the complementary error function.

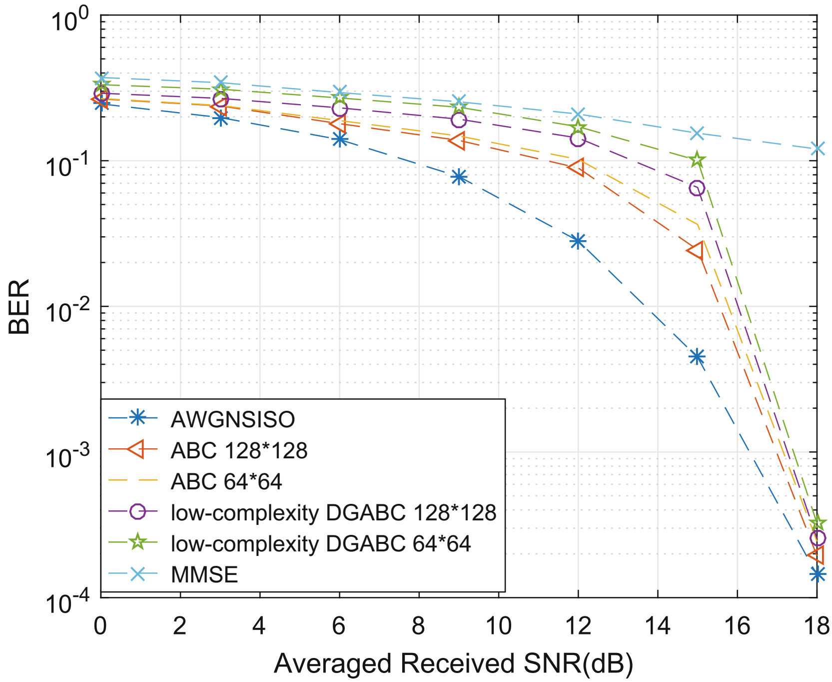

Fig. 3. The bit error (BER) performance of the proposed discrete gbest-guided artificial bee colony (DGABC) detection algorithm for massive MIMO system at 16QAM; AWGN, addictive White Gaussian noise; MMSE, minimum mean square error; SISO, single-in-single-out.

The BER performance of the proposed DGABC algorithm is shown as in Fig. 3. The original ABC algorithm achieves the optimum BER performance, while low-complexity DGABC algorithm obtains a sub-optimum BER performance with little gap. For example, low-complexity DGABC algorithm needs

13 dB to achieve the BER at a magnitude of 10^{-1}, which is less than 1 dB higher than that of the ABC algorithm. When the SNR approaches 18 dB, BER performance of low-complexity DGABC detection algorithm converges to the BER performance of both ML and ABC algorithm.

5 Conclusion

In this paper, we present a low-complexity DGABC algorithm for massive MIMO detection. With the prior information of the matched filter in MMSE detection, the initialization of solution vector is simplified. From the simulation and data analysis in both 64×64 and 128×128 massive MIMO system with 16QAM signals, the computation complexity of the proposed low-complexity DGABC algorithm is decreased with one order lower than the ABC algorithm in [3]. The SNR of the low-complexity DGABC that required to obtain the same BER is less than 1 dB higher than that of ABC algorithm, which can be regarded as near-optimum. Therefore, the proposed DGABC detection is efficient in computational complexity for massive MIMO system uplink detection.

References

1. Rusek, F., Persson, D., Lau, B.K., Larsson, E.G., Marzetta, T.L., Edfors, O., Tufvesson, F.: Scaling up MIMO: opportunities and challenges with very large arrays. IEEE Sign. Process. Mag. **30**(1), 4060 (2013)
2. Bonabeau, E., Dorigo, M., Theraulaz, G.: Swarm Intelligence: From Natural to Artificial Systems. Oxford University Press, New York (1999)
3. Li, L., Meng, W., Ju, S.: A novel artificial bee colony detection algorithm for massive MIMO system. Wirel. Commun. Mob. Comput. **16**(17), 3139–3152 (2016)
4. Khachan, A.M., Tenenbaum, A.J., Adve, R.S.: Linear processing for the downlink in multiuser MIMO systems with multiple data streams. In: Proceedings of IEEE International Conference on Communications (ICC), Istanbul, Turkey, pp. 4113–4118, June 2006
5. Yang, Y., Li, C.Q., Guo, Z.H.: Low-complexity soft-input soft-output detection based on EVD for MIMO systems. In: International Conference on Signal Processing (ICSP), pp. 1546–1550 (2014)
6. Larsson, E.G.: MIMO detection methods: how they work. IEEE Sign. Process. Mag. **26**, 9195 (2009)
7. Huo, Y., Zhuang, Y., Gu, J., Ni, S., Xue, Y.: Discrete gbest-guided artificial bee colony algorithm for cloud service composition. Appl. Intell. **42**, 661–678 (2015)
8. Kong, B.Y., Park, I.-C.: Low-complexity symbol detection for massive MIMO uplink based on Jacobi method. In: 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC), pp. 1–5 (2016)
9. Cho, K., Yoon, D.: On the general BER expression of one- and two-dimensional amplitude modulations. IEEE Trans. Commun. **50**, 10741080 (2002)