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A Novel Detector for Massive MIMO with Gray Wolf Optimization and Artificial Bee Colony Algorithm

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Abstract:
Objective: Massive multi-input multi-output (M-MIMO) technology is a research hotspot of 5G. Due to the increase of channel matrix dimension in the system, the conventional MIMO detection algorithm is not suitable for the Massive antenna. **Methods:** A novel hybrid low complexity detection algorithm is proposed for M-MIMO, which is inspired by the well-known algorithms namely, Artificial Bee Colony (ABC) algorithm and grey wolf optimization (GWO) algorithm, called GWO-ABC detector. **Findings:** The GWO algorithm is used to estimate the most optimal communication channel, and the ABC algorithm is used to detect the receiver signal at the receiver antenna. The proposed GWO-ABC algorithm is compared with other traditional MIMO detectors, as well as heuristic MIMO detection approaches from the literature, in terms of both performance and complexity. **Improvements:** Experiments show that the proposed GWO-ABC algorithm is superior to the original ABC algorithm and MMSE algorithm in BER and complexity.

Keywords: Massive MIMO, artificial bee colony, grey wolf optimization, GWO-ABC detector, MMSE

I. INTRODUCTION

In recent years, massive multiple input multiple output (M-MIMO) has been one of the challenging technologies in 5G [1]. Because of its large number of antennas, the M-MIMO system has many advantages over the traditional MIMO system[2,3]. M-MIMO has higher energy efficiency and lower transmit signal power. The spectrum efficiency of M-MIMO also has been improved. Although compared with traditional MIMO, M-MIMO has many advantages, there are still some technical problems to be overcome in future research, the most important of which is an effective M-MIMO detection algorithm.

Although compared with traditional MIMO, M-MIMO has many advantages, there are still some technical problems to be overcome in future research, the most important of which is an effective M-MIMO detection algorithm. On one hand, The minimum bit error rate performance (BER) can be achieved by using maximum likelihood (ML) search-based detection, but it is computationally impractical when the number of transmit antennas increases [4]. On the other hand, the performance of existing other detections is not so good.

Among the well-known linear detectors, techniques based on zero-forcing (ZF) and minimum mean square error (MMSE) have lower complexity and the ability to work under ill-conditioned channel matrices. however, these two MIMO linear detection techniques are lower than the performance of the maximum likelihood (ML) detector. Recently, the sphere decoder (SD) method [5] has become an alternative to ML, and its performance is close to optimal. However, in actual communication systems, the SD method is implemented in low or medium signal-to-noise ratio (SNR). In fact, in the low signal-to-noise ratio work area, the complexity of SD becomes of the same order of ML complexity [6].
Therefore, a balance between BER performance and complexity should be considered.

In this work, a heuristic artificial bee colony (ABC) algorithm is deployed in conjunction with a grey wolf optimization (GWO) algorithm, called grey wolf optimization with an artificial bee colony (GWO-ABC) algorithm, aiming to improve the performance-complexity tradeoff of detection schemes in M-MIMO system.

The GWO algorithm is used to estimate the most optimal communication channel, and the ABC algorithm is used for detecting the receiver signal at the receiver antenna. The proposed GWO-ABC algorithm is compared with other traditional MIMO detectors, as well as heuristic MIMO detection approaches from the literature, in terms of both performance and complexity. Numerical results show that the proposed GWO-ABC outperforms the conventional ABC MIMO detector, as well as the conventional linear detectors, with a significant complexity reduction and a substantial BER performance improvement. The experiments results suggest that the proposed GWO-ABC detector is a promising solution for the M-MIMO system.

The study is formulated as follows. Section 2 describes the system model of M-MIMO in detail. The proposed GWO-ABC algorithm is dealt with in section 3. The simulation results are depicted in section 4 which summarizes the BER performance comparison and computational complexity. Section 5 is a conclusion which infers that the GWO-ABC detector provides significantly outperforms than the conventional methods.

II. SYSTEM MODEL OF M-MIMO

As shown in Fig. 1, we consider an M-MIMO system with hundreds of thousands of antennas located in the M-MIMO system. The transmitting antennas' number is denoted as N_T, and the receiving antennas' number is denoted as N_R, where both N_T and N_R are natural numbers and $N_T = N_R$. At the transmitter, the signal source generates a random bitstream. After serial-parallel conversion (S/P), the bitstream is transformed into N_T parallel ones. Each stream is mapped to its equivalent transmitted antenna directly.

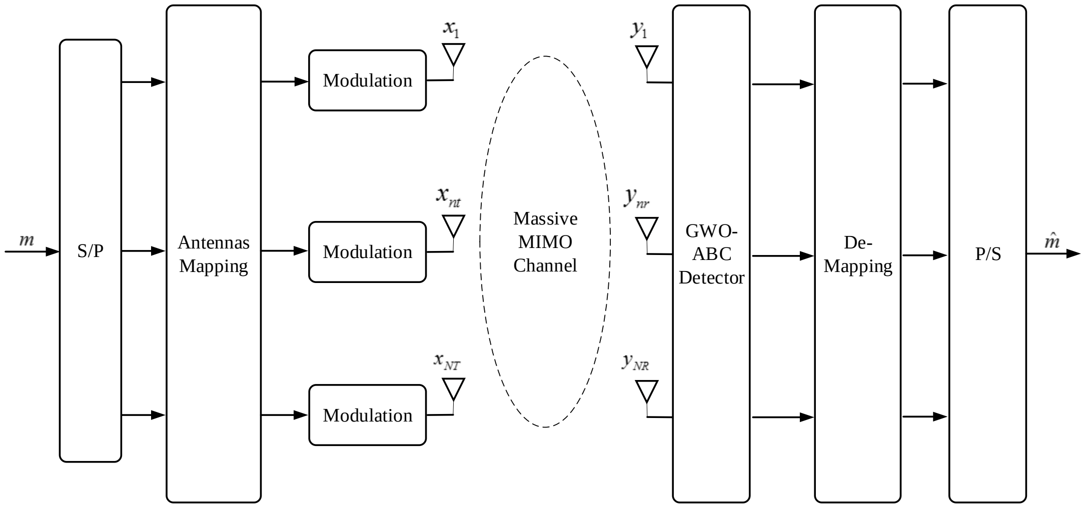

Figure1: The Model of M-MIMO System

After modulation, each data stream is transformed from bit domain into symbol domain based on the signal modulation alphabet $\mathbb{S}$. In this paper, we choose M -quadrature amplitude modulation (M-QAM), where M is the modulation order. According to [7], its complex alphabet is $\mathbb{S} = \mathbb{A} + j\mathbb{A}$, where $\mathbb{A}$ is the real part of the alphabet as in (1) and M is a number of the modulation points.

$$\mathbb{A} = [-(\sqrt{M}-1), \cdots, -3, -1, 1, 3, \cdots, (\sqrt{M}-1)] \quad (1)$$

During a symbol time, the symbol from the nt-th transmitting antenna is denoted as $x_{nt} \in \mathbb{S}$, which is a complex number and nt is the index number of the transmitting antennas $1 \le nt \le NT$. All the transmitting symbols construct a $NT \times 1$ dimensional complex vector, which is denoted as

$$\mathbf{x} = [x_1, \cdots, x_{nt}, \cdots, x_{NT}]^T \in \mathbb{C}^{NT \times 1} \quad (2)$$

The symbol vector $\mathbf{x}$ is transmitted simultaneously into the M-MIMO channel space. The channel gain matrix is a $NR \times NT$ dimensional complex matrix and denoted as $\mathbf{H} \in \mathbb{C}^{NR \times NT}$. The entries $\mathbf{H}$ are as shown in (3),

$$\mathbf{H} = \begin{bmatrix} h_{1,1} & h_{1,2} & \cdots & h_{1,NT} \\ h_{2,1} & h_{2,2} & \cdots & h_{2,NT} \\ \vdots & \vdots & \ddots & \vdots \\ h_{NR,1} & h_{NR,2} & \cdots & h_{NR,NT} \end{bmatrix} \quad (3)$$

where $h_{nr,nt}$ is the channel gain from the nt-th transmitting antenna to the nr-th receiving antenna and nr is the index number of the receiving antennas, $1 \le nr \le NR$ $h_{nr,nt}$ is a complex number and obeys to $\mathcal{CN}(0,1)$, which is independent identical distribution complexity Gaussian random distribution with zero mean and unit variance. In quasi-static environment, the channel is flat fading, which means that the entries $\mathbf{H}$ are invariant during a frame and change independently from frame to frame. The channel state information is well known at the receiver. After propagation through the M-MIMO channel, the signal is received by the receiving antennas. The received signal is a $NR \times 1$ complex vector and denoted as

$$\mathbf{y} = [y_1, \cdots, y_{nr}, \cdots, y_{NR}]^T \in \mathbb{C}^{NR\times 1} \tag{4}$$

where the entry $\mathbf{y}$ is the received symbol by the nr-th receiving antenna. According to [8], the signal propagation process is expressed as in (5).

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{5}$$

where $\mathbf{n}$ is a $NR \times 1$ dimensional complex Additive White Gaussian noise (AWGN) vector, The optimum BER performance for MIMO is obtained by ML detection algorithm. According to [9], ML makes every received symbol to search all the points in the modulation alphabet S in order to minimize the likelihood cost as in (6).

$$\hat{\mathbf{x}}_{ML} = \arg\min_{\mathbf{x}\in S} \| \mathbf{y} - \mathbf{H}\mathbf{x} \|^2 \tag{6}$$

Although the ML detection algorithm has the optimum BER performance, its computational complexity, the exponential computational complexity is too high when the transmitting antennas are in a large number. So it is important that to find a better detector for M-MIMO.

III. THE GWO-ABC ALGORITHM

3.1 GWO algorithm

The performance of BER is seriously affected by the channel condition. Therefore, the channel estimation is very much needed. Here the best channel is estimated using Grey Wolf Optimization. The properties of Grey wolf onto searching and prey chasing is carried out in this algorithm. The best solution of GWO is called alpha (α). The second-best and third-best solutions are named as beta (β) and delta (δ), respectively. The other solutions of GWO are known as omega (ω). To mathematically model the encircling mechanism, equation (7) is used as follows [10]:

$$\mathbf{S}(i+1) = \mathbf{S}_p(i) - \mathbf{A} \cdot \left| \mathbf{C} \cdot \mathbf{S}_p(i) - \mathbf{S}(i) \right| \tag{7}$$

where $\mathbf{S}$ is the position vector of the wolf, i is the current iteration, $\mathbf{S}_p$ is the position vector of the prey, A and C are the coefficient matrix, respectively, and are calculated as follows:

$$\mathbf{A} = 2\mathbf{a} \cdot \mathbf{r}_1 - \mathbf{a} \tag{8}$$

$$\mathbf{C} = 2 \cdot \mathbf{r}_2 \tag{9}$$

where $\mathbf{r}_1$ $\mathbf{r}_2$ and are the randomly generated vector from [0,1], respectively. a is called control parameter and is a linearly decreasing vector from 2 to 0 over iterations:

$$\mathbf{a}(i) = 2 - 2 \cdot \frac{i}{I} \tag{10}$$

where I is the maximum number of iterations. The other wolves in the population update their positions according to the positions of α β, and δ as follows [10]:

$$\begin{aligned} \mathbf{S}_1(i) &= \mathbf{S}_\alpha(i) - \mathbf{A}_1 \cdot \left| \mathbf{C}_1 \cdot \mathbf{S}_\alpha(i) - \mathbf{S}(i) \right| \\ \mathbf{S}_2(i) &= \mathbf{S}_\beta(i) - \mathbf{A}_2 \cdot \left| \mathbf{C}_2 \cdot \mathbf{S}_\beta(i) - \mathbf{S}(i) \right| \\ \mathbf{S}_3(i) &= \mathbf{S}_\delta(i) - \mathbf{A}_3 \cdot \left| \mathbf{C}_3 \cdot \mathbf{S}_\delta(i) - \mathbf{S}(i) \right| \end{aligned} \tag{11}$$

$$\mathbf{S}(i+1) = \frac{\mathbf{S}_1(i) + \mathbf{S}_2(i) + \mathbf{S}_3(i)}{3} \tag{12}$$

where $\mathbf{A}_1$, $\mathbf{A}_2$ and $\mathbf{A}_3$ are similar to $\mathbf{A}$ $\mathbf{C}_1$ $\mathbf{C}_2$, and $\mathbf{C}_3$ are similar to $\mathbf{C}$.

The selection of optimal channels is depending upon the Mean Squared Error (MSE) in the GWO algorithm. To optimize MSE, a random population of the solution is created by GWO. Here, the candidate solution is the channel matrix. The initialized solution is given in equation (13).

$$\mathbf{X}_i = \{ X_1, X_2, \ldots, X_i, \ldots, X_N \} \tag{13}$$

Here, $\mathbf{H}_c$ represents the candidate solution. After the solution initialization, the fitness is evaluated. The fitness evaluation is used to determine the effectiveness of the candidate solutions. The fitness is calculated for all the solutions. Here, the Mean squared error is considered as the main criterion for fitness evaluation. The fitness function f is calculated by (14).

$$f = \min\left(\frac{1}{N}\sum_{i=1}^{N}(\mathbf{X}_i - \hat{\mathbf{X}}_i)^2\right) \tag{14}$$

Where the signal sent from the sender is represented by $\mathbf{X}_i$ and the signal at the system's receiver end is represented by $\hat{\mathbf{X}}_i$. At the end of the GWO, the optimal channel $\mathbf{H}_{opt} = \{H_1, H_2, \ldots, H_i, \ldots, H_{opt}\}$ is obtained by the GWO algorithm.

3.2 ABC algorithm

After using the GWO algorithm to select the best channel $\mathbf{H}_{opt}$, the GWO-ABC detector uses the ABC algorithm to detect the signal. The principle of ABC optimization simulates the process of bee foraging for nectar. When bees gather honey, there are three mission roles: scouter bee, leader bee, and follower bee. When starting to forage, all bees are scouter bees. They randomly search for nectar. Once they find the nectar, they return to the place where they danced in the hive, where the bees communicate information to each other through swing dances. Then, the bees exchange roles according to the amount of nectar: when the amount of nectar is too low, the unemployed foragers in the hive are the scouter bees. They randomly search for candidate nectar sources. When the nectar source is local optimal and the amount of nectar is close to the adjacent value, the unemployed foragers are the follower bees. They follow the dancer (boy bee or leader bee) to the corresponding nectar source; when the nectar source is globally optimal and the amount of honey is higher than the adjacent value, the unemployed feeder is the leader bee. They continue to recruit more follower bees in the dancing places, collecting honey from the best nectar sources in the world.

In [4], an ABC detection algorithm for massive MIMO is proposed. The main step of the ABC algorithm is to turn the complex number domain into a real number domain. Then, the channel $\mathbf{H}_r$ in the real number domain is obtained by converting the optimal channel $\mathbf{H}_{opt}$.

$$\mathbf{H}_r \triangleq \begin{bmatrix} \Re(\mathbf{H}_{opt}) & -\Im(\mathbf{H}_{opt}) \\ \Im(\mathbf{H}_{opt}) & \Re(\mathbf{H}_{opt}) \end{bmatrix} \tag{15}$$

Similarly, the transmit signal $\mathbf{x}_r$, the white Gaussian noise $\mathbf{n}_r$, the received signal $\mathbf{y}_r$ in the real number domain is obtained by (16)

$$\mathbf{x}_r \triangleq \begin{bmatrix} \Re(\mathbf{x}) \\ \Im(\mathbf{x}) \end{bmatrix} \quad \mathbf{n}_r \triangleq \begin{bmatrix} \Re(\mathbf{n}) \\ \Im(\mathbf{n}) \end{bmatrix} \quad \mathbf{y}_r \triangleq \begin{bmatrix} \Re(\mathbf{y}) \\ \Im(\mathbf{y}) \end{bmatrix} \tag{16}$$

Its cost function $F(\hat{\mathbf{x}})$ as in (17) is equivalent to the nectar amount. The real modulation alphabet A is corresponding to the searching space where the bees forage honey.

$$F(\hat{\mathbf{x}}) = 2\mathbf{y}_r^H \mathbf{H}_r \hat{\mathbf{x}} - \hat{\mathbf{x}}^H \mathbf{H}_r^H \mathbf{H}_r \hat{\mathbf{x}} \tag{17}$$

It is noted that the solution vector $\hat{\mathbf{x}}$, cost function $F(\hat{\mathbf{x}})$, real modulation alphabet A in a massive MIMO system correspond to the nectar source, nectar amount, space where bees forage in the ABC algorithm, respectively. The detection algorithm searches the global optimum solution vector $\hat{\mathbf{x}}_{\mathrm{opt}}$ in the real modulation alphabet A until maximizing the cost function $F(\hat{\mathbf{x}})$ as in (18). The maximum of the cost function equivalents to the biggest nectar amount. The procedure of searching for the global optimum solution vector is corresponding to the process of bees foraging for the global optimum nectar source that has the biggest nectar amount.

$$\hat{\mathbf{x}}_{\mathrm{opt}} = \arg\max_{\mathbf{x}\in \mathrm{A}} F(\mathbf{x}) \tag{18}$$

Furthermore, let $\hat{\mathbf{x}}_{\mathrm{s}}$ denote the candidate solution vector randomly found out by the scouter bees in the modulation alphabet A. The local optimum solution vector acquired by the follower bees is denoted as $\hat{\mathbf{x}}_{\mathrm{f}}$. $\hat{\mathbf{x}}_{\mathrm{opt}}$ represents the global optimum solution vector found out by the leader bees.

3.3 GWO-ABC Algorithm

The GWO-ABC algorithm uses the GWO algorithm to find the optimal channel H and then uses the ABC algorithm to detect the signal. The flowchart of the GWO-ABC algorithm is below. The GWO-ABC algorithm:

1 : $t = 0$

2 : randomly initialize the grey wolf
population $\mathbf{X}_i (i = 1, 2, \ldots, N)$

3 : initialize the parameters a, A, C;

4 : calculate the objective function value of each grey wolf;

5 : $\mathbf{X}_\alpha$ = the best solution;

6 : $\mathbf{X}_\beta$ = the second best solution;

7 : $\mathbf{X}_\delta$ = the third best solution;

8 : while$(t < T)$

9 : for each grey wolf

10 : update the position of the current grey wolf by Eq.(7)

11 : end for

12 : update the parameter a, A, C by Eqs.(8) – (10);

13 : calculate the objective function values of all grey wolf;

14 : update $\mathbf{X}_\alpha, \mathbf{X}_\beta, \mathbf{X}_\delta$

15 : $t = t + 1$

16 : end while

17 : $\mathbf{H}_{opt} = \mathbf{X}_\alpha, (i = 1, 2, \ldots, N)$

18 : calculate $\mathbf{x}_r$, $\mathbf{H}_r$, $\mathbf{n}_r$, $\mathbf{y}_r$ by Eqs.(15) – (16);

19 : $F_{\max} \leftarrow F\left(\widehat{\mathbf{x}}^{s}\right), \tau[n,k] \leftarrow \tau_0, n = 1 \text{ to } N, k = 1 \text{ to } K$

for $iter = 1$ to $Maxiter$
$\quad limit = 0$
$\quad$ for $n_f = 1$ to N_g
for $d = 0$ to SN
$\quad v_d^i \leftarrow \hat{x}_d^i + \lfloor \phi_d^i \times (\hat{x}_d^i - \hat{x}_e^i) \rfloor + \lfloor \varphi_d^i \times (x_{best}^i - \hat{x}_d^i) \rfloor$
$\quad$ if $f(\mathbf{v}_d) > f(\hat{\mathbf{x}}_d)$
$\qquad \hat{\mathbf{x}}_d \leftarrow \mathbf{v}_d,\ f(\hat{x}_d) \leftarrow f(v_d)$
$\quad$ end if
end for
for $f = 0$ to SN
$\quad$ The fth onlooker bee selects jth food source through the wheel selection method.
$\quad v_f^i \leftarrow \hat{x}_j^i + \lfloor \phi_f^i \times (\hat{x}_j^i - \hat{x}_e^i) \rfloor + \lfloor \varphi_f^i \times (x_{best} - \hat{x}_f^i) \rfloor$
$\quad$ if $f(\mathbf{v}_f) > f(\hat{\mathbf{x}}_j)$
$\qquad \hat{\mathbf{x}}_j \leftarrow \mathbf{v}_f,\ f(\hat{x}_j) \leftarrow f(v_f)$
$\quad$ end if
end for
$\quad$ if the kth solution $(k = 1, 2, \cdots, SN)$ is not updated after limititerations
$\qquad x_k^i \leftarrow \lfloor \mathrm{rand}(0,1) \times (ub - lb) \rfloor + lb$
$\quad$ end if
end for
update $\widehat{F(\mathbf{x})}$ and $\hat{\mathbf{x}}_{\mathrm{opt}}$
get the global optimum solution vector $\hat{\mathbf{x}}_{\mathrm{opt}}$.

IV. SIMULATION RESULTS

The number of transmitting and receiving antennas in the massive MIMO system is denoted as $NT \times NR$, where $NT = NR$ changes from 64 to 128 unless otherwise stated. The transmitted signals are uncoded and modulated by 4-QAM, 16-QAM. The symbols are transmitted from each transmitting antenna at the same time. The length of the transmitted symbols per transmitting antenna is set $L = 1000000$. The GWO-ABC algorithm parameters are shown in Table 1.

Detectors	Complexity
Pheromone	$\alpha = 0.8$
heuristic factor	$\beta = 1$
updating coefficient	$\rho = 0.7$
number of bees groups	$N_g = 4$
maximum number of iteration	$Maxiters = 100$

Table 1: Parameters Setting.

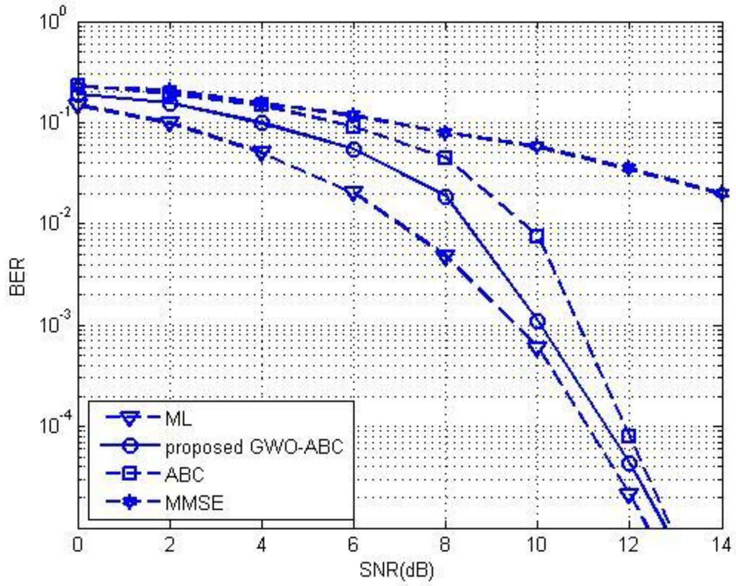

Figure 2: The BER of the GWO-ABC detector at 4QAM

Figure 2 shows the BER performance comparison of the proposed GWO-ABC algorithm using the 4QAM modulation scheme and existing other detection methods. The proposed GWO-ABC algorithm is a simulation in a 64×64 M-MIMO system. The BER performance of the proposed GWO-ABC algorithm is better than that of the original ABC algorithm. For example, the GWO-ABC algorithm needs 2 dB to achieve the BER at a magnitude of 10^{-1}, however, the ABC algorithm needs 4 dB to achieve the same BER performance. When the SNR approaches 12 dB, the BER performance of the GWO-ABC detection algorithm converges to the BER performance of the ML algorithm.

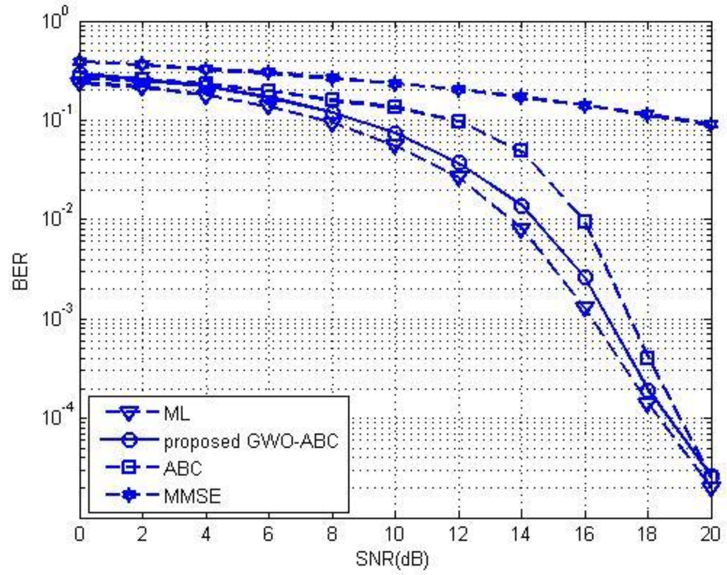

Figure 3: The BER performance of the GWO-ABC detector at 16QAM

When the signals are modulated by 16-QAM, the BER performance of the proposed GWO-ABC algorithm is shown as in Fig. 3. The proposed GWO-ABC algorithm is a simulation in a 128×128 M-MIMO system. From the BER simulation figure, it is inferred that the proposed GWO-ABC methods tend to have better performance in terms of good BER performance.

The BER performance of the proposed GWO-ABC algorithm outperforms that of the original ABC algorithm. For example, the GWO-ABC algorithm needs 14 dB to achieve the BER at a magnitude of 10^{-2}, however, the ABC algorithm needs 16 dB to achieve the same BER performance. When the SNR approaches 18 dB, the BER performance of the GWO-ABC detection algorithm converges to the BER performance of the ML algorithm.

V. COMPLEXITY ANALYSIS

The evaluation criterion of computational complexity is the order of magnitude of $O(\cdot)$ with the number of floating point operations. As shown in Table 2, there is four main detection algorithm computational complexity. 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 computational complexity of the proposed ABC detection algorithm is an order of magnitude $O\left(N_T^2\right)$. The computational complexity of the MMSE algorithm [11] is an order of magnitude $O\left(N_T^3\right)$. The computational complexity of the ML detection algorithm increases with the number of transmitting antennas at an exponential rate, as table 2 shown, its computational complexity is $O\left(M^{N_T}\right)$ where M is modulation order. What can be calculated is that the complexity of the proposed GWO-ABC algorithm is also $O\left(N_T^2\right)$.

Detectors	Complexity
ABC	$O\left(N_T^2\right)$
MMSE	$O\left(N_T^3\right)$
ML	$O\left(M^{N_T}\right)$
GWO-ABC	$O\left(N_T^2\right)$

Table 2: The Computational Complexity of Detectors

The computational complexity of the proposed GWO-ABC detector is shown in Figure 4. It is clear that the computational complexity of the ML detection algorithm increases with the number of transmitting antennas at an exponential rate, the computational complexity of the MMSE grows with the transmitting antennas' number in three orders polynomial rate, and the computational complexity of the proposed GWO-ABC detector increases with the number of transmitting antennas in two orders polynomial rate, which is one order lower than that of the MMSE. The computational complexity of the proposed GWO-ABC detection algorithm is polynomial lowest and appropriate for the M-MIMO system.

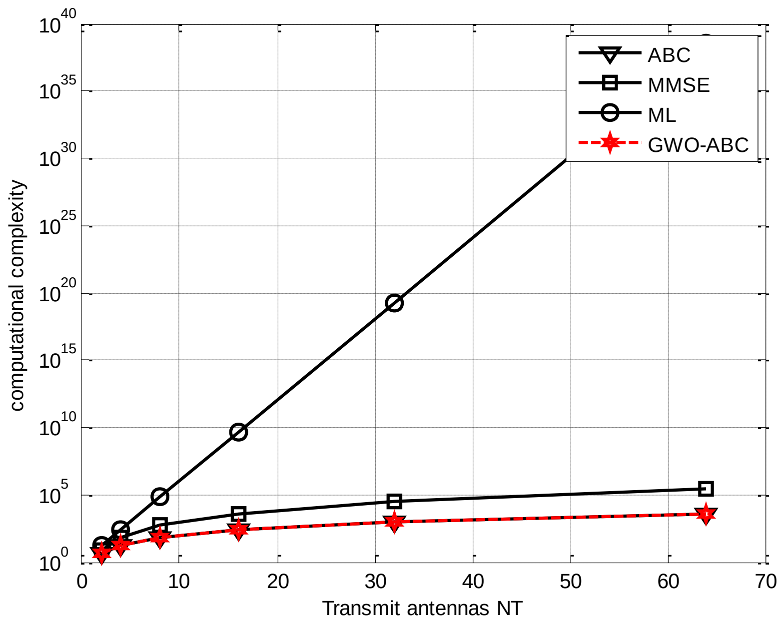

Figure 4: The computational complexity of the GWO-ABC detector

VI. CONCLUSION

In this paper, a hybrid detection algorithm, called the GWO-ABC detector is proposed. The GWO-ABC detector uses the idea of heuristic algorithms, such as the GWO algorithm and ABC algorithm. For a larger number of antennas and higher modulation schemes, the proposed detector is expected to give near-optimal ML results with a much lower complexity level as compared to the ML detector. The performance of the proposed GWO-ABC detector is evaluated along with existing ABC and MMSE algorithms in terms of BER and complexity metrics. Simulation results have clearly depicted that the GWO-ABC algorithm can achieve good BER performance at the cost of slightly increased complexity. The resistance to being trapped in local minima, convergence to a reasonable solution in fewer iterations, good BER performance makes GWO-ABC a suitable candidate detector for M-MIMO systems.

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REFERENCES

[1]. Andrews JG, Buzzi S, Choi W, Hanly SV, Lozano A, Soong ACK, Zhang JC. What will 5G be? IEEE Journal on Selected Areas in Communications 2014; 32(6): 1065–1082

[2]. Larsson EG, Edfors O, Tufvesson F, Marzetta TL. Massive MIMO for next-generation wireless systems. IEEE Communications Magazine 2014; 52 (2): 186–195.

[3]. Rusek F, Persson D, Lau BK, Larsson EG, Marzetta TL, Edfors O, Tufvesson F. Scaling up MIMO: opportunities and challenges with very large arrays. IEEE Signal Processing Magazine 2013; 30(1):40–60.

[4]. Li, Lin & Meng, Weixiao & Ju, Shihao. (2016). A novel artificial bee colony detection algorithm for a massive MIMO system. Wireless Communications and Mobile Computing. 16.

[5]. L. Barbero and J. Thompson, Fixing the complexity of the sphere decoder for Mimo detection, Wireless Communications, IEEE Transactions on, vol. 7, no. 6, pp. 2131–2142, June 2008.

[6]. Filho, José Carlos & Abrao, Taufik. (2020). LR-Aided Detection for Large-MIMO System Via Ant Colony Optimisation. 10.14209/SBRT.2013.45.

[7]. 10.1002/WCM.2754.

[8]. Larsson EG. MIMO detection methods: how they work. IEEE Signal Processing Magazine 2009; 26(3): 91–95.

[9]. Loyka S, Gagnon F. Performance analysis of the V-BLAST algorithm: an analytical approach. IEEE Transactions on Wireless Communications 2004; 3(4): 1326–1337.

[10]. Özdemir, Özgür & Yilmaz, Ali. (2012). ML performance analysis of digital relaying in bi‐directional relay channels. Wireless Communications and Mobile Computing. 12.676-688. 10.1002/WCM.1003.

[11]. Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. Advances in engineering software, 69, 46-61.

[12]. Kasiselvanathan M, Sathish Kumar, N. Bit error rate aware accurate prediction of original signals with low distortion using low complexity detection algorithms, Concurrency Computation, and Practice Experience. 2019. https://doi. org/10.1002/CPE.5192.

[13]. H. B. Almelah and K. A. Hamdi, "Spectral efficiency of distributed large-scale MIMO systems with ZF receivers," IEEE Transactions on Vehicular Technology, vol. 66, no. 6, pp. 4834–4844, 2017.

[14]. E. Björnson, J. Hoydis, and L. Sanguinetti, "Massive MIMO have unlimited capacity," IEEE Trans. Wireless Commun., vol. 17, no. 1, pp. 574–590, 2018.

[15]. Agarwal, S, Sah, A. K, & Chaturvedi, A. K (2017), 'Likelihood Based Tree Search for Low Complexity Detection in Large MIMO Systems', IEEE Wireless Communications Letters, vol. 6, no. 4, pp. 450-453.

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