

Adaptive Coordinated Motion Control for Swarm Robotics Based on Brain Storm Optimization

Jian Yang

*Department of Computer Science and Engineering
Southern University of Science and Technology
Shenzhen, China
yangj33@sustech.edu.cn*

Yuhui Shi

*Department of Computer Science and Engineering
Southern University of Science and Technology
Shenzhen, China
shiyh@sustech.edu.cn*

Abstract—Coordinated motion control in swarm robotics aims to ensure the coherence of members in space, i.e., the robots in a swarm perform coordinated movements to maintain spatial structures. This problem can be modeled as a tracking control problem, in which individuals in the swarm follow a target position with the consideration of specific relative distance or orientations. To keep the communication cost low, the PID controller can be utilized to achieve the leader-follower tracking control task without the information of leader velocities. However, the controller’s parameters need to be optimized to adapt to situations changing, such as the different swarm population, the changing of the target to be followed, and the anti-collision demands, etc. In this letter, we apply a modified Brain Storm Optimization (BSO) algorithm to an incremental PID tracking controller to get the relatively optimal parameters adaptively for leader-follower formation control for swarm robotics. Simulation results show that the proposed method could reach the optimal parameters during robot movements. The flexibility and scalability are also validated, which ensures that the proposed method can adapt to different situations and be a good candidate for coordinated motion control for swarm robotics in more realistic scenarios.

Index Terms—Swarm Robotics, Brain Storm Optimization, Formation Control, Leader-follower, Optimal PID Control

I. INTRODUCTION

By taking inspiration from social insects or animals’ self-organized behaviors, swarm robotics is a particular method to realize collaborative behaviors of multi-robot systems [1]. It aims to achieve robust and scalable collaborative behavior through simple interaction between members or between members and the environment [2]. This field has been perceived to have the potential in applications of exploration in unknown environments [3], searching particular signal or feature [4], [5], military defense or disaster rescue, etc [6], [7]. Coordinated motion control in swarm robotics aims to ensure the coherence of members in space, i.e., the robots in a swarm perform coordinated movements to maintain spatial structures [8].

Correspondence: Yuhui Shi. This work is partially supported by National Key R&D Program of China under the Grant No. 2017YFC0804002, National Science Foundation of China under grant number 61761136008, Shenzhen Peacock Plan under Grant No. KQTD201611251435531, Program for Guangdong Introducing Innovative and Entrepreneurial Teams under grant number 2017ZT07X386, and the Science and Technology Innovation Committee Foundation of Shenzhen under the Grant No. ZDSYS201703031748284 and JCYJ20200109141235597.

Many works in the literature have designed both loosen and rigid coordinated motion control for robotic swarms. For example, some works dealing with the flocking behaviors, which mimics the self-organized behavior of bird flocks or fish schools, belong to loosen coordinated motion control [9], [10]. The goal is to let the swarm moving together without collision, without concern about the specific relative positions and orientations among swarm members. Reynolds proposed a representative study using simple rules to achieve flocking: collision avoidance with nearby flockmates, velocity matching with nearby flockmates, and flocking centering with nearby flockmates [11]. From the engineering perspective, to make a group of robots more useful, some other works were presented to deal with the rigid moving formation control problems [12]. Those methods are taking inspiration from both macroscopic and multicellular mechanisms [13], such as leader-follower structure [14], virtual structure [15], potential field [16], etc. Among them, the leader-follower structure has been widely used [17]. It can be modeled as a tracking control problem, in which individuals in the swarm follow a target position with the consideration of specific relative distance or orientations [18].

However, some control strategies, such as the traditional leader-follower approach, need the leader’s velocity to be exchanged with the followers, which increased the communication costs. Some works dealt with this problem by introducing a PID control law into the leader-follower structure to avoid velocity communication [19], but the PID parameters can not be adjusted adaptively in case of environmental or swarm changes during movements. To compensate for this shortcoming, this paper propose an adaptive online-tuning formation control approach. The proposed method uses the BSO algorithm to refine a set of optimal PID parameters of the tracking controller during movements. The BSO algorithm is a type of swarm intelligence optimization algorithm inspired by human collaborative problem-solving, i.e., the brainstorming process [20]. Through a series of iterative operations of convergence and divergence, it can find a relatively optimal solution to a specific problem. The BSO has been widely used in many aspects such as data science [21], electric power systems [22], optimal control [23], computer vision applications [24], wireless sensor networks [25], electromagnetic design problems

[26], as well as multi-robot systems [27]. By applying it to the PID based leader-follower control mechanism, the control parameters will be continuously refined online as the system runs.

The remainder of this paper is as follows: Section 2 reviews the related works. Section 3 states the problems. Section 4 proposes the proposed BSO based coordinated motion control method. Section 5 gives the simulation results with discussions, followed by conclusion in Section 6.

II. RELATED WORKS

As mentioned, there are mainly two types of coordinated motion control in mobile swarm robotics: flocking and rigid formation motion. Flocking is a procedure observed when a group of birds is foraging or in flight [11]. Rigid moving formation control is a high level of flocking, and it needs not only to keep close together but also to keep some spatial patterning during moving. The rigid formation control approaches include structured approaches and behavioral approaches [28]. The structured approaches include leader-follower structure [29], virtual structure [15], and behavioral approaches contain the probability finite state machine [30], the potential field methods [31], as well as the consensus-based approaches [32].

The leader-follower structure is an excellent method for rigid formation control. By assigning a leader in the swarm, the formation control problem can be modeled as a tracking control problem, where the follower tracks the leader with a specific distance or angle, known as the $l - \varphi$ control [33]. Firstly, Alur et al. presented a leader-follower control scheme, which calculates the control inputs of a swarm of mobile robots with a unicycle model to achieve the formation [34]. However, this method needs the velocity of the leader to be transmitted to the followers. Shen et al. proposed an adaptive PID control strategy without the leader velocity, which determines the inputs under a feedback control law by measuring the errors to the target pose. It has been proven to be stable under the Lyapunov principle [19]. Nevertheless, in this work, the turning of the PID parameters is not optimized for different populations or other changes. Another drawback of the leader-follower structure is that when the leader is unavailable, the whole swarm may fail as well. There are some dynamic leader election strategies proposed to tackle this problem [35].

The virtual structure method makes a group of robots behave as if they are mass points embedded in a rigid structure [15]. The advantage of this method is that during the formation and movement of the formation, the robots in a group always maintain this relative geometric relationship, which is easy to analyze its convergence and stability. However, the member robot needs to maintain communication and calculation during formation forming and coordinated motion, introducing high complexity of calculation and communication. It is easy to cause excessive throughput and even make the algorithm invalid in a large scale swarm system.

It should be noted that there are also some strategies inspired by the multi-cellular mechanisms [36], [37], or designed by

evolutionary algorithms [38]–[40]. This paper focuses on co-ordinated tracking control for swarm robotics. We will propose an online tuning adaptive control strategy for the leader-follower structure for rigid formation control. We emphasize the following contributions: 1) An online adaptive incremental PID controller without the leader's velocity is designed for coordinated control for swarm robotics. 2) The parameters of the controller are continuously optimized during the swarm movements. 3) The proposed method can adapt to different maneuver actions and the number of robots in the swarm, which has good flexibility and scalability.

III. PROBLEM STATEMENT

A. Assumptions

First, we assume the swarm will perform actions in a 2-D space. Furthermore, members in the swarm do not have the ability of global positioning. In order to achieve rigid formations, we assign a global leader in the swarm as guidance, but not all of the members can perceive it at any time. The perception and communication are only taking place between the neighbors in a specific range. For the single robot, we adopt the non-holonomic wheeled robot kinematics for single members, i.e., the unicycle model [41]:

$$\begin{bmatrix} x_i(t + \Delta t) \\ y_i(t + \Delta t) \\ \alpha_i(t + \Delta t) \end{bmatrix} = \begin{bmatrix} x_i(t) \\ y_i(t) \\ \alpha_i(t) \end{bmatrix} + \begin{bmatrix} \cos \alpha_i(t) & 0 \\ \sin \alpha_i(t) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \quad (1)$$

where in (x_i, y_i, α_i) , x_i, y_i the position coordinates of the robot in the reference coordinate system XOY , α is its orientation angle, v and ω indicate the forward and turing speed respectively in each robot's frame x_ioy_i . Assume that the robot is equipped with sensors that can detect other member robots' distance and bearing angle, which denote as l_{ij} and φ_{ij} respectively for measured distance and bearing angle of robot j in robot i 's field of view, then we have:

$$(x_{ij}, y_{ij}) = (l_{ij} \cos \varphi_{ij}, l_{ij} \sin \varphi_{ij}) \quad (2)$$

The coordinated motion problem now can be translated to control a robot reach a target pose that keeps the distance and bearing angle to a reference position. For the flocking motion control, we can define the reference position as the central location of the members in a robot's field of view, without considering the exact distance and bearing angle to this position. The heading is also the average heading angle of all the members heading received. For the rigid formation control, the members are required to follow a specific member in their field of view. For example, the V-shaped moving formation, which imitates some large birds flying formation, have to keep the exact distance and bearing angle to a neighbor. For this goal of coordinated motion control, the swarm leader firstly broadcasts its heading to the surrounding members. If the leader is in someone's field of view, it will determine its role for which side it would follow the leader. And then broadcast its side-role and received leader headings. Other neighbors who can not see the leader, will synchronize its role to the nearest member who already had a role. Based

on the synchronized role, the member will follow the closest member in its top-left (for right side member) or top-right (for left side members), which defined as a cascade approach [29].

B. Tracking Control without Velocity Broadcasting

As shown in Figure 1, suppose the follower R_F is tracking the (virtual) leader R_L , and denote the desired position and pose is R_D , then the target position and heading can be described as:

$$\begin{cases} x_d = x_l - l_d \cos(\theta_l + \varphi_d) \\ y_d = y_l - l_d \sin(\theta_l + \varphi_d) \\ \theta_d = \theta_l \end{cases} \quad (3)$$

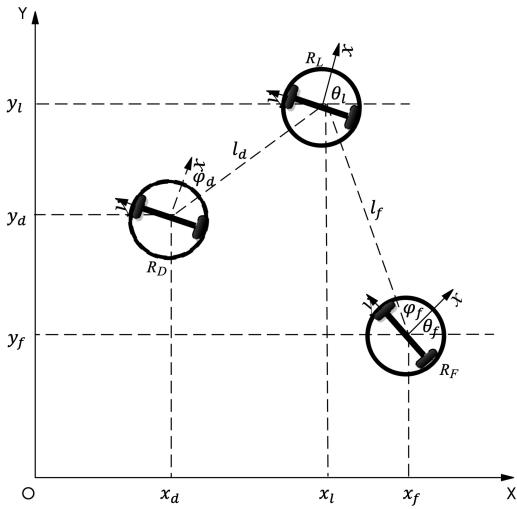


Fig. 1. Leader-Follower Structure

Then the errors in the reference frame are:

$$\begin{cases} \Delta X = x_d - x_f \\ \Delta Y = y_d - y_f \\ \Delta \Theta = \theta_d - \theta_f \end{cases} \quad (4)$$

By translating the above errors to the follower's frame (R_F), we have:

$$\begin{bmatrix} e_x \\ e_y \\ e_\theta \end{bmatrix} = \begin{bmatrix} \cos \theta_f & \sin \theta_f & 0 \\ -\sin \theta_f & \cos \theta_f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta X \\ \Delta Y \\ \Delta \Theta \end{bmatrix} \quad (5)$$

In the individual's coordinate system, the forward speed is only relevant to the error component in the y -direction (e_y), and the turning speed is relevant to the error component in the x -direction (e_x), and the heading error e_θ , then we can use the following PID controller to achieve the tracking control [19]:

$$\begin{bmatrix} v \\ \omega \end{bmatrix} = \mathbf{H}(t, e) \mathbf{K}_{pid}(t, e) \quad (6)$$

where:

$$\mathbf{H}(t, e) = \begin{bmatrix} \mathbf{E}_x(t) & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{E}_y(t) & \mathbf{E}_\theta(e) \end{bmatrix} \quad (7)$$

$$\mathbf{K}_{pid}(t, e) = [\mathbf{K}_x \quad \mathbf{K}_y \quad \mathbf{K}_\theta] \quad (8)$$

$$\mathbf{E}_\gamma(t) = [e_\gamma(t) \quad \int e_\gamma(t) \quad \dot{e}_\gamma(t)] \quad (9)$$

$$\mathbf{K}_\gamma(t) = [k_{\gamma p}(t) \quad k_{\gamma i}(t) \quad k_{\gamma d}(t)] \quad (10)$$

In equation (9) and (10), we use $\gamma \in \{x, y, \theta\}$ to represent the parameters relevant to the components corresponding to x , y , and θ . Furthermore, it is unnecessary to remember each one's historical positions and headings in real applications, so the incremental form of the PID controller is adopted in this paper, which needs only the information of the past two time slots. With discrete consideration, it can be expressed as:

$$\begin{bmatrix} \Delta v \\ \Delta \omega \end{bmatrix} = \Delta \mathbf{H}(k, e) \mathbf{K}_{pid}(k, e) \quad (11)$$

$$\Delta \mathbf{H}(k, e) = \begin{bmatrix} \Delta \mathbf{E}_x(k) & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \Delta \mathbf{E}_y(k) & \Delta \mathbf{E}_\theta(k) \end{bmatrix} \quad (12)$$

where:

$$\Delta \mathbf{E}_\gamma(k) = \begin{bmatrix} e_\gamma(k) - e_\gamma(k-1) \\ e_\gamma \\ [e_\gamma(k) - 2e_\gamma(k-1) + e_\gamma(k-2)] \end{bmatrix} \quad (13)$$

$$\mathbf{K}_\gamma(k) = [k_{\gamma p}(k) \quad k_{\gamma i}(k) \quad k_{\gamma d}(k)] \quad (14)$$

where $\gamma \in \{x, y, \theta\}$.

C. Objective Function

For equation (12), we can use the traditional PID tuning method to reach an available parameter set, but in our situation, in order to get good scalability, the population size may change, i.e., the swarm is required to work under any number of members. Furthermore, during the motion, the target position and pose may dynamically change. We can not use a unique parameter set for all circumstances. Consequently, the controller parameters \mathbf{K}_{pid} need to be optimized during moving. Since the objective for the tracking control is to keep the tracking errors as small as possible, so the objective function for optimization can be simply written as:

$$\min_{\mathbf{K}_{pid}} \|e(v, w)\|, \quad s.t. \quad v \leq v_{max}, w \leq w_{max} \quad (15)$$

where $e(v, w) = [X_e(v, w) \quad Y_e(v, w) \quad \Theta_e(v, w)]$, v_{max} and w_{max} are the maximum forward speed and turning speed of the robot respectively.

IV. THE PROPOSED METHOD

The proposed control scheme is shown in Figure 2, the input to the member robot will be calculated by a self-tuning controller based on the tracking error. Using the objective function represented in (15), we will utilize a modified version of BSO to optimize the control parameters $\mathbf{K}_\gamma(k)$ during each step of movements. Based on the outputs, the current error of each step, and the archived solutions with corresponding historical errors, the tuning module will send an optimized set of parameters to the controller for the next move.

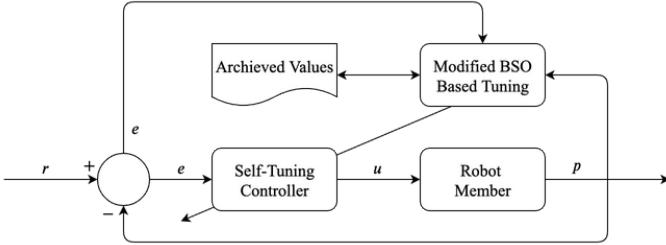


Fig. 2. Adaptive Control Scheme

A. Brain Strom Optimization

The Brain Storm Optimization (BSO) is a relatively new swarm intelligence optimization algorithm, which is inspired by the process of collaborative problem-solving means of human beings, i.e., the brainstorming process. This algorithm can find a relatively optimal solution to a particular problem through convergence and divergence operations within a certain period of time. It generally includes three basic operations, clustering, new solution generation, and selection. The original BSO algorithm uses k-means to cluster in the solution space [20]. Then it generates new solutions based on the clustering results and selects the better solution in each iteration to retain. Since the k-means clustering is time-consuming, there are many followed efforts to improve the clustering operation. The most representative method is the clustering method in the objective space, namely BSO-OS [42]. Each iteration uses every individual's fitness value to divide the entire population into two clusters: elite solutions and normal solutions. Then based on these two clusters, it generates new solutions for the next round of evaluation. Since the fitness value is generally a scalar, this method can significantly increase the calculation speed and can be used in the online PID parameter tuning applications.

The procedure of BSO-OS is shown in Algorithm 1, in which clustering in the objective space divides the population into two categories: elitists and normals, i.e., the top $perc_e\%$ of the population individuals will be clustered as elitists, and the remaining $(100 - perc_e)\%$ will be categorized as normals. Then select one or two individuals to generate a new individual based on the selecting operation. Besides, a disruption operation will be performed on a random individual in the population to increase diversity. This operation is performed by replacing one dimension of a randomly selected individual with a value within a specific range.

Algorithm 1 Procedure of BSO-OS

- 1: Population Initialization
 - 2: **while** not terminated **do**
 - 3: Evaluation individuals;
 - 4: Taking top $perc_e$ percentage as elitists and remaining as normals;
 - 5: Selecting a new individual based on selecting operation
 - 6: Disrupting a randomly selected individual;
 - 7: Updating individuals;
-

Algorithm 2 shows the operation of selecting individuals, where $rand$ is a randomly generated number in $(0, 1)$, p_e is the probability to use elitists not normals to generate a new individual, p_{one} is the probability to generate a new individual based on one selected individual rather than two selected individuals.

Algorithm 2 Procedure of Selecting Individuals

- 1: **if** $rand < p_e$ **then** \triangleright generate a new individual based on elitists
 - 2: **if** $rand < p_{one}$ **then**
 - 3: Generate a new individual based on one randomly selected elitist;
 - 4: **else**
 - 5: Generate a new individual based on two randomly selected elitists;
 - 6: **else** \triangleright generate a new individual based on normals
 - 7: **if** $rand < p_{one}$ **then**
 - 8: Generate a new individual based on one randomly selected normal;
 - 9: **else**
 - 10: Generate a new individual based on two randomly selected normals;
-

A new solution is realized by adding the a Gaussian random number to the selected solution, according to Eq.(16).

$$x_{new}^i(t+1) = x_{selected}^i + \text{random}(t)\xi(t) \quad (16)$$

where x_{new}^i is the i th dimension of the newly created individual, and $x_{selected}^i$ is the corresponding dimension of the selected individual based on Algorithm 2, which can be determined by Eq.(17), and $\text{random}()$ is a random value that obeys the Gaussian distribution.

$$x_{selected}^i(t) = \begin{cases} x_{old1}^i(t), & rand < p_e \\ \text{rand}(t)x_{old1}^i(t) + (1 - \text{rand}(t))x_{old2}^i(t), & \text{Others} \end{cases} \quad (17)$$

where x_{old1} and x_{old2} represent two individuals selected from the current population. $\text{rand}()$ returns a random value in the range of $(0, 1)$, and the $\xi(t)$ is the step size, which relevant to the predefined total iteration numbers, can be determined by (18).

$$\xi(t) = \text{logsig}\left(\frac{\frac{T}{2} - t}{k}\right)r(t) \quad (18)$$

where $\text{logsig}()$ is a logarithmic sigmoid transfer function, T is the predefined maximum number of iterations, t is the current iteration number, k is for changing $\text{logsig}()$ function's slope, and $r(t)$ is a random value within $(0, 1)$.

B. Modified BSO Based Tracking Control

The proposed BSO based online tuning PID control for each member is shown in Algorithm 3. The inputs are sensor data from the robot detector, which can indicate the range and bearing of other robots in its field of view. The predefined

parameters include safe distance for anti-collision, and parameters for BSO, such as the elite percentage, and probability values defined in the algorithm. By keeping an elite and normal list, the robot controller updates the PID parameters in every step and gets the relatively optimal value for the next move. It needs to be mentioned that the target pose may change during the movements. The present method is able to track changing targets with relatively optimal control parameters.

Algorithm 3 Adaptive Coordinated Motion Control

```

1: Input: Robot Detections, Obstacle Detections
2: Initialize arguments: Safe Distance ( $d_s$ ), Population Size
   ( $N$ ),  $perce$ ,  $p_e$ , and  $p_{one}$ ;
3: Randomly Generate  $N$  Solutions;
4: Evaluate the Generated  $N$  Solutions;
5: Initialize Elite List and Normal List.
6: while True do
7:   if  $rand < p_e$  then       $\triangleright$  new solution from based on
    elitists
8:     if  $rand < p_{one}$  then
9:       Generate a new individual based on one ran-
      domly selected solution from elite list;
10:    else
11:      Generate a new individual based on two ran-
      domly selected solutions from elite list;
12:    else       $\triangleright$  generate a new individual based on normals
13:      if  $rand < p_{one}$  then
14:        Generate a new individual based on one ran-
      domly selected solution from normal list;
15:      else
16:        Generate a new individual based on two ran-
      domly selected solutions from normal list;
17:    Evaluate the Generated New Solution;
18:    Update the Elite and Normal Lists;
19:     $K_{pid}^*$  = The best solution in Elist;
20:    Follow the reference using (9);

```

V. RESULTS

A. Configuration

The sensor range of a single robot is set to 10m, and the safe distance d_s is set to 0.5m. The desired distance and bearing angle to the target robot is 1m and $\pm\pi/4$, respectively. For the left part of a v-shaped formation, this angle is $\pi/4$, while the right part is $\pi/4$ correspondingly. Initially, the swarm members are randomly distributed in an $N \times N$ m area, and a swarm leader is assigned to guide the whole swarm to follow a specific trajectory. The position of the swarm leader is located at $((N - 1)/2, (N - 1)/2)$, where N is the total number of the swarm members. We set N to be odd for convenience. For example, as shown in Figure 3, a swarm with 11 members is randomly distributed in an area of 30×30 , the leader for the whole swarm is located at (5, 5). The Mobile Robot Simulation Toolbox for Matlab is used for the verification of the proposed method. All the tests were implemented on an iMac with 3.6 GHz Intel Core i9, 8GB DDR4 memory with Matlab 2019b.

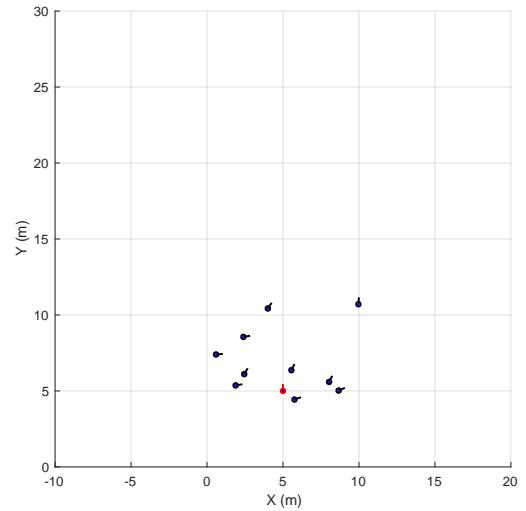


Fig. 3. Initial Configuration

B. Formation Control

We first tested the proposed formation control method under the above initial distribution. The leader is configured to move from (5, 5) to (5, 25), the trajectories, and the final formation of the swarm are shown in Figure 4.

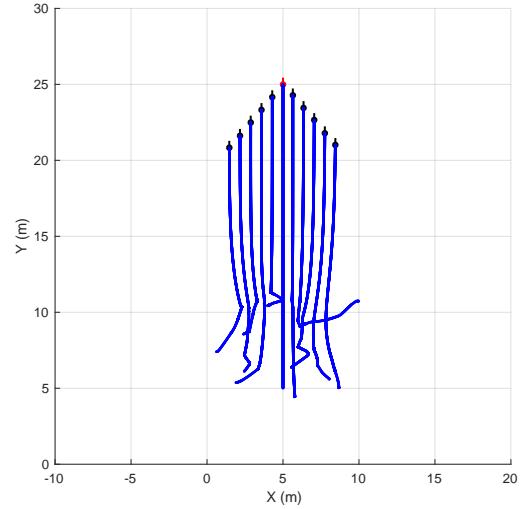


Fig. 4. Formation trajectories of with followers

It should be noted that the swarm leader here is adopted only to guide the whole swarm, but not every member will follow it. Each follower will track the nearest neighbor in a particular direction. The parameters' changes for each follower are shown in Figure 5. The control parameters for the PID tracking controller for each member is optimized during iterations. From those curves, we know that some of the controller parameters converged after a few iterations, such as for robots 1, 2, and 8, while the controller parameters of other robots converged after certain steps of guided searching

operations. The simulation indicated that the proposed method can determine the controller parameters with optimized values.

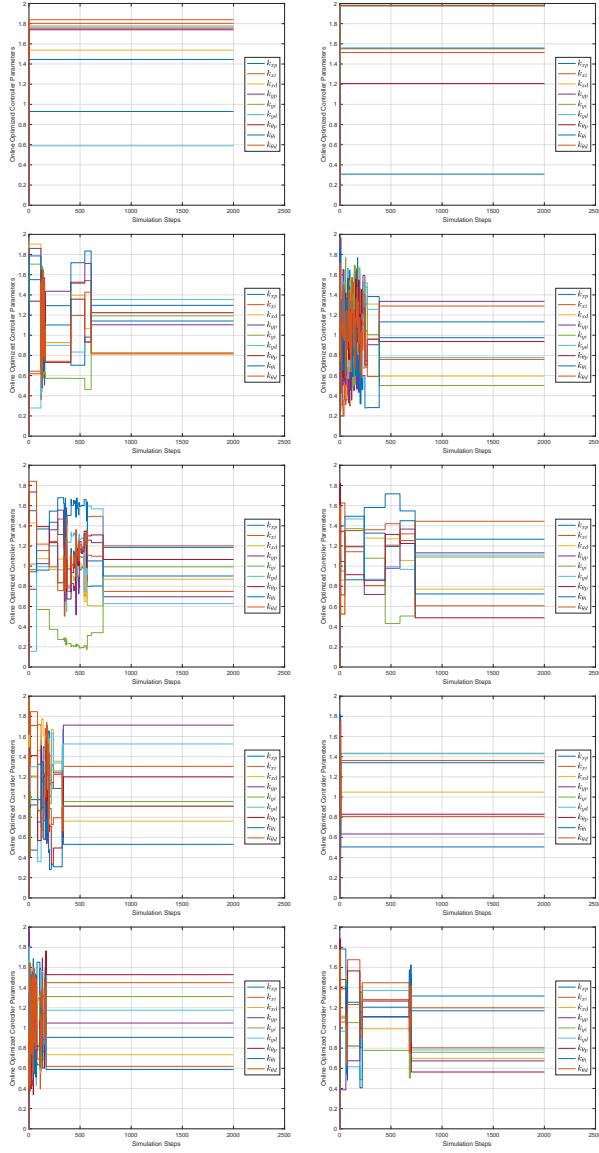


Fig. 5. The control parameters convergence process of each member

Furthermore, the tracking errors of each robot in the swarm are also converged to satisfactory values, as shown in Figure 6. Due to the followed target may change during the formation procedure, or because of the anti-collision operations, the errors curve may have some vibrations, but after the formation is formed and keep stable, the errors will decrease and converge to minimal values.

C. Flexibility

We also tested the flexibility of the proposed method by letting the swarm leader perform a U-turn. The initial distribution and trajectories of the swarm are shown in 7a and Figure 7b, respectively.

We can see from the figures, although the leader did not broadcast its velocity to others, the proposed method is able

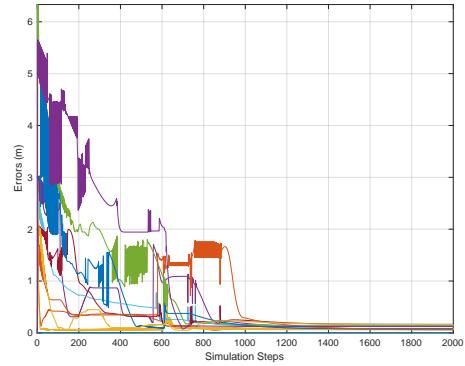
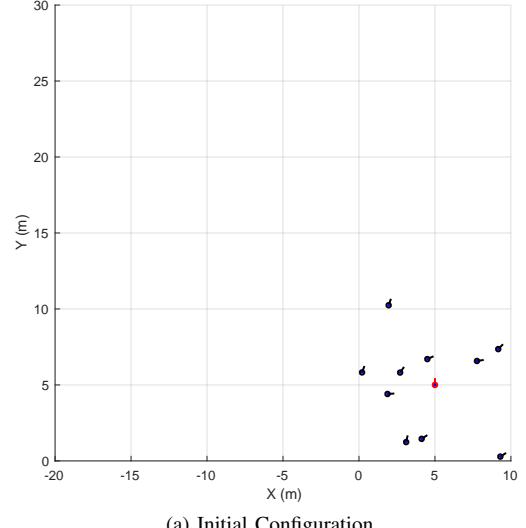
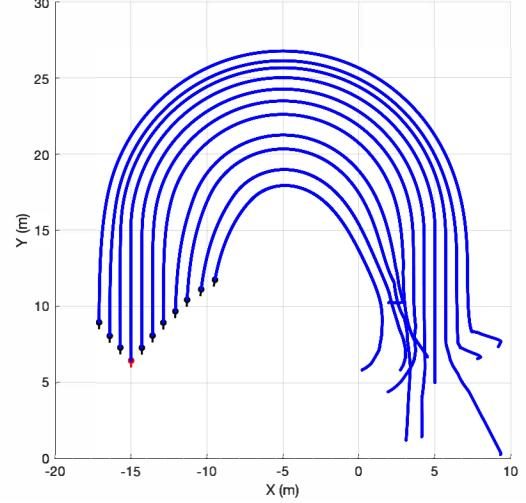


Fig. 6. Tracking Errors of each robot



(a) Initial Configuration



(b) Final formation and traces

Fig. 7. Results of Flexibility Simulation

to follow the target member to form a predefined formation, with the online tuning optimal controller. In this simulation, the parameters reach the convergent values after the maximum

of 1000 simulation steps, which are shown in Figure 8. The corresponding errors' changes are given in Figure 9. Since we constrained the maximum forward and turning speed of each robot, the errors were increasing slightly when the whole swarm was making a U-turn.

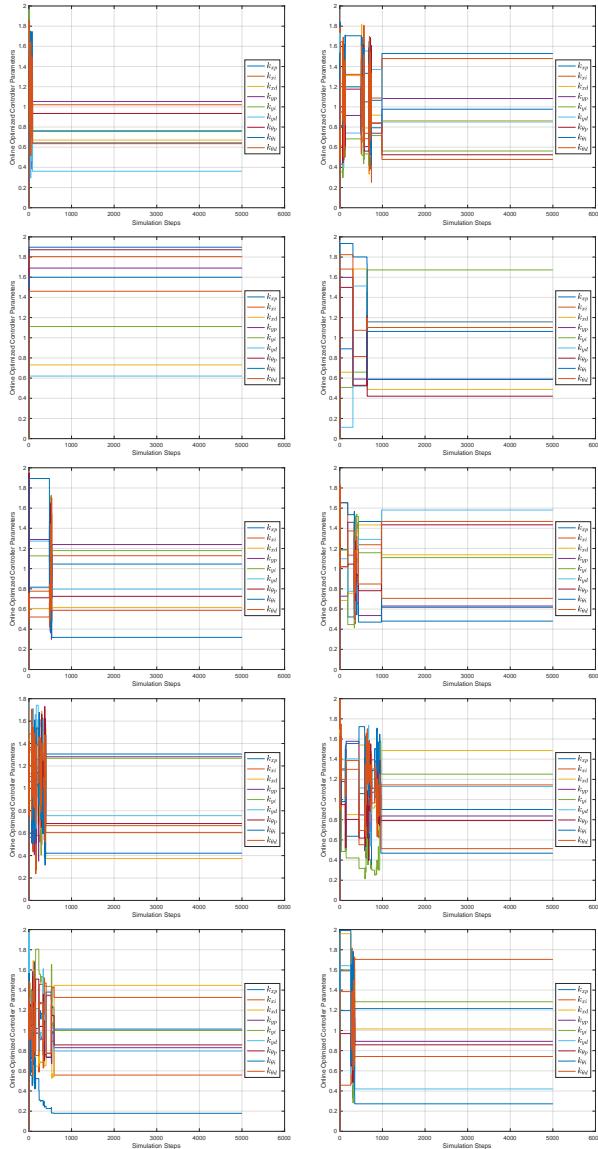


Fig. 8. The control parameters convergence process of each member

D. Scalability

To test the scalability of the proposed method, we conducted the simulation under different population sizes of the swarm. The statistical results are presented in Figure 10. We test the method 10 times for each population configuration, i.e., 5, 7, 9, 11, 13, 15, 17, 19, 21, 31, 41 and 51 respectively. Each bar set in the figure indicates the average errors after convergence, as well as the average convergence time. The convergence time is increasing with the population. However, the final average errors for each swarm is at the same level. A figure

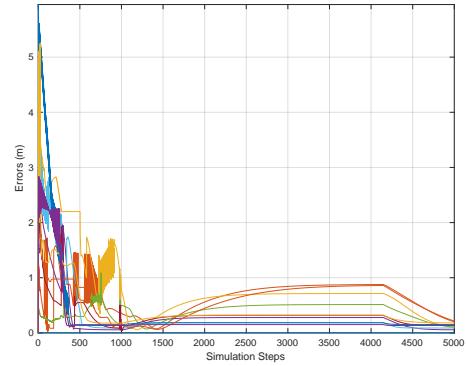


Fig. 9. Errors changing during simulation

of error change for a 51 robot swarm is shown in Figure 11. This simulation indicates that the proposed method is effective under different population size, i.e. with good scalability.

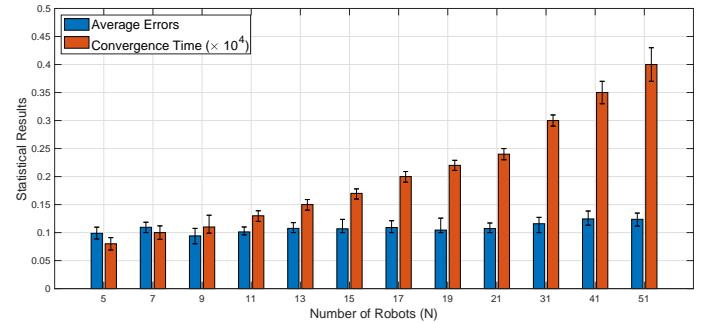


Fig. 10. Statistical results for scalability

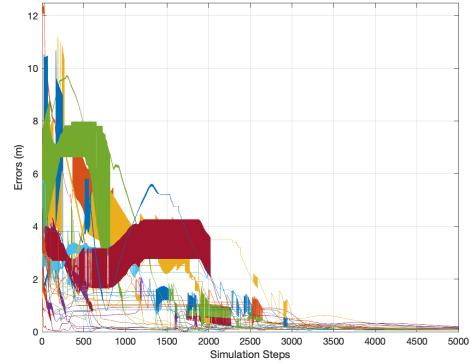


Fig. 11. Errors change with 50 followers

VI. CONCLUSION

This paper proposed an online optimization strategy based on the Brain Storm Optimization (BSO) algorithm for the coordinated motion control of swarm robotics. By adopting an incremental PID control law, the method is able to control the coordinated motion of a swarm of robots without knowing the leader's velocities. Furthermore, the controller

parameters were optimized online with the adoption of the BSO algorithm, which can deal with the dynamical target change and anti-collision requirements. The simulation results have demonstrated that the proposed method is effective for the coordinated motion problem of robotic swarms. The flexibility and scalability have also been validated to ensure that the proposed method can adapt to different situations, which makes this method be a good candidate for coordinated motion control for swarm robotics under different application scenarios.

REFERENCES

- [1] V. Trianni and A. Campo, "Fundamental collective behaviors in swarm robotics," in *Springer Handbook of Computational Intelligence*. Springer, 2015, pp. 1377–1394.
- [2] Y. Tan and I. Giannoccaro, Eds., *Handbook of Research on Design, Control, and Modeling of Swarm Robotics*; ser. Advances in Computational Intelligence and Robotics. IGI Global, 2016.
- [3] J. Yang, X. Wang, and P. Bauer, "Formation forming based low-complexity swarms with distributed processing for decision making and resource allocation," in *2016 14th International Conference on Control, Automation, Robotics and Vision (ICARCV)*. IEEE, 2016, pp. 1–6.
- [4] J. Yang, R. Xiong, X. Xiang, and Y. Shi, "Exploration enhanced rpsos for collaborative multitarget searching of robotic swarms," *Complexity*, vol. 2020, 2020.
- [5] J. Yang, X. Wang, and P. Bauer, "Extended pso based collaborative searching for robotic swarms with practical constraints," *IEEE Access*, vol. 7, pp. 76328–76341, 2019.
- [6] R. Fierro, L. Chaumowicz, and V. Kumar, "Multi-robot cooperation," in *Autonomous Mobile Robots*. CRC Press, 2018, pp. 417–460.
- [7] A. Weinstein, A. Cho, G. Loianno, and V. Kumar, "Visual inertial odometry swarm: An autonomous swarm of vision-based quadrotors," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 1801–1807, 2018.
- [8] S. Liu, D. Sun, and C. Zhu, "Coordinated Motion Planning for Multiple Mobile Robots Along Designed Paths With Formation Requirement," *IEEE/ASME Transactions on Mechatronics*, vol. 16, no. 6, pp. 1021–1031, 2012.
- [9] A. Stranieri, E. Ferrante, A. E. Turgut, V. Trianni, C. Pincioli, M. Birattari, and M. Dorigo, "Self-organized flocking with an heterogeneous mobile robot swarm," in *ECAL*, 2011, pp. 789–796.
- [10] A. E. Turgut, H. Çelikkannat, F. Gökçe, and E. Şahin, "Self-organized flocking in mobile robot swarms," *Swarm Intelligence*, vol. 2, no. 2–4, pp. 97–120, 2008.
- [11] C. W. Reynolds, "Flocks, herds and schools: A distributed behavioral model," in *ACM SIGGRAPH Computer Graphics*, vol. 21. ACM, 1987, pp. 25–34.
- [12] M. Brambilla, E. Ferrante, M. Birattari, and M. Dorigo, "Swarm robotics: A review from the swarm engineering perspective," *Swarm Intelligence*, vol. 7, no. 1, pp. 1–41, 2013.
- [13] H. Oh, A. R. Shirazi, C. Sun, and Y. Jin, "Bio-inspired self-organising multi-robot pattern formation: A review," *Robotics and Autonomous Systems*, vol. 91, pp. 83–100, 2017.
- [14] X. Liu, S. S. Ge, and C.-H. Goh, "Vision-Based Leader–Follower Formation Control of Multiagents With Visibility Constraints," *IEEE Transactions on Control Systems Technology*, vol. 27, no. 3, pp. 1326–1333, May 2019.
- [15] M. A. Lewis and K.-H. Tan, "High precision formation control of mobile robots using virtual structures," *Autonomous robots*, vol. 4, no. 4, pp. 387–403, 1997.
- [16] W. M. Spears and D. F. Spears, *Physicomimetics: Physics-Based Swarm Intelligence*. Springer Science & Business Media, 2012.
- [17] J. Yang, X. Wang, and P. Bauer, "Line and V-Shape Formation Based Distributed Processing for Robotic Swarms," *Sensors*, vol. 18, no. 8, p. 2543, Aug. 2018.
- [18] Z. Jiang, X. Wang, and J. Yang, "Distributed line formation control in swarm robots," in *2018 IEEE International Conference on Information and Automation (ICIA)*. IEEE, 2018, pp. 636–641.
- [19] D. Shen, W. Sun, and Z. Sun, "Adaptive PID formation control of nonholonomic robots without leader's velocity information," *ISA Transactions*, vol. 53, no. 2, pp. 474–480, Mar. 2014.
- [20] Y. Shi, "An Optimization Algorithm Based on Brainstorming Process," *International Journal of Swarm Intelligence Research (IJSIR)*, vol. 2, no. 4, pp. 35–62, 2011.
- [21] J. Yang, L. Qu, Y. Shen, Y. Shi, S. Cheng, J. Zhao, and X. Shen, "Swarm intelligence in data science: Applications, opportunities and challenges," in *International Conference on Swarm Intelligence*. Springer, 2020, pp. 3–14.
- [22] B. Mahdad and K. Srarri, "Security optimal power flow considering loading margin stability using hybrid ffa-ps assisted with brainstorming rules," *Applied Soft Computing*, vol. 35, pp. 291–309, 2015.
- [23] H. Qiu and H. Duan, "Receding horizon control for multiple uav formation flight based on modified brain storm optimization," *Nonlinear dynamics*, vol. 78, no. 3, pp. 1973–1988, 2014.
- [24] J. Yang, Y. Shen, and Y. Shi, "Visual fixation prediction with incomplete attention map based on brain storm optimization," *Applied Soft Computing*, vol. 96, p. 106653, 2020.
- [25] E. Tuba, D. Simian, E. Dolicanin, R. Jovanovic, and M. Tuba, "Energy efficient sink placement in wireless sensor networks by brain storm optimization algorithm," in *2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC)*. IEEE, 2018, pp. 718–723.
- [26] A. Aldhafeeri and Y. Rahmat-Samii, "Brain storm optimization for electromagnetic applications: Continuous and discrete," *IEEE Transactions on Antennas and Propagation*, vol. 67, no. 4, pp. 2710–2722, 2019.
- [27] J. Yang, Y. Shen, and Y. Shi, "Brain storm robotics: an automatic design framework for multi-robot systems," in *2020 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2020, pp. 1–8.
- [28] H. Oh, A. R. Shirazi, C. Sun, and Y. Jin, "Bio-inspired self-organising multi-robot pattern formation: A review," *Robotics and Autonomous Systems*, vol. 91, pp. 83–100, 2017.
- [29] J. Yang, X. Wang, and P. Bauer, "V-Shaped Formation Control for Robotic Swarms Constrained by Field of View," *Applied Sciences*, vol. 8, no. 11, p. 2120, Nov. 2018.
- [30] O. Soysal and E. Sahin, "Probabilistic aggregation strategies in swarm robotic systems," in *Swarm Intelligence Symposium, 2005. SIS 2005. Proceedings 2005 IEEE*. IEEE, 2005, pp. 325–332.
- [31] V. Gazi, "Swarm aggregations using artificial potentials and sliding-mode control," *IEEE Transactions on Robotics*, vol. 21, no. 6, pp. 1208–1214, 2005.
- [32] W. Ren and R. W. Beard, "Consensus seeking in multiagent systems under dynamically changing interaction topologies," *IEEE Transactions on automatic control*, vol. 50, no. 5, pp. 655–661, 2005.
- [33] J. Desai, J. Ostrowski, and V. Kumar, "Controlling formations of multiple mobile robots," in *Proceedings. 1998 IEEE International Conference on Robotics and Automation (Cat. No.98CH36146)*, vol. 4. Leuven, Belgium: IEEE, 1998, pp. 2864–2869.
- [34] R. Alur, A. Das, J. Esposito, R. Fierro, G. Grudic, Y. Hur, V. Kumar, I. Lee, J. Ostrowski, G. Pappas et al., "A framework and architecture for multirobot coordination," in *Experimental Robotics VII*. Cham: Springer, 2001, pp. 303–312.
- [35] A. J. Nebro, J. J. Durillo, and C. A. C. Coello, "Analysis of leader selection strategies in a multi-objective particle swarm optimizer," in *2013 IEEE Congress on Evolutionary Computation*. IEEE, 2013, pp. 3153–3160.
- [36] I. Slavkov, D. Carrillo-Zapata, N. Carranza, X. Diego, F. Jansson, J. Kaandorp, S. Hauert, and J. Sharpe, "Morphogenesis in robot swarms," *Science Robotics*, vol. 3, no. 25, p. eaau9178, Dec. 2018.
- [37] H. Sayama, "Swarm chemistry," *Artificial life*, vol. 15, no. 1, pp. 105–114, 2009.
- [38] D. Roy, M. Maitra, and S. Bhattacharya, "Study of formation control and obstacle avoidance of swarm robots using evolutionary algorithms," in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. Budapest, Hungary: IEEE, Oct. 2016, pp. 003154–003159.
- [39] V. Sathiya and M. Chinnadurai, "Evolutionary Algorithms-Based Multi-Objective Optimal Mobile Robot Trajectory Planning," *Robotica*, vol. 37, no. 08, pp. 1363–1382, Aug. 2019.
- [40] G. Capi and Z. Mohamed, "Multiple Robots Formation—A Multiobjective Evolution Approach," *Procedia Engineering*, vol. 41, pp. 156–162, 2012.
- [41] Z. Qu, *Cooperative Control of Dynamical Systems: Applications to Autonomous Vehicles*. New York: Springer, 2009.
- [42] Y. Shi, "Brain storm optimization algorithm in objective space," in *2015 IEEE Congress on evolutionary computation (CEC)*. IEEE, 2015, pp. 1227–1234.