Online Planning-based Gene Regulatory Network for Swarm in Constrained Environment

1st Yutong Yuan
College of Systems Engineering
National University of Defense Technology
Changsha, China
foreveryyt@qq.com

2nd Xiaomin Zhu
College of Systems Engineering
National University of Defense Technology
Changsha, China
xmzhu@nudt.edu.cn

3rd Zhun Fan
Department of Electronic Engineering
Shantou University
Shantou, China
zfan@stu.edu.cn

4th Li Ma
College of Systems Engineering
National University of Defense Technology
Changsha, China
mali10@nudt.edu.cn

5th Ji Ouyang
College of Systems Engineering
National University of Defense Technology
Changsha, China
oyangji15@nudt.edu.cn

6th Ji Wang
College of Systems Engineering
National University of Defense Technology
Changsha, China
wangji@nudt.edu.cn

2021 7th International Conference on Big Data and Information Analytics (BigDIA) | 978-1-6654-2466-0/21/$31.00 ©2021 IEEE | DOI: 10.1109/BIGDIA53151.2021.9619649

***Abstract*—Swarm intelligence inspired by the all kinds of theory from nature has developed rapidly towards dealing with complicated problems. In realm of collective robots, a main stream is to urge robots more intelligent in performance of tasks, such as distributed system, complete self-organization and reliance only on local information. Gene regulatory networks (GRNs) construct the cell theory about the regulatory activities between genes and protein and succeeded in being exerted to multirobot system and achieving the collective entrapping and tracking function. The excellent self-organized and robust characteristic in GRNs guarantees collective tasks more fault-tolerant. Unfortunately, swarm robots are easily trapped into perplexed stuck and stagnate still when robots lose contact with targets because of obstacle blocking. To overcome the dilemma, we proposed online planning-based gene regulatory network (OP-GRN) to bring robots to normal orbit and supply guidance to reconstruct the contact with targets, which involves online grouping planning (OGP) and online path planning (OPP). The experiment results demonstrate the efficacy and superiority of our model in constrained environment.**

***Index Terms*—swarm intelligence, gene regulatory networks, target lost, online planning, constrained environment**

I. Introduction

Recently, swarm intelligence has developed to deal with some complex problems [1] and tilted toward fully unmanned and self-organized feature. When equipped with sophisticated and advanced intelligence, the action of swarm robots could accomplish complex tasks independently and there is no need in people's participation. However, there is a long way to go. Some self-organized swarm intelligence is easily trapped into stuck when some external basic condition fails to be detected, e.g., swarm lose contact with their target or beacon. Hierarchal gene regulatory networks (H-GRN) is type of bio-inspired swarm intelligence model for entrapping targets [2], building the mephor between cell mechanism and entrapment task of swarm robots. There are three necessary input for H-GRN: target information, neighbor information and environment information. Target information is a key to construct protein concentration to generate trapping pattern for swarm. Unavoidably, a target sometimes could rely on its advantage of small bulk to escape from the sight line of the swarm robots, e.g., a small bulk one could get through tunnel or narrow path but swarm robots merely bypass. When losing information of the target, swarm robots merely rely on simple motion, e.g., most of robots follow few robots that still detect the target until all of them lose sight of the target and wait in place or most of robots start to bypass the "obstacle" they have no idea how large and complicated it is, which both makes original tasks stuck in backwater. Hence, we proposed online planning-based gene regulatory network (OP-GRN) to break the dilemma constrained environment brings. OP-GRN contains online grouping planing (OGP) and online path planing (OPP). OGP instructs the swarm robots that cannot detect targets to regroup online and the number of group in need counts on analysis of situation awareness, e.g., the possible position targets escape to or the command specific tasks require. OPP utilizes improved rapidly-exploring random tree (RRT*-ϵ) supply suitable paths for all sub-swarms.

Our proposed model makes several contributions to swarm robots in constrained scenario where leads to a target lost. Firstly, OP-GRN enables swarm robots to reconstruct task when swarm robots cannot detect targets and get stuck, compared with traditional GRNs. Secondly, OGP uses a spot of

This research was supported by the National Natural Science Foundation of China 61872378, the National Natural Science Foundation of China under grant 62002369, the Scientific Research Project of National University of Defense Technology under grant ZK19-03, the Key Laboratory of Digital Signal and Image Processing of Guangdong Province, the Key Laboratory of Intelligent Manufacturing Technology (Shantou University), Ministry of Education, the Science and Technology Planning Project of Guangdong Province of China (grant number 180917144960530), the Project of Educational Commission of Guangdong Province of China (grant number 2017KZDXM032), the State Key Lab of Digital Manufacturing Equipment & Technology (grant number DMETKF2019020), and the Science and Technology Planning Project of Guangdong Province of China (grant number 180917144960530, 190827105585418, 2019A050519008, 2019A050520001, 2021A0505070003, 2021A0505030072).

communication cost to regroup lost robots to form sub-swarms and most of lost robots join the nearest group in voluntary way. Thirdly, OPP is used to bring the sub-swarm to the correct orbit that points to strategic position to besiege a escaped target. Finally, OP-GRN extends the application of GRNs in constrained environment and describes the corresponding dynamic equation in detail.

The rest of this paper is organized as follows. Sect. II reviewed related work. Sect. III proposed the OP-GRN model, consisting of online grouping planning, online path planning and corresponding GRN dynamic equation. Sect. IV presented the experimental setting. Sect. V exhibited experimental results and disccusion. Finally, the paper made conclusions and discusses some future work in Sect. VI.

II. Related Work

Swarm intelligence is exerted to deal with practical problems through imitating biological behaviors, e.g., fish schooling [3], bird flocking [4] and ant colonies [5]. These intelligent bio-inspired behaviors help them to survive in this cruel world including strategies engraved into nature instincts for predation and avoiding predators. Besides, there are some microscopic swarm behaviors morphogen diffusion [6], reaction–diffusion model (RD) [7], gene regulatory networks(GRNs) [2], and chemotaxis [8]. Grouping plays a key role in swarm intelligence because chaotic individual behaviors could upgrade to collective behaviors and emerge to swarm intelligence when individuals unite together. Traditional grouping methods revolve around a potential center control, such as global optimization and clustering. Al-Obaidy et al. [9] achieve balanced centralized grouping in terms of genetic algorithm. Although this method guarantees fewer grouping centers and harmonious number of members in each group, it does not consider the robots' communication load in the process of grouping. Unfornately, designating the specific members for a group in central controller not only comsumes lots of time in calculation but also the time lag between calculation results and practical dynamic situation is easily to account for inexistence that some designated member has gone away and leave the communication range. Wang et al. [10] proposed a chained-grouping method based on the K-nearest neighbor and a joining mechanism for those that were not in each group after chain grouping.The chained-grouping lacks efficiency in grouping and makes group pattern long-stripe ribbon shape, which leads to a dispersive pattern and obstructs the efficiency in the group departing from the original swarm. A remarkable strategy in his work is to empower individuals to voluntarily join the group that an individual is close to. Although the strategy may make the number of members in one group out of control, yet, it is well-suited to dynamic situation and to reduce the time lag mentioned before. Therefore, we propose an online grouping method to rapidly reconstruct swarm based on this mechanism.

Path planning is a hot issue in robot system, but most of work concentrates on single robot. Actually, swarm path planning should be emphasized because more complicated environment requires more ordered path planning to enhance the intelligence of swarm. I believe most of intelligent methods used into single robot systems should be beneficial to multirobot system. The difference is that swarm robots need to consider pattern problem but a single robot does not. For the sake of adaptation in unknown or changeable environment, LaValle et al. [11] proposed rapid-exploring random tree (RRT) that could rapidly search in map and find a good path in constrained environment. However, the path from RRT is not optimal enough. Karaman et al. [12] proposed RRT*, an improved version, backtracks the path planning cost between parents and their child to optimize the final result of path planning. Online path planning in our work does not need real-time path planning and support swarm robots only when they need. Besiders, we slightly improve RRT* for keeping swarm pattern when swarm robots bypass obstacles.

III. Online Planning-based Gene Regulatory Network

In traditional gene regulatory networks, swarm of robots perform excellently in a self-organized way to entrap or track targets. Also, some of gene regulatory networks consider the influence of obstacles and there are some strategy for avoiding obstacles used in confined environment and even for cooperating with obstacles to improve efficiency in entrapment task. However, there is no doubt that these networks proposed in a indispensable assumption that robots need possess positional information of targets are easier to fail in confined environment because unpredicted confined environment could obstruct those movement and make robots lose the sight or detection on the target. For example, swarm robots taken up big area are hard to go through narrow tunnel. When a target easily passes through a narrow tunnel, swarm robots chasing for the target are easily trapped into a stuck around the access and have to bypass to torpidly discover possible path. As losing the positional information about the target evolving with time, those robots farther away from the target start to swtich to non-organized status that merely follows organized robots who still possess positional information about the target. Hence, less and less robots possess positional information about the target, as with chronic death, and the target finally escape from entrapment or tracking. The feature of self-organization GRNs bring to robots may greatly decline action capability of swarm robots in the condition. For the description, we define an organized robot as a robot that detects a target, a non-organized or lost robot as a robot that doesn't detect a target, and a reorganized robot as a robot that are reintegrated through online planning. The state transition diagram in Fig.2 reveal the relationship between the three statuses.

In this section, we introduce online grouping planning, online path planning and dynamic equation of OP-GRN. The process of OP-GRN is to extend the function of traditional GRNs when swarm robots trapped into target loss(shown in Fig.1). When swarm robots cannot detect a target, they independently send task failure information and request for assist to cloud. Cloud consistently receives information from

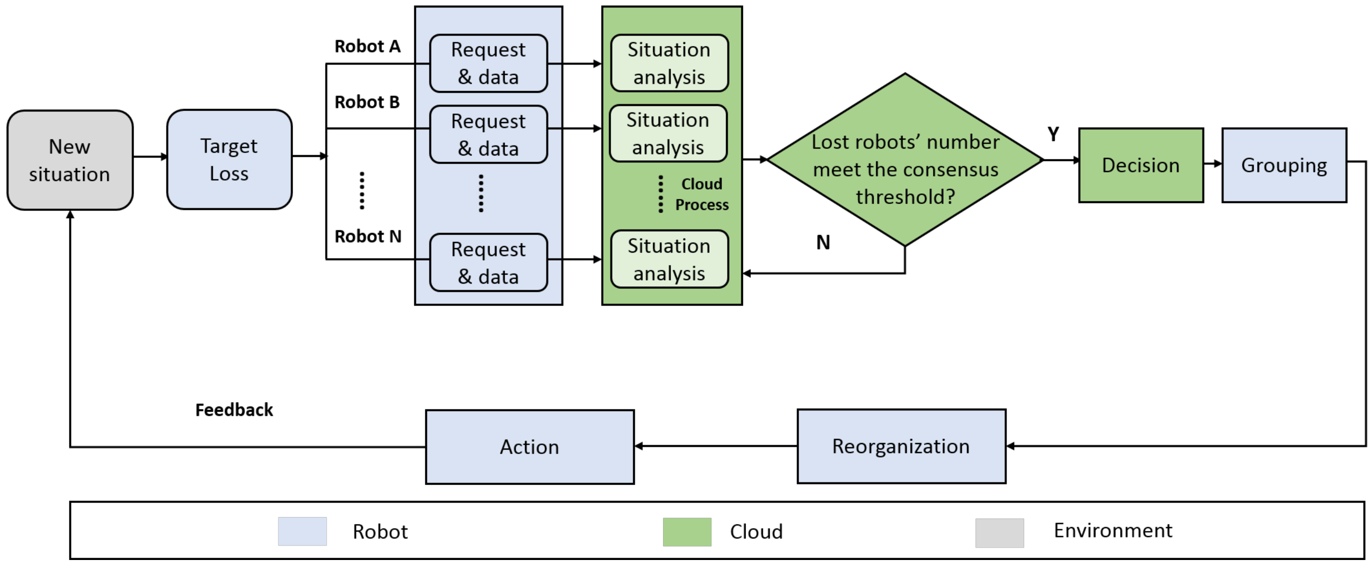


Fig. 1: The process of OP-GRN

robots and analyzes the situation. When the lost robots' number comes to the threshold set beforehand, the cloud starts to accept those request, calculate the information of lost robots and make decision on regrouping. In this part, some reorganized organizers will be reckoned to be beacon to attract other non-organized robots to join them. Afterwards, these reorganized organizers download the expected path from cloud and take action to reach designated places where robots may refind the target lost before. Other reorganized robots follow their organizers until they discover targets again. If these organized robots find the target, they will transform their status to organized robots and entrap the target. Maybe there are many sub-swarms following different paths to different places, yet, they could still cooperate to entrap the same target after "reorganized" status switches to "organized" without conflict because GRNs has distributed characteristic.

A. *Online Grouping Planning*

Online route-planning based gene regulatory network is proposed to improve the situation where more and more swarm robots are losing contact with a target owing to environment obstruction and plan shortest routes for non-organized robots to bypass obstacles and reach the strategic locations which the lost target could have passed through. In this process, the non-organized robots are going to undergo online grouping planning and online path planning, including status transformation from non-orgniazed status to reorganized status and from reorganized status to organized status(shown in Fig.2).

As more and more non-organized robots sending request for online support and reaching threshold value t_g for online planning, online grouping planning starts to reintegrate these non-organized robots(shown in Fig.3). Firstly, online grouping planning separates non-organized robots into c sub-swarms and designates c reorganizers as the center robots of the sub-swarms. c reorganizers are the c robots who possess the most neighbors and who are more than r_g apart respectively. Then, the other non-organized robots are voluntary to join corresponding sub-swarm in terms of proximity principle. In general, the c is usually decided by task requirement, e.g., there should be c potential positions to implement a target pursuit and interception. Similarly, c also decides on the population size of sub-swarms, which influences the performance of sub-swarms. In pratice, c is a expected grouping number and a better performance of OGP can be attained by controlling appropriate distance between organizers r_g. For non-organized robots, the positional information, the unique ID and the neighbors number need sending to cloud and updating consistently. Commonly, most of non-organized robots get stuck and stand still so that the positional information is always changeless.

To conveniently describe the spatial grouping of swarm robots, we established an abstract model of swarm robots. We assumed that U was the set of swarm robots. Each robot u is a tuple $\{s, id, n, d, l, pos\}$, where (1) s represents the current grouping state of robot u, (2) id is the unique identification number of robot u, (3) n is the number of neighbors of the robot u, (4) d is the relative distance between the neighbors and the robot, and (5) l is the special boolean flag for convener when cloud accepts request for regrouping, (6)pos represents the robot's current positional information. The robots' states were "organized," "unorganized," and "reorganized," which are denoted as $S = \{S_{org}, S_{uno}, S_{reo}\}$. Non-roganized robots send u_{id}, u_{pos}, u_n to the cloud, then the cloud sorts u_n in descending rank. The c robots with the most u_n is chosen to be reorganized organizers. Once the u_d between c robots satisfies the seperation distance r_g, the cloud will send reorganization order to these robots. If there are insufficient robots to satisfy the condition above, the seperation distance r_g will be self-adaptively decreased until c organizers are selected successfully.

B. Online Path Planning

Considering the time of uploading request and downloading predicted path, RRT* has competence for rapidly planning appropriate path in unknown or confined environment. The c reorganizers as terminals send current position information to cloud, then cloud analyzes situational information and calculates potential end position. RRT* searches feasible paths in the map and finally find the shortest path under little computational cost. Through RRT*, the shortest paths and corresponding predicted waypoint set $\mathbf{Q}_i^j$ are generated, which represents the i_{th} predicted waypoint of the j_{th} group. The predicted waypoint as beacons guides reorganized organizer to designated place the cloud reckons. Given that the path just guides the reorganized organizers and there are many following fellow around them, the sub-swarm bulk should be taken into account. A collision-free situation between robots and obstacles should be considered in RRT*. An inflated distance ϵ is added to RRT*, which leads to a virtual inflation in obstacles and smooths the change of sub-swarms' pattern when they bypass obstacles. Hence, the improved RRT*-ϵ is customized to lessen unnecessary avoidance to lower speed of swarm.

C. Dynamics of OP-GRN

H-GRN is one of most successful GRN to achieve swarm entrapment to a target, which mainly revolve pattern generation and formation around. In phase of pattern generation, the trap pattern is calculated in forms of maximal protein concentration. In phase of pattern formation, swarm robots independently goes to the pattern. The top-down model modularized information and control parts respectively so that robots could be easily custimized their own control strategy. Nonetheless, we propose two new dynamics for reorganized organizer and other reorganized robots. In our previous work [13], conflict-free strategy for GRN has been developed to achieve obstacle avoidance. Due to the fact that OPP has discovered a conflict-free path for reorganized organizers, the phase of pattern formation should slightly weaken the avoidance factor in motion.

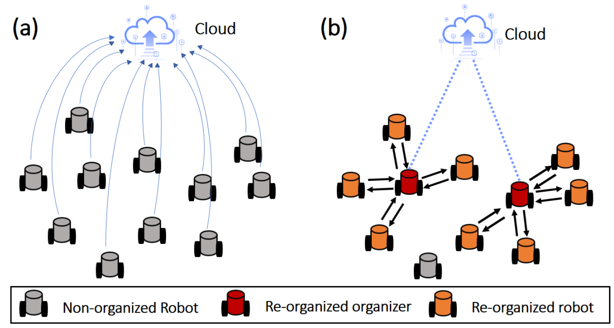


Fig. 3: The process of OGP.

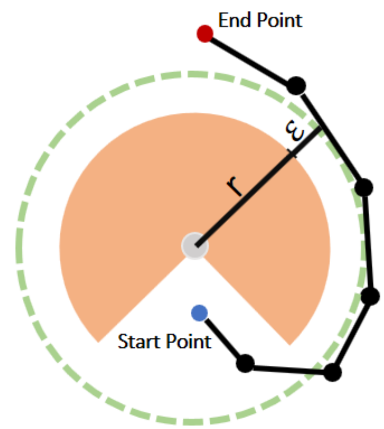


Fig. 4: The inflated distance ϵ used in RRT*.

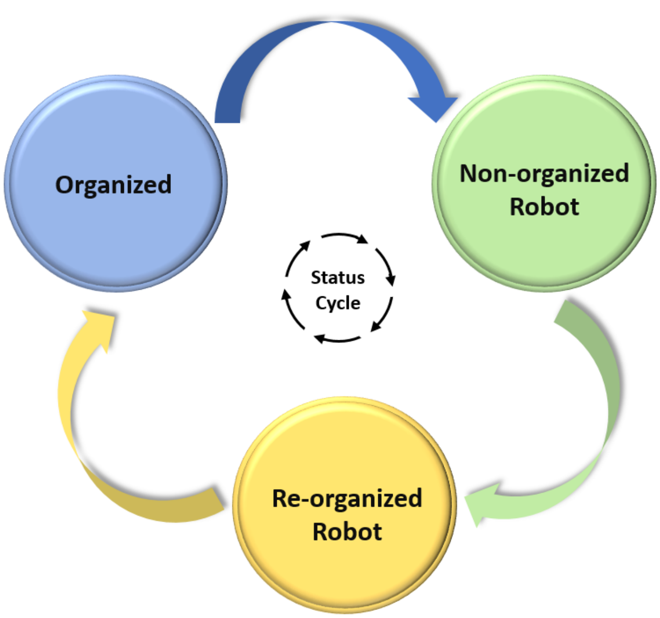


Fig. 2: The state transition diagram of swarm robots.

D. Upper Layer: Trap Pattern Generation

For generation of target tracking pattern, each organizing robots will utilize the following gene regulatory dynamics to generate the concentrations:

$$\frac{dp_j}{dt} = -p_j + \bigtriangledown^2 p_j + \gamma_j, \tag{1}$$

$$p = \sum_{j=1}^{n_t} p_j, \tag{2}$$

$$\frac{dg_1}{dt} = -g_1 + sig(p, \theta_1, k), \tag{3}$$

$$\frac{dg_2}{dt} = -g_2 + [1 - sig(p, \theta_2, k)], \tag{4}$$

$$\frac{dg_3}{dt} = -g_3 + sig(g1 + g2, \theta_3, k), \tag{5}$$

$$sig(x, z, k) = \frac{1}{1 + e^{-k(x-z)}}, \tag{6}$$

where p_j, an internal state, denotes the protein concentration produced by the j_{th} target. $\bigtriangledown^2$, a Laplacian operator, which is defined as the second-order derivative of p_j in the spatial domain and can be treated as the diffusion process in the biological system. p denotes the sum of concentrations from all n_t targets. k, a positive constant, controls the slope of sigmoid function. g_1, g_2 and g_3 denote the protein concentrations. The g_3, whose concentration defines the contour of target pattern, is regarded as the input of B-spline.θ_1, θ_2 and θ_3 are thresholds of a sigmoid function.

B-Spline is used to extract the contour of the target pattern generated by the upper layer of TH-GRN, and supply prediction function for the robots' location. NURBS (Non-uniform Rational B-spline) [14] can generate pattern evenly according to the equations as follow:

$$\mathbf{C}(u) = \frac{\sum_{i=0}^{n} N_{i,p}(u)\omega_i \mathbf{P}_i}{\sum_{i=0}^{n} N_{i,p}(u)\omega_i}, \tag{7}$$

where $\mathbf{C}(u)$ is polynomial curves fitting function, $N_{i,p}$ is B-spline basis functions with knot $u \in$[0,1] and $\mathbf{P}_i$ is matrix of control points. The knot needs to be set so as to approximate a uniform parameterization because of the uneven distribution of points on the pattern.

E. Lower Layer: Pattern formation

In this part, we describe the dynamics of four pattern formation respectively from organized robots, non-organized robots, reorganized robots.

1) Organized Robot:

$$G_i^1 = o_{11}A + o_{12}P_i + o_{13}D + o_{14}\beta(t)O, \tag{8}$$

$$\beta(t) = \begin{cases} 1, & when \quad avoiding \quad obstacle \\ 0, & else \end{cases} \tag{9}$$

where A is the factor of avoiding neighbors, P_i is the factor of direction to pattern , including $\mathbf{z_i}$ and α_t in Fig.1. D is neighbor density factor(guiding i_{th} robot to low density), O is the factor to keep away from obstacles and D is the factor pointing to low density within neighbor. $\beta(t)$ is a switching function to control avoiding mode. G_i is final sum of all direction factors. The coefficient $o_{11}, o_{12}, o_{13}, o_{14}$ are positive constant,where o_{14} goes beyond another three.

2) Non-organized Robot:

$$G_i^2 = o_{21}A + o_{22}C_1 + o_{23}\beta(t)O, \tag{10}$$

For those robots that do not detect any target, their movement behavior is governed by the following dynamics. Assume that a non-organizing robot has N_n neighbors, which are within its sensing range. The dynamics of this robot is determined by:

$$C_1 = \frac{dx}{dt} = \sum_{i=1}^{N_n}(\frac{dx_i}{dt} - \frac{dx}{dt}) \tag{11}$$

where C_1 is the direction toward neighbors, x denotes the current position of the non-organized robot and $\frac{dx}{dt}$ is the velocity of the robot.

3) Reorganized Robot:

$$G_i^{3,j} = r_{11}A + r_{12}C_2 + r_{13}D + r_{14}\beta(t)O, \tag{12}$$

where C_2 is the direction toward the corresponding reorganized organizer, $G_i^{3,j}$ is the final sum of all direction of the i_{th} robot of the j_{th} sub-swarm.

4) Reorganized Organizer:

$$G_i^{4,j} = r_{21}A + r_{22}Q_i^j + r_{23}\beta(t)O, \tag{13}$$

where Q_i^j is the i_{th} waypoint of the j_{th} sub-swarm's planning path RRT*-ϵ, $G_i^{4,j}$ is the final sum of all direction of the i_{th} robot of the j_{th} sub-swarm. A organizer goes to Q_{i+1}, once it reaches Q_i.

IV. EXPERIMENTAL SETTING

The experiment is set to 25m $\times$ 25m scenario. There are 5 circle obstacles with a radius of 3m and 1 circle obstacle with a radius of 1m. The smaller one is set to a typical swarm constrained obstacle, which accounts for a narrow lane nearly obstructing swarm's bulk and merely permitting single individual through. The 6 obstacles constructs only two exits on left and right hand for the target's escaping. There are 20 non-organized robots generated within 2m around the coordinates (20, 20) and 1 target generated in coordinates (20, 20). The robots and the target initially defaults to moving upward. The target and robots keep a unfair condition, i.e., the target could pass through tunnel entrance because of small bulk. Whereas, swarm cannot pass it directly and have to bypass all obstacle. The task of robots is to entrap a escaping target and the task of the target is to try its best to avoid entrapment. Velocity of the target we set is smaller than swarm robots, which guarantees robots could catch up with the target and entrap it in collision-free environment. The tunnel terrain halves the velocity of the target after it enters the tunnel. Nonetheless, there is still a big challenge for swarm robots to besiege the escaping target.

In OPP process, the number of sample point is set to 2000. The path planning executes at per 500 sample points, therefore, there are four potential paths generated by RRT*-ϵ. In terms of the distance cost, the smallest one is chosen to send to reorganized organizers. The start point is the position the reorganized organizers stand at and the end point is the potential besiege position that the cloud reckons after analyzing the terrain and situation.

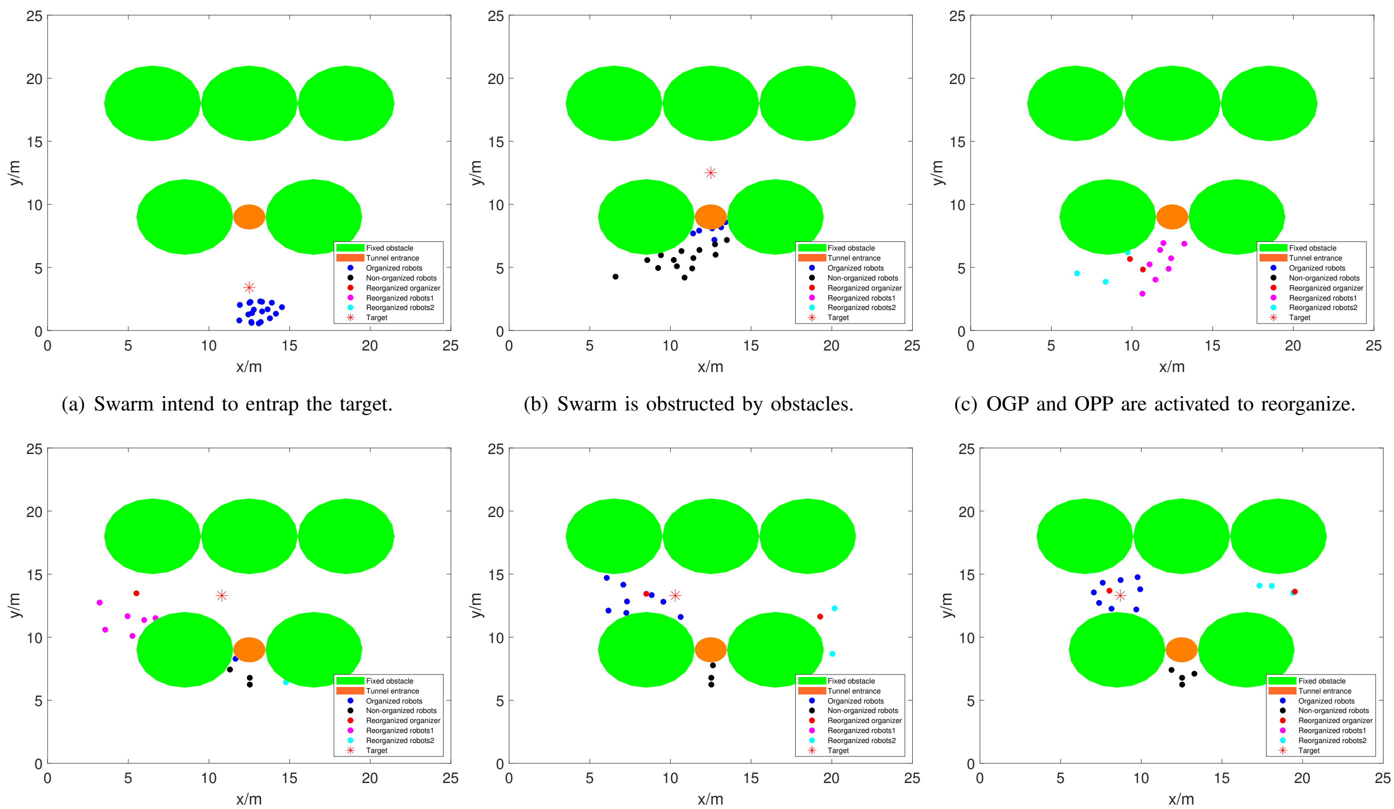
The overall notation in simulations is shown in TABLE I.

V. RESULTS AND DISCUSSION

The experimental process exhibits in Fig.5. Firstly, 20 non-organized robots detecting the escaping target turn their status to "organized" and endeavor to chasing (shown in Fig.5(a)). When swarm robots start to entrap the escaping target, the obstacles interrupt the closed pattern formation and many of robots have to avoid obstacles. Then, the target darts into tunnel and temporarily escapes from the entrapment. As more and more swarm robots cannot detect the escaping target, more and more swarm robots turn their status from "organized"

TABLE I: Notations used in simulations

Parameters	Description	Values
c	Expected number of grouping in OGP	2
r_g	Distance between groups in OGP	0.8
t_g	Threshold of cloud accepting requests to regroup	15
ϵ	Inflated distance for RRT*-ϵ in OPP	0.3
$\theta_1, \theta_2, \theta_3$	Thresholds of a sigmoid function in $Eq.(3)(4)(5)$	0.25,0.3,1.2
k	Slope of sigmoid function in $Eq.(6)$	1
$o_{11}, o_{12}, o_{13}, o_{14}$	Coefficient of the controller in a organized robot	1,1,1,1.5
o_{21}, o_{22}, o_{23}	Coefficient of the controller in a non-organized robot	1, 1, 1.5
$r_{11}, r_{12}, r_{13}, r_{14}$	Coefficient of the controller in a reorganized robot	1,1,1,1.5
r_{21}, r_{22}, r_{23}	Coefficient of the controller in a reorganized organizer	1,1,0.5
δ	Detection distance of a robot	5
ϕ	Communication range of a robot	5
v_r	Velocity of swarm robots	0.5
v_t, v_t'	Velocity of a target before and after entering the tunnel	0.2,0.1

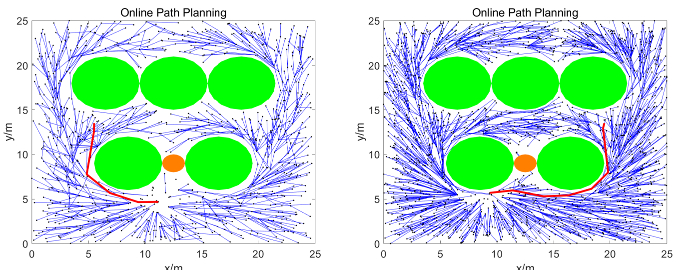


(a) Swarm intend to entrap the target.
(b) Swarm is obstructed by obstacles.
(c) OGP and OPP are activated to reorganize.
(d) Two sub-swarm go to designated places.
(e) One sub-swarm succeeds in detecting the target.
(f) The target is finally trapped.

Fig. 5: Process of OP-GRN entrapping an escaped target in a constrained environment.

to "non-organized". Then, all of robots get stuck to stand still and the requests for guidance consistently are received by cloud (shown in Fig.5(b)). The number of non-organized robots reaches threshold t_g and the OGP is triggered to regroup the swarm. The 2 reorganized organizers whose status changes to "reorganized" are chosen and the other non-organized robots join the sub-swarm those reorganized organizers live, according to principle of proximity . After joining sub-swarms, these non-organized robots turn their status to "reorganized" (shown in Fig.5(c)). Soon, the OPP is activated to push cloud to reckon potential positions to besiege the escaping target and to send predicted besiege paths to different reorganized organizers. The two reorganized sub-swarms start to obey the respective path planing to reach the desiganted position (shown in Fig.5(d)). The sub-swarm at left side is the first to detect the target again. The members of this sub-swarm turn their status to "organized" (shown in Fig.5(e)). Finally, the sub-swarm succeeds in entrapping the escaping target (shown in Fig.5(f)).

In OPP process, the predicted paths are reckoned respectively and sent to reorganized organizers by cloud. Owing to two potential postions reckoned by cloud, therefore, there are two predicted paths on the left side and the right side. The path planning results reflect on Fig.6. The path planning on left side is the result from 1000 sample points and the path planning on right side is the result from 2000 sample points. The results of OPP is shown in TABLE II and the processor of cloud is Inter(R) Core(TM) i7-9700F CPU @ 3.00GHz.



(a) Left Path (b) Right Path

Fig. 6: The results of RRT*-ϵ in simulations.

TABLE II: Results of OPP

RRT*-ϵ Information		
Sample Number	***Average Running Time***	***Average Waypoint Number***
2000	5.4s	8

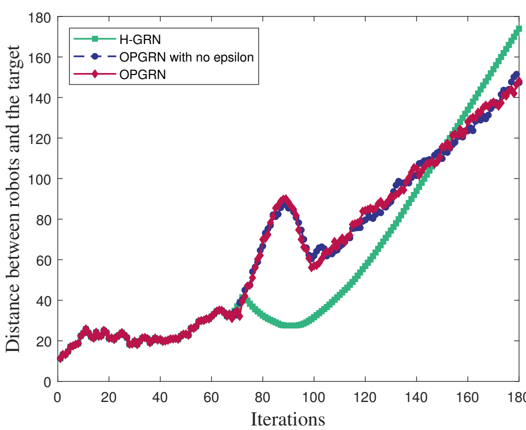


Fig. 7: The comparative experimental results between H-GRN and OP-GRN.

In the Fig.7, the comparative results between H-GRN and OP-GRN reveals the change of the distance between robots and the target in the overall process the Fig.5 shows. Before the iteration number is less than 67, the curves the three comparative models show are nearly same. Until the iteration number comes to 67, the knee point from H-GRN (green line) reflects most of robots are still following the target and even one or two finds the way to get in channel, which accounts for a descending trend. As for OP-GRN and OP-GRN with no epsilon, robots turn to request the cloud for help, start to group and reorganize and bypass the obstacles from two sides, therefore, the distance between robots and the target begins to rise. Obviously, most of robots get stuck outside the channel in H-GRN, so the distance between robots and the target consistently keeps going up. When the iteration number comes to 89, the OP-GRN and OP-GRN with no epsilon reach local peak, i.e., one of reorganized sub-swarm is truly being close to the target. Then, the distance between robots and the target starts to decline. Moreover, one of reorganized sub-swarm detects the target again and its members turn state to "organized" and entrap the target. When the iteration number comes to 99, the OP-GRN encounters the last knee point because one of sub-swarm has eventually entrapped the target successfully and there are other robots further getting away from the target, such as those non-organized robots stuck outside the channel and other sub-swarm stands by in another strategical position. Compared with OP-GRN, the OP-GRN with no epsilon makes sub-swarms suffer a unsmooth process because online path planning could not supply an action path considering the shape of swarm formation. The defective path planning may leads to a unnecessary inner positional harmonization when the sub-swarms bypass the obstacles.

VI. Conclusions and Future Works

We proposed online planning-based gene regulatory network (OP-GRN) to improve the traditional GRNs in being trapped into stuck when robots cannot detect an escaping target's information, which strategically brings robots to places where robots could detect and besiege the target again. In addition, OGP module has competence for reorganizing swarm in cloud-end synchronization and OPP module utilizes RRT*-ϵ to achieve inflated collision-free path planning for swarm robots. The experiment results demonstrate the efficacy and superiority of our model in constrained environment. Future works shall include accelerating the path planning for swarm, designing the entry and exit mechanism for grouping to achieve self-adapting adjustment in balancing number of members in each sub-swarm and applying the model to a larger-scale and complex scenario.

Acknowledgment

This research was supported by the National Natural Science Foundation of China 61872378, the National Natural Science Foundation of China under grant 62002369, the Scientific Research Project of National University of Defense Technology under grant ZK19-03, the Key Laboratory of Digital Signal and Image Processing of Guangdong Province, the Key Laboratory of Intelligent Manufacturing Technology (Shantou University), Ministry of Education, the Science and Technology Planning Project of Guangdong Province of China (grant number 180917144960530), the Project of Educational Commission of Guangdong Province of China (grant number 2017KZDXM032), the State Key Lab of Digital Manufacturing Equipment & Technology (grant number DMETKF2019020), and the Science and Technology Planning Project of Guangdong Province of China (grant number 180917144960530, 190827105585418, 2019A050519008, 2019A050520001, 2021A0505070003, 2021A0505030072).

REFERENCES

[1] Levent Bayındır. A review of swarm robotics tasks. *Neurocomputing*, 172:292–321, 2016.

[2] Yaochu Jin, Hongliang Guo, and Yan Meng. A hierarchical gene regulatory network for adaptive multirobot pattern formation. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 42(3):805–816, 2012.

[3] Shigeru Kondo and Takashi Miura. Reaction-diffusion model as a framework for understanding biological pattern formation. *science*, 329(5999):1616–1620, 2010.

[4] Craig W Reynolds. Flocks, herds and schools: A distributed behavioral model. In *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, pages 25–34, 1987.

[5] Akira Okubo. Dynamical aspects of animal grouping: swarms, schools, flocks, and herds. *Advances in biophysics*, 22:1–94, 1986.

[6] Jamie Davies. *Mechanisms of morphogenesis*. Academic Press, 2013.

[7] I Slavkov, D Carrillo-Zapata, N Carranza, X Diego, F Jansson, J Kaandorp, S Hauert, and J Sharpe. Morphogenesis in robot swarms. *Science Robotics*, 3(25):eaau9178, 2018.

[8] Hiroki Sayama. Swarm chemistry. *Artificial life*, 15(1):105–114, 2009.

[9] Mohaned Al-Obaidy, Aladdin Ayesh, and Alaa F Sheta. Optimizing the communication distance of an ad hoc wireless sensor networks by genetic algorithms. *Artificial Intelligence Review*, 29(3-4):183, 2008.

[10] Qiuzhen Wang, Xinjun Mao, Shuo Yang, Yin Chen, and Xinwang Liu. Grouping-based adaptive spatial formation of swarm robots in a dynamic environment. *International Journal of Advanced Robotic Systems*, 15(3):1729881418782359, 2018.

[11] Steven M LaValle et al. Rapidly-exploring random trees: A new tool for path planning. 1998.

[12] Sertac Karaman and Emilio Frazzoli. Incremental sampling-based algorithms for optimal motion planning. *Robotics Science and Systems VI*, 104(2), 2010.

[13] Yutong Yuan, Zhun Fan, Xiaomin Zhu, Meng Wu, Li Ma, Taosheng Fang, Zhaojun Wang, Weidong Bao, Yun Zhou, Huangke Chen, et al. Th-grn model based collective tracking in confined environment. In *International Conference on Swarm Intelligence*, pages 33–43. Springer, 2019.

[14] Les Piegl and Wayne Tiller. *The NURBS book*. Springer Science & Business Media, 1996.