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Study on Collaborative Task Assignment of Sphere Multi-Robot based on Group Intelligence Algorithm

Chenqi Li[1], Jian Guo[1,2*]
[1]*Tianjin Key Laboratory for Control Theory& Applications In Complicated systems and Intelligent Robot Laboratory Tianjin University of Technology BinshuiXidao Extension 391,Tianjin,300384,China*
fuqiang6369@hotmail.com; 1921934087@qq.com

Shuxiang Guo[1,2,3*]
[2] *Shenzhen Institute of Advanced Biomedical Robot Co., Ltd.*
No.12, Ganli Sixth Road, Jihua Street, Longgang District, Shenzhen,518100,China
**corresponding author : jianguo@tjut.edu.cn*

and Qiang Fu[1]
[2] *Key Laboratory of Convergence Medical Engineering Systems and Healthcare Technology, The Ministry of Industry and Information Technology, School of Life Science Beijing Institute of Technology*
No.5, Zhongguancun South Street, Beijing,100081, China
**corresponding author : guoshuxiang@hotmail.com*

***Abstract* - With the development of science and technology, many complex problems cannot be completed efficiently by a single robot and require multiple robots to work together. For complex task scenarios with multiple robots, the multi-robot task allocation problem is the key to coordinating robots to work efficiently. In this paper, for the application scenario of multi-robot collaborative inspection task allocation, the task allocation problem is first mathematically modelled using the multi-robot problem model, and simulations based on the resource balance search algorithm and the genetic population intelligence algorithm are applied respectively. Incorporating constraints in the population intelligence genetic algorithm, which transforms robot power constraints into distance constraints for research, allows for targeted simulation solutions for practical multi-robot collaborative detection. The results show that the genetic algorithm based on population intelligence can solve the problem well and minimise the total cost of multi-ball robot clustering, enhance the optimised search capability of the algorithm, improve the rationality of multi-robot task allocation and increase the efficiency of task completion.**

Index Terms - Resource balancing search algorithm, genetic algorithms, Task allocation Multi-robot collaboration

I. INTRODUCTION

Multi-spherical robotic systems can work in different complex or uncertain environments and are widely used to perform a variety of military tasks, including in the areas of security patrols, target search, area detection and more. Multi-robot collaboration can increase mission efficiency compared to single robots. Coordinating multiple robots so that they can cooperate efficiently with each other has become a hot topic in robotics research, and is an important way to improve the effectiveness of combat command and the efficiency of mission execution [1].The core problem of multi-robot systems is to ensure that the robots in the system are safer and more stable than a single robot system, which depends on the ability of each robot in the system to achieve high-quality cooperation and form a unified action. Therefore, it is important to allocate effective mission planning to multi-robot systems. When the amount of suspicious targets in the collaborative detection area is large, the strategy of each machine in the system takes measures to ensure that the multi-robot collaboration is completed with maximum efficiency. The task allocation problem is a class of combinatorial optimisation problems, and solving the task allocation problem can be divided into mathematical modelling and optimisation algorithms. The multi-robot collaborative detection problem is similar to the MTSP problem [2]. Firstly, the MTSP model is used to model the multi-robot task allocation. Although resource balancing search algorithm has a simple structure and balanced allocation for complex tasks, the algorithm has a tedious computational process, and when the number of probes increases, the ability to find the best is slow and the efficiency of performing the task is low.

Researchers at home and abroad have increasingly addressed the multi-robot task allocation problem. ZITOUNI [25] proposed a distributed method for solving the multi-robot task allocation problem in the field of UAV search and rescue with the goal of achieving the maximum number of survivors as well as the minimum completion time, which outperformed other algorithms in terms of maximum completion time, travel distance and exchange of information. In the literature [26] et al. propose a distribution method based on a resource balancing search algorithm for the problems caused by uneven task distribution in multi-robot systems. The method effectively solves the problem of uniform allocation of goals to each robot. The completion time of the multi-robot task allocation problem was shortened. The literature [27] models the multi-robot task allocation problem as a multi-traveler problem and proposes a market-based multirobot task allocation method that enables optimal allocation of multiple heterogeneous robots to multiple heterogeneous tasks.

In contrast to resource balancing search algorithm, population-based intelligent genetic algorithms search multiple regions in the solution space simultaneously through crossover variation. The algorithm has a simple structure, low computational effort, and can effectively achieve the shortest path for multiple robots to efficiently detect a random amount number of suspicious targets in a region and obtains [3]. Finally, it can improve the rationality of robot task allocation, the minimum total robot cost with the minimum number of iterations, and the efficiency of effective multi-robot collaborative exploration.

The second part focuses on the laboratory multi-sphere robotic platform and its topology. The third part presents a model for the multi-robot collaborative exploration task allocation problem. The fourth part presents resource balancing search algorithm and analyses it in simulation. The fifth section introduces the use of population intelligence based genetic algorithm and performs simulation analysis. The simulation results show that the population intelligence genetic algorithm is more reasonable for solving the multi-robot collaborative task allocation problem and reduces the total cost consumed by the robotic exploration task.

II. The Platform of Sphere Multi-robot

The spherical multi-robot collaborative control system is shown in Figure 1. The multi-sphere robot is assembled from a number of individual modules. The individual robot consists of several main parts, the upper part consists of a waterproof sphere housing, acrylic board, Raspberry Pi, Arduino Mega 2560 control board, servo driver board, motor driver board, LIDAR, MPU and power supply module, and the lower part consists of a level switch, two wheels and four sets of drivers. The multi-robot collaborative control structure in this paper uses a centralised topology [4]. Each slave robot receives commands sent from the master robot, and after receiving the commands from the master robot, the slave robot groups perform different tasks. Communication between robots is important to perform important tasks, and in low signal-to-noise conditions, multiple spherical robots communicate with each other using the XBee communication module, which uses the ZigBee communication protocol to connect one device to the others. The structural composition of the spherical multi-robot communication system consists of a spherical master robot part and a spherical sub-robot part, where the spherical master robot is used to coordinate the entire spherical multi-robot network acting as a leader [23]. The spherical master robot sends control information to the wireless communication module and multiple sub-robots act as followers to receive commands and execute them simultaneously. Each spherical sub-robot is designed to execute a movement program upon receiving a command from the spherical master robot. Upon receiving a control command, the spherical robots perform their respective detection tasks, and upon completion of the detection, the data can be transmitted to the spherical master robot via the wireless communication module. For complex tasks, such as collaborative detection, the single-robot mode of operation is inefficient and multiple robots working together to complete the task can effectively improve mission efficiency [5]. Co-operative robotic exploration is the simultaneous exploration of an area by multiple robots, with multiple robots departing at the same time to complete the exploration task efficiently. In a real-world environment, spherical robots will be limited by their own capabilities, detection task time and other constraints, and using limited resources to complete the task efficiently requires reasonable and effective mission planning based on the spherical robot.

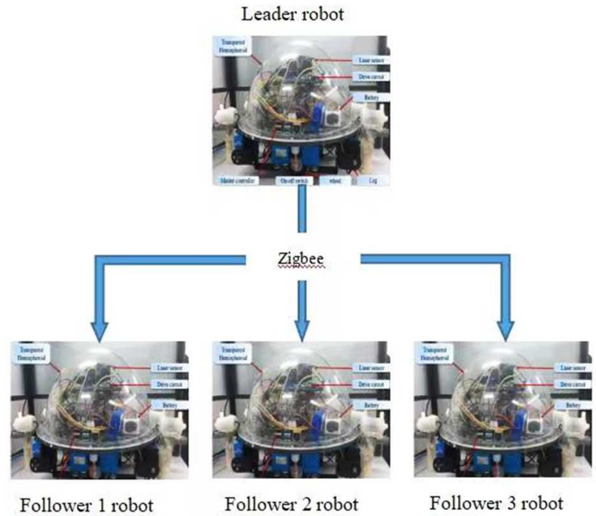

Fig. 1 The structure of spherical multi-robot cooperative control

III. Task Assignment of Sphere Multi-robot

A. Analysis of task allocation issues

Cooperative multi-robot detection task allocation is a problem of optimal combination. At the heart of this problem is the solution of how to improve efficiency by spending the least amount of money on robots to complete the task. The idea is to work with single or multiple robots in parallel to find the shortest path in the shortest possible time [6].

A detection site is divided into a detection area, there is a total of a area to be detected, and there are b detection robots (a>b) with the required detection target wi for each area; (i denotes the i-th area), and the capacity of each robot to detect the area per unit time is set as its work efficiency as Q[14]. The objective of task allocation is to allocate this a area to these b detection robots in a reasonable manner in order to the total completion time is minimised.

In real-world environmental detection, the number of task targets is much larger than the number of robots, so when performing collaborative task allocation, each robot is required to perform multiple target tasks; all tasks should be assigned to robots; and each task should be performed by only one robot.

B. Mathematical modelling of task allocation problems

A probe site is divided into a number of areas, and the number of targets in each area is w. The efficiency of the b spherical robots is Q_k, so that the total time spent by the b robots is minimized[7].

The decision variable X=(x1,x2,x3......xa), the region explored by the kth robot is i, xi=k, the amount of targets contained in the corresponding region is w_{ik} plus The total amount of targets that can be detected by the kth robot is: $\sum_i w_{ik}$ The time used by the kth robot to detect the region is k=1, 2 , 3 ......b:

$$f_k(X) = \frac{\sum_i w_{ik}}{Q_K}, \forall x_i = k \tag{1}$$

Type (1): Q_K is the robotic detection efficiency, w_{ik} is the amount of suspicious targets in the region [15].

The mathematical model for the objective function of the multi-sphere robot collaborative exploration allocation problem is represented as follows[8]:

$$\min(\max(f_k(X))) \qquad (2)$$

Type (2): $f_k(X)$is the kth robotic detection efficiency

Where the distance of robot i from the start point to task j can be expressed as:

$$d_{ij}^{1} = \left((p_{rx}^{i} - p_{tj,x})^2 + (p_{ry}^{i} - p_{tj,y})^2\right)^{\frac{1}{2}} \quad (3)$$

Type (3): p_{rx}^{i} p_{ry}^{i} is the horizontal and vertical coordinates of robot i on the x- and y-axes respectively[16]; $p_{tj,x}$ $p_{tj,y}$ is the horizontal and vertical coordinates of task j on the x and y axes respectively[9].

Based on the coordinates of the robot's arrival at the task point, the distance travelled by the robot can be obtained and the power consumption during the respective execution can be calculated [10]. It is required that all power elements of the robot should be higher than the power consumed after completing any task to ensure the safety of the robot itself.

IV. Analysis based on resource balancing algorithms

The resource balancing search algorithm aims to identify the distribution of random suspicious target points in a region and distribute the amount of suspicious targets in the region evenly to each robot according to the number of robots performing the task [11], so that each robot receives the task and one robot visits multiple target points, each visited by a robot.

A. Analysis of task allocation issues

This experiment simulates the application scenario of multi-robot collaborative area detection, and chooses to conduct a simulation test in a 10*10 area [20]. Four robots will be sent for collaborative detection task assignment, and the suspicious target volume in the area is randomly distributed, and the number of suspicious targets in the area is set to 20,40 respectively. The distribution of suspicious target points in the area is shown in Figure 2 and Figure 3

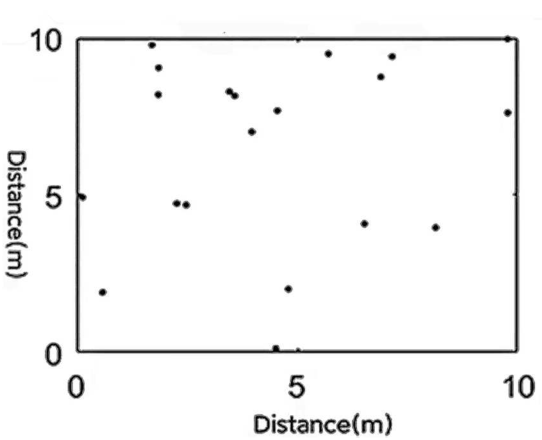

Fig. 2 Map of the 20 suspicious target sites

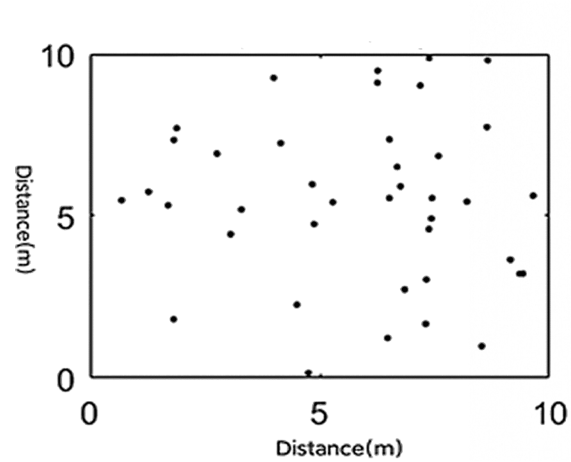

Fig. 3 Map of the 40 suspicious target sites

The above diagram shows two different distributions of different numbers of suspicious target points in the same 10*10 area, with both horizontal and vertical coordinates indicating distances in m.

B. Results of the resource balancing search algorithm

The number of suspicious targets in the area was simulated in MATLAB software using the resource balancing search algorithm [17]. When the number of suspicious targets in the region is 20, the simulation results of the resource balancing search algorithm task allocation graph are shown in Figure 4.

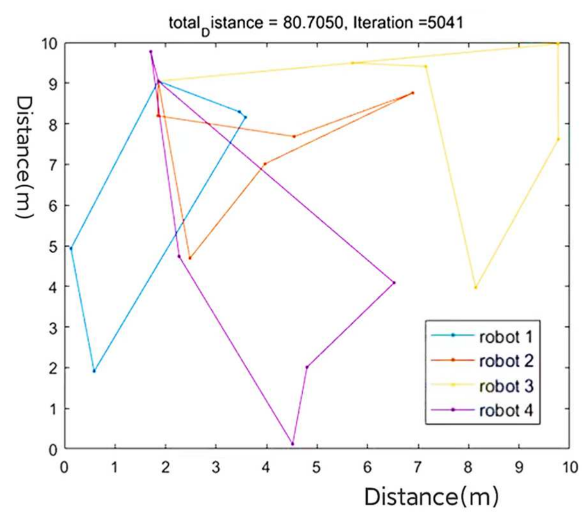

Fig. 4 Resource balancing search algorithm task allocation diagram

Through simulation experiments, the blue line represents the path track by robot 1, the red line represents the path travelled by robot 2, the yellow line represents the path travelled by robot 3 and the purple line represents the route travelled by robot 4.It was found that when the suspicious target point in the area is 20, the area detection task is assigned out using the resource balancing search algorithm simulation and the total cost of the robot is 80.71, and the optimal solution is found at iteration number 5041.

In a 10*10 region with a suspicious target volume of 40, resource balancing search algorithm was used for the solution of the task assignment and the simulation results are shown in Figure 5.

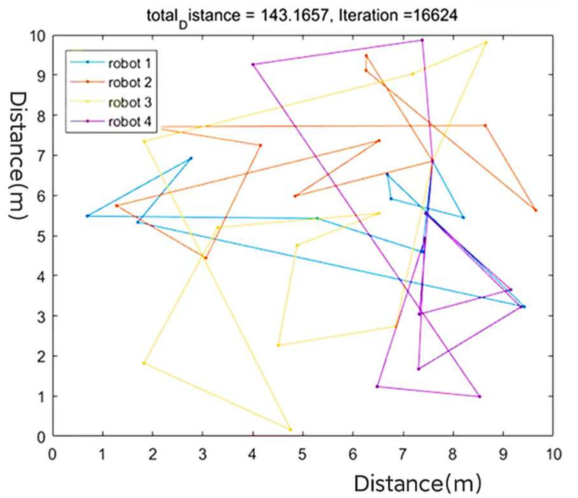

Fig. 5 Resource balancing search algorithm task allocation diagram

The simulation plot shows that when the suspicious target point in the region is 40, the total cost of the robot at this point is 143.16, and the optimal solution is found at an iteration number of 16624. The simulation plots show that the suspicious target points in the area are effectively and evenly distributed, with complex results as the number of suspicious targets increases.

V. ANALYSIS BASED ON POPULATION INTELLIGENCE GENETIC ALGORITHMS

Population Intelligent Genetic Algorithms simulate the principles of genetic evolution of organisms in their natural environment by taking all individuals in a population and using randomisation techniques to guide an efficient search of an encoded parameter space. First, an initial population is generated and coded to initialise the parameters [22]. Next, in order to find the best individuals better suited to the environment, the fitness of all individuals in the population is calculated, those with low fitness are eliminated and those left behind are subjected to replication, crossover and mutation operations, resulting in a new generation as the population continues to reproduce and select, a feasible optimal route is eventually found [12]. When all populations have completed the above operations, it is judged whether the termination condition has been reached and the current optimal individual is output, which is the optimal solution of the algorithm [18]. Each individual in the population is represented by a chromosome to indicate the order of visiting cities, the chromosome is represented by a string of numbers to indicate the number and order of visiting cities, and the quality of the chromosome is evaluated by the fitness function [19]. The quality of chromosomes is evaluated by the fitness function [13]. In this experiment, the suspect target parameters were set to 20 and 40, the variance probability was set to 0.005 and the crossover probability was set to 0.75.

The Population-based intelligent genetic algorithm flow chart is shown in Figure 6.

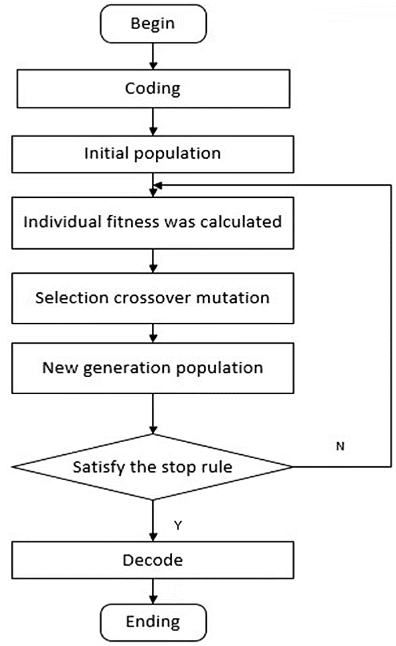

Fig. 6 Population-based intelligent genetic algorithm flow chart

We used the same 10*10 area for suspicious target point search and simulated the analysis using the population intelligence genetic algorithm. A simulation of the task assignment for a randomly distributed area with 20 suspicious target points is shown in Figure 7.

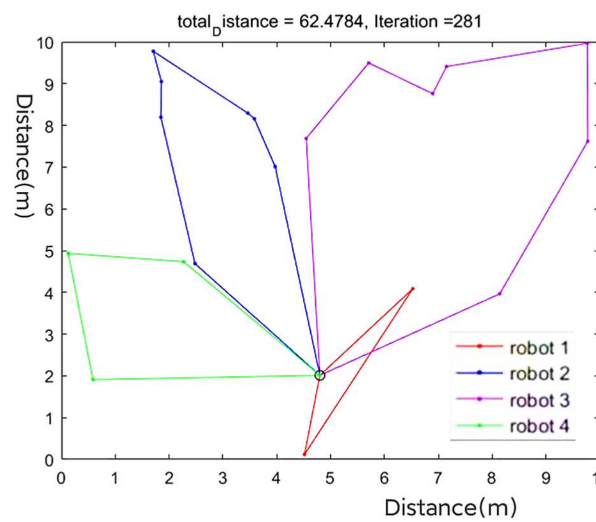

Fig. 7 Genetic algorithm task allocation diagram

The simulation analysis shows that the total cost of the robot is 62.48 at this point when the regional suspect target is 20, and the optimal solution is found at the 281st iteration. 20, and the optimal solution is found at the 281st iteration. The 4 different coloured lines in the diagram above represent the trajectory of each of the 4 robots. It can be seen that the paths are shortened and the crossings are reduced compared to resource balancing search algorithm search algorithm.

When the suspect target parameter is set to 40, the simulation is carried out using a population intelligence based genetic algorithm as shown in Figure 8.

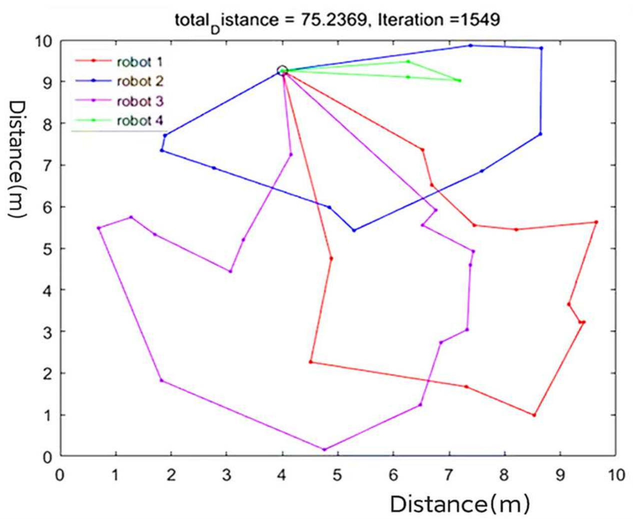

Fig. 8 Genetic algorithm task allocation diagram

The simulation plot shows that when the suspicious target point in the region is 40, the total cost of the robot at this point is 75.24, and the optimal solution is found at an iteration number of 1549. The simulation diagram shows that suspicious targets in the area are effectively searched and the robot's exploration route is optimized.

VI. THE DATA ANALYSIS OF THE ALGORITHMS

Simulation analysis of the two algorithms revealed that the population intelligent genetic algorithm is effective for the multi-robot collaborative detection task allocation problem [21], and the larger the amount number of targets that need to be detected, the more obvious the advantage of the population intelligent genetic algorithm. Simulation results for the resource balancing search algorithm and the population intelligent genetic algorithm are integrated in Tables 1 and 2 to allow a more intuitive comparison of the two algorithms.

TABLE I
COMPARISON OF ALGORITHMS WITH A REGIONAL SUSPICIOUS TARGET VOLUME OF 20

Type of algorithm	Total robot cost	Number of iterations
Resource balancing search algorithm	80.71	5041
Population intelligent genetic algorithm	62.48	281

TABLE II
COMPARISON OF ALGORITHMS WITH A REGIONAL SUSPICIOUS TARGET VOLUME OF 40

Type of algorithm	Total robot cost	Number of iterations
Resource balancing search algorithm	143.16	16624
Population intelligent genetic algorithm	75.24	1549

From table 1 and table 2, the population intelligence genetic algorithm has an advantage over the resource balancing search algorithm in solving the multi-robot collaborative detection task allocation problem. In addition, the number of iterations of the population intelligent genetic algorithm is less than that of the resource balancing search algorithm [24]. When the number of suspicious targets in the region was 20, the population intelligence genetic algorithm improved by 22.6% over the resource balancing search algorithm, while when the number of suspicious targets in the region was 40, the population intelligence genetic algorithm improved by 47.4% over the resource balancing search algorithm. This means that as the number of suspicious targets in the region increases, the population intelligence genetic algorithm has clear advantages.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, a mathematical model of multi-robot collaborative detection task allocation, converts robot power constraints into distance constraints for research, and compares the resource balance-based genetic population-based intelligent search algorithm through MATLAB simulations. Through simulation analysis and performance index comparison, it was found that the population-based intelligent genetic algorithm has stronger search capability, is less likely to be trapped in a local optimal solution, can effectively shorten the robot search path and reduce the total robot cost. In a comprehensive analysis, the population-based intelligent genetic algorithm is more effective in solving the task allocation problem of multiple robots than the resource balance-based search algorithm. Finally, the group's self-developed multi-sphere robot was tested, and the results fully validated the feasibility of the algorithm in practical engineering, effectively improving the search capability of the robot and reducing the total cost.

Future research will continue to expand the study of practical application scenarios, using distributed structures, integrating various factors, performing more complex mathematical modelling of the robot, and continuing to improve the existing population intelligence genetic algorithm.

ACKNOWLEDGMENTS

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REFERENCE

[1] He Yin, Shuxiang Guo, Meng Liu, "A Virtual Linkage-based Dual Event-triggered Formation Control Strategy for Multiple Amphibious Spherical Robots in Constrained Space with Limited Communication", *IEEE Sensors Journal*, vol. 4, no. 7, pp. 1558-1748,2022.

[2] Yue Yuan, Qu Gaomin. Research on target allocation of distributed multi-uav cooperative reconnaissance. *Journal of Ordnance Equipment Engineering,* vol. 2, no. 8, pp. 13-16, 2018

[3] Garcia-Fidalgo, E.; Ortiz, A.Massot-Campos, M. Vision-Based Control for an AUV in a Multi-robot Undersea Intervention Task. *In Proceedings of the Iberian Robotics Conference,* vol. 6, no. 20, pp. 20-22, 2017.

[4] Ruochen An, Shuxiang Guo, Liang Zheng, Hideyuki Hirata, Shuoxin Gu, "Uncertain Moving Obstacles Avoiding Method in 3D Arbitrary Path Planning for a Spherical Underwater Robot", *Robotics and Autonomous Systems*, vol.151, no.5, pp.189-201,2021.

[5] R. Z. Li, H. Z. Yang, and C. S. Xiao, "Multi-robot collaborative strategy based on dynamic capture points," *Control Engineering*, vol. 26, no. 3, pp.40-46,2019.

[6] Ruochen An, Shuxiang Guo, Yuanhua Yu, Chunying Li and Tendeng Awa, "Task Planning and Collaboration of Jellyfish-inspired Multiple Spherical Underwater Robots", *Journal of Bionic Engineering*, vol. 26, no. 3, pp.25-30, 2022.

[7] Shuxiang Guo, Sheng Cao, Jian Guo, "Study on Decentralization of Spherical Amphibious Multi-Robot Control System Based on Smart Contract and Blockchain", *Journal of Bionic Engineering,* vol. 142, no. 6, pp.23-26, 2021.

[8] Molinos E J, L lamazares, "Dynamic window based approaches for avoiding obstacles in moving," *Robotics and Autonomous Systems*, vol. 118, no. 34, pp.112-130, 2019.

[9] J S. Chopra, G. Notarstefano, M. Rice, and M. Egerstedt, "A distributed version of the hungarian method for multirobot assignment, " *IEEE Trans. Robot,* vol. 33, no. 4, pp. 932–947, Aug. 2017.

[10] G. V. Lakhekar, L. M. Waghmare, and R. G. Roy, "Disturbance Observer-Based Fuzzy Adapted S-Surface Controller for Spatial Trajectory Tracking of Autonomous Underwater Vehicle", *IEEE Transacations on Intelligent Vehicles,* vol. 4, no. 4, pp. 622–636, 2019.

[11] H. Xing, S. Guo, L. Shi, and et al, "A novel small-scale turtleinspired amphibious spherical robot", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* vol. 2, no. 4, pp.1702–1707, 2019.

[12] L. Qiao and W. Zhang, "Trajectory Tracking Control of AUVs via Adaptive Fast Nonsingular Integral Terminal Sliding Mode Control", *IEEE Transactions on Industrial Informatics,* vol.16, no.2, pp.1248–1258, 2020.

[13] Y. Cao, B. Li, Q. Li, and et al, "A nonlinear model predictive controller for remotely operated underwater vehicles with disturbance rejection", *IEEE Access,* vol. 8, no.2, pp.1248–1258, 2020.

[14] Huang Kaikai, Wang Sai-sai, Ye Tao, WANG Xin-jian, "Robot Local Path Planning based on Fuzzy Improved Artificial Potential Field Method", *Modular Machine Tool and Automatic Manufacturing Technology*, vol. 67, no. 9, pp. 2177-2187, 2019.

[15] A.E.Ezugwu, O. J. Adeleke, A. A. Akinyelu, and S. Viriri, "A conceptual comparison of several Metaheuristic algorithms on continuous optimisation problems",*Neural Appl.,* vol. 32, no. 10, pp. 6207–6251, 2020.

[16] Huiming Xing, Liwei Shi, Xihuan Hou, Yu Liu, Yao Hu, Debin Xia, Zan Li, Shuxiang Guo, "Design, Model and Control of a Miniature Bio-inspired Amphibious Spherical Robot", *Mechatronics,* vol.77, no.1, pp.3 2021.

[17] L. Xie, Y. Miao, S. Wang, P. Blunsom, Z. Wang, C. Chen, A. Markham, and N. Trigoni, "Learning with stochastic guidance for robot navigation", *IEEE Trans. Neural Learn.* vol. 32, no. 1, pp. 166–176, 2021.

[18] D. Wang, H. Wang, and L. Liu, "Unknown environment exploration of multi-robot system with the FORDPSO", *Swarm Evol Computy,* vol. 26, pp.157–174,2016.

[19] Dang Q, Nguyen CT, Rudová H."Scheduling of Mobile Robots for Transportation and Manufacturing Tasks",*Springer Us.* vol. 25, no. 2, pp. 234-362, 2019.

[20] Yanlin He, Lianqing Zhu, Guangkai Sun, Junfei Qiao, Shuxiang Guo, "Underwater motion characteristics evaluation of multi amphibious spherical robots", *Microsystem Technologies*, vol.25, no.2, pp.499-508, 2019.

[21] Yan Fei, Zhu Xiaoping, Zhou Zhou, Tang Yang. "Real-time Task Allocation for a Heterogeneous Multi-UAV Simultaneous", *Scientia Sinica Informationis.* vol. 49, no.5, pp. 555-569, 2019.

[22] Wang Jianfeng, Jia Gaowei, Lin Juncan, Hou Zhongxi. "Cooperative Task Allocation for Heterogeneous Multi-UAV Using Multi-objective Optimization Algorithm", *Journal of Central South University,* vol. 49, no.5, pp.432-448, 2019.

[23] N. Molina-Padrón, F. Cabrera-Almeida, V. Araña, M. Tichavska and B. Dorta-Naranjo, "Monitoring in Near-Real Time for Amateur UAVs Using the AIS", *IEEE Access,* vol. 8, pp. 33380-33390, 2020.

[24] Shuoxin Gu, Shuxiang Guo, Liang Zheng, "A highly stable and efficient spherical underwater robot with hybrid propulsion devices", *Autonomous Robots,* vol.44, no.5, pp.759-771,2020.

[25] ZITOUNI F, HAROUS S, MAAMRI R, "A distributed approach to the multi-robot task allocation problem using the consensus-based bundle algorithm and ant colony system", *IEEE Access*, vol. 8, pp. 27479-27494, 2020.

[26] Jiang J, Yan J H, Zang X Z, "Pheromone based multi-robot cooperative task allocation", *Computer Engineering and Applications*, vol.44, no.2, pp.20-22,2018.

[27] HUSSEIN A, KHAMIS A, "Market-based approach to Multi-robot Task Allocation", *IEEE Sensors Journal*, vol. 4, no. 7, pp. 69-74, 2019.