Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

# A Novel Algorithm of Cooperative Foraging for Swarm Robot Based on Neural Network*

Yong Song, Hai Liu, Chengjin Zhang, Qingfu Du

*School of Mechanical, Electrical, and Information Engineering*
*Shandong University at Weihai*
*Weihai, China*

songyong@sdu.edu.cn

***Abstract* - Swarm robotics is an emerging discipline that has a great deal of potential real-world applications. Swarm robotics aims to produce robust, scalable, and flexible self-organizing behaviors through local interactions of large numbers of simple robots. In this paper, a novel pheromone model of swarm foraging behavior is developed based on a neural network. The output of the neurons corresponds to the density or pheromone. The output diffuses to the neighboring neurons through their local connections. The neural network is updated based on the proposed evaporation model. The evolution of the neural network can mimic the features of pheromones. Simulation experiments are performed under different foraging scenarios. The experimental results verify the effectiveness of the proposed pheromone model.**

***Index Terms* - *swarm robot; cooperative foraging; neural network; pheromone***

## I. INTRODUCTION

Swarm intelligence is an emerging interdisciplinary field, which mimics nature to model the collective behavior of social swarms [1]. The desired swarm behavior emerges through simple rules and local interactions of a large number of homogeneous, simple individual robots. The self-organizing coordination mechanisms in social insects have been effectively implemented in swarm robotic systems [2]. The application of swarm intelligence in robotics is known as swarm robotics, which has been successfully applied in different fields, such as self-driving, delivery robots, autonomous agricultural robots and automated warehouses [3].

Swarm robotics is a relatively new field in robotics, and to date there is no complete theoretical framework on the group architecture. Parker described a comprehensive control architecture called ALLIANCE, which facilitates fault tolerant cooperative control of teams of heterogeneous mobile robots [4]. ALLIANCE is a fully distributed architecture based upon individual robot behavior. Mathematical modelling was used to achieve adaptive action selection for each robot. Silva et al. proposed a parallel multi-agent architecture for hybridization of metaheuristics for multi-objective problems, which is called MO-MAHM [5]. Some concepts, such as particle position and velocity were redefined. The framework had been applied to the multi-objective symmetric travelling salesman problem. Leng et al. put forward a task-oriented hierarchical control architecture for swarm robotics systems, including three layers: human-computer interaction layer, planning layer and execution layer [6]. A hierarchical organizational model for the system was presented, which is used to establish management relationships between different layers and individuals. With the development of artificial intelligent techniques many kinds of novel methods have been used in the organization of swarm robots. Timmis et al. presented a neural-endocrine architecture for foraging in swarm robotics systems [7]. A number of individual behaviors gave rise to emergent swarm behavior to allow a swarm of robots to collaborate in the task of foraging. Mendonca et al. presented a cooperative architecture for swarm robotics based on dynamic fuzzy cognitive maps (DFCM) [8]. Reinforcement learning was used to self-tune the navigation system parameters allowing the DFCM model to be self-adaptive. Two strategies were analyzed for data and experience exchange between robots. Peres et al. presented a modular multi-agent architecture to assist the development of swarm robotics systems [9]. In the proposed architecture heterogeneous robots can interact with each other and with humans in order to accomplish several types of missions.

Resource conflict is one of the key issues in swarm robot cooperation, which mainly includes: spatial interference and resource competition. When a large number of mobile robots share a central area (e.g. the nest) the spatial interference will increase for a swarm system. The higher the group size, the more spatial interference is experienced by individual robots sharing a limited workspace. Furthermore, the swarm robots collaboratively work together towards a common goal (e.g. foraging behavior), resulting in common resource competition. Therefore, conflict resolution is a challenging problem in swarm robotics, which has been widely studied nowadays. Shahriari et al. developed a mathematical formula describing multi-robot motion [10]. Two metaheuristic optimization methods were used to minimize the time that each robot takes to reach the target while avoiding collisions to solve the conflict

* This work is supported by This work is supported by the National Natural Science Foundation of China under Grants (61573213, 61673245, 61603214, 61803227), National Key Research and Development Plan of China under Grant 2017YFB1300205, Shandong Province Key Research and Development Plan under Grants (2016ZDJS02A07, 2018GGX101039), China Postdoctoral Science Foundation under Grant 2018M630778 and Independent Innovation Foundation of Shandong University under Grant 2018ZQXM005.



978-1-7281-6321-5/19//$31.00 ©2019 IEEE

resolution problem in a highly cluttered environment. Solum et al. demonstrated a collective movement algorithm [11]. The mechanism was integrated into the group's control systems to minimize conflict while maintaining the group consensus. Lima et al. proposed a cellular automata ant system model to control a robot swarm with nests [12]. The robot movements were chosen by a stochastic conflict solver with non-deterministic characteristics.

In swarm robotics systems, the complex swarm behaviors emerge through relatively simple individual rules. All swarm robots have a set of decision making mechanisms to realize the collective behaviors. But it is very difficult to understand the relationship between local rules and the emerging behaviors. Machine learning and evolutionary techniques have been widely used to design the individual rules of swarm robotics systems. Nurmaini et al. proposed a RAM-based neural network architecture to improve the localization of mobile sensor nodes for multi-robots in indoor environments [13]. Tarapore et al. presented an immune system-inspired algorithm to distinguish between normal behaviors and abnormal behaviors of multi-robot systems online [14]. The system's capacity and performance in a foraging task were analyzed for collective behaviors. Watchanupaporn et al. proposed a combined learning algorithm based on reinforcement learning and particle swarm optimization [15]. The reinforcement learning algorithm was modified to learn a policy for certain robot actions. Particle swarm optimization was used to accelerate the learning process.

Although task allocation and self-organizing behaviors have been implemented on some swarm robot platforms, the dynamic real-time control of a swarm robot system is still considered to be challenging in many cases. Swarm foraging behavior is a classical benchmark problem in swarm robotics. The biggest challenge is to develop a self-organizing search and collection algorithm for swarm robot foraging behaviors. The main contribution of this paper is to propose a novel neural network based pheromone model of swarm foraging behavior. In this paper .a novel pheromone model of swarm foraging behavior is developed based on a neural network. If the foraging robots lay down pheromone the output of corresponding neurons will increase. And the output will diffuse to the neighboring neurons through the local connections. The output of the neural network will be updated based on the proposed pheromone evaporation model. The evolution of the neural network can mimic the features of pheromones. Various scenarios have been presented to verify the effectiveness of the proposed pheromone model of cooperative swarm foraging.

## II. Related works

Swarm robotic systems consist of large numbers of simple mobile robots. All robots share a limited workspace. The robots must avoid collisions and perform available behaviours satisfying the constraints of system. Therefore, task allocation, communication, and cooperation are the most challenging problems of swarm robotics.

### *A. Task allocation*

In swarm robot systems, a large number of simple robots interact with each other and interact with the environment [16]. The desired collective behaviours will emerge by the cooperation among robots. Therefore, task allocation to groups of robots is necessary when the special tasks cannot be performed by a single robot. Significant attention has recently been devoted to the task allocation in swarm robotics [17]. Furthermore, some mechanisms of task allocation have been proposed. Depending on the style of communication the task allocation can be divided into two classes, intentional and self-organized task allocation [18].

The swarm individuals communicate explicitly to emerge collective behaviours with global knowledge in intentional task allocation [19]. Liang et al. proposed a novel task optimal allocation approach based on an improved contract net protocol [20]. The algorithm decreased the network communication in multiple stages to improve the quality of the task and the efficiency of the swarm robot system. Shenoy et al. proposed task allocation based on clustered scalable networks [21]. The method is suitable for handling different types of multi-robot task allocation problems. Jamshidpey et al. proposed several self-organized threshold methods for solving the task allocation problem [22]. The performance of static and dynamic communication methods were presented. Irfan et al. proposed an algorithm for task allocations with an auction mechanism to perform a complex task requiring multiple robots [23]. The individual robots may execute a special task during the collective task execution.

Swarm robot systems consist of many simple robots with local communication capability. Therefore, the task allocation, in general, is self-organized by local and stochastic decisions of the individual team members [24]. Pang et al. proposed a dynamic response threshold model to perform task allocation in a self-organized manner [25]. The amount of food items in a nesting site was considered as the stimulus to individual robots and the threshold can be computed dynamically according to the number of resting robots. Brutschy et al. presented a self-organized method for task allocation of the individuals in swarm robot systems [26]. The proposed method was based on the delay of robots working on one subtask while waiting for another subtask. Nedjah et al. proposed a distributed control algorithm of dynamic task allocation for swarm robotic systems inspired by particle swarm optimization [27]. The algorithm in each robot must run periodically to control the underlying decisions or actions.

### *B. Communication and Cooperation*

In swarm robotic systems, a large group of simple individuals cooperate with each other to achieve complex tasks. The cooperation strategies of the individual robots are conducted through implicit or explicit communication depending on the size (capability) of the robots [28]. The individuals in social insect societies mainly change the shared environment by depositing pheromones to emerge swarm behaviours, which is called stigmergy. Swarm robotics systems mostly rely only on local information, and exchange information implicitly to mimic natural swarms. Schroeder et al. proposed a Keller-Segel model for chemotaxis to develop a virtual-pheromone-based method of area coverage [29]. Several control rules for efficient area coverage were conducted inspired by the swarm behaviours of ant colonies. Kuyucu et al. proposed a simple efficient way to coordinate a large number of homogeneous robots in unknown environments [30]. The exploration in an unknown environment is achieved based on pheromone-based stigmergic strategy via random movements. Wei et al. developed a communication system comprised of emitter and receiver modules [31]. The system communicates by producing volatile pheromone components and decodes the transmitted information via sensors.

Although the pheromone can work well in most robotic swarms, creating artificial pheromones is not easy in artificial swarms. In many swarm robotics systems the robots have the capability of sending and receiving messages. The most common modes for exchanging messages among robots in swarm robots are bluetooth, wireless LAN and infrared. Turkoral et al. presented an indoor positioning system for swarm robotic applications using bluetooth and WiFi communication infrastructures [32]. The information fusion of several position estimation methods was studied. Couceiro et al. proposed two deployment strategies of a wireless sensor robot network [33]. The scouting robots were autonomously deployed through explicit cooperation with rangers. A hierarchical approach was used to maintain the connectivity of the Mobile Ad hoc Network (MANET) within each robot. Rubenstein et al. presented Kilobot, a low-cost robot to test collective algorithms on a large number of robots [34]. Each Kilobot has an infrared LED transmitter and photodiode receiver to communicate with other neighboring robots.

## III. Pheromone Diffusion Model

Ants commonly use trail pheromones to mark their foraging paths. Some ants with food items will lay down a trail of pheromones to guide other ants to find the food source. The pheromones will propagate and evaporate quickly. Meanwhile, ants will continuously renew the trail of pheromone to maintain the foraging paths. So the pheromone will distribute in the work space while foraging.

In this work, a new pheromone diffusion model is developed based on a neural network to imitate the physical pheromones of ants. A dynamic wave expansion neural network (DWENN) is used to model the pheromone diffusion. The neural network has a set of neurons with local connections[35]. The topological structure corresponds to the robot work space. The local connection of the immediate neighbors of the $i$th neuron is shown as Figure. 1.

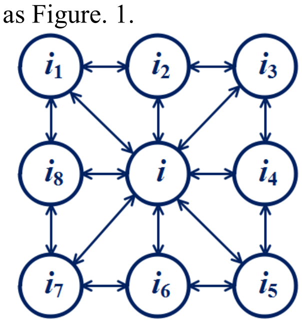



Fig. 1 Network neighborhood.

When a robot lays down a pheromone at a certain position, the corresponding neuron will have a positive external input. The output of the neuron will diffuse through the immediate neighboring neurons. The pheromone diffusion model is defined as

$$x_i(t+1) = f\left(\sum_{j=1}^{8} w_{ij} x_j(t) + I_i(t)\right) \tag{1}$$

where $x_i(t+1)$ is the output of the $i$th neuron at time $t+1$, $x_j(t)$ is the output of the immediate neighboring neurons of the $i$th neuron at time $t$, $w_{ij}$ is the connection weight from the $i$th neuron to the $j$th neuron, and $I_i(t)$ is the input of the $i$th neuron at time $t$. The connection weight matrix $\boldsymbol{W}$ is calculated by

$$w_{ij} = \begin{cases} e^{-\eta|i-j|^2} & if\ |i-j| = 1 \\ 0 & if\ |i-j| > 1\,, \end{cases} \tag{2}$$

where $|i\text{-}j|$ is the Euclidian distance between the $i$th and $j$th neurons, $\eta$ is a real positive number.

The external input $I_i(t)$ depends on the pheromone at a particular position. When a scouting ant discovers a food item it will try to bring it back to the nesting site while laying down an attractive pheromone $P_a$ on the ground. The other ants will be attracted to the food source by the pheromone trail. Once an exploring ant finds an obstacle, it will release a repulsive pheromone $Po$. When the ants walk randomly and explore the environment they will release a repulsive pheromone $P_e$ to avoid other ants re-exploring the same area. The external input $I_i(t)$ is defined as

$$I_i(t) = \begin{cases} P_a\ Homing\ on\ x_i(t) \\ P_o\ Avoiding\ Obstacle\ on\ x_i(t) \\ P_e\ Searching\ on\ x_i(t) \end{cases}, \tag{3}$$

where $P_a$ is a positive minor constant, $P_o$ and $P_o$ are both negative minor constants.

The transfer function $f$ is defined as

$$f(x) = \frac{1}{1+e^{-x}} \tag{4}$$

## IV. Pheromone Evaporation Model

In the pheromone field, the update of the pheromone values goes through two stages. After the foraging ants lay down pheromone trails, the trails will start to evaporate. Evaporation reduces the pheromone density in order to favor the scouting ants exploring new areas in the workspace. The evaporation of the pheromones is updated by

$$x_i(t+1) = (1-\rho)x_i(t) + f\left(\sum_{j=1}^{8} w_{ij}\, \Delta x_j(t)\right) \tag{5}$$

where $x_i(t+1)$ and $x_i(t)$ are the density of the pheromone at time $t+1$ and $t$ at the position of the $i$th neuron, respectively. $\rho$ is the evaporation rate, $w_{ij}$ is the connection weight from the $i$th neuron to the $j$th neuron, $\Delta x_j(t)$ is the variations of the pheromones neighboring the $i$th neuron $x_i$, $f$ is the transfer function.

## V. Foraging Algorithm Based on Performance

The cooperative foraging task is one benchmark testbed for swarm robotics. In a foraging system a collection of robots will scout and deliver objects to a specific area. When foraging begins, the searching robots inspect the search space for a food source starting from the nest site. There is no pheromone in the shared environment. The output of the neural network is initialized to zero. When exploring, the swarm robots release repulsive pheromones on the ground to repulse their mates from already visited regions. Once searching robots encounter a food source, the robots try to carry it and deposit attractive pheromones to attract their mates to the food source. Meanwhile, the pheromone will gradually diffuse into the whole space and evaporate from the ground. With more and more robots marching to food sources, the intensity on the pheromone trail will be reinforced successively. Eventually, all foraging robots will migrate to the trail from the nest to the food source. The cooperative foraging behavior will emerge based on the pheromones. The foraging algorithm based on performance may be summarized as shown as following:

**Initialize output of neural network to zero**

$x_i(t=0)=0$

**While foraging until the food is consumed**

**While exploring until finding the food source**

Walk randomly/follow pheromone trails

Release repulsive pheromone, and update the output of repulsive network:

$x_i(t+1)=f(\sum_{j=1}^{8} w_{ij}\, x_j(t)+I_i(t)),\ I_i(t)=P_o\ or P_e$

**End while exploring**

**Wait for the optimal waiting time**

**While homing until arriving the nest site**

Follow pheromone trails

Release attractive pheromones, and update the output of attractive network:

$x_i(t+1)=f(\sum_{j=1}^{8} w_{ij}\, x_j(t)+I_i(t)),\ I_i(t)=P_a$

**End while homing**

Pheromones evaporate from the ground:

$x_i(t+1)=(1-\rho)x_i(t)+f\left(\sum_{j=1}^{8} w_{ij}\,\Delta x_j(t)\right)$

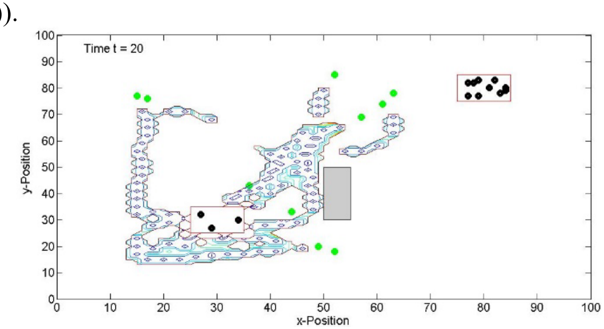
**End while foraging**

## VI. SELF-ORGANIZING BEHAVIORS BASED ON PERFORMANCE

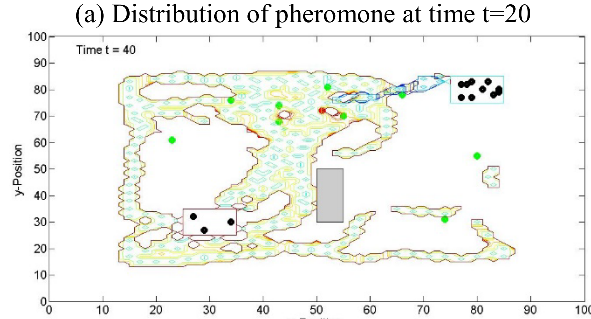
Two computer experiments were carried out with one and two food sources in a dynamic environment. The maximum simulation time is 600s in each foraging experiment. The size of the robot colony is 20, and the number of foraging robots is 10. The initial fluctuation intensity is set to zero, the growth rate of fluctuation intensity is 0.02, and the evaporation rate of pheromone is 0.01. The sensing radius of robots is 10, and the step size of robots is 3.

In the experiment, the ant nesting site is placed in the lower left corner of the world. The robots start from the nesting site to search for the food source, which is positioned at the upper right corner (shown as Fig.2 (a)). The gray rectangle obstacle is placed randomly, and can move freely. The repulsive pheromone is released by the scouting robots (green dots) according to equation (1), and gradually diffuses into the workspace. The space marked by the repulsive pheromone is the area which has been explored. In response to the repulsive pheromone, the mates of the scouting robots will strive to explore unknown territory. Therefore, the scouting robots will find the food source effectively. The distribution of pheromone is shown as Figure 2 at different times.

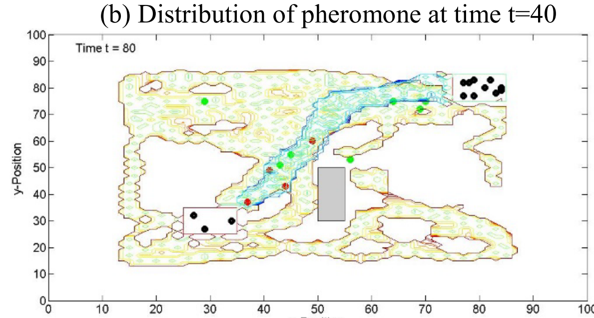
When the scouting robots discover the food source they will pick up the food items and bring them back to the nesting site. The homing robots (red dots) will lay down the attractive pheromone from the food source to the nesting site on the ground (shown as Figure 2 (b)). Likewise, the attractive pheromone diffuses into the workspace gradually. When homing robots arrive at the nesting site they are capable of recruiting other robots in the nesting site, and scouting the food source together. The pheromone trail attracts the other scouting robots (shown as Figure 2 (c)). The scouting robots follow this trail to find the food source and return to the nesting site. More and more homing robots release attractive pheromones along the trail. The intensity of the trail will be reinforced by a large number of homing robots. Meanwhile the pheromone will evaporate gradually. In the end, all robots scout the food source and return to the nesting site along the trail (shown as Figure 2 (d)).



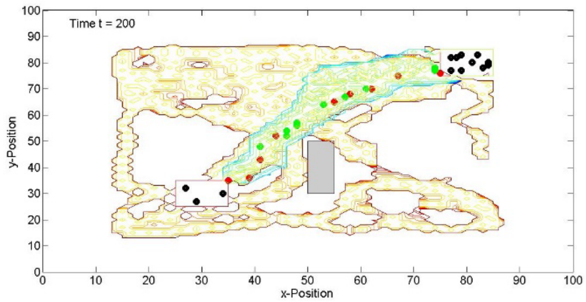

(a) Distribution of pheromone at time t=20




(b) Distribution of pheromone at time t=40




(c) Distribution of pheromone at time t=80




d) Distribution of pheromone at time t=200

Fig. 2 Snapshots of pheromone distribution at different times with one food source

## VII. Conclusions

In this paper a novel neural network based pheromone model of swarm foraging behavior is developed based on a neural network. A dynamic wave expansion neural network (DWENN) is used to model the pheromone diffusion. The neurons of the neural network correspond to different positions in the workspace. When the robots release pheromones, the corresponding neuron will get an external input. The pheromones will diffuse through the local connections among the neurons. The pheromone is also updated based on the proposed pheromone evaporation model. The simulation has been performed in the context of cooperative foraging and the performance have been identified.

## Acknowledgment

We gratefully acknowledge the technical assistance of Xiaoli Wang with DL850E ScopeCorder.

## References

[1] M. Brambilla, E. Ferrante, M. Birattari, et al, "Swarm robotics: a review from the swarm engineering perspective", *Swarm Intelligence*, vol. 7, no. 1, pp. 1-41, 2013.

[2] Y. Song, C. J. Zhang, H. Liu, "Method of quantitative analysis for multirobot cooperative hunting behaviors", *Mathematical Problems in Engineering*, pp. 1-8, 2016.

[3] L. Pitonakova, R. Crowder, S. Bullock, "The information-cost-reward framework for understanding robot swarm foraging", *Swarm Intelligence*, vol. 12, no. 1, pp. 71-96, 2018.

[4] L. E. Parker, "ALLIANCE: An architecture for fault tolerant multi-robot cooperation", *IEEE Transactions on Robotics and Automation*, vol. 14, no. 2, pp. 220-240, 1998.

[5] I. R. M. Silva, E. F. G. Goldbarg, E. B. De Carvalho, et al, "MO-MAHM: A parallel multi-agent architecture for hybridization of metaheuristics for multi-objective problems", *In Proceedings of IEEE Congress on Evolutionary Computation*, pp. 580-587, 2017.

[6] Y. Q. Leng, C. Yu, W. Zhang, et al, "Task-oriented hierarchical control architecture for swarm robotic system", *Natural Computing*, vol. 16, no. 4, pp. 579-596, 2017.

[7] J. Timmis, L. Murray, M. Neal, "A neural-endocrine architecture for foraging in swarm robotic systems", *In Proceedings of International Workshop on Nature Inspired Cooperative Strategies for Optimization,* pp. 319-330, 2010.

[8] M. Mendonca, I. R. Chrun, F. Neves, et al, "A cooperative architecture for swarm robotic based on dynamic fuzzy cognitive maps", *Engineering Applications of Artificial Intelligence*, vol. 59, pp. 122-132, 2017.

[9] J. Peres, P. F. F. Rosa, R. Choren, "A multi-agent architecture for swarm robotics systems", *In Proceedings of IEEE International Symposium on Robotics and Intelligent Sensors*, pp. 130-135, 2017.

[10] M. Shahriari, M. Biglarbegian, "Conflict resolution of cluttered multi-robot systems using metaheuristic optimization algorithms", *In Proceedings of IEEE International Conference on Systems, Man, and Cybernetics: Big Data Analytics for Human-Centric Systems*, pp. 210-215, 2015.

[11] T. Solum, B. E. Eskridge, I. Schlupp, "Consensus costs and conflict in a collective movement, *In Proceedings of Genetic and Evolutionary Computation Conference,* pp. 49-56, 2014.

[12] D. A. Lima, G. M. S. Oliveira, "A cellular automata ant memory model of foraging in a swarm of robots", *Applied Mathematical Modelling*, vol. 47, pp. 551-572, 2017.

[13] S. Nurmaini, A. Zarkasi, "Simple pyramid RAM-based neural network architecture for localization of swarm robots", *Journal of Information Processing Systems*, vol. 11, no. 3, pp. 370-388, 2015.

[14] D. Tarapore, A. L. Christensen, J. Timmis, "Generic, scalable and decentralized fault detection for robot swarms", *Plos One*, vol. 12, no. 8, pp. 1-29, 2017.

[15] O. Watchanupaporn, P. Pudtuan, "Multi-robot target reaching using modified Q-Iearning and PSO", *In Proceedings of International Conference on Control, Automation and Robotics*, pp. 66-69, 2016.

[16] S. Hoshino, R. Takisawa, Y. Kodama, "Swarm robotic systems based on collective behavior of chloroplasts", *Journal of Robotics Mechatronics*, vol. 29, no. 3, pp. 602-612, 2017.

[17] Y. Jiang, "A survey of task allocation and load balancing in distributed systems", *IEEE Transactions on Parallel and Distributed Systems*, vol. 27, no. 2, pp. 585-599, 2016.

[18] G. Pini, A. Brutschy, M. Birattari, et al, "Interference reduction through task partitioning in a robotic swarm", *In Proceedings of the IEEE International Conference on Informatics in Control, Automation and Robotics*, pp. 52-59, 2009.

[19] K. Lerman, C. Jones, A. Galstyan, et al, "Analysis of dynamic task allocation in multi-robot systems", *International Journal of Robotics Research*, vol. 25, no. 3, pp. 225-241, 2006.

[20] H. T. Liang, F. J. Kang, "A novel task optimal allocation approach based on contract net protocol for agent-oriented UUV swarm system modeling", *Optik*, vol. 127, no. 8, pp. 3928-3933,2016.

[21] M. V. Shenoy, K. R. Anupama, "DTTA - Distributed, time-division multiple access based task allocation framework for swarm robots", *Defence Science Journal*, vol. 67, no. 3, pp. 316-324, 2017.

[22] A. Jamshidpey, M. Afsharchi, "Task allocation in robotic swarms: explicit communication based approaches", *In Proceedings of the Canadian Conference on Artificial Intelligence,* pp. 59-67, 2015.

[23] M. Irfan, A. Farooq, "Auction-based task allocation scheme for dynamic coalition formations in limited robotic swarms with heterogeneous capabilities", *In Proceedings of the IEEE International Conference on Intelligent Systems Engineering*, pp. 210-215, 2016.

[24] Z. X. Zhu, B. W. Tang, J. P. Yuan, "Multi-robot task allocation based on an improved particle swarm optimization approach", *International Journal of Advanced Robotic Systems,* vol. 14, no. 3, 1-22, 2017.

[25] B. Pang, C. J. Zhang, Y. Song, et al, "Self-organized task allocation in swarm robotics foraging based on dynamical response threshold approach". *In Proceedings of the IEEE International Conference on Advanced Robotics*, pp. 256-261, 2017.

[26] A. Brutschy, G. Pini, C. Pinciroli, et al, "Self-organized task allocation to sequentially interdependent tasks in swarm robotics", *Autonomous Agents and Multi-Agent Systems*, vol. 28, no. 1, pp. 101-125, 2014.

[27] N. Nedjah, R. M. De Mendonca, L. D. Mourelle, "PSO-based distributed algorithm for dynamic task allocation in a robotic swarm". PhD thesis, The University of Sheffield, England, 2015.

[28] Chen, Jianing, "Cooperation in swarms of robots without communication", PhD thesis, The University of Sheffield, England, 2015.

[29] A. Schroeder, S. Ramakrishnan, M. Kumar, et al, "Efficient spatial coverage by a robot swarm based on an ant foraging model and the Levy distribution", *Swarm Intelligence*, vol. 11, no. 1, no. 39-69, 2017.

[30] T. Kuyucu, I. Tanev, K. Shimohara, "Superadditive effect of multi-robot coordination in the exploration of unknown environments via stigmergy", *Neurocomputing*, vol. 148, no. 19, pp. 83-90, 2015.

[31] G. F. Wei, S. Thomas, M. Cole, et al, "Ratiometric decoding of pheromones for a biomimetic infochemical communication system", *Sensors-Basel*, vol. 17, no. 11, pp. 1-16, 2017.

[32] T. Turkoral, O. Tamer, S. Yetis, et al, "Indoor localization for swarm robotics with communication metrics without initial position

information", *In Proceedings of the Springer International Conference on Mechatronics and Robotics Engineering*, pp. 207-215, 2017.
[33] M. S. Couceiro, D. Portugal, R. P. Rocha, et al, "Marsupial teams of robots: deployment of miniature robots for swarm exploration under communication constraints". *Robotica*, vol. 32, no. 7, pp. 1017-1038, 2014.
[34] M. Rubenstein, C. Ahler, N. Hoff, et al, "Kilobot: A low cost robot with scalable operations designed for collective behaviors", *Robotics and Autonomous Systems*, vol. 62, no. 7, pp. 966-975, 2014.
[35] Y. Song, Y. B. Li, C. H., Li, et al, "An efficient initialization approach of Q-learning for mobile robots", *International Journal of Control, Automation, and Systems*, vol. 10, no. 1, pp. 166-172, 2012.