VOL. 10, NO 22, DECEMEBER, 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

COLLABORATION IN MULTI-ROBOT SYSTEMS

Marwan A. Badran, Md. Raisuddin Khan, Siti Fauziah Toha and Zulkifli Zainal Abidin
Department of Mechatronics Engineering, Faculty of Engineering, International Islamic University Malaysia
Jalan Gombak, Kuala Lumpur, Malaysia

ABSTRACT

Multi Robot System (MRS) is one of the most important research areas in the field of Robotics and Artificial Intelligence. The study of Multi Robot Systems may take many aspects; therefore, it is useful to study the Multi Robot Systems from a specific point of view to get a more focused idea. In this paper, we present a review of the recent trends in Multi Robot Systems research by focusing at the collaborative aspect. Furthermore, we address the structure of Multi Robot Systems, their applications and the techniques and algorithms used in the collaborative MRS.

Keywords: multi-robot, collaboration, localization, path planning and mapping.

INTRODUCTION

Multi robot system has been discussed in the literature in the recent past in a variety of settings and applications. More emphasize has been given to MRS operates in dynamic environment, where unexpected changes can happen due to robots or the surrounding environment [1-4]. MRS has the potential to be far more useful and more efficient than a single robot. Furthermore, a team of robots is more robust to failure and can achieve tasks that are impossible for a single robot. Reaching that potential can be extremely difficult, especially in the case where multiple robots make task achievement possible, rather than simply better [5]. Including mapping, search and rescue; many applications cannot be achieved without the collaboration of agents in multi robot systems.

In collaborative MRS (Figure-1), several robots have one or more common goals and each robot has its own individual goal. Robots are aware of their teammates, whilst their actions do help achieving the goals of others. Example: a collaborative team is a group of robots that each must reach a unique position. Robots could work together by sharing sensory capabilities to help all team members to reach their individual goals [6].

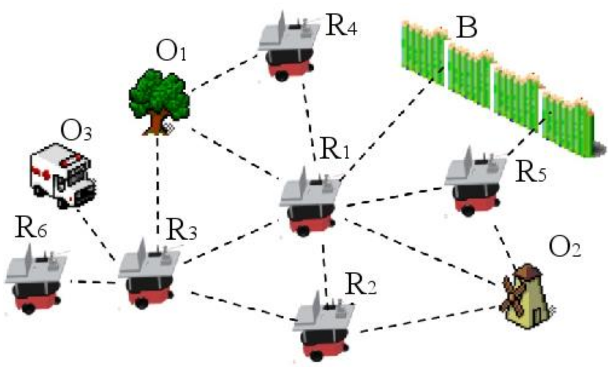

Figure-1. MRS in a general 2D environment [7].

In order to control the interaction among agents in collaborative MRS, three main problems need to be considered; localization, task allocation and path planning. Localization is needed to determine the location and orientation of each robot in the workspace, while task allocation is used to assign jobs to each member of the team. Finally, path planning is guiding robots through obstacles on their way to a final destination. For this purpose, many techniques and algorithms were proposed in the literature. In this paper, we discuss some of these techniques and algorithms based on recent research trends in collaborative MRS. The rest of this paper is divided as follows: Section 2 describes the architecture of MRS including distribution and relation among all agents in the collaborative system. Common techniques and algorithms used in collaborative MRS are discussed in Section 3. In that section, we addressed several techniques and algorithms that have been used for interaction among the collaborative robots in order to achieve a final goal. These techniques and algorithms usually aim to achieve the optimal solution among several propositions. The main purpose of using such techniques and algorithms is to minimize the cost of system resources such as time and number of involved agents. Section 4 discusses some applications of collaborative MRS in the real life, such as industrial and social tasks.

ARCHITECTURE OF MRS

The architecture for the MRS team extremely affects the robustness and scalability of the system. Several different philosophies of MRS architecture are proposed in the literature [8]. Some of these philosophies have shared categories. Here, we illustrate two of the most common categories:

Type of control: (Centralized / Decentralized)

In centralized architecture, a single robot can controls all robots in the field. In this situation, only one controller is needed and all calculations are centralized which reduce the cost and the complicity of system. In this architecture, any failure of the central controller can cause the whole system to fail. On the other hand, decentralized system is more flexible and fault tolerant. A failure of a single robot will not affect the whole system. But, this will lead to extra cost since every robot in the system behaves as an independent controller.

Despite its well-known drawbacks, centralized control can be used in situations where the controller has a clear vantage viewpoint to observe robots and can easily broadcast messages for all [9]. An example of centralized control can be found in [10, 26]. On the other hand, most of researchers used decentralized control for its advantages. Khan *et al*. [11] proposed a decentralized method for collaborative MRS. In that method; robots can achieve collaboration using basic behaviour with a little or no indirect communication. Another example of decentralized control is proposed in [12] for local path- planning of MRS. Decentralized control is most suitable in distributed systems as demonstrated in [6].

Capabilities: (Homogeneous / Heterogeneous)

Homogeneous robots have similar capabilities so they have the advantage of being exchangeable (Figure-2). Besides, the control process will be easier when dealing with identical robots. On the contrary, the team members of heterogeneous system have different capabilities and less similarity. In this case, tasks are not exchangeable and the control process will be more complicated. While most of MRS researchers considered the homogeneous system, we can find several papers that consider heterogeneous system. Wang *et al*. [13] for instance, proposed a multi robot system approach based on the collaboration between heterogeneous robots. The system included humanoid robot, wheeled robots, cameras, and remote computer. Many other studies have also discussed heterogeneous system like [14-16, 35].

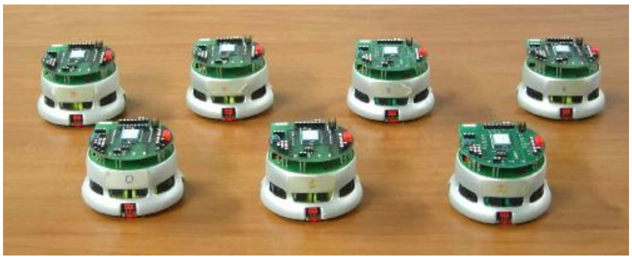

Figure-2. Homogeneous robots [17].

However, selection of the proper architecture (either homogeneous or heterogeneous) is not arbitrary, but depends on the nature of workspace environment, the objective of MRS and the availability of resources.

TECHNIQUES AND ALGORITHMS USED IN COLLABORATIVE MRS

As mentioned in the previous section, most of researches on collaborative MRS focused on three main common topics: localization, path planning and task allocation. The trends of recent research, that cover these topics, showed more concern about artificial intelligence based techniques and algorithms. In this section, we demonstrate the most common techniques and algorithms discussed in the literature of MRS in the past few years.

Localization

Localization is the most important process in MRS; it is used to determine the location and orientation of each robot in the target area. This will help each robot to be aware of other robots and emphasize coordination among the team. At the same time, this will help the system to use robots' locations for task allocation purpose. Localization was discussed in the literature with more focus on the methods and algorithms used to determine the status of each robot in the system. Wu *et al*. [18] proposed an intelligent method to improve the accuracy of localization in wireless sensor network. The proposed algorithm uses wireless sensor network to calculate the position of the tracked robot. The received signal strength indicators were used for distance measurement. In another research, Gasparri *et al*. [19] presented what they called a bacterial colony growth framework for multi-robot localization problem. In the proposed algorithm, collaboration can be set-up between two robots when they are within their range of visibility. The sensory data along with relative distance and orientation are exchanged among the communicated robots. According to the authors, the integration of the exchanged information into the proposed framework enhanced the sensorial and localization capabilities of the robots. Bori *et al*. [20] used genetic algorithm based on a "collaborative" fitness-sharing technique to deal with the multi-robot localization problem. They used fitness-sharing technique, one of niching methods, to minimize the effect of genetic drift by reducing the payoff in densely-populated regions; and that will allow parallel investigation of many solutions in the population. Genetic algorithm also used by Gasparri *et al*. [21]. They proposed a framework based on a spatially structured genetic algorithm for multi-robot localization problem. The complex network theory is used for modeling the search space to achieve a more effective exploration.

Path planning

Robots in MRS need a road map to assist them to reach the target location and avoid collision with obstacles or other robots in the field. Dynamic environment adds more challenges to the interacting team. Here the role of path planning becomes essential to guide the robots to their target location through the surrounding environment. Path planning has been discussed by many researchers like Belkhouche and Jin [22]. They proposed a model-based strategy for path planning in multi robot system by integrating collision detection and navigation algorithm. The proposed collision detection algorithm is an improved version of the swept volume method. Ulusoy *et al*. [23, 24] presented a method for planning robust optimal paths for a team of robots subject to temporal constraints. The proposed method uses a weighted transition system to model the robot's motion, and gives the mission a linear temporal logic formula over a set of propositions that must be repeatedly satisfied. Xu *et al.* [12] presented a decentralized method for local path-planning of multi robot system. In this method, each robot calculates its path planning using the optimal way representative point to find the shortest path. The artificial moments are used in that study as follows: The motion controller uses attractive and repulsive moments to move robots closer to the optimal path and to avoid obstacles. On the other hand, the coordinated moments are used to resolve any conflict between robots. However, according to the authors, the proposed method has a disadvantage of difficulty of solving conflicts between robots in dynamic environment or narrow passages. Otte *et al.* [25] presented algorithm called "Any-Com intermediate solution sharing" for multi-robot path planning. The algorithm finds a suboptimal solution quickly and then refines that solution subject to communication constraints. The main focus of the study is to find a coordinated set of collision-free paths for all robots in a common area. In the proposed algorithm, the computational load of calculating a solution is distributed among all robots. The main idea of the proposed algorithm is that the agents share intermediate solutions in a collaborative way, so that the whole team can focus remaining effort on finding better solutions. Path planning may require the robots to coordinate their actions to avoid any interference among the team members. Coordination in MRS has been studied by many researchers, and several methods have been proposed in this context. For example, Fan et al. [26] proposed a method that combines the role transformation and reinforcement learning to improve the learning ability of MRS coordination. The authors used a coordination policy based on maximum behavior value to plan the collision avoidance action. Particularly, Q-Learning method was used to optimize the weights of the robot behavior through interacting with environment. Another study done by Pereda [27] also used reinforcement learning for MRS coordination. He used Q-Learning to identify the actions that the robots need to apply in each state in order to perform the given task. The proposed system in that study used a central camera to determine the positions of robots and object without using any sensors. However, this means that the system is fully dependent on that camera.

Task allocation

Task allocation plays an important role in MRS; it is related to assigned job for each robot in the system. Based on the algorithm used for task allocation, jobs will be distributed among the team of robots. So, it is possible that some robots may be assigned more jobs than the others based on some conditions like robot position or capabilities. Task allocation systems can be classified according to the following criteria:

Time of computations (Online/Offline)

In an online allocation system, tasks are identified while the system is functioning. The allocation process takes place after initialization, and new tasks are introduced after that time. Basilico *et al.* [28] used Multi-Criteria Decision Making to define exploration strategies in the domain of search and rescue. Online algorithm was also introduced by Jolly *et al*. [29], this time in the domain of Robot Soccer Systems. They used fuzzy neural network in order to plan tasks and select actions. Korsah *et al*. [30] used the offline approach. They introduced the XBOTS system architecture, where tasks are known a priori.

Architecture

In a centrally managed system we can make optimal decisions as the coordinator has global knowledge of the environment. A fault in the coordinator however, makes them team members unable to operate. A Centralized task allocation can be found in [31] where a market-based approach is proposed to solve task allocation problem in surveillance systems. On the other hand, decentralized systems can distribute the load of required processing. Furthermore, they are scalable and more effective in communication. Most recent proposals used the latter approach. For instance, Dasgupta *et al*. [32] proposed a market-based algorithm, along with swarm-based coordination. Agents that encounter new tasks

ARPN Journal of Engineering and Applied Sciences

communicate their task lists to nearby robots, and use a dynamic pricing algorithm in order to sell them the task.

Type of interaction

Types of interaction in multi-robot system can be categorized as follows [6]:

Collective: robots are not aware of each other, but they share goals, and their actions are helpful to their teammates.

Cooperative: robots are aware of each other, they have shared goals, and their actions are helpful to their teammates. **Example:** group of robots working together to push a box in a specific direction.

Collaborative: robots have their individual goals, but also they are aware of each other, and their actions are helpful to achieve the goals of others. Example: a collaborative team of robots in which every single robot must reach a unique position. Robots could work together by sharing sensory capabilities to help all robots to achieve their individual goals.

Coordinative: robots are aware of each other, but they do not have a common goal, and their actions are not helpful to their teammates. Example: robots who share a common workspace need to coordinate their actions to minimize the interference among team members.

Zhang *et al*. [33] presented a multi-robot task allocation method for exploring unknown environments. The authors used the virtual pheromone self-organizing logic, inspired by the ant colony, to indicate the difficulty of the explored areas. Xu *et al*. [34] presented a Modified Ant Colony System algorithm to solve a constrained multiple traveling salesman problem and applied to the multi-robot dynamic task allocation problem. The proposed algorithm put all ants on the starting or ending depots of robots randomly. Besides, the pheromone and the cost from one depot to all targets are calculated and stored. In the proposed algorithm an initial task allocation is run by a leader robot, while the result of allocation is sent to each robot in the system. Task reallocation is performed in case of conduct failures. Shi *et al*. [35] presented a reputation-based task allocation model to solve the task allocation problem in collaborative multi-robot system. The study considered the “reputation” of a robot by assigning a specific task to the robot with high reputation. According to the authors, this will improve the success rate of implementation of its mandate, thereby reducing the time of the system task recovery and redistribution. However, in this method, the robots with the highest reputation values will handle most of the load. As a result, the low contribution of the other robots may decrease the efficiency of the system. Tolmidis *et al*. [36] proposed a solution for the multi-robot dynamic task allocation problem. In their study, the authors used multi-objective optimization for estimation and making offer for task assignment. The study aims to better utilize resources like time and energy. Many factors were taken in account in the proposed algorithm, such as: the distance traveled and the efficiency of a robot in a specific task. In the proposed algorithm, genetic algorithm and Pareto optimality are used for task allocation purpose.

APPLICATIONS OF COLLABORATIVE MRS

The fast development of robot technology made MRS more applicable and increasingly desired in various aspects of life. Consequently, researchers are motivated to develop new techniques and algorithms that are applicable to MRS. The result of this development can be noticed in many applications where MRS is used. These applications include industrial, social, military, and many other fields.

Industry is a good example of MRS application where both collaboration and high performance are required; such as in assembly, welding, and laser cutting (see Figure-3). The application of MRS from an industrial perspective is discussed in [37]. The author focused on the control development of industrial robots such as: model-based, cost/performance-driven and application-driven control development. According to the author, such control development improves the quality of the robot-based manufacturing and increase the productivity of robot automation.

Figure-3. Collaborative robots performing a team task [37].

Exploration is another well-known application of collaborative MRS. In this type of systems, a team of robots is used for exploration of unknown environment. Usually, each robot is supplied with sensors for detecting the surrounding environment. The collected data from attached sensors may be used by robots to avoid obstacles or for mapping purpose, etc. Exchanging sensors data among robots will enhance the efficiency of the collaborative system. The problem of estimating the robot pose and the surrounding environment representation is usually defined as simultaneous localization and mapping (SLAM). This problem has been studied by many researchers such as [38, 39] especially for exploration purpose.

Like exploration, mapping is one of the important tasks of MRS. Mapping aims at obtaining the space model of mobile robot's physical work environment. For this purpose, robot may use camera, laser range finder, sonar and other vehicle sensors to build the environmental map after data processing. Mapping needs localization, and localization depends on the environment maps, so localization and mapping are usually simultaneous. Using a single robot for mapping showed some significant progress in some cases. But, using collaborative MRS has the advantages of high efficiency, high precision, high fault tolerance and re-configurability [40]. Map-merging is another topic related to mapping. In order to improve the accuracy of map merging, Lee *et al*. [41] proposed a grid map-merging technique based on virtual emphasis for multi robot systems. The proposed technique uses one-way observation instead of mutual observation, curvature-based map matching and particle swarm optimization.

Collaborative MRS may also be very beneficial in rescue missions where robots have the advantage of performing exploration over a disaster area looking for survivors. An example of this application is proposed in [42] where robots explore the disaster area searching for victims while they have communication with human operator. Another study on using MRS for rescue mission is proposed in [43]. The authors used genetic algorithm to optimize the cost function that determines the most suitable robot that can perform a particular task or help another teammate to do the same task.

Finally, social robot is now considered as one of the most interesting applications of MRS where robots interact with human. *Service robot* is a well-known type of social robots where multi robots work together to provide service for human or surrounding environment. An example of collaborative service robots is described in [44]. Some of the recent research on long-term interaction between users and social robots are reviewed in [45].

CONCLUSIONS

In this paper, we discussed different aspects of MRS as reflected in the recent research with more focus on the collaborative aspect. Furthermore, we addressed the structure and the applications of MRS, besides the techniques and algorithms used for collaboration purpose. Distributed systems are preferred for their advantages over the centralized ones, yet the latter still inevitable in some applications. The general trend observed from the recent research is towards the artificial intelligent based algorithms, like Genetic Algorithm, Ant Colony and Reinforcement Learning for their potency to improve the efficiency of the collaborative behaviour of MRS. However, some robots such as snake robots may have various shapes while operating and that leads to a new challenge for future research. Robots inspired from natural creatures, such as spider, fish, worms, etc. have more complex features than the traditional robots. Consequently, the collaboration process among these bio-inspired robots becomes more difficult, and that opens a new avenue for research.

Finally, it is noticed that the results presented in many studies in the literature of MRS were obtained by simulation and not verified experimentally. This opens another challenge for future work to apply the proposed techniques and algorithms using field experiments in real life environment.

REFERENCES

[1] Iocchi, L., Nardi, D. and Salerno, M. 2001. Reactivity and deliberation: a survey on multi-robot systems. In Balancing reactivity and social deliberation in multi-agent systems (pp. 9-32). Springer Berlin Heidelberg.

[2] Arai, T., Pagello, E., and Parker, L. E. 2002. Editorial: Advances in multi-robot systems. IEEE Transactions on robotics and automation, 18(5), 655-661.

[3] Xiong, N., He, J., Yang, Y., He, Y., Kim, T. H. and Lin, C. 2010. A survey on decentralized flocking schemes for a set of autonomous mobile robots. Journal of Communications, 5(1), 31-38.

[4] Gautam, A. and Mohan, S. 2012, August. A review of research in multi-robot systems. In Industrial and Information Systems (ICIIS), 2012 7th IEEE International Conference on (pp. 1-5). IEEE.

[5] Gerkey B. P., Thrun S. and Gordon G. 2005. Parallel Stochastic Hill-Climbing with Small Teams. Multi-Robot Systems. From Swarms to Intelligent Automata, Volume III, Springer.

[6] Parker, L. 2008. Distributed intelligence: overview of the field and its application in multi-robot systems. J. Phys. Agents 2, 5-14.

[7] Zhou, Y. 2010. Distributed control of multi-robot deployment motion. INTECH Open Access Publisher.

[8] Parker, L. E. 2008. Multiple mobile robot systems. In Springer Handbook of Robotics (pp. 921-941). Springer Berlin Heidelberg.

[9] Khoshnevis, B. and Bekey, G. 1998. Centralized sensing and control of multiple mobile robots. Computers and industrial engineering, 35(3), 503-506.

[10] Milutinovic, D., and Lima, P. 2006. Modeling and optimal centralized control of a large-size robotic population. Robotics, IEEE Transactions on, 22(6), 1280-1285.

[11] Khan, M. R., Billah, M. M., Ahmed, M., and Aziz, N. A. 2011, May. A novel algorithm for collaborative behavior of multi-robot in autonomous reconnaissance. In Mechatronics (ICOM), 2011 4th International Conference on (pp. 1-6). IEEE.

[12] Xu, W. B., Chen, X. B., Zhao, J. and Huang, T. Y. 2013. A Decentralized Method Using Artificial Moments for Multi-Robot Path-Planning. Int J Adv Robotic Sy, 10 (24).

[13] Wang, T., Ramik, D. M., Sabourin, C. and Madani, K. 2012. Intelligent systems for industrial robotics: application in logistic field. Industrial Robot: An International Journal, 39(3), 251-259.

[14] LeBlanc, K., and Saffiotti, A. 2008, May. Cooperative anchoring in heterogeneous multi-robot systems. In Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on (pp. 3308-3314). IEEE.

[15] Chand, P., and Carnegie, D. A. 2013. Mapping and exploration in a hierarchical heterogeneous multi-robot system using limited capability robots. Robotics and autonomous Systems, 61(6), 565-579.

[16] Hu, C., Hu, C., He, D. and Gu, Q. 2015, May. New ROS-based hybrid architecture for heterogeneous multi-robot systems. In Control and Decision Conference (CCDC), 2015 27th Chinese (pp. 4721-4726). IEEE.

[17] Webuser.unicas.it, 2015. Retrieved 15/9/2015, from http://webuser.unicas.it/lai/robotica/immagini/plotone.jpg

[18] Wu, H., Tian, G. and Huang, B. 2008, September. Multi-robot collaborative localization methods based on Wireless Sensor Network. In Automation and Logistics, 2008. ICAL 2008. IEEE International Conference on (pp. 2053-2058). IEEE.

[19] Gasparri, A. and Prosperi, M. 2008, May. A bacterial colony growth framework for collaborative multi-robot localization. In Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on (pp. 2806-2811). IEEE.

[20] Bori, F., Gasparri, A. and Panzieri, S. 2009, October. A fitness-sharing based genetic algorithm for collaborative Multi Robot Localization. In Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on (pp. 3968-3973). IEEE.

[21] Gasparri, A., Panzieri, S. and Pascucci, F. 2009. A spatially structured genetic algorithm for multi-robot localization. Intelligent Service Robotics, 2(1), 31-40.

[22] Belkhouche, F. and Jin, T. 2009, October. An approach for collaborative path planning in multi-robot systems. In Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on (pp. 2356-2361). IEEE.

[23] Ulusoy, A., Smith, S. L., Ding, X. C. and Belta, C. 2012, May. Robust multi-robot optimal path planning with temporal logic constraints. In Robotics and Automation (ICRA), 2012 IEEE International Conference on (pp. 4693-4698). IEEE.

[24] Ulusoy, A., Smith, S. L., Ding, X. C., Belta, C. and Rus, D. 2013. Optimality and robustness in multi-robot path planning with temporal logic constraints. The International Journal of Robotics Research, 32(8), 889-911.

[25] Otte, M. and Correll, N. 2013. Any-com multi-robot path-planning: Maximizing collaboration for variable bandwidth. In Distributed Autonomous Robotic Systems (pp. 161-173). Springer Berlin Heidelberg.

[26] Fan, J., Fei, M., Shao, L. and Huang, F. 2008. A Novel Multi-robot Coordination Method Based on Reinforcement Learning. In Advanced Intelligent Computing Theories and Applications. With Aspects of Theoretical and Methodological Issues (pp. 1198-1205). Springer Berlin Heidelberg.

[27] Pereda, J., Martín-Ortiz, M., de Lope, J., and de la Paz, F. 2011. Study of a multi-robot collaborative task through reinforcement learning. In Foundations on Natural and Artificial Computation (pp. 185-191). Springer Berlin Heidelberg.

[28] Basilico, N., and Amigoni, F. 2011. Exploration strategies based on multi-criteria decision making for searching environments in rescue operations. Autonomous Robots, 31(4), 401-417.

[29] Jolly, K. G., Kumar, R. S., and Vijayakumar, R. 2010. Intelligent task planning and action selection of a mobile robot in a multi-agent system through a fuzzy neural network approach. Engineering Applications of Artificial Intelligence, 23(6), 923-933.

[30] Korsah, G. A., Kannan, B., Browning, B., Stentz, A. and Dias, M. B. 2012, May. xBots: An approach to generating and executing optimal multi-robot plans with cross-schedule dependencies. In Robotics and Automation (ICRA), 2012 IEEE International Conference on (pp. 115-122). IEEE.

[31] Khamis, A. M., Elmogy, A. M. and Karray, F. O. 2011. Complex task allocation in mobile surveillance systems. Journal of Intelligent and Robotic Systems, 64(1), 33-55.

[32] Dasgupta, P. and Hoeing, M. 2008. Dynamic pricing algorithms for task allocation in multi-agent swarms. In Massively Multi-Agent Technology (pp. 64-79). Springer Berlin Heidelberg.

[33] Zhang, Z., Xu, D., Liu, X. and Zhao, J. 2009, December. Self-Organizing Task Allocation of Multi-robot. In Internet Computing for Science and Engineering (ICICSE), 2009 Fourth International Conference on (pp. 286-289). IEEE.

[34] Xu, Z., Xia, F. and Zhang, X. 2009. Multi-robot dynamic task allocation using modified ant colony system. In Artificial Intelligence and Computational Intelligence (pp. 288-297). Springer Berlin Heidelberg.

[35] Shi, Z., Wei, J., Wei, X., Tan, K. and Wang, Z. 2010, July. The task allocation model based on reputation for the heterogeneous multi-robot collaboration system. In Intelligent Control and Automation (WCICA), 2010 8th World Congress on (pp. 6642-6647). IEEE.

[36] Tolmidis, A. T. and Petrou, L. 2013. Multi-objective optimization for dynamic task allocation in a multi-robot system. Engineering Applications of Artificial Intelligence, 26(5), 1458-1468.

[37] Brogårdh, T. 2009. Robot control overview: An industrial perspective. Modeling, Identification and Control, 30(3), 167.

[38] Pham, V. C. and Juang, J. C. 2013. A Multi-Robot, Cooperative, and Active SLAM Algorithm for Exploration. International Journal of Innovative Computing, Information and Control, 9(6).

[39] Liu, Y., Fan, X. and Zhang, H. 2013. A fast map merging algorithm in the field of multirobot SLAM. The Scientific World Journal, 2013.

[40] Yi, Z., Yan-Le, L. and Yuan, L. 2011, July. Multi-robot map building based on Ad hoc network communication. In Control Conference (CCC), 2011 30th Chinese (pp. 4007-4010). IEEE.

[41] Lee, H., Cho, Y., and Lee B. 2013. Accurate map merging with virtual emphasis for multi-robot systems. Electronics Letters, 49(15), 932-934.

[42] Sugiyama, H., Tsujioka, T. and Murata, M. 2013. Real-time exploration of a multi-robot rescue system in disaster areas. Advanced Robotics, 27(17), 1313-1323.

[43] Khan, M. T., Chan, B., Khan, A., Haq, Z., and Iqbal, J. 2012. Optimized Dynamic Task Allocation and Priority Assignments in an Immunized Autonomous Multi-Robot Search and Rescue Operation. SCIENCE AND TECHNOLOGY, 15(2), 129-145.

[44] Suh, J. and Woo, C. W. 2010. A Framework for Collaborative Aspects of Intelligent Service Robot. In Machine Learning and Systems Engineering (pp. 17-29). Springer Netherlands.

[45] Leite, I., Martinho, C. and Paiva, A. 2013. Social robots for long-term interaction: a survey. International Journal of Social Robotics, 5(2), 291-308.