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A Survey on Multi-robot Systems

Yifan Cai and Simon X. Yang
School of Engineering, University of Guelph
Guelph, Ontario, Canada, N1G 2W1
{ycai; syang}@uoguelph.ca

***Abstract*— This paper reviews the state-of-the-art research on multi-robot systems, with a focus on multi-robot cooperation and coordination. By primarily classifying multi-robot systems into active and passive cooperative systems, three main research topics of multi-robot systems are focused on: task allocation, multi-sensor fusion and localization. In addition, formation control and coordination methods for multi-robots are reviewed.**

***Index Terms*— Multi-robot cooperation, robot localization, multi-sensor fusion, task allocation, formation control.**

I. Introduction

Multi-robot system came into applications in early 1980s [1], when researchers and scientists wished to improve the efficiency of robots and achieve some complex tasks that cannot be finished by single robot. An individual robot is found to be weak at reactions to dynamic surroundings and intricate assignments. As a consequence, people pay attentions to multi-robot systems. The noticeable advantage is that they are low-cost to produce and able to improve the stability and robustness by their parallel character and redundancy [1]. Though a single robot may not be powerful enough, by cooperating in a team, multi-robots can concentrate on details respectively and compensate disadvantages of other members.

When multi-robot systems start working, cooperation will be essential during the whole process. How to have an accurate definition on cooperation has raised discussions among scientists. The classical Oxford English Dictionary defines cooperation as "team work together, or conjunction". But as a fact, no absolutely explicit explanation is recognized in applications. It can be wide and broad. Surveillance on several robots, at least two, can be regarded as cooperation. Of course, they should have their own regulations and protocols to follow. Furthermore, special commands are needed to effectively coordinate the team members. Like ants or bees in nature, robots make effects to demonstrate their abilities to collaborate to solve a complex task together [2].

Nowadays, scientists make a conclusion to have two opposite definitions [2] on multi-robot cooperative systems: one is active [3] while the other one is passive cooperative system [4]. In the former one, robots themselves have a communication link to coordinate their actions and make decisions [2]. They can connect with each other in a special period and pick up information from other members. Sometimes they need the communications to react to the environment or deal with new tasks [5]. This type of cooperative system is supposed to deal with real-time task [6]. On the contrary, the passive cooperation means no evident communications among robots [4]. Sometimes a single robot just takes others as obstacles and tries to avoid them. They do not wish to share information and make decisions together [7]. What they have to do is just to meet individual requirements. This type of cooperative system is easy to design and offers good robustness.

Both of these two types of multi-robot cooperative systems are widely applied in application and industry [8]. A great deal of achievements are attained in the robotic research fields to improve the performance of the multi-robot system, such as the efficiency, feasibility and robustness. In this paper, three important research fields of multi-robot systems are selected, including task allocation, multi-sensor fusion and localization.

II. Task Allocation

Task allocation in multi-robot cooperative systems defines the problem to find an assignment connecting the robots or a task, which can accomplish some system issues such as improving the efficiency, reducing the cost, optimizing the global robustness or distributing the resources scientifically. Traditional methods are to adopt various kinds of optimal algorithms into applications. The common process of multi-robot task allocation is shown in Fig. 1. During the procedure, the robot will process the task once it receives the task allocation solution. Simultaneously, it will locate itself in virtue of wireless sensors so that it can go from the initial place to the final place of the task. Based on this idea, a large number of communications and computations are inevitable.

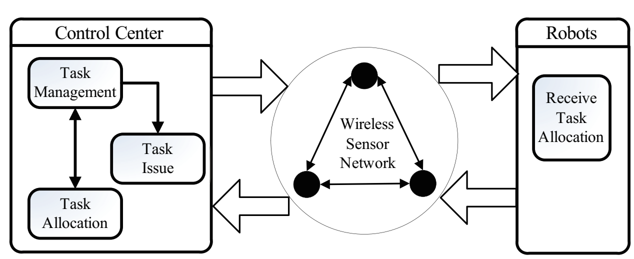

Fig. 1. Multi-robot task allocation process. (Modified from [5])

To improve it, researchers propose threshold-based and market-based task allocations, with L-Allicance and Murdoch as representative applications respectively [9]. They can decrease the demands for communication but are not able to promise the best solutions. However, these methods are not competent when the numbers of robots and tasks increase. In order to resolve this problem, Li *et al.* [9] developed a layered learning approach and distributed the robotic soccer task into three layers: task decomposition layer, task evaluation layer and task selection layer, as shown in Fig. 2. Machine learning skills are taken to deal with the task at each level.

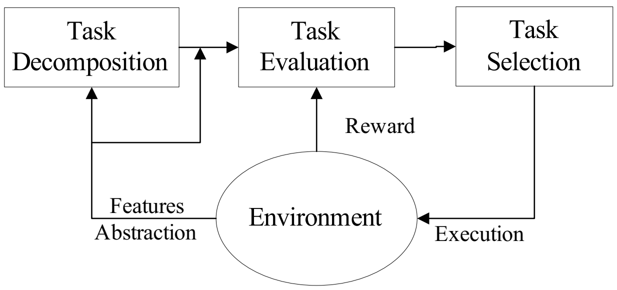

Fig. 2. Architecture layered task allocation approach. (Redraw from [9])

In the simulation process, task allocation is realized step by step. The results, shown in Fig. 3, indicate that the layered task allocation method noticeably improves the performances of multi-robot cooperation, where w_{ij} in Fig. 3 is a learning factor. Especially, individual robot can get an optimized task allocation solution and effectively learn the task after training [9].

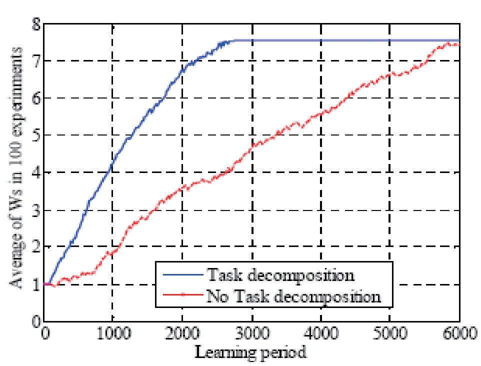

Fig. 3. The learning curves of adopting task decomposition against unadopting. (From [9])

Besides dealing with multi-tasks, scientists also pay attention to meet the requirement of dynamic environment. Tian *et al.* [10] presented the approach based on the reinforcement learning to fulfill the task allocation in intricate environments. Fire alarm system is chosen in the research and simulation results demonstrate the applicability of the method [10]. In addition, sometimes the real surrounding is uncertain to robots. To handle it, Mataric *et al.* [11] proposed multi-robot task allocation under uncertainty. General guidelines are presented for task allocation strategies based on experience. Then four distinct task allocation strategies are defined. The messages from the simulations indicate that a combination of the strategies is better then a solo one for the cooperation.

Furthermore,together with the development of artificial intelligence, some corresponding research is raised on multi-robot task allocation. In 2007, Banik *et al.* [12] introduced an emotion-based approach shown in Fig. 4. In the scheme, each robot requests the assistance from another robot in case that they need the cooperation to finish the tasks. Cooperation behaviors are generated based on a stochastic model of emotion and are endued with high emotional capability. In the simulation experiment, every robot can recognize and distinguish the dynamic surrounding, and then would have proper reactions. Markov Modeling Theory is chosen to build the emotion model.

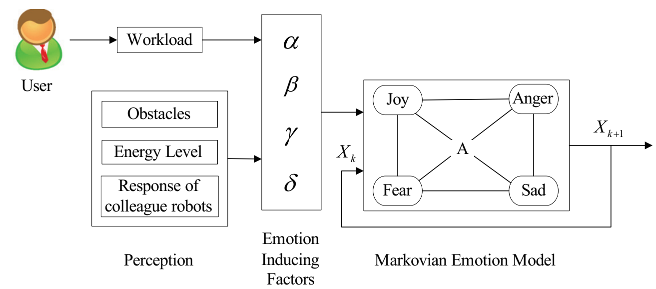

Fig. 4. Emotional state generation with Markovian model. (Redraw from [12])

Same in 2007, Schwertfeger and Jenkins [13] from Brown University proposed Multi-Robot Belief Propagation (MRBP) method. The scheme is designed to combine distributed probabilistic inference with notions of theory-of-mind. The propagation algorithm is adopted to incorporate task-related intentions and beliefs of robots into the assignment process, in which each robot decides its own actions based on its observation and beliefs of other robots. The advantage is that no explicit protocols or command hierarchies are indispensable in the group work.

Current task allocation schemes show an exponential growth in calculation work with the increase of tasks and robots, and it is infeasible to map the whole environment state for task allocation schemes. In order to decrease the complexity, it is expected to develop more efficient and faster methods in good generalization capacity in future [14].

III. Multi-Sensor Fusion

Multi-sensor fusion technology is the foundation of robot intelligent control. In order to meet the demand of the detecting and gathering data for multi-robot systems, different types of sensors are proposed to indicate the internal relationships and surrounding characteristics. Multi-sensor fusion technology integrates several skills, such as data collecting, signal process, visual perception and image manipulation. Through corresponding algorithms, it can fuse the information provided by the sensors, eliminate the redundancy among the multi-sensor information, reduce uncertainty and provide with relatively comprehensive description about the surroundings. In [15], Zhao *et al.* listed several typical applications of Multi-sensor fusion technologies, which are shown in Table 1.

Fusion algorithm is the core of information fusion. Nowadays, the main information fusion methods in robotic fields include weighted average method, Bayes estimation, Kalman filtering, fuzzy logic and neural networks (NNs) [15].

Among all the popular methods, weighted average method is easy to build. The messages from the sensors will be added weights to attain the fusion results. Though low cost on calculation, there are not effective ways to tune the weights and it's less competent to deal with complicated environments. To improve it, Gao *et al.* [16] proposed the approach based on random weighting estimation. It is designed to attain optimal weighted fusion of multi-sensor observation data. Algorithms of random weighting estimation are adopted to calculate sensor variances for determination of optimal random weighting factors. The experiment results indicate that the approach can noticeably decrease the mean square error. More advanced than weighted average method, Bayes estimation can be implemented in static environments. It utilizes probability distribution for the information description and is applied to estimate the status of the robot or the objects. Mutphy [17] adopted Dempster-Shafer evidential reasoning, which is able to handle premise and is an extension of Bayes estimation. It uses instable unknown prior probability to improve the tolerance and precision of the robot. Different from Bayes estimation, Kalman filtering can work in the dynamic environments. It attains the optimal fusion estimation by statistical recursion. But it requires that the system model is linear and the noise is Gauss White noise, otherwise the optimal estimation cannot be ensured. Currently, Kalman filtering is widely applied in multi-sensor fusion [18].

When deal with uncertainty problem, fuzzy logic and NNs can effectively lead the reasoning process. Fuzzy logic utilizes a number between 0 and 1 to express the membership while NNs implements the learning process to fuses the uncertain relationships into comprehensible signs or labels. Current research has already improved the calculation speed and the tolerance. For example, Han *et al.* [19] proposed a multi-sensor target recognition fusion method based on fuzzy theory. The mutual supportability of multiple sensors is obtained from the correlation function and it avoids huge computations. The simulation results demonstrate that the approach can accurately and effectively recognize the objects. Another good example is that Yaginuma *et al.* [20] implemented an auto-encoder neural network in multi-sensor fusion model to recognize three-dimensional objects.

It is the trend that researchers use several fusion algorithms to compensate their inherent shortcomings, e.g., fuzzy logic can improve the self-applicability of NNs learning process, and it's better to implement them comprehensively. However, calculation speed and storage space will be expanded due to the complexity of the mixed algorithms. As a consequence, an innovation of the multiple fusion algorithm is highly expected now.

IV. LOCALIZATION

The localization is to estimate the position of a robot that moves in known/unknown environments. Scientists consider that localization has been regarded as one of the most crucial problems in multi-robot cooperative systems in that almost all the cooperation task need information on pose changes and moving distances. Reliable and effective information is the base to execute a normal task. But the real situation is that robots related to the circumstance are not easy to calculate their parameters while noise and disturbs from the sensor contribute to the data confusion.

Gasparri and Prosperi [21] implemented a new biology-inspired approach to deal with the multi-robot localization problem. It makes full use of the models of species reproduction to offer a proper structure for carrying on the multi-hypothesis, together with suitable regulations on both autonomous and collaborative contexts. Robots share sensory data on distance and orientation. These messages are adopted into the proposed framework so that the convergence aptitude is improved [21]. The information from the sender is received by the receiver to redefine areas that can be valuable to its estimate. As a consequence, the sensorial capabilities of the receiver are extended and its localization capability is enhanced. Simulations results show that the localization performance acts more perfectly when collaboration is involved [21].

Cooperative multi-robots estimate their positions by sensors. Most of current approaches are designed to collect the data instantly as soon as the robot detects another robot. However, such instant update does not always contribute positively to the localization process in case that all the robot messages could be uncertain at the time of detection. Wu and Su [22] developed a new information exchange mechanism for collaborative multi-robot localization. In the design, only necessary information exchanges, which contribute positively to the localization process, are permitted and needed. Other redundant messages will be neglected. This proposed scheme is implemented and tested in real mobile robots as well as simulations. The results show that significant improvements in localization speed and accuracy occur when compared to the single mobile robot localization approach [22].

Besides above research, Leung and Gallagher [23] proposed the simultaneous localization and map building (SLAM) strategy to explore unknown environment. The tradition active obstacle detector is abandoned and a new approach, which only needs tactile sensors and inter-robot distance measurements, is proposed. A dynamic spanning tree structure is implemented for multi-robot coordination. In the experiment, an online behavior-based finite state machine is used to drive the structure. When an obstacle is detected, it will be recorded on a map shared by all other robots. The advantage of the exploration technique is its independence of GPS and obstacles recognition, which leads to low-cost in computation [23].

For accurate localization task, Jiang and Chen [24] developed a method based on multi-sensor fusion. In the research,

TABLE I

RESEARCH STATUS OF MULTI-SENSOR FUSION TECHNOLOGY. (FROM [15])

Name	Sensors	Working Surroundings	Fusion Algorithm
Hilare	Ultrasonic sensors, CCD range finder	Unknown man-made surroundings	Weighted average method
Stanford	Laser range finder, tactile sensor, ultrasonic sensors	Unknown man-made surroundings	Kalman filtering
Lias	Ultrasonic sensors, infrared sensors	Unknown outdoor surroundings	Multiple fusion algorithm
Crowley	Ultrasonic sensors, tactile sensor	Known man-made surroundings	Credibility coefficient matching
Dappaalv	Ultrasonic sensors, CCD range finder	Unknown natural environment	Means comparison in small scope
Hannibal	Infrared sensors, ultrasonic sensors, ultrasonic sensors CCD	Complex unstructured environment	Fuzzy logic and neural network

the kind of master-slave robots are selected. For the fusion model, laser scanner and vision sensor are implemented, while the master robot uses the latter one to receive the target bearing. Experiment involved with real robots certifies the feasibility and perfect implementation characters of the proposed scheme [24].

For the parameters are unknown and variable, Pillonetto and Carpin [25] proposed the idea to take Tikhonov Regularization as foundation. The noticeable advantage is that it sends few requirements for the individual sensor of each robot to evaluate their movements. Instead, robots are designed to have a single sensor that could send back noisy measurements of mutual distances while they take a motion along unknown tracks. The selected algorithm could estimate the robot poses and position on-line, which liberates the operator from the task of estimating a priori system and measurement noises. In addition, estimating these variances online helps to estimating more precise bounds due to localization error bounds based on noise covariance matrices [25].

Recent research has focused primarily on reducing the computational requirements of cooperative localization (CL). However, all the communication requirements of CL are substantial because, depending on the approach, either measurements from sensors or state estimates have to be exchanged. Communicating all these quantities may be infeasible. So research on highly efficient communication with reliable and feasible characters will be the new trend of localization in future.

V. FORMATION CONTROL

In multi-robot control, formation control can be regarded as the formal standard for implementation. For a multi-robot system, formation control is essentially a coordinated scheme for the positions and orientations of the members. It can be applied into several typical scenarios, which require certain shapes of the robot team to accomplish the tasks. Current research has already proposed several effective methods to solve the formation control problem.

In [26], common formation control methods are proposed for multi-vehicle cooperation. They are simple but easily to be accomplished. But actually the multi-robot system usually needs to deal with dynamic or uncertain environments. The traditional formation control scheme may lack of sufficient communications. To resolve it, Desai *et al.* [27] proposed the scheme that individual robots are allocated specific identification tags with predefined positions. It helps to build effective an way under limited communications. Furthermore, Hou *et al.* [28] showed the formation control category to lead a group of robots in a dynamic region. The contribution of the scheme is to endow the robots the ability to adjust the formation during the course of maneuver. No single member can affect others when it join or exit the formation. Lyapunov-like function for convergence analysis supports the proposed scheme in theory [28].

With the development of formation control methods, it is the trend to combine several effective approaches to praise innovative improvements. In 2008, Chen and Xu [29] proposed the idea to present a coordination method based on discrete orientation bias control. In the proposed scheme, firstly a moving structure graph is specified, and then a model of the formation is got, which comes from the artificial potential functions. The advantage is that it is free on orientation constraints to describe the adjacent pair-wise robots in the formation. Furthermore, when the orientation bias between robots comes to zero, the proposed control strategy makes the global potential function to be maximum. Consequently it promotes the stability by Lyapunov [29].

As common, formation control is just implemented to organize one team of robots. But in 2005, Hsu and Liu [30] introduced the plans to operate several teams of robots. Virtual Operator Multi-Agent System (VOMAS) architecture is built in the strategy, shown in Fig. 5. VOMAS is a hybrid architecture with two main agents. The user agent handles high level missions and team control, while the robot agent deals with low level formation control. Joining, removing, splitting, and merging requests are four basic services for the virtual operator to adopt. The advantage of this scheme is that new single robot could be easily added into the group and kinematic control could be efficiently achieved no matter the robots are holonomic and nonholonomic [30].

VI. COORDINATION AND COOPERATION

Coordination and cooperation in multi-robot systems are defined as joint operation or action among a group of robots [2]. In cooperation, not only robots pay attention to their own works but also need to know if there are more urgent tasks

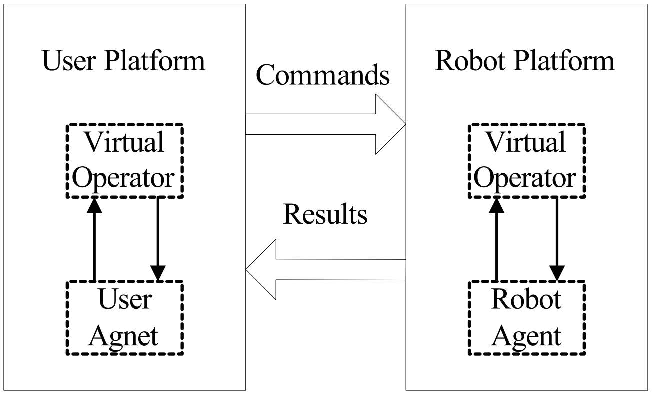

Fig. 5. VOMAS architecture. (Modified from [30])

from the partners. Sometimes a single robot may postpone the individual work to help its partners in order to improve the global work efficiency. In the scenario of cooperative works, coordination is essential to the accomplishment of team work. In other words, multi-robot systems cannot work effectively without essential cooperation among the team members.

Many research topics related to multi-robot systems start out from cooperation for exploration or surveillance task. Take exploration task as an example, multi-robot systems require the information from all the robot members to build the map. At this case, coordination among the members is essential for the efficient work of the whole system. Zhao *et al.* [31] proposed a multi-robot coordination algorithm for area exploration tasks. Based on a distributed bidding model, the distances between robots are considered in the bidding algorithm and a map synchronization mechanism is proposed to reduce the exchanged data volume when robot sub-networks merge. It works with satisfied results.

Current research shows that cooperation and coordination in multi-robot systems can effectively deal with complicated tasks and dynamic environments. Wang and Tan [32] presented a kind of kinematics algorithm, facing to manipulation of huge elliptical ship module. In the proposed design, the multi-robot system can adjust the position and pose of the elliptical work-piece in 6 degree of freedom (DOF), by the coordination of multiple 3 DOF robots. Based on the motion strategy, the inverse kinematics algorithm is given, which is also a simplified algorithm applied to real time control [32]. Experiment data demonstrates the feasibility of the method.

Another problem in cooperation is the number of the individuals. The control category will need large space for data storage. Sentis *et al.* [33] effectively solved the problem of coordinating great numbers of vehicles in large geographical areas under network connective constraints. A special proposed framework calculates trajectories that comply with priority constraints, which optimize the desired task objectives in their null spaces. A model-based dynamics approach is used to provide a direct map to generate smooth and accurate trajectory. The required space is efficiently utilized.

The new trend of multi-robot cooperation is intelligence with autonomous control. Zhao *et al.* [34] presented a cooperative multi-robot map-building approach based on Hilbert curve exploring method. Genetic Algorithms is implemented to select sub-region. It is demonstrated by experiments that the proposed approach significantly reduces the probability to repeatedly explore the same region and also provide individual robot with an optimized choice in region selection [34]. As another intelligent control example, Ahmadi and Stone [35] proposed a good approach for continuous area sweeping tasks. The feature of this method is adaptive control and decentralized task assignment in continuous areas with dynamic factors, such as robot malfunctions or the addition of new robots to the team. In future research, intelligent control with more powerful functions are expected for multi-robot cooperation.

VII. Summary

This paper presents the main features of multi-robot systems. Three main research fields of the cooperative systems are reviewed: task allocation, multi-sensor fusion and localization. After that, formation control is presented. Typical applications and current research on multi-robot systems are reported in the paper. Furthermore, comparisons of different methods and potential future work are discussed.

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