A Survey and Analysis of Multi-Robot Coordination

Regular Paper

Zhi Yan[1,*], Nicolas Jouandeau[1] and Arab Ali Cherif [1]

1 Advanced Computing Laboratory of Saint-Denis (LIASD), Paris 8 University, Saint-Denis, France
* Corresponding author E-mail: yz@ai.univ-paris8.fr

Abstract In the field of mobile robotics, the study of multi-robot systems (MRSs) has grown significantly in size and importance in recent years. Having made great progress in the development of the basic problems concerning single-robot control, many researchers shifted their focus to the study of multi-robot coordination. This paper presents a systematic survey and analysis of the existing literature on coordination, especially in multiple mobile robot systems (MMRSs). A series of related problems have been reviewed, which include a communication mechanism, a planning strategy and a decision-making structure. A brief conclusion and further research perspectives are given at the end of the paper.

Keywords Multi-Robot System, Coordination, Task Planning, Motion Planning

1. Introduction

Multi-robot systems (MRSs) are an important part of robotics research. In the late 1980s, a group of scientists began investigating this direction of research. A series of projects have been realized successfully, such as ACTRESS [1], GOFER [2], CEBOT [3], ALLIANCE [4], M+ [5], MURDOCH [6] and ASyMTRe [7]. One of the major challenges for MRSs is to design appropriate coordination strategies between the robots that enable them to perform operations efficiently in terms of time and working space.

Most of today's robots fall into one of three primary categories, namely manipulators, mobile robots and humanoid robots. This paper focuses on multiple mobile robot systems (MMRSs), in which robots should work together to accomplish a given task by moving around in the environment. We should be careful not to confuse MRSs with multi-agent system (MASs) and distributed artificial intelligence (DAIs), because MAS usually refers to the traditional distributed computer system in which individual nodes are stationary, and the DAI field is primarily concerned with problems involving software agents. In contrast, the area of MRS involves mobile robots that can move in the physical world and must interact with each other physically [9].

So far, a number of papers have been published regarding the research review, taxonomy and survey analysis for MRS. Dudek et al. [8] presented a taxonomy that classifies MASs according to communication, computational capacity and certain other capabilities. They also presented additional results concerning the MAS to illustrate the usefulness of the taxonomy and

demonstrate that a collective can be more powerful than a single unit of the collective. Cao et al. [9] gave a critical survey of the cooperative mobile robotics literature up to the mid-1990s. They synthesized five research axes that were: group architecture, resource conflict, origin of cooperation, learning and geometric problems. They also discussed the constraints arising from technological limitations and possible lacunae in existing works. Stone and Veloso [10] presented four multi-agent scenarios: homogeneous non-communicating agents, heterogeneous non-communicating agents, homogeneous communicating agents and heterogeneous communicating agents. They illustrated the scenarios by using the pursuit domain and described existing works in the field. The techniques presented are biased towards machine learning approaches. Arai et al. [11] identified seven primary research topics within the MRS: biological inspirations, communication, architectures, localization / mapping / exploration, object transport and manipulation, motion coordination, and reconfigurable robots. They also discussed a number of special issue articles and suggested several additional research issues. Farinelli et al. [12] presented a survey of works up to the early 2000s in the area of cooperation and coordination in MRS. Moreover, they proposed a taxonomy for classification focused on coordination that is characterized by two groups of dimensions: coordination dimensions and system dimensions. Other works on the review of the MRS include [13] [14] [15] [16] [17].

The main contributions of this paper are threefold: 1) a systematic review about the problems of multi-robot coordination is conducted and the relationship between them is clearly indicated; 2) a detailed classification and comparison is conducted for each related problem; 3) an analysis of the coordination problems, especially from the perspective of multi-robot task planning and motion planning, is conducted.

The remainder of the paper is organized as follows: Section 2 describes MRSs as compared with single-robot systems; Section 3 describes two multi-robot environments: cooperative and competitive; Section 4 discusses the inherent problem of MRSs: resource conflict; Section 5 discusses the key to gaining the benefits of MRSs: coordination; Section 6 presents two types of communication mechanism: explicit and implicit; Section 7 discusses the problem of planning based on coordination, which includes task planning and motion planning; Section 8 presents two decision-making mechanisms: centralized and decentralized; the paper is concluded with a discussion in 9.

2. Robotic Systems: Single-robot Versus Multi-robot

A single-robot system contains only one individual robot that is able to model itself, the environment and their

interaction [10]. Several individual robots are well known, such as RHINO [18], ASIMO [19], MER-A [20], BigDog [21], NAO [22] and PR2 [147]. The robot in a single-robot system is often designed to deal with a task on its own account. Such robots are usually integrated with multiple sensors, which themselves need a complex mechanism and an advanced intelligent control system. Although a single-robot system give have a relatively strong performance, some tasks may be inherently too complex or even impossible for it to perform, such as spatially separate tasks. For example, Dudek et al. [8] gave an example of a missile launch task that requires some sort of synchronization: there are two keys separated by a large distance in space that need to be activated simultaneously. Hence, an inherent restriction to the single-robot system is that it is spatially limited.

A MRS contains more than one individual robot, whether group homogeneous or heterogeneous. Using a MRS can have several potential advantages over a single-robot system:

- A MRS has a better spatial distribution.
- A MRS can achieve better overall system performance. The performance metrics could be the total time required to complete a task [23] or the energy consumption of the robots [24].
- A MRS introduces robustness that can benefit from data fusion and information sharing among the robots, and fault-tolerance that can benefit from information redundancy. For example, multiple robots can localize themselves more efficiently if they exchange information about their position whenever they sense each other [25] [26] [27].
- A MRS can have a lower cost. Using a number of simple robots can be simpler (to program), cheaper (to build) than using a single powerful robot (that is complex and expensive) to accomplish a task.
- A MRS can exhibit better system reliability, flexibility, scalability [161] and versatility. Robots with diverse abilities can be combined together to deal with complex task, and one or several robots may fail without affecting the task completion.

A MRS can be homogeneous or heterogeneous. In homogeneous robot teams, the capabilities of the individual robots are identical (physical structures do not need to be the same). Some works considering the use of homogeneous robot teams include [28] [29] [30] [31] [24]. In heterogeneous robot teams, the capabilities of robots are different, whereby robots can be specialized for specific tasks. Some works considering the use of heterogeneous robot teams include [1] [4] [6] [27] [32] [159] [167]. In general, heterogeneous systems are more complex than homogeneous systems because the task planning becomes more difficult (see Section 7.1 below for more details).

3. Multi-robot Environment: Cooperative Versus Competitive

Like human society, there is collective behaviour in multi-robot environments. Popenoe [33] defined collective behaviour as follows: collective behaviour is behaviour that occurs in response to a common influence or stimulus in relatively spontaneous, unpredictable, unstructured and unstable situations. The collective behaviour includes cooperative behaviour and competitive behaviour. In other words, multi-robot environments can be *cooperative* or *competitive* [34]. Cooperation refers to a situation whereby multiple robots need to interact together in order to complete a task while increasing the total utility of the system. Alternatively, cooperation is the interaction between the robots, which work towards a common interest or reward [35]. The cooperative robots have a joint goal, which gives rise to various sub-goals. This subject involves the multi-robot planning problem, which we will discuss in more detail in Section 7. There are several representative examples of multi-robot cooperation, such as multi-robot localization [25] [26] [27] [36] [149] [161], multi-robot exploration [23] [37] [29] [38] [39] [40] [41] [42] [43] [44] [159] [164], multi-robot search and rescue [45] [46] [47] [30], and multi-robot transportation [48] [28] [24] [49] [59].

Competition refers to a situation whereby robots compete against each other to best fulfil their own self-interest. Alternatively, robots with conflicting utility functions are in competition with each other [34]. The competitive behaviour is the opposite of cooperative behaviour. Typical examples of multi-robot competition are two-player zero-sum games such as chess [50] and robot soccer leagues, such as RoboCup [51]. A multi-robot environment, cooperative or competitive, will need some sort of consensus (a communication mechanism, see Section 6) and a decision-making mechanism (see Section 8). This paper only discusses the problem of cooperation. The problem of competition is beyond the scope of this paper.

Robots might be selfish from the sociological point of view, because a single robot tends to make decisions motivated by self-preservation. For instance, consider two robots moving in opposite directions and wanting to cross a narrow passage, but where only one may cross at a time. If the two robots move simultaneously, a congestion or collision will occur. The cooperation can overcome groupthink and individual cognitive bias, and this requires some form of *coordination*. Such coordination can be achieved by *communication*, which is often used as a rational behaviour in multi-robot environments. The paper will discuss the coordination in detail in Section 5, and the communication in Section 6.

4. Inherent Problem: Resource Conflict

Generally, if multiple requests targeting the same resource arrive simultaneously, *resource conflict* will occur. This issue has been studied in many forms. A well-known case of a general resource conflict problem is the *mutual exclusion* problem [52] in distributed computing systems or multi-access networks, where only a single resource is available. In MMRS, resource conflict arises when multiple robots need to share space, manipulable object or communication media. To deal with this problem, we need to coordinate the robots. This coordination can be reflected in a *plan* (i.e., task planning and motion planning).

As previously mentioned, communication is important for a MRS because it can help robots to be cooperative by learning information that is observed or inferred by others. Explicit communication (another means is implicit communication) must use communication media. However, the communication media cannot always be shared, therefore it is necessary for the robots to obtain exclusive access to them. The problem of communication media sharing is often associated with bandwidth limitation. Ye et al. [53] presented a method to evaluate control and communication strategies for a group of wireless-networked robots. In this method, they used a network simulator [148] to handle the bandwidth limitation problem, which took into account protocol characteristics and propagation conditions. Rybski et al. [54] described a distributed software control architecture designed for the control of multiple robots over a low-bandwidth communications channel. In this architecture, robots share communication bandwidth by using the time slot (time-division multiplexing). They also showed how sharing bandwidth affects the performance of the robots when they are used in a surveillance task. Nerurkar et al. [149] presented a hybrid estimation framework for the problem of multi-robot cooperative localization under a very low bandwidth. Their framework allows each robot to communicate only a single bit per real-valued (analogue) measurement. Other works include [55] [56] [57] [150].

Another resource conflict arises when multiple robots need to manipulate the same object. A well-studied topic for object sharing is the multi-robot box-pushing problem, in which robots should work together to transport a box to a destination. Matarić et al. [58] addressed the problem of cooperative box-pushing with two autonomous six-legged robots. They presented a strategy whereby the robots need to communicate with each other to take turns controlling the actions at each time step in order to coordinate the delivery of the box to the goal. Kube and Bonabeau [59] presented empirical observations of cooperative transport in ants and robots,

and described a case study of pushing a box with a swarm of robots that are controlled by using a finite-state machine (FSM). Coordination is achieved without any direct inter-robot communication. Gerkey and Matarić [60] presented a box-pushing experiment with a heterogeneous robot team by using an auction-based task-allocation system called MURDOCH. This system is able to allocate and coordinate manipulation tasks in a fault-tolerant manner, showing a tightly coupled cooperation among the robots. Miyata et al. [61] proposed a task assignment method for cooperative transport by multiple mobile robots in an unknown static environment. This method divides a robot's actions into small units of work to perform and assign tasks by considering whether an adequate number of robots is available for cooperation, and whether the time-space distributions of the task instances and the robots are adequate. Wang and Silva [151] employed two types of multi-agent reinforcement learning algorithms, single-agent Q-learning and team Q-learning, for a multi-robot box-pushing task. They showed that single-agent Q-learning does a better job than team Q-learning in a complicated and unknown environment with many obstacles. Other works include [62] [63] [64] [65] [66].

The third type of resource conflict is the space sharing problem, which has been studied mainly in relation to multi-robot motion planning, collision, congestion and deadlock avoidance problems (a detailed discussion is given in Section 7.2). Jäger and Nebel [67] described a decentralized method for coordinating the independently planned trajectories of multiple mobile robots to avoid collisions and deadlocks among them. Their idea is: for the collision, when the distance between two robots drops below a certain value, they will exchange information about their planned trajectories and determine whether they are in danger of a collision or not. If a potential collision is detected, they will monitor their movements and, if necessary, insert time gaps between certain segments of their trajectories to avoid collision. For the deadlock, when a deadlock is detected, the trajectory planners of each robot involved are successively asked to plan an alternative trajectory until the deadlock is resolved. Marcolino and Chaimowicz [69] proposed a decentralized coordination algorithm to control the traffic of a swarm of robots while avoiding congestion situations when large groups of robots move in opposite directions. The proposed algorithm allows the robots to perceive the possibility of collision and warn their teammates through local sensing and communication, following which the group's members change their trajectories to avoid congestion. They also proposed another coordination algorithm for the control of traffic when robots try to reach the same target, where the robots control their actions by using a probabilistic finite state machine and continuously rely on local sensing and communication to

coordinate themselves [70]. Luna and Bekris [71] proposed a graph-based algorithm for multi-robot path planning problems in which there are at most n-2 robots in a connected graph of n vertices. The proposed algorithm uses two primitives: "push", where a robot moves toward its goal until no progress can be made, and "swap", which allows two robots to swap positions without altering the position of any other robot. Other works include [68] [72] [73] [74] [75] [76] [77] [78] [152] [153] [154] [157].

Our latest investigations focus on the space sharing problem. A very common situation in motion planning for a group of mobile robots is when multiple robots move to the same waypoint, leading to collision, congestion and deadlock. We have defined this kind of dynamic standstill of a system caused by waypoint conflict as a *waiting situation* problem. This is because, in solving this problem, a robot should wait until the others pass the waypoint first or else all the robots should wait for the planner to re-plan their trajectories. However, these solutions may compromise the MRS system's performance.

In our previous work, we focused on how to alleviate the waiting situation problems by planning separate kinematic paths for mobile robots. We presented a method involving the iterative sampling of an occupancy grid map to construct a separate topological graph for robots [43]. We also presented another method by using a probabilistic roadmap (PRM) based on adaptive cross-sampling (ACS) [79]. This method, which we called ACS-PRM, includes three steps: C-space sampling, roadmap building and motion planning. Firstly, an adequate number of points should be generated in the C-space on an occupancy grid map by using an ACS method. Secondly, a separated roadmap should be built while the milestones are extracted by post-processing the result of sampling. Finally, robots plan their motion by querying the constructed roadmap.

5. Coordination: Static Versus Dynamic

Multi-robot coordination is the core task of MRSs. The overall system performance can be directly affected by the quality of coordination and control. Coordination can be static or dynamic. Static coordination (also known as deliberative coordination [14] or offline coordination [13]) generally refers to the adoption of a convention prior to engaging in the task. For example, some rules in traffic control problems include "keep right", "stop at intersection" and "keep sufficient space between yourself and the robot in front of you" [80]. Dynamic coordination (also known as reactive coordination [14] or online coordination [13]) occurs during the execution of a task, and is generally based on the analysis and synthesis of

information. The information can be obtained through the means of communication.

Dynamic coordination can also be divided into two categories: explicit coordination and implicit coordination. Gerkey and Matarić [81] defined explicit coordination as techniques employing intentional communication and collaboration methods, much like those employed in MAS (which is often used to deal with comparatively more sophisticated robots), and implicit coordination as those techniques employing the dynamics of interaction among the robots and the environment in order to achieve the desired collective performance, which is often in the form of designed emergent behaviour. Explicit coordination is usually associated with explicit communication, which is produced by a robot's active behaviour. Implicit coordination is usually associated with implicit communication, which requires the robot to perceive, model and reason others' behaviour. Fusing explicit and implicit information appropriately could improve the coordination performance of the whole robotic system. Both explicit and implicit communications will be discussed in detail in Section 6.

The static method can handle complex tasks, but its real-time controlling might be poor. The dynamic method can well meet the capability of real-time, but it has difficulty in dealing with more complex tasks. For MMRS, the external environment where the robots are placed may be too complex. It would be difficult to use only one method coping with all tasks. In our opinion, it would be best to use it by combining both the static and dynamic methods appropriately, based on the specific characteristics of the task at hand.

Current research on the theoretical aspects of the multi-robot coordination is not numerous. Agmon et al. [155] discussed three coordination mechanisms in the problem of a multi-robot patrol, including no coordination, loose coordination and tight coordination. They showed that an uncoordinated patrol performed better than a loosely coordinated patrol in terms of the average waypoint visitation frequency, and that tight coordination is theoretically optimal but it is not practical in practice. Kaminka et al. [166] presented a reinforcement learning approach to multi-robot coordination algorithm selection. They defined a reward function in the approach - called an effectiveness index - which can reduce the time and resources spent coordinating, and maximize the time between conflicts that require coordination.

6. Communication: Explicit Versus Implicit

Communication, as a means of coordination, often emerges as a rational behaviour in multi-robot environments. In fact, the communication is a mode of interaction between robots. By this interaction, on the one hand, robots can share position information, the state of the environment and sensor data with others in the system; on the other hand, an individual robot can get information as to the intentions, goals and actions of other robots.

Cao et al. [9] classified the communication structure into three types according to the mode of interaction, which includes: interaction via the environment, interaction via sensing and interaction via explicit communications. Farinelli et al. [12] distinguished two different types of communication depending on the way in which the robots exchange information, which includes direct and indirect communication. In this paper, we follow the taxonomy based on the information transfer modes, namely explicit and implicit communication.

Explicit communication refers to the means for the direct exchange of information between the robots, which can be made in the form of unicast or broadcast intentional messages. This often requires a dedicated on-board communication module. Existing coordination methods are mainly based on the use of explicit communication. Balch and Arkin [82] presented a behaviour-based formation control strategy for multi-robot teams. In order to communicate with the formation's unit-centre, each robot communicates its position to the other over a wireless network. Gerkey and Matarić [83] presented a general framework of inter-robot communication for dynamic task allocation for teams of cooperative mobile robots. Klavins [84] introduced a notion of communication complexity as a means to investigate the scalability of multi-robot algorithms in terms of how much coordination they require. Madhavan et al. [27] described an extended Kalman filter-based algorithm for the localization of a team of robots through a wireless local area network. Nett and Schemmer [85] presented an architecture based on wireless communication to schedule the intersection of two paths in real-time so that mobile robots could cross the intersection efficiently without collisions. Wang et al. [86] presented an *ad hoc* robot wireless communication scheme for a large system with many mobile robots to exchange information. Pimentel and Campos [87] developed an algorithm that enables a group of cooperating mobile robots to establish and maintain a wireless *ad hoc* network to exchange task-related data. Rekleitis et al. [88] examined the problem of multi-robot coverage path planning for a team of robots with limited communication, where the robots operate under the restriction that communication between two robots is only available when they are within the line of sight of each other. Berna-Koes et al. [89] focused on an agent communication language (ACL) and described a two-tiered communication architecture. Rooker and Birk [90] presented an approach for multi-robot exploration

that took the constraints of wireless networking into account. Bicchi et al. [32] proposed a platform for decentralized multi-robot traffic control with secure communication among vehicles by using cryptographic keys and rekeying policies. Bayram and Bozma [91] presented an approach for the navigation of dynamically communicating robots via a bidirectional interaction model between the robot network and the continuous states. Other works based on explicit communication include [92] [93] [94] [95] [96] [97] [98] [158] [161].

Implicit communication refers to the way in which the robot gets information about other robots in the system through the environment. This should be achieved by embedding different kinds of sensors in the robot. Implicit communication can also be divided into two categories: active implicit communication (e.g., interaction via the environment) and passive implicit communication (e.g., interaction via sensing). Active implicit communication refers to the fact that the robots communicate by collecting the remaining information of others in the environment. The use of this form is generally related to the field of biomimetics, and is usually inspired by the collective behaviour of bees and ants. Passive implicit communication refers to the fact that the robots communicate by perceiving a change of environment through the use of sensors. For example, a robot needs to compute the context information (e.g., position and attitude) of others by modelling and reasoning based on the perceived data in order to cooperate with them. Pagello et al. [99] presented an approach for coordinating a team of soccer playing robots through implicit communication where the cooperation between the robots was based on the form of the observed behaviour of other robots. Stulp et al. [100] presented a computational model for implicit coordination and applied it to a typical coordination task of robotic soccer: regaining ball possession. Yamada and Saito [63] described an adaptive action selection method without explicit communication for dynamic multi-robot box-pushing. Pereira et al. [65] addressed the problem of coordinating multiple mobile robots for a box-carrying task by using only local sensor information. Hollinger et al. [101] presented an approximation algorithm using implicit coordination to solve the multi-robot efficient search path-planning problem in indoor environments with a known floor plan. Other works based on implicit communication include [58] [102].

The use of explicit communication can ensure the accuracy of the exchange of information between robots. However, the communication load of a system will increase as the number of robots increases. This may cause a decrease in system performance or else lead to an overall system failure in extreme cases. In using implicit communication, and although the information obtained by a robot is not completely reliable, the stability, reliability and fault tolerance of the whole MRS are better than in using an explicit pattern. Therefore, applying both explicit and implicit methods in practice can make the two methods complement each other.

7. Planning: Task Planning and Motion Planning

The task of coming up with a sequence of actions that will achieve a goal is called 'planning' [34]. In MRS, planning can be used to coordinate robots in accomplishing the team mission. Unfortunately, the optimal planning for a MRS is typically an NP-hard problem. Therefore, the current challenge is to ensure tractable planning that produces good solutions [103]. Multi-robot planning is usually divided into two aspects: task planning and motion planning. Task planning is primarily designed to solve the problem of which robot should execute which task. This involves task decomposition and task allocation. Motion planning is primarily designed to generate the path of each robot. In addition, a robot should take into account the paths of others in order to avoid any collision, congestion or deadlock that may come along.

There is a key characteristic of robotics problems: uncertainty, which arises from the partial observability of the environment and from the stochastic (or unmoulded) effects of the robot's actions [34]. This is why the benchmarking of robotics research is inherently difficult (especially for MRSs).

7.1 Task Planning

Multi-robot task planning (MRTP) includes two aspects: task decomposition and task allocation. So far, the research on task planning for MRSs has been mainly concentrated on the task allocation problem, with relatively little on the task decomposition problem. In fact, task decomposition is an important research topic because the effect of task allocation could be directly influenced by it.

Multi-robot task decomposition (MRTD) mainly refers to how the team mission to be completed is decomposed into several single subtasks that can be completed by a robot independently, according to the characteristics, requirements and resource allocation of the team mission itself [104]. Stone and Veloso [105] achieved collaboration between agents through the introduction of formations, which decompose the task space defining a set of roles with associated behaviours. Botelho and Alami [5] presented a decentralized system to describe and perform task planning, decomposition and allocation in multi-robot environments called the M+ protocol. This work was developed from an early European project called MARTHA [48]. Zlot and Stentz [46] focused on complex

tasks that can be decomposed into multiple inter-related subtasks. They addressed the task decomposition problem by generalizing tasks to task trees within a peer-to-peer trading market. Tang and Parker [7] considered that, in typical approaches to multi-robot team working, the decomposition of the team's task into subtasks is defined by the human designer in advance of the robot team's performance, and that this pattern also outlines the available multi-robot task solutions in advance of the mission. As such, they described a methodology for automatically synthesizing task solutions for heterogeneous multi-robot teams. Other relevant works on MRTD include [106].

In our previous work, we considered task allocation and also took task decomposition into account. In [43] [44], we first decomposed the whole multi-robot exploration mission into several subtasks (i.e., the exploration of several unknown regions), which can be identified by topologizing the grid map of the environment. Next, we discussed how to assign the subtasks to each individual robot in a reasonable manner.

Multi-robot task allocation (MRTA) can be considered as an instance of the well-known optimal assignment problem, whereby the general form of this problem can be expressed as follows:

> There are a number of agents and a number of tasks. Any agent can be assigned to perform any task, incurring some cost that may vary depending on the agent-task assignment. It is required to perform all tasks by assigning exactly one agent to each task in such a way that the total cost of the assignment is minimized.

In those domains where group dynamics have a significant effect on group performance, MRTA is known to be NP-hard [15] [31]. The task allocation in a MRS generally undertakes assigning robots to tasks (or tasks to robots) so as to maximize the expected overall system performance. However, because MRTA becomes a dynamic decision problem - which varies in time with environmental changes - the static assignment method is no longer applicable. Thus, an alternative solution is to iteratively solve the static assignment problem over time.

Gerkey and Matarić [107] [15] gave a formal analysis and domain-independent taxonomy of MRTA problems, in which the MRTA problems have been classified into seven categories according to the ability of the robot to perform tasks, the number of robots required for a task, and the manner of the task assignment. They also analysed and compared some iterated assignment architectures: ALLIANCE [4], BLE [108], and M+ [5] and some online assignment architectures: MURDOCH

(auction-based MRTA) [60], first-price auctions (market-based MRTA) [109] and dynamic role assignment [110], for MRTA, respectively.

The contract net protocol (CNP) [111] has been developed to achieve task assignment with distributed control by a negotiation process in multi-agent systems. So far, most methods for MRTA are based on the CNP model. Botelho and Alami [5] presented the M+ system, which used a scheme for multi-robot cooperation through negotiated task allocation and achievement. This system is the first CNP-based approach to MRTA. Stentz and Dias [109] presented the ideas of a free market architecture for coordinating a group of robots to achieve a given objective (the market-based approach). This architecture defines revenue and cost functions across a range of possible plans for executing a specified task. The task is accomplished by dividing it into sub-tasks and allowing the robots to bid and negotiate to carry out these sub-tasks. The objective is achieved by individual robots cooperating and competing with each other to further their own self-interest. Zlot et al. [29] applied these ideas to the multi-robot mapping and exploration problem. Their work borrows a market architecture, which seeks to maximize the benefit while minimizing the cost, thus aiming to maximize the utility. The benefit is the information gained by visiting a goal point, the cost is the estimated distance travelled to reach the goal (by using the D* algorithm), and then the utility is the difference between the benefit and the cost. It is worth pointing out that the market-based coordination architecture has been applied to a Mars exploration scenario (combined with the D* algorithm for robot motion planning). Gerkey and Matarić [60] presented the first online assignment architecture called MURDOCH, which uses a first-price auction to assign each task (an auction-based approach). The auction proceeds in five steps: task announcement, metric evaluation, bid submission, close of auction and progress monitoring / contract renewal. The MURDOCH system has been tested in two different domains: a tightly coupled multi-robot physical manipulation task, and a loosely coupled multi-robot experiment involving long-term autonomy. The major differences between an auction-based approach and a market-based approach are that: 1) an auction-based approach uses bids based on estimated costs, but a market-based approach takes into account both costs and benefits; 2) an auction-based approach does not allow task reassignment, but a market-based approach allows for later reassignments.

We developed a lightweight and robust MRTA approach based on trade rules in a market economy (a trade-based approach) [44]. This approach is designed to simulate the relationship between buyers and sellers in a business system and to achieve dynamic task allocation by using a mechanism of unsolicited bids. A comparison between

	Market-based approach	Auction-based approach	Trade-based approach
Negotiation (communication) model	publish / subscribe	publish / subscribe	apply / allocate
Task allocation algorithm	greedy algorithm (first-price auction)	greedy algorithm (first-price auction)	greedy algorithm (first-price auction)
Task allocation ability per iteration (trading round)	single task	single task	multiple tasks
Role determination of the robots	voluntary	voluntary	negotiation
Utility consideration	cost and benefit	cost	cost
Task reassignment	allowed	not allowed	allowed
Communication complexity	$O(1)$ / bidder, $O(n)$ / auctioneer	$O(1)$ / bidder, $O(n)$ / auctioneer	$O(1)$ / buyer, $O(n)$ / seller
Computation complexity	$O(n)$	$O(n)$	$O(n)$

Table 1. A Comparison of Three CNP-based Online Multi-robot Task Allocation Approaches

market-based, auction-based and trade-based approaches is given in Table 1.

In addition to the above CNP-based approaches, there are many other interesting strategies. Dahl et al. [31] presented an algorithm for task allocation in groups of homogeneous robots that is based on vacancy chains, a resource distribution strategy common in human and animal societies. This algorithm uses local task selection, reinforcement learning for the estimation of task utility, and reward structures based on the vacancy chain framework. Hanna [112] proposed an approach that allows robots to take into account the uncertainty of task execution. They decomposed the MRTA problem into two stages. In the first stage, each robot selects its own tasks based on the expected benefit by using a Markov decision process (MDP). In the second stage, an auction-based mechanism is applied to assign tasks to the robots. Michael et al. [113] proposed a distributed market-based coordination algorithm in which agents are able to bid for task assignment with the assumption that the agents have knowledge of all the tasks and the maximum number of agents that can be assigned to every individual task. Each auction is performed among neighbouring groups of agents and requires only local communication. They verified their algorithm in a multi-robot formation control problem. Shiroma and Campos [114] proposed a framework called CoMutaR, which is designed to tackle both task allocation and task coordination problems in MRS. This framework enables a single robot to perform multiple tasks concurrently by periodically checking and updating task-related information during implementation. It was tested and evaluated in the simulation of object transportation, area surveillance and multi-robot box-pushing problems. Wawerla and Vaughan [24] presented two task allocation strategies for a multi-robot transportation system. One is based on a centralized planner that uses domain knowledge to solve the assignment problem in linear time. The other

enables individual robots to make individual task allocation decisions by only using locally-obtainable information and single value communication. Other relevant works on MRTA include [48] [115] [116] [46] [117] [156] [160] [164] [167].

Moreover, the task allocation for heterogeneous and homogeneous systems may be different. In heterogeneous systems, task allocation may be determined by each robot's individual capabilities. However, in homogeneous systems robots have no preference for roles, and they may then need to differentiate into different roles at design-time, or dynamically at run-time [44]. Parker [118] introduced the concept of task coverage, which measures the ability of a given team member to achieve a given task. This parameter can be used as an index to organize a robot team from the available pool of heterogeneous robots in order to perform a mission. The task coverage reaches the maximum value in homogeneous teams and decreases as teams become more heterogeneous.

7.2 Motion Planning

In robotics, the motion planning problem involves producing a *continuous* robot motion from one configuration to another in a configuration space while avoiding collision with obstacles. Motion planning is eminently necessary for mobile robots since, by definition, a robot accomplishes tasks by moving in the real world [119].

Multi-robot motion planning (MRMP) should consider not only any obstacles (whether static or dynamic) in the environment, but also any possible interference between robots. This is because, when robots in a team are used to perform independent tasks in a shared workspace, each one will become a mobile obstacle for the others. Therefore, the motion planning of each individual robot in the team should take into account the movement of others. One well-studied example of MRMP is the multi-robot space sharing problem (see Section 4).

A multi-robot environment must definitely be dynamic, in which robot motion planning is inherently difficult. Even for a simple case in two dimensions, the problem is NP-hard and not solvable in polynomial time [120]. Among existing MRMP methods, the environment for an autonomous mobile robot is usually represented by an occupancy grid map, and the robot is reduced to a point in a two-dimensional plane (i.e., the workspace). Next, the motion is represented as a path in the workspace space.

Most of the existing approaches to MRMP are expanded from the results of a single-robot system. Three major families of approaches are the cell decomposition, potential field and roadmap approaches. They all reduce the continuous motion planning problem to a discrete graph search problem by identifying some canonical states and paths within the free space.

The cell decomposition approach decomposes the free space into a finite number of contiguous regions, called cells. This approach is often applied for the multi-robot area coverage problem. Bennewitz et al. [121] presented a strategy based on the A* path planning algorithm [122] to optimize the priorities of the decoupled and prioritized path planning methods for groups of mobile robots. The proposed approach is a randomized method, which repeatedly reorders the robots to find a sequence for which a plan can be computed and to minimize the overall path lengths. Guo and Parker [120] proposed a strategy based on the D* path planning algorithm [123], which contains two modules: path planning and velocity planning. The detailed process can be described as follows: initially, each robot plans its own path independently and then a coordination diagram is constructed based on collision checks among all the robots' paths. Hazon et al. [128] presented an online robust multi-robot spanning tree coverage (ORMSTC) algorithm based on an approximate cellular decomposition for covering an unknown environment. The algorithm is online because the robots do not have prior knowledge of the work area, and it is robust and complete because so long as a single robot is able to move, the coverage will be completed. Other works based on the cell decomposition approach include [129] [88] [130] [131].

The potential field approach generates a path by combining repulsion from obstacles with attraction to a goal. This approach is extensively used in the multi-robot formation control problem. Tanner and Kumar [124] presented a strategy based on an artificial potential field, which can ensure the near-global asymptotic convergence of the robots on a particular oriented formation shape while guaranteeing collision avoidance in the process. Other works based on the potential field approach include [125] [126] [127].

The roadmap approach reduces the robot's free space to a set of one-dimensional curves connecting a set of nodes, called a roadmap. A typical roadmap approach is a Voronoi diagram, which specifies the set of all points equidistant from two or more closest obstacles. Following the Voronoi diagram may not give the shortest path, but the resulting paths tend to maximize clearance [34]. The Voronoi diagram is often applied to the problem of robotic exploration. Wurm et al. [40] presented a strategy for coordinating a team of exploring robots by using the Voronoi diagram for the segmentation of the environmental map. The strategy extracts the critical points [132] as the targets to assign them to the robots for task allocation. The critical points are those nodes in the Voronoi diagram at which the distance to the closest obstacle in the map is a local minimum. Other works based on the Voronoi diagram include [39] [41] [42].

Another roadmap approach is the probabilistic roadmap (PRM) [133], which has been widely used for robot arms in engineering and manufacturing. This method randomly generates a large number of collision-free configurations and achieves motion planning by connecting some of them. Several studies address multi-robot coordination based on PRM, but focus on manipulator arms [134] [135]. As for the application of MMRS, Švestka and Overmars [136] presented a PRM-based approach for multiple non-holonomic car-like robots' motion planning in the same static workspace in which the roadmaps for the composite robot are derived from roadmaps for the underlying simple robots, and the roadmaps for the simple robots are computed by a probabilistic single-robot learning method. Kumar and Chakravorty [165] proposed a multi-agent generalized PRM (MAGPRM) method to solve MRMP problems in stochastic maps with uncertainty in the motion model. This method can construct a roadmap between every pair of start and goal locations for each robot by using an adaptive sampling technique. Other works based on the PRM include [92] [137].

Another probabilistic method is the rapidly-exploring random tree (RRT) [138], which takes the motion planning as a tree search problem. The tree is constructed incrementally in such a way that any random configuration in the free space is added by connecting it to the closest configuration already in the tree. Bruce and Veloso [139] described a RRT-based method for MRMP, called extended RRT (ERRT), in which the mechanism of a waypoint cache was implemented to store the knowledge of where a plan might again be found in the near future, and another mechanism of an adaptive beta search was used as well, where the planner adaptively modified a parameter to help it find shorter paths. Wagner et al. [163] applied a technique called sub-dimensional expansion in order to enhance the

	Cell decomposition approach	Potential field approach	Roadmap approach	
			Voronoi diagram	Sampling-based method
Strength	optimal paths can be found	efficient and easy to implement	resulting paths tend to maximize clearance	efficient for high-dimensional problems
Weakness	strongly depends on the grid resolution of the world	easy to fall into local minima	inefficient and complex to implement	solutions often sub-optimal
Completeness	complete			probabilistically complete
Performance	computational complexity depends on the number of points			rate of convergence depends on the use of local planner
Main applied field	multi-robot area coverage	multi-robot formation control	multi-robot exploration	industrial manipulators

Table 2. A Comparison of Three Major Families of Multi-robot Motion Planning Approaches

performance of probabilistic planners (RRTs and PRMs) for multi-robot path planning. This technique can construct a search space while being explored by a planner, the partial results of which are used to guide the construction of the search space. They showed that the technique could decrease the time required to find a solution by more than an order of magnitude, especially for systems of four or more robots.

It is worth pointing out that both PRM and RRT are sampling-based methods, both of which are currently considered state-of-the-art for motion planning in high-dimensional configurations or geometrically complex spaces. This is because, unlike with the cell decomposition, potential field and Voronoi diagram approaches (these approaches are difficult to apply to high-dimensional problems), the running time of the sampling-based methods does not grow exponentially with the dimension of the configuration space; they are also easier to implement. In addition, the sampling-based methods are probabilistically complete, meaning that sometimes they fail to find a solution even if one exists. A comparison of three major families of MRMP approaches is given in Table 2.

The existing motion planning methods have their own strengths and weaknesses. Using only one method may entail difficulties in dealing with complex environments, such as the MRS. Combining multiple methods together is more coincident with the MRS requirements of reliability, flexibility, scalability and versatility [43]. This notion of a hybrid approach has been mentioned several times in the previous text (see Section 5 and 6). Schwager et al. [140] introduced a unifying optimization framework for multi-robot deployment that brings together several different existing strategies, including geometric, probabilistic and potential field approaches. Other relevant works on MRMP include [141] [66] [142] [143] [162].

In addition, and for the purpose of dealing with problems about limited communication, computational speed and complex environments in MMRS, various MRMP approaches have been proposed based on wireless sensor networks (WSNs). Clark et al. [92] presented a framework for multiple mobile robots' motion planning by using dynamic networks that are capable of: 1) forming dynamically whenever communication and sensing capabilities permit; 2) sharing world models and robot goals within each network; and 3) constructing on-the-fly coordinated trajectories for all robots in each network using a fast, centralized motion planner. Other related works include [144] [137] [145].

8. Decision-making: Centralized Versus Decentralized

Decision-making can be regarded as a cognitive process resulting in the selection of a course of action among several alternative scenarios. Every decision-making process produces a final choice. In MRS, the decision-making guided by planning can be centralized or decentralized in accordance with the group architecture of the robots.

There is a central control agent in centralized architectures that has the global information about the environment as well as all information about the robots, and which can communicate with all the robots to share them. The central control agent could be a computer or a robot. The advantage of the centralized architecture is that the central control agent has a global view of the world, whereby the globally optimal plans can be produced. Nevertheless, this architecture: 1) is typical for a small number of robots and ineffectual for large teams with more robots; 2) is not robust in relation to dynamic environments or failures in communications and other uncertainties; 3) produces a highly vulnerable system, and if the central control agent malfunctions a new agent must be available or else the

entire team is disabled. A typical MRS using a centralized architecture is GOFER [2], in which there is a central task planning and scheduling system with a global view of the tasks to be performed in the environment and the availability of robots to perform the tasks. Certain studies outlined in the previous sections belonging to the centralized architecture approach include [66] [92] [7] [124] [40] [71] [43] [49].

Decentralized architectures can be further divided into two categories: distributed architectures and hierarchical architectures. There is no central control agent in distributed architectures, such that all the robots are equal with respect to control and are completely autonomous in the decision-making process. In hierarchical architectures, there exist one or more local central control agents which organize robots into clusters. The hierarchical architecture is a hybrid architecture, intermediate between a centralized architecture and a distributed architecture. In contrast to a centralized architecture, a decentralized architecture can better respond to unknown or changing environments, and usually has better reliability, flexibility, adaptability and robustness. Nevertheless, the solutions they reach are often suboptimal. Feddema et al. [146] have focused on input / output reachability, structural observability, system controllability and connection stability for decentralized control systems. They also show how these theories are applicable to multi-robot formation control, perimeter surveillance and (surround and monitor an enemy facility). A typical MRS using a distributed architecture is M+ [5], in which each robot has its own local knowledge of the world and can decide its future actions by taking into account its current context and task, its own capacities and the capacities of the other robots, through a negotiation process. A typical MRS using a hierarchical architecture is CEBOT [3], in which cells (robots) can be physically coupled to others and some master cells are selected to coordinate tasks' execution. Certain studies outlined in the previous sections belonging to the decentralized architecture approach include [4] [121] [67] [63] [125] [29] [60] [26] [28] [56] [32] [69] [44] [158] [161].

9. Conclusion

In this paper, we systematically surveyed and analysed the key research problems in the field of MMRS, focusing on those approaches involving multi-robot coordination. We started by surveying the potential advantages of MRSs in contrast to single-robot systems. Afterwards, we discussed two multi-robot environments, namely cooperative and competitive environments. Next, we analysed three aspects of the problem of resource conflict in MMRS, including communication media sharing, object sharing and space sharing. Next, we discussed

multi-robot coordination in two respects, including static and dynamic, and communication as a means of coordination. Following this, we made a special effort to investigate and study the multi-robot planning problem, including task planning and motion planning, which is inseparable from multi-robot coordination. Finally, we identified two decision-making architectures including centralized and decentralized approaches.

The investigation of the related literature shows that considerable progress has been made in multi-robot localization / mapping / exploration and search and rescue, as well as intelligent transportation. However, these problems are still not fully resolved. In the previous sections, we identified several key open research challenges and presented a number of existing methods that are popular or interesting. There remain many other challenges, such as:

- How to enable the MRS to handle more complex tasks like human beings? This means that we need more a powerful coordination scheme, especially in the process of MRTP. A simple two-layer task planning scheme (MRTD and MRTA) may no longer be suitable. A multi-layer scheme including task analysis, task negotiation, task execution and task supervision becomes important [167] [168].
- How to ensure the reliability of the motion of a physical MRS in the real world? As we know, there are still a lot of problems to be solved in MRMP, such as collision, congestion and deadlock. In complex and dynamic environments like MMRSs, rule-based and graph-based methods are difficult to deal with. A high-level coordination concept combined with reactive control for robots should be more efficient [169] [170].
- How to fuse and analyse the information acquired by each individual robot more rationally (and then make the decision more efficient)? A decision-making architecture for a MRS - centralized or decentralized - has a requirement for information sharing because a robot in the team can only perceive local information. Effective data fusion may help us to produce an effective plan and then conduct multi-robot coordination [171] [172].
- How to make humans to easily intervene MRSs according to what is needed? Currently, many tasks are still too complex for robots, and coordination between humans and robots needs to be explored [173] [174] [175]. Human-machine interactions are ubiquitous in today's world, although this paper focuses on the use of autonomous mobile robots.

Moreover, on the basis of our review some promising avenues for future research become apparent:
- So far, much more attention has been paid to coordination for the same types of robot

(homogeneous and heterogeneous). Coordination between different types of robots, such as UUV, UGV and UAV, would present a very interesting challenge. MASs with rich diversity should be more efficient.

- Energy must be the single most important problem that we confront today. Therefore, energy consumption as a system performance metric should be given more consideration.

- The sampling-based algorithm is a very important and useful approach to robot motion planning. It is widely used in manufacturing environments with industrial robots, but there is greater development potential in MMRSs.

- The centralized and distributed decision-making structures have their own strengths and weaknesses. For the near future, an effective way is to build a hybrid mechanism (i.e., a hierarchical architecture).

10. References

[1] Hajime Asama, Akihiro Matsumoto, and Yoshiki lshida. Design of an autonomous and distributed robot system: ACTRESS. In Proceedings of IROS'89, pages 283-290, Tsukuba, Japan, September 1989.

[2] Philippe Caloud, Wonyun Choi, Jean-Claude Latombe, Claude Le Pape, and Mark Yim. Indoor automation with many mobile robots. In Proceedings of IROS'90, pages 67-72, Ibaraki, Japan, July 1990.

[3] Toshio Fukuda, Tsuyoshi Ueyama, Yoshio Kawauchi, and Fumihito Arai. Concept of cellular robotic system (CEBOT) and basic strategies for its realization. Computers and Electrical Engineering, 18(1):11-39, 1992.

[4] Lynne E. Parker. ALLIANCE: An architecture for fault tolerant, cooperative control of heterogeneous mobile robots. In Proceedings of IROS'94, pages 776-783, Munich, Germany, September 1994.

[5] Silvia C. Botelho and Rachid Alami. M+: A scheme for multi-robot cooperation through negotiated task allocation and achievement. In Proceedings of ICRA'99, pages 1234-1239, Detroit, MI, USA, May 1999.

[6] Brian P. Gerkey and Maja J Matarić. Murdoch: Publish/subscribe task allocation for heterogeneous agents. In Proceedings of Agents'00, pages 203-204, Barcelona, Spain, June 2000.

[7] Fang Tang and Lynne E. Parker. Asymtre: Automated synthesis of multi-robot task solutions through software reconfiguration. In Proceedings of ICRA'05, pages 1501-1508, Barcelona, Spain, April 2005.

[8] Gregory Dudek, Michael R. M. Jenkin, Evangelos Milios, and David Wilkes. A taxonomy for multi-agent robotics. Autonomous Robots, 3(4):375-397, 1996.

[9] Y. Uny Cao, Alex S. Fukunaga, and Andrew B. Kahng. Cooperative mobile robotics: Antecedents and directions. Autonomous Robots, 4(1):7-27, 1997.

[10] Peter Stone and Manuela Veloso. Multiagent systems: A survey from a machine learning perspective. Autonomous Robots, 8(3):345-383, 2000.

[11] Tamio Arai, Enrico Pagello, and Lynne E. Parker. Editorial: Advances in multi-robot systems. IEEE Transactions on Robotics and Automation, 18(5):655-661, 2002.

[12] Alessandro Farinelli, Luca Iocchi, and Daniele Nardi. Multi-robot systems: A classification focused on coordination. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 34(5):2015-2028, 2004.

[13] Eduardo Todt, Gustavo Raush, and Raúl Suárez. Analysis and classification of multiple robot coordination methods. In Proceedings of ICRA'00, pages 3158-3163, San Francisco, CA, USA, April 2000.

[14] Luca Iocchi, Daniele Nardi, and Massimiliano Salerno. Reactivity and deliberation: a survey on multi-robot systems. Lecture Notes in Computer Science, 2103:9-32, 2001.

[15] Brian P. Gerkey and Maja J. Matarić. A formal analysis and taxonomy of task allocation in multi-robot systems. International Journal of Robotics Research, 23(9):939-954, September 2004.

[16] Jun Ota. Multi-agent robot systems as distributed autonomous systems. Advanced Engineering Informatics, 20(1):59-70, 2006.

[17] Lynne E. Parker. Distributed intelligence: Overview of the field and its application in multi-robot systems. Journal of Physical Agents, special issue on multi-robot systems, 2(2):5-14, 2008.

[18] Joachim Buhmann, Wolfram Burgard, Armin B. Cremers, Dieter Fox, Thomas Hofmann, Frank E. Schneider, Jiannis Strikos, and Sebastian Thrun. The mobile robot RHINO. AI Magazine, 16(2):31-38, 1995.

[19] Yoshiaki Sakagami, Ryujin Watanabe, Chiaki Aoyama, Shinichi Matsunaga, Nobuo Higaki, and Kikuo Fujimura. The intelligent ASIMO: system overview and integration. In Proceedings of IROS'02, pages 2478-2483, Lausanne, Switzerland, September 2002.

[20] http://marsrover.nasa.gov/home/index.html

[21] Marc Raibert, Kevin Blankespoor, Gabriel Nelson, Rob Playter, and the BigDog Team. BigDog, the rough-terrain quadruped robot. In Proceedings of the 17th World Congress of the International Federation of Automatic Control, pages 10822-10825, Seoul, Korea, July 2008.

[22] David Gouaillier, Vincent Hugel, Pierre Blazevic, Chris Kilner, Jérôme Monceaux, Pascal Lafourcade, Brice Marnier, Julien Serre, and Bruno Maisonnier. Mechatronic design of NAO humanoid. In Proceedings of ICRA'09, pages 769-774, Kobe, Japan, May 2009.

[23] Wolfram Burgard, Mark Moors, Dieter Fox, Reid Simmons, and Sebastian Thrun. Collaborative multirobot exploration. In Proceedings of ICRA'00, pages 476-481, San Francisco, CA, USA, April 2000.

[24] Jens Wawerla and Richard T. Vaughan. A fast and frugal method for team-task allocation in a multirobot transportation system. In Proceedings of ICRA'10, pages 1432-1437, Anchorage, AK, USA, May 2010.

[25] Dieter Fox, Wolfram Burgard, Hannes Kruppa, and Sebastian Thrun. A probabilistic approach to collaborative multi-robot localization. Autonomous Robots, 8(3):325-344, 2000.

[26] Stergios I. Roumeliotis and George A. Bekey. Distributed multirobot localization. IEEE Transactions on Robotics and Automation, 18(5):781-795, 2002.

[27] Raj Madhavan, Kingsley Fregene, and Lynne E. Parker. Distributed heterogeneous outdoor multi-robot localization. In Proceedings of ICRA'02, pages 374-381, Washington, DC, USA, May 2002.

[28] Richard T. Vaughan, Kasper Stoy, Gaurav S. Sukhatme, and Maja J. Matarić. LOST: Localization-space trails for robot teams. IEEE Transactions on Robotics and Automation, 18(5):796-812, October 2002.

[29] Robert Zlot, Anthony (Tony) Stentz, M. Bernardine Dias, and Scott Thayer. Multi-robot exploration controlled by a market economy. In Proceedings of ICRA'02, pages 3016-2023, Washington, DC, USA, May 2002.

[30] Joseph L. Baxter, Edmund K. Burke, Jonathan M. Garibaldi, and Mark Norman. Shared potential fields and their place in a multi-robot co-ordination taxonomy. Robotics and Autonomous Systems, 57(10):1048-1055, October 2009.

[31] Torbjorn S. Dahl, Maja J. Matarić, and Gaurav S. Sukhatme. Multi-robot task allocation through vacancy chain scheduling. Robotics and Autonomous Systems, 57(6-7):674-687, June 2009.

[32] Antonio Bicchi, Antonio Danesi, Gianluca Dini, Silvio Porta, Lucia Pallottino, Ida Savino, and Riccardo Schiavi. Heterogeneous wireless multirobot system. IEEE Robotics and Automation Magazine, 15(1):62-70, March 2008.

[33] David Popenoe. Sociology (11th Edition). Prentice Hall, 1999.

[34] Stuart J. Russell and Peter Norvig. Artificial Intelligence: A Modern Approach (2nd Edition). Prentice Hall, 2002.

[35] D. P. Barnes and J. O. Gray. Behaviour synthesis for co-operant mobile robot control. In Proceedings of Control'91, pages 1135-1140, Edinburgh, UK, March 1991.

[36] Agostino Martinelli, Frederic Pont, and Roland Siegwart. Multi-robot localization using relative observations. In Proceedings of ICRA'05, pages 2797-2802, Barcelona, Spain, April 2005.

[37] Ioannis M. Rekleitis, Gregory Dudek, and Evangelos E. Milios. Multi-robot collaboration for robust exploration. In Proceedings of ICRA'00, pages 3164-3169, San Francisco, CA, USA, April 2000.

[38] Weihua Sheng, Qingyan Yang, Song Ci, and Ning Xi. Multi-robot area exploration with limited-range communications. In Proceedings of IROS'04, pages 1414-1419, Sendai, Japan, September 2004.

[39] Ling Wu, Miguel Angel Garcia, Domenec Puig, and Albert Sole. Voronoi-based space partitioning for coordinated multi-robot exploration. Journal of Physical Agents, 1(1):37-44, September 2007.

[40] Kai M. Wurm, Cyrill Stachniss, and Wolfram Burgard. Coordinated multi-robot exploration using a segmentation of the environment. In Proceedings of IROS'08, pages 1160-1165, Nice, France, September 2008.

[41] A. Dominik Haumann, Kim D. Listmann, and Volker Willert. Discoverage: A new paradigm for multirobot exploration. In Proceedings of ICRA'10, pages 929-934, Anchorage, AK, USA, May 2010.

[42] Anthony Cowley, Camillo J. Taylor, and Ben Southall. Rapid multi-robot exploration with topometric maps. In Proceedings of ICRA'11, pages 1044-1049, Shanghai, China, May 2011.

[43] Zhi Yan, Nicolas Jouandeau, and Arab Ali Cherif. Sampling-based multi-robot exploration. In Proceedings of ISR/ROBOTIK 2010, pages 44-49, Munich, Germany, June 2010.

[44] Zhi Yan, Nicolas Jouandeau, and Arab Ali Cherif. Multi-robot decentralized exploration using a trade-based approach. In Proceedings of ICINCO'11, pages 99-105, Noordwijkerhout, The Netherlands, July 2011.

[45] James S. Jennings, Greg Whelan, and William F. Evans. Cooperative search and rescue with a team of mobile robots. In Proceedings of ICAR'97, pages 193-200, Monterey, CA, USA, July 1997.

[46] Robert Zlot and Anthony Stentz. Complex task allocation for multiple robots. In Proceedings of ICRA'05, pages 1515-1522, Barcelona, Spain, April 2005.

[47] Stephen Balakirsky, Stefano Carpin, Alexander Kleiner, Michael Lewis, Arnoud Visser, Jijun Wang, and Vittorio Amos Ziparo. Towards heterogeneous robot teams for disaster mitigation: Results and performance metrics from RoboCup rescue. Journal of Field Robotics, 24(11-12):943-967, November 2007.

[48] Rachid Alami, Sara Fleury, Matthieu Herrb, Félix Ingrand, and Frédéric Robert. Multi-robot cooperation in the MARTHA project. IEEE Robotics and Automation Magazine, 5(1):36-47, March 1998.

[49] Zhi Yan, Nicolas Jouandeau, and Arab Ali Cherif. Multi-robot heuristic goods transportation. In Proceedings of IS'12, Sofia, Bulgaria, September 2012.

[50] http://www.grappa.univ-lille3.fr/icga

[51] http://www.robocup.org

[52] Edsger W. Dijkstra. Cooperating sequential processes. In F. Genuys, editor, Programming Languages: NATO Advanced Study Institute, pages 43-112. Academic Press, 1968.

[53] Wei Ye, Richard T. Vaughan, Gaurav S. Sukhatme, John Heidemann, Deborah Estrin, and Maja J. Matarić. Evaluating control strategies for wireless-networked robots using an integrated robot and network simulation. In Proceedings of ICRA'01, pages 2941-2947, Seoul, Korea, May 2001.

[54] Paul E. Rybski, Sascha A. Stoeter, Maria Gini, Dean F. Hougen, and Nikolaos P. Papanikolopoulos. Performance of a distributed robotic system using shared communications channels. IEEE Transactions on Robotics and Automation, 18(5):713-727, 2002.

[55] Paul E. Rybski, Sascha A. Stoeter, Maria Gini, Dean F. Hougen, and Nikolaos P. Papanikolopoulos. Effects of limited bandwidth communications channels of the control of multiple robots. In Proceedings of IROS'01, pages 369-374, Maui, HI, USA, October 2001.

[56] Eric Nettleton, Sebastian Thrun, Hugh Durrant-Whyte, and Salah Sukkarieh. Decentralised slam with low bandwidth communication for teams of vehicles. In Proceedings of FSR'03, pages 179-188, Lake Yamanaka, Japan, July 2003.

[57] Dhananjay Raghunathan and John Baillieul. Motion based communication channels between mobile robots - A novel paradigm for low bandwidth information exchange. In Proceedings of IROS'09, pages 702-708, St. Louis, MO, USA, October 2009.

[58] Maja J. Matarić, Martin Nilsson, and Kristian T. Simsarian. Cooperative multi-robot box-pushing. In Proceedings of IROS'95, pages 556-561, Pittsburgh, PA, USA, August 1995.

[59] C. Ronald Kube and Eric Bonabeau. Cooperative transport by ants and robots. Robotics and Autonomous Systems, 30(1-2):85-101, 2000.

[60] Brian P. Gerkey and Maja J. Matarić. Sold! Auction methods for multirobot coordination. IEEE Transactions on Robotics and Automation, 18(5):758-768, October 2002.

[61] Natsuki Miyata, Jun Ota, Tamio Arai, and Hajime Asama. Cooperative transport by multiple mobile robots in unknown static environments associated with real-time task assignment. IEEE Transactions on Robotics and Automation, 18(5):769-780, 2002.

[62] Zhidong Wang, Yasuhisa Hirata, and Kazuhiro Kosuge. Control a rigid caging formation for cooperative object transportation by multiple mobile robots. In Proceedings of ICRA'04, pages 1580-1585, New Orleans, LA, USA, April 2004.

[63] Seiji Yamada and Junya Saito. Adaptive action selection without explicit communication for multi-robot box-pushing. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 31(3):398-404, 2001.

[64] Brian P. Gerkey and Maja J. Matarić. Pusher-watcher: An approach to fault-tolerant tightly-coupled robot coordination. In Proceedings of ICRA'02, pages 464-469, Washington, DC, USA, May 2002.

[65] Guilherme A. S. Pereira, Bruno S. Pimentel, Luiz Chaimowicz, and Mário F. M. Campos. Coordination of multiple mobile robots in an object carrying task using implicit communication. In Proceedings of ICRA'02, pages 281-286, Washington, DC, USA, May 2002.

[66] Atsushi Yamashita, Tamio Arai, Jun Ota, and Hajime Asama. Motion planning of multiple mobile robots for cooperative manipulation and transportation. IEEE Transactions on Robotics and Automation, 19(2):223-237, 2003.

[67] Markus Jäger and Bernhard Nebel. Decentralized collision avoidance, deadlock detection, and deadlock resolution for multiple mobile robots. In Proceedings of IROS'01, pages 1213-1219, Maui, HI, USA, October 2001.

[68] Chaomin Luo, Simon X. Yang, and Deborah A. Stacey. Real-time path planning with deadlock avoidance of multiple cleaning robots. In Proceedings of ICRA'03, pages 4080-4085, Taipei, Taiwan, September 2003.

[69] Leandro Soriano Marcolino and Luiz Chaimowicz. Traffic control for a swarm of robots: Avoiding group conflicts. In Proceedings of IROS'09, pages 1949-1954, St. Louis, MO, USA, October 2009.

[70] Leandro Soriano Marcolino and Luiz Chaimowicz. Traffic control for a swarm of robots: Avoiding target congestion. In Proceedings of IROS'09, pages 1955-1961, St. Louis, MO, USA, October 2009.

[71] Ryan Luna and Kostas E. Bekris. Efficient and complete centralized multi-robot path planning. In Proceedings of IROS'11, pages 3268-3275, San Francisco, CA, USA, September 2011.

[72] Stefan Schemmer, Edgar Nett, and Michael Mock. Reliable real-time cooperation of mobile autonomous systems. In Proceedings of SRDS'01, pages 238-246, New Orleans, LA, USA, October 2001.

[73] Amalia F. Foka and Panos E. Trahanias. Predictive autonomous robot navigation. In Proceedings of IROS'02, pages 490-495, Lausanne, Switzerland, September 2002.

[74] Wee Kiat Ng, Gerard S. B. Leng, and Yee Leong Low. Coordinated movement of multiple robots for searching a cluttered environment. In Proceedings of IROS'04, pages 400-405, Sendai, Japan, September 2004.

[75] Shirong Liu and Linbo Mao Jinshou Yu. Path planning based on ant colony algorithm and distributed local navigation for multi-robot systems. In Proceedings of ICMA'06, pages 1733-1738, Luoyang, China, June 2006.

[76] Harunori Gakuhari, Kunikatsu Takase, and Yoshiro Hada. Real-time deadlock-free navigation for multiple mobile robots. In Proceedings of ICMA'07, pages 2773-2778, Harbin, China, August 2007.

[77] Antonio Bicchi, Adriano Fagiolini, and Lucia Pallottino. Towards a society of robots. IEEE Robotics and Automation Magazine, 17(4):26-36, December 2010.

[78] Vinicius Graciano Santos and Luiz Chaimowicz. Hierarchical congestion control for robotic swarms. In Proceedings of IROS'11, pages 4372-4377, San Francisco, CA, USA, September 2011.

[79] Zhi Yan, Nicolas Jouandeau, and Arab Ali Cherif. ACS-PRM: Adaptive cross sampling based probabilistic roadmap for multi-robot motion planning. In Proceedings of IAS'12, Jeju Island, Korea, June 2012.

[80] Shin Kato, Sakae Nishiyama, and Jun'ichi Takeno. Coordinating mobile robots by applying traffic rules. In Proceedings of IROS'92, pages 1535-1541, Raleigh, NC, USA, July 1992.

[81] Brian P. Gerkey and Maja J. Matarić. Are (explicit) multi-robot coordination and multi-agent coordination really so different? In Proceedings of the AAAI Spring Symposium 2004 on Bridging the Multi-Agent and Multi-Robotic Research Gap, pages 1-3, Palo Alto, CA, USA, March 2004.

[82] Tucker Balch and Ronald C. Arkin. Behavior-based formation control for multi-robot teams. IEEE Transactions on Robotics and Automation, 14(6):926-939, December 1998.

[83] Brian P. Gerkey and Maja J. Matarić. Principled communication for dynamic multi-robot task allocation. In Proceedings of ISER'00, pages 353-362, Honolulu, HI, USA, December 2000.

[84] Eric Klavins. Communication complexity of multi-robot systems. Algorithmic Foundations of Robotics V, 7:275-292, 2002.

[85] Edgar Nett and Stefan Schemmer. Reliable real-time communication in cooperative mobile applications. IEEE Transactions on Computers, 52(2):166-180, February 2002.

[86] Zhi Gang Wang, Meng Chu Zhou, and Nirwan Ansari. Ad-hoc robot wireless communication. In Proceedings of SMC'03, pages 4045-4050, Washington, DC, USA, October 2003.

[87] Bruno S. Pimentel and Mario F. M. Campos. Cooperative communication in ad hoc networked mobile robots. In Proceedings of IROS'03, pages 2876-2881, Las Vegas, NV, USA, October 2003.

[88] Ioannis Rekleitis, Vincent Lee-Shue, Ai Peng New, and Howie Choset. Limited communication, multi-robot team based coverage. In Proceedings of ICRA'04, pages 3462-3468, New Orleans, LA, USA, April 2004.

[89] Mary Berna-Koes, Illah Nourbakhsh, and Katia Sycara. Communication efficiency in multi-agent systems. In Proceedings of ICRA'04, pages 2129-2134, New Orleans, LA, USA, April 2004.

[90] Martijn N. Rooker and Andreas Birk. Multi robot exploration under the constraints of wireless networking. Control Engineering Practice, 15(4):435-445, 2007.

[91] Halûk Bayram and H. Isil Bozma. Multi-robot navigation with limited communication - deterministic vs. game-theoretic networks. In Proceedings of IROS'10, pages 1825-1830, Taipei, Taiwan, October 2010.

[92] Christopher M. Clark, Stephen M. Rock, and Jean-Claude Latombe. Motion planning for multiple mobile robots using dynamic networks. In Proceedings of ICRA'03, pages 4222-4227, Taipei, Taiwan, September 2003.

[93] Yun Xie, Yi Ming Yang, Ze Ming Deng, Bing Ru Liu, and Bo Yi. Design and realization of communication mechanism of autonomous robot soccer based on multi-agent system. In Proceedings of SMC'03, pages 66-71, Washington, DC, USA, October 2003.

[94] Chris Jones and Maja J. Matarić. Automatic synthesis of communication-based coordinated multi-robot systems. In Proceedings of IROS'04, pages 381-387, Sendai, Japan, September 2004.

[95] Jorge Cortés, Sonia Martínez, Timur Karatas, and Francesco Bullo. Coverage control for mobile sensing networks. IEEE Transactions on Robotics and Automation, 20(2):243-255, 2004.

[96] Patricio Nebot and Enric Cervera. A framework for the development of cooperative robotic applications. In Proceedings of ICAR'05, pages 901-906, Seattle, WA, USA, July 2005.

[97] Leandro Soriano Marcolino and Luiz Chaimowicz. No robot left behind: Coordination to overcome local minima in swarm navigation. In Proceedings of ICRA'08, pages 1904-1909, Pasadena, CA, USA, May 2008.

[98] Sonia Chernova and Manuela Veloso. Teaching multi-robot coordination using demonstration of communication and state sharing. In Proceedings of AAMAS'08, pages 1183-1186, Estoril, Portugal, May 2008.

[99] Enrico Pagello, Antonio D'Angelo, Federico Montesello, Francesco Garelli, and Carlo Ferrari. Cooperative behaviors in multi-robot systems through implicit communication. Robotics and Autonomous Systems, 29(1):65-77, October 1999.

[100] Freek Stulp, Michael Isik, and Michael Beetz. Implicit coordination in robotic teams using learned prediction models. In Proceedings of ICRA'06, pages 1330-1335, Orlando, FL, USA, May 2006.

[101] Geoffrey Hollinger, Sanjiv Singh, Joseph Djugash, and Athanasios Kehagias. Efficient multi-robot search for a moving target. International Journal of Robotics Research, 28(2):201-219, February 2009.

[102] Monica Anderson and Nikolaos Papanikolopoulos. Implicit cooperation strategies for multi-robot search

of unknown areas. Journal of Intelligent and Robotic Systems, 53(4):381-397, December 2008.

[103] M. Bernardine Dias, Robert Zlot, Nidhi Kalra, and Anthony Stentz. Market-based multirobot coordination: A survey and analysis. Technical Report CMU-RI-TR-05-13, Carnegie Mellon University, Pittsburgh, PA, USA, April 2005.

[104] Jianping Chen, Yimin Yang, and Liang Wei. Research on the approach of task decomposition in soccer robot system. In Proceedings of ICDMA'10, pages 284-289, Changsha, China, December 2010.

[105] Peter Stone and Manuela Veloso. Task decomposition, dynamic role assignment, and low-bandwidth communication for real-time strategic teamwork. Artificial Intelligence, 110(2):241-273, June 1999.

[106] Shimon Whiteson, Nate Kohl, Risto Miikkulainen, and Peter Stone. Evolving keepaway soccer players through task decomposition. Machine Learning, 59(1):5-30, May 2005.

[107] Brian P. Gerkey and Maja J. Matarić. Multi-robot task allocation: Analyzing the complexity and optimality of key architectures. In Proceedings of ICRA'03, pages 3862-3868, Taipei, Taiwan, September 2003.

[108] Barry Brian Werger and Maja J. Matarić. Broadcast of local eligibility for multi-target observation. In Proceedings of DARS'00, pages 347-356, Knoxville, TN, USA, October 2000.

[109] Anthony Stentz and M. Bernardine Dias. A free market architecture for coordinating multiple robots. Technical Report CMU-RI-TR-99-42, Carnegie Mellon University, Pittsburgh, PA, USA, December 1999.

[110] Luiz Chaimowicz, Mario F. M. Campos, and Vijay Kumar. Dynamic role assignment for cooperative robots. In Proceedings of ICRA'02, pages 293-298, Washington, DC, USA, May 2002.

[111] Reid G. Smith. The contract net protocol: High-level communication and control in a distributed problem solver. IEEE Transactions on Computers, 29(12):1104-1113, December 1980.

[112] Hossam Hanna. Decentralized approach for multi-robot task allocation problem with uncertain task execution. In Proceedings of IROS'05, pages 535-540, Alberta, Canada, August 2005.

[113] Nathan Michael, Michael M. Zavlanos, Vijay Kumar, and George J. Pappas. Distributed multi-robot task assignment and formation control. In Proceedings of ICRA'08, pages 128-133, Pasadena, CA, USA, May 2008.

[114] Pedro M. Shiroma and Mario F. M. Campos. CoMutaR: A framework for multi-robot coordination and task allocation. In Proceedings of IROS'09, pages 4817-4824, St. Louis, MO, USA, October 2009.

[115] M. Bernardine Dias and Anthony Stentz. A free market architecture for distributed control of a multirobot system. In Proceedings of IAS'00, pages 115-122, Venice, Italy, July 2000.

[116] Esben H. Ostergaard, Maja J. Matarić, and Gaurav S. Sukhatme. Multi-robot task allocation in the light of uncertainty. In Proceedings of ICRA'02, pages 3002-3007, Washington, DC, USA, May 2002.

[117] Sanem Sariel, Tucker Balch, and Nadia Erdogan. Incremental multi-robot task selection for resource constrained and interrelated tasks. In Proceedings of IROS'07, pages 2314-2319, San Diego, CA, USA, October 2007.

[118] Lynne E. Parker. Heterogeneous Multi-Robot Cooperation. PhD thesis, Massachusetts Institute of Technology, February 1994.

[119] Jean-Claude Latombe. Robot Motion Planning. Kluwer Academic Publishers, 1991.

[120] Yi Guo and Lynne E. Parker. A distributed and optimal motion planning approach for multiple mobile robots. In Proceedings of ICRA'02, pages 2612-2619, Washington, DC, USA, May 2002.

[121] Maren Bennewitz, Wolfram Burgard, and Sebastian Thrun. Optimizing schedules for prioritized path planning of multi-robot systems. In Proceedings of ICRA'01, pages 271-276, Seoul, Korea, May 2001.

[122] Peter E. Hart, Nils J. Nilsson, and Bertram Raphael. A formal basis for the heuristic determination of minimum cost paths. IEEE Transactions on Systems Science and Cybernetics, 4(2):100-107, 1968.

[123] Anthony Stentz. Optimal and efficient path planning for partially-known environments. In Proceedings of ICRA'94, pages 3310-3317, San Diego, CA, USA, May 1994.

[124] Herbert G. Tanner and Amit Kumar. Towards decentralization of multi-robot navigation functions. In Proceedings of ICRA'05, pages 4132-4137, Barcelona, Spain, April 2005.

[125] Peng Song and R. Vijay Kumar. A potential field based approach to multi-robot manipulation. In Proceedings of ICRA'02, pages 1217-1222, Washington, DC, USA, May 2002.

[126] Luke M. Wachter, John Murphy, and Laura E. Ray. Potential function control for multiple high-speed. Nonholonomic robots. In Proceedings of ICRA'08, pages 1781-1782, Pasadena, CA, USA, May 2008.

[127] Russell Gayle, William Moss, Ming C. Lin, and Dinesh Manocha. Multi-robot coordination using generalized social potential fields. In Proceedings of ICRA'09, pages 106-113, Kobe, Japan, May 2009.

[128] Noam Hazon, Fabrizio Mieli, and Gal A. Kaminka. Towards robust on-line multi-robot coverage. In Proceedings of ICRA'06, pages 1710-1715, Orlando, FL, USA, May 2006.

[129] Thierry Siméon, Stéphane Leroy, and Jean-Paul Laumond. Path coordination for multiple mobile robots: A resolution-complete algorithm. IEEE Transactions on Robotics and Automation, 18(1):42-49, 2002.

[130] Noam Hazon and Gal A. Kaminka. Redundancy, efficiency and robustness in multi-robot coverage. In Proceedings of ICRA'05, pages 735-741, Barcelona, Spain, April 2005.

[131] Xiaoming Zheng, Sonal Jain, Sven Koenig, and David Kempe. Multi-robot forest coverage. In Proceedings of IROS'05, pages 3852-3857, Alberta, Canada, August 2005.

[132] Sebastian Thrun. Learning metric-topological maps for indoor mobile robot navigation. Artificial Intelligence, 99(1):21-71, 1998.

[133] Lydia E. Kavraki, Mihail N. Kolountzakis, and Jean-Claude Latombe. Analysis of probabilistic roadmaps for path planning. In Proceedings of ICRA'96, pages 3020-3025, Minneapolis, MN, USA, April 1996.

[134] Gildardo Sánchez and Jean-Claude Latombe. Using a PRM planner to compare centralized and decoupled planning for multi-robot systems. In Proceedings of ICRA'02, pages 2112-2119, Washington, DC, USA, May 2002.

[135] Mitul Saha and Pekka Isto. Multi-robot motion planning by incremental coordination. In Proceedings of IROS'06, pages 5960-5963, Beijing, China, October 2006.

[136] Petr Švestka and Mark H. Overmars. Coordinated motion planning for multiple car-like robots using probabilistic roadmaps. In Proceedings of ICRA'95, pages 1631-1636, Nagoya, Japan, May 1995.

[137] Christopher M. Clark. Probabilistic road map sampling strategies for multi-robot motion planning. Robotics and Autonomous Systems, 53(3-4):244-264, 2005.

[138] Steven M. LaValle. Rapidly-exploring random trees: A new tool for path planning. Technical Report TR 98-11, Iowa State University, Ames, IA, USA, October 1998.

[139] James Bruce and Manuela Veloso. Real-time randomized path planning for robot navigation. In Proceedings of IROS'02, pages 2383-2388, Lausanne, Switzerland, September 2002.

[140] Mac Schwager, Daniela Rus, and Jean-Jacques Slotine. Unifying geometric, probabilistic, and potential field approaches to multi-robot deployment. International Journal of Robotics Research, 30(3):371-383, March 2011.

[141] Sebastian Buck, Ulrich Weber, Michael Beetz, and Thorsten Schmitt. Multi robot path planning for dynamic environments: A case study. In Proceedings of IROS'01, pages 1245-1250, Maui, HI, USA, October 2001.

[142] Stephen Kloder and Seth Hutchinson. Path planning for permutation-invariant multi-robot formations. In Proceedings of ICRA'05, pages 1797-1802, Barcelona, Spain, April 2005.

[143] Geoffrey Hollinger and Sanjiv Singh. Multi-robot coordination with periodic connectivity. In Proceedings of ICRA'10, pages 4457-4462, Anchorage, AK, USA, May 2010.

[144] Andrew Howard, Maja J. Matarić, and Gaurav S Sukhatme. Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem. In Proceedings of DARS'02, pages 299-308, Fukuoka, Japan, June 2002.

[145] Silvia Ferrari and Greg Foderaro. A potential field approach to finding minimum-exposure paths in wireless sensor networks. In Proceedings of ICRA'10, pages 335-341, Anchorage, AK, USA, May 2010.

[146] John T. Feddema, Chris Lewis, and David A. Schoenwald. Decentralized control of cooperative robotic vehicles: Theory and application. IEEE Transactions on Robotics and Automation, 18(5):852-864, 2002.

[147] Jonathan Bohren, Radu Bogdan Rusu, E. Gil Jones, Eitan Marder-Eppstein, Caroline Pantofaru, Melonee Wise, Lorenz Mösenlechner, Wim Meeussen, and Stefan Holzer. Towards autonomous robotic butlers: Lessons learned with the PR2. In Proceedings of ICRA'11, pages 5568-5575, Shanghai, China, May 2011.

[148] http://www.isi.edu/nsam/

[149] Esha D. Nerurkar, Ke X. Zhou, and Stergios I. Roumeliotis. A hybrid estimation framework for cooperative localization under communication constraints. In Proceedings of IROS'11, pages 502-509, San Francisco, CA, USA, September 2011.

[150] Athanasios Krontiris and Kostas E. Bekris. Using minimal communication to improve decentralized conflict resolution for non-holonomic vehicles. In Proceedings of IROS'11, pages 3235-3240, San Francisco, CA, USA, September 2011.

[151] Ying Wang and Clarence W. de Silva. Multi-robot box-pushing: single-agent Q-Learning vs. team Q-Learning. In Proceedings of IROS'06, pages 3694-3699, Beijing, China, October 2006.

[152] Shahar Sarid and Amir Shapiro. A time competitive heterogeneous multi robot path finding algorithm. In Proceedings of IROS'10, pages 4590-4595, Taipei, Taiwan, October 2010.

[153] Alphan Ulusoy, Stephen L. Smith, Xu Chu Ding, Calin Belta, and Daniela Rus. Robust multi-robot optimal path planning with temporal logic constraints. In Proceedings of ICRA'12, pages 4693-4698, Saint Paul, MN, USA, May 2012.

[154] Ryan Luna and Kostas E. Bekris. Network-guided multi-robot path planning in discrete representations. In Proceedings of IROS'10, pages 4596-4602, Taipei, Taiwan, October 2010.

[155] Noa Agmon, Chien-Liang Fok, Yehuda Emaliah, Peter Stone, Christine Julien, and Sriram Vishwanath. On coordination in practical multi-robot patrol. In Proceedings of ICRA'12, pages 650-656, Saint Paul, MN, USA, May 2012.

[156] G. Ayorkor Korsah, Balajee Kannan, Brett Browning, Anthony Stentz, and M. Bernardine Dias.

xBots: An approach to generating and executing optimal multi-robot plans with cross-schedule dependencies. In Proceedings of ICRA'12, pages 115-122, Saint Paul, MN, USA, May 2012.

[157] Javier Alonso-Mora, Andreas Breitenmoser, Paul Beardsley, and Roland Siegwart. Reciprocal collision avoidance for multiple car-like robots. In Proceedings of ICRA'12, pages 360-366, Saint Paul, MN, USA, May 2012.

[158] Shuai Li and Yi Guo. Distributed source seeking by cooperative robots: All-to-all and limited communications. In Proceedings of ICRA'12, pages 1107-1112, Saint Paul, MN, USA, May 2012.

[159] Yuanteng Pei and Matt W. Mutka. Steiner traveler: Relay deployment for remote sensing in heterogeneous multi-robot exploration. In Proceedings of ICRA'12, pages 1551-1556, Saint Paul, MN, USA, May 2012.

[160] Lingzhi Luo, Nilanjan Chakraborty, and Katia P. Sycara. Competitive analysis of repeated greedy auction algorithm for online multi-robot task assignment. In Proceedings of ICRA'12, pages 4792-4799, Saint Paul, MN, USA, May 2012.

[161] Amanda Prorok, Alexander Bahr, and Alcherio Martinoli. Low-cost collaborative localization for large-scale multi-robot systems. In Proceedings of ICRA'12, pages 4236-4241, Saint Paul, MN, USA, May 2012.

[162] Alphan Ulusoy, Stephen L. Smith, Xu Chu Ding, and Calin Belta. Robust multi-robot optimal path planning with temporal logic constraints. In Proceedings of ICRA'12, pages 4693-4698, Saint Paul, MN, USA, May 2012.

[163] Glenn Wagner, Minsu Kang, and Howie Choset. Probabilistic path planning for multiple robots with subdimensional expansion. In Proceedings of ICRA'12, pages 2886-2892, Saint Paul, MN, USA, May 2012.

[164] Jan Faigl, Miroslav Kulich, and Libor Preucil. Goal assignment using distance cost in multi-robot exploration. In Proceedings of IROS'12, pages 3741-3746, Vilamoura, Portugal, September 2012.

[165] Sandip Kumar and Suman Chakravorty. Multi-agent Generalized Probabilistic RoadMaps: MAGPRM. In Proceedings of IROS'12, pages 3747-3753, Vilamoura, Portugal, September 2012.

[166] Gal A. Kaminka, Dan Erusalimchik, and Sarit Kraus. Adaptive multi-robot coordination: A game-theoretic perspective. In Proceedings of ICRA'10, pages 328-334, Anchorage, AK, USA, May 2010.

[167] Paula García, Pilar Caamaño, Richard J. Duro, and Francisco Bellas. Scalable task assignment for heterogeneous multi-robot teams. International Journal of Advanced Robotic Systems, 10(105):1-10, February 2013.

[168] Hugo Costelha and Pedro U. Lima. Robot task plan representation by Petri nets: modelling, identification, analysis and execution. Autonomous Robots, 33(4):337-360, November 2012.

[169] Emmett Lalish and Kristi A. Morgansen. Distributed reactive collision avoidance. Autonomous Robots, 32(3):207-226, April 2012.

[170] Javier Alonso-Mora, Andreas Breitenmoser, Martin Rufli, Paul Beardsley, and Roland Siegwart. Optimal reciprocal collision avoidance for multiple non-holonomic robots. Distributed Autonomous Robotic Systems, 83:203-216, 2013.

[171] Alexander Cunningham, Kai M. Wurm, Wolfram Burgard, and Frank Dellaert. Fully distributed scalable smoothing and mapping with robust multi-robot data association. In Proceedings of ICRA'12, pages 1093-1100, Saint Paul, MN, USA, May 2012.

[172] Jesus Capitan, Matthijs T. J. Spaan, Luis Merino and Aníbal Ollero: Decentralized multi-robot cooperation with auctioned POMDPs. International Journal of Robotic Research, 32(6):650-671, May 2013.

[173] Shih Yi Chien, Michael Lewis, Siddharth Mehrotra, Nathan Brooks, and Katia P. Sycara. Scheduling operator attention for multi-robot control. In Proceedings of IROS'12, pages 473-479, Vilamoura, Portugal, September 2012.

[174] Fei Gao, Missy L. Cummings, and Luca F. Bertuccelli. Teamwork in controlling multiple robots. In Proceedings of HRI'12, pages 81-88, Boston, MA, USA, March 2012.

[175] Kuanhao Zheng, Dylan F. Glas, Takayuki Kanda, Hiroshi Ishiguro, and Norihiro Hagita. Supervisory control of multiple social robots for navigation. In Proceedings of HRI'13, pages 17-24, Tokyo, Japan, March 2013.