

Handbook of Robotics

Chapter 40: Multiple Mobile Robot Systems

Lynne E. Parker
Department of Electrical Engineering and Computer Science
University of Tennessee
Knoxville, Tennessee, USA
email: parker@cs.utk.edu

Contents

40 Multiple Mobile Robot Systems	1
40.1 Introduction	1
40.2 Architectures for Multi-Robot Systems	2
40.2.1 The Nerd Herd	3
40.2.2 The ALLIANCE Architecture	3
40.2.3 The Distributed Robot Architecture	4
40.3 Communication	5
40.4 Swarm Robots	6
40.5 Heterogeneity	7
40.6 Task Allocation	9
40.6.1 Taxonomy for Task Allocation	9
40.6.2 Representative Approaches	10
40.7 Learning	11
40.8 Applications	12
40.8.1 Foraging and Coverage	12
40.8.2 Flocking and Formations	12
40.8.3 Box Pushing and Cooperative Manipulation	13
40.8.4 Multi-Target Observation	13
40.8.5 Traffic Control and Multi-Robot Path Planning	13
40.8.6 Soccer	14
40.9 Conclusions and Further Reading	14

Chapter 40

Multiple Mobile Robot Systems

Researchers generally agree that multi-robot systems have several advantages over single robot systems [1, 2]. The most common motivations for developing multi-robot system solutions are that: (1) the task complexity is too high for a single robot to accomplish; (2) the task is inherently distributed; (3) building several resource-bounded robots is much easier than having a single powerful robot; (4) multiple robots can solve problems faster using parallelism; and (5) the introduction of multiple robots increases robustness through redundancy. The issues that must be addressed in developing multi-robot solutions are dependent upon the task requirements and the sensory and effector capabilities of the available robots.

The types of robots considered in the study of multiple *mobile* robot systems are those robots that move around in the environment, such as ground vehicles, aerial vehicles, or underwater vehicles. This chapter focuses specifically on the interaction of multiple *mobile* robots, as distinguished from other types of multi-robot interaction. For example, a special case of multiple mobile robot systems are the *reconfigurable* or *modular* robots that interconnect with each other for the purposes of navigation or manipulation. This type of multi-robot system is covered in detail in Chapter 39. *Networked* robotics, covered in Chapter 41, is also very closely related to multiple mobile robot systems; however, the focus in networked robotics is on systems of robots, sensors, embedded computers, and human users that are all connected by networked communication. Another variant of multi-robot cooperation is multiple manipulator arm cooperation. Chapter 29 describes these systems in detail.

Thus, within the context of multiple *mobile* robot systems, this chapter explores the current state of the art. After a brief introduction, we first examine architectures for multi-robot cooperation, exploring the alternative approaches that have been developed. Next, we explore

communications issues and their impact on multi-robot teams in Section 40.3, followed by a discussion of swarm robot systems in Section 40.4. While swarm systems typically assume large numbers of homogeneous robots, other types of multi-robot systems include heterogeneous robots. We therefore next discuss heterogeneity in cooperative robot teams in Section 40.5. Once robot teams allow for individual heterogeneity, then issues of task allocation become important; Section 40.6 therefore discusses common approaches to task allocation. Section 40.7 discusses the challenges of multi-robot learning, and some representative approaches. We outline some of the typical application domains which serve as testbeds for multi-robot systems research in Section 40.8. Finally, we conclude in Section 40.9 with some summary remarks and suggestions for further reading.

40.1 Introduction

Since the earliest work on multiple mobile robot systems in the 1980's, the field has grown significantly, and covers a large body of research. At the most general level, approaches to multiple mobile robot systems fall into one of two broad categories: *collective swarm* systems and *intentionally cooperative* systems. *Collective swarm* systems are those in which robots execute their own tasks with only minimal need for knowledge about other robot team members. These systems are typified by the assumption of a large number of homogeneous mobile robots, in which robots make use of local control laws to generate globally coherent team behaviors, with little explicit communication among robots. On the other hand, robots in *intentionally cooperative* systems have knowledge of the presence of other robots in the environment and act together based on the state, actions, or capabilities of their teammates in order to

accomplish the same goal. Intentionally cooperative systems vary in the extent to which robots take into account the actions or state of other robots, and can lead to either strongly cooperative or weakly cooperative solutions [3]. *Strongly cooperative* solutions require robots to act in concert to achieve the goal, executing tasks that are not trivially serializable. Typically, these approaches require some type of communication and synchronization among the robots. *Weakly cooperative* solutions allow robots to have periods of operational independence, subsequent to coordinating their selection of tasks or roles. Intentionally cooperative multi-robot systems can deal with heterogeneity in the robot team members, in which team members vary in their sensor and effector capabilities. In these teams, the coordination of robots can be very different than in collective swarm approaches, since robots are no longer interchangeable.

Most of the work specific to multiple mobile robot cooperation can be categorized into a set of key topics of study. These topics, which are the foci of this chapter, include *architectures*, *communication*, *swarm robots*, *heterogeneity*, *task allocation*, and *learning*. *Architectures* and *communication* in multi-robot systems are relevant for all types of multi-robot systems, as these approaches specify how the robot team members are organized and interact. *Swarm robots* is a particular type of multi-robot system, typified by large numbers of homogeneous robots that interact implicitly with each other. Such systems are often contrasted with *heterogeneous* robots, in which team members may vary significantly in their capabilities. When robots vary in capabilities, challenges arise in determining which robots should perform which tasks – a challenge commonly referred to as *task allocation*. Finally *learning* in multi-robot teams is of particular interest in designing teams that are adaptive over time and can learn new behaviors. Illustrating the advances in each of these areas often takes place in a set of representative application domains; these *applications* are the final major topic of discussion in this chapter.

40.2 Architectures for Multi-Robot Systems

The design of the overall control architecture for the multi-robot team has a significant impact on the robustness and scalability of the system. Robot architectures for multi-robot teams are composed of the same fundamental components as in single-robot systems, as described in Chapter 8. However, they also must address

the interaction of robots and how the group behavior will be generated from the control architectures of the individual robots in the team. Several different philosophies for multi-robot team architectures are possible; the most common are *centralized*, *hierarchical*, *decentralized*, and *hybrid*.

Centralized architectures that coordinate the entire team from a single point of control are theoretically possible [4], although often practically unrealistic due to vulnerability to a single point of failure, and due to the difficulty of communicating the entire system state back to the central location at a frequency suitable for real-time control. Situations in which these approaches are relevant are cases when the centralized controller has a clear vantage point from which to observe the robots, and can easily broadcast group messages for all robots to obey [5].

Hierarchical architectures are realistic for some applications. In this control approach, each robot oversees the actions of a relatively small group of other robots, each of which in turn oversees yet another group of robots, and so forth, down to the lowest robot that simply executes its part of the task. This architecture scales much better than centralized approaches, and is reminiscent of military command and control. A point of weakness for the hierarchical control architecture is recovering from failures of robots high in the control tree.

Decentralized control architectures are the most common approach for multi-robot teams, and typically require robots to take actions based only on knowledge local to their situation. This control approach can be highly robust to failure, since no robot is responsible for the control of any other robot. However, achieving global coherency in these systems can be difficult, because high level goals have to be incorporated into the local control of each robot. If the goals change, it may be difficult to revise the behavior of individual robots.

Hybrid control architectures combine local control with higher-level control approaches to achieve both robustness and the ability to influence the entire team's actions through global goals, plans, or control. Many multi-robot control approaches make use of hybrid architectures.

A plethora of multi-robot control architectures have been developed over the years. We focus here on three approaches that illustrate the spectrum of control architectures. The first, the Nerd Herd, is representative of a pure *swarm* robotics approach using large numbers of homogeneous robots. The second, ALLIANCE, is representative of a behavior-based approach that enables co-

ordination and control of possibly heterogeneous robots without explicit coordination. The third, Distributed Robot Architecture (DIRA), is a hybrid approach that enables both robot autonomy and explicit coordination in possibly heterogeneous robot teams.

40.2.1 The Nerd Herd

One of the first studies of social behaviors in multi-robot teams was conducted by Mataric [6], with results being demonstrated on the Nerd Herd team of 20 identical robots (shown in Figure 40.1). This work is an example of swarm robotic systems, as described further in Section 40.4. The decentralized control approach was based on the subsumption architecture (see Chapter 8), and assumed that all robots were homogeneous, but with relatively simple individual capabilities, such as detecting obstacles and “kin” (i.e., other robot team members). A set of basic social behaviors (see also Chapter 38) were defined and demonstrated, including obstacle avoidance, homing, aggregation, dispersion, following, and safe wandering. These basic behaviors were combined in various ways to yield more composite social behaviors, including flocking (composed of safe wandering, aggregation and dispersion), surrounding (composed of safe wandering, following, and aggregation), herding (composed of safe wandering, surrounding, and flocking), and foraging (composed of safe wandering, dispersion, following, homing, and flocking). The behaviors were implemented as rules, such as the following rule for aggregate:

```
Aggregate:
  If agent is outside aggregation distance
    turn toward aggregation centroid and go.
  Else
    stop.
```

This work showed that collective behaviors could be generated through the combination of lower-level basic behaviors. Related work on this project studied issues such as using bucket brigades to reduce interference [7], and learning [8].

40.2.2 The ALLIANCE Architecture

Another early work in multi-robot team architectures is the ALLIANCE architecture (shown in Figure 40.2), developed by Parker [9] for fault tolerant task allocation in heterogeneous robot teams. This approach builds on the subsumption architecture by adding behavior sets and motivations for achieving action selection without ex-



Figure 40.1: The Nerd Herd robots.

PLICIT negotiations between robots. Behavior sets group low-level behaviors together for the execution of a particular task. The motivations consist of levels of impatience and acquiescence that can raise and lower a robot’s interest in activating a behavior set corresponding to a task that must be accomplished.

In this approach, the initial motivation to perform a given behavior set is set to zero. Then, at each time step, the motivation level is recalculated based on (1) the previous motivation level, (2) the rate of impatience, (3) whether the sensory feedback indicates the behavior set is needed, (4) whether the robot has another behavior set already activated, (5) whether another robot has recently begun work on this task, and (6) whether the robot is willing to give up the task, based on how long it has been attempting the task. Effectively, the motivation continues to increase at some positive rate unless one of four situations occurs: (1) the sensory feedback indicates that the behavior set is no longer needed, (2) another behavior set in the robot activates, (3) some other robot has just taken over the task for the first time, or (4) the robot has decided to acquiesce the task. In any of these four situations, the motivation returns to zero. Otherwise, the motivation grows until it crosses a threshold value, at which time the behavior set is activated and the robot can be said to have selected an action. When an action is selected, cross-inhibition within that robot prevents other tasks from being activated within that same robot. When a behavior set is active in a robot, the robot broadcasts its current activity to other robots at a periodic rate.

The L-ALLIANCE extension [10] allows a robot to adapt the rate of change of the impatience and acquies-

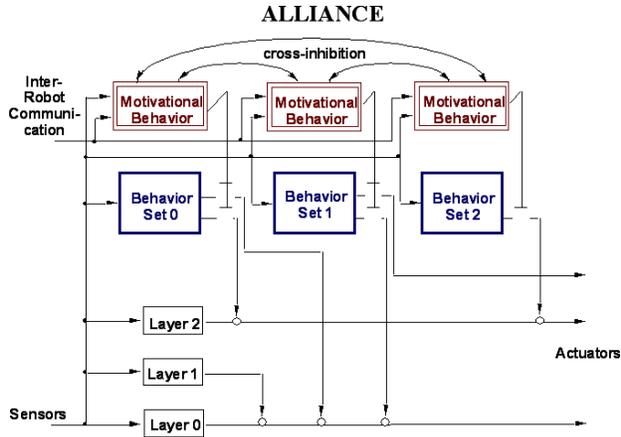


Figure 40.2: The ALLIANCE architecture.

cence values depending on the quality with which that robot is expected to accomplish a given task. The result is that robots that have demonstrated their ability to better accomplish certain tasks are more likely to choose those tasks in the future. Additionally, if problems occur during team performance, then robots may dynamically reallocate their tasks to compensate for the problems. This approach was demonstrated on a team of three heterogeneous robots performing a mock clean-up task, two robots performing a box-pushing task, and four robots performing a cooperative target observation problem. The approach has also been demonstrated in simulation on a janitorial service task and a bounding overwatch task. Figure 40.3 shows robots using ALLIANCE to perform the mock clean-up task.

40.2.3 The Distributed Robot Architecture

Simmons, et al. [11] have developed a hybrid architecture called the Distributed Robot Architecture (DIRA). Similar to the Nerd Herd and ALLIANCE approaches, the DIRA approach allows autonomy in individual robots. However, unlike the previous approaches, DIRA also facilitates explicit coordination among robots. This approach is based on layered architectures that are popular for single-robot systems (see Chapter 8). In this approach (shown in Figure 40.4), each robot's control architecture consists of a *planning* layer that decides how to achieve high-level goals; an *executive* layer that synchronizes agents, sequences tasks and monitors task execution; and a *behavioral* layer that interfaces to the robot's

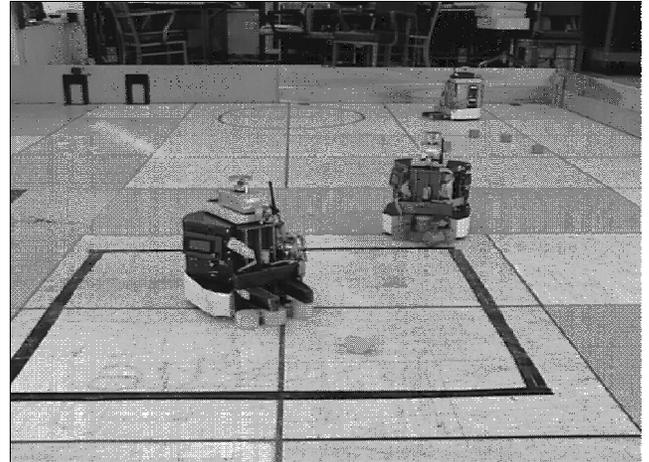


Figure 40.3: Robots using the ALLIANCE architecture for a mock clean-up task.

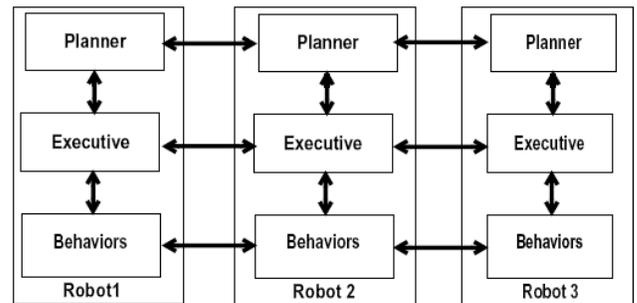


Figure 40.4: The Distributed Robot Architecture.

sensors and effectors. Each of these layers interacts with those above and below it. Additionally, robots can interact with each other via direct connections at each of the layers.

This architecture has been demonstrated in a team of three robots – a crane, a roving eye, and a mobile manipulator – performing a construction assembly task (see Figure 40.5). This task requires the robots to work together to connect a beam at a given location. In these demonstrations, a “foreman” agent decides which robot should move the beam at which times. Initially, the crane moves the beam to the vicinity of the emplacement based on encoder feedback. The foreman then sets up a behavioral loop between the roving eye and the crane robot to servo the beam closer to the point of emplacement. Once the beam is close enough, the foreman tasks the roving eye and the mobile manipulator to servo the arm to grasp the beam. After contact is made, the foreman



Figure 40.5: Robots using the Distributed Robot Architecture for assembly tasks.

tasks the roving eye and the mobile manipulator to coordinate to servo the beam to the emplacement point, thus completing the task.

40.3 Communication

A fundamental assumption in multi-robot systems research is that globally coherent and efficient solutions can be achieved through the interaction of robots lacking complete global information. However, achieving these globally coherent solutions typically requires robots to obtain information about their teammates' states or actions. This information can be obtained in a number of ways; the three most common techniques are (1) the use of implicit communication "through the world" (called *stigmergy*), in which robots sense the effects of teammate's actions through their effects on the world (e.g., [12, 13, 14, 6, 15, 16]), (2) passive action recognition, in which robots use sensors to directly observe the actions of their teammates (e.g., [17]), and (3) explicit (intentional) communication, in which robots directly and intentionally communicate relevant information through some active means, such as radio (e.g., [18, 19, 9, 20]).

Each of these mechanisms for exchanging information between robots has its own advantages and disadvantages [21]. *Stigmergy* is appealing because of its simplicity and its lack of dependence upon explicit communications channels and protocols. However, it is limited by the extent to which a robot's perception of the world reflects the salient states of the mission the robot team must accomplish. *Passive action recognition* is appealing

because it does not depend upon a limited-bandwidth, fallible communication mechanism. As with implicit cooperation, however, it is limited by the degree to which a robot can successfully interpret its sensory information, as well as the difficulty of analyzing the actions of robot team members. Finally, the *explicit communication* approach is appealing because of its directness and the ease with which robots can become aware of the actions and/or goals of its teammates. The major uses of explicit communication in multi-robot teams are to synchronize actions, exchange information, and to negotiate between robots. Explicit communication is a way of dealing with the *hidden state* problem [22], in which limited sensors cannot distinguish between different states of the world that are important for task performance. However, explicit communication is limited in terms of fault tolerance and reliability, because it typically depends upon a noisy, limited-bandwidth communications channel that may not continually connect all members of the robot team. Thus, approaches that make use of explicit communications must also provide mechanisms to handle communication failures and lost messages.

Selecting the appropriate use of communication in a multi-robot team is a design choice dependent upon the tasks to be achieved by the multi-robot team. One needs to carefully consider the costs and benefits of alternative communications approaches to determine the method that can reliably achieve the required level of system performance. Researchers generally agree that communication can have a strong positive impact on the performance of the team. One of the earliest illustrations of this impact was given in the work of MacLennan [23], which investigates the evolution of communication in simulated worlds and concludes that the communication of local robot information can result in significant performance improvements. Interestingly, for many representative applications, researchers have found a non-linear relationship between the amount of information communicated and its impact on the performance of the team. Typically, even a small amount of information can have a significant impact on the team, as found in the study of Balch and Arkin [24]. However, more information does not necessarily continue to improve performance, as it can quickly overload the communications bandwidth without providing an application benefit. The challenge in multi-robot systems is to discover the "optimal" pieces of information to exchange that yield these performance improvements without saturating the communications bandwidth. Currently, no general approaches to identifying this critical information

are available; thus, the decision of what to communicate is an application-specific question to be answered by the system designer. Dudek’s taxonomy of multi-robot systems [25] includes axes related to communication, including communication range, communication topology, and communication bandwidth. These characteristics can be used to compare and contrast multi-robot systems.

Several related issues of active research in communications for multi-robot teams deal with dynamic network connectivity and topologies. For example, robot teams must either be able to maintain communications connectivity as they move, or employ recovery strategies that allow the robot team to recover when the communications connectivity is broken. These concerns may require robots to adapt their actions in response to the anticipated effects on the communications network, or in response to knowledge of the anticipated propagation behavior of information through the dynamic network. These and related issues are discussed in some detail in the the context of *networked robotics*; see Chapter 41 for more information.

40.4 Swarm Robots

Historically, some of the earliest work in multi-robot systems [12, 26, 27, 28, 29, 30, 13, 31, 32, 33] dealt with large numbers of homogeneous robots, called *swarms*. Still undergoing active study today, the swarm approaches obtain inspiration from biological societies – particularly ants, bees, and birds – to develop similar behaviors in multi-robot teams. Because biological societies are able to accomplish impressive group capabilities, such as the ability of termites to build large, complex mounds, or the ability of ants to collectively carry large prey, robotics researchers aim to reproduce these capabilities in robot societies.

Swarm robotics systems are often called “collective” robotics, indicating that individual robots are often unaware of the actions of other robots in the system, other than information on proximity. These approaches aim to achieve a desired team-level global behavior from the interaction dynamics of individual robots following relatively simple local control laws. Swarm robotic systems typically involve very little explicit communication between robots, and instead rely on stigmergy (i.e., communication through the world) to achieve emergent cooperation. Individual robots are assumed to have minimal capabilities, with little ability to solve meaningful tasks on their own. However, when grouped with other simi-

lar robots, they are collectively able to achieve team-level tasks. Ideally, the entire team should be able to achieve much more than individual robots working alone (i.e., it is *superadditive*, meaning that the whole is bigger than the sum of the parts). These systems assume very large numbers of robots (at least dozens, and often hundreds or thousands) and explicitly address issues of scalability. Swarm robotic approaches achieve high levels of redundancy because robots are assumed to be identical, and thus interchangeable with each other.

Many types of swarm behaviors have been studied, such as foraging, flocking, chaining, search, herding, aggregation, and containment. The majority of these swarm behaviors deal with spatially distributed multi-robot motions, requiring robots to coordinate motions either (1) relative to other robots, (2) relative to the environment, (3) relative to external agents, (4) relative to robots and the environment, or (5) relative to all (i.e., other robots, external agents, and the environment). Table 40.1 categorizes swarm robot behaviors according to these groupings, citing representative examples of relevant research.

Much of the current research in swarm robotics is aimed at developing specific solutions to one or more of the swarm behaviors listed in Table 40.1. Some of these swarm behaviors have received particular attention, notably formations, flocking, search, coverage, and foraging. Section 40.8 discusses these behaviors in more detail. In general, most current work in the development of swarm behaviors is aimed not just at demonstrating group motions that are similar to biological systems, but also at understanding the formal control theoretic principles that can predictably converge to the desired group behaviors, and remain in stable states.

Demonstration of physical robot swarms is both a hardware and a software challenge. As discussed in Section 40.2, the first demonstrations were by Mataric [6], involving about 20 physical robots performing aggregation, dispersion, and flocking. This work defined composable *basis behaviors* as primitives for structuring more complex systems (see Chapter 38 for more information). More recently, McLurkin [50] developed an extensive catalog of swarm behavior software, and demonstrated these behaviors on about 100 physical robots (called the SwarmBot robots), developed by iRobot, as shown in Figure 40.6. He created several group behaviors, such as `avoidManyRobots`, `disperseFromSource`, `disperseFromLeaves`, `disperseUniformly`, `computeAverageBearing`, `avoidManyRobots`, `followTheLeader`, `orbitGroup`, `navigateGradient`, `clusterOnSource`, and `cluster-`

Table 40.1: Categories of swarm behaviors.

Relative motion requirements	Swarm Behaviors
Relative to other robots	Formations [34, 35], Flocking [29], Natural herding (as in herds of cattle), Schooling, Sorting [14], Clumping [14], Condensation, Aggregation [36], Dispersion [37]
Relative to the environment	Search [38], Foraging [39], Grazing, Harvesting, Deployment [40], Coverage [41], Localization [42], Mapping [43], Exploration [44]
Relative to external agents	Pursuit [45], Predator-prey [46], Target tracking [47], Forced herding/shepherding (as in shepherding sheep)
Relative to other robots and the environment	Containment, Orbiting, Surrounding, Perimeter search [48]
Relative to other robots, external agents, and the environment	Evasion, Tactical overwatch, Soccer [49]

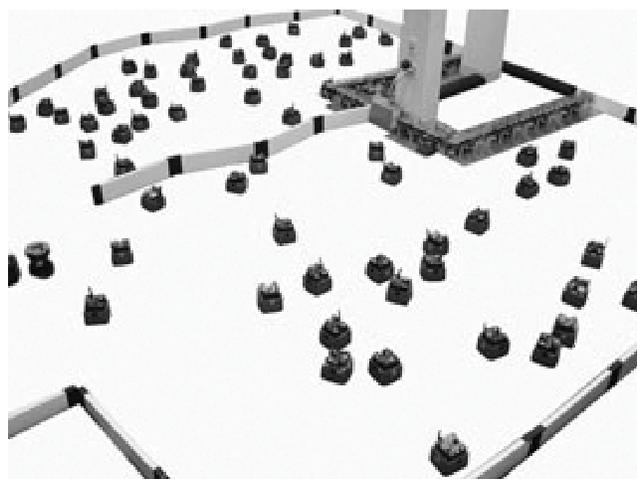


Figure 40.6: The SwarmBot robots.

IntoGroups. A swarm of 108 robots used the developed dispersion algorithms in an empty schoolhouse of area of about 3000 square feet, and were able to successfully locate an object of interest and lead a human to its location [37].

The European Union has sponsored several swarm robot projects, leading toward decreasingly smaller sized individual robots. The I-SWARM project, for instance, is aimed at developing millimeter-sized robots with full onboard sensing, computation, and power for performing biologically-inspired swarming behaviors, as well as collective perception tasks. This project is both a hardware and a software challenge, in that developing micro-

scale robots that are fully autonomous and can perform meaningful cooperative behaviors will require significant advances in the current state of the art.

Another notable effort in swarm robotics research is the U.S. multi-university SWARMS initiative led by the University of Pennsylvania. Research in this project is aimed at developing a new system-theoretic framework for swarming, developing models of swarms and swarming behavior, analyzing swarm formation, stability, and robustness, synthesizing emergent behaviors for active perception and coverage, and algorithms for distributed localization.

Besides the hardware challenges of dealing with large numbers of small robots, there are many important software challenges that remain to be solved. From a practical perspective, the usual approach to creating homogeneous multi-robot swarms is to hypothesize a possible local control law (or laws), and then study the resulting group behavior, iterating until the desired global behavior is obtained. However, the longer term objective is to be able to both predict group performance based on known local control laws, and to generate local control laws based upon a desired global group behavior. Active research by many investigators is ongoing to develop solutions to these key research challenges.

40.5 Heterogeneity

Robot heterogeneity can be defined in terms of variety in robot behavior, morphology, performance quality, size, and cognition. In most large-scale multi-robot systems

work, the benefits of parallelism, redundancy, and solutions distributed in space and time are obtained through the use of homogeneous robots, which are completely interchangeable (i.e., the swarm approach, as described in Section 40.4). However, certain complex applications of large-scale robot teams may require the simultaneous use of multiple types of sensors and robots, all of which cannot be designed into a single type of robot. Some robots may need to be scaled to smaller sizes, which will limit their payloads, or certain required sensors may be too expensive to duplicate across all robots on the team. Other robots may need to be large to carry application-specific payload or sensors, or to navigate long distances in a limited time. These applications, therefore, require the collaboration of large numbers of heterogeneous robots.

The motivation for developing heterogeneity in multi-robot teams is thus two-fold: heterogeneity may be a design feature beneficial to particular applications, or heterogeneity may be a necessity. As a design feature, heterogeneity can offer economic benefits, since it can be easier to distribute varying capabilities across multiple team members rather than building many copies of monolithic robots. Heterogeneity can also offer engineering benefits, as it may simply be too difficult to design individual robots that incorporate all of the sensing, computational, and effector requirements of a given application. Heterogeneity in behavior may also arise in an emergent manner in physically homogeneous teams, as a result of behavior specialization.

A second compelling reason to study heterogeneity is that it may be a necessity, in that it is nearly impossible in practice to build a truly homogeneous robot team. The realities of individual robot design, construction, and experience will inevitably cause a multi-robot system to drift to heterogeneity over time. This is recognized by experienced roboticists, who have seen that several copies of the same model of robot can vary widely in capabilities due to differences in sensor tuning, calibration, etc. Over time, even minor initial differences among robots will grow due to individual robot drift and wear-and-tear. The implication is that to employ robot teams effectively, we must understand diversity, predict how it will impact performance and enable robots to adapt to the diverse capabilities of their peers. In fact, it is often advantageous to build diversity explicitly into the design of a robot team.

There are a variety of research challenges in heterogeneous multi-robot systems. A particular challenge to achieving efficient autonomous control is when overlap in team member capabilities occurs, thus affecting task

allocation or role assignments [51]. Techniques as described in Section 40.6 can typically deal with heterogeneous robots for the purposes of task allocation. Another important topic in heterogeneity is how to recognize and quantify heterogeneity in multi-robot teams. Some types of heterogeneity can be evaluated quantitatively, using metrics such as the social entropy metric developed by Balch [52]. Most research in heterogeneous multi-robot systems assumes that robots have a common language and a common understanding of symbols in their language; developing a common understanding of communicated symbols among robots with different physical capabilities is a fundamental challenge, addressed by Jung in [53].

As discussed in Section 40.2, one of the earliest research demonstrations of heterogeneity in physical robot teams was in the development of the ALLIANCE architecture by Parker [9]. This work demonstrated the ability of robots to compensate for heterogeneity in team members during task allocation and execution. Murphy has studied heterogeneity in the context of marsupial robot deployment, where a “mothership” robot assists smaller robots in applications such as search and rescue [54]. Grabowski, et al. [43] developed modular millibots for surveillance and reconnaissance that could be composed of interchangeable sensor and effector components, thus creating a variety of different heterogeneous teams. Simmons, et al. [11] demonstrated the use of heterogeneous robots for autonomous assembly and construction tasks relevant to space applications. Sukatme, et al. [55] demonstrate a helicopter robot cooperating with two ground robots in tasks involving marsupial-inspired payload deployment and recovery, cooperative localization, and reconnaissance and surveillance tasks, as shown in Figure 40.7. Parker, et al. [56] demonstrated assistive navigation for sensor network deployment using a more intelligent leader robot for guiding navigationally-challenged simple sensor robots to goal locations, as part of a larger demonstration by Howard, et al. [57] of 100 robots performing exploration, mapping, deployment, and detection. Chaimowicz, et al. [58] demonstrated a team of aerial and ground robots cooperating for surveillance applications in urban environments. Parker and Tang [59] developed ASyMTRe, which enables heterogeneous robots to share sensory resources to enable the team to accomplish tasks that would be impossible without tightly coupled sensor sharing.

Many open research issues remain to be solved in heterogeneous multi-robot teams. For example, the issue of optimal team design is a very challenging problem.



Figure 40.7: Heterogeneous team of an air and two ground vehicles that can perform cooperative reconnaissance and surveillance.

Clearly, the required behavioral performance in a given application dictates certain constraints on the physical design of the robot team members. However, it is also clear that multiple choices may be made in designing a solution to a given application, based upon cost, robot availability, ease of software design, flexibility in robot use, and so forth. Designing an optimal robot team for a given application requires significant analysis and consideration of the tradeoffs in alternative strategies.

40.6 Task Allocation

In many multi-robot applications, the mission of the team is defined as a set of tasks that must be completed. Each task can usually be worked on by a variety of different robots; conversely, each robot can usually work on a variety of different tasks. In many applications, a task is decomposed into independent subtasks [9], hierarchical task trees [60], or roles [61, 11, 58, 62] either by a general autonomous planner or by the human designer. Independent subtasks or roles can be achieved concurrently, while subtasks in task trees are achieved according to their interdependence. Once the set of tasks or subtasks have been identified, the challenge is to determine the preferred mapping of robots to tasks (or subtasks). This is the *task allocation* problem.

The details of the task allocation problem can vary in many dimensions, such as the number of robots required per task, the number of tasks a robot can work on at a time, the coordination dependencies among tasks, and the time frame for which task assignments are determined. Gerkey and Mataric [63] defined a taxonomy for task allocation that provides a way of distinguishing task

allocation problems along these dimensions, which is referred to as the MRTA (Multi-Robot Task Allocation) taxonomy.

40.6.1 Taxonomy for Task Allocation

Generally, tasks are considered to be of two principal types: *single-robot tasks* (SR, according to the MRTA taxonomy) are those that require only one robot at a time, while *multi-robot tasks* (MR) are those that require more than one robot working on the same task at the same time. Commonly, single-robot tasks that have minimal task interdependencies are referred to as *loosely coupled tasks*, representing a *weakly cooperative* solution. On the other hand, multi-robot tasks are often considered to be sets of subtasks that have strong interdependencies. These tasks are therefore often referred to as *tightly coupled tasks* that require a *strongly cooperative* solution. The subtasks of a loosely-coupled multi-robot task require a high level of synchronization or coordination between subtasks, meaning that each task must be aware of the current state of the coordinated subtasks within a small time delay. As this time delay becomes progressively larger, coordinated subtasks become more loosely coupled, representing weakly cooperative solutions.

Robots can also be categorized as either *single-task robots* (ST), which work on only one task at a time or *multi-task robots* (MT), which are able to make progress on more than one task at a time. Most commonly, task allocation problems assume robots are single-task robots, since more capable robots that perform multiple tasks in parallel are still beyond the current state of the art.

Tasks can either be assigned to optimize the instantaneous allocation of tasks (IA), or to optimize the assignments into the future (TA, for time-extended assignment). In the case of instantaneous assignment, no consideration is made for the effect of the current assignment on future assignments. Time-extended assignments attempt to assign tasks so that the performance of the team is optimized for the entire set of tasks that may be required, not just the current set of tasks that need to be achieved at the current time step.

Using the MRTA taxonomy, triples of these abbreviations are used to categorize various task allocation approaches, such as SR-ST-IA, which refers to an assignment problem in which single robot tasks are assigned once to single task robots. Different variations of the task allocation problem have different computational complexities. The easiest variant is the ST-SR-IA prob-

lem, which can be solved in polynomial time since it is an instance of the Optimal Assignment Problem [64]. Other variants are much more difficult, and do not have known polynomial time solutions. For example, the ST-MR-IA variant can be shown to be an instance of the Set Partitioning Problem [65], which is strongly NP-hard. The ST-MR-TA, MT-SR-IA, and MT-SR-TA variants have also all been shown to be NP-hard problems. Because these problems are computationally complex, most approaches to task allocation in multi-robot teams generate approximate solutions.

40.6.2 Representative Approaches

Approaches to task allocation in multi-robot teams can be roughly divided into behavior-based approaches and market-based (sometimes called negotiation-style or auction-based) approaches. The following subsections describe some representative architectures for each of these general approaches. Refer to [63] for a comparative analysis of some of these approaches, in terms of computation and communications requirements and solution quality.

Behavior-Based Task Allocation

Behavior-based approaches typically enable robots to determine task assignments without explicitly discussing individual tasks. In these approaches, robots use knowledge of the current state of the robot team mission, robot team member capabilities, and robot actions to decide, in a distributed fashion, which robot should perform which task.

One of the earliest architectures for multi-robot task allocation that was demonstrated on physical robots was the behavior-based ALLIANCE architecture [9] and the related L-ALLIANCE architecture [10]. ALLIANCE addresses the ST-SR-IA and ST-SR-TA variants of the task allocation problem without explicit communication among robots about tasks. As described in Section 40.2.2, ALLIANCE achieves adaptive action selection through the use of motivational behaviors, which are levels of impatience and acquiescence within each robot that determine its own and its teammates' relative fitness for performing certain tasks. These motivations are calculated based upon the mission requirements, the activities and capabilities of teammates, and the robots' internal states. These motivations effectively calculate utility measures for each robot-task pair.

Another behavior-based approach to multi-robot task allocation is BLE (Broadcast of Local Eligibility) [66],

which addresses the ST-SR-IA variant of task allocation. BLE uses a subsumption style behavior control architecture [67] that allows robots to efficiently execute tasks by continuously broadcasting locally-computed eligibilities and only selecting the robot with the best eligibility to perform the task. In this case, task allocation is achieved through behavior inhibition. BLE uses an assignment algorithm that is very similar to Botelho and Alami's M+ architecture [68].

Market-Based Task Allocation

Market-based (or negotiation-based) approaches typically involve explicit communications between robots about the required tasks, in which robots bid for tasks based on their capabilities and availability. The negotiation process is based on market theory, in which the team seeks to optimize an objective function based upon individual robot utilities for performing particular tasks. The approaches typically greedily assign subtasks to the robot that can perform the task with the highest utility.

Smith's Contract Net Protocol (CNP) [69] was the first to address the problem of how agents can negotiate to collectively solve a set of tasks. The use of a market-based approach specifically for multi-robot task allocation was first developed by Botelho and Alami with their M+ architecture [68]. In the M+ approach, robots plan their own individual plans for the task they have been assigned. They then negotiate with other teammates to incrementally adapt their actions to suit the team as a whole, through the use of social rules that facilitate the merging of plans.

Since these early developments, many alternative approaches to market-based task allocation have been developed. A thorough survey on the current state of the art in market-based techniques for multi-robot task allocation is given in [70], comparing alternative approaches in terms of solution quality, scalability, dynamic events and environments, and heterogeneous teams.

Most of the current approaches in market-based task allocation address the ST-SR problem variant, with some approaches (e.g., [71, 72, 11, 73]) dealing with instantaneous assignment (IA), and others (e.g., [74, 44, 75, 76]) addressing time-extended assignments (TA). More recent methods are beginning to address the allocation of multi-robot tasks (i.e., the MR-ST problem variant), including [77, 78, 79, 80, 81, 59]. An example approach to the MR-MT problem variant is found in [82].

Some representative market-based techniques include MURDOCH [71], TraderBots [76, 60], and Hoplites [78].

The MURDOCH approach [71] employs a resource centric, publish/subscribe communication model to carry out auctions, which has the advantage of anonymous communication. In this approach a task is represented by the required resources, such as the environmental sensors. The methods for how to use such a sensor to generate satisfactory results is preprogrammed into the robot.

The TraderBots approach [76, 60] applies market economy techniques for generating efficient and robust multi-robot coordination in dynamic environments. In a market economy, robots act based on selfish interests. A robot receives revenue and incurs cost when trying to accomplish a task. The goal is for robots to trade tasks through auctions/negotiations such that the team profit (revenue minus cost) is optimized.

The Hoplites approach [Kalra et al., 2005] focuses on the selection of an appropriate joint plan for the team to execute by incorporating joint revenue and cost into the bid. This approach couples planning with passive and active coordination strategies, enabling robots to change coordination strategies as the needs of the task change. Strategies are predefined for a robot to accomplish a selected plan.

Some alternative approaches formulate the objects to be assigned as *roles*, which typically package a set of tasks and/or behaviors that a robot should undertake when acting in a particular role. Roles can then be dynamically assigned to robots in a similar manner as in the auction-based approaches (e.g. [61, 11]).

40.7 Learning

Multi-robot learning is the problem of learning new cooperative behaviors, or learning in the presence of other robots. The other robots in the environment, however, have their own goals and may be learning in parallel [83]. The challenge is that having other robots in the environment violates the Markov property that is a fundamental assumption of single-robot learning approaches [83]. The multi-robot learning problem is particularly challenging because it combines the difficulties of single-robot learning with multi-agent learning. Particular difficulties that must be considered in multi-robot learning include continuous state and action spaces, exponential state spaces, distributed credit assignment, limited training time and insufficient training data, uncertainty in sensing and shared information, nondeterministic actions, difficulty in defining appropriate abstractions for learned information, and difficulty of merging informa-

tion learned from different robot experiences.

The types of applications that have been studied for multi-robot learning include multi-target observation [84, 85], air fleet control [86], predator/prey [87, 88, 46], box pushing [89], foraging [22], and multi-robot soccer [49, 90]. Particularly challenging domains for multi-robot learning are those tasks that are *inherently* cooperative. Inherently cooperative tasks are those that cannot be decomposed into independent subtasks to be solved by individual robots. Instead, the utility of the action of one robot is dependent upon the current actions of the other team members. This type of task is a particular challenge in multi-robot learning, due to the difficulty of assigning credit for the individual actions of the robot team members.

The credit assignment problem is a particular challenge, since it is difficult for a robot to determine whether the fitness (either good or bad) is due to its own actions, or due to the actions of another robot. As discussed by Pugh and Martinoli in [91], this problem can be especially difficult in situations where robots do not explicitly share their intentions. Two different variations of the credit assignment problem are common in multi-robot learning. The first is when robots are learning individual behaviors in the presence of other robots that can affect their performance. The second is when robots are attempting to learn a task with a shared fitness function. It can be difficult to determine how to decompose the fitness function to appropriately reward or penalize the contributions of individual robots.

While learning has been explored extensively in the area of single robot systems (see, for example, a discussion of learning in behavior based systems in Chapter 38, and a discussion of fundamental learning techniques in Chapter 9) and in multi-*agent* systems [92], much less work has been done in the area of multi-*robot* learning, although the topic is gaining increased interest. Much of the work to date has focused on reinforcement learning approaches. Some examples of this multi-robot learning research include the work by Asada et al. [93], who propose a method for learning new behaviors by coordinating previously learned behaviors using Q-learning, and apply it to soccer-playing robots. Mataric [8] introduces a method for combining basic behaviors into higher-level behaviors through the use of unsupervised reinforcement learning, heterogeneous reward functions, and progress estimators. This mechanism was applied to a team of robots learning to perform a foraging task. Kubo and Kakazu [94] proposed another reinforcement learning mechanism that uses a progress value for de-

termining reinforcement, and applied it to simulated ant colonies competing for food. Fernandez, et al. [84] apply a reinforcement learning algorithm that combines supervised function approximation with generalization methods based on state space discretization, and apply it to robots learning the multi-object tracking problem. Bowling and Veloso [83] developed a general-purpose, scalable learning algorithm called GraWoLF, which combines gradient-based policy learning techniques with a variable learning rate, and demonstrated the results in the adversarial multi-robot soccer application.

Other multi-robot learning approaches not based on reinforcement include Parker’s L-ALLIANCE architecture [10] which uses parameter tuning, based on statistical experience data, to learn the fitness of different heterogeneous robots in performing a set of tasks. Pugh and Martinoli [91] apply particle swarm optimization techniques to distributed unsupervised robot learning in groups, for the task of learning obstacle avoidance.

40.8 Applications

Many real-world applications can potentially benefit from the use multiple mobile robot systems. Example applications include container management in ports [95], extra-planetary exploration [96], search and rescue [54], mineral mining, transportation, industrial and household maintenance, construction [11], hazardous waste cleanup [9], security [97, 98], agriculture, and warehouse management [99]. Multiple robot systems are also used in the domain of localization, mapping, and exploration; chapter 37 mentions some of the work in multi-robot systems applied to these problems. Section VI of this Handbook outlines many application areas that are relevant not only to single robot systems, but also to multiple mobile robot systems. To date, relatively few real-world implementations of these multi-robot systems have occurred, primarily due to the complexities of multiple robot systems and the relative newness of the supporting technologies. Nevertheless, many proof-of-principle demonstrations of physical multi-robot systems have been achieved, and the expectation is that these systems will find their way into practical implementations as the technology continues to mature.

Research in multiple mobile robot systems is often explored in the context of common application test domains. While not yet elevated to the level of benchmark tasks, these common domains do provide opportunities for researchers to compare and contrast alterna-

tive strategies to multi-robot control. Additionally, even though these common test domains are usually just laboratory experiments, they do have relevance to real-world applications. This section outlines these common application domains; see also [2] and [100] for a discussion of these domains and a more detailed listing of related research.

40.8.1 Foraging and Coverage

Foraging is a popular testing application for multi-robot systems, particularly for those approaches that address swarm robotics, involving very large numbers of mobile robots. In the foraging domain, objects such as pucks or simulated food pellets are distributed across the planar terrain, and robots are tasked with collecting the objects and delivering them to one or more gathering locations, such as a home base. Foraging lends itself to the study of weakly cooperative robot systems, in that the actions of individual robots do not have to be tightly synchronized with each other. This task has traditionally been of interest in multi-robot systems because of its close analogy to the biological systems that motivate swarm robotics research. However, it also has relevance to several real-world applications, such as toxic waste cleanup, search and rescue, and demining. Additionally, since foraging usually requires robots to completely explore their terrain in order to discover the objects of interest, the *coverage* domain has similar issues to the foraging application. In coverage, robots are required to visit all areas of their environment, perhaps searching for objects (such as landmines) or executing some action in all parts of the environment (e.g., for floor cleaning). The coverage application also has real-world relevance to tasks such as demining, lawn care, environmental mapping, and agriculture.

In foraging and coverage applications, a fundamental question is how to enable the robots to quickly explore their environments without duplicating actions or interfering with each other. Alternative strategies can include basic stigmergy [14], forming chains [28], and making use of heterogeneous robots [39]. Other research demonstrated in the foraging and/or coverage domain includes [101, 102, 103, 104, 105, 106, 41, 22].

40.8.2 Flocking and Formations

Coordinating the motions of robots relative to each other has been a topic of interest in multiple mobile robot systems since the inception of the field. In particular, much

attention has been paid to the flocking and formation control problems. The flocking problem could be viewed as a subcase of the formation control problem, requiring robots to move together along some path in the aggregate, but with only minimal requirements for paths taken by specific robots. Formations are more strict, requiring robots to maintain certain relative positions as they move through the environment. In these problems, robots are assumed to have only minimal sensing, computation, effector, and communications capabilities. A key question in both flocking and formation control research is determining the design of local control laws for each robot that generate the desired emergent collective behavior. Other issues include how robots cooperatively localize themselves to achieve formation control (e.g., [107, 42]), and how paths can be planned for permutation-invariant multi-robot formations (e.g., [108]).

Early solutions to the flocking problem in artificial agents were generated by Reynolds [109] using a rule-based approach. Similar behavior- or rule-based approaches have been used physical robot demonstrations and studies, such as in [29, 110]. These earlier solutions were based on human-generated local control rules that were demonstrated to work in practice. More recent work is based on control theoretic principles, with a focus on proving stability and convergence properties in multi-robot team behaviors. Examples of this work include [111, 112, 113, 114, 115, 36, 116, 117, 118, 119].

40.8.3 Box Pushing and Cooperative Manipulation

Box pushing and cooperative manipulation are popular domains for demonstrating multi-robot cooperation, because they offer a clear domain where close coordination and cooperation is required. Box pushing entails robot teams to move boxes from their starting positions to defined goal configurations, sometimes along specified paths. Typically, box pushing operates in the plane, and the assumption is made that the boxes are too heavy or too long to enable single robots to push alone. Sometimes there are several boxes to be moved, with ordering dependencies constraining the sequence of motions. Cooperative manipulation is similar, except it requires robots to lift and carry objects to a destination. This testbed domain lends itself to the study of strongly cooperative multi-robot strategies, since robots often have to synchronize their actions to successfully execute these tasks. The domain of box pushing and cooperative manipulation is also popular because it has rel-

evance to several real-world applications [100], including warehouse stocking, truck loading and unloading, transporting large objects in industrial environments, and assembly of large-scale structures.

Researchers usually emphasize different aspects of their cooperative control approach in the box pushing and cooperative manipulation domain. For example, Kube and Zhang [13] demonstrate how swarm-type cooperative control techniques could achieve box pushing, Parker [120, 10] illustrates aspects of adaptive task allocation and learning, Donald, et al. [121] illustrates concepts of information invariance and the interchangeability of sensing, communication, and control, and Simmons, et al. [11] demonstrate the feasibility of cooperative control for building planetary habitats. A significant body of additional research has been illustrated in this domain; representative examples include [122, 123, 124, 31, 125, 3, 6, 126, 127, 128, 129, 130, 71, 96].

40.8.4 Multi-Target Observation

The domain of multi-target observation requires multiple robots to monitor and/or observe multiple targets moving through the environment. The objective is to maximize the amount of time, or the likelihood, that the targets remain in view by some team member throughout task execution. The task can be especially challenging if there are more targets than robots. This application domain can be useful for studying strongly cooperative task solutions, since robots have to coordinate their motions or the switching of targets to follow in order to maximize their objective. In the context of multiple mobile robot applications, the planar version of this testbed was first introduced in [131] as CMOMMT (Cooperative Multi-robot Observation of Multiple Moving Targets). Similar problems have been studied by several researchers, and extended to more complex problems such as environments with complex topography or three dimensional versions for multiple aerial vehicle applications. This domain is also related to problems in other areas, such as art gallery algorithms, pursuit evasion, and sensor coverage. This domain has practical application in many security, surveillance, and reconnaissance problems. Research applied to the multi-target observation problem in multi-robot systems includes [47, 66, 132, 133, 134, 135, 136].

40.8.5 Traffic Control and Multi-Robot Path Planning

When multiple robots are operating in a shared environment, they must coordinate their actions to prevent interference. These problems typically arise when the space in which robots operate contains bottlenecks, such as networks of roadways, or when the robots take up a relatively large portion of the navigable space. In these problems, the open space can be viewed as a resource that robots must share as efficiently as possible, avoiding collisions and deadlocks. In this domain, robots usually have their own individual goals, and must work with other robots to ensure that they receive use of the shared space to the extent needed to achieve their goals. In some variants, the entire paths of multiple robots need to be coordinated with each other; in other variants, robots simply must avoid interfering with each other.

A variety of techniques have been introduced to address this problem, including traffic rules, subdividing the environment into single-ownership sections, and geometric path planning. Many of the earliest research approaches to this problem were based on heuristic approaches, such as predefining motion control (or traffic) rules that were shown to prevent deadlock [137, 138, 139, 140], or using techniques similar to mutual exclusion in distributed computing [141, 142]. These approaches have the benefit of minimizing the planning cost for obtaining a solution. Other, more formal, techniques view the application as a geometric multi-robot path planning problem that can be solved precisely in configuration space-time. Chapter 5 includes a discussion of motion planning for multiple robots relevant to this domain. While geometric motion planning approaches provide the most general solutions, they can often be too computationally intensive for practical application, impractical due to the dynamic nature of the environment, or simply unnecessary for the problem at hand. In these cases, heuristic approaches may be sufficient.

40.8.6 Soccer

Since the inception of the RoboCup multi-robot soccer domain as a proposed challenge problem for studying coordination and control in multi-robot systems [143], research in this domain has grown tremendously. This domain incorporates many challenging aspects of multi-robot control, including collaboration, robot control architectures, strategy acquisition, real-time reasoning and action, sensor fusion, dealing with adversarial environ-



Figure 40.8: Legged robot teams competing in robot soccer.

ments, cognitive modeling, and learning. Annual competitions show the ever-improving team capabilities of the robots in a variety of settings, as shown in Figure 40.8. A key aspect of this domain that is not present in the other multi-robot test domains is that robots must operate in *adversarial* environments. This domain is also popular because of its educational benefits, as it brings together students and researchers from across the world in competitions to win the RoboCup challenges. The RoboCup competitions have added an additional search and rescue category of competition [144], which has also become a significant area of research. (See Chapter 50 for more details on robotic search and rescue research.) Annual proceedings of the RoboCup competitions document much of the research that is incorporated into the multi-robot soccer teams. Some representative research works include [145, 146, 147, 148, 149].

40.9 Conclusions and Further Reading

This chapter has surveyed the current state of the art in multi-robot systems, examining architectures, communications issues, swarm robot systems, heterogeneous teams, task allocation, learning, and applications. Clearly, significant advances have been made in the field in the last decade. The field is still an active area of research, however, since many open research issues still remain to be solved. Key open research questions remain in the broad areas of system integration, robustness, learning, scalability, generalization, and dealing with hetero-

geneity.

For example, in the area of system *integration*, an open question is how to effectively allow robot teams to combine a spectrum of approaches toward achieving complete systems that can perform more than a limited set of tasks. In the area of *robustness*, multi-robot teams still need improvements in the ability to degrade gracefully, reason for fault tolerance, and to achieve complexity without escalating failure rates. The area of *learning* in multi-robot teams is still in its infancy, with open questions including how to achieve continual learning in multi-robot teams, how to facilitate the use of complex representations, and how to enable humans to influence and/or understand the results of the team learning. *Scalability* is still a challenging problem, in terms of more complex environments as well as ever larger numbers of robots. Open issues in *generalization* include enabling the robot team to reason about context and increasing the versatility of systems so that they can operate in a variety of different applications. In dealing with *heterogeneity*, open questions include determining theoretical approaches to predicting system performance when all robots are not equal, and determining how to optimally design a robot team for a given application. These problems, and others, promise to keep the field of multiple mobile robot systems active for many years to come.

For further reading on the topic of multiple mobile robot systems, the reader is referred to several survey articles, including [100, 2, 150, 151]. Additionally, several special journal issues on this topic have appeared, including [1, 152, 153, 154]. Some taxonomies of multi-robot systems are given in [100, 25, 155]. A variety of symposia and workshops have been held on a regular basis on the topic of multi-robot systems; recent proceedings of these workshops and symposia include [156, 157, 158, 159, 160, 161, 162, 163]. An additional edited text on this topic is [164].

Bibliography

- [1] T. Arai, E. Pagello, L. E. Parker: Editorial: Advances in Multi-Robot Systems, *IEEE Transactions on Robotics and Automation* **18**(5) (2002) 655–661
- [2] Y. Cao, A. Fukunaga, A. Kahng: Cooperative Mobile Robotics: Antecedents and Directions, *Autonomous Robots* **4** (1997) 1–23
- [3] Russell G. Brown, James S. Jennings: A Pusher/Steerer Model for Strongly Cooperative Mobile Robot Manipulation, *Proceedings of 1995 IEEE International Conference on Intelligent Robots and Systems (IROS '95)*, Pittsburgh 1995 (IEEE, 1995) 562–568
- [4] D. Milutinović, P. Lima: Modeling and Optimal Centralized Control of a Large-Size Robotic Population, *IEEE Transactions on Robotics* **22**(6) (2006)
- [5] B. Khoshnevis, G. A. Bekey: Centralized sensing and control of multiple mobile robots, *Computers in Industrial Engineering* **35**(3-4) (1998) 503–506
- [6] M. J. Matarić: Issues and Approaches in the Design of Collective Autonomous Agents, *Robotics and Autonomous Systems* **16** (1995) 321–331
- [7] E. Ostergaard, G. S. Sukhatme, M. J. Matarić: Emergent Bucket Brigading, *Fifth International Conference on Autonomous Agents*, Montreal 2001, 2001)
- [8] Maja Matarić: Reinforcement Learning in the Multi-Robot Domain, *Autonomous Robots* **4** (1997) 73–83
- [9] L. E. Parker: ALLIANCE: An Architecture for Fault-Tolerant Multi-Robot Cooperation, *IEEE Transactions on Robotics and Automation* **14**(2) (1998) 220–240
- [10] L. E. Parker: Lifelong Adaptation in Heterogeneous Teams: Response to Continual Variation in Individual Robot Performance, *Autonomous Robots* **8**(3) (July 2000)
- [11] R. Simmons, S. Singh, D. Hershberger, J. Ramos, T. Smith: First results in the coordination of heterogeneous robots for large-scale assembly, *Proc. of the ISER Seventh International Symposium on Experimental Robotics*, Honolulu 2000 (Springer-Verlag, New York 2000)
- [12] J. Deneubourg, S. Goss, G. Sandini, F. Ferrari, P. Dario: Self-organizing collection and transport of objects in unpredictable environments, *Japan-U.S.A. Symposium on Flexible Automation*, Kyoto, Japan, 1093–1098
- [13] C. R. Kube, H. Zhang: Collective Robotics: From Social Insects to Robots, *Adaptive Behavior* **2**(2) (1993) 189–219
- [14] R. Beckers, O. Holland, J. Deneubourg: From Local Actions to Global Tasks: Stigmergy and Collective Robotics, *Proceedings of the 14th International Workshop on Synthesis and Simulation of Living Systems 1994*, ed. by R. Brooks, P. Maes (MIT Press, Cambridge, MA 1994) 181–189
- [15] S. Onn, M. Tennenholtz: Determination of Social Laws for Multi-agent Mobilization, *Artificial Intelligence* **95** (1997) 155–167
- [16] B. B. Werger: Cooperation without deliberation: A minimal behavior-based approach to multi-robot teams, *Artificial Intelligence* **110**(2) (1999) 293–320
- [17] M. J. Huber, E. Durfee: Deciding when to commit to action during observation-based coordination, *Proceedings of the First International Conference on Multi-Agent Systems 1995*, 163–170

- [18] H. Asama, K. Ozaki, A. Matsumoto, Y. Ishida, I. Endo: Development of Task Assignment System Using Communication for Multiple Autonomous Robots, *Journal of Robotics and Mechatronics* **4**(2) (1992) 122–127
- [19] N. Jennings: Controlling Cooperative Problem Solving in Industrial Multi-agent Systems using Joint Intentions, *Artificial Intelligence* **75**(2) (1995) 195–240
- [20] M. Tambe: Towards flexible teamwork, *Journal of Artificial Intelligence Research* **7** (1997) 83–124
- [21] L. E. Parker: The Effect of Action Recognition and Robot Awareness in Cooperative Robotic Teams, *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Pittsburgh, PA 1995 (IEEE, 1995) 212–219
- [22] M. Mataric: Behavior-Based Control: Examples from Navigation, Learning, and Group Behavior, *Journal of Experimental and Theoretical Artificial Intelligence* **19**(2-3) (1997) 323–336
- [23] B. MacLennan, G. M. Burghardt: Synthetic Ethology and the Evolution of Cooperative Communication, *Adaptive Behavior* **2** (1993) 161–188
- [24] T. Balch, R. C. Arkin: Communiation in Reactive Multiagent Robotic Systems, *Autonomous Robots* **1**(1) (1995) 27–52
- [25] G. Dudek, M. Jenkin, E. Milios, D. Wilkes: A Taxonomy for Multi-Agent Robotics, *Autonomous Robots* **3** (1996) 375–397
- [26] Guy Theraulaz, Simon Goss, Jacques Gervet, Jean-Louis Deneubourg: Task differentiation in *Polistes* wasp colonies: a model for self-organizing groups of robots, *Proceedings of the First International Conference on Simulation of Adaptive Behavior*, Paris, France 1990, 1990) 346–355
- [27] Luc Steels: Cooperation Between Distributed Agents Through Self-Organization, , ed. by Yves Demazeau, Jean-Pierre Muller (Elsevier Science, 1990)
- [28] A. Drogoul, J. Ferber: From Tom Thumb to the Dockers: Some Experiments with Foraging Robots, *Proceedings of the Second International Conference on Simulation of Adaptive Behavior*, Honolulu, Hawaii, 1992) 451–459
- [29] M. J. Mataric: Designing Emergent Behaviors: From Local Interactions to Collective Intelligence, *Proceedings of the Second International Conference on Simulation of Adaptive Behavior*, Honolulu, Hawaii 1992, ed. by J. Meyer, H. Roitblat, S. Wilson (MIT Press, Cambridge, MA 1992) 432–441
- [30] G. Beni, J. Wang: Swarm intelligence in cellular robotics systems, *Proceedings of NATO Advanced Workshop on Robots and Biological System* 1989, 1989)
- [31] D. Stilwell, J. Bay: Toward the Development of a Material Transport System using Swarms of Ant-like Robots, *Proceedings of IEEE International Conference on Robotics and Automation*, Atlanta, GA, 1993) 766–771
- [32] T. Fukuda, S. Nakagawa, Y. Kawauchi, M. Buss: Self Organizing Robots Based on Cell Structures — CEBOT, *Proceedings of IEEE International Workshop on Intelligent Robots and Systems* 1988 (IEEE, 1988) 145–150
- [33] J. H. Reif, H. Y. Wang: A distributed behavior control for autonomous robots, *Robotics and Autonomous Systems* **27**(3) 171–194
- [34] L. E. Parker: Designing Control Laws for Cooperative Agent Teams, *Proceedings of the IEEE Robotics and Automation Conference*, Atlanta, GA 1993 (IEEE, 1993) 582–587
- [35] K. Sugihara, I. Suzuki: Distributed algorithms for formation of goemetric patterns with many mobile robots, *Journal of Robotic Systems* **13**(3) (1996) 127–139
- [36] V. Gazi: Swarm Aggregations using Artificial Potentials and Sliding-Mode Control, *IEEE Transactions on Robotics* **21**(6) (2005) 1208–1214
- [37] J. McLurkin, J. Smith: Distributed Algorithms for Dispersion in Indoor Environments using a Swarm of Autonomous Mobile Robots, *Symposium on Distributed Autonomous Robotic Systems* 2004 (Springer, 2004)
- [38] Douglas Gage: Randomized search strategies with imperfect sensors, *Proceedings of SPIE Mobile Robots VIII*, Boston 1993 (SPIE, 1993) 270–279

- [39] T. Balch: The Impact of Diversity on Performance in Robot Foraging, Proceedings of the Third Annual Conference on Autonomous Agents, Seattle 1999 (ACM Press, 1999) 92–99
- [40] Andrew Howard, Maja J Mataric, Gaurav S. Sukhatme: An Incremental Self-Deployment Algorithm for Mobile Sensor Networks, Autonomous Robots, Special Issue on Intelligent Embedded Systems **13**(2) (2002) 113–126
- [41] Z. J. Butler, A. A. Rizzi, R. L. Hollis: Cooperative coverage of rectilinear environments, Proceedings of IEEE International Conference on Robotics and Automation, San Francisco 2000 (IEEE, 2000)
- [42] A. I. Mourikis, S. I. Roumeliotis: Performance Analysis of Multirobot Cooperative Localization, IEEE Transactions on Robotics **22**(4) (2006) 666–681
- [43] R. Grabowski, L.E. Navarro-Serment, C.J. Paredis, P.K. Khosla: Heterogeneous Teams of Modular Robots for Mapping and Exploration, Autonomous Robots **8**(3) (2000) 271–298
- [44] M. Berhault, H. Huang, P. Keskinocak, S. Koenig, W. Elmaghraby, P. Griffin, A. Kleywegt: Robot exploration with combinatorial auctions, Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems 2003 (IEEE, 2003) 1957–1962
- [45] J. Kim, J. M Esposito, V. Kumar: An RRT-Based Algorithm for Testing and Validating Multi-Robot Controllers, Proceedings of Robotics: Science and Systems I 2005,
- [46] Z. Cao, M. Tin, L. Li, N. Gu, S. Wang: Cooperative Hunting by Distributed Mobile Robots Based on Local Interaction, IEEE Transactions on Robotics **22**(2) (2006) 403–407
- [47] R. W. Beard, T. W. McLain, M. Goodrich: Coordinated target assignment and intercept for unmanned air vehicles, Proceedings of IEEE International Conference on Robotics and Automation, Washington, D.C. 2002 (IEEE, 2002)
- [48] J. Clark, R. Fierro: Cooperative hybrid control of robotic sensors for perimeter detection and tracking, American Control Conference (IEEE, 3500–3505
- [49] P. Stone, M. Veloso: A layered approach to learning client behaviors in the RoboCup soccer server, Applied Artificial Intelligence **12** (1998) 165–188
- [50] J. McLurkin: Stupid Robot Tricks: Behavior-Based Distributed Algorithm Library for Programming Swarms of Robots, M.S. Thesis, Massachusetts Institute of Technology, Cambridge, MA, 2004)
- [51] L. E. Parker: The Effect of Heterogeneity in Teams of 100+ Mobile Robots, Multi-Robot Systems Volume II: From Swarms to Intelligent Automata, ed. by A. Schultz, L. E. Parker, F. Schneider (Kluwer, 2003)
- [52] T. Balch: Hierarchic Social Entropy: An Information Theoretic Measure of Robot Team Diversity, Autonomous Robots **8**(3) (2000) 209–238
- [53] D. Jung, A. Zelinsky: Grounded Symbolic Communication between Heterogeneous Cooperating Robots, Autonomous Robots **8**(3) (July 2000) 269–292
- [54] R. R. Murphy: Marsupial robots for urban search and rescue, IEEE Intelligent Systems **15**(2) (2000) 14–19
- [55] G. Sukhatme, J. F. Montgomery, R. T. Vaughan: Experiments with Cooperative Aerial-Ground Robots, Robot Teams: From Diversity to Polymorphism, ed. by T. Balch, L. E. Parker (A K Peters, Natick, MA 2002) 345–368
- [56] L. E. Parker, B. Kannan, F. Tang, M. Bailey: Tightly-Coupled Navigation Assistance in Heterogeneous Multi-Robot Teams, Proceedings of IEEE International Conference on Intelligent Robots and Systems 2004 (IEEE, 2004)
- [57] A. Howard, L. E. Parker, G. S. Sukhatme: Experiments with a Large Heterogeneous Mobile Robot Team: Exploration, Mapping, Deployment, and Detection, International Journal of Robotics Research **25** (2006) 431–447
- [58] L. Chaimowicz, B. Grocholsky, J. F. Keller, V. Kumar, C. J. Taylor: Experiments in Multirobot Air-Ground Coordination, Proceedings of IEEE International Conference on Robotics and Automation, New Orleans 2004 (IEEE, 2004)

- [59] L. E. Parker, F. Tang: Building Multi-Robot Coalitions through Automated Task Solution Synthesis, Proceedings of the IEEE, special issue on Multi-Robot Systems **94**(7) (2006) 1289–1305
- [60] R. Zlot, A. Stentz: Market-based multirobot coordination for complex tasks, International Journal of Robotics Research **25**(1) (January 2006) 73–101
- [61] J. Jennings, C. Kirkwood-Watts: Distributed mobile robotics by the method of dynamic teams, Proc. of Fourth International Symposium on Distributed Autonomous Robotic Systems, Karlsruhe 1998, ed. by T. Leuth, R. Dillman, P. Dario, H. Worn (Springer, Tokyo 1998)
- [62] E. Pagello, A. D’Angelo, E. Menegatti: Cooperation issues and distributed sensing for multirobot systems, Proceedings of the IEEE **94** (2006) 1370–1383
- [63] B. Gerkey, M. J. Matarić: A formal analysis and taxonomy of task allocation in multi-robot systems, International Journal of Robotics Research **23**(9) (2004) 939–954
- [64] D. Gale: *The Theory of Linear Economic Models* (McGraw-Hill Book Company, Inc., New York 1960)
- [65] E. Balas, M. W. Padberg: On the Set-Covering Problem, Operations Research **20**(6) (1972) 1152–1161
- [66] B. B. Werger, M. J. Matarić: Broadcast of Local Eligibility for Multi-Target Observation, Distributed Autonomous Robotic Systems 4, Knoxville 2000, ed. by L. E. Parker, G. Bekey, J. Barhen (Springer, Tokyo 2000) 347–356
- [67] R. A. Brooks: A Robust Layered Control System for a Mobile Robot, IEEE Journal of Robotics and Automation **RA-2**(1) (March 1986) 14–23
- [68] S. Botelho, R. Alami: M+: A scheme for multi-robot cooperation through negotiated task allocation and achievement, Proceedings of the IEEE International Conference on Robotics and Automation, Detroit 1999 (IEEE, 1999) 1234–1239
- [69] R. G. Smith: The Contract Net Protocol: high-level communication and control in a distributed problem solver, IEEE Transactions on Computers **C-29**(12) (December 1980)
- [70] B. Dias, R. Zlot, N. Kalra, A. Stentz: Market-Based Multirobot Coordination: A Survey and Analysis, Proceedings of the IEEE **94**(7) (July 2006) 1257–1270
- [71] B. P. Gerkey, M. J. Matarić: Sold! Auction methods for multi-robot coordination, IEEE Transactions on Robotics and Automation **18**(5) (2002) 758–768
- [72] H. Kose, U. Tatlidede, C. Mericli, K. Kaplan, H. L. Akin: Q-learning based market-driven multi-agent collaboration in robot soccer, Proceedings of the Turkish Symposium on Artificial Intelligence and Neural Networks, Izmir 2004, 2004) 219–228
- [73] D. Vail, M. Veloso: Multi-robot dynamic role assignment and coordination through shared potential fields, Multi-Robot Systems: From Swarms to Intelligent Automata: Proceedings of 2003 International Workshop on Multi-Robot Systems, Washington, D.C. 2003, ed. by A. Schultz, L. E. Parker, F. Schneider (Springer, Dordrecht 2003) 87–98
- [74] M. Lagoudakis, E. Markakis, D. Kempe, P. Keshinocak, A. Kleywegt, S. Koenig, C. Tovey, A. Meyerson, S. Jain: Auction-based multi-robot routing, Robotics: Science and Systems I, Cambridge 2005 (MIT Press, Cambridge 2005)
- [75] G. Rabideau, T. Estlin, S. Schien, A. Barrett: A comparison of coordinated planning methods for cooperating rovers, Proceedings of AIAA Space Technology Conference 1999, 1999)
- [76] R. Zlot, A. Stentz, M. B. Dias, S. Thayer: Multi-Robot Exploration Controlled by a Market Economy, Proceedings of IEEE International Conference on Robotics and Automation, Washington, D.C. 2002 (IEEE, 2002) 3016–3023
- [77] J. Guerrero, G. Oliver: Multi-robot task allocation strategies using auction-like mechanisms, Proc. of Sixth Congr. Catalan Association for Artificial Intelligence 2003, 2003) 111–122
- [78] N. Kalra, D. Ferguson, A. Stentz: Hoplites: A Market-Based Framework for Planned Tight Coordination in MultiRobot Teams, Proceedings of the IEEE International Conference on Robotics and Automation, Barcelona 2005 (IEEE, 2005)

- [79] L. Lin, Z. Zheng: Combinatorial bids based multi-robot task allocation method, Proceedings of the IEEE International Conference on Robotics and Automation, Barcelona 2005 (IEEE, 2005) 1145–1150
- [80] C.-H. Fua, S. S. Ge: COBOS: Cooperative Back-off Adaptive Scheme for Multirobot Task Allocation, IEEE Transactions on Robotics **21**(6) (2005) 1168–1178
- [81] E. G. Jones, B. Browning, M. B. Dias, B. Argall, M. Veloso, A. Stentz: Dynamically formed heterogeneous robot teams performing tightly-coupled tasks, Proceedings of the IEEE International Conference on Robotics and Automation, Orlando 2006 (IEEE, 2006) 570–575
- [82] L. Vig, J. A. Adams: Multi-Robot Coalition Formation, IEEE Transactions on Robotics **22**(4) (2006) 637–649
- [83] M. Bowling, M. Veloso: Simultaneous adversarial multi-robot learning, Proceedings of International Joint Conference on Artificial Intelligence 2003, 2003)
- [84] F. Fernandez, L. E. Parker: A Reinforcement Learning Algorithm in Cooperative Multi-Robot Domains, Journal of Intelligent and Robotic Systems **43** (2005) 161–174
- [85] C. F. Touzet: Robot Awareness in Cooperative Mobile Robot Learning, Autonomous Robots **2** (2000) 1–13
- [86] Randall Steeb, Stephanie Cammarata, Frederick Hayes-Roth, Perry Thorndyke, Robert Wesson: Distributed Intelligence for Air Fleet Control, Rand Corp. Technical Report, Number R-2728-AFPA 1981, 1981)
- [87] M. Benda, V. Jagannathan, R. Dodhiawalla: On optimal cooperation of knowledge sources, Boeing AI Center Technical Report BCS-G2010-28 1985, 1985)
- [88] T. Haynes, S. Sen: Evolving Behavioral Strategies in Predators and Prey, Adaptation and Learning in Multi-Agent Systems 1986, ed. by G. Weiss, S. Sen (Springer, 1986) 113–126
- [89] S. Mahadevan, J. Connell: Automatic Programming of Behavior-Based Robots Using REinforcement Learning, Proceedings of AAAI 1991, 1991) 8–14
- [90] S. Marsella, J. Adibi, Y. Al-Onaizan, G. Kaminka, I. Muslea, M. Tambe: On being a teammate: Experiences acquired in the design of RoboCup Teams, Proceedings of the Third Annual Conference on Autonomous Agents 1999, ed. by O. Etzioni, J. Muller, J. Bradshaw, 1999) 221–227
- [91] J. Pugh, A. Martinoli: Multi-robot learning with particle swarm optimization, Proceedings of the fifth International Joint Conference on Autonomous Agents and Multiagent Systems, Hakodate, Japan 2006 (ACM Press, New York 2006) 441–448
- [92] P. Stone, M. Veloso: Multiagent Systems: A survey from a machine learning perspective, Autonomous Robots **8**(3) (2000) 345–383
- [93] M. Asada, E. Uchibe, S. Noda, S. Tawaratsumida, K. Hosoda: Coordination of Multiple Behaviors Acquired by a Vision-Based Reinforcement Learning, Proceedings of IEEE/RSJ/GI International Conference on Intelligent Robots and Systems, Munich 1994, 1994) 917–924
- [94] Masao Kubo, Yukinori Kakazu: Learning Coordinated Motions in a Competition for Food between Ant Colonies, Proceedings of the Third International Conference on Simulation of Adaptive Behavior 1994, ed. by D. Cliff, P. Husbands, J.-A. Meyer, S. Wilson (MIT Press, 1994) 487–492
- [95] R. Alami, S. Fleury, M. Herrb, F. Ingrand, F. Robert: Multi-robot cooperation in the MARTHA project, Robotics and Automation Magazine **5**(1) (1998) 36–47
- [96] A. Stroupe, A. Okon, M. Robinson, T. Huntsberger, H. Aghazarian, E. Baumgartner: Sustainable cooperative robotic technologies for human and robotic outpost infrastructure construction and maintenance, Autonomous Robots **20**(2) (2006) 113–123
- [97] H. R. Everett, R. T. Laird, D. M. Carroll, G. A. Gilbreath, T. A. Heath-Pastore, R. S. Inderieden, T. Tran, K. J. Grant, D. M. Jaffee: Multiple Resource Host Architecture (MRHA) for the

- Mobile Detection Assessment Response System (MDARS), SPAWAR Systems Technical Document 3026, Revision A 2000, 2000)
- [98] Y. Guo, L. E. Parker, R. Madhavan: Towards Collaborative Robots for Infrastructure Security Applications, Proceedings of International Symposium on Collaborative Technologies and Systems 2004, 2004) 235–240
- [99] C. Hazard, P. R. Wurman, R. D’Andrea: Alphabet Soup: A Testbed for Studying Resource Allocation in Multi-vehicle Systems, Proceedings of AAAI Workshop on Auction Mechanisms for Robot Coordination, Boston 2006 (AAAI, 2006) 23–30
- [100] D. Nardi A. Farinelli, L. Iocchi: Multirobot systems: a classification focused on coordination, IEEE Transactions on Systems, Man, and Cybernetics, Part B **34**(5) (2004) 2015–2028
- [101] K. Passino: Biomimicry of bacterial foraging for distributed optimization and control, IEEE Control Systems Magazine **22**(3) (2002) 52–67
- [102] M. Fontan, M. Mataric: Territorial multi-robot task division, IEEE Transactions on Robotics and Automation **15**(5) (1998) 815–822
- [103] I. Wagner, M. Lindenbaum, A. M. Bruckstein: Mac vs. PC – Determinism and randomness as complementary approaches to robotic exploration of continuous unknown domains, International Journal of Robotics Research **19**(1) (2000) 12–31
- [104] K. Sugawara, M. Sano: Cooperative behavior of interacting simple robots in a clockface arranged foraging field, Distributed Autonomous Robotic Systems 2002, ed. by H. Asama, T. Arai, T. Fukuda, T. Hasegawa (Springer, 2002) 331–339
- [105] P. Rybski, S. Stoeter, C. Wyman, M. Gini: A cooperative multi-robot approach to the mapping and exploration of Mars, Proceedings of AAAI/IAAI-97, Providence (AAAI,
- of Mobile Robot Formations, IEEE Transactions on Robotics **22**(5) (2006) 917–931
- [108] S. Kloder, S. Hutchinson: Path Planning for Permutation-Invariant Multirobot Formations, IEEE Transactions on Robotics **22**(4) (2006) 650–665
- [109] C. W. Reynolds: Flocks, herds and schools: A distributed behavioral model, ACM SIGGRAPH Computer Graphics **21** (1987) 25–34
- [110] T. Balch, R. Arkin: Behavior-based Formation Control for Multi-robot Teams, IEEE Transactions on Robotics and Automation **14**(6) (December 1998) 926–939
- [111] A. Jadbabaie, J. Lin, A. S. Morse: Coordination of Groups of Mobile Autonomous Agents Using Nearest Neighbor Rules, IEEE Transactions on Automatic Control **48**(6)
- [112] C. Belta, V. Kumar: Abstraction and Control for Groups of Robots, IEEE Transactions on Robotics **20**(5) (2004) 865–875
- [113] C. M. Topaz, A. L. Bertozzi: Swarming patterns in two-dimensional kinematic model for biological groups, SIAM Journal of Applied Math **65**(1) (2004) 152–174
- [114] J. A. Fax, R. M. Murray: Information Flow and Cooperative Control of Vehicle Formations, IEEE Transactions on Automatic Control **49**(9) (2004)
- [115] J. A. Marshall, M. E. Broucke, B. R. Francis: Formations of vehicles in cyclic pursuit, IEEE Transactions on Automatic Control **49**(11) (2004)
- [116] S. S. Ge, C.-H. Fua: Queues and Artificial Potential Trenches for Multirobot Formations, IEEE Transactions on Robotics **21**(4) (2005) 646–656
- [117] P. Tabuada, G. Pappas, P. Lima: Motion Feasibility of Multi-Agent Formations, IEEE Transactions on Robotics **21**(3) (2005) 387–392
- [118] G. Antonelli, S. Chiaverini: Kinematic Control of Platoons of Autonomous Vehicles, IEEE Transactions on Robotics **22**(6) (2006) 1285–1292
- [119] J. Fredslund, M. J. Mataric: A general algorithm for robot formations using local sensing and minimal communication, IEEE Transactions on Robotics and Automation **18**(5) 837–846

- [120] L. E. Parker: ALLIANCE: An Architecture for Fault Tolerant, Cooperative Control of Heterogeneous Mobile Robots, Proc. of the IEEE/RSJ/GI Int'l Conf. on Intelligent Robots and Systems, Munich, Germany 1994 (IEEE, 1994) 776–783
- [121] B. Donald, J. Jennings, D. Rus: Analyzing Teams of Cooperating Mobile Robots, Proceedings of IEEE International Conference on Robotics and Automation 1994 (IEEE, 1994) 1896–1903
- [122] S. Sen, M. Sekaran, J. Hale: Learning to coordinate without sharing information, Proceedings of AAAI 1994 (AAAI, Seattle 1994) 426–431
- [123] B. Tung, L. Kleinrock: Distributed control methods, Proceedings of the Second International Symposium on High Performance Distributed Computing 1993, 1993) 206–215
- [124] Z.-D. Wang, E. Nakano, T. Matsukawa: Cooperating multiple behavior-based robots for object manipulation, Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Munich 1994 (IEEE, 1994) 1524–1531
- [125] P. J. Johnson, J. S. Bay: Distributed control of simulated autonomous mobile robot collectives in payload transportation, *Autonomous Robots* **2**(1) (1995) 43–63
- [126] D. Rus, B. Donald, J. Jennings: Moving Furniture with Teams of Autonomous Robots, Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Pittsburgh 1995, 1995) 235–242
- [127] F. Hara, Y. Yasui, T. Aritake: A kinematic analysis of locomotive cooperation for two mobile robots along a general wavy road, Proceedings of IEEE International Conference on Robotics and Automation, Nagoya 1995 (IEEE, 1995) 1197–1204
- [128] J. Sasaki, J. Ota, E. Yoshida, D. Kurabayashi, T. Arai: Cooperating grasping of a large object by multiple mobile robots, Proceedings of IEEE International Conference on Robotics and Automation, Nagoya 1995 (IEEE, 1995) 1205–1210
- [129] C. Jones, M. J. Matarić: Automatic Synthesis of Communication-Based Coordinated Multi-Robot Systems, Proceedings of IEEE/RJS International Conference in Intelligence Robots and Systems, Sendai, Japan 2004 (IEEE, 2004) 381–387
- [130] Z. Wang, V. Kumar: Object closure and manipulation by multiple cooperating mobile robots, Proceedings of IEEE International Conference on Robotics and Automation 2002 (IEEE, 2002) 394–399
- [131] L. E. Parker: Cooperative Robotics for Multi-Target Observation, *Intelligent Automation and Soft Computing* **5**(1) (1999) 5–19
- [132] S. Luke, K. Sullivan, L. Panait, G. Balan: Tunably decentralized algorithms for cooperative target observation, Proceedings of the fourth international joint conference on Autonomous Agents and Multi-agent Systems, The Netherlands 2005 (ACM Press, New York) 911–917
- [133] S. M. LaValle, H. H. Gonzalez-Banos, C. Becker, J.-C. Latombe: Motion Strategies for Maintaining Visibility of a Moving Target, Proceedings of the 1997 IEEE International Conference on Robotics and Automation, Albuquerque 1997 (IEEE, 1997) 731–736
- [134] A. Kolling, S. Carpin: Multirobot cooperation for surveillance of multiple moving targets – a new behavioral approach, Proceedings of the IEEE International Conference on Robotics and Automation, Orlando 2006 (IEEE, 2006) 1311–1316
- [135] B. Jung, G. Sukhatme: Tracking targets using multiple mobile robots: The effect of environment occlusion, *Autonomous Robots* **13**(3) (2002) 191–205
- [136] Z. Tang, U. Ozguner: Motion Planning for Multitarget Surveillance with Mobile Sensor Agents, *IEEE Transactions on Robotics* **21**(5) (2005) 898–908
- [137] D. Grossman: Traffic control of multiple robot vehicles, *IEEE Journal of Robotics and Automation* **4** (1988) 491–497
- [138] Philippe Caloud, Wonyun Choi, Jean-Claude Latombe, Claude Le Pape, Mark Yim: Indoor Automation with Many Mobile Robots, Proceedings of the IEEE International Workshop on Intelligent Robots and Systems, Tsuchiura, Japan 1990 (IEEE, 1990) 67–72
- [139] H. Asama, K. Ozaki, H. Itakura, A. Matsumoto, Y. Ishida, I. Endo: Collision avoidance among mul-

- multiple mobile robots based on rules and communication, Proceedings of IEEE/RJS International Conference on Intelligent Robots and Systems 1991 (IEEE, 1991)
- [140] S. Yuta, S. Premvuti: Coordinating autonomous and centralized decision making to achieve cooperative behaviors between multiple mobile robots, Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, Raleigh, NC 1992 (IEEE, 1992) 1566–1574
- [141] Jing Wang: Fully distributed traffic control strategies for many-AGV systems, Proceedings of the IEEE International Workshop on Intelligent Robots and Systems 1991 (IEEE, 1991) 1199–1204
- [142] Jing Wang, Gerardo Beni: Distributed Computing Problems in Cellular Robotic Systems, Proceedings of the IEEE International Workshop on Intelligent Robots and Systems, Tsuchiura, Japan 1990 (IEEE, 1990) 819–826
- [143] H. Kitano, M. Asada, Y. Kuniyoshi, I. Noda, E. Osawa, H. Matasubara: RoboCup: A challenge problem of AI, AI Magazine **18**(1) (1997) 73–86
- [144] H. Kitano, S. Tadokoro: RoboCup rescue: A grand challenge for multiagent and intelligent systems, AI Magazine **22**(1) (2001) 39–52
- [145] B. Browning, J. Bruce, M. Bowling, M. Veloso: STP: Skills, tactics and plays for multi-robot control in adversarial environments, IEEE Journal of Control and Systems Engineering **219** (2005) 33–52
- [146] M. Veloso, P. Stone, K. Han: The CMUnited-97 robotic soccer team: Perception and multiagent control, Robotics and Autonomous Systems **29**(2-3) (1999) 133–143
- [147] T. Weigel, J.-S. Gutmann, M. Dietl, A. Kleiner, B. Nebel: CS Freiburg: coordinating robots for successful soccer playing, IEEE Transactions on Robotics and Automation **5**(18) (2002) 685–699
- [148] P. Stone, M. Veloso: Task decomposition, dynamic role assignment, and low-bandwidth communication for real-time strategic teamwork, Artificial Intelligence **110**(2) (1999) 241–273
- [149] C. Candea, H. S. Hu, L. Iocchi, D. Nardi, M. Piaggio: Coordination in multi-agent Robocup teams, Robotics and Autonomous Systems **36**(2) (2001) 67–86
- [150] L. E. Parker: Current Research in MultiRobot Teams, Artificial Life and Robotics **7**(2-3) (2005) 1–5
- [151] K. R. Baghaei, A. Agah: Task allocation and communication methodologies for multi-robot systems, Intelligent Automation and Soft Computing **9** (2003) 217–226
- [152] T. Balch, L. E. Parker: Guest Editorial, Special Issue on Heterogeneous Multi-Robot Systems, Autonomous Robots **8**(3) (2000) 207–208
- [153] M. Dorigo, E. Sahin: Guest Editorial, Special Issue on Swarm Robotics, Autonomous Robots **17**(2-3) (2004) 111–113
- [154] M. Veloso, D. Nardi: Special issue on multirobot systems, Proceedings of the IEEE **94** (2006) 1253–1256
- [155] T. Balch: Taxonomies of Multi-Robot Task and Reward, Robot Teams: From Diversity to Polymorphism, ed. by T. Balch, L. E. Parker (A K Peters, Natick, MA 2002)
- [156] L.E. Parker, G. Bekey, J. Barhen (Eds.): *Distributed Autonomous Robotic Systems 4* (Springer-Verlag, 2000)
- [157] H. Asama, T. Arai, T. Fukuda, T. Hasegawa (Eds.): *Distributed Autonomous Robotic Systems 5* (Springer, 2002)
- [158] A. Schultz, L. E. Parker (Eds.): *Multi-Robot Systems: From Swarms to Intelligent Automata* (Kluwer, 2002)
- [159] A. Schultz, L. E. Parker, F. Schneider (Eds.): *Multi-Robot Systems Volume II: From Swarms to Intelligent Automata* (Kluwer, 2003)
- [160] E. Sahin, W. M. Spears (Eds.): *Swarm Robotics: SAB 2004 International Workshop* (Springer-Berlag, 2004)
- [161] L. E. Parker, F. Schneider, A. Schultz (Eds.): *Multi-Robot Systems Volume III: From Swarms to Intelligent Automata* (Kluwer, 2005)
- [162] R. Alami, R. Chatila, H. Asama (Eds.): *Distributed Autonomous Robotic Systems 6* (Springer, 2006)

- [163] M. Gini, R. Voyles (Eds.): *Distributed Autonomous Robotic Systems 7* (Springer, 2006)
- [164] T. Balch, L. E. Parker (Eds.): *Robot Teams: From Polymorphism to Diversity* (A K Peters, 2002)