

40. Multiple Mobile Robot Systems

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

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Researchers generally agree that multirobot systems have several advantages over single-robot systems [40.1, 2]. The most common motivations for developing multirobot 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 multirobot 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 multirobot 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 multirobot system is covered in detail in Chap. 39. *Networked* robotics, covered in Chap. 41, is also very closely re-

lated 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 multirobot cooperation is multiple manipulator arm cooperation; Chap. 29 describes these systems in detail.

40.1 History

Since the earliest work on multiple mobile robot systems in the 1980s, 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 or weakly cooperative solutions [40.3]. *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. Inten-

tionally cooperative multirobot 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 from 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 multirobot systems are relevant for all types of multirobot systems, as these approaches specify how the robot team members are organized and interact. *Swarm robots* is a particular type of multirobot 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 multirobot 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 Multirobot Systems

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

action 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 multirobot 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 [40.4], although often practically unrealistic due to their 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 in which 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 [40.5].

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, which 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 multirobot 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 multirobot control approaches make use of hybrid architectures.

A plethora of multirobot 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 coordination 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 multirobot teams was conducted by Mataric [40.6], with results being demonstrated on the Nerd Herd team of 20 identical robots (shown in Fig. 40.1). This work is an example of swarm robotic systems, as described further in Sect. 40.4. The decentralized control approach was based on the subsumption architecture (see Chap. 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 Chap. 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



Fig. 40.1 The Nerd Herd robots

issues such as using bucket brigades to reduce interference [40.7], and learning [40.8].

40.2.2 The ALLIANCE Architecture

Another early work in multirobot team architectures is the ALLIANCE architecture (shown in Fig. 40.2), developed by Parker [40.9] 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 explicit 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
6. whether the robot is willing to give up the task, based on how long it has been attempting the task

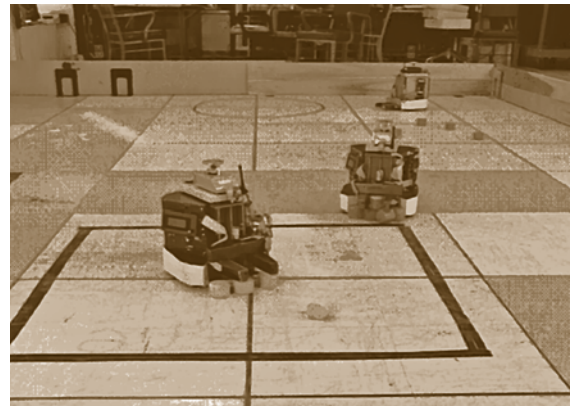


Fig. 40.3 Robots using the ALLIANCE architecture for a mock clean-up task

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
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 [40.10] allows a robot to adapt the rate of change of the impatience and acquiescence 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 the simulation of a janitorial service task and a bound-

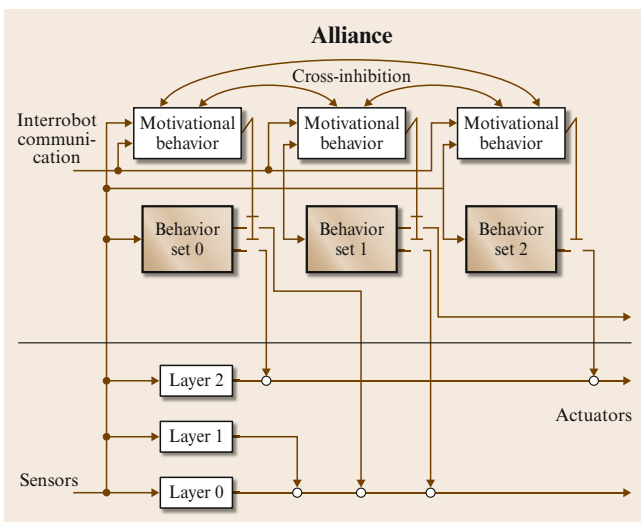


Fig. 40.2 The ALLIANCE architecture

ing 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. [40.11] 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 Chap. 8). In this approach (shown in Fig. 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 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 Fig. 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

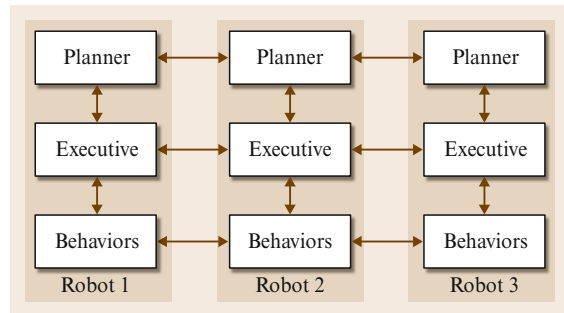


Fig. 40.4 The distributed robot architecture

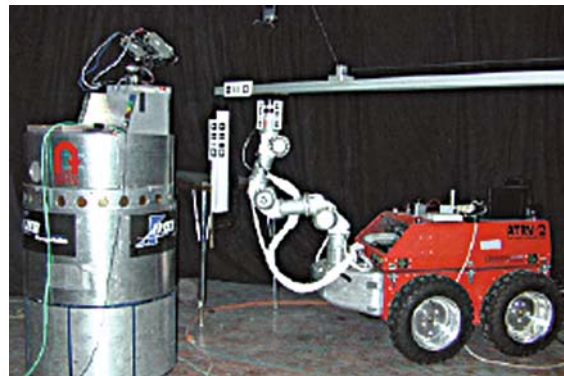


Fig. 40.5 Robots using the distributed robot architecture for assembly tasks

roving eye and the mobile manipulator to servo the arm to grasp the beam. After contact is made, the foreman 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 multirobot 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., [40.6, 12–16])
2. passive action recognition, in which robots use sensors to directly observe the actions of their teammates (e.g., [40.17])
3. explicit (intentional) communication, in which robots directly and intentionally communicate relevant information through some active means, such as radio (e.g., [40.9, 18–20])

Each of these mechanisms for exchanging information between robots has its own advantages and disadvantages [40.21]. *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 multirobot teams are to synchronize actions, exchange information, and to negotiate between robots. Explicit communication is a way of dealing with the *hidden-state* problem [40.22], 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 multirobot team is a design choice dependent upon the tasks to be achieved by the multirobot 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 [40.23], 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 nonlinear 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 [40.24]. 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 multirobot 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 multirobot systems [40.25] includes axes related to communication, including communication range, communication topology, and communication bandwidth. These characteristics can be used to compare and contrast multirobot systems.

Several related issues of active research in communications for multirobot 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 context of *networked robotics*; see Chap. 41 for more information.

40.4 Swarm Robots

Historically, some of the earliest work in multirobot systems [40.12, 13, 26–33] 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 multirobot 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 similar 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
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 Sect. 40.2, the first demonstrations were by *Mataric* [40.6], involving about 20 physical robots performing aggregation, dispersion, and flocking. This work defined composable *basis behaviors* as primitives for structuring more complex systems (see Chap. 38 for more information). More recently, *McLurkin* [40.50] developed an extensive catalog of swarm behavior software, and demonstrated these behaviors on about 100 physical robots (called the

Table 40.1 Categories of swarm behaviors

Relative motion requirements	Swarm behaviors
Relative to other robots	Formations [40.34, 35], flocking [40.29], natural herding (as in herds of cattle), schooling, sorting [40.14], clumping [40.14], condensation, aggregation [40.36], dispersion [40.37]
Relative to the environment	Search [40.38], foraging [40.39], grazing, harvesting, deployment [40.40], coverage [40.41], localization [40.42], mapping [40.43], exploration [40.44]
Relative to external agents	Pursuit [40.45], predator–prey [40.46], target tracking [40.47], forced herding/shepherding (as in shepherding sheep)
Relative to other robots and the environment	Containment, orbiting, surrounding, perimeter search [40.48]
Relative to other robots, external agents, and the environment	Evasion, tactical overwatch, soccer [40.49]

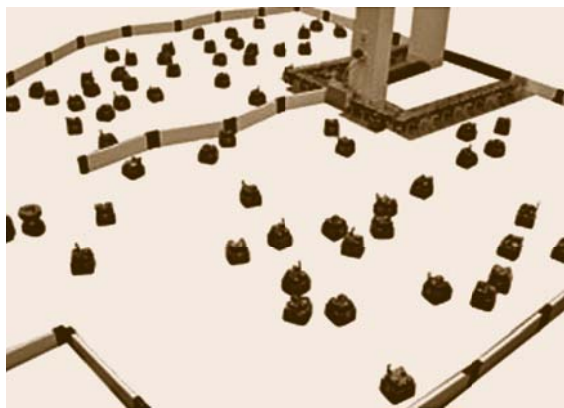


Fig. 40.6 The SwarmBot robots

SwarmBot robots), developed by iRobot, as shown in Fig. 40.6. He created several group behaviors, such as `avoidManyRobots`, `disperseFromSource`, `disperseFromLeaves`, `disperseUniformly`, `computeAverageBearing`, `avoidManyRobots`, `followTheLeader`, `orbitGroup`, `navigateGradient`, `clusterOnSource`, and `clusterIntoGroups`. A swarm of 108 robots used the developed dispersion algorithms in an empty schoolhouse of area of about 300 m², and were able to locate an object of interest and lead a human to its location [40.37].

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

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 multirobot 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 Sect. 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

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 microscale 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 US 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 developing 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 multirobot 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.

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 multirobot teams is thus twofold: 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 to build 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 multirobot 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 multirobot systems. A particular challenge to achieving efficient autonomous control is when overlap in team member capabilities occurs, thus affecting task allocation or role assignments [40.51]. Techniques as described in Sect. 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 multirobot teams. Some types of heterogeneity can be evaluated quantitatively, using metrics such as the social entropy metric developed by *Balch* [40.52]. Most research in heterogeneous multirobot 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 [40.53].

As discussed in Sect. 40.2, one of the earliest research demonstrations of heterogeneity in physical robot teams was in the development of the ALLIANCE architecture by *Parker* [40.9]. 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 [40.54]. *Grabowski* et al. [40.43] 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. [40.11]



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

demonstrated the use of heterogeneous robots for autonomous assembly and construction tasks relevant to space applications. *Sukatme* et al. [40.55] demonstrated 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 Fig. 40.7. *Parker* et al. [40.56] 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. [40.57] of 100 robots performing exploration, mapping, deployment, and detection. *Chaimowicz* et al. [40.58] demonstrated a team of aerial and ground robots cooperating for surveillance applications in urban environments. *Parker* and *Tang* [40.59] developed ASyMTRe (Automated Synthesis of Multirobot Task solutions through software Reconfiguration), 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 multirobot teams; for example, the issue of optimal team design is a very challenging problem. 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 multirobot 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 [40.9], hierarchical task trees [40.60], or roles [40.11, 58, 61, 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* [40.63] defined a taxonomy for task allocation that provides a way of distinguishing task allocation problems along these dimensions, which is referred to as the multirobot task allocation (**MRTA**) 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 *multirobot 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, multirobot 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 multirobot 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 *multitask 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 **MTRA** 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** problem, which can be solved in polynomial time since it is an instance of the optimal assignment problem [40.64]. 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 [40.65], 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 multirobot teams generate approximate solutions.

40.6.2 Representative Approaches

Approaches to task allocation in multirobot 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 [40.63] 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 multirobot task allocation that was demonstrated on physical robots was the behavior-based ALLIANCE architecture [40.9] and the related L-ALLIANCE architecture [40.10]. 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 Sect. 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 multirobot task allocation is broadcast of local eligibility (*BLE*) [40.66], which addresses the *ST-SR-IA* variant of task allocation. *BLE* uses a subsumption style behavior control architecture [40.67] 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 [40.68].

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) [40.69] 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 multirobot task allocation was first developed by *Botelho* and *Alami* with their *M+* architecture [40.68]. 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 multirobot task allocation is given in [40.70], 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., [40.11, 71–73]) dealing with instantaneous assignment (*IA*), and others (e.g., [40.44, 74–76]) addressing time-extended assignments (*TA*). More recent methods are beginning to address the allocation of multirobot tasks (i.e., the *MR-ST* problem variant), including [40.59, 77–81]. An example approach to the *MR-MT* problem variant is found in [40.82].

Some representative market-based techniques include *MURDOCH* [40.71], *TraderBots* [40.60, 76], and *Hoplites* [40.78]. The *MURDOCH* approach [40.71] 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 [40.60, 76] applies market economy techniques for generating efficient and robust multirobot 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 [40.78] 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., [40.11, 61]).

40.7 Learning

Multirobot 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 [40.83]. The challenge is that having other robots in the environment violates the Markov property that is a fundamental assumption of single-robot learning approaches [40.83]. The multirobot learning problem is particularly challenging because it combines the difficulties of single-robot learning with multiagent learning. Particular difficulties that must be considered in multirobot 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 information learned from different robot experiences.

The types of applications that have been studied for multirobot learning include multitarget observation [40.84, 85], air fleet control [40.86], predator–prey [40.46, 87, 88], box pushing [40.89], foraging [40.22], and multirobot soccer [40.49, 90]. Particularly challenging domains for multirobot 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 multirobot 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 [40.91], 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 multirobot 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, the discussion of learning in behavior-based systems in Chap. 38, and a discussion of fundamental learning techniques in Chap. 9) and in multiagent systems [40.92], much less work has been done in the area of multirobot learning, although the topic is gaining increased interest. Much of the work to date has focused on reinforcement learning approaches. Some examples of this multirobot learning research include the work by *Asada* et al. [40.93], who propose a method for learning new behaviors by coordinating previously learned behaviors using Q-learning, and apply it to soccer-playing robots. *Mataric* [40.8] 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* [40.94] proposed another reinforcement learning mechanism that uses a progress value for determining reinforcement, and applied it to simulated ant colonies competing for food. *Fernandez* et al. [40.84] 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 multiobject tracking problem. *Bowling* and *Veloso* [40.83] developed a general-purpose, scalable learning algorithm called GraWoLF (Gradient-based Win or Learn Fast), which combines gradient-based policy learning techniques with a variable learning rate, and demonstrated the results in the adversarial multirobot soccer application.

Other multirobot learning approaches not based on reinforcement include *Parker's* L-ALLIANCE architecture [40.10], 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* [40.91] 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 of multiple mobile robot systems. Example applications include container management in ports [40.95], extraplanetary exploration [40.96], search and rescue [40.54], mineral mining, transportation, industrial and household maintenance, construction [40.11], hazardous waste cleanup [40.9], security [40.97, 98], agriculture, and warehouse management [40.99]. Multiple robot systems are also used in the domain of localization, mapping, and exploration; Chap. 37 mentions some of the work in multirobot systems applied to these problems. Part F 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 multirobot 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 multirobot 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 alternative strategies to multirobot 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 [40.2] and [40.100] 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 multirobot 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 multirobot 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 explore their environments quickly without duplicating actions or interfering with each other. Alternative strategies can include basic stigmergy [40.14], forming chains [40.28], and making use of heterogeneous robots [40.39]. Other research demonstrated in the foraging and/or coverage domain includes [40.22, 41, 101–106].

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 stricter, 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., [40.42, 107]), and how paths can be planned for permutation-invariant multirobot formations (e.g., [40.108]).

Early solutions to the flocking problem in artificial agents were generated by *Reynolds* [40.109] using a rule-based approach. Similar behavior- or rule-based approaches have been used physical robot demonstrations and studies, such as in [40.29, 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 multirobot team behaviors. Examples of this work include [40.36, 111–119].

40.8.3 Box Pushing and Cooperative Manipulation

Box pushing and cooperative manipulation are popular domains for demonstrating multirobot cooperation, because they offer a clear domain where close coordination and cooperation is required. Box pushing requires 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 test bed domain lends itself to the study of strongly cooperative multirobot 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 relevance to several real-world applications [40.100], 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* [40.13] demonstrate how swarm-type cooperative control techniques could achieve box pushing, *Parker* [40.10, 120] illustrates aspects of adaptive task allocation and learning, *Donald* et al. [40.121] illustrates concepts of information invariance and the interchangeability of sensing, communication, and control, and *Simmons* et al. [40.11] 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 [40.3, 6, 31, 71, 96, 122–130].

40.8.4 Multitarget Observation

The domain of multitarget 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 test bed was first introduced in [40.131] as cooperative multirobot observation of multiple moving targets (CMOMMT). 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 multitarget observation problem in multirobot systems includes [40.47, 66, 132–136].

40.8.5 Traffic Control and Multirobot 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 must simply 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 [40.137–140], or using techniques similar to mutual exclusion in distributed computing [40.141, 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 multirobot 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 multirobot soccer domain as a proposed challenge problem for studying coordination and control in multirobot systems [40.143], research in this domain has grown tremendously. This domain incorporates many challenging aspects of multirobot control, including collaboration, robot control architectures, strategy acquisition, real-time reasoning and action, sensor fusion, dealing with adversarial environments, cognitive modeling, and learning. Annual competitions show the ever-improving team capabilities of the robots in a variety of settings, as shown



Fig. 40.8 Legged robot teams competing in robot soccer

in Fig. 40.8. A key aspect of this domain that is not present in the other multirobot 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 to the competition [40.144], which has also become a significant area of research (see Chap. 50 for more details on this field). Annual proceedings of the RoboCup competitions document much of the research that is incorporated into the multirobot soccer teams. Some representative research works include [40.145–149].

40.9 Conclusions and Further Reading

This chapter has surveyed the current state of the art in multirobot 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 heterogeneity.

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*, multirobot teams still need improvements in the ability to degrade

gracefully, to reason for fault tolerance, and to achieve complexity without escalating failure rates. The area of *learning* in multirobot teams is still in its infancy, with open questions including how to achieve continual learning in multirobot 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 design a robot team optimally 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 survey articles in the field, including [40.2, 100, 150, 151]. Additionally, several special journal issues on this topic have

appeared, including [40.1, 152–154]. Some taxonomies of multirobot systems are given in [40.25, 100, 155]. A variety of symposia and workshops have been held on a regular basis on the topic of multirobot systems; recent proceedings of these workshops and symposia include [40.156–163]. An additional edited text on this topic is [40.164].

References

- 40.1 T. Arai, E. Pagello, L.E. Parker: Editorial: Advances in multi-robot systems, *IEEE Trans. Robot. Autom.* **18**(5), 655–661 (2002)
- 40.2 Y. Cao, A. Fukunaga, A. Kahng: Cooperative mobile robotics: Antecedents and directions, *Auton. Robot.* **4**, 1–23 (1997)
- 40.3 R.G. Brown, J.S. Jennings: A pusher/steerer model for strongly cooperative mobile robot manipulation, *Proc. IEEE Int. Conf. Intell. Robot. Syst. (IROS '95)* (IEEE, Pittsburgh 1995) pp. 562–568
- 40.4 D. Milutinović, P. Lima: Modeling and optimal centralized control of a large-size robotic population, *IEEE Trans. Robot.* **22**(6), 1280–1285 (2006)
- 40.5 B. Khoshnevis, G.A. Bekey: Centralized sensing and control of multiple mobile robots, *Comput. Ind. Eng.* **35**(3–4), 503–506 (1998)
- 40.6 M.J. Mataric: Issues and approaches in the design of collective autonomous agents, *Robot. Auton. Syst.* **16**, 321–331 (1995)
- 40.7 E. Ostergaard, G.S. Sukhatme, M.J. Mataric: Emergent bucket brigading, *Fifth International Conference on Autonomous Agents* (Montreal 2001)
- 40.8 M. Mataric: Reinforcement learning in the multi-robot domain, *Auton. Robot.* **4**, 73–83 (1997)
- 40.9 L.E. Parker: ALLIANCE: An Architecture for Fault-Tolerant Multi-Robot Cooperation, *IEEE Trans. Robot. Autom.* **14**(2), 220–240 (1998)
- 40.10 L.E. Parker: Lifelong adaptation in heterogeneous teams: Response to continual variation in individual robot performance, *Auton. Robot.* **8**(3), 239–267 (2000)
- 40.11 R. Simmons, S. Singh, D. Hershberger, J. Ramos, T. Smith: First results in the coordination of heterogeneous robots for large-scale assembly, *Proc. ISER 7th Int. Symp. Exp. Robot.* (Springer, New York 2000)
- 40.12 J. Deneubourg, S. Goss, G. Sandini, F. Ferrari, P. Dario: Self-organizing collection and transport of objects in unpredictable environments. (Kyoto) pp. 1093–1098
- 40.13 C.R. Kube, H. Zhang: Collective robotics: From social insects to robots, *Adapt. Behav.* **2**(2), 189–219 (1993)
- 40.14 R. Beckers, O. Holland, J. Deneubourg: From local actions to global tasks: Stigmergy and collective robotics, *Proc. 14th Int. Workshop Synth. Simul. Living Syst.*, ed. by R. Brooks, P. Maes (MIT Press, Cambridge 1994) pp. 181–189
- 40.15 S. Onn, M. Tennenholtz: Determination of social laws for multi-agent mobilization, *Artif. Intell.* **95**, 155–167 (1997)
- 40.16 B.B. Werger: Cooperation without deliberation: A minimal behavior-based approach to multi-robot teams, *Artif. Intell.* **110**(2), 293–320 (1999)
- 40.17 M.J. Huber, E. Durfee: Deciding when to commit to action during observation-based coordination, *Proc. 1st Int. Conf. Multi-Agent Syst.* (1995) pp. 163–170
- 40.18 H. Asama, K. Ozaki, A. Matsumoto, Y. Ishida, I. Endo: Development of task assignment system using communication for multiple autonomous robots, *J. Robot. Mechatron.* **4**(2), 122–127 (1992)
- 40.19 N. Jennings: Controlling cooperative problem solving in industrial multi-agent systems using joint intentions, *Artif. Intell.* **75**(2), 195–240 (1995)
- 40.20 M. Tambe: Towards flexible teamwork, *J. Artif. Intell. Res.* **7**, 83–124 (1997)
- 40.21 L.E. Parker: The Effect of action recognition and robot awareness in cooperative robotic teams, *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IEEE, Pittsburgh 1995)* pp. 212–219
- 40.22 M. Mataric: Behavior-based control: Examples from navigation, learning, and group behavior, *J. Exp. Theor. Artif. Intell.* **19**(2–3), 323–336 (1997)
- 40.23 B. MacLennan, G.M. Burghardt: Synthetic ethology and the evolution of cooperative communication, *Adapt. Behav.* **2**, 161–188 (1993)
- 40.24 T. Balch, R.C. Arkin: Communication in reactive multiagent robotic systems, *Auton. Robot.* **1**(1), 27–52 (1995)
- 40.25 G. Dudek, M. Jenkin, E. Miliotis, D. Wilkes: A taxonomy for multi-agent robotics, *Auton. Robot.* **3**, 375–397 (1996)
- 40.26 G. Theraulaz, S. Goss, J. Gervet, J.-L. Deneubourg: Task differentiation in *Polistes* wasp colonies: A model for self-organizing groups of robots, *Proc. 1st Int. Conf. Simul. Adaptive Behavior* (Paris 1990) pp. 346–355
- 40.27 L. Steels: *Cooperation Between Distributed Agents Through Self-Organization*, ed. by Y. Demazeau, J.-P. Muller (Elsevier Science, Amsterdam 1990)

- 40.28 A. Drogoul, J. Ferber: From tom thumb to the dockers: Some experiments with foraging robots, Proc. 2nd Int. Conf. Simul. Adaptive Behavior (Honolulu 1992) pp. 451–459
- 40.29 M.J. Mataric: Designing emergent behaviors: From local interactions to collective intelligence, Proc. 2nd Int. Conf. Simul. Adaptive Behavior, ed. by J. Meyer, H. Roitblat, S. Wilson (MIT Press, Cambridge 1992) pp. 432–441
- 40.30 G. Beni, J. Wang: Swarm intelligence in cellular robotics systems, Proc. NATO Adv. Workshop Robot. Biol. Syst. (1989)
- 40.31 D. Stilwell, J. Bay: Toward the development of a material transport system using swarms of ant-like robots, Proc. IEEE Int. Conf. Robot. Autom. (Atlanta 1993) pp. 766–771
- 40.32 T. Fukuda, S. Nakagawa, Y. Kawauchi, M. Buss: Self organizing robots based on cell structures – CEBOT, Proc IEEE Int. Workshop Intell. Robot. Syst. (IEEE, 1988) pp. 145–150
- 40.33 J.H. Reif, H.Y. Wang: Social Potential fields: A distributed behavior control for autonomous robots, Robot. Auton. Syst. **27**(3), 171–194 (1999)
- 40.34 L.E. Parker: Designing control laws for cooperative agent teams, Proc. IEEE Robot. Autom. Conf. (IEEE, Atlanta 1993) pp. 582–587
- 40.35 K. Sugihara, I. Suzuki: Distributed algorithms for formation of geometric patterns with many mobile robots, J. Robot. Syst. **13**(3), 127–139 (1996)
- 40.36 V. Gazi: Swarm aggregations using artificial potentials and sliding-mode control, IEEE Trans. Robot. **21**(6), 1208–1214 (2005)
- 40.37 J. McLurkin, J. Smith: Distributed algorithms for dispersion in indoor environments using a swarm of autonomous mobile robots, Symp. Distrib. Auton. Robot. Syst. (Springer, 2004)
- 40.38 D. Gage: Randomized search strategies with imperfect sensors, Proc. SPIE Mobile Robots VIII (SPIE, Boston 1993) pp. 270–279
- 40.39 T. Balch: The impact of diversity on performance in robot foraging, Proc. 3rd Ann. Conf. Auton. Agents (ACM Press, Seattle 1999) pp. 92–99
- 40.40 A. Howard, M.J. Mataric, G.S. Sukhatme: An incremental self-deployment algorithm for mobile sensor networks, Auton. Robot. **13**(2), 113–126 (2002), Special Issue on Intelligent Embedded Systems
- 40.41 Z.J. Butler, A.A. Rizzi, R.L. Hollis: Cooperative coverage of rectilinear environments, Proc. IEEE Int. Conf. Robot. Autom. (IEEE, San Francisco 2000)
- 40.42 A.I. Mourikis, S.I. Roumeliotis: Performance analysis of multirobot cooperative localization, IEEE Trans. Robot. **22**(4), 666–681 (2006)
- 40.43 R. Grabowski, L.E. Navarro-Serment, C.J. Paredis, P.K. Khosla: Heterogeneous teams of modular robots for mapping and exploration, Auton. Robot. **8**(3), 271–298 (2000)
- 40.44 M. Berhault, H. Huang, P. Keskinocak, S. Koenig, W. Elmaghraby, P. Griffin, A. Kleywegt: Robot exploration with combinatorial auctions, Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst. (IEEE, 2003) pp. 1957–1962
- 40.45 J. Kim, J.M. Esposito, V. Kumar: An RRT-based algorithm for testing and validating multi-robot controllers, Proc. Robot.: Sci. Syst. I (2005)
- 40.46 Z. Cao, M. Tin, L. Li, N. Gu, S. Wang: Cooperative hunting by distributed mobile robots based on local interaction, IEEE Trans. Robot. **22**(2), 403–407 (2006)
- 40.47 R.W. Beard, T.W. McLain, M. Goodrich: Coordinated target assignment and intercept for unmanned air vehicles, Proc. IEEE Int. Conf. Robot. Autom. (IEEE, Washington 2002)
- 40.48 J. Clark, R. Fierro: Cooperative hybrid control of robotic sensors for perimeter detection and tracking. (IEEE) pp. 3500–3505
- 40.49 P. Stone, M. Veloso: A layered approach to learning client behaviors in the RoboCup soccer server, Appl. Artif. Intell. **12**, 165–188 (1998)
- 40.50 J. McLurkin: Stupid Robot Tricks: Behavior-Based Distributed Algorithm Library for Programming Swarms of Robots. M.S. Thesis (Massachusetts Institute of Technology, Cambridge 2004)
- 40.51 L.E. Parker: The Effect of Heterogeneity in Teams of 100+ Mobile Robots. In: *Multi-Robot Systems Volume II: From Swarms to Intelligent Automata*, ed. by A. Schultz, L.E. Parker, F. Schneider (Kluwer, Dordrecht 2003)
- 40.52 T. Balch: Hierarchic social entropy: An information theoretic measure of robot team diversity, Auton. Robot. **8**(3), 209–238 (2000)
- 40.53 D. Jung, A. Zelinsky: Grounded symbolic communication between heterogeneous cooperating robots, Auton. Robot. **8**(3), 269–292 (2000)
- 40.54 R.R. Murphy: Marsupial robots for urban search and rescue, IEEE Intell. Syst. **15**(2), 14–19 (2000)
- 40.55 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 2002) pp. 345–368
- 40.56 L.E. Parker, B. Kannan, F. Tang, M. Bailey: Tightly-coupled navigation assistance in heterogeneous multi-robot teams, Proc. IEEE Int. Conf. Intell. Robot. Syst. (IEEE, 2004)
- 40.57 A. Howard, L.E. Parker, G.S. Sukhatme: Experiments with a large heterogeneous mobile robot team: Exploration, mapping, deployment, and detection, Int. J. Robot. Res. **25**, 431–447 (2006)
- 40.58 L. Chaimowicz, B. Grocholsky, J.F. Keller, V. Kumar, C.J. Taylor: Experiments in multirobot air-ground coordination, Proc. IEEE Int. Conf. Robot. Autom. (IEEE, New Orleans 2004)
- 40.59 L.E. Parker, F. Tang: Building multi-robot coalitions through automated task solution synthesis, Proc.

- IEEE **94**(7), 1289–1305 (2006), special issue on Multi-Robot Systems
- 40.60 R. Zlot, A. Stentz: Market-based multirobot coordination for complex tasks, *Int. J. Robot. Res.* **25**(1), 73–101 (2006)
- 40.61 J. Jennings, C. Kirkwood-Watts: Distributed mobile robotics by the method of dynamic teams, *Proc. 4th Int. Symp. Distrib. Auton. Robot. Syst. Karlsruhe 1998*, ed. by T. Leuth, R. Dillman, P. Dario, H. Worn (Springer, Tokyo 1998)
- 40.62 E. Pagello, A. D'Angelo, E. Menegatti: Cooperation issues and distributed sensing for multirobot systems, *Proc. IEEE* **94**, 1370–1383 (2006)
- 40.63 B. Gerkey, M.J. Mataric: A formal analysis and taxonomy of task allocation in multi-robot systems, *Int. J. Robot. Res.* **23**(9), 939–954 (2004)
- 40.64 D. Gale: *The Theory of Linear Economic Models* (McGraw-Hill, New York 1960)
- 40.65 E. Balas, M.W. Padberg: On the set-covering problem, *Oper. Res.* **20**(6), 1152–1161 (1972)
- 40.66 B.B. Werger, M.J. Mataric: Broadcast of local eligibility for multi-target observation. In: *Distributed Autonomous Robotic Systems 4*, ed. by L.E. Parker, G. Bekey, J. Barhen (Springer, Tokyo 2000) pp. 347–356
- 40.67 R.A. Brooks: A robust layered control system for a mobile robot, *IEEE J. Robot. Autom.* **RA-2**(1), 14–23 (1986)
- 40.68 S. Botelho, R. Alami: M+: A scheme for multi-robot cooperation through negotiated task allocation and achievement, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Detroit 1999) pp. 1234–1239
- 40.69 R.G. Smith: The contract net protocol: High-level communication and control in a distributed problem solver, *IEEE Trans. Comput.* **C-29**(12), 1104–1113 (1980)
- 40.70 B. Dias, R. Zlot, N. Kalra, A. Stentz: Market-based multirobot coordination: A survey and analysis, *Proc. IEEE* **94**(7), 1257–1270 (2006)
- 40.71 B.P. Gerkey, M.J. Mataric: Sold! Auction methods for multi-robot coordination, *IEEE Trans. Robot. Autom.* **18**(5), 758–768 (2002)
- 40.72 H. Kose, U. Tatlidede, C. Mericli, K. Kaplan, H. L.Akin: Q-learning based market-driven multi-agent collaboration in robot soccer, *Proc. Turkish Symp. Artif. Intell. Neural Networks (Izmir 2004)* pp. 219–228
- 40.73 D. Vail, M. Veloso: Multi-robot dynamic role assignment and coordination through shared potential fields, multi-robot systems: From swarms to intelligent automata, *Proc. Int. Workshop Multi-Robot Syst.*, Washington, D.C., ed. by A. Schultz, L.E. Parker, F. Schneider (Springer, Dordrecht 2003) pp. 87–98
- 40.74 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* (MIT Press, Cambridge 2005)
- 40.75 G. Rabideau, T. Estlin, S. Schien, A. Barrett: A comparison of coordinated planning methods for cooperating rovers, *Proc. AIAA Space Technol. Conf.* (1999)
- 40.76 R. Zlot, A. Stentz, M.B. Dias, S. Thayer: Multi-robot exploration controlled by a market economy, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Washington 2002) pp. 3016–3023
- 40.77 J. Guerrero, G. Oliver: Multi-robot task allocation strategies using auction-like mechanisms, *Proc. 6th Congr. Catalan Assoc. Artif. Intell.* (2003) pp. 111–122
- 40.78 N. Kalra, D. Ferguson, A. Stentz: Hoplites: A market-based framework for planned tight coordination in multirobot teams, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Barcelona 2005)
- 40.79 L. Lin, Z. Zheng: Combinatorial bids based multi-robot task allocation method, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Barcelona 2005) pp. 1145–1150
- 40.80 C.-H. Fua, S.S. Ge: COBOS: Cooperative backoff adaptive scheme for multirobot task allocation, *IEEE Trans. Robot.* **21**(6), 1168–1178 (2005)
- 40.81 E.G. Jones, B. Browning, M.B. Dias, B. Argall, M. Veloso, A. Stentz: Dynamically formed heterogeneous robot teams performing tightly-coupled tasks, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Orlando 2006) pp. 570–575
- 40.82 L. Vig, J.A. Adams: Multi-robot coalition formation, *IEEE Trans. Robot.* **22**(4), 637–649 (2006)
- 40.83 M. Bowling, M. Veloso: Simultaneous adversarial multi-robot learning, *Proc. Int. Joint Conf. Artif. Intell.* (2003)
- 40.84 F. Fernandez, L.E. Parker: A reinforcement learning algorithm in cooperative multi-robot domains, *J. Intell. Robot. Syst.* **43**, 161–174 (2005)
- 40.85 C.F. Touzet: Robot awareness in cooperative mobile robot learning, *Auton. Robot.* **2**, 1–13 (2000)
- 40.86 R. Steeb, S. Cammarata, F. Hayes-Roth, P. Thorndyke, R. Wesson: *Distributed Intelligence for Air Fleet Control*, Rand Corp. Technical Report, Number R-2728-AFPA (1981)
- 40.87 M. Benda, V. Jagannathan, R. Dodhiawalla: On optimal cooperation of knowledge sources, *Boeing AI Center Technical Report BCS-G2010-28* (1985)
- 40.88 T. Haynes, S. Sen: *Evolving Behavioral Strategies in Predators and Prey, Adaptation and Learning in Multi-Agent Systems*, ed. by G. Weiss, S. Sen (Springer, Berlin, Heidelberg 1986) pp. 113–126
- 40.89 S. Mahadevan, J. Connell: Automatic programming of behavior-based robots using reinforcement learning, *Proc. AAAI* (1991) pp. 8–14
- 40.90 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,

- Proc. 3rd Ann. Conf. Auton. Agents, ed. by O. Etzioni, J. Muller, J. Bradshaw (1999) pp. 221–227
- 40.91 J. Pugh, A. Martinoli: Multi-robot learning with particle swarm optimization, Proc. 5th Int. Joint Conf. Auton. Agents Multiagent Syst., Hakodate (ACM, New York 2006) pp. 441–448
- 40.92 P. Stone, M. Veloso: Multiagent systems: A survey from a machine learning perspective, *Auton. Robot.* **8**(3), 345–383 (2000)
- 40.93 M. Asada, E. Uchibe, S. Noda, S. Tawaratsumida, K. Hosoda: Coordination of multiple behaviors acquired by a vision-based reinforcement learning, Proc. IEEE/RSJ/GI Int. Conf. Intell. Robot. Syst. (Munich 1994) pp. 917–924
- 40.94 M. Kubo, Y. Kakazu: Learning coordinated motions in a competition for food between ant colonies, Proc. 3rd Int. Conf. Simul. Adaptive Behavior, ed. by D. Cliff, P. Husbands, J.-A. Meyer, S. Wilson (MIT Press, Cambridge 1994) pp. 487–492
- 40.95 R. Alami, S. Fleury, M. Herrb, F. Ingrand, F. Robert: Multi-robot cooperation in the MARTHA project, *Robot. Autom. Mag.* **5**(1), 36–47 (1998)
- 40.96 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, *Auton. Robot.* **20**(2), 113–123 (2006)
- 40.97 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)
- 40.98 Y. Guo, L.E. Parker, R. Madhavan: Towards collaborative robots for infrastructure security applications, Proc. Int. Symp. Collab. Technol. Syst. (2004) pp. 235–240
- 40.99 C. Hazard, P.R. Wurman, R. D’Andrea: Alphabet Soup: A testbed for studying resource allocation in multi-vehicle systems, Proc. AAAI Workshop Auction Mechan. Robot Coord. (AAAI, Boston 2006) pp. 23–30
- 40.100 D. Nardi, A. Farinelli, L. Iocchi: Multirobot systems: A classification focused on coordination, *IEEE Trans. Syst. Man Cybernet. Part B* **34**(5), 2015–2028 (2004)
- 40.101 K. Passino: Biomimicry of bacterial foraging for distributed optimization and control, *IEEE Contr. Syst. Mag.* **22**(3), 52–67 (2002)
- 40.102 M. Fontan, M. Mataric: Territorial multi-robot task division, *IEEE Trans. Robot. Autom.* **15**(5), 815–822 (1998)
- 40.103 I. Wagner, M. Lindenbaum, A.M. Bruckstein: Mac vs. PC – Determinism and randomness as complementary approaches to robotic exploration of continuous unknown domains, *Int. J. Robot. Res.* **19**(1), 12–31 (2000)
- 40.104 K. Sugawara, M. Sano: Cooperative behavior of interacting simple robots in a clockface arranged foraging field. In: *Distributed Autonomous Robotic Systems*, ed. by H. Asama, T. Arai, T. Fukuda, T. Hasegawa (Springer, Berlin, Heidelberg 2002) pp. 331–339
- 40.105 P. Rybski, S. Stoeter, C. Wyman, M. Gini: A cooperative multi-robot approach to the mapping and exploration of Mars, Proc. AAAI/IAAI–97 (AAAI, Providence 1997)
- 40.106 S. Sun, D. Lee, K. Sim: Artificial immune-based swarm behaviors of distributed autonomous robotic systems, Proc. IEEE Int. Conf. Robot. Autom. (IEEE, 2001) pp. 3993–3998
- 40.107 A.I. Mourikis, S.I. Roumeliotis: Optimal sensor scheduling for resource-constrained localization of mobile robot formations, *IEEE Trans. Robot.* **22**(5), 917–931 (2006)
- 40.108 S. Kloder, S. Hutchinson: Path planning for permutation-invariant multirobot formations, *IEEE Trans. Robot.* **22**(4), 650–665 (2006)
- 40.109 C.W. Reynolds: Flocks, herds and schools: A distributed behavioral model, *ACM SIGGRAPH Computer Graphics* **21**, 25–34 (1987)
- 40.110 T. Balch, R. Arkin: Behavior-based Formation Control for Multi-robot Teams, *IEEE Trans. Robot. Autom.* **14**(6), 926–939 (1998)
- 40.111 A. Jadbabaie, J. Lin, A.S. Morse: Coordination of groups of mobile autonomous agents using nearest neighbor rules, *IEEE Trans. Autom. Contr.* **48**(6), 988–1001 (2002)
- 40.112 C. Belta, V. Kumar: Abstraction and control for groups of robots, *IEEE Trans. Robot.* **20**(5), 865–875 (2004)
- 40.113 C.M. Topaz, A.L. Bertozzi: Swarming patterns in two-dimensional kinematic model for biological groups, *SIAM J. Appl. Math.* **65**(1), 152–174 (2004)
- 40.114 J.A. Fax, R.M. Murray: Information flow and cooperative control of vehicle formations, *IEEE Trans. Autom. Contr.* **49**(9), 1465–1476 (2004)
- 40.115 J.A. Marshall, M.E. Broucke, B.R. Francis: Formations of vehicles in cyclic pursuit, *IEEE Trans. Autom. Contr.* **49**(11), 1963–1974 (2004)
- 40.116 S.S. Ge, C.-H. Fua: Queues and artificial potential trenches for multirobot formations, *IEEE Trans. Robot.* **21**(4), 646–656 (2005)
- 40.117 P. Tabuada, G. Pappas, P. Lima: Motion feasibility of multi-agent formations, *IEEE Trans. Robot.* **21**(3), 387–392 (2005)
- 40.118 G. Antonelli, S. Chiaverini: Kinematic control of platoons of autonomous vehicles, *IEEE Trans. Robot.* **22**(6), 1285–1292 (2006)
- 40.119 J. Fredslund, M.J. Mataric: A general algorithm for robot formations using local sensing and minimal communication, *IEEE Trans. Robot. Autom.* **18**(5), 837–846 (2002)
- 40.120 L.E. Parker: ALLIANCE: An architecture for fault tolerant, cooperative control of heterogeneous mobile robots, Proc. IEEE/RSJ/GI Int. Conf. Intell. Robot. Syst. (IEEE, Munich 1994) pp. 776–783

- 40.121 B. Donald, J. Jennings, D. Rus: Analyzing teams of cooperating mobile robots, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, 1994) pp. 1896–1903
- 40.122 S. Sen, M. Sekaran, J. Hale: Learning to coordinate without sharing information, *Proc. AAAI (AAAI, Seattle 1994)* pp. 426–431
- 40.123 B. Tung, L. Kleinrock: Distributed control methods, *Proc. 2nd Int. Symp. High Perform. Distrib. Comput.* (1993) pp. 206–215
- 40.124 Z.-D. Wang, E. Nakano, T. Matsukawa: Cooperating multiple behavior-based robots for object manipulation. (IEEE, Munich) pp. 1524–1531
- 40.125 P.J. Johnson, J.S. Bay: Distributed control of simulated autonomous mobile robot collectives in payload transportation, *Auton. Robot.* **2**(1), 43–63 (1995)
- 40.126 D. Rus, B. Donald, J. Jennings: Moving furniture with teams of autonomous robots, *Proc. IEEE/RJS Int. Conf. Intell. Robot. Syst.* (Pittsburgh 1995) pp. 235–242
- 40.127 F. Hara, Y. Yasui, T. Aritake: A kinematic analysis of locomotive cooperation for two mobile robots along a general wavy road, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Nagoya 1995) pp. 1197–1204
- 40.128 J. Sasaki, J. Ota, E. Yoshida, D. Kurabayashi, T. Arai: Cooperating grasping of a large object by multiple mobile robots, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Nagoya 1995) pp. 1205–1210
- 40.129 C. Jones, M.J. Mataric: Automatic synthesis of communication-based coordinated multi-robot systems, *Proc. IEEE/RJS Int. Conf. Intell. Robot. Syst.* (IEEE, Sendai 2004) pp. 381–387
- 40.130 Z. Wang, V. Kumar: Object closure and manipulation by multiple cooperating mobile robots, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, 2002) pp. 394–399
- 40.131 L.E. Parker: Cooperative robotics for multi-target observation, *Intell. Autom. Soft Comput.* **5**(1), 5–19 (1999)
- 40.132 S. Luke, K. Sullivan, L. Panait, G. Balan: Tunably decentralized algorithms for cooperative target observation, *Proc. 4th Int. Joint Conf. Auton. Agents Multiagent Syst., The Netherlands (ACM, New York 2005)* pp. 911–917
- 40.133 S.M. LaValle, H.H. Gonzalez-Banos, C. Becker, J.-C. Latombe: Motion strategies for maintaining visibility of a moving target, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Albuquerque 1997) pp. 731–736
- 40.134 A. Kolling, S. Carpin: Multirobot cooperation for surveillance of multiple moving targets – a new behavioral approach, *Proc. IEEE Int. Conf. Robot. Autom.* (IEEE, Orlando 2006) pp. 1311–1316
- 40.135 B. Jung, G. Sukhatme: Tracking targets using multiple mobile robots: The effect of environment occlusion, *Auton. Robot.* **13**(3), 191–205 (2002)
- 40.136 Z. Tang, U. Ozguner: Motion planning for multi-target surveillance with mobile sensor agents, *IEEE Trans. Robot.* **21**(5), 898–908 (2005)
- 40.137 D. Grossman: Traffic control of multiple robot vehicles, *IEEE J. Robot. Autom.* **4**, 491–497 (1988)
- 40.138 P. Caloud, W. Choi, J.-C. Latombe, C. Le Pape, M. Yim: Indoor automation with many mobile robots, *Proc. IEEE Int. Workshop Intell. Robot. Syst.* (IEEE, Tsuchiura 1990) pp. 67–72
- 40.139 H. Asama, K. Ozaki, H. Itakura, A. Matsumoto, Y. Ishida, I. Endo: Collision avoidance among multiple mobile robots based on rules and communication, *Proc. IEEE/RJS Int. Conf. Intell. Robot. Syst.* (IEEE, 1991)
- 40.140 S. Yuta, S. Premvuti: Coordinating autonomous and centralized decision making to achieve cooperative behaviors between multiple mobile robots, *Proc. IEEE/RJS Int. Conf. Intell. Robot. Syst.* (IEEE, Raleigh 1992) pp. 1566–1574
- 40.141 J. Wang: Fully distributed traffic control strategies for many-AGV systems, *Proc. IEEE Int. Workshop Intell. Robot. Syst.* (IEEE, 1991) pp. 1199–1204
- 40.142 J. Wang, G. Beni: Distributed computing problems in cellular robotic systems, *Proc. IEEE Int. Workshop Intell. Robot. Syst.* (IEEE, Tsuchiura 1990) pp. 819–826
- 40.143 H. Kitano, M. Asada, Y. Kuniyoshi, I. Noda, E. Osawa, H. Matasubara: RoboCup: A challenge problem of AI, *AI Mag.* **18**(1), 73–86 (1997)
- 40.144 H. Kitano, S. Tadokoro: RoboCup rescue: A grand challenge for multiagent and intelligent systems, *AI Mag.* **22**(1), 39–52 (2001)
- 40.145 B. Browning, J. Bruce, M. Bowling, M. Veloso: STP: Skills, tactics and plays for multi-robot control in adversarial environments, *IEEE J. Contr. Syst. Eng.* **219**, 33–52 (2005)
- 40.146 M. Veloso, P. Stone, K. Han: The CMUnited-97 robotic soccer team: Perception and multiagent control, *Robot. Auton. Syst.* **29**(2–3), 133–143 (1999)
- 40.147 T. Weigel, J.-S. Gutmann, M. Dietl, A. Kleiner, B. Nebel: CS Freiburg: coordinating robots for successful soccer playing, *IEEE Trans. Robot. Autom.* **5**(18), 685–699 (2002)
- 40.148 P. Stone, M. Veloso: Task decomposition, dynamic role assignment, and low-bandwidth communication for real-time strategic teamwork, *Artif. Intell.* **110**(2), 241–273 (1999)
- 40.149 C. Candea, H.S. Hu, L. Iocchi, D. Nardi, M. Piaggio: Coordination in multi-agent Robocup teams, *Robot. Auton. Syst.* **36**(2), 67–86 (2001)
- 40.150 L.E. Parker: Current research in multirobot teams, *Artif. Life Robot.* **7**(2–3), 1–5 (2005)
- 40.151 K.R. Baghaei, A. Agah: Task allocation and communication methodologies for multi-robot systems, *Intell. Autom. Soft Comput.* **9**, 217–226 (2003)
- 40.152 T. Balch, L.E. Parker: Guest editorial, special issue on heterogeneous multi-robot systems, *Auton. Robot.* **8**(3), 207–208 (2000)

- 40.153 M. Dorigo, E. Sahin: Guest editorial, special issue on swarm robotics, *Auton. Robot.* **17**(2-3), 111-113 (2004)
- 40.154 M. Veloso, D. Nardi: Special issue on multirobot systems, *Proc. IEEE* **94**, 1253-1256 (2006)
- 40.155 T. Balch: Taxonomies of multi-robot task and reward. In: *Robot Teams: From Diversity to Polymorphism*, ed. by T. Balch, L.E. Parker (A K Peters, Natick 2002)
- 40.156 L.E. Parker, G. Bekey, J. Barhen (Eds.): *Distributed Autonomous Robotic Systems 4* (Springer, Berlin, Heidelberg 2000)
- 40.157 H. Asama, T. Arai, T. Fukuda, T. Hasegawa (Eds.): *Distributed Autonomous Robotic Systems 5* (Springer, Berlin, Heidelberg 2002)
- 40.158 A. Schultz, L.E. Parker (Eds.): *Multi-Robot Systems: From Swarms to Intelligent Automata* (Kluwer, Dordrecht 2002)
- 40.159 A. Schultz, L.E. Parker, F. Schneider (Eds.): *Multi-Robot Systems Volume II: From Swarms to Intelligent Automata* (Kluwer, Dordrecht 2003)
- 40.160 E. Sahin, W.M. Spears (Eds.): *Swarm Robotics: SAB 2004 International Workshop* (Springer, Berlin, Heidelberg 2004)
- 40.161 L.E. Parker, F. Schneider, A. Schultz (Eds.): *Multi-Robot Systems Volume III: From Swarms to Intelligent Automata* (Kluwer, Dordrecht 2005)
- 40.162 R. Alami, R. Chatila, H. Asama (Eds.): *Distributed Autonomous Robotic Systems 6* (Springer, Berlin, Heidelberg 2006)
- 40.163 M. Gini, R. Voyles (Eds.): *Distributed Autonomous Robotic Systems 7* (Springer, Berlin, Heidelberg 2006)
- 40.164 T. Balch, L.E. Parker (Eds.): *Robot Teams: From Polymorphism to Diversity* (A K Peters, Natick 2002)