Classification of Multi-UAV Architectures 38

Ivan Maza, Aníbal Ollero, Enrique Casado, and David Scarlatti

Contents

Abstract

This chapter presents a classification of different schemes for the cooperation of multiple UAVs, taking into account the coupling between the vehicles and the type of cooperation. Then, the research and development activities in load

I. Maza (✉)
Robotics, Vision and Control Group, University of Seville, Seville, Spain
e-mail: imaza@us.es

A. Ollero
Robotics, Vision and Control Group, University of Seville, Seville, Spain

Center for Advanced Aerospace Technologies (CATEC), Parque Tecnologico y Aeron autico de Andaluca, La Rinconada, Spain
e-mail: aollero@us.es

E. Casado • D. Scarlatti
Boeing Research & Technology Europe, Madrid, Spain
e-mail: Enrique.Casado@boeing.com; David.Scarlatti@boeing.com

K.P. Valavanis, G.J. Vachtsevanos (eds.), *Handbook of Unmanned Aerial Vehicles*,
DOI 10.1007/978-90-481-9707-1_119,

transportation, formation control, swarm approaches, and intentional cooperation architectures are revised. The chapter also considers UAVs networked with other elements in the environment to support their navigation and, in general, their operation. The chapter refers theoretical work but also emphasizes practical field outdoor demonstrations involving aerial vehicles.

38.1 Introduction

This chapter considers the cooperation of multiple UAVs performing jointly missions such as search and rescue, reconnaissance, surveying, detection and monitoring in dangerous scenarios, exploration and mapping, and hazardous material handling. The coordination of a team of autonomous vehicles allows to accomplish missions that no individual autonomous vehicles can accomplish on its own. Team members can exchange sensor information, collaborate to track and identify targets, perform detection and monitoring activities (Ollero and Maza 2007), or even actuate cooperatively in tasks such as the transportation of loads.

The advantages of using multiple UAVs when comparing to a single powerful one can be categorized as follows:

- *Multiple simultaneous interventions.* A single autonomous vehicle is limited at any one time to sense or actuate in a single point. However, the components of a team can simultaneously collect information from multiple locations and exploit the information derived from multiple disparate points to build models that can be used to take decisions. Moreover, multiple UAVs can apply simultaneously forces at different locations to perform actions that could be very difficult for a single UAV.
- *Greater efficiency.* The execution time of missions such as exploration and searching for targets can be decreased when using simultaneously multiple vehicles.
- *Complementarities of team members.* Having a team with multiple heterogeneous vehicles offers additional advantages due to the possibility of exploiting their complementarities. Thus, for example, ground and/or aerial vehicles with quite different characteristics and onboard sensors can be integrated in the same platform. For instance, the aerial vehicles could be used to collect information from locations that cannot be reached by the ground vehicles, while these ground members of the team could be equipped with heavy actuators. Then, the aerial and ground vehicles could be specialized in different roles. But even considering the UAVs themselves complementarities can be found: the fixed-wing airplanes typically have longer flight range and time of flight, whereas helicopters have vertical take-off and landing capability, better maneuverability, and therefore can hover to obtain detailed observations of a given target.
- *Reliability.* The multi-UAV approach leads to redundant solutions offering greater fault tolerance and flexibility including reconfigurability in case of failures of individual vehicles.
- *Technology evolution.* The development of small, relatively low-cost UAVs is fuelled by the progress of embedded systems together with the developments on

technologies for integration and miniaturization. Furthermore, the progress on communication technologies experienced in the last decade plays an important role in multiple vehicle systems.
- *Cost.* A single vehicle with the performance required to execute some tasks could be an expensive solution when comparing to several low-cost vehicles performing the same task. This is clear for UAVs and particularly in small-size, light, and low-cost versions, where constraints such as power consumption, weight, and size play an important role.

Section 38.2 of this chapter will deal with the general concepts and contains a rough classification of systems with multiple autonomous UAVs. Then, the joint load transportation, formation control, swarm approaches, and teams with intentional cooperation are examined in more detail along Sects. 38.3–38.6. The networking of UAVs with other sensors and actuators in the environment is considered in Sect. 38.7. Finally, Sect. 38.8 concludes the chapter.

38.2 General Concepts and Classification

In the first part of this section, the concepts of coordination and cooperation are briefly presented due to their relevance in any system with multiple autonomous vehicles. Then, the important role of communications in these systems is summarized. Finally, a classification based on the coupling between the vehicles is outlined.

38.2.1 Coordination and Cooperation

In platforms involving multiple vehicles, the concepts of coordination and cooperation play an important role. In general, the coordination deals with the sharing of resources, and both temporal and spatial coordination should be considered. The temporal coordination relies on synchronization among the different vehicles, and it is required in a wide spectrum of applications. For instance, for objects monitoring, several synchronized perceptions of the objects could be required. In addition, spatial coordination of UAVs deals with the sharing of the space among them to ensure that each UAV will be able to perform safely and coherently regarding the plans of the other UAVs and the potential dynamic and/or static obstacles. Some formulations are based on the extension of robotics path planning concepts. In this context, the classical planning algorithms for a single robot with multiple bodies (Latombe 1990; LaValle 2006) may be applied without adaptation for centralized planning (assuming that the state information from all the UAVs is available). The main concern, however, is that the dimension of the state space grows linearly in the number of UAVs. Complete algorithms require time that is at least exponential in dimension, which makes them unlikely candidates for such problems. Sampling-based algorithms are more likely to scale well in practice when there are many UAVs, but the resulting dimension might still be too high. For such cases, there are also decoupled path planning approaches such as the prioritized planning that considers one vehicle at a time according to a global priority.

Cooperation can be defined as a "joint collaborative behavior that is directed toward some goal in which there is a common interest or reward" (Barnes and Gray 1991). According to Cao et al. (1997), given some task specified by a designer, a multiple-robot system displays cooperative behavior if, due to some underlying mechanism (i.e., the "mechanism of cooperation"), there is an increase in the total utility of the system. The cooperation of heterogeneous vehicles requires the integration of sensing, control, and planning in an appropriated decisional architecture. These architectures can be either centralized or decentralized depending on the assumptions on the knowledge's scope and accessibility of the individual vehicles, their computational power, and the required scalability. A centralized approach will be relevant if the computational capabilities are compatible with the amount of information to process and the exchange of data meets both the requirements of speed (up-to-date data) and expressivity (quality of information enabling well-informed decision-taking). On the other hand, a distributed approach will be possible if the available knowledge within each distributed vehicle is sufficient to perform "coherent" decisions, and this required amount of knowledge does not endow the distributed components with the inconveniences of a centralized system (in terms of computation power and communication bandwidth requirements). One way to ensure that a minimal global coherence will be satisfied within the whole system is to enable communication between the vehicles of the system, up to a level that will warranty that the decision is globally coherent. One of the main advantages of the distributed approach relies on its superior suitability to deal with the scalability of the system.

38.2.2 Communication and Networking

It should be noticed that communication and networking also play an important role in the implementation of these schemes for multiple unmanned vehicles. Single vehicle communication systems usually have an unshared link between the vehicle and the control station. The natural evolution of this communication technique toward multi-vehicle configurations is the star-shaped network configuration. While this simple approach to vehicles intercommunication may work well with small teams, it could not be practical or cost-effective as the number of vehicles grows. Thus, for example, in multi-UAV systems, there are some approaches of a wireless heterogeneous network with radio nodes mounted at fixed sites, on ground vehicles, and in UAVs. The routing techniques allow any two nodes to communicate either directly or through an arbitrary number of other nodes which act as relays. When autonomous teams of UAVs should operate in remote regions with little/no infrastructure, using a mesh of ground stations to support communication between the mobile nodes is not possible. Then, networks could be formed in an ad hoc fashion, and the information exchanges occur only via the wireless networking equipment carried by the individual UAVs. Some autonomous configurations (such as close formation flying) result in relatively stable topologies. However, in others, rapid fluctuations in the network topology may occur when individual vehicles suddenly veer away from one another or when wireless transmissions are blocked by terrain features, atmospheric conditions, signal jamming, etc. In spite of such dynamically changing conditions, vehicles in an autonomous team should maintain close communications with others in order to avoid collisions and facilitate collaborative team mission execution. In order to reach these goals, two different approaches have been adopted. One, closer to the classical networks architecture, establishes a hierarchical structure and routes data in the classical down-up-down traversing as many levels of the hierarchy as needed to reach destination. The other prospective direction to assist routing in such an environment is to use location information provided by positioning devices, such as global positioning systems (GPS), thus using what it is called location aware protocols. These two techniques are compatible and can be mixed. For example, some of the levels in a hierarchical approach could be implemented using location aware methods.

38.2.3 Classification of Multi-UAV Architectures

Multi-UAV systems can be classified from different points of view. One possible classification is based on the coupling between the UAVs (see Fig. 38.1):

1. *Physical coupling*. In this case, the UAVs are connected by physical links and then their motions are constrained by forces that depend on the motion of other UAVs. The lifting and transportation of loads by several UAVs lies in this category and will be addressed in Sect. 38.3 of this chapter. The main problem is the motion-coordinated control, taking into account the forces constraints. From the point of view of motion planning and collision avoidance, all the members of the team and the load can be considered as a whole. As the number of vehicles is usually low, both centralized and decentralized control architectures can be applied.
2. *Formations*. The vehicles are not physically coupled, but their relative motions are strongly constrained to keep the formation. Then, the motion planning problem can be also formulated considering the formation as a whole. Regarding the collision avoidance problem within the team, it is possible to embed it in the formation control strategy. Scalability properties to deal with formations of many individuals are relevant, and then, decentralized control architectures are usually preferred. Section 38.4 of the chapter will deal with the formations and will also show how the same techniques can be applied to control coordinated motions of vehicles even if they are not in formation.
3. *Swarms*. They are homogeneous teams of many vehicles which interactions generate emerging collective behaviors. The resulting motion of the vehicles does not lead necessarily to formations. Scalability is the main issue due to the large number of vehicles involved, and then pure decentralized control architectures are mandatory. Section 38.5 of the chapter will be devoted to the swarm approaches.

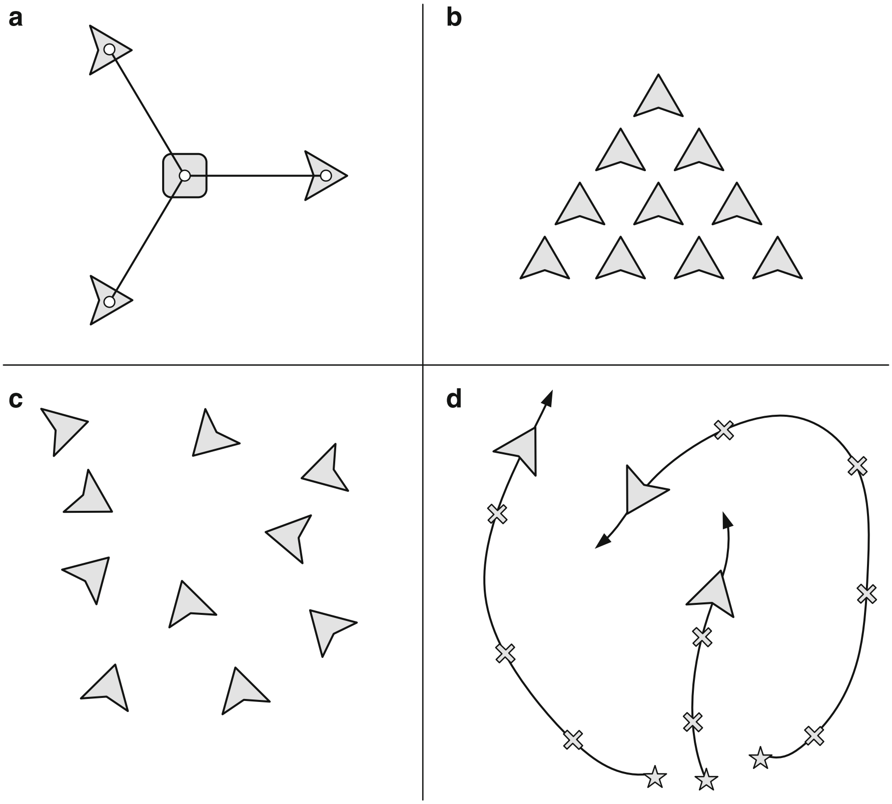

Fig. 38.1 Graphical illustration of a possible classification for multiple UAVs systems: (**a**) physical coupling (3 UAVs transporting one object), (**b**) formations, (**c**) swarms, and (**d**) team executing tasks represented by crosses following an intentional cooperation approach. The UAVs are represented by *gray arrows*

4. *Intentional cooperation.* The UAVs of the team move according to trajectories defined by individual tasks that should be allocated to perform a global mission (Parker 1998). These UAV trajectories typically are not geometrically related as in the case of the formations. This cooperation will be considered in Sect. 38.6 of this chapter. In this case, problems such as multi-UAV task allocation, high-level planning, plan decomposition, and conflict resolution should be solved, taking into account the global mission to be executed and the different UAVs involved. In this case, both centralized and decentralized decisional architectures can be applied.

In the rest of sections of this chapter, each type of multi-vehicle system is discussed in further detail. But before to proceed with each one, a general model for each UAV of the team is presented. This model can be particularized to fit any of the types of the above classification, as it will be shown later.

38.2.4 General Model for Each UAV in the Team

Let us consider a team of UAVs that plan their actions according to a set of coordination and cooperation rules R. In particular, it is assumed that the set R includes k possible *tasks* $\Omega = \{\tau_1, \tau_2, \ldots, \tau_k\}$ with n *logical conditions* requiring a change of task in the current plan. Let $E = \{e_1, e_2, \ldots, e_n\}$ be a set of discrete events associated with n *logical conditions* requiring a change of task during the execution. Each task has a set of m parameters $\Pi = \{\pi^1, \pi^2, \ldots, \pi^m\}$ defining its particular characteristics.

Systems composed of a physical plant and a decisional and control engine implementing such kind of cooperation rules R can be modeled as hybrid systems (Fierro et al. 2002; Chaimowicz et al. 2004; Fagiolini et al. 2007; Li et al. 2008). Figure 38.2 shows a simplified hybrid model that summarizes the different interactions that can be found in each member of the classification presented above.

The i-th UAV's current task has a discrete dynamics $\delta : \Omega \times E \rightarrow \Omega$, i.e.,

$$\tau_i^{\,+} = \delta(\tau_i, e_i), \tag{38.1}$$

where $e_i \in E$ is an event (internal or external) requiring a change of task from τ_i to $\tau_i^{\,+}$, both from the set of tasks Ω.

It should be noticed that each task can have a different control algorithm or a different set of parameters for the same controller. The control reconfiguration is triggered in the transition between tasks associated to different events. Event activation is generated by

$$e_i = \Phi(q_i, \varepsilon_i, X_i, \bar{\mu}_i), \tag{38.2}$$

where ε_i represents the internal events (such as changes in the execution states of the tasks) and $\bar{\mu}_i$ is a vector $\bar{\mu}_i = (\mu_{i_1}, \mu_{i_2}, \ldots, \mu_{i_{N_m}})$ containing the messages coming from N_m UAVs cooperating with the i-th UAV. Those messages are used, for example, in the negotiation processes involved in the intentional cooperation mechanisms and are generated onboard each UAV by a decisional module Δ (see Fig. 38.2). This module encompasses high-level reasoning and planning, synchronization among different UAVs, negotiation protocols for task allocation and conflict resolution purposes, task management and supervision, complex task decomposition, etc.

Regarding the perception of the environment, a database ED with "a priori" knowledge about the environment, including static obstacles, objects of interest, and threats can be available and updated with the new information gathered during the mission. On the other hand, object detection and localization (Merino 2007) is usually required in many applications. The state x of the object to be tracked obviously includes its position p, and for moving objects, it is also convenient to add the velocity $\dot{p}$ into the kinematic part of the state to be estimated. But further information is needed in general. An important objective in some missions is to

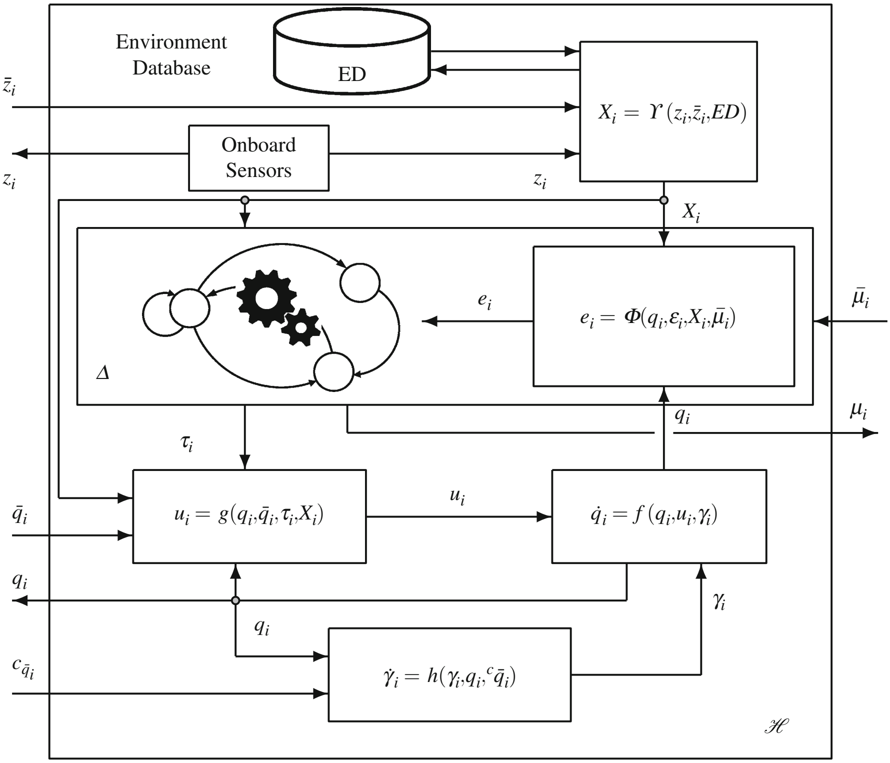

Fig. 38.2 General blocks and interactions considered in the hybrid model for each UAV described in Sect. 38.2

confirm that an object belongs to a certain class within a set Ξ (for instance, in the case of fire alarms detection, this set will include as classes of fire alarms and false alarms). Therefore, the state will include information regarding the classification of the object. Also, in certain applications, some appearance information could be needed to characterize an object, which also can help in the task of data association between different UAVs with different cameras. Additionally, this information could even include the 3D volume of the object that can be added to the obstacles database. In general, the appearance information is static and will be represented by θ.

The complete dynamic state to be estimated is composed by the status of all the objects, N_o, and the number of objects can vary with the time. The state estimated by the i-UAV at time t is then represented by the vector $x_i = [x_{i_1}^T, \ldots, x_{i_{N_o}}^T]^T$. Each potential object m is defined by $x_{i_m} = [p_{i_m} \dot{p}_{i_m} \theta_{i_m}]^T$. The information about the objects will be inferred from all the measurements z_i from the sensors onboard the UAVs and $\bar{z}_i$ gathered by the fleet of N_s UAVs that can communicate with the i-th UAV $\{\bar{z}_j, j = 1, \ldots, N_s\}$. The latter vector can be completed with the measurements from sensors located around the environment, such as static surveillance cameras, or nodes from wireless sensor networks (WSNs) deployed in the area of interest. Notice that z_i also contains the forces/torques derived from the interaction with the environment that are measured with the sensors onboard.

On the other hand, let $q_i \in \Theta$ be a vector describing the state of the i-th UAV taking values in the configuration space Θ, and let $\tau_i \in \Omega$ be the task τ that the i-th UAV is currently executing. This UAV's configuration q_i has a continuous dynamics

$$\dot{q}_i = f(q_i, u_i, \gamma_i), \tag{38.3}$$

where $u_i \in \mathscr{U}$ is a control input and $\gamma_i \in \Gamma$ models the dynamics associated to the possible physical interaction with the environment and/or other UAVs

$$\dot{\gamma}_i = h(\gamma_i, q_i, {}^c\bar{q}_i), \tag{38.4}$$

with vector ${}^c\bar{q}_i = (q_{i_1}, q_{i_2}, \ldots, q_{i_{N_c}})$ containing the configurations of the N_c neighbors physically connected to the i-th UAV. Then $\gamma_i \neq 0$ only if there is physical interaction.

Regarding u_i, it is a feedback law generated by a low-level controller $g : \Theta \times \bar{\Theta} \times \Omega \times \Upsilon \rightarrow \mathscr{U}$, i.e.,

$$u_i = g(q_i, \bar{q}_i, \tau_i, X_i), \tag{38.5}$$

so that the UAV's trajectory $q_i(t)$ corresponds to the desired current task τ_i, taking into account the configurations of the N neighbors $\bar{q}_i = (q_{i_1}, q_{i_2}, \ldots, q_{i_N})$ with influence in the control of the i-th UAV. This influence can be found, for example, in the control problem of swarms and formations. On the other hand, Eq. (38.5) also includes the vector $X_i \in \Upsilon$, taking values in the environment model space Υ, that encompasses estimations about forces/torques derived from the interaction with the environment, targets to the tracked, obstacles detected during the mission and/or known "a priori," threats to be avoided, etc.

In conclusion, the hybrid dynamics $\mathscr{H}$ of the i-th UAV shown in Fig. 38.2 has $\bar{z}_i$, $\bar{\mu}_i$, $\bar{q}_i$, and ${}^c\bar{q}_i$ as inputs and z_i, μ_i, and q_i as outputs. This diagram is not intended to be exhaustive or to cover all the possible architectures and existing systems. Instead, it is aimed at providing a general overview of all the possible interactions in order to put into context the approaches presented in the next sections of the chapter.

38.3 Physical Coupling: Joint Load Transportation

The transportation of a single object by multiple autonomous vehicles is a natural extension of the moving by several persons of a large and heavy object that cannot be handled by a single person. The coordinated control of the motion of each vehicle should consider the involved forces induced by the other vehicles and the load itself. Thus, in the scheme depicted in Fig. 38.2, there is a term $\gamma_i \neq 0$ modelling those forces, which is taken into account in the design of the controller in Eq. 38.5.

It should be also mentioned that γ_i can be measured using onboard sensors. For instance, in the case of several UAVs transporting a load using ropes, a force sensor in the rope can provide a measurement of the influence of the other UAVs and the load being transported. Each UAV could be controlled around a common compliance center attached to the transported object. Under the assumption that each UAV holds the object firmly with rigid links, the real trajectories of all of the UAVs are equal to the real trajectory of the object. However, in some transportation problems, this assumption cannot be applied, and the transported object moves with a dynamic behavior that can be expressed by means of Eq. 38.4.

A suitable approach for the required coordinated control is the leader-follower scheme that will be more detailed in the next section. In this scheme, the desired trajectory is the trajectory of the leader. The followers estimate the motion of the leader by themselves through the motion of the transported object. Several examples of this approach can be found in the robotics community. The leader-follower scheme extended to multiple followers and to robots with non-holonomic constraints (Kosuge and Sato 1999) has been implemented in an experimental system with three tracked mobile robots with a force sensor. In Sugar and Kumar (2002), the decentralized control of cooperating mobile manipulators is studied with a designated lead robot being responsible for task planning. The control of each robot is decomposed (mechanically decoupled) into the control of the gross trajectory and the control of the grasp. The excessive forces due to robot positioning errors and odometry errors are accommodated by the compliant arms. In Huntsberger et al. (2004), distributed coordinated control of two rovers carrying a 2.5 m long mockup of a photovoltaic tent is presented and demonstrated as an example of the CAMPOUT behavior-based control architecture. Borenstein (2000) details the OmniMate system, which uses a compliant linkage platform between two differential drive mobile robots (Labmate) that provide a loading deck for up to 114 kg of payload.

Lifting and transportation of loads by using multiple helicopters has been also a research topic for many years motivated by the payload constraints of these vehicles and the high cost of helicopters with significant payload. In addition, the use of multiple manned helicopters is also problematic and only simple operations, like load transportation with two helicopters, can be performed by extremely skillful and experienced pilots. The level of stress is usually very high, and practical applications are therefore rarely possible. Load transportation and deployment by one and several helicopters is very useful for many applications including the delivery of first-aid packages to isolated victims in disasters (floods, earthquakes, fires, industrial disasters, and many others) and is also a basic technology for other future applications: the building of platforms for evacuation of people in rescue operations and the installation of platforms in uneven terrains for landing of manned and unmanned VTOL aircrafts. This later application would first require the installation of the supporting units defining the horizontal surface and later the installation of the surface itself.

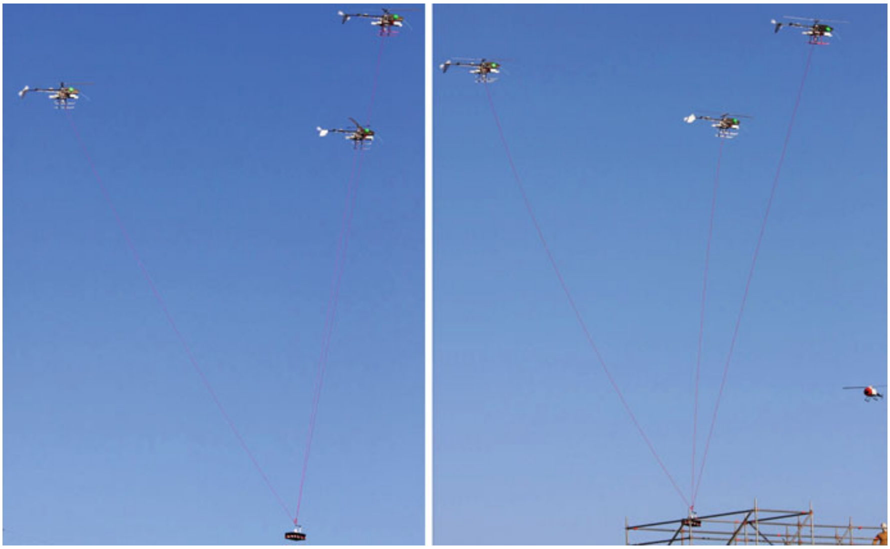

Fig. 38.3 Three autonomous helicopters from the Technical University of Berlin (*TUB-H* model) transporting a wireless camera to the top floor of a building with a height of 12 m in May 2009. A device onboard each helicopter is equipped with a force sensor to estimate the influence of the other helicopters and the load itself – term γ_i in Eq. 38.4. The images show the mission during the actual load transportation (*left*) and shortly before the load deployment (*right*). A fourth helicopter which was used to acquire airborne video footage of the mission is visible on the *right*

The autonomous lifting and transportation by two helicopters (twin lift) has been studied since the beginning of the nineties by means of nonlinear adaptive control (Mittal et al. 1991) and H_∞ control (Reynolds and Rodriguez 1992). In Lim et al. (1999) an interactive *modeling, simulation, animation, and real-time control* (MoSART) tool to study the twin lift helicopter system is presented. However, only simulation experiments have been found until December 2007, when lifting and transportation of a load by means of three autonomous helicopters (Bernard and Kondak 2009) was demonstrated experimentally in the framework of the AWARE project. After that first successful test, the load transportation system was used again in 2009 to deploy a camera on the roof of a building with a height of 12 m (see Fig. 38.3) in the framework of the same project (Bernard et al. 2011). Notice that in this case, the physical coupling between UAS are involved through direct interactions of each unmanned aerial vehicle with the joint load.

Small-size single or multiple autonomous quadrotors are also considered for load transportation and deployment in Michael et al. (2011), Palunko et al. (2012), and Sreenath et al. (2013). Dynamically coupled quadrotors should cooperate safely to transport load, in contrast to the existing results on formation control of decoupled multi-UAV systems that are addressed in the next section.

38.4 Vehicle Formations and Coordinated Control

In the formations, the members of the group of vehicles must keep user-defined distances with the other group members. The control problem consists of maintaining these user-defined distances, and consequently the configurations of the N neighbors $\bar{q}_i = (q_{i_1}, q_{i_2}, \ldots, q_{i_N})$ in the formation should be taken into account in the control law (see Eq. 38.5). Those configurations can be either received via inter-vehicle communication or estimated using the sensors onboard. Anyway, formation control involves the design of distributed control laws with limited and disrupted communication, uncertainty, and imperfect or partial measurements.

Vehicle formation is a basic strategy to perform multi-vehicle missions including searching and surveying, exploration and mapping, active reconfigurable sensing systems, and space-based interferometry. An added advantage of the formation paradigm is that new members can be introduced to expand or upgrade the formation or to replace a failed member. The stability of the formation has been studied by many researchers that have proposed robust controllers to provide insensitivity to possibly large uncertainties in the motion of nearby agents, transmission delays in the feedback path, and the consideration of the effect of quantized information.

The close formation flight control of homogeneous teams of fixed-wing UAVs airplanes received attention in the last 10 years. The large group formation of small UAVs also offers benefits in terms of drag reduction and then increased payoffs in the ability to maintain persistent coverage of a large area. Both linear (Giulietti et al. 2000) and nonlinear control laws (Schumacher and Singh 2000) have been proposed and tested in simulation. However, practical implementations are still very scarce. In How et al. (2004) a demonstration of two fixed-wing UAVs simultaneous flying, the same flight plan (tracking waypoints in open-loop formation) is reported. In the same paper, two UAVs were linked to the same receding horizon trajectory planner, and independent timing control was performed about the designed plans.

The leader-follower approach mentioned in the previous section has been also used to control general formations where the desired positions of followers are defined relative to the actual state of a leader. It should be noted that every formation can be further divided into simplest leader-follower schemes. Then, in this approach, some vehicles are designated as leaders and track predefined trajectories, while the followers track transformed versions of these trajectories according to given schemes. In the leader-follower approach, path planning only needs to be performed in the leader workspace. The leader-follower pattern is adopted in Yun et al. (2010) to maintain a fixed geometrical formation of unmanned helicopters while navigating following certain trajectories. The leader is commanded to fly on some predefined trajectories, and each follower is controlled to maintain its position in formation using the measurement of its inertial position and the information of the leader position and velocity, obtained through a wireless modem. In Gu et al. (2006) two-aircraft formation flights confirmed the performance of a formation controller designed to have an inner- and outerloop structure, where the outerloop guidance control laws minimized the forward, lateral, and vertical distance error by controlling the engine propulsion and generating the desired pitch and roll angles to be tracked by the innerloop controller. In the formation flight configuration, a radio control pilot maintained ground control of the leader aircraft, while the autonomous follower aircraft maintained a predefined position and orientation with respect to the leader aircraft. The leader-follower approach is applied in Galzi and Shtessel (2006) in the design of robust and continuous controllers to achieve collision-free path-tracking formation in the presence of unknown bounded disturbances acting on each UAV. In Bayraktar et al. (2004) an experiment with two fixed-wing UAVs is presented. The leader UAV was given a predetermined flight plan, and the trajectory of the UAV was updated once per second in real time through the ground station to keep the follower at a fixed distance offset from the leader. Finally, the vehicles platooning can be considered as a particular case consisting of a leader followed by vehicles in a single row. Both lateral and longitudinal control to keep the safe headway, and lateral distance should be considered. The simplest approach relies on individual vehicle control from the data received from the single immediate front vehicle (Bom et al. 2005).

Other methods are based on a virtual leader, a moving reference point whose purpose is to direct, herd, and/or manipulate the vehicle group behavior. The lack of a physical leader among the vehicles implies that any vehicle is interchangeable with any other in the formation. A solution based on a virtual leader approach combined with an extended local potential field is presented in Paul et al. (2008) for formation flight and formation reconfiguration of small-scale autonomous helicopters. And for fixed-wing models, experimental results with YF-22 research aircrafts can be found in Campa et al. (2007), validating the performance of a formation control law using also a virtual leader configuration.

Practical applications of formation control should include a strategy for obstacle avoidance and reconfiguration of the formation. The avoidance of big obstacles could be performed by changing the trajectory of the whole formation to go around the obstacle or to pass through a narrow tunnel (Desai et al. 2001). If the obstacles are smaller than the size of the formation, the vehicles should be able to compromise the formation until the obstacle is passed. In order to do so, the obstacle avoidance behavior should be integrated in the control strategy of the individual members of the formation to avoid/bypass obstacles. Hybrid control techniques have been applied to avoid obstacles and solve the formation reconfiguration (Zelinski et al. 2003).

Formation is not the only cooperative scheme for UAVs in applications such as exploration and mapping. The cooperation of multiple UAVs can be also examined from the point of view of the intentionality to achieve a given mission. Then, according to Parker (1998), it is possible to distinguish between intentional cooperation and swarm-type cooperation. Those approaches are considered in the following two sections:

38.5 Swarms

The key concept in the swarms is that complex collective global behaviors can arise from simple interactions between large numbers of relatively unintelligent agents. This swarm cooperation is based on concepts from biology (Sharkey 2006) and typically involves a large number of homogeneous individuals, with relatively simple sensing and actuation, and local communication and control that collectively achieve a goal. This can be considered as a bottom-up cooperation approach. It usually involves numerous repetitions of the same activity over a relatively large area. The agents execute the same program and interact only with other nearby agents by measuring distances and exchanging messages.

Thus, according to Fig. 38.2 the configurations of the N neighbors $\bar{q}_i = (q_{i_1}, q_{i_2}, \ldots, q_{i_N})$ should be considered as well as the messages $\bar{\mu}_i = (\mu_{i_1}, \mu_{i_2}, \ldots, \mu_{i_{N_m}})$ coming from N_m UAVs cooperating with the i-th UAV. Nevertheless, it should be mentioned that depending on the particular communication and sensing capabilities of the UAVs in the swarm, simplified mechanisms based on partial or imperfect information could be required. For example, the estimation of the full vector $\bar{q}_i$ is not possible in many swarm-based systems, and partial information such as the distances with the neighbors is the only measurement available. The same is applicable to the messages interchanged that can range from data packets sent through wireless links to simple visual signals based on lights of different colors.

The concept of operations for a micro-UAV system is adopted from nature from the appearance of flocking birds, movement of a school of fish, and swarming bees among others. This "emergent behavior" is the aggregate result of many simple interactions occurring within the flock, school, or swarm. Exploration of this emergent behavior in a swarm is accomplished through a high-performance computing parallel discrete event simulation in Corner and Lamont (2004). In Kube and Zhang (1993) different mechanisms that allow populations of behavior-based robots to perform collectively tasks without centralized control or use of explicit communication are presented. Matarić (1992) provides the results of implementing group behaviors such as dispersion, aggregation, and flocking on a team of robots. In Kovacina et al. (2002) a rule-based, decentralized control algorithm that relies on constrained randomized behavior and respects UAV restrictions on sensors, computation, and flight envelope is presented and evaluated in a simulation of an air vehicle swarm searching for and mapping a chemical cloud within a patrolled region. Another behavior-based decentralized control strategy for UAV swarming by using artificial potential functions and sliding-mode control technique is presented in Han et al. (2008). Individual interactions for swarming behavior are modeled using the artificial potential functions. For tracking the reference trajectory of the swarming of UAVs, a swarming center is considered as the object of control. The sliding-mode control technique is adopted to make the proposed swarm control strategy robust with respect to the system uncertainties and varying mission environment.

The bio-inspired motivation of swarms can be found, for example, in Zhang et al. (2007), which describes an adaptive task assignment method for a team of fully distributed vehicles with initially identical functionalities in unknown task environments. The authors employ a simple self-reinforcement learning model inspired by the behavior of social insects to differentiate the initially identical vehicles into "specialists" of different task types, resulting in stable and flexible division of labor; on the other hand, in dealing with the cooperation problem of the vehicles engaged in the same type of task, the so-called *ant system* algorithm was adopted to organize low-level task assignment. Dasgupta (2008) presents a multiagent-based prototype system that uses swarming techniques inspired from insect colonies to perform automatic target recognition using UAVs in a distributed manner within simulated scenarios. In Altshuler et al. (2008) a swarm of UAVs is used for searching one or more evading targets, which are moving in a predefined area while trying to avoid a detection by the swarm (Cooperative Hunters problem). By arranging themselves into efficient geometric flight configurations, the UAVs optimize their integrated sensing capabilities, enabling the search of a maximal territory.

In general, the above approaches deal with homogeneous teams without explicit consideration of tasks decomposition and allocation, performance measures, and individual efficiency constraints of the members of the team. Those aspects are considered in the intentional cooperation schemes described in the next section.

38.6 Intentional Cooperation Schemes

In the intentional cooperation approaches, each individual executes a set of tasks (subgoals that are necessary for achieving the overall goal of the system and that can be achieved independently of other subgoals) explicitly allocated to perform a given mission in an optimal manner according to planning strategies (Parker 1998). The UAVs cooperate explicitly and with purpose but also has the limitation of independent subgoals: If the order of task completion is mandatory, additional explicit knowledge has to be provided to state ordering dependencies in the preconditions. It is also possible to follow a design based on "collective" interaction, in which entities are not aware of other entities in the team, yet they do share goals, and their actions are beneficial to their teammates (Parker 2008).

Key issues in these systems include determining which UAV should perform each task (task allocation problem) so as to maximize the efficiency of the team and ensuring the proper coordination among team members to allow them to successfully complete their mission. In order to solve the multi-robot task allocation problem, some metrics to assess the relevance of assigning given tasks to particular robots are required. In Gerkey and Matarić (2004) a domain-independent taxonomy for the multiagent task allocation problem is presented. In the last years, a popular approach to solve this problem in a distributed way is the application of market-based negotiation rules. An usual implementation of those distributed negotiation rules (Botelho and Alami 1999; Dias and Stenz 2002; Gerkey and Matarić 2002) is based on the Contract Net Protocol (Smith 1980). In those approaches, the messages $\bar{\mu}_i = (\mu_{i_1}, \mu_{i_2}, \ldots, \mu_{i_{N_m}})$ coming from N_m UAVs cooperating with the i-th UAV are those involved in the negotiation process: announce a task, bid for a task, allocate a task, ask for the negotiation token, etc.

Once the tasks have been allocated, it is necessary to coordinate the motions of the vehicles, which can be done by means of suitable multi-vehicle path/velocity planning strategies, as mentioned in Sect. 38.2. The main purpose is to avoid potential conflicts among the different trajectories when sharing the same working space. It should be mentioned that even if the vehicles are explicitly cooperating through messages, a key element in many motion coordination approaches is the updated information about the configurations of the N neighbors $\bar{q}_i = (q_{i_1}, q_{i_2}, \ldots, q_{i_N})$. Formal approaches to the collision avoidance problem and different approaches that can be applied to solve it can be found in LaValle (2006) and Latombe (1990).

On the other hand, teams composed by heterogeneous members involve challenging aspects, even for the intentional cooperation approach. In Ollero and Maza (2007) the current state of the technology, existing problems, and potentialities of platforms with multiple UAVs (with emphasis on systems composed by heterogeneous UAVs) are studied. This heterogeneity is twofold: firstly in the UAV platforms looking to exploit the complementarities of the aerial vehicles, such as helicopters and airships, and secondly in the information-processing capabilities onboard, ranging from pure remotely teleoperated vehicles to fully autonomous aerial robots.

The multi-UAV coordination and control architecture developed in the European COMETS project (Gancet et al. 2005) was demonstrated for the autonomous detection and monitoring of fires (Ollero and Maza 2007) by using two helicopters and one airship (see Fig. 38.4). Regarding teams involving aerial and ground vehicles, the CROMAT architecture also implemented cooperative perception and task allocation techniques (Viguria et al. 2010) that have been demonstrated in fire detection, monitoring, and extinguishing. Multiagent (combined ground and air) tasking and cooperative target localization have been also demonstrated recently (Hsieh et al. 2007) as well as multi-target tracking (ground vehicles) with a micro-UAV (He et al. 2010).

In Maza et al. (2011) a distributed architecture for the autonomous coordination and cooperation of multiple UAVs for civil applications is presented. The architecture is endowed with different modules that solve the usual problems that arise during the execution of multipurpose missions, such as task allocation, conflict resolution, and complex task decomposition. One of the main objectives in the design of the architecture was to impose few requirements to the execution capabilities of the autonomous vehicles to be integrated in the platform. Basically, those vehicles should be able to move to a given location and activate their payload when required. Thus, heterogeneous autonomous vehicles from different manufacturers and research groups can be integrated in the architecture developed, making it easily usable in many multi-UAV applications. The software implementation of the architecture was tested in simulation and finally validated in field experiments with four autonomous helicopters. The validation process included several multi-UAV missions for civil applications in a simulated urban setting: surveillance applying

Fig. 38.4 Coordinated flights in the COMETS project involving an airship and two autonomous helicopters

the strategies for multi-UAV cooperative searching presented in Maza and Ollero (2007); fire confirmation, monitoring, and extinguishing; load transportation and deployment with single and multiple UAVs; and people tracking.

Finally, cooperative perception can be considered as an important tool in many applications based on intentional cooperation schemes. It can be defined as the task of creating and maintaining a consistent view of a world containing dynamic objects by a group of agents each equipped with one or more sensors. Thus, a team of vehicles can simultaneously collect information from multiple locations and exploit the information derived from multiple disparate points to build models that can be used to take decisions. In particular, cooperative perception based on artificial vision has become a relevant topic in the multi-robot domain, mainly in structured environments (Thrun 2001; Schmitt et al. 2002). In Merino et al. (2006) cooperation perception methods for multi-UAV system are proposed. Each UAV extracts knowledge, by applying individual perception techniques, and the overall cooperative perception is performed by merging the individual results. This approach requires knowing the relative position and orientation of the UAVs. In many outdoor applications, it is assumed that the position of all the UAVs can be obtained by means of GPS and broadcasted through the communication system. However, if this is not the case, the UAVs should be capable of identifying and of localizing each other (Konolige et al. 2003) which could be difficult with the onboard sensors. Another approach consists of identifying common objects in the scene. Then, under certain assumptions, the relative pose displacement between the vehicles can be computed from these correspondences. In Merino et al. (2006) this strategy has been demonstrated with heterogeneous UAVs. In the ANSER project (see, e.g., Sukkarieh et al. 2003), decentralized sensor data fusion using multiple aerial vehicles is also researched and experimented with fixed-wing UAVs with navigation and terrain sensors.

38.7 UAVs Networked with Sensors and Actuators in the Environment

The development of wireless communication technologies in the last 10 years makes possible the integration of autonomous vehicles with the environment infrastructure. Particularly, the integration with wireless sensor and actuator networks is very promising. The benefit of this integration can be seen from two different points of view:

- The use of UAVs to complement the information collected by the wireless sensor network (WSN), to perform as mobile "data mules," to act as communication relays, to improve the connectivity of the network, and to repair it in case of malfunctioning nodes.
- The use of WSNs as an extension of the sensorial capabilities of the UAVs. In this case, the information about the objects in the environment will be inferred from all the measurements z_i from the sensors onboard and $\bar{z}_i$ gathered by the fleet of N_s UAVs and nodes that can communicate with the i-th UAV $\{\bar{z}_j, j = 1, \ldots, N_s\}$.

Static wireless sensor networks have important limitations as far as the required coverage and the short communication range in the nodes are concerned. The use of mobile nodes could provide significant improvements. Thus, they can provide the ability to dynamically adapt the network to environmental events and to improve the network connectivity in case of static nodes failure. Node mobility for ad hoc and sensor networks has been studied by many researchers (Grossglauser and Tse 2002; Venkitasubramaniam et al. 2004). Moreover, mobile nodes with single-hop communication and the ability to recharge batteries, or refueling, have been proposed as data mules of the network, gathering data while they are near of fixed nodes and saving energy in static node communications (Jain et al. 2006). The coordinated motion of a small number of nodes in the network to achieve efficient communication between any pair of other mobile nodes has been also proposed.

An important problem is the localization of the nodes of a WSN. This is an open problem because GPS-based solutions in all the nodes are usually not viable due to the cost, the energy consumption, and the satellite visibility from each node. In Caballero et al. (2008) a probabilistic framework for the localization of an entire WSN based on a vehicle is presented. The approach takes advantage of the good localization capabilities of the vehicle and its mobility to compute estimation of the static nodes positions by using the signal strength of the messages interchanged with the network.

However, in many scenarios, the motion of the mobile nodes installed on ground vehicles or carried by persons is very constrained, due to the characteristics of the terrain or the dangerous conditions involved, such as in civil security and disaster scenarios. The cooperation of aerial vehicles with the ground wireless sensor network offers many potentialities. The use of aircrafts as data sinks when they fly over the fixed sensor networks following a predictable pattern in order to

Fig. 38.5 Sensor deployment from an autonomous helicopter in the AWARE project experiments carried out in 2009

gather data from them has been proposed by several authors in the WSN community. In Corke et al. (2003) an algorithm for path computation and following is proposed and applied to guide the motion of an autonomous helicopter flying very close to the sensor nodes deployed on the ground.

It should be noticed that flight endurance and range of the currently available low-cost UAVs is very constrained (Ollero and Merino 2004). Moreover, reliability and fault tolerance is a main issue in the cooperation of the aerial vehicles. Furthermore, these autonomous vehicles need communication infrastructure to cooperate or to be teleoperated by humans in emergency conditions. Usually this infrastructure is not available, or the required communication range is too large for the existing technology. Then, the deployment of this communication infrastructure is a main issue. In the same way, in most wireless sensor networks projects, it is assumed that the wireless sensor network has been previously fully deployed without addressing the problems to be solved when the deployment is difficult. Moreover, in the operation of the network, the infrastructure could be damaged or simply the deployment is not efficient enough. Then, the problem is the repairing of the coverage or the connectivity of the network by adding suitable sensor and communication elements. In Corke et al. (2004) the application of an autonomous helicopter for the deployment and repairing of a wireless sensor network is proposed. This approach has been also followed in the AWARE project (Maza et al. 2010), whose platform has self-deployment and self-configuration features for the operation in sites without sensing and communication infrastructure. The deployment includes not only wireless sensors (see Fig. 38.5) but also heavier loads such as communication equipment that require the transportation by using several helicopters (see Fig. 38.3).

38.8 Conclusions

The concepts of coordinated and cooperative control of multiple UAVs deserved significant attention in the last years in the control, robotics, artificial intelligence, and communication communities. The implementation of these concepts involve integrated research in the control, decision, and communication areas. For instance, the communication and networking technologies play an important role in the practical implementation of any multi-vehicle system. Thus, the integrated consideration of communication and control problems is a relevant research and development topic.

This chapter has first reviewed the existing work on the transportation of a single load by different autonomous vehicles. In order to solve this problem, control theory based on models of the vehicles and their force interactions have been applied. The chapter also studied formation control. In this problem, the application of control theory based on models of the vehicles is dominant. However, behavior-based approaches that do not use these models have been also demonstrated. The work on swarms has been also reviewed. Approaches inspired in biology and multiagent systems are common. The problems are typically formulated for large number of individuals, but up to now, the practical demonstrations involve few physical UAVs. The intentional task-oriented cooperation of robotic vehicles, possibly heterogeneous, has been also addressed. The task allocation problem and the path planning techniques play an important role here, as well as the application of cooperative perception methods.

Finally, the chapter has explored the integration and networking of one or many UAVs with sensors and actuators in the environment pointing out the benefits of this integration. The self-deployment of the network and the motion planning to maintain quality of service are promising approaches that have been preliminarily studied but still require significant attention.

References

Y. Altshuler, V. Yanovsky, I. Wagner, A. Bruckstein, Efficient cooperative search of smart targets using UAV swarms. Robotica **26**(4), 551–557 (2008)

D. Barnes, J. Gray, Behaviour synthesis for co-operant mobile robot control, in *International Conference on Control*, Edinburgh, 1991, vol. 2, pp. 1135–1140

S. Bayraktar, G.E. Fainekos, G.J. Pappas, Experimental cooperative control of fixed-wing unmanned aerial vehicles, in *Proceedings of the IEEE Conference on Decision and Control*, Atlantis, Paradise Island, the Bahamas, 2004

M. Bernard, K. Kondak, Generic slung load transportation system using small size helicopters, in *Proceedings of the International Conference on Robotics and Automation*, Kobe, Japan (IEEE, 2009), pp. 3258–3264

M. Bernard, K. Kondak, I. Maza, A. Ollero, Autonomous transportation and deployment with aerial robots for search and rescue missions. J. Field Robot. **28**(6), 914–931 (2011)

J. Bom, B. Thuilot, F. Marmoiton, P. Martinet, Nonlinear control for urban vehicles platooning, relying upon a unique kinematic GPS, in *Proceedings of the IEEE International Conference on Robotics and Automation*, Barcelona, Spain, 2005, pp. 4138–4143

J. Borenstein, The OmniMate: a guidewire- and beacon-free AGV for highly reconfigurable applications. Int. J. Prod. Res. **38**(9), 1993–2010 (2000)

S.C. Botelho, R. Alami, M+: a scheme for multi-robot cooperation through negotiated task allocation and achievement, in *Proceedings of the IEEE International Conference on Robotics and Automation*, Detroit, 1999, vol. 2, pp. 1234–1239

F. Caballero, L. Merino, P. Gil, I. Maza, A. Ollero, A probabilistic framework for entire WSN localization using a mobile robot. Robot. Auton. Syst. **56**(10), 798–806 (2008)

G. Campa, Y. Gu, B. Seanor, M. Napolitano, L. Pollini, M. Fravolini, Design and flight-testing of non-linear formation control laws. Control Eng. Pract. **15**(9), 1077–1092 (2007)

Y.U. Cao, A.S. Fukunaga, A. Kahng, Cooperative mobile robotics: antecedents and directions. Auton. Robots **4**(1), 7–27 (1997)

L. Chaimowicz, V. Kumar, M.F.M. Campos, A paradigm for dynamic coordination of multiple robots. Auton. Robots **17**(1), 7–21 (2004)

P. Corke, R. Peterson, D. Rus, Networked robots: flying robot navigation using a sensor net, in *Proceedings of the International Symposium of Robotic Research*, Siena, 2003

P. Corke, S. Hrabar, R. Peterson, D. Rus, S. Saripalli, G. Sukhatme, Autonomous deployment and repair of a sensor network using an unmanned aerial vehicle, in *Proceedings of the IEEE International Conference on Robotics and Automation*, New Orleans, LA, USA, 2004, pp. 3602–3608

J.J. Corner, G.B. Lamont, Parallel simulation of UAV swarm scenarios, in *Proceedings of the 36th Conference on Winter Simulation, WSC'04*, Washington, DC, USA, 2004, pp. 355–363

P. Dasgupta, A multiagent swarming system for distributed automatic target recognition using unmanned aerial vehicles. IEEE Trans. Syst. Man Cybern. Part A Syst. Hum. **38**(3), 549–563 (2008)

J.P. Desai, J.P. Ostrowski, V. Kumar, Modeling and control of formations of nonholonomic mobile robots. IEEE Trans. Robot. Autom. **17**(6), 905–908 (2001)

M.B. Dias, A. Stenz, Opportunistic optimization for market-based multirobot control, in *Proceedings IEEE/RSJ International Conference on Intelligent Robots and Systems*, Lausanne, 2002, pp. 2714–2720

A. Fagiolini, G. Valenti, L. Pallottino, G. Dini, A. Bicchi, Decentralized intrusion detection for secure cooperative multi-agent systems, in *Proceedings of the IEEE International Conference on Decision and Control*, New Orleans, LA, USA, 2007, pp. 1553–1558

R. Fierro, A. Das, J. Spletzer, J. Esposito, V. Kumar, J.P. Ostrowski, G. Pappas, C.J. Taylor, Y. Hur, R. Alur, I. Lee, G. Grudic, B. Southall, A framework and architecture for multi-robot coordination. Int. J. Robot. Res. **21**(10–11), 977–995 (2002)

D. Galzi, Y. Shtessel, UAV formations control using high order sliding modes, in *Proceedings of the American Control Conference*, Minneapolis, MN, USA, 2006, vol. 2006, pp. 4249–4254

J. Gancet, G. Hattenberger, R. Alami, S. Lacroix, Task planning and control for a multi-UAV system: architecture and algorithms, in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Edmonton, Canada, 2005, pp. 1017–1022

B. Gerkey, M. Matarić, Sold!: auction methods for multi-robot coordination. IEEE Trans. Robot. Autom. **18**(5), 758–768 (2002)

B. Gerkey, M. Matarić, A formal analysis and taxonomy of task allocation in multi-robot systems. Int. J. Robot. Res. **23**(9), 939–954 (2004)

F. Giulietti, L. Pollini, M. Innocenti, Autonomous formation flight. IEEE Control Syst. Mag. **20**(6), 34–44 (2000)

M. Grossglauser, D.N.C. Tse, Mobility increases the capacity of ad hoc wireless networks. IEEE/ACM Trans. Netw. **10**(4), 477–486 (2002)

Y. Gu, B. Seanor, G. Campa, M. Napolitano, L. Rowe, S. Gururajan, S. Wan, Design and flight testing evaluation of formation control laws. IEEE Trans. Control Syst. Technol. **14**(6), 1105–1112 (2006)

K. Han, J. Lee, Y. Kim, Unmanned aerial vehicle swarm control using potential functions and sliding mode control. Proc. Inst. Mech. Eng., Part G: J. Aerosp. Eng. **222**(6), 721–730 (2008)

R. He, A. Bachrach, N. Roy, Efficient planning under uncertainty for a target-tracking micro-aerial vehicle, in *IEEE International Conference on Robotics and Automation, 2010*, Kobe, Japan, 2010

J. How, E. King, Y. Kuwata, Flight demonstrations of cooperative control for UAV teams, in *Proceedings of the AIAA 3rd Unmanned-Unlimited Technical Conference, Workshop, and Exhibit*, Chicago, 2004, vol. 1, pp. 505–513

M.A. Hsieh, L. Chaimowicz, A. Cowley, B. Grocholsky, J.F. Keller, V. Kumar, C.J. Taylor, Y. Endo, R.C. Arkin, B. Jung, D.F. Wolf, G. Sukhatme, D.C. MacKenzie, Adaptive teams of autonomous aerial and ground robots for situational awareness. J. Field Robot. **24**(11), 991–1014 (2007)

T.L. Huntsberger, A. Trebi-Ollennu, H. Aghazarian, P.S. Schenker, P. Pirjanian, H.D. Nayar, Distributed control of multi-robot systems engaged in tightly coupled tasks. Auton. Robots **17**(1), 79–92 (2004)

S. Jain, R.C. Shah, W. Brunette, G. Borriello, S. Roy, Exploiting mobility for energy efficient data collection in wireless sensor networks. Mobile Netw. Appl. **11**(3), 327–339 (2006)

K. Konolige, D. Fox, B. Limketkai, J. Ko, B. Stewart, Map merging for distributed robot navigation, in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, Las Vegas, 2003, pp. 212–217

K. Kosuge, M. Sato, Transportation of a single object by multiple decentralized-controlled non-holonomic mobile robots, in *Proceedings of the IEEE International Conference on Intelligent Robots and Systems*, Kyongju, Korea, 1999, vol. 3, pp. 1681–1686

M. Kovacina, D. Palmer, G. Yang, R. Vaidyanathan, Multi-agent control algorithms for chemical cloud detection and mapping using unmanned air vehicles, in *Proceedings of the IEEE International Conference on Intelligent Robots and Systems*, Lausanne, Switzerland, 2002, vol. 3, pp. 2782–2788

C.R. Kube, H. Zhang, Collective robotics: from social insects to robots. Adapt. Behav. **2**(2), 189–218 (1993)

J.C. Latombe, *Robot Motion Planning* (Kluwer, 1990)

J.C. Latombe, Robot Motion Planning (Kluwer Academic Publishers, Boston, MA, 1991)

S.M. LaValle, *Planning Algorithms* (Cambridge University Press, Cambridge, 2006) Available at http://planning.cs.uiuc.edu/

H. Li, F. Karray, O. Basir, I. Song, A framework for coordinated control of multiagent systems and its applications. IEEE Trans. Syst. Man Cybern., Part A: Syst. Hum. **38**(3), 534–548 (2008)

C. Lim, R.P. Metzger, A. Rodriguez, Interactive modeling, simulation, animation and real-time control (MoSART) twin lift helicopter system environment, in *Proceedings of the American Control Conference*, San Diego, CA, USA, 1999, vol. 4, pp. 2747–2751

M.J. Matarić, Designing emergent behaviors: from local interactions to collective intelligence, in *From Animals to Animats 2, 2nd International Conference on Simulation of Adaptive Behavior (SAB-92)*, ed. by J.-A. Meyer, H. Roitblat, S. Wilson (MIT, Cambridge, Honolulu, Hawaii, USA, 1992), pp. 432–441

I. Maza, A. Ollero, Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms, in *Distributed Autonomous Robotic Systems 6*, ed. by R. Alami, R. Chatila, H. Asama. Volume 6 of Distributed Autonomous Robotic Systems (Springer, Tokyo/New York, 2007), pp. 221–230

I. Maza, K. Kondak, M. Bernard, A. Ollero, Multi-UAV cooperation and control for load transportation and deployment. J. Intell. Robot. Syst. **57**(1–4), 417–449 (2010)

I. Maza, F. Caballero, J. Capitan, J.M. de Dios, A. Ollero, A distributed architecture for a robotic platform with aerial sensor transportation and self-deployment capabilities. J. Field Robot. **28**(3), 303–328 (2011)

L. Merino, Cooperative perception techniques for multiple unmanned aerial vehicles: applications to the cooperative detection, localization and monitoring of forest fires. PhD thesis, Dpto. Ingenieria de Sistemas y Automatica – University of Seville

L. Merino, F. Caballero, J.M. de Dios, J. Ferruz, A. Ollero, A cooperative perception system for multiple UAVs: application to automatic detection of forest fires. J. Field Robot. **23**(3–4), 165–184 (2006)

N. Michael, J. Fink, V. Kumar, Cooperative manipulation and transportation with aerial robots. Auton. Robots **30**(1), 73–86 (2011)

M. Mittal, J.V.R. Prasad, D.P. Schrage, Nonlinear adaptive control of a twin lift helicopter system. IEEE Control Syst. Mag. **11**(3), 39–45 (1991)

A. Ollero, I. Maza (eds.), *Multiple Heterogeneous Unmanned Aerial Vehicles*. Springer Tracts on Advanced Robotics (Springer, Berlin/New York, 2007)

A. Ollero, L. Merino, Control and perception techniques for aerial robotics. Annu. Rev. Control **28**(2), 167–178 (2004)

I. Palunko, P. Cruz, R. Fierro, Agile load transportation: safe and efficient load manipulation with aerial robots. IEEE Robot. Autom. Mag. **19**(3), 69–79 (2012)

L. Parker, ALLIANCE: an architecture for fault-tolerant multi-robot cooperation. IEEE Trans. Robot. Autom. **14**(2), 220–240 (1998)

L. Parker, Distributed intelligence: overview of the field and its application in multi-robot systems. J. Phys. Agents **2**(1), 5–14 (2008)

T. Paul, T. Krogstad, J. Gravdahl, Modelling of UAV formation flight using 3D potential field. Simul. Model. Pract. Theory **16**(9), 1453–1462 (2008)

H.K. Reynolds, A.A. Rodriguez, H_∞ control of a twin lift helicopter system, in *Proceedings of the 31st IEEE Conference on Decision and Control*, Tucson, AZ, USA, 1992, pp. 2442–2447

T. Schmitt, R. Hanek, M. Beetz, S. Buck, B. Radig, Cooperative probabilistic state estimation for vision-based autonomous mobile robots. IEEE Trans. Robot. Autom. **18**, 670–684 (2002)

C. Schumacher, S. Singh, Nonlinear control of multiple UAVs in close-coupled formation flight, in *Proceedings of the AIAA Guidance, Navigation, and Control Conference*, Denver, CO, USA, 2000, pp. 14–17

A.J.C. Sharkey, Robots, insects and swarm intelligence. Artif. Intell. Rev. **26**(4), 255–268 (2006)

G. Smith, The Contract Net Protocol: high-level communication and control in a distributed problem solver. IEEE Trans. Comput. **29**(12), 1104–1113 (1980)

K. Sreenath, N. Michael, V. Kumar, Trajectory generation and control of a quadrotor with a cable-suspended load – a differentially-flat hybrid system, in *Proceedings of the IEEE International Conference on Robotics and Automation*, Karlsruhe, Germany, 2013

T.G. Sugar, V. Kumar, Control of cooperating mobile manipulators. IEEE Trans. Robot. Autom. **18**(1), 94–103 (2002)

S. Sukkarieh, E. Nettleton, J.-H. Kim, M. Ridley, A. Goktogan, H. Durrant-Whyte, The ANSER project: data fusion across multiple uninhabited air vehicles. Int. J. Robot. Res. **22**(7–8), 505–539 (2003)

S. Thrun, A probabilistic online mapping algorithm for teams of mobile robots. Int. J. Robot. Res. **20**(5), 335–363 (2001)

P. Venkitasubramaniam, S. Adireddy, L. Tong, Sensor networks with mobile agents: optimal random access and coding. IEEE J. Sel. Areas Commun. (Special issue on Sens. Netw.) **22**(6), 1058–1068 (2004)

A. Viguria, I. Maza, A. Ollero, Distributed service-based cooperation in aerial/ground robot teams applied to fire detection and extinguishing missions. Adv. Robot. **24**(1–2), 1–23 (2010)

B. Yun, B. Chen, K. Lum, T. Lee, Design and implementation of a leader-follower cooperative control system for unmanned helicopters. J. Control Theory Appl. **8**(1), 61–68 (2010)

S. Zelinski, T.J. Koo, S. Sastry, Hybrid system design for formations of autonomous vehicles, in *Proceedings of the IEEE Conference on Decision and Control*, Maui, HI, USA, 2003, vol. 1, pp. 1–6

D. Zhang, G. Xie, J. Yu, L. Wang, Adaptive task assignment for multiple mobile robots via swarm intelligence approach. Robot. Auton. Syst. **55**(7), 572–588 (2007)