Chapter 1

Introduction

1.1 MONOGRAPH ROADMAP

This monograph focuses on how to design and employ unmanned systems for remote sensing and distributed control purposes in the current information-rich world. The target scenarios include river/reservoir surveillance, wind profiling measurement, distributed control of chemical leaks, and the like, which are all closely related to the physical environment. Nowadays, threats of global warming and climate change demand accurate and low-cost techniques for a better modeling and control of the environmental physical processes. Unmanned systems could serve as mobile or stationary sensors and actuators. They could save human beings from dangerous, tedious, and repetitious outdoor work, whether it is deep in the ocean or high up in the sky. With the modern wireless communication technologies, unmanned vehicles could even work in groups for some challenging missions such as forest fire monitoring, ocean sampling, and so on. However, unmanned systems still require physics-coupled algorithms to accomplish such tasks mostly in the outdoor unstructured environments. Questions such as what to measure, when to measure, where to measure, and how to control all need to be properly addressed. This monograph presents our approach about how to build and employ unmanned vehicles (ground, air, or combined) to solve the problem of distributed sensing and distributed control of agricultural/environmental systems.

1.1.1 Sensing and Control in the Information-Rich World

Advances in electronics technologies such as embedded systems, microelectromechanical systems, and reliable wireless networks make it possible to deploy low-cost sensors and actuators in large amounts in a large-scale system. This poses a problem for control scientists and engineers on how to deploy and employ those vast amount of networked sensors/actuators optimally. The sensors and actuators can be static or mobile, single or multiple, isolated or networked, all depending on the application scenario. The options for sensor and actuator types are shown in Fig. 1.1. For example, both the temperature probe (point-wise sensing) and the thermal camera

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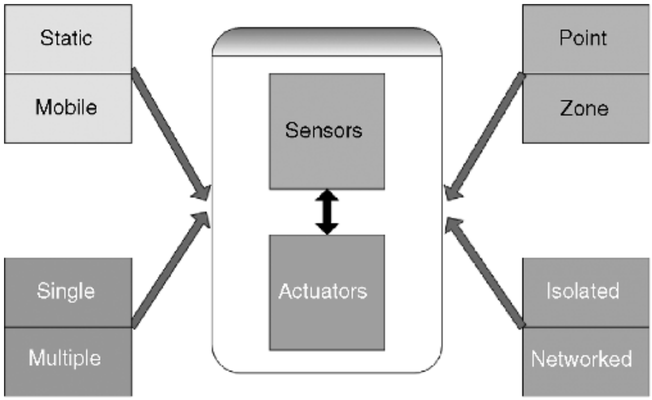

Figure 1.1 Sensors and actuators in an information-rich world.

(zone sensing) could be used to measure the temperature of the crop canopy in a given field of interest. But which one to use? Proper sensing techniques are essential for the high-precision farming that can support the sensing of a large-scale system with an acceptable cost. Thermal aerial images are better for this mission. On the other hand, there are also coarse agricultural applications, which only need the temperature probe due to the cost limits. Another typical example is to use unmanned vehicles to monitor the forest fires. It is intuitive to use multiple unmanned aerial vehicles (UAVs), since they could provide more real-time information. However, there are questions regarding what information to share among UAVs and how often to share.

Unmanned vehicles can add the mobility to the sensors and actuators, which is especially beneficial for most outdoor environment monitoring applications. Different kinds of sensors and actuators could be installed on the unmanned vehicles based on specific application scenarios, as shown in Fig. 1.2. For instance, contact sensors can be installed on unmanned underwater vehicles (UUVs) to make accurate measurements of the temperature and humidity of the sea current. Cameras or radars can be mounted on UAVs for a more complete view of a farm or a reservoir. Chemical sprayers could be installed on unmanned ground vehicles (UGVs) for neutralizing gas leaks or extinguishing fires.

In this monograph, the unmanned system is defined as the unmanned vehicle together with onboard payload sensors or actuators. The fundamental functions of a typical unmanned systems include the mobility, computation, decision making, communication, and sensing/actuation, as shown in Fig. 1.3. Most unmanned systems have a powerful embedded processor to coordinate all the functions and make decisions based on information collected from its own or shared from other neighboring vehicles. With the communication subsystems, groups comprising of heterogeneous unmanned systems can now be designed to cooperate with each other to maximize their capabilities and the team's collective performance.

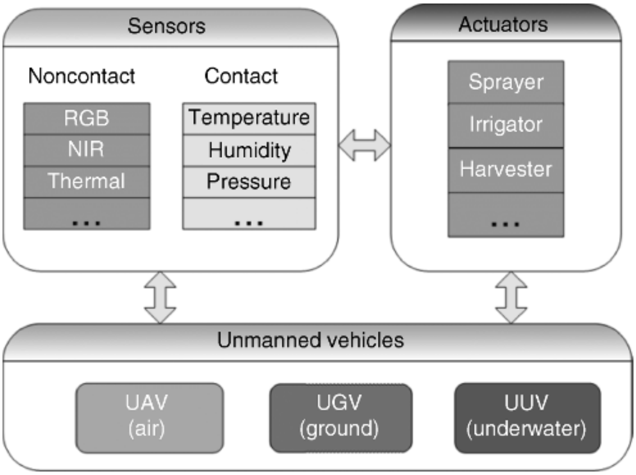

Figure 1.2 Unmanned vehicles as mobile sensors/actuators.

1.1.2 Typical Civilian Application Scenarios

This monograph focuses mostly on the monitoring and control of environmental or agricultural systems or processes, which are of course closely related to human beings. Such systems could be categorized into two groups: fast-evolving ones such as chemical spill, gas leak, or forest fire and slow-evolving ones including heat transfer, moisture changing, wind profiling, and the like. The objective of monitoring these kinds of systems is to characterize how one or several physical entities evolve with both time and space. One typical example is an agricultural farm, as shown in Fig. 1.4. Water managers are interested in knowing how the soil moisture evolves with time in a farm to minimize the water consumption for irrigations. However, the evolution of

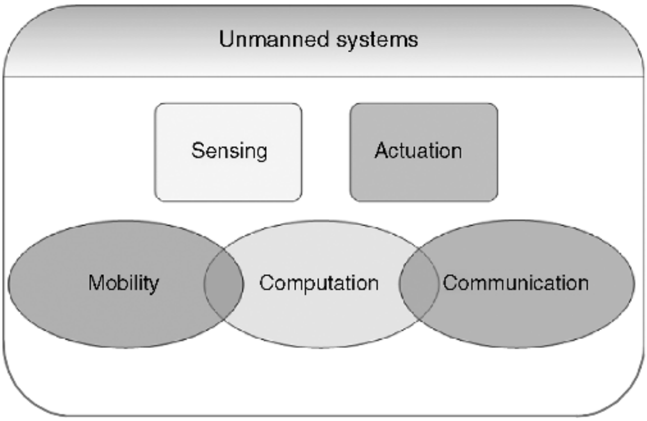

Figure 1.3 System structures of unmanned vehicles.

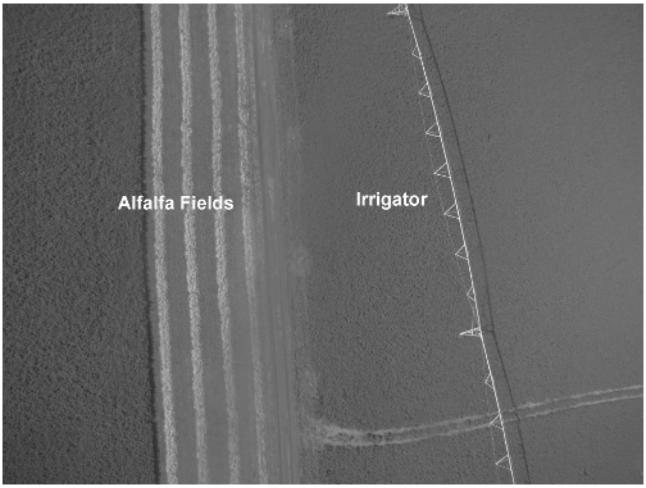

Figure 1.4 Typical agricultural field (Cache Junction, UT). (*See insert for color representation of this figure*.)

soil moisture is affected by many other factors such as water flows, weather conditions (e.g., wind), and vegetation types, which all require measurements over a large scale (typically tens of square miles or even bigger). For such missions, ground probe stations are expensive to build and can only provide sensor data with very limited range. Satellite images can cover a large area, but have a low spatial resolution and a slow temporal update rate. Small UAVs cost less money but can provide more accurate information from low altitudes with less interference from clouds. In addition, small UAVs combined with ground and orbital sensors can form a multiscale remote sensing system, shown in Fig. 1.5.

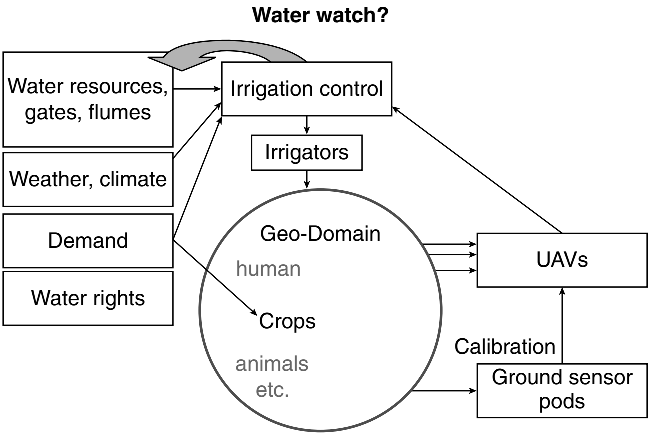

Figure 1.5 Water watch concept.

Figure 1.6 Fog evolution (taken in Yellowstone National Park). (*See insert for color representation of this figure*.)

Other typical civilian applications of unmanned systems include:

- *Forest Fire Monitoring and Containment Control*: The monitoring, prediction, and containment control of forest fires could greatly reduce the potential property damages. Unmanned systems have obvious advantages over manned vehicles because human operators are not required onboard.
- *Fog Evolution or Chemical Leaking Monitoring and Control*: The evolution of hazardous fogs under emergency conditions can cost human lives without accurate and real-time measurements from unmanned systems. Example harmless fog evolutions are shown in Fig. 1.6.
- *Wind Field Measurement*: The wind direction and wind speed could have a significant impact on the diffusion of heat, water, or wind powers. However, the wind field is hard to measure because of its high variation, both temporally and spatially. Unmanned vehicles can be easily sent into the air for accurate 3D measurements.
- *Canopy Moisture Measurement and Irrigation Control*: The moisture on the vegetation canopy represents how much water could be absorbed by the plants. This information can be used for accurate irrigation control. The large scale of most agriculture fields requires cheap sensing techniques.

1.1.3 Challenges in Sensing and Control Using Unmanned Vehicles

The problem of monitoring an environmental field can be defined as below. Let $\Omega \subset R^3$ be a polytope including the interior, which can be either convex or nonconvex.

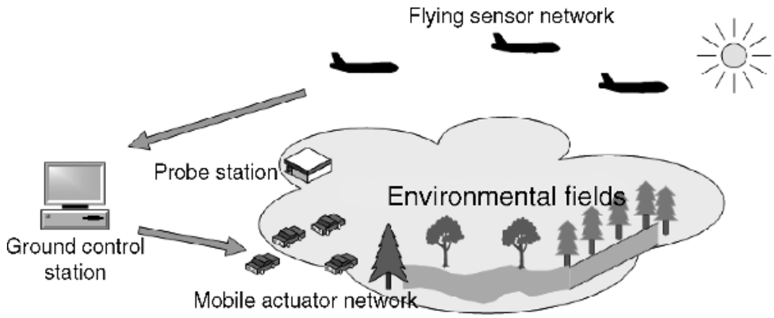

Figure 1.7 Cyber-physical systems.

A series of density functions $\varrho_1, \varrho_1, \varrho_3, \ldots$ are defined as $\varrho_i(q,t) \in [0, \infty), \forall q \in \Omega$. For instance, ϱ_i could be wind direction, surface temperature, soil moisture level, and the like. The goal of monitoring a spatial–temporal process is to find the distribution of the required density functions:

$$\varrho_1(q,t), \varrho_2(q,t), \varrho_3(q,t), \ldots \quad \forall q \in \Omega, \forall t \in [t_1, t_2],$$

with preset spatial and temporal resolutions. The concept of using mobile sensor and actuator network to finish the remote sensing and distributed control missions is shown in Fig. 1.7. For example, a flying sensor network is sent out to collect the information of environmental fields. The ground probe station can be used for sensing validation. A group of ground robots serve as the actuator network to achieve the control missions. The whole system can also be called a cyber-physical system.

There are many challenges to realize this mission, especially for water, agriculture, or environmental applications, as stated in the following:

- *Low-Cost Solutions*: Most civilian applications are highly constrained by the cost. Sometimes, even satellite images are not affordable in a routine way for farmers.
- *Large-Scale Sensing*: Most water lands, agricultural fields are large-scale systems as big as tens or hundreds square miles.
- *High Temporal Requirements*: Some applications require the collections of images while the day light is as strong as possible.
- *High Spatial Requirements*: Many scenarios such as vegetation classification need much higher resolution image than what the normal satellite image can provide.
- *Easy Manipulation*: The civilian applications require the data collection procedure to be as easy as possible and as simple as possible.
- *Advanced Sensor/Actuator Allocation Algorithms*: Both the slow- and fast-evolving processes require properly designed strategies for sensing and control missions.

The above challenges could also be summarized as:

- What to measure and control? What entity needs to be measured and controlled?
- How to measure and control? What sensing or actuation systems are needed given a specific mission?
- When to measure and control? What time or how frequently to perform it?
- Where to measure and control? How to plan the trajectories of mobile sensors and actuators?

1.2 RESEARCH MOTIVATIONS

Several research motivations are listed in the following sections for the sensing and actuation missions of environmental or agricultural fields.

1.2.1 Small Unmanned Aircraft System Design for Remote Sensing

Many farms and environmental fields are tens or hundreds of square miles big. It is too expensive to build ground probes for monitoring purposes in all the interested areas. Remote sensing can provide a good solution here because of the wider sensing footprint from the air. There are several options for remote sensing including satellites, manned aircrafts, and UAVs. Satellite images can cover a large area, but they have low spatial resolutions and slow update rates. Manned aerial imagery is expensive to acquire. Small UAVs cost less money and can provide more accurate information from low altitudes with less interference from clouds. Small UAVs combined with ground and orbital sensors can even form a multiscale remote sensing system.

Technological advances in wireless networks and microelectromechanical systems make it possible to capture aerial images using small and inexpensive UAVs for civilian applications [1]. Small UAVs have a relatively short wingspan and light weight. They can be operated by one to two people [2]. Many of them can even be hand-carried and hand-launched. In fact, small UAVs are designed to fly at low altitude (normally less than 1000 m above the ground) to provide a close observation of the ground objects and phenomena.

The problem of remote sensing using small UAVs can be divided into three subproblems.

1.2.1.1 UAS Integration Problem

The primary problem for using small UAVs in remote sensing is the system integration because there are no commercial off-the-shelf (COTS) inexpensive multispectral UAV solutions for civilian applications to the author's best knowledge. To achieve the autonomous navigation and image capture functions, the minimal UAV system requires the navigation subsystem (autopilot) and the image subsystem. However, the autopilot alone costs around $5000 or more [2]. The integration of the image subsystem to the UAV also requires special considerations not only for the space and weight limits but also for the postflight image georeferencing processes. Different imagers (red–green–blue (RGB), near infrared (NIR), or thermal band) may have special requirements. It is very challenging to integrate all the COTS units and open-source projects into a robust and fully functional UAS.

1.2.1.2 Image Collection Problem

The image collection problem is how to plan the waypoints or trajectory of the UAV or group UAVs so that the images could be captured in a fastest way. The problem can be defined as follows. Given a random area of interest Ω; UAVs with functions of altitude and speed keeping and waypoint navigation: speed v, flight height h; camera with specification: focal length F, image sensor pixel size $PS_h \times PS_v$, image sensor pixel pitch $PP_h \times PP_v$, the "camera shooting interval" t_{shoot}; the desired image resolution res; the control objective is

$$\min t_{flight} = g(\Omega, h, v, \{q_1, \ldots, q_i\}, t_{shoot}, res), \tag{1.1}$$

subject to $v \in [v_1, v_2]$, $h \in [h_1, h_2]$, $t_{shoot} = k \times t_{shoot_{min}}$, where t_{flight} is the flight time of the UAV for effective coverage, $g(\Omega, h, v, t_{shoot})$ is the function to determine the flight path and flight time for effective coverage, $\{q_1, q_2, \ldots, q_i\}$ is a set of preset UAV waypoints, and k is a positive integer. This solution of this optimal problem is also the endurance time of the unmanned system, since both the image acquisition and the UAV trajectory following need to be considered.

1.2.1.3 Image Registration and Postprocessing Problem

After the images are captured, the next problem is to correlate the images with the temporal and spatial data, which is also called georeferencing or image registration. The image information could be further processed to get the final environmental data such as soil temperature, vegetation distributions, and so on.

All three subproblems need to be addressed to design a cheap and robust small UAS for the remote sensing mission.

1.2.2 State Estimation for Small UAVs

The estimation accuracy of the UAV states in the air can greatly affect the UAV flight control performance and the later image georeferencing results. However, many required states are either not directly measurable (e.g., the orientation) or sampled slowly (e.g., the position) with current MEMS sensors. With the emergence of cheaper and smaller MEMS inertial measurement units (IMUs), it is necessary to develop our own state estimation algorithm to further reduce the system costs and to provide more flexibilities in post-flight georeferencing. The following states are indispensable for both the autonomous control and image registration:

- *Position States*: Many civilian GP receivers can only provide position updates at 4 Hz or less, which can introduce a big error if the UAV is moving very fast.
- *Orientation States*: The orientation data are not directly measurable with the current MEMS technology. It can only be estimated using advanced filters from gyros, accelerometers, magnetometers, and the like.

The estimation of the above states requires sophisticated nonlinear filter design techniques and extensive fight test validations for UAV navigation uses. Many researchers have looked into this problem with different hardware platforms. The extended Kalman filter is introduced for MNAV IMU as part of an open-source project [3]. Other researchers also take the speed measurement into consideration for more accurate acceleration estimation [4]. With the current trend of modularization and standardization in the UAV design, UAV developers can save a large amount of time by buying cheap COTS IMUs and configure them into a complete navigation system. Thus, a systematic procedure for the state filter design, tuning, and validation needs to be developed to support these cheap COTS IMUs. Especially, the Kalman filter must be carefully designed to avoid divergence [5].

1.2.3 Advanced Flight Control for Small UAVs

The UAV has an obvious safety advantage over a manned aircraft at extremely low altitudes (e.g., ∼100 m above the ground) because the autopilot can be used for the autonomous navigation replacing the human pilot. The autopilot or flight control system plays a key role not only for the flight stability and navigation but also for sensor interpretation considerations [2]. In a remote surveillance task, the navigation performance of UAVs while flying horizontally could highly affect the georeferencing accuracy of the acquired aerial images. Small or micro-UAV autonomous flight can be easily affected by many factors:

- *Wind*: Wind gusts present a significant control challenge for low-mass airplanes.
- *Flight Altitude*: UAVs may need to fly at a broad range of altitudes for different missions.
- *Payload Variations*: A good UAV flight controller should be robust to payload variations so that it will not stall with little perturbation.
- *Manufacturing Variations and Modeling Difficulties*: Many research UAVs are built from remote controlled (RC) air frames, making it hard to get an accurate dynamic model.
- *Resource Limitations*: Small or micro-UAVs are also constrained by the onboard resources such as limited accuracy for onboard inertial sensors, limited computational power, limited size and weight, and the like.

All the above factors make it very important to design a robust and flexible flight controller. A lot of researchers have looked into the problem of UAV modeling and control. Open-loop steady-state flight experiments are proposed for the aileron-(roll rate) and elevator-(pitch rate) loop system identification (ID) [6]. But the open-loop system ID has to have special requirements on UAV flight stability, which limits the roll and pitch reference signals to be as small as 0.02 rad. UAV model ID experiments can also be performed with human operators controlling the UAVs remotely. Different types of autoregressive with exogenous input (ARX) models are identified while the UAV is flying in loiter mode [7]. Human operators could generate open-loop responses but it may be impossible for some specially designed reference like pseudo-random binary signals (PRBS). Other researchers also tried closed-loop system ID method on separate channels of unmanned helicopters [8–10]. In summary, it is still challenging to accurately model and control small low-cost UAVs. More work on new modeling and controlling techniques are needed.

1.2.4 Cooperative Remote Sensing Using Multiple UAVs

Because of the large-scale characteristics of most environmental fields, many applications may require remote sensing of a large land area (more than 30 square miles) within a short time (less than 1 hour). Acquisition of imagery on this geographic scale is difficult for a single UAV. However, groups of UAVs (which we refer to as "covens") can solve this problem because they can provide images from more spectral bands in a shorter time than a single UAV.

The following missions will need multiple UAVs (covens) operating cooperatively for remote sensing:

- Measure $\eta_1, \eta_2, \eta_3, \ldots$ simultaneously;
- Measure $\eta_i(q, t)$ within a short time.

To fulfill the above requirements, UAVs equipped with imagers having different wavelength bands must fly in some formation to acquire the largest number of images simultaneously. The reason for this requirement is that electromagnetic radiation may change significantly, even over a period of minutes, which in turn may affect the final product of remote sensing.

Many researchers have already looked into the problem of using multiple unmanned vehicles or robots for environmental monitoring problem. A model-free robot path planning algorithm is introduced for the coverage control problem of a density field [11]. The adaptive and singular value-based sampling algorithms are proposed for the ocean field sampling problem [12,13]. However, most of the reported efforts focus on the density field instead of a more complex vector field. Rotary wing UAVs are also used for heat flux estimation with user customized pressure sensing unit [14]. To achieve the optimal measurement of the wind field, groups of UAVs could fly in formations for faster estimation [15]. It is still an open research problem on how to optimally employ groups of unmanned vehicles for specific remote sensing missions.

1.2.5 Diffusion Control Using Mobile Actuator and Sensor Networks

The monitoring and control of a diffusion process can be viewed as an optimal sensor/actuator placement problem in a distributed system [16]. Basically, a series of desired actuator positions are generated based on centroidal Voronoi tessellations (CVT) and later integrated with PID controllers for neutralizing control based on Voronoi partitions. CVT algorithm provides a non-model-based method for coverage control and diffusion control using groups of vehicles. The CVT algorithm is robust and scalable [17,18], and it can guarantee the groups asymptotically converging to the affected area even in multiple/mobile sources application [11].

1.3 MONOGRAPH CONTRIBUTIONS

The major contributions of this monograph include, but are not limited to, the following:

- Explained the system design and test of the AggieAir UAS, a low-cost multispectral remote sensing platform, which is one of the major contributions of this monograph work.
- Summarized several state estimation algorithms for attitude estimation using low-cost IMUs for small UAVs.
- Designed and implemented the very first fractional-order flight controller to guide the UAV in real flights.
- Jointly developed the path planning algorithm for the remote sensing mission using a single UAV with different ground resolution requirements.
- Implemented and validated the multivehicle consensus algorithm on MASnet platform with different communication topologies.
- Proposed the consensus CVT-based path planning algorithm for the diffusion control problem.

Most of the algorithms and theories are validated on the following simulation or experimental platforms:

- Aerosonde UAV software simulation platform for flight controller design, state estimation algorithm tests;
- AggieAir UAV experimental platform for remote sensing, flying sensor network;
- MASnet hardware simulation platform for formation control, consensus validations;
- DiffMAS2D software simulation platform for diffusion control simulation.

1.4 MONOGRAPH ORGANIZATION

The monograph is organized as the following. The research motivations and monograph contributions are introduced in Chapter 1. Chapter 2 is dedicated to the introduction of AggieAir UAS platform, a low-cost multispectral remote sensing platform, with detailed explanation on the system design requirements, subsystem structures, and flight test protocol developments. Chapter 3 focuses on the state estimation problems for small UAVs. The fractional order PI^{α} controller is designed and implemented on the roll-channel in Chapter 4 including model ID methods, controller designing procedure, and simulation/experimental validation results. Chapter 5 explains how to finish a typical remote sensing task using a single UAV with lots of application scenarios such as water area, farmland, road coverage, and the like. The remote sensing problem using multiple unmanned vehicles is presented in Chapter 6. The multivehicle consensus algorithm is first tested on the MASnet platform and then a new algorithm for wind profiling measurement using multiple UAVs is proposed and tested in the simulation. Chapter 7 is devoted to the distributed control of a diffusion process using mobile sensor and actuator networks. The consensus and CVT-based path planning algorithm is proposed and tested in simulations. Chapter 8 is for the conclusions and some future research suggestions.

REFERENCES

1. D. W. Casbeer, S. M. Li, R. W. Beard, T. W. McLain, and R. K. Mehra. Forest fire monitoring with multiple small UAVs. In *Proceedings of the American Control Conference*, pages 3530–3535, June 2005.
2. H. Chao, Y. Cao, and Y. Q. Chen. Autopilots for small unmanned aerial vehicles: a survey. *International Journal of Control, Automation, and Systems*, 8(1):36–44, 2010.
3. J. S. Jang and D. Liccardo. Small UAV automation using MEMS. *IEEE Aerospace and Electronic Systems Magazine*, 22(5):30–34, 2007.
4. D. B. Kingston and R. W. Beard. Real-time attitude and position estimation for small UAVs using low-cost sensors. In *Proceedings of the AIAA 3rd Unmanned Unlimited Systems Conference and Workshop*, number AIAA-2007-6514, Chicago, IL, September 2004.
5. L. Perea, J. How, L. Breger, and P. Elosegui. Nonlinearity in sensor fusion: divergence issues in EKF, modified truncated SOF, and UKF. In *Proceedings of the AIAA Guidance, Navigation and Control Conference and Exhibit*, number AIAA-2007-6488, August 2007.
6. J. Nino, F. Mitrachea, P. Cosynb, and R. D. Keyser. Model identification of a micro air vehicle. *Journal of Bionic Engineering*, 4(4):227–236, 2007.
7. H. Wu, D. Sun, K. Peng, and Z. Zhou. Modeling identification of a micro air vehicle in loitering flight based on attitude performance evaluation. *IEEE Transactions on Robotics and Automation*, 20(4):702–712, 2004.
8. Y. Lee, S. Kim, and J. Suk. System identification of an unmanned aerial vehicle from automated flight tests. In *Proceedings of the AIAA's 1st Technical Conference and Workshop on Unmanned Aerospace Vehicles*, May 2002.

9. G. Cai, B. M. Chen, K. Peng, M. Dong, and T. H. Lee. Modeling and control of the yaw channel of a UAV helicopter. *IEEE Transactions on Industrial Electronics*, 55(9):3426–3434, 2008.
10. S. Duranti and G. Conte. In-flight identification of the augmented flight dynamics of the RMAX unmanned helicopter. In *Proceedings of the Seventeenth IFAC Symposium on Automatic Control in Aerospace*, June 2007.
11. J. Cortés, S. Matínez, T. Karatas, and F. Bullo. Coverage control for mobile sensing networks. *IEEE Transactions on Robotics and Automation*, 20(20):243–255, 2004.
12. A. Caiti, G. Casalino, E. Lorenzi, A. Turetta, and R. Viviani. Distributed adaptive environmental sampling with AUVs: cooperation and team coordination through minimum-spanning-tree graph searching algorithms. In *Proceedings of the Second IFAC Workshop on Navigation, Guidance and Control of Underwater Vehicles*, April 2008.
13. D. O. Popa, A. C. Sanderson, V. Hombal, R. J. Komerska, S. S. Mupparapu, D. R. Blidberg, and S. G. Chappel. Optimal sampling using singular value decomposition of the parameter variance space. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3131–3136, August 2005.
14. J. Bange, P. Zittel, T. Spieß, J. Uhlenbrock, and F. Beyrich. A new method for the determination of area-averaged turbulent surface fluxes from low-level flights using inverse models. *Boundary-Layer Meteorology*, 119(3):527–561, 2006.
15. Y. Q. Chen and Z. Wang. Formation control: a review and a new consideration. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 3181–3186, August 2005.
16. D. Ucinski. *Optimal Measurement Methods for Distributed Parameter System Identification*. CDC Press, Boca Raton, FL, 2004.
17. Y. Q. Chen, Z. Wang, and J. Liang. Actuation scheduling in mobile actuator networks for spatial-temporal feedback control of a diffusion process with dynamic obstacle avoidance. In *Proceedings of the IEEE International Conference on Mechatronics and Automation*, pages 1630–1635, June 2005.
18. H. Chao, Y. Q. Chen, and W. Ren. A study of grouping effect on mobile actuator sensor networks for distributed feedback control of diffusion process using central voronoi tessellations. *International Journal of Intelligent Control Systems*, 11(2):185–190, 2006.