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Lucian Buşoniu · Levente Tamás  
Editors

# Handling Uncertainty and Networked Structure in Robot Control

 Springer

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# Acronyms

This list below collects the acronyms used in this book, in alphabetical order. Common-knowledge abbreviations such as WLAN, RGB, etc., are not included.

A-IDA-AC	Algebraic Interconnection Damping Assignment Actor–Critic
A-opt	A-optimality criterion
AE	Analysis Engine
AUV	Autonomous Underwater Vehicle
BMI	Bilinear Matrix Inequality
BP-AR-HMM	Beta-Process Autoregressive Hidden Markov Model
CAS	Common Analysis Structure
CGP	Cox Gaussian Process
CRAM	Cognitive Robot Abstract Machine
D-opt	D-optimality criterion
DCF	Distributed Coordination Function
DI	Damping Injection
DMP	Dynamical Movement Primitives
DoA	Domain of Attraction
DoF	Degree(s) of Freedom
E-opt	E-optimality criterion
EIEIO	Exploitation by Informed Exploration between Isolated Operatives
EIG	Expected Information Gain
EKF	Extended Kalman Filter
EPSAC	Extended Prediction Self-Adaptive Control
ES-DI	Energy-Shaping and Damping-Injection
FOL	First Order Logic
FoV	Field of View
FoW	Fog of War
GP	Gaussian Process
GP-NBC	Gaussian Process Non-Bayesian Clustering
GP-NBC-MBRL	Gaussian Process Non-Bayesian Clustering Model-Based RL



GPC	Gaussian Process Clustering
GPR	Gaussian Process Regression
GPS	Global Positioning System
GT	Ground Truth
GUES	Globally Uniformly Exponentially Stable
HT	Hough Transformation
ICP	Iterative Closest Point
IDA-PBC	Interconnection and Damping Assignment Passivity-Based Control
ILC	Iterative Learning Control
IMU	Inertial Measurement Unit
KL	Kullback–Leibler
Lidar	Light Detection and Ranging
LKF	Linear Kalman Filter
LM	Levenberg Marquardt
LMI	Linear Matrix Inequality
LTA	Long-Term Assignment
MAC	Medium Access Control
MAS	Multi-Agent System
MBRL	Model-Based Reinforcement Learning
MCM	Naval Mine Countermeasure Missions
MDP	Markov Decision Process
MF	Membership Function
MLN	Markov Logic Network
MongoDB	Mongo Data Base
MPC	Model-based Predictive Control
MRF	Markov Random Field
MTU	Maximum Transmission Unit
N-MDP	Nonstationary Markov Decision Process
NARF	Normal Aligned Radial Feature
NDT	Normal Distribution Transform
OCR	Optical Character Recognition
P-CGP	Poisson–Cox Gaussian Process
PA	Precision agriculture
PANDORA	Persistent Autonomy through learning, adaptation, Observation and Replanning
PBC	Passivity Based Control
PCA	Principal Component Analysis
PCL	Point Cloud Library
PF	Particle Filter
PHT	Probabilistic Hough Transformation
POMDP	Partially Observable Markov Decision Process
PRM	Probabilistic RoadMaps
RANSAC	Random Sample Consensus
RFDM	Reactive Fuzzy Decision Maker

RGB-D	Red Green Blue and Depth
RIFT	Rotation Invariant Feature Transform
RL	Reinforcement Learning
RMB	Rotating Multi-Beam
ROS	Robotic Operating System
SAC	SAmple Consensus
SC-RL	Sequential Composition Reinforcement Learning
SDK	Software Development Kit
SHOT	Signature of Histograms of OrienTations
SIFT	Scale Invariant Feature Transform
SLAM	Simultaneous Localization and Mapping
SofA	Subject of Analysis
SoS	Sum of Squares
SPLAM	Simultaneous Planning, Localization and Mapping
SRL	Statistical Relational Learning
STA	Short-Term Assignment
STRIPS	Stanford Research Institute Problem Solver
SVD	Singular Value Decomposition
SVM	Support Vector Machine
TCP	Transmission Control Protocol
TOED	Theory of Optimal Experimental Design
TS	Takagi–Sugeno
UAS	Unmanned Aerial System
UAV	Unmanned Aerial Vehicle
UDP	User Datagram Protocol
UGS	Unattended Ground Sensors
UGV	Unmanned Ground Vehicle
UIM	Unstructured Information Management
UIMA	Unstructured Information Management Architecture
UKF	Unscented Kalman Filter
VFH	Viewpoint Feature Histogram
VoI	Value of Information
VP	Vanishing Point
VSL	Visuospatial Skill Learning
WDS	Wireless Distribution System
WF	Weighting Function

# Introduction

## Brief Background

The field of robotics started in the nineteenth century, with teleoperated vehicles. The motivation to further develop these devices arose from military interests, especially after the World Wars. The switch from remote controlled vehicles to autonomous ones began after the Second World War, when the early mobile robot called *Machina Speculatrix* was designed, which was able to follow a light source. The first boom in autonomous robotics was in the late 1960s, and continues to the present day.

Robots are generally designed for transportation, manipulation, and surveillance tasks. Based on their configuration in space and the range of movement they can perform, one can distinguish between mobile robots (e.g. wheeled, underwater, or flying vehicles) (Ge and Lewis 2006) and fixed object manipulators (Lewis et al. 2006). The mixture of these two types is usually referred to as mobile manipulators. For all these classes of robots, achieving autonomy crucially requires *automatic control*: algorithms that, without human assistance, are able to actuate the robot so as to achieve a desired configuration, to navigate through the environment, or to manipulate this environment in a useful way (Spong and Hutchinson 2005; Lewis et al. 2006; Bruno and Oussama 2008; Siegwart et al. 2011). Feedback from sensors is required since an exact model of the task is never available, and the robot must be able to compensate for model errors as well as unmodeled effects, such as a varying mass of the transported objects.

Traditionally, robot control deals with industrial robots, where the environment is predictable and the robot can function using models of the environment and precomputed movements, with limited sensing. During the 1980s the trend shifted from this classical way of thinking, dominant in the 1970s, towards the reactive paradigm, which focuses more on sensor feedback (Brady et al. 1982). A further extension was the hybrid approach, using reactive principles at lower levels and higher-level model-based approximations (Khatib and Craig 1989). More recently, the probabilistic robotics framework became dominant in research (Thrun et al.

2005). This framework explicitly takes into account the inaccuracy in the models and sensors, and handles it in the control algorithms. This is important for robots to achieve autonomy outside the industrial setting, and to perform their tasks in uncertain, open environments. Sensing the environment is absolutely essential in this paradigm, and with new hardware such as stereo cameras, inertial units, and depth sensors, the autonomy of the robots is greatly expanded. High-speed and application-specific microprocessors enable the use of robots in real-time applications, by processing challenging large-volume sensing data from, e.g. stereo cameras or depth sensors, and by allowing better control laws that take into account the complexity of the robot and environment dynamics.

The importance of robotic control is reflected by the focus placed on it in the top publication outlets on robotics on the one hand, and in systems and control on the other. For example, the International Conference on Robotics and Automation includes automatic control in the very title, and its 2014 edition included six workshops related to control; the same number was hosted by the 2014 International Conference on Intelligent Robots and Systems. The latest editions of the two main control events, the Conference on Decision and Control and the American Control Conference, dedicated specific tracks to control and sensing for (primarily mobile) robots. Robot control is also prominent in leading journals in the two fields: IEEE Transactions on Robotics, Robotics and Autonomous Systems, Automatica, Control Engineering Practice, etc.

Against this background, our book focuses on learning and sensing approaches to address the environment uncertainty, as well as on the control of networked and interconnected robots, as described next.

## Goal and Motivation of the Book

While robots have long left factory floors, real penetration of advanced robotics outside the industry has been slow over the past decades, with research outcomes mainly remaining within the academia. The situation has however changed dramatically in recent years, with many novel marketable applications and robotic platforms appearing:

- domestic and assistive robots, such as Roomba, Mowbot, Create, and Aibo;
- research and educational robots: Robotino, Mindstorm, PR2, TurtleBot;
- surveillance in large, open environments for mapping, search & rescue, etc., with robots like the PackBot, Ranger, PatrolBot;
- and of course the unprecedented explosion in unmanned aerial vehicles (UAVs) over the last couple of years, with proposed civilian applications ranging from package delivery, through parking guidance, to delivering defibrillators to heart attack patients, see e.g. SUAS (2015).

Additional application domains are emerging, including surgical robots, surveillance in agriculture, space robotics, etc.

The defining characteristic of all these applications is the unpredictability and open, large-scale structure of the environment—which is often shared with humans. These features create several challenges for robot control, among which in this book we focus on two major ones. The first is *uncertainty* about the environment, coming either from the *limited sensors* available to measure the variables relevant for control or, more fundamentally, because the robot does not know how the environment *evolves and reacts* to its actions. Dealing with uncertainty is a traditional topic in robotics (Thrun et al. 2005; Stachniss 2009) and overall in systems and control (Ristic et al. 2004), although it is still unsolved in general. In the absence of prior knowledge about the environment dynamics, learning a controller is the method of choice (Sutton and Barto 1998; Sigaud and Peters 2010; Lewis and Liu 2012).

The second challenge we focus on is *networked structure*, which appears in many of the applications mentioned above. This is because the robot and its controller are often separated by a significant distance, while for mobile ground robots or UAVs wired connections are not feasible, and the robot must instead be controlled wirelessly. In all these cases, exchanging signals over a network is the best solution, but this comes with its own constraints and challenges that must be taken into account. Networked structure is also very important in large environments, where teams of robots are required (Balch and Parker 2002) and communication among them to arrive at coherent sensor measurements or control actions is highly nontrivial. A particularly interesting problem occurs at the intersection of uncertainty and networked robotic teams: distributed sensing under uncertainty. When the uncertainty is driven by the physically distributed nature of the system, consensus algorithms can help in reaching an agreement on measurements. Overall, networked and interconnected systems comprise quite a new topic and their intersection with robotics is still in its starting phase, but the advance in the field has been quite significant in recent years (Shamma 2007; Bullo et al. 2009; Bemporad et al. 2010).

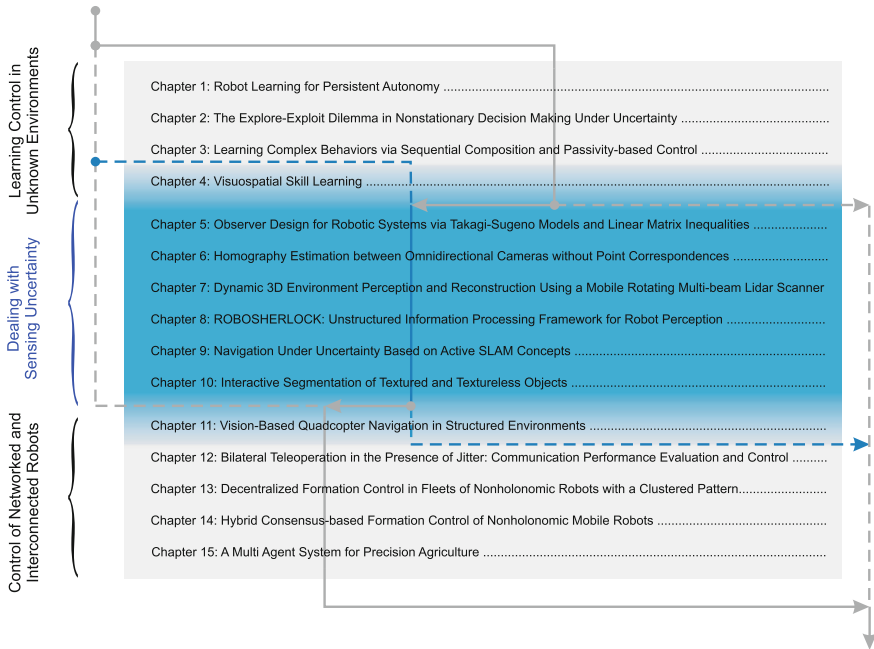
For both classical and newer topics, however, the recent growth in human–environment robotics has increased the pace of novel research. For the researcher or graduate student who is working on robot control, a resource is needed that presents recent advances on dealing with uncertainty and networked structure. Such a resource would also help researchers or Ph.D. students who wish to enter robot control arriving from a related area (e.g. general control systems or computer vision). The aim of our book is to provide this resource: a snapshot of this area as it stands now, collecting in a single, coherent monograph a representative selection of state-of-the-art techniques. To this end, we have invited chapter contributions from experts in the relevant fields: robot control, learning control, state estimation, robot perception, and the control of networked and interconnected systems. To achieve a balanced viewpoint, we have included both already established, highly influential experts as well as younger researchers that have nevertheless already had a significant impact.

## Book Structure

We structure the book along the three main challenges identified above: learning control to handle uncertainty about the dynamics; sensing under uncertainty, particularly as it pertains to control; and networked control of robots and multirobot systems. An overall view of this structure including chapter titles is given in Fig. 1, and more details, including chapter outlines, are provided next.

The book starts with Part I: **Learning Control in Unknown Environments**, with a selection of learning-based techniques to handle uncertain dynamics. In order to develop robots that solve long-term missions in unknown, open environments, it is important to deal with failures (Chap. 1), to explore efficiently environments that change in time (Chap. 2), and to approach the problem in a practical way that exploits any available prior knowledge while learning to deal with the unknown parts of the environment (Chaps. 3 and 4). Starting off by imitating a human expert (Chaps. 1 and 4) is particularly promising.

In more detail, Chap. 1, *Robot Learning for Persistent Autonomy*, presents an overarching view and a significant step towards the major robotics goal of performing long-term autonomous missions. This is achieved by a combination of learning from expert demonstrations, and learning to recover from failures. Practical experiments illustrate the technique: valve-turning with the Kuka robot arm, and



**Fig. 1** Organization of the book. The *background* color changes for each main part, and the *arrows* indicate possible ways of reading the book

recovery from thruster failures with the Girona500 Autonomous Underwater Vehicle (AUV). Chapter 2, *The Explore–Exploit Dilemma in Nonstationary Decision Making Under Uncertainty*, again uses reinforcement learning methods in unknown environments but focuses on a complementary aspect: choosing when to exploit the information already gathered, versus exploration to learn more about the environment. This is done in the particularly challenging case of an environment that changes in time, and two methods are proposed to anticipate interesting changes. Simulated applications are given: planning least-visible paths for unmanned aerial vehicles (UAVs) in human environments, and surveillance via unattended ground sensors assisted by UAVs. Chapter 3, *Learning Complex Behaviors via Sequential Composition and Passivity-Based Control*, gives a modular approach where local controllers are learned with reinforcement learning and then sequentially composed with a finite-state machine, which is itself adaptive by finding the domains of attraction of each local controller. This idea is very useful for robots that operate in several modes, such as UAVs, which switch between takeoff, hovering, cruise flight, and landing modes. The approach allows including partial prior knowledge about the solution structure and dynamics, but does not require a full model—and learning tackles the unknown part. Chapter 4, *Visuospatial Skill Learning*, gives another modular approach that assumes predefined motor primitives such as grasping are available. Exploiting these primitives, learning is performed directly in the visual task space, starting from an expert demonstration and aiming to reproduce a given object configuration. The method is illustrated in simulations and on the Barret WAM robotic arm, which uses it to solve several real-life tasks.

The approach in Chap. 4 blurs the line between control and visual sensing, and so provides a transition to Part II: **Dealing with Sensing Uncertainty**. Even if the dynamics of the environment are fully known, before the robot can effectively solve a task there still remains the problem of finding the values of variables that are needed as inputs for control decisions. These variables are subject to uncertainty because the sensors of the robot cover a limited area, and extracting useful information often requires high-complexity processing of the raw data they provide (e.g. for stereo cameras or high density Lidars). We start by covering two basic problems for which research is still ongoing: determining the state variables (pose and velocities) of the robot itself (Chap. 5) and the relative poses of different cameras (Chap. 6). We then move on to higher-level perception methods for scene reconstruction and understanding (Chaps. 7 and 8). We end Part II by two chapters that focus on the active sensing paradigm, which closes the loop between sensing and control in an interesting way, by *controlling* the robot so as to reduce the uncertainty in sensing. Active sensing is exploited to obtain better localization (Chap. 9) and to improve object segmentation (Chap. 10).

Specifically, Chap. 5, *Observer Design for Robotic Systems via Takagi–Sugeno Models and Linear Matrix Inequalities* deals with state estimation, which is made challenging by the nonlinearity of the dynamics. The mass matrix appearing in the structure is exploited when representing the dynamics in a Takagi–Sugeno form, and the state estimator is proven to be convergent by Lyapunov techniques that boil

down to solving linear matrix inequalities. A simulated example involving a two-wheeled mobile robot is provided. Chapter 6, *Homography Estimation between Omnidirectional Cameras without Point Correspondences*, presents a method to estimate the homography mapping between two omnidirectional cameras that look at the same scene. The method is novel in its use of matching segmented surfaces rather than pairs of points in the images, and its viability on real images is demonstrated.

Moving on to higher-level perception, Chap. 7, *Dynamic 3D Environment Perception and Reconstruction Using a Mobile Rotating Multi-beam Lidar Scanner*, describes a complete pipeline for online detection and tracking of pedestrians and vehicles, and for offline analysis of urban scenes, both from multi-beam LIDAR data. The method is evaluated in real urban environments. Chapter 8, *ROBOSHERLOCK: Unstructured Information Processing Framework for Robot Perception* describes an overall framework for perception that is able to respond to sensing queries from the controller phrased as high-level questions (such as ‘Where is object X?’). The framework was implemented in an open-source package and tested in a household environment using data acquired from a PR2 robot.

In Chap. 9, *Navigation Under Uncertainty Based on Active SLAM Concepts*, the objective is to control the robot so as to reduce the uncertainty in the robot’s location. The chapter provides an extensive overview of the active SLAM field, and describes a state-of-the-art approach that constructs a graph of robot configurations and then computes a minimal-uncertainty path using a graph search algorithm. The approach is validated on several public datasets. Chapter 10, *Interactive Segmentation of Textured and Textureless Objects*, goes beyond planning the trajectory, by allowing the robot to interact with the environment in order to reduce uncertainty. Specifically the robot grasps and moves objects in order to better segment them. Real-life evaluation is performed on cluttered scenes using the PR2 humanoid robot.

Part III: **Control of Networked and Interconnected Robots** deals with the network effects that appear for wirelessly controlled mobile robots and in communicating robot teams. This last part of the book starts with a transition Chap. 11, which still devotes significant attention to sensing but starts taking into account networked control effects. Chapter 12 studies the impact of such effects in robotic teleoperation. For the remainder of the book, we move to multirobot systems and tackle issues of agreement in the presence of communication constraints (Chaps. 13 and 14) and of cooperative control for a mixed ground-and-aerial robot team (Chap. 15).

Chapter 11, *Vision-Based Quadcopter Navigation in Structured Environments*, uses vision to detect and track the vanishing point of lines in perspective, in corridor and corridor-like environments. The robot (an AR.Drone 2 UAV) then navigates the environment by moving forward while keeping the vanishing point centered. Significant challenges arise due to the WiFi network interposed between the controller and the system: image frames arrive at varying intervals and many are dropped. This is compensated by running the filter in prediction mode. Chapter 12, *Bilateral Teleoperation in the Presence of Jitter: Communication Performance*



*Evaluation and Control*, studies in detail the impact of time-varying delays in robotic teleoperation—still a single-robot system like in Chap. 11, but now operated through a haptic device. A controller designed in the passivity framework is proposed that can effectively deal with these delays. Practical experimental results are shown on a Kuka robot arm operated with the Sensable Phantom Omni haptic device.

In Chap. 13, *Decentralized Formation Control in Fleets of Nonholonomic Robots with a Clustered Pattern*, the objective is for a team of nonholonomic mobile robots to reach a given formation in a decentralized way. The robots are organized in subteams that communicate internally, and the team leaders communicate sporadically among themselves to achieve overall agreement. The network is limited to a graph structure due to limited range, both within the teams as well as between the leaders. Chapter 14, *Hybrid Consensus-Based Formation Control of Nonholonomic Mobile Robots*, considers a similar problem of decentralized formation control, but with the addition that the robots must also navigate to a goal area. The robots form a single team (graph), and a control law is given that switches between two modes: formation-alignment, and navigating to the goal. Both Chaps. 13 and 14 validate the techniques in simulations of mobile robot teams. Finally, Chap. 15, *A Multi-Agent System for Precision Agriculture*, is focused on the emerging application of monitoring crops. A two-layer multirobot system is proposed, consisting of ground robots that navigate the cultivated field, and UAVs that act as longer-range sensors for the ground robots, by e.g. directing them to areas of interest and around obstacles. The components of the approach are tested in experiments on Surveyor SRV-1 ground robots and AR.Drone UAVs.

The book can be read in several ways, by following the arrows in Fig. 1. Besides the default order of reading all the chapters in sequence (continuous line), the three parts are sufficiently self-contained to be read individually (dashed lines), with the following note. If the reader chooses to focus only on Part II, it is recommended to additionally read the connecting Chaps. 4 and 11, since these contain important elements of sensing under uncertainty.

For the more application-oriented reader, an alternative way of looking at the book is by the type of robotic platform used in the experimental validation. Table 1 organizes the chapters by this criterion. Note that although they do not appear in this table, Chaps. 3, 6, and 9 of course still provide experimental validations, but this validation does not concern a specific robotic platform since the method is general and can be applied to any platform (e.g. vision methods that are tested on public datasets).

**Table 1** Chapters organized by the type of robotic platform used in the evaluations

Mobile ground robots	Chapters 5, 7, 13, 14, 15
Unmanned aerial vehicles	Chapters 2, 11, 15
Autonomous underwater vehicles	Chapter 1
Robot arms	Chapters 1, 4, 12
Humanoid robots	Chapters 8, 10

Boldface font indicates real-life experiments, while the other chapters contain simulations

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