Preface

We have witnessed a surge of applications using static or mobile sensor networks interacting with uncertain environments. To treat a variety of useful tasks such as environmental monitoring, adaptive sampling, surveillance, and exploration, this book introduces a class of problems and efficient spatio-temporal models when scalar fields need to be predicted from noisy observations collected by mobile sensor networks. The book discusses how to make inference from the observations based on the proposed models and also explores adaptive sampling algorithms for robotic sensors to maximize the prediction quality subject to constraints on memory, communication, and mobility.

The objective of the book is to provide step-by-step progress in chapters for readers to gain better understanding of the interplay between all the essential constituents such as resource-limited mobile sensor networks, spatio-temporal models, data-driven prediction, prediction uncertainty, and adaptive sampling for making better predictions. The book builds on previous collective works by the authors and is not meant to provide a comprehensive review of the topics of interest. Specifically, materials from the previous publications by the authors [1–5] make up a large portion of the book.

In this book, a spatio-temporal scalar field is used to represent the collection of scalar quantities of interest, such as chemical concentration or biomass of algal blooms (e.g., see Fig. 1.3), transported via physical processes. To deal with complexity and practicality, phenomenological and statistical modeling techniques are used to make inference from noisy observations collected, taking into account a large scope of uncertainties. To this end, nonparametric models such as Gaussian processes and Gaussian Markov random fields (GMRFs), along with their prediction and adaptive sampling algorithms, will be explored and tailored to our needs. The importance of selecting a Gaussian process prior via hyperparameters for given experimental observations is illustrated (Chap. 3). Adaptive sampling to improve the quality of hyperparameters is proposed (Chap. 3). Memory efficient prediction based on truncated observations in space and time as well as the collective mobility based on distributed navigation are discussed (Chap. 4). While the book starts with a rather simple empirical Bayes approach (Chap. 3), as we move through further chapters, we discuss recent efforts with a fully Bayesian perspective to maximize the flexibility of the models under various uncertainties while minimizing the computational complexity (Chaps. 5 and 7). A fully Bayesian framework is adopted here as it offers several advantages when inferring parameters and processes from highly complex models (Chaps. 5 and 7). The Bayesian approach requires prior distributions to be elicited for model parameters that are of interest. Once the priors are elicited, the Bayesian framework is flexible and effective in incorporating all uncertainties as well as information (limited or otherwise from data) into a single entity, namely, the posterior. The fully Bayesian approach thus allows additional sources and extent of uncertainties to be integrated into the inferential framework, with the posterior distribution effectively capturing all aspects of uncertainties involved. Subsequently, the practitioner needs only to focus on different components of the posterior to obtain inference separately for the parameters of interest, nuisance parameters, and hyperparameters. The fully Bayesian approach also allows data to select the most appropriate values for nuisance parameters and hyperparameters automatically and achieve optimal inference and prediction for the scalar field. In this book, a fully Bayesian approach for spatio-temporal Gaussian process regression will be formulated for resource-constrained robotic sensors to fuse multifactorial effects of observations, measurement noise, and prior distributions for obtaining the predictive distribution of a scalar environmental field of interest. Traditional Markov Chain Monte Carlo (MCMC) methods cannot be implemented on resource-constrained mobile sensor networks due to high computational complexity. To deal with complexity, the Bayesian spatio-temporal models will be carefully tailored (Chap. 5). For example, we will approximate a Gaussian process with a GMRF for computational efficiency (Chaps. 6 and 7). A new spatial model is proposed via a GMRF (Chap. 6). In addition, ways to improve computational efficiency will be proposed in form of empirical Bayes and approximate Bayes instead of MCMC-based computation. For some special cases, the developed centralized algorithms will be further refined in a distributed manner such that mobile robots can implement distributed algorithms only using local information available from neighboring robots over a proximity communication graph (Chaps. 4–6).

We note that although regression problems for sensor networks under location uncertainty have practical importance, they are not considered in this book. The interested reader is referred to [6, 7] (centralized scheme) and [8] (distributed scheme) for further information on this topic.

Organization

This book is organized as follows: Chapter 1 gives some background information and a summary for each chapter. In Chap. 2, we introduce the basic mathematical notation that will be used throughout the book. We then describe the general

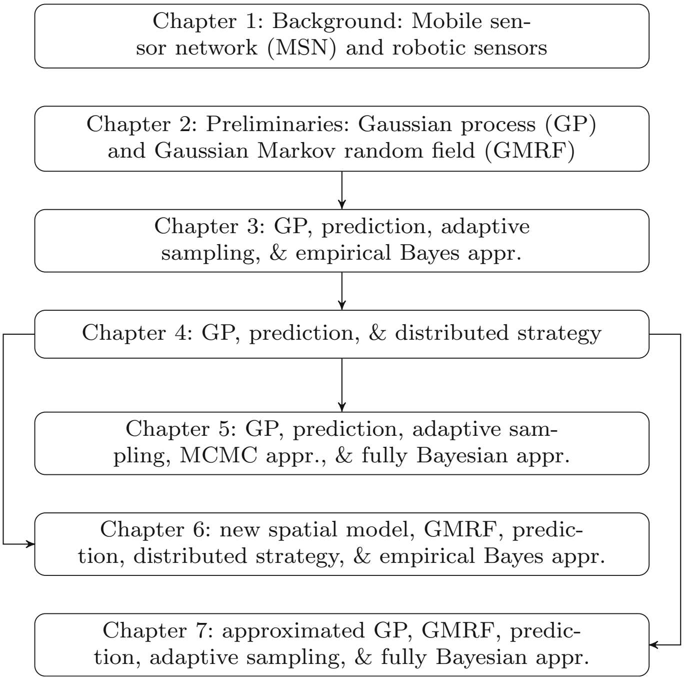

Fig. 1 Organization of chapters along with keywords

Gaussian process and its usage in nonparametric regression problems. The notations for mobile sensor networks are also introduced in Chap. 2. In Chap. 3, we deal with the case where hyperparameters in the covariance function is deterministic but unknown. We design an optimal sampling strategy to improve the maximum likelihood estimation of these hyperparameters. In Chap. 4, we assume the hyperparameters in the covariance function are given; they can be obtained using the approach proposed in Chap. 3. We then analyze the error bounds of prediction error using Gaussian process regression with truncated observations. Inspired by the error analysis, we propose both centralized and distributed navigation strategies for mobile sensor networks to move in order to reduce prediction error variances at points of interest. In Chap. 5, we consider a fully Bayesian approach for Gaussian process regression in which the hyperparameters are treated as random variables. Using discrete prior probabilities and compactly supported kernels, we provide a way to design sequential Bayesian prediction algorithms that can be computed in constant time as the number of observations increases. To cope with the computational complexity brought by using standard Gaussian processes with covariance functions, in Chap. 6, we exploit the sparsity of the precision matrix by using Gaussian Markov random fields (GMRFs). We first introduce a new class of Gaussian processes with built-in GMRF and show its capability of representing a wide range of nonstationary physical processes. We then derive the formulas for predictive statistics and design sequential prediction algorithms with fixed complexity. In Chap. 7, we consider a discretized spatial field that is modeled by a GMRF with unknown hyperparameters. From a Bayesian perspective, we design a sequential prediction algorithm to exactly compute the predictive inference of the random field. An adaptive sampling strategy is also designed for mobile sensing agents to find the most informative locations in taking future measurements in order to minimize the prediction error and the uncertainty in the estimated hyperparameters simultaneously.

Keywords for chapters are summarized in Fig. 1. While each chapter is self-contained and so can be read independently, arrows in Fig. 1 recommend possible reading sequences for readers.

Acknowledgments

We would like to thank Songhwai Oh at Seoul National University for his suggestions and contribution to Chap. 4. We also thank the National Science Foundation RET teacher, Alexander Robinson, undergraduate student David York, and Ph.D. student Huan N. Do at Michigan State University for collecting the experimental data using a robotic boat in Chap. 3. We thank Jeffrey W. Laut, Maurizio Porfiri (NYU Polytechnic School of Engineering), Xiaobo Tan (Michigan State University), and Derek A. Paley (University of Maryland) for providing pictures of their robots used in the introduction of Chap. 1.

The authors Yunfei Xu and Jongeun Choi have been supported in part by the National Science Foundation through CAREER Award CMMI-0846547. This support is gratefully acknowledged. Any opinions, findings, and conclusions, or recommendations expressed in this book are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Santa Clara, California — Yunfei Xu
East Lansing, Michigan — Jongeun Choi
Seri Iskandar, Malaysia — Sarat Dass
East Lansing, Michigan — Tapabrata Maiti
May 2015

http://www.springer.com/978-3-319-21920-2

Bayesian Prediction and Adaptive Sampling Algorithms for Mobile Sensor Networks
Online Environmental Field Reconstruction in Space and Time
Xu, Y.; Choi, J.; Dass, S.; Maiti, T.
2016, XII, 115 p. 43 illus., 2 illus. in color., Softcover
ISBN: 978-3-319-21920-2