
This book represents a synergistic combination of stochastic processes, estimation, optimization and the analysis of recursive stochastic algorithms. Readers with varying interests and mathematical backgrounds may easily approach the book. It deals with powerful and convenient approaches to a great variety of problems and it is written from an engineering point of view enabling the reader to use the theory for solving practice problems. The book contains four chapters and two appendices. The corresponding references are given separately at the end of each chapter.

Chapter 1 is devoted to the foundations of probability theory and stochastic processes where the intuitive definition of probability as well as probability distribution and density are introduced. The expectation and the conditional mathematical expectation are defined. Then random variables and stochastic sequences (processes) are considered. Particularly, the properties (including convergence of different types) of orthogonal and uncorrelated sequences are discussed. The modern concepts of renewal processes, Markov chains, martingales and sub/super martingales are considered in details. Many examples are given in order to illustrate and to help reader deeply understand the notions discussed in this chapter. The authors avoided the use of measure theory trying to make content easily accessible for readers not familiar with Lebesgue integration and related topics.

Chapter 2 contains the analysis of main distributions (Bernoulli, Poisson, Gaussian, Laplace, Cauchy, Gamma and many others) and the algorithms used for probability density estimation. The method of moments, followed by the kernel approach, is presented. This method seems to be natural when a priori information is available and leads to the solution of a collection of algebraic equations. The authors explain how real random phenomena are distributed according to such-and-such a probability distribution. The model validation technique is also discussed. They focus the attention on three parametric approaches, namely, expectation maximization, which is an iterative procedure for approximating maximum-likelihood estimates for mixture density problems, the method based on stochastic approximation technique, and, finally, the method exploiting neural network approach. Many numerical examples dealing with calculation the different probability characteristics (mean, variance and etc.) are presented too.

Chapter 3 is dedicated to some optimization approaches such as Stochastic Approximation, Learning Automata, Simulated Annealing and Genetic Global Optimization. All the optimization algorithms described in this chapter belong to the class of random search technique, and hence, they are not doomed by local optima. Both unconstrained and constrained optimization problems are considered.

Chapter 4 presents a set of recursive stochastic algorithms and their analysis. Typically, a sequence of estimates is obtained by means of some recursive statistical procedure in such a manner that the nth estimate is a function of the (n−1)th previous estimates and some new observation data, and the aim is to study convergence and other qualitative properties (for example, rate of convergence) of the algorithm. To do that, the authors use the stochastic approximation technique (such as the Robbins–Monro), some of well-known inequalities (Cauchy, Jensen, Hadamard), the Lyapunov approach and the martingale theory (the Robbins–Siegmund theorem, etc.). The analysis of the rate of stochastic optimization is based on asymptotic normality property. The best selection of the gain matrix of the optimization algorithm is related with the analysis of a matrix Lyapunov equation. Global optimization technique is presented by Learning Automata technique including Single Learning Automaton as well as a Team of Binary Learning Automata.

Appendices contain the proofs of more important tools (Appendix A) as well as a set of Matlab programs ready for use (Appendix B).

It seems to be more or less evident that any book on advanced methods is predetermined to be incomplete. Evidently also that the authors have selected for the inclusion in the book a set of methods based on their own preferences, reflected by their experience—and, undoubtedly, lack of experience—among of wide spectrum of modern approaches. In spite of that, they have managed to put together a solid package of materials making the book valuable for students in automatic control, mechanical and electrical engineering, as well as for all engineers dealing with stochastic processes.

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Receding Horizon Control (RHC), which is the subject and title of this book by Kwon and Han, is very often compared to chess. Let us therefore first consider what it is like to play a game of chess.

When it is my turn to make a move, I mentally play out a sequence of potential moves for both myself and my opponent, only thinking a handful of moves deep. I choose the best strategy amongst all of those that I had considered and only make the first move in the sequence. If my opponent replies with a move that I had not considered, then I would have to think very carefully and may even have to discard my original strategy. However, the case where my opponent plays as predicted also deserves extremely careful consideration.

While deciding how best to respond to my opponent’s move, I can rule out a large number of previously considered scenarios, which corresponded to moves that my opponent had not made. As a consequence, my mind is freed up and I can now see one or two moves further into the game than during my previous turn. Because of this, it is quite likely that I may discover a new strategy, which I believe to be better than the one I had previously chosen to implement. The important point to note, since it is directly related to problems that arise in RHC, is that the actual sequence of moves quite often does not correspond to any of the strategies that I would have considered at any one of my turns.

Let us now return to RHC. Given a dynamic model of the system to be controlled, the basic idea in RHC is to implement, at each time instant, only the first part of the solution to a given finite horizon optimal control problem. At the next sample instant, a new measurement of the system is taken and the optimal control problem is updated with this information. This process of updating the data of the finite horizon optimal problem and implementing only the first part of the solution is repeated at all future time instants.

The receding horizon principle is at the heart of a subset of popular optimal control design methods commonly referred to as model predictive control (MPC). MPC has been extremely successful in the chemical process industries (Qin and Badgwell, 2003), mainly because of its ability to incorporate time-domain constraints on the input and output directly in the problem formulation. Another important reason for the growing interest in MPC is because it allows one to synthesize controllers for systems with nonlinear dynamics (Findeisen et al., 2003; Mayne et al., 2000).

Two questions immediately come to mind. Why solve the optimal control problem over a finite horizon and not over an infinite horizon? Why implement only the first part of the solution and not the whole policy? Perhaps the best answer is: because the computational power and the mathematics are not available to solve the infinite horizon problem.

The presence of time-domain constraints or nonlinearities in the problem formulation make it very difficult to compute an explicit expression for the solution to an infinite-horizon optimal control problem.\(^1\) The usual way to proceed in practice is to formulate a finite horizon version of the optimal control problem as a constrained optimization problem, such as a quadratic program (QP) if the system and constraints are linear and the cost quadratic, and solve it on-line at each sample instant using numerical optimization software. This method turns a computationally intractable problem into one that can be solved efficiently using standard, off-the-shelf software. However, this gain in computational tractability comes at a price—not only is the solution to the finite horizon problem sub-optimal when evaluated with the original, infinite-horizon cost, but system-theoretic issues arise that are not present in the infinite-horizon formulation.

As with chess, because the optimal control problem in RHC is solved over a finite horizon and only the first part of the solution is implemented at each sample instant, it is quite often the case that the implemented input sequence does not match the optimal control policy that was computed at the corresponding sample instant. This mismatch between actual and predicted trajectories is the main source of problems, such as instability, which arise if care is not taken in the design and implementation of an RHC scheme. The book “Receding Horizon Control” is a detailed treatise on system-theoretic problems that arise, and ways of avoiding them, when only part of the solution to a finite-horizon optimal control or filtering problem is used.

In the book, the authors assume throughout that the system dynamics are given in a discrete-time, state-space form. This modern approach of adopting a state-space framework\(^2\) is also advocated in other recent books on the topic of RHC and MPC.

\(^1\) Though methods exist for which one can compute the explicit solution to an infinite-horizon optimal control problem with constraints and nonlinearities (see, for example, Bemporad et al., 2002, for the solution to the constrained LQR problem), these solutions are generally limited to low-dimensional systems.

\(^2\) The reader is referred to Camacho and Bordons (2004) and Rossiter (2003) for books on MPC with a detailed treatment of the transfer-function-based approach.
such as Goodwin et al. (2005) and Maciejowski (2002), and the excellent survey papers by Mayne et al. (2000) and Findeisen et al. (2003). It is with these reference in mind with which “Receding Horizon Control” was assessed.

After a brief introduction in Chapter 2 to dynamic programming and Pontryagin’s Minimum Principle, the authors review some of the main results from linear optimal control theory; this chapter serves as a handy reference on the solutions to the finite-horizon and infinite-horizon LQG, $H_2$ and $H_\infty$ control problems. The authors have taken particular care to treat both state- and output-feedback versions of these problems and they also give a brief discussion of the duality between the various control and state estimation problems. In each of Chapters 3–5, the authors carry through the theme of working out what would happen if the solution to suitably modified versions of the finite-horizon LQG, $H_2$ or $H_\infty$ problems were implemented in a receding horizon fashion; Chapter 3 deals with the state feedback problem, Chapter 4 considers the dual of the RHC problem, namely the Receding Horizon Filter (RHF) problem, and Chapter 5 combines the ideas from the previous two chapters for RHC with output feedback. In all these three chapters, the authors assume that the system is linear and that no input or state constraints are present in the problem formulation; Chapters 6 and 7 discuss the case when there are constraints and/or nonlinearities present in the problem formulation. The appendices contain revision material on basic results from matrix calculus, systems theory, random variables, semidefinite programming, a survey of applications and examples of MATLAB code for computing an RHC feedback law.

The end of each chapter contains a large number of exercises, most of which can be worked out by hand. These are a valuable resource for someone putting together a course on RHC or for an independent student wanting to “learn by doing”. The exercises achieve the aim of stressing the main points of each chapter and introducing the reader to RHC based on alternative formulations of finite-horizon optimal control problems. Many of the proofs of the results in each chapter have also been left as exercises.

One aspect that sets this book apart from other books in this field, and which would very much appeal to the research community, is its treatment in nearly every chapter of the LQG, $H_2$ and $H_\infty$ formulations. Another good feature of this book is that the output feedback case is covered much more extensively than in most of the existing literature on RHC, which mainly focuses on the state feedback case. The incorporation of these two elements into the text helps the reader to see how one may proceed in the design of receding horizon controllers that are robust to disturbances, model uncertainty and measurement noise.

A reader of a textbook on a well-established topic, such as RHC, would expect a broad overview of some of the well-known results and methods in the field with few, if any, recent or non-peer reviewed results. The majority of the content of a research monograph, on the other hand, is likely to contain cutting-edge research with a strong bias towards the authors’ own research. Though “Receding Horizon Control” advertises itself as a textbook, it is perhaps closer in flavour to a research monograph; large parts of Chapters 3–7 contain summaries and extensions of published and previously unpublished research done by the authors. The primary audience of the book is therefore more likely to be researchers in RHC who would like to get a good overview of the authors’ old and new research, rather than advanced undergraduates or postgraduates wanting to learn about RHC for the first time.

Most RHC schemes with guarantees of stability are obtained by modifying the original finite horizon optimal control problem in one way or the other. Typical modifications include adding a suitably defined constraint on the terminal state and choosing the terminal cost function to be a control Lyapunov function inside the constraint set. Stability is then proven by using the value function as a Lyapunov function for the closed-loop system (Mayne et al., 2000). This approach is also adopted throughout the book. However, rather than first describing the main results in Mayne et al. (2000) for the general, nonlinear formulation and showing how the various optimal control problems can be seen as special cases of these results, the authors work out the stability proofs in detail for each new case, building up from linear, unconstrained systems to nonlinear systems with constraints. This approach is slightly awkward, since not only does it add to the amount of equations that the reader has to cope with, but it also does not help illuminate what the main ideas behind all the proofs are. The equation-intensive presentation of this book may deter a novice to the field; in many cases, results and equations are derived without motivation or discussion about why the details of the problem are being developed in full. It is possible to explain the basics of RHC and its implementation, even with constraints and nonlinearities in the problem formulation, without much advanced control theory or mathematics; one cannot help but feel that the authors have assumed throughout that the reader already has a very advanced knowledge of linear algebra, optimal and robust control theory and has some experience with RHC. The readability of the book can be much improved if the nonlinear and constrained cases were treated first, along the lines of Mayne et al. (2000), before proceeding to work out the results for the cases where the dynamics and constraints are linear.

As discussed earlier, perhaps the only case when RHC is preferred over other optimal control methods is when it is computationally impractical to compute an explicit expression of the solution to an infinite-horizon optimal control problem. One of the chief strengths of RHC is that one can compute (sub-optimal, but stabilizing) solutions to optimal control problems with constraints and nonlinearities for which very few, if any, computationally tractable solutions exist for the infinite-horizon case. This point is echoed by the title and contents of the books by Maciejowski (2002) and Goodwin et al. (2005). I find it therefore strange that the authors have chosen to emphasize the linear, unconstrained case and leave the constrained and nonlinear cases to the end of the book (less than 20% of the book is devoted to these topics), rather than treating it upfront. The authors claim that RHC and RHF of linear, unconstrained systems have some advantages over linear controllers and filters that are optimal with respect to an infinite-horizon cost. These claims would have been more convincing if they had been backed up
by strong theoretical results, rather than small, numerical examples. The book would have been able to reach a broader audience if the amount of material on the linear, unconstrained case had been cut down and the section on constraints and nonlinearities were expanded and moved to the first part of the book. This change of emphasis is important because many of the results on the unconstrained case, especially those in Chapters 4 and 5 that mainly contain recent results by the authors on RHF and RHC with output feedback, do not readily extend to the constrained or nonlinear cases. Current research in RHC is mainly oriented towards problems with constraints and nonlinearities and it would have been nice to have seen this fact reflected in this book.

In summary, this book contains an in-depth treatment of RHC for a variety of different cost functions and considers the robust and output feedback cases throughout. Educators and students of RHC will find the exercises at the end of each chapter particularly useful and researchers in RHC can find inspiration in some of the results on output feedback and robust RHC. However, the authors could have focussed less on the linear, unconstrained case, and significantly extended the sections on the constrained and nonlinear cases; not only would this have made it easier to read for the novice to the field, but it would also have resonated more closely with current industrial practice and the interests of researchers in RHC. Though the book is a handy reference on the authors’ own research and perspectives on RHC, this has come at the expense of a thorough treatment of related work by others on RHC of constrained and nonlinear systems; the book therefore falls a little short of qualifying as an authoritative textbook on the field and is perhaps better approached as a research monograph on RHC for linear, unconstrained systems, which also contains some preliminary results on extensions to the constrained and nonlinear cases.

References


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doi:10.1016/j.automatica.2006.03.009