MODEL-BASED SIGNAL PROCESSING

James V. Candy

Lawrence Livermore National Laboratory
University of California
Santa Barbara, CA

IEEE

IEEE PRESS

WILEY-INTERSCIENCE

A JOHN WILEY & SONS, INC., PUBLICATION

MODEL-BASED SIGNAL PROCESSING

MODEL-BASED SIGNAL PROCESSING

James V. Candy

Lawrence Livermore National Laboratory
University of California
Santa Barbara, CA

IEEE

IEEE PRESS

WILEY-INTERSCIENCE

A JOHN WILEY & SONS, INC., PUBLICATION

Published by John Wiley & Sons, Inc., Hoboken, New Jersey.
Published simultaneously in Canada.

For general information on our other products and services or for technical support, please contact our Customer Care Department within the United States at (800) 762-2974, outside the United States at (317) 572-3993 or fax (317) 572-4002.

Wiley also publishes its books in a variety of electronic formats. Some content that appears in print may not be available in electronic formats. For more information about Wiley products, visit our web site at www.wiley.com.

Library of Congress Cataloging-in-Publication Data:

Candy, J. V.
Model-based signal processing / James V. Candy.
p. cm.
ISBN-13 978-0-471-23632-0 (cloth)
ISBN-10 0-471-23632-2 (cloth)
1. Signal processing—Digital techniques—Textbooks. I. Title.
TK5102.9.C32 2005
621.382'2–dc22

2004065042

Printed in the United States of America.

10 9 8 7 6 5 4 3 2 1

Praise the Lord, Jesus Christ, Our Savior! In times of great need and distress—He comforts us!

CONTENTS

PREFACE

This text develops the "model-based approach" to signal processing for a variety of useful model-sets, including what has become popularly termed "physics-based" models. It presents a unique viewpoint of signal processing from the model-based perspective. Although designed primarily as a graduate text, it will prove useful to practicing signal processing professionals and scientists, since a wide variety of case studies are included to demonstrate the applicability of the model-based approach to real-world problems. The prerequisite for such a text is a melding of undergraduate work in linear algebra, random processes, linear systems, and digital signal processing. It is somewhat unique in the sense that many texts cover some of its topics in piecemeal fashion. The underlying model-based approach of this text is uniformly developed and followed throughout in the algorithms, examples, applications, and case studies. It is the model-based theme, together with the developed hierarchy of physics-based models, that contributes to its uniqueness. This text has evolved from two previous texts, Candy ([1], [2]) and has been broadened by a wealth of practical applications to real-world model-based problems.

The place of such a text in the signal processing textbook community can best be explained by tracing the technical ingredients that form its contents. It can be argued that it evolves from the digital signal processing area, primarily from those texts that deal with random or statistical signal processing or possibly more succinctly "signals contaminated with noise." The texts by Kay ([3], [4], [5]), Therrien [6], and Brown [7] provide the basic background information in much more detail than this text, so there is little overlap with them.

This text additionally prepares the advanced senior or graduate student with enough theory to develop a fundamental basis and go onto more rigorous texts like Jazwinski [8], Sage [9], Gelb [10], Anderson [11], Maybeck [12], Bozic [13], Kailath [14], and more recently, Mendel [15], Grewel [16], and Bar-Shalom [17]. These texts are rigorous and tend to focus on Kalman filtering techniques, ranging from continuous to discrete with a wealth of detail in all of their variations. The model-based approach discussed in this text certainly includes the state-space models as one of its model classes (probably the most versatile), but the emphasis is on various classes of models and how they may be used to solve a wide variety of signal processing problems. Some more recent texts of about the same technical level, but again, with a different focus, are Widrow [18], Orfanidis [19], Sharf [20], Haykin [21], Hayes [22], Brown [7], and Stoica [23]. Again, the focus of these texts is not the model-based approach but rather a narrow set of specific models and the development of a variety of algorithms to estimate them. The system identification literature and texts therein also provide some overlap with this text, but the approach is again focused on estimating a model from noisy data sets and is not really aimed at developing a model-based solution to a particular signal processing problem. The texts in this area are Ljung ([24], [25]), Goodwin [26], Norton [27] and Soderstrom [28].

The approach we take is to introduce the basic idea of model-based signal processing (MBSP) and show where it fits in terms of signal processing. It is argued that MBSP is a natural way to solve basic processing problems. The more a priori information we know about data and its evolution, the more information we can incorporate into the processor in the form of mathematical models to improve its overall performance. This is the theme and structure that echoes throughout the text. Current applications (e.g., structures, tracking, equalization, and biomedical) and simple examples to motivate the organization of the text are discussed. Next, in Chapter 2, the "basics" of stochastic signals and systems are discussed, and a suite of models to be investigated in the text, going from simple time series models to state-space and wave-type models, is introduced. The state-space models are discussed in more detail because of their general connection to "physical models" and their availability limited to control and estimation texts rather than the usual signal processing texts. Examples are discussed to motivate all the models and prepare the reader for further developments in subsequent chapters. In Chapter 3, the basic estimation theory required to comprehend the model-based schemes that follow are developed establishing the groundwork for performance analysis (bias, error variance, Cramer-Rao bound, etc.). The remaining chapters then develop the model-based processors for various model sets with real-world-type problems discussed in the individual case studies and examples. Chapter 4 develops the model-based scheme for the popular model sets (*AR*, *MA*, *ARMA*, etc.) abundant in the signal processing literature and texts today, following the model-based approach outlined in the first chapter and presenting the unified framework for the algorithms and solutions. Highlights of this chapter include the real-world case studies as well as the "minimum variance" approach to processor design along with accompanying performance analysis. Next we begin to lay the foundation of the "physics-based" processing approach by developing the linear state-space, Gauss-Markov model-set, leading to the well-known Kalman filter solution in Chapter 5. The Kalman filter is developed from the innovations viewpoint with its optimality properties analyzed within. The solution to the minimum variance design is discussed (tuned filter) along with a “practical” cookbook approach (validated by theory). Next critical special extensions of the linear filter are discussed along with a suite of solutions to various popular signal processing problems (identification, deconvolution/bias estimation, etc.). Here the true power of the model-based approach using state-space models is revealed and developed for difficult problems that are easily handled within this framework. A highlight of the chapter is a detailed processor design for a storage tank, unveiling all of the steps required to achieve a minimum variance design. Chapter 6 extends these results even further to the case of nonlinear state-space models. Theoretically each processor is developed in a logical fashion leading to some of the more popular structures with example problems throughout. This chapter ends with a case study of tracking the motion of a super tanker during docking. Next the adaptive version of the previous algorithms is developed, again, within the model-based framework. Here many interesting and exciting examples and applications are presented along with some detailed case studies demonstrating their capability when applied to real-world problems. Here, in Chapter 7, we continue with the basic signal processing models and apply them to a suite of applications. Next, in Chapter 8, we extend the state-space model sets (linear and nonlinear) to the adaptive regime. We develop the adaptive Kalman-type filters and apply them to a real-world ocean acoustic application (case study). Finally, in Chapter 9, we develop a suite of physics-based models ranging from reentry vehicle dynamics (*ARMAX*), to nondestructive evaluation using laser ultrasound (*FIR*), to a suite of state-space models for vibrating structures, ocean acoustics, dispersive waves, and distributed groundwater flow. In each case the processor along with accompanying simulations is discussed and applied to various data sets, demonstrating the applicability and power of the model-based approach.

In closing, we must mention some of the new and exciting work currently being performing in nonlinear estimation. Specifically, these are the unscented Kalman filter [29] (Chapter 6), which essentially transforms the nonlinear problem into an alternate space without linearization (and its detrimental effects) to enhance performance, and the particle filter, which uses probabilistic sampling-resampling theory (Markov chain/Monte Carlo methods) (MCMC) to handle the non-gaussian type problems. Both approaches are opening new avenues of thought in estimation that has been stagnant since the 1970s. These approaches have evolved because of the computer power (especially the MCMC techniques) now becoming available ([29], [30]).

JAMES V. CANDY
Danville, CA

REFERENCES

1. J. Candy, *Signal Processing: The Model-Based Approach*, New York: McGraw-Hill, 1986.
2. J. Candy, *Signal Processing: The Modern Approach*, New York: McGraw-Hill, 1988.
3. S. Kay, *Modern Spectral Estimation: Theory and Applications*, Englewood Cliffs, NJ: Prentice-Hall, 1988.
4. S. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*, Englewood Cliffs, NJ: Prentice-Hall, 1993.
5. S. Kay, *Fundamentals of Statistical Signal Processing: Detection Theory*, Englewood Cliffs, NJ: Prentice-Hall, 1998.
6. C. Therrien, *Random Signal Processing: Detection Theory*, Englewood Cliffs, NJ: Prentice-Hall, 1991.
7. R. Brown and P. Hwang, *Introduction to Random Signals and Applied Kalman Filtering*, New York: Wiley, 1997.
8. A. Jazwinski, *Stochastic Processes and Filtering Theory*, New York: Academic Press, 1970.
9. A. Sage and J. Melsa, *Estimation Theory with Applications to Communications and Control*, New York: McGraw-Hill, 1971.
10. A. Gelb, *Applied Optimal Estimation*, Cambridge: MIT Press, 1974.
11. B. Anderson and J. Moore, *Optimum Filtering*, Englewood Cliffs, NJ: Prentice-Hall, 1979.
12. P. Maybeck, *Stochastic Models, Estimation and Control*, New York: Academic Press, 1979.
13. M. S. Bozic, *Linear Estimation Theory*, Englewood Cliffs, NJ: Prentice-Hall, 1979.
14. T. Kailath, *Lectures on Kalman and Wiener Filtering Theory*, New York: Springer-Verlag, 1981.
15. J. Mendel, *Lessons in Estimation Theory for Signal Processing, Communications, and Control*, Englewood Cliffs, NJ: Prentice-Hall, 1995.
16. M. Grewal and A. Andrews, *Kalman Filtering: Theory and Practice*, Englewood Cliffs, NJ: Prentice-Hall, 1993.
17. Y. Bar-Shalom and X. Li, *Estimation and Tracking: Principles, Techniques and Software*, Norwood, MA: Artech House, 1993.
18. B. Widrow and S. Stearns, *Adaptive Signal Processing*, Englewood Cliffs, NJ: Prentice-Hall, 1985.
19. S. Orfanidis, *Optimal Signal Processing*, New York: Macmillan, 1988.
20. L. Sharf, *Statistical Signal Processing: Detection, Estimation and Time Series Analysis*, Reading, MA: Addison-Wesley, 1991.
21. S. Haykin, *Adaptive Filter Theory*, Englewood Cliffs, NJ: Prentice-Hall, 1993.
22. M. Hayes, *Statistical Digital Signal Processing and Modeling*, New York: Wiley, 1996.
23. P. Stoica and R. Moses, *Introduction to Spectral Analysis*, Englewood Cliffs, NJ: Prentice-Hall, 1997.
24. L. Ljung, *System Identification: Theory for the User*, Englewood Cliffs, NJ: Prentice-Hall, 1987.

25. L. Ljung and T. Soderstrom, *Theory and Practice of Recursive Identification*, Cambridge: MIT Press, 1983.
26. G. Goodwin and K. S. Sin, *Adaptive Filtering, Prediction and Control*, Englewood Cliffs, NJ: Prentice-Hall, 1984.
27. J. Norton, *An Introduction to Identification*, New York: Academic Press, 1986.
28. T. Soderstrom and P. Stoica, *System Identification*, New York: Academic Press, 1989.
29. S. Haykin and N. de Freitas, eds., "Sequential state estimation: From Kalman filters to particle filters," *Proc. IEEE*, **92** (3), 399–574, 2004.
30. P. Djuric, J. Kotecha, J. Zhang, Y. Huang, T. Ghirmai, M. Bugallo, and J. Miguez, "Particle filtering," *IEEE Signal Proc. Mag.*, **20** (5), 19–38, 2003.

ACKNOWLEDGMENTS

My beautiful wife, Patricia, and children, Kirstin and Christopher, have shown extraordinary support and patience during the writing of this text. I would like to thank Dr. Simon Haykin whose kindness and gentle nudging helped me achieve the most difficult "first step" in putting together this concept. My colleagues, especially Drs. Edmund Sullivan and David Chambers, have always been inspirational sources of motivation and support in discussing many ideas and concepts that have gone into the creation of this text. The deep questions by UCSB student, Andrew Brown, led to many useful insights during this writing. God bless you all.

JVC

1

INTRODUCTION

1.1 BACKGROUND

Perhaps the best way to start a text such as this is through an example that will provide the basis for this discussion and motivate the subsequent presentation. The processing of noisy measurements is performed with one goal in mind—to extract the desired information and reject the extraneous [1]. In many cases this is easier said than done. The first step, of course, is to determine what, in fact, *is* the desired information, and typically this is not the task of the signal processor but that of the phenomenologist performing the study. In our case we assume that the investigation is to extract information stemming from measured data. Many applications can be very complex, for instance, in the case of waves propagating through various media such as below the surface of the earth [2] or through tissue in biomedical [3] or through heterogeneous materials of critical parts in nondestructive evaluation (NDE) investigations [4]. In any case, the processing typically involves manipulating the measured data to extract the desired information, such as location of an epicenter, or the detection of a tumor or flaw in both biomedical and NDE applications.

Another view of the underlying processing problem is to decompose it into a set of steps that capture the strategic essence of the processing scheme. Inherently, we believe that the more "a priori" knowledge about the measurement and its underlying phenomenology we can incorporate into the processor, the better we can expect the processor to perform—as long as the information that is included is correct! One strategy called the *model-based approach* provides the essence of model-based

Model-Based Signal Processing, by James V. Candy

signal processing [1]. Some believe that all signal processing schemes can be cast into this generic framework. Simply, the model-based approach is "incorporating mathematical models of both physical phenomenology and the measurement process (including noise) into the processor to extract the desired information." This approach provides a mechanism to incorporate knowledge of the underlying physics or dynamics in the form of mathematical process models along with measurement system models and accompanying noise as well as model uncertainties directly into the resulting processor. In this way the model-based processor enables the interpretation of results directly in terms of the problem physics. The model-based processor is actually a modeler's tool enabling the incorporation of any a priori information about the problem to extract the desired information. As depicted in Figure 1.1, the fidelity of the model incorporated into the processor determines the complexity of the model-based processor with the ultimate goal of increasing the inherent signal-to-noise ratio (*SNR*). These models can range from simple, implicit, nonphysical representations of the measurement data such as the Fourier or wavelet transforms to parametric black-box models used for data prediction, to lumped mathematical representations characterized by ordinary differential equations, to distributed representations characterized by partial differential equation models to capture the underlying physics of the process under investigation. The dominating factor of which model is the most appropriate is usually determined by how severe the measurements are contaminated with noise and the underlying uncertainties. If the *SNR* of the measurements is high, then simple nonphysical techniques can be used to extract the desired information; however, for low *SNR* measurements more and more of the physics and instrumentation must be incorporated for the extraction.

This approach of selecting the appropriate processing technique is pictorially shown in Figure 1.1. Here we note that as we progress up the *modeling steps*

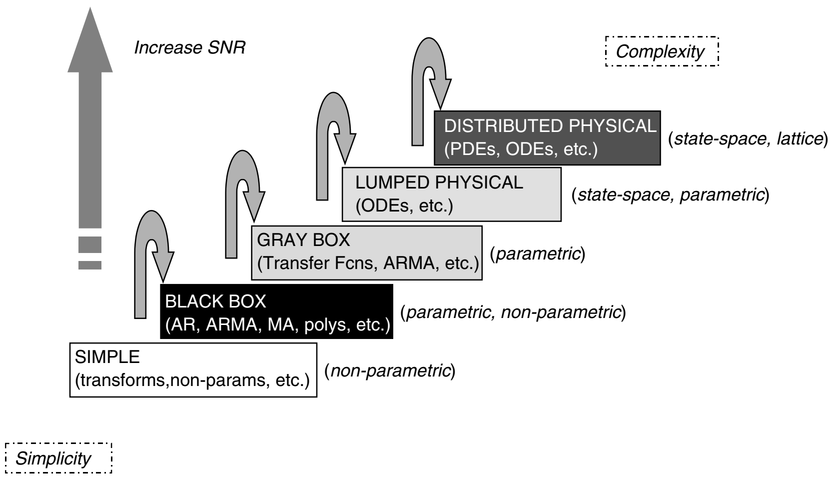

Figure 1.1. Model-based signal processing: model staircase.