Stochastic models, estimation, and control

VOLUME 1

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Introduction

1.1 WHY STOCHASTIC MODELS, ESTIMATION, AND CONTROL?

When considering system analysis or controller design, the engineer has at his disposal a wealth of knowledge derived from *deterministic* system and control theories. One would then naturally ask, why do we have to go beyond these results and propose *stochastic* system models, with ensuing concepts of estimation and control based upon these stochastic models? To answer this question, let us examine what the deterministic theories provide and determine where the shortcomings might be.

Given a physical system, whether it be an aircraft, a chemical process, or the national economy, an engineer first attempts to develop a mathematical model that adequately represents some aspects of the behavior of that system. Through physical insights, fundamental "laws," and empirical testing, he tries to establish the interrelationships among certain variables of interest, inputs to the system, and outputs from the system.

With such a mathematical model and the tools provided by system and control theories, he is able to investigate the system structure and modes of response. If desired, he can design compensators that alter these characteristics and controllers that provide appropriate inputs to generate desired system responses.

In order to observe the actual system behavior, measurement devices are constructed to output data signals proportional to certain variables of interest. These output signals and the known inputs to the system are the only information that is directly discernible about the system behavior. Moreover, if a feedback controller is being designed, the measurement device outputs are the only signals directly available for inputs to the controller.

There are three basic reasons why deterministic system and control theories do not provide a totally sufficient means of performing this analysis and

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design. First of all, *no mathematical system model is perfect*. Any such model depicts only those characteristics of direct interest to the engineer's purpose. For instance, although an endless number of bending modes would be required to depict vehicle bending precisely, only a finite number of modes would be included in a useful model. The objective of the model is to represent the dominant or critical modes of system response, so many effects are knowingly left unmodeled. In fact, models used for generating online data processors or controllers must be pared to only the basic essentials in order to generate a computationally feasible algorithm.

Even effects which are modeled are necessarily *approximated* by a mathematical model. The "laws" of Newtonian physics are adequate approximations to what is actually observed, partially due to our being unaccustomed to speeds near that of light. It is often the case that such "laws" provide adequate system *structures*, but various *parameters* within that structure are not determined absolutely. Thus, there are many sources of uncertainity in any mathematical model of a system.

A second shortcoming of deterministic models is that dynamic systems are driven not only by our own control inputs, but also by *disturbances which we can neither control nor model deterministically*. If a pilot tries to command a certain angular orientation of his aircraft, the actual response will differ from his expectation due to wind buffeting, imprecision of control surface actuator responses, and even his inability to generate exactly the desired response from his own arms and hands on the control stick.

A final shortcoming is that *sensors do not provide perfect and complete data* about a system. First, they generally do not provide all the information we would like to know: either a device cannot be devised to generate a measurement of a desired variable or the cost (volume, weight, monetary, etc.) of including such a measurement is prohibitive. In other situations, a number of different devices yield functionally related signals, and one must then ask how to generate a best estimate of the variables of interest based on partially redundant data. Sensors do not provide exact readings of desired quantities, but introduce their own system dynamics and distortions as well. Furthermore, these devices are also always noise corrupted.

As can be seen from the preceding discussion, to assume perfect knowledge of all quantities necessary to describe a system completely and/or to assume perfect control over the system is a naive, and often inadequate, approach. This motivates us to ask the following four questions:

(1) How do you develop system models that account for these uncertainties in a direct and proper, yet practical, fashion?

(2) Equipped with such models and incomplete, noise-corrupted data from available sensors, how do you optimally estimate the quantities of interest to you?

(3) In the face of uncertain system descriptions, incomplete and noise-corrupted data, and disturbances beyond your control, how do you optimally control a system to perform in a desirable manner?

(4) How do you evaluate the performance capabilities of such estimation and control systems, both before and after they are actually built?

This book has been organized specifically to answer these questions in a meaningful and useful manner.

1.2 OVERVIEW OF THE TEXT

Chapters 2–4 are devoted to the stochastic modeling problem. First Chapter 2 reviews the pertinent aspects of deterministic system models, to be exploited and generalized subsequently. Probability theory provides the basis of all of our stochastic models, and Chapter 3 develops both the general concepts and the natural result of static system models. In order to incorporate dynamics into the model, Chapter 4 investigates stochastic processes, concluding with practical linear dynamic system models. The basic form is a linear system driven by white Gaussian noise, from which are available linear measurements which are similarly corrupted by white Gaussian noise. This structure is justified extensively, and means of describing a large class of problems in this context are delineated.

Linear estimation is the subject of the remaining chapters. Optimal filtering for cases in which a linear system model adequately describes the problem dynamics is studied in Chapter 5. With this background, Chapter 6 describes the design and performance analysis of practical online Kalman filters. Square root filters have emerged as a means of solving some numerical precision difficulties encountered when optimal filters are implemented on restricted word-length online computers, and these are detailed in Chapter 7.

Volume 1 is a complete text in and of itself. Nevertheless, Volume 2 will extend the concepts of linear estimation to smoothing, compensation of model inadequacies, system identification, and adaptive filtering. Nonlinear stochastic system models and estimators based upon them will then be fully developed. Finally, the theory and practical design of stochastic controllers will be described.

1.3 THE KALMAN FILTER:
AN INTRODUCTION TO CONCEPTS

Before we delve into the details of the text, it would be useful to see where we are going on a conceptual basis. Therefore, the rest of this chapter will provide an overview of the optimal linear estimator, the Kalman filter. This will be conducted at a very elementary level but will provide insights into the

underlying concepts. As we progress through this overview, contemplate the ideas being presented: try to conceive of graphic *images* to portray the concepts involved (such as time propagation of density functions), and to generate a *logical structure* for the component pieces that are brought together to solve the estimation problem. If this basic conceptual framework makes sense to you, then you will better understand the need for the details to be developed later in the text. Should the idea of where we are going ever become blurred by the development of detail, refer back to this overview to regain sight of the overall objectives.

First one must ask, what is a Kalman filter? A Kalman filter is simply an *optimal recursive data processing algorithm*. There are many ways of defining *optimal*, dependent upon the criteria chosen to evaluate performance. It will be shown that, under the assumptions to be made in the next section, the Kalman filter is optimal with respect to virtually any criterion that makes sense. One aspect of this optimality is that the Kalman filter incorporates all information that can be provided to it. It processes all available measurements, regardless of their precision, to estimate the current value of the variables of interest, with use of (1) knowledge of the system and measurement device dynamics, (2) the statistical description of the system noises, measurement errors, and uncertainty in the dynamics models, and (3) any available information about initial conditions of the variables of interest. For example, to determine the velocity of an aircraft, one could use a Doppler radar, or the velocity indications of an inertial navigation system, or the pitot and static pressure and relative wind information in the air data system. Rather than ignore any of these outputs, a Kalman filter could be built to combine all of this data and knowledge of the various systems' dynamics to generate an overall best estimate of velocity.

The word *recursive* in the previous description means that, unlike certain data processing concepts, the Kalman filter does not require all previous data to be kept in storage and reprocessed every time a new measurement is taken. This will be of vital importance to the practicality of filter implementation.

The "filter" is actually a *data processing algorithm*. Despite the typical connotation of a filter as a "black box" containing electrical networks, the fact is that in most practical applications, the "filter" is just a computer program in a central processor. As such, it inherently incorporates discrete-time measurement samples rather than continuous time inputs.

Figure 1.1 depicts a typical situation in which a Kalman filter could be used advantageously. A system of some sort is driven by some known controls, and measuring devices provide the value of certain pertinent quantities. Knowledge of these system inputs and outputs is all that is explicitly available from the physical system for estimation purposes.

The *need* for a filter now becomes apparent. Often the variables of interest, some finite number of quantities to describe the "state" of the system, cannot

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