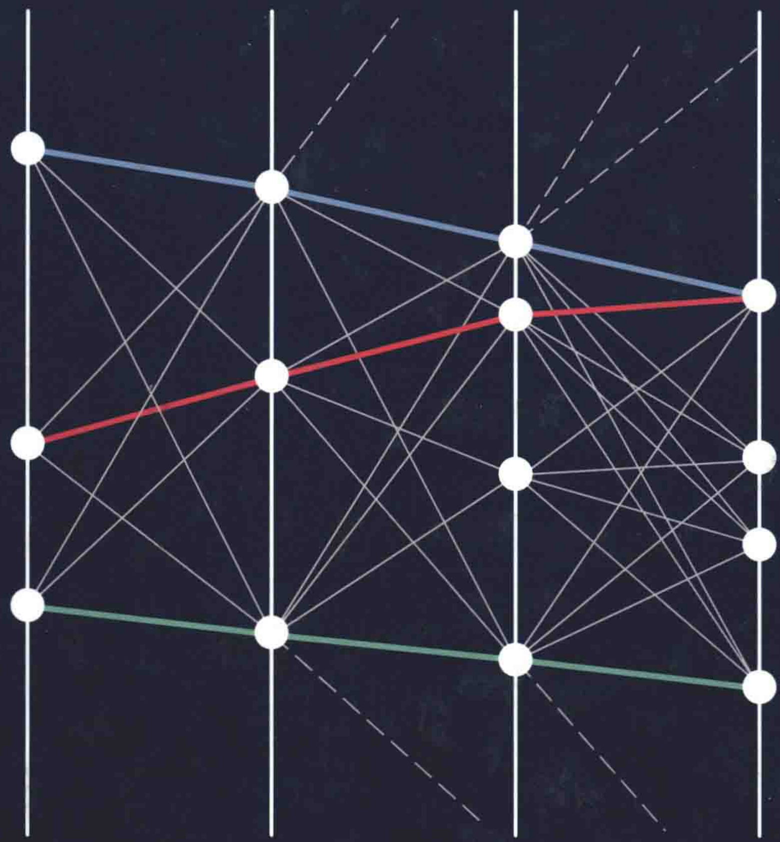
Applied State Estimation and Association

Chaw-Bing Chang and Keh-Ping Dunn



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Dedication

To
Kia-Ling Chang and Ning Dunn
Our Better Halves,
Their
Encouragement,
Patience, and
Support
Helped Make This Project a Reality

Preface

This book is intended to provide readers with a rigorous introduction to the theory and application of estimation and association techniques. Skills taught in this book will prepare students for solving application problems in this technical area.

Applied estimation and association is an important area for practicing engineers in aerospace, electronics, and defense industries. A feature of this book is that it uses a unified approach in problem formulation and solution. This approach serves to help the students to build a sound theoretical foundation as well as to attain skills and tools for practical applications. Many technical subjects and examples in this book represent a collection of the most relevant and important areas in state estimation and association for practicing engineers based upon the authors' decades of experiences in this field. For this reason, this book could be used by engineering schools offering courses in this area as a textbook, as well as a reference book for students interested in engineering applications and practical solutions when taking a more theoretical course. For practicing engineers, this book can be used for self-study or as a textbook for an in-house class. It can also be used for self-study by practitioners in the area of state estimation and association.

The technical level of this book is equivalent to an advanced first- or second-year graduate course in a control or system engineering curriculum. The students are required to be familiar with the state-variable representation of systems and basic probability theory including random variables and stochastic processes. The main content of this book spans 10 chapters. Chapters 1 to 6 address the problem of estimation with a single sensor observing a single object. Chapter 7 expands from a single sensor to multiple sensors. Chapters 8 through 10 address the problem of measurement-to-track association and track-to-track correlation by expanding the problem to multiple objects. A chapter-by-chapter description is included in the Introduction with Concluding Remarks given at the end.

It is our goal that after learning the skills presented in this book, students will be able to derive solutions to problems, or to conduct further research when needed in order to solve their problems.

About the Authors

Chaw-Bing Chang received his BS degree from National Cheng Kung University, Taiwan, and MS and PhD degrees from the State University of New York at Buffalo, all in electrical engineering. He joined Lincoln Laboratory in 1974, and his initial project was on radar signal processing and trajectory estimation for ballistic missile defense (BMD). He became an Assistant Group Leader in 1984 to lead projects in air defense (AD) technology development for the US Navy. He was appointed Group Leader of the Air Defense and Sensor Technology Group in 1998, and was responsible for technology development for the Navy's airborne surveillance radar system. During this time he led a multiyear data collection and experimentation campaign supporting the Navy's Mountaintop Program. As part of the Navy AD program, he contributed to algorithm development and performance evaluation for both surface and airborne radar systems. Upon returning to the Laboratory's BMD program in 2004, he participated in advanced algorithm development and phenomenology research for radar and optical sensors and led an airborne optical sensor technology program for BMD. He has published more than 70 journal articles, conference papers, and Lincoln Laboratory reports. He is currently a senior staff member of the BMD System Integration Group.

Keh-Ping Dunn received his BS degree in control system engineering from the National Chiao Tung University in Taiwan, and MS and DSc degrees in systems science and mathematics from Washington University in St. Louis, Missouri. Before joining the Laboratory in 1976, he was with the Electronic System Laboratory of MIT in charge of a NASA project on a multiple model adaptive control system for the F-8C aircraft. At Lincoln Laboratory, he has worked in many areas of ballistic missile defense (BMD). He became the Group Leader of Systems Testing and Analysis in 1992, managing the first two campaigns of the Theater Missile Defense (TMD) Critical Measurement Program (TCMP) that conducted a series of live missile tests in the Pacific in the 1990s. He won the Missile Defense Agency's (MDAs) 2010 Technology Achievement Award for his effort on this project. He consequently managed Theater

Missile Defense (1999–2003), Advanced Concepts and Technology (2003–2008), and Missile Defense Elements (2008–2010) groups, all for MDA projects. He chaired the Panel of Tracking Parameters of the SDI Tracking Panels in the late 1980s for the Strategic Defense Initiative Organization (SDIO). He has worked on multiple target/multiple sensor tracking, target identification, and sensor fusion and decision architecture for various BMD sensor (both optics and radar) systems at the Laboratory. He is currently a senior staff member in the BMD System Integration Group.

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Introduction

This book is intended to provide the reader with a rigorous introduction to the theory and application of estimation and association techniques. Skills taught in this book will prepare the student for solving practical problems in this technical area.

Estimation and association involves the extraction of information from noisy measurements. Example applications include signal processing, tracking, navigation, and so on [1, 2, 3]. The extraction of parameter values from signals in order to estimate such attributes as time-of-arrival and sensor pointing angle is called parameter estimation. A sensor signal may have come from a moving object. Determining the kinematics of a moving object is called state estimation. Associating measurements with state estimates in a multiple object environment is a joint estimation and association problem that is known as tracking [2–5]. Example applications include sensor surveillance systems for air traffic control, guiding space vehicles toward a planet, extracting information regarding a moving object with multiple-degree-of-freedom motions, and so on.

The authors of this book, together with their colleagues, have been applying the theory and techniques of estimation and association to real-world problems for the past 40 years. They have taught classes to Lincoln Laboratory staff members who are involved in applying these skills as well as solving problems of their own. The content of this book represents their collective experience in applying estimation and association techniques. The technical level of this book is equivalent to a first year graduate course in a control or system engineering curriculum. The students are required to be familiar with the state-variable representation of systems, and basic probability theory including random variables and stochastic processes. This book can also be used for self-study by practitioners in the area of state estimation and association.

Theory and techniques developed in this book are for discrete time systems. Although all physical systems are continuous in time, the measurements are taken in discrete time and the computational system that exploits the measurements operates in discrete time. Furthermore, unique discrete time equivalence to continuous time systems can be easily derived and implemented. The use of discrete time models enables us to solve the problem without resorting to more abstract mathematics such as measure theory and Ito calculus [6]. Homework problems are included at the end of each chapter. The purpose is two-fold: (a) to develop students confidence in their derivation skills so that they are able to apply them to new problems, and (b) to build computer models so that they will have a useful set of tools for problem solving.

The theory and application of estimation has been a rich field of research for decades. The landmark papers by Kalman [4], and Kalman and Bucy [5] gave the optimal solution for state estimation of linear systems having Gaussian system and measurement noise processes. The Kalman filter (KF) algorithm using state space modeling makes it suitable for implementation with digital computers. Kalman's paper also laid the foundation for the concept of observability of a linear system, and its relationship with the Fisher information matrix and the Cramer–Rao bound (CRB) [1] for all unbiased state estimators. For this reason, it has gained enormous interest from practicing engineers. However, most of the real-world application problems are nonlinear. After Kalman's publication, considerable effort was devoted to finding the optimal filter for nonlinear systems (the counterpart of the KF for linear systems) [6]. All these studies came to the same conclusion: the solution of the optimal filter requires an infinite dimensional representation that cannot be practically constructed. Consequently, follow-on efforts focused on searching for suboptimal but practical solutions.

The approach used in this book has two features: (a) it formulates the estimation problem as an optimization problem using measurement data and a priori knowledge of the system, and (b) it develops CRB solutions for each estimation problem addressed. The first feature stresses that the solution to the estimation problem provides a best fit to the measurement data, the system model, and the a priori knowledge. It will be shown that solution algorithms for most of the estimation problems can be obtained this way. The CRB has been well known in signal processing for estimating parameters embedded in the signal [1]. It has been applied to a wide range of state estimation problems at Lincoln Laboratory [7]. In keeping with the second feature, the CRB models for parameter and state estimation are derived for the examples considered or are included as part of the homework problem assignments.

In many engineering applications, noisy measurements are obtained on some unknown variables. Variables of interest can collectively be represented as a vector. Measurements can be arranged as a measurement vector or a set of measurement vectors. In the case where the vector of interest is constant or random, it is referred to as a parameter vector. In the case where the vector of interest is time-varying and follows a set of differential equations for a continuous-time system, or difference equations for a discrete-time system, it is termed a state vector. A parameter vector is a special case of the state vector. The concept of a state vector is identical to the state vector used in the state space representation of control systems [8]. A state vector can be deterministic or random, depending on whether the system is deterministic or driven by a random process.

The estimation problem is to find a solution to the unknown vector using measurements and knowledge about the vector of interest. The measurements used in an estimator are assumed to have come from a single object or dynamic system. This assumption may not be true when multiple objects are closely spaced in sensor measurements. The problem of state association is to determine whether a measurement or a set of measurements comes from the same object.

This book has 10 chapters. Chapters 1 to 6 focus on solving the problem of estimation with a single sensor observing a single object. Chapter 7 expands consideration from a single sensor observer to multiple sensors. Chapters 8 through 10 address the problem of association by expanding the problem to multiple objects and multiple sensors. Concluding remarks and three appendices are offered at the end. They are introduced individually below.

Chapter 1: Parameter Estimation

In this text, a parameter vector can be a constant vector or a random vector with known distribution, but is never a random process. The foundation of estimation can be understood most easily by solving the problem of parameter estimation. The estimate of an unknown vector is obtained by selecting the vector that optimizes a performance criterion or a cost function given the noisy measurements. Six performance criteria are introduced in this chapter, namely, least squares, weighted least squares, maximum likelihood, maximum a posteriori probability, conditional mean, and linear least squares expressed as functions of the measurements [1, 4]. Explicit estimator solutions for linear measurements with Gaussian measurement noise are developed and the equivalence of all six estimators is discussed. It is shown that the a posteriori density function of the parameter vector conditioned on measurements contains all the information for estimating this parameter vector, regardless of whether the measurement relationship is linear or nonlinear, and the conditional mean is the minimum norm solution in the parameter space. For the linear measurement relationship, the closed form solution can be found. For nonlinear measurements, a numerical solution to the weighted least squares estimator is derived. The Cramer–Rao bounds for all cases are derived. The relationship between weighted least squares estimator, minimum variance estimator, and the conditional mean estimator is shown in the appendix.

Chapter 2: State Estimation for Linear Systems

A state vector is the solution of a first order vector differential equation for a continuous system, or difference equation for a discrete system [8]. When the initial condition is a random variable and/or when the system is driven by a random system noise process, the state vector represents a random process. For linear systems with Gaussian system and measurement noise, the a posteriori density of the state conditioned on measurements remains Gaussian, and the state estimate can therefore be completely characterized by the conditional mean and covariance. This result is known as the Kalman filter [4]. The techniques used in Chapter 1 to derive the parameter estimator are extended in this chapter to derive the KF solution for linear systems. These include the conditional mean, weighted least squares, and Bayesian recursive evolution of the a posteriori density function. The concept of smoothing is introduced, and the chapter ends with derivations for the CRB for all cases of interest.

Chapter 3: State Estimation for Nonlinear Systems

Many physical systems and measurement devices are nonlinear. As mentioned before, the conditional mean is the minimum norm estimate, and the a posteriori density function of a state conditioned on measurements contains all the information necessary for estimation. For linear systems with Gaussian noise, the a posteriori density remains Gaussian. This property is, however, no longer true for nonlinear systems even when the input and measurement noise processes are Gaussian. The recursive Bayesian relationship governing the time evolution of the a posteriori density for arbitrary nonlinear systems was published within a few years of Kalman filter [9, 10], but its exact solution for estimation remains open. For this reason, only approximated solutions for the nonlinear estimation problems have found applications. The approximated solutions include the use of the first order Taylor series expansion (the extended Kalman filter) and the addition of the second order term in the Taylor series expansion (the second order filter) [11]. Both filters are aimed at providing approximated conditional means and covariance solutions for the state estimator. Additional nonlinear