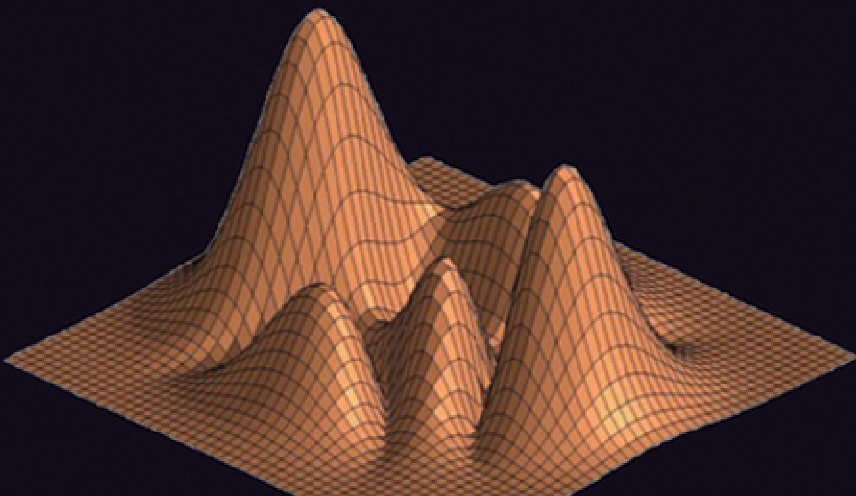
Integrated Tracking, Classification, and Sensor Management

Theory and Applications



Edited by

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INTEGRATED TRACKING, CLASSIFICATION, AND SENSOR MANAGEMENT

THEORY AND APPLICATIONS

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PREFACE

This book has been a long time in the making, starting with a series of conversations in 2007 during the Colloquium on Information Fusion in Xi'an China, followed by many discussions at various conferences as well as phone calls from half way around the globe. These conversations were centered on the ever-growing interest in tracking and sensor management in the wider community and the accessibility of the state-of-the-art techniques to graduate students, researchers, and engineers.

The research on multitarget tracking and sensor management was driven by aerospace and space applications such as radar, sonar, guidance, navigation, air traffic control, and space exploration in the 1960s. Since then, these research areas have flourished into other diverse disciplines such as image processing, oceanography, autonomous vehicles and robotics, remote sensing, biomedical research, and space debris tracking. Recent efficient multitarget tracking techniques and advances in sensing and computing technology have opened up prospective applications in areas such as driving safety and traffic monitoring, homeland security, and surveillance of public facilities.

While interest in this discipline is rapidly growing with many exciting advances during the last decade, comprehensive and accessible account of significant developments in the field are few and far between. The focus of our book is on expository writing, clear description of theoretical developments, and real-world applications in these areas. The chapters of the book are divided into five groups under the headings: Filtering, Multitarget Multisensor Tracking, Sensor Management and Control, Estimation and Classification, and Decision Fusion and Decision Support. Each chapter is solicited from internationally renowned experts in their respective areas. By providing concise and detailed descriptions, such as pseudo codes for algorithms, we endeavor to facilitate the implementations of the state-of-the-art algorithms, thereby making a wealth of approaches and techniques accessible to a wider audience.

Chapter 1 develops three classes of filtering algorithms for the angle-only filtering problem in 3D using bearing and elevation measurements. The dynamic models used by these filtering algorithms are the nearly constant velocity model for the relative Cartesian state vector, exact discrete-time dynamic model for modified spherical coordinates (MSC), and exact continuous-time dynamic model for MSC. The extended Kalman filter (EKF), unscented Kalman filter (UKF), and particle filter (PF) are developed for each class, of which the UKF and PF based on the exact continuous-time dynamic model for MSC represent new algorithms. Finally, a comparative evaluation of their accuracy and computational complexity is presented using Monte Carlo simulations.

Chapter 2 presents a recently introduced approach called box particle filtering which emerged from the synergy between sequential Monte Carlo (SMC) methods and interval analysis. A theoretical derivation of the box particle filter is given based on mixtures of uniform probability density functions with box supports. Experiments with both simulated and real data show the advantages of the box particle filter over the conventional particle filter for certain classes of problems.

Chapter 3 presents an accessible account of developments in the random finite set approach to the multitarget tracking problem. This chapter is classified under the filtering part of the book because fundamentally, the random finite set approach poses the multitarget tracking problem as a Bayesian filtering problem (in the space of finite subsets or simple finite point patterns). In this chapter, we discuss the notion of a mathematically consistent error metric for multitarget tracking and present arguments for the finite set representation of the multitarget state. We also detail random finite set-based algorithms such as the probability hypothesis density (PHD), Cardinalized PHD (CPHD), and Multitarget Multi-Bernoulli filters.

The interacting multiple model (IMM) filter is a well-established and widely used algorithm at present for maneuvering target tracking. Currently, almost all IMM filtering algorithms used are discrete-time filtering algorithms. However, it is rather unknown that the original IMM filter was developed in a purely continuous-time setting, which subsequently led to the development of the discrete-time IMM filter. Chapter 4 presents in detail the mathematical development of exact continuous-time nonlinear filtering for jump Markov systems, including the continuous-time IMM filter as well as continuous-discrete-time IMM and particle filters.

The track-oriented multiple hypothesis tracking (MHT) for multisensor multitarget tracking is regarded as one of the most advanced tracking algorithms at present, relative to which other tracking algorithms are compared. Chapter 5 presents a hybrid-state derivation of the track-oriented MHT equations that is closely related to the original treatment by Kurien [1] with some minor modifications. The target death problem inherent in PHD filtering is also addressed and it is shown that it does not arise in the track-oriented MHT. A number of illustrative examples are considered to demonstrate the merits of MHT. In order to make the chapter self-contained, a comprehensive review of the state-of-the-art filtering and tracking algorithms are summarized in the beginning of the chapter, with extensive references.

Chapter 6 describes several strategies to improve airborne ground surveillance by enhanced tracking performance. The following topics are considered: specific sensor modeling, improved data association using signal strength measurements, exploitation of digital road maps, and detection and tracking of target groups. The proposed algorithms are shown to enhance track precision and track continuity over conventional techniques.

Chapter 7 presents a review of recent developments in the calculation of mean square error tracker performance bounds, together with examples that demonstrate how such bounds can be used as a basis for performing online sensor management. The review concentrates on the posterior Cramér–Rao lower bound (PCRLB), and describes computationally efficient formulations of the PCRLB that take account of real-world complexity. Two applications, concerned with the deployment of passive sonobuoys, and UAV trajectory planning, demonstrate that the PCRLB provides an efficient mechanism for performing sensor management in order to accurately track an evasive target.

Chapter 8 presents a review of the track-before-detect (TBD) problem, namely tracking when the measurement is an intensity map. It describes the different methods that have been applied to this problem and compares their performance on a simple scenario. A case study fusing data from an infra-red camera and microwave radar illustrate the advantages that can be gained through the improved sensitivity offered by the track-before-detect algorithm.

While centralized detection and estimation are known to outperform distributed approaches, the same is not always true when one is confronted with measurement origin uncertainty. Indeed, all known approaches to multitarget tracking are suboptimal. Thus, judicious multistage processing may outperform single-stage processing. In a sense, we are choosing between (suboptimal) distributed and (suboptimal) centralized processing. Chapter 9 identifies a number of scenarios where multistage fusion architectures lead to promising results.

Chapter 10 presents an overview of meta-level tracking algorithms for inferring target intent. Such meta-level trackers are fully compatible with existing target tracking algorithms and form the sensor–human interface. To capture the complex spatial trajectories of targets, stochastic context free grammars are used. Then Bayesian signal processing algorithms are used to estimate the target trajectory.

Chapter 11 presents an overview of stochastic control methods for radar resource management. Radar resource management is intrinsically a partially observed stochastic control problem since decisions need to be made based on the estimates provided by a tracker. Such problems are typically intractable unless the underlying structure is exploited. The chapter shows how supermodularity and lattice programming methods can be used to characterize the structure of the optimal radar scheduling policy.

Chapter 12 addresses the problem of multisensor resource management with application to multitarget tracking. Specifically, sensor selection, sensor placement, and performance evaluation are considered in detail. A particular contribution of this chapter is the derivation of the Posterior Cramér–Rao Lower Bound (PCRLB) to quantify the achievable estimation accuracy in multitarget tracking problem, which is used as the key metric for sensor management.

Chapter 13 on efficient inference in general hybrid Bayesian networks for classification introduces a probabilistic inference framework for hybrid Bayesian networks, in which both discrete and continuous variables are present and their functional relationship can be nonlinear. This type of model is very common in classification applications where discrete random variables representing entity types or situational hypotheses are to be assessed given noisy observations represented by mixed discrete and continuous variables.

Chapter 14 presents a new analytical approach for quantifying the long-run performance of a multisensor classification system modeled by a Bayesian network. The methodology has been applied to fusion performance evaluation of practical tracking and classification systems involving multiple sensor types. It illustrates the use of off-line evaluation to estimate marginal performance gains and sensor mode selection using measures and metrics derived herein.

Chapter 15 considers the problem of detecting, estimating, and searching for point and distributed sources of radiation. A Bayesian approach is adopted with the posterior density approximated using the notion of progressive correction combined with either Monte Carlo approximation or linearization.

In Chapter 16, important problems of distributed detection and decision fusion for a multisensor system are discussed. With known local sensors' performance indices, the design for optimal decision fusion rule at the fusion center and the optimal local decision rules at sensors are presented in both parallel and serial networks under either the Bayesian or Neyman–Pearson criterion. When local sensors are nonidentical and their performance indices are unknown, the counting rule is proposed and its exact as well as approximated performance are analyzed. For the challenging problem of distributed detection with correlated observations, a decision fusion framework using copula theory is described, which is shown particularly useful for non-Gaussian distributed and nonlinearly dependent sensor observations.

Chapter 17 presents the development of an automatic knowledge-based information fusion system to support the decision making process in a reliable, timely, and consistent manner even in conditions of uncertainty. This is obtained by using the framework of valuation algebra for knowledge representation and reasoning under uncertainty together with the algorithms for performing local computations in valuation algebra. These algorithms are then specialized to the theory of belief functions. Two practical examples are discussed: decision support systems for target identification and threat assessment.

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PART I

FILTERING

CHAPTER 1

Angle-Only Filtering in Three Dimensions

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1.1 INTRODUCTION

The angle-only filtering problem in 3D using bearing and elevation measurements is an important problem in many passive tracking applications. For example, it arises in passive ranging using an infrared search and track (IRST) sensor [1, 2], passive sonar, passive radar in the presence of jamming, and satellite to satellite passive tracking [3, 4]. It is the counterpart of the bearings-only filtering problem in 2D. For the 3D case, the objective is to estimate the three-dimensional state of a target, such as position and velocity, using noisy measurements of bearing and elevation from a single maneuvering platform. A great deal of research has been carried out for the bearings-only filtering problem in 2D—see for example, [5–9] and the references therein. However, the number of publications for the angle-only filtering problem in 3D is relatively small [3, 4, 10–18].

Research in angle-only filtering in 3D began by extending the methods developed for the counterpart problem in 2D. For the 2D bearings-only filtering problem, it is well known that, for a target moving with uniform motion, target range cannot be observed without an ownship (sensor) maneuver [19]. Though the prior distribution of the initial state aids in improving observability, its contribution degrades with time. In addition, the accuracy of the state estimate is highly dependent on the nature of the maneuver and the particular target–observer geometry. Early recursive algorithms for this problem were based on the extended Kalman filter (EKF) [20–22] using Cartesian coordinates [23]. Researchers noted that the performance of these algorithms was poor due to premature collapse of the covariance matrix. This led to the formulation of the modified polar coordinates (MPC) [5, 24, 25], in which improved performance was demonstrated.

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The state vector in MPC consists of bearing, bearing-rate, range-rate divided by range, and the inverse of range [5, 9, 24]. The important difference between the MPC and the Cartesian coordinates is that in MPC, the first three elements of the state are observable even before an ownship maneuver. By decoupling the observable and unobservable components of the state vector, this approach was demonstrated to prevent ill-conditioning of the covariance matrix which led to better filter performance [5, 24, 25]. The continuous-time dynamic model for the MPC is nonlinear and is represented by four continuous-time stochastic differential equations (SDEs). The key difficulty of using MPC is that the commonly applied nearly constant velocity model (NCVM) for nonmaneuvering targets is highly nonlinear in MPC. In fact, there has been some confusion in the literature as to how to convert the widely used NCVM from Cartesian coordinates to MPC. In the original work on bearings-only filtering in MPC [24, 25], these equations are numerically integrated to obtain the predicted state and covariance at the discrete measurement times. Subsequently, Aidala and Hammel [5] noted that exact, closed-form discrete-time stochastic difference equations in MPC can be obtained by using the nonlinear transformations between MPC and Cartesian coordinates. They proposed an EKF in these coordinates and claimed superior performance relative to its Cartesian counterpart.

Angle-only filtering in 3D is beset by the same observability issues that arise in the 2D case [19, 26]. As such, most of the research in the 3D angle-only filtering problem has focused on developing algorithms in the modified spherical coordinates (MSC) [17]—the 3D equivalent of MPC. The components of MSC are elevation, elevation-rate, bearing, bearing-rate times cosine of elevation, the inverse of range, and range-rate divided by range. As with MPC in 2D filtering, the main problem when using MSC in 3D filtering is the nonlinear dynamic model which arises when a target moves with the NCVM in Cartesian coordinates. Again, a number of ways of transforming the NCVM in Cartesian coordinates to MSC have been proposed.

As with MPC, the derivation of a dynamic model for MSC begins with a given motion model in Cartesian coordinates. The MSC dynamic model can then be obtained by transformation from MSC to relative Cartesian coordinates at time t_{k-1}, prediction using the NCVM for relative Cartesian coordinates during the time interval $[t_{k-1}, t_k]$, and then transformation from relative Cartesian coordinates to MSC at time t_k. In [17], this approach is used only to compute the predicted state estimate. The predicted covariance matrix is found by a linear, discretized approximation of the continuous-time dynamic model. The underlying Cartesian dynamic model is the Singer model [27]. A similar method is adopted in [4, 10, 11]. Li et al. [4] derived closed form analytic expressions for the discrete-time nonlinear dynamic model in MSC using an approach similar to that used by Aidala and Hammel [5] for MPC, but they do not describe calculation of the predicted covariance. In [13], the EKF is implemented using a discretized linear approximation for both the predicted state estimate and covariance matrix. A particle filter (PF) [9, 28, 29] was implemented using a multistep Euler approximation. In [14], first exact SDEs for MSC and log spherical coordinates (LSC) were derived from the NCVM in 3D for the relative Cartesian state vector. Then EKFs were implemented for MSC and LSC by numerically integrating nonlinear differential equations for the predicted state estimate and covariance matrix.