KNOWLEDGE-BASED RADAR DETECTION, TRACKING, AND CLASSIFICATION

EDITED BY

Fulvio Gini and Muralidhar Rangaswamy

WILEY-INTERSCIENCE

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INTRODUCTION[1]

Fulvio Gini and Muralidhar Rangaswamy

The use of surveillance for a variety of applications in the dynamically changing civilian and military environments has led to a great demand for innovative sensors and sensing configurations based on cutting-edge technologies, such as knowledge-based (KB) signal and data processing, waveform diversity, wireless networking, robotics, advanced computer architectures, and supporting software languages [1]. Improved sensor signal and data processing performance will be gained from KB and a priori information, multiple processing paradigms, and sensor fusion. A knowledge-based system (KBS) uses a priori information to improve the performance of deterministic and adaptive systems. Although the exact form of this prior knowledge is problem-dependent, a KBS consists of a knowledge base containing information specific to a problem domain and an inference engine that employs reasoning to yield decisions.

With maturing electronics and radar hardware, advanced radar systems will use KB techniques to perform signal and data processing cooperatively within and between platforms of sensors and communication systems while exercising waveform diversity, as well as reconnaissance, surveillance, imaging and communications within the same sensor system. In addition, these sensors will cooperate with other users and sensors, sharing information and data. Sensor system performance can be enhanced by changing a sensor's algorithms as the environment changes. This is the fundamental concept underlying KB or cognitive radar, known to the radar community since the pioneering papers of Vannicola and colleagues [2, 3], Haykin [4], and Baldygo et al. [5]. The operational radar environment is subject to rapid spatio-temporal variation. Hence, the key to efficient adaptation is real-time

1. ©2006 IEEE. Reprinted in part, with permission, from "Knowledge-based systems for adaptive radar: guest editorial," *IEEE Signal Processing Magazine* 2006;23(1): 14–17.

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exploitation of a priori knowledge pertaining to the operational environment. For example, if an airborne radar system is aware of certain features of the Earth and its surroundings, then it can significantly improve performance by exploiting degrees of freedom such as the transmit waveform, polarization, frequency, phase, power, modulation, and coding. The adaptive and optimal use of all available degrees of freedom is broadly termed "waveform diversity." Waveform diversity is the technology that will allow one or more sensors onboard a platform to automatically change operating parameters [e.g. frequency, gain pattern, pulse repetition frequency (PRF)] to meet the varying environments. Also, the system of sensors should operate with multiple goals managed by an intelligent platform network that can control the dynamics of each sensor to meet the common goals of the platform, rather than each sensor operate as an independent system. Intelligent software processing is required at all stages of signal, data, and system processing from the filtering, detection, tracking, imaging, and identification stages to the communications, command, and control (C3) stages. Examples of a priori knowledge are archival radar data, Geographic Information Systems (GISs), Digital Terrain Elevation Data (DTED), Land Cover Land Use (LCLU) data, information on the radar kinematical parameters, off-board sensor data, roadway maps, and background of air/surface traffic. Recent advances in environmental measurements, DTED, future information quality and accessibility, digital processing, mass and random-access memory technologies, have opened up many possibilities, unrealizable in the past, for radar systems to improve their on-line performance. New real-time processing techniques are required for [e.g. for the constant false alarm rate (CFAR) behavior of the radar system [6]] to take advantages of these advances to bring radar performance back to optimum under difficult operation conditions such as littorals that include mixed sea and variable terrain.

The great interest in the application of KB techniques to adaptive radar signal and data processing is evident from the following examples:

1. The Defence Advanced Research Projects Agency (DARPA) has been pioneering the development of the first ever real-time knowledge-aided adaptive radar architecture. In particular, the Knowledge Aided Sensor Signal Processing and Expert Reasoning (KASSPER) program has as its aim the development and application of a revolutionary new approach to demanding multidimensional adaptive sensor systems, with a near-term focus on military applications of Ground Moving Target Indicator (GMTI) radar and Synthetic Aperture Radar (SAR). Annual KASSPER workshops started in 2002 to allow the exchange of ideas across the spectrum of R&D activities, including knowledge-based space–time adaptive processing (KB-STAP), environmental knowledge-base generation and maintenance, and real-time KB embedded computing [7].
2. The US Air Force Research Laboratory's Sensors Directorate has been pursuing some of the most progressive work in employing KB techniques in the radar signal processing chain, specifically in the CFAR portion of the chain [5, 8].

3. The US Air Force (USAF) has an ongoing project called Autonomous Intelligent Radar System (AIRS) that is performing research in applying KB techniques to radar signal processing. The AIRS architecture design leverages advanced technologies developed by the World Wide Web Consortium (W3C) and the DARPA Agent Markup Language (DAML) program to define the next-generation Internet, also called the Semantic Web [9].
4. A series of lectures has been devoted to Knowledge-Based Radar Signal and Data Processing [10]. They were sponsored by the NATO Research and Technology Organization (RTO) with the following scope: promoting cooperative research and information exchange to support the development and effective use of national defense research and technology to meet the military needs of the alliance; maintaining a technological lead; and providing advice to NATO decision makers. This Lecture Series was held in Sweden, Hungary, and Italy in 2003; Poland and Spain in 2004; and in the Czech Republic, Belgium, and the UK in 2006.
5. A special section of the *IEEE Signal Processing Magazine* devoted to "Knowledge-Based Systems for Adaptive Radar: Detection, Tracking, and Classification," published in January 2006, edited by Fulvio Gini [11].
6. A special section of *IEEE Transactions on Aerospace and Electronic Systems* devoted to "Knowledge-Aided Sensor Signal and Data Processing," published in July 2006, co-edited by William Melvin and Joseph Guerci [12].

The aim of this book is to highlight recent advances in both knowledge-based systems and radar signal and data processing, in a common forum, in order to present a range of perspectives and innovative results with potential to enable practical adaptive radar systems design. The chapters of this book describe the current developments in the area and present examples of improved radar performance for augmented and upgraded systems, and project the impact of KB technology on future systems.

1.1 ORGANIZATION OF THE BOOK

The book is organized into ten chapters. This first chapter is the introduction to the concept of KB radar. The remaining nine chapters focus on the application of KB concepts to a specific radar function, that is, detection, tracking, or classification. Each of them is essentially self-contained, starting with introductory remarks, following with a discussion, and ending with a list of references. Their contribution is briefly summarized in the following.

Chapter 2, entitled "Cognitive Radar" (by Haykin), discusses the idea of cognitive radar. The radar environment is usually nonstationary, and adaptivity is the method implemented in modern radar systems for dealing with nonstationarity. In current designs of radar systems, adaptivity is usually confined to the receiver. In this chapter it is argued that for the radar to be cognitive, adaptivity has to be extended to the transmitter too. Three important conclusions are drawn:

1. Intelligence is a necessary requirement for the radar to be cognitive;
2. Feedback from the receiver to the transmitter is the facilitator of intelligent signal processing; and
3. The preservation of information in radar returns is of crucial importance to improved receiver performance.

Two potential applications of cognitive radars are finally presented, one dealing with multifunction radars and the other dealing with a network of noncoherent marine radars.

Chapter 3, entitled “Knowledge-Based Radar Signal and Data Processing: A Tutorial Overview” (by Capraro, Farina, Griffiths, and Wicks), describes the role of KB processing in exploiting available information such as positioning, waveform selection, and modes of operation to enhance radar performance. This chapter provides a brief overview of artificial intelligence (AI) and a rationale for knowledge bases and robotics, which are the two main areas of emphasis for bringing KB into fielded radar systems. Also, the role of Semantic Web technologies in KB radar systems is discussed. An end-to-end radar signal and data processing architecture for airborne surveillance radar and its over-arching KB processing and control are described in detail. The chapter ends with the authors’ view of the future of KB radar research, including waveform diversity and intelligent sensor systems.

Chapter 4, entitled “An Overview of Knowledge-Aided Adaptive Radar at DARPA and Beyond” (by Guerci and Baranoski), provides a breezy tour of the KASSPER program, highlighting both the benefits of knowledge-aided (KA) adaptive radar, key algorithmic concepts, and a new “look-ahead” radar scheduling approach that is the cornerstone of High Performance Embedded Computing (HPEC) architectures. Methods in which prior knowledge can be incorporated into the space–time adaptive beamformer, which is the most demanding component of modern GMTI radar, are described in some detail. Finally, the chapter introduces the notion of extending KA processing to the adaptive MIMO (Multi-Input Multi-Output) radar problem. The methods described here are potentially applicable in many other adaptive sensor signal processing systems such as hyperspectral imaging, lidar, sonar, and other multidimensional sensor arrays where environmental disturbance is a dominant source of interference.

Chapter 5, entitled “Space–Time Adaptive Processing for Airborne Radar: A Knowledge-Based Perspective” (by Wicks, Rangaswamy, Adve, and Hale), provides an overview of radar STAP from its inception to state-of-the-art developments. The topic is treated with regard to both intuitive and theoretical aspects. A key requirement of space–time adaptive processing is knowledge of the spectral characteristics underlying the interference scenario of interest. However, these are seldom known in practice and must be estimated using training data. Two central problems arise in the application of STAP:

1. The homogeneity of the sample support needed to train the adaptive filter; and
2. The computational load of the algorithm. No algorithm is the best one and the only practical approach suggested in this article is to use a KB scheme that best matches the signal processing to the interference scenario at hand. The article illustrates the immense potential of KB approaches in solving these problems.

Chapter 6, entitled "CFAR Knowledge-Aided Detection and its Demonstration Using Measured Airborne Data" (by C. Capraro, G. Capraro, De Maio, Farina, and Wicks), addresses the design and analysis of a KA detector for airborne radar applications. The two building blocks of the proposed processor are the training data selector and the detector. The training data selector has the goal to choose the secondary cells that best represent the clutter statistics in the cell under test. It is a hybrid algorithm, which pre-screens training data through the use of terrain information from the United States Geological Survey (USGS). The second stage of processing is a data-driven selector, which attempts to eliminate residual training data heterogeneities. The performance of the proposed KA detector is analyzed using measured airborne radar data, obtained from the Multi-Channel Airborne Radar Measurements (MCARM) program, and is compared with alternative detectors proposed in the open literature.

Chapter 7, entitled "STAP via Knowledge-Aided Covariance Estimation and the FRACTA Meta-Algorithm" (by Blunt, Gerlach, Rangaswamy, and Shackelford), describes the development of a KB approach to airborne/space-based radar for GMTI in the presence of severely heterogeneous training data. In particular it addresses the benefit provided by model-based prior knowledge when used to supplement the FRACTA meta-algorithm, a multistage/multimetric approach that is robust to training data heterogeneity. The FRACTA meta-algorithm utilizes three stages of detection, which, individually, systematically identify potential targets while eliminating data contamination (censoring), detect targets within the clutter-suppressed environment (cell-averaging CFAR), and eliminate false alarms that may arise due to undernulled clutter and/or space–time filter sidelobes (Adaptive Coherence Estimator (ACE) detector). In the chapter it is demonstrated how approximate prior knowledge in the form knowledge-aided covariance estimation (KACE) further improves the robustness of the detector by supplementing interference covariance estimation in scenarios with insufficient sample support that would otherwise lead to "sample starvation" problems.

Chapter 8, entitled "Knowledge-Based Radar Tracking" (Benavoli, Chisci, Farina, Immediata, and Timmoneri), describes how to efficiently exploit a priori knowledge in the tracking of multiple radar targets. In many scenarios, heterogeneity of the surveillance region makes conventional tracking systems (not using the KB) very sensitive to false alarms and/or missed detections. In this chapter it is demonstrated that an effective use of a priori knowledge at various levels of the tracking algorithms significantly reduces the number of false alarms, missed detections, false tracks, and improves true target track life The main ingredients of the tracker are (1) Extended Kalman filtering to take into account nonlinearities; (2) Interacting Multiple Model for managing the target maneuvers; (3) Nearest Neighbour Cheap Joint Probabilistic Data Association for robust plot–track association; (4) M out of N logic for track initiation; (5) use of the Knowledge Base (geographical maps and targets characteristics) and of Amplitude Information; (6) use of fuzzy logic for classification of the surveillance region. The proposed algorithm is tested against simulated and live data pertaining from a SELEX-SI naval surveillance radar. The results demonstrate that the KB approach provides meaningful advantages, allowing for the reduction of false and tentative tracks while permitting the continuous track of useful targets.

Chapter 9, entitled "Knowledge-Based Radar Target Classification" (by Bilik and Tabrikian), addresses the problem of automatic target recognition by means of ground surveillance Doppler, in particular, the classification between a walking person, a pair of walking persons, and a slowly moving vehicle. The maximum likelihood (ML) and the "majority voting" decision rules were applied to the proposed classification problem. Two sources of knowledge were considered for target classification: statistical and physical. Statistical knowledge is obtained from a training database of recorded target echos, and physical knowledge is available by developing locomotion models for the different targets. The statistical classifier was applied to a seven-class problem of radar targets such as walking person, group of walking persons, tracked vehicle, wheeled vehicle, animals, and clutter. The human operator's performance has also been evaluated. In many cases, a training database may not be available, and in some cases, it may be insufficient to represent the different classes. On the other hand, the inaccuracy in the locomotion models results in limited classification performance. In the chapter it is shown that the best performance is achieved via a combined approach, which incorporates both the statistical and physical knowledge sources. The performances of the physical, statistical, and combined knowledge-based algorithms are tested using real data records from three classes: one person, two persons, and vehicle.

The final chapter, entitled "Knowledge-Based Resource Management for Multifunction Radar" (Miranda, Baker, Woodbridge, and Griffiths), focuses on the multifunction radar (MFR) resource management problem, that is, the allocation of finite resources in an optimal and intelligent way. The dynamic and interactive interplay between the setting of radar parameters to optimize the tasks to be carried out and perception of environment motivates the centrality of knowledge-based data processing in determining MFR performance. The chapter focuses on two related aspects of radar resource management: scheduling and task prioritization. Two different methods of scheduling are examined and compared, and their differences and similarities highlighted. The analysis indicates that prioritization is a key component to determining overall performance. A fuzzy logic approach for prioritizing radar tasks in changing environment conditions is described. By assessing the priorities of targets and sectors of surveillance according to a set of rules, an attempt is made to imitate the human decision-making process such that the resource manager can distribute the radar resources in a more effective way. Results suggest that the fuzzy approach is a valid means of evaluating the relative importance of the radar tasks; the resulting priorities are adapted by the fuzzy logic prioritization method, according to how the radar system perceives the surrounding environment.

We hope that this book will stimulate the interest of the scientific community in this new and exciting field of research, which offers a rich set of challenges and problems spanning a broad spectrum of basic and applied research.

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2

COGNITIVE RADAR

Simon Haykin

In this chapter, we discuss "cognitive radar," the idea of which was first published in reference 1. Cognitive radar builds on three basic ingredients:

1. *Intelligent signal processing*, which itself builds on learning through interactions of the radar with the surrounding environment;
2. *Feedback from the receiver to the transmitter*, which is a facilitator of intelligence;
3. *Preservation of the information content of radar returns*, which is realized by the Bayesian approach to radar signal processing.

All three ingredients feature in the echo-location system of a bat, which may therefore be viewed as a physical realization (albeit in neurobiological terms) of what we mean by cognitive radar.

The chapter concludes with two potential applications of cognitive radar, one dealing with multifunction radars, and the other dealing with a network of noncoherent radars for homeland security.

2.1 INTRODUCTION

Radar is a remote-sensing system that is widely used for surveillance, tracking, and imaging applications, for both civilian and military needs. In this chapter, we focus attention on future possibilities of radar with particular emphasis on the notion of *cognition.* As an illustrative case study along the way, we consider the radar surveillance problem.

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According to the *Oxford English Dictionary*, cognition is "knowing, perceiving, or conceiving as an act. . .". Given three distinct capabilities,

1. the inherent ability of radar to sense its environment on a continuous basis and thereby getting to *perceive* it,
2. the ability of phased-array antennas to electronically scan the environment in a fast manner, and
3. the ever-increasing power of computers to digitally process signals,

it is our conviction that it is not only feasible but also highly beneficial to build a cognitive radar system using today's technology. Indeed, if ever there was a remote-sensing system well suited for cognition, radar is it.

From the moment a surveillance radar system is switched on, the system becomes electromagnetically linked to its surrounding environment, in the sense that the environment has a strong and continuous influence on the radar returns (i.e. echoes). In so doing, the radar builds up its knowledge of the environment from one scan to the next, and makes decisions of interest on possible targets at unknown locations in the environment. The locations are not known before the radar is switched on, but they become determined by the radar receiver once the targets under surveillance are declared.

From signal-processing and control theory, we know that it is not necessary for the radar to keep the entire record of past data. Rather, by adopting a *state-space model* of the environment, and recursively updating the state vector representing an estimate of certain parameters pertaining to the environment, the need for storing the entire history of radar data on the environment is eliminated. The challenge is how to formulate the state-space model of the environment.

The requirement to update estimation of the environmental state is necessitated by the fact that the radar environment is *nonstationary*. Primary causes of nonstationarity include statistical variations in the weather, the presence of unknown targets at unknown locations, and the ever-present radar *clutter*, which refers to radar returns from unwanted objects. Recursive updating of a state is synonymous with *adaptivity*, which is the natural method for dealing with nonstationarity. In current designs of radar systems, however, adaptivity is usually confined to the receiver. For the radar to be cognitive, adaptivity has to be extended to the transmitter too, hence the need for a feedback channel from the receiver to the transmitter. Moreover, the radar has to learn from experience on how to deal with different targets, large and small, and at widely varying ranges, all in an effective and robust manner. We may therefore say that a cognitive radar implies adaptivity, but not the other way round.

2.2 COGNITIVE RADAR SIGNAL-PROCESSING CYCLE

The dictionary definition of cognition mentioned above also includes "conceiving," which might be taken to mean the following statement:

> The formulation of a hypothesis, and then testing that hypothesis for the likelihood of its correctness.

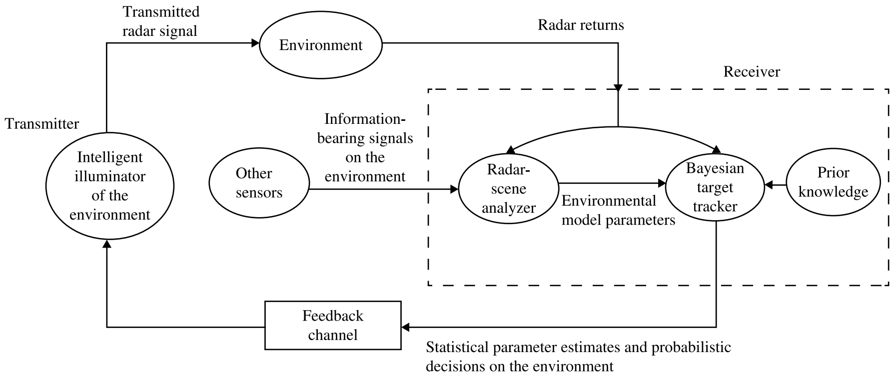

Figure 2.1 Block diagram of cognitive radar viewed as a closed-loop dynamic system.

This statement is in the spirit of the Bayesian approach to state estimation, with a probabilistic rating of alternatives. We are therefore emboldened to embrace the idea of Bayesian inference under the umbrella of cognitive radar.

This way of thinking leads us to the block diagram of Fig. 2.1, which depicts a picture of the cognitive radar signal-processing cycle. The cycle begins with the transmitter illuminating the environment. The radar returns produced by the environment are fed into two functional blocks: the radar-scene analyzer, and the Bayesian target-tracker. The tracker makes decisions on the possible presence of targets on a continuing time basis, in light of information on the environment provided to it by the radar-scene analyzer. The transmitter, in turn, illuminates the environment in light of the decisions made on possible targets, which initiates the next cycle of operation. The cycle is then repeated over and over again. Unlike a communication system, the feedback mechanism — a necessary requirement of a cognitive system — is easy to implement as the radar transmitter and receiver are usually co-located. Note also that although the process of target detection is not explicitly shown in the cognitive cycle of Fig. 2.1, it is part and parcel of the Bayesian target-tracker, which performs "detection through tracking" as explained later.

Based on the picture depicted in Fig. 2.1, a cognitive radar distinguishes itself from an adaptive radar in three important respects:

1. The radar continuously learns about the environment through experience gained from interactions of the receiver with the environment and, in a corresponding way, continually updates the receiver with relevant information on the environment.
2. The transmitter adjusts its illumination of the environment in an intelligent manner, taking into account such practical matters as the size of the target and its range, and consequently, making adjustments to the transmitted signal in an effective and robust manner.
3. The whole radar system constitutes a closed-loop dynamic system, encompassing the transmitter, the surrounding environment, the feedback channel, and the receiver. In other words, we have global feedback acting around the whole system.

It is well known that feedback is like a double-edged sword, in that it can become harmful if it is used improperly. Care must therefore be exercised in how the transmitter is designed in relation to the environment and receiver, so as to maintain a stable and reliable operation at all times.

One other important comment is in order. In reality, cognition is a two-way process, one being inside-out and the other being outside-in. These two parts of the cognitive process are so referred to, depending on whether the source of information leading to cognition resides inside or outside the receiver, respectively, as explained in the following[1]:

1. The "inside-out" part of cognition is represented by prior knowledge on the environment; it is an integral part of the receiver, as shown in Fig. 2.1. The form of prior knowledge is naturally application-dependent. For example, it may take the form of a geographic map, a clutter map of the environment, an elevation model, or kinematics of noncooperative targets. The Bayesian target-tracker retrieves information from the prior-knowledge base and utilizes it for improved radar performance on a need-be basis. Prior knowledge may therefore be viewed as the long-term memory of the receiver.
2. In contrast, the "outside-in" part of cognition may be viewed as short-term memory, which is developed by the receiver on the fly. It is initiated by the radar-scene analyzer in response to information-bearing signals gathered on the outside environment by the radar itself as well as other sensors working cooperatively with the radar.

2.3 RADAR-SCENE ANALYSIS

The function of the radar-scene analyzer is to provide the receiver with information on the environment on a continuous basis. This information is of critical importance to the decisions made by the receiver on possible targets of interest. This function builds on two sources of information-bearing signals:

1. radar returns, which are produced by the environment in response to the radar's own transmitted signal.
2. other relevant information on the environment (e.g. temperature, humidity, pressure, sea state), which is gathered on the fly by sensors other than the radar itself.

These two sources of inputs constitute the stimuli for the outside-in part of radar cognition.

1. The knowledge-based (KB) radar system described in subsequent chapters of the book may be viewed as a kind of inside-out cognitive system, embodying heuristics for determining how and when the signal-processing chain in the radar should be changed. The heuristics are developed through prior experimentation using a KB approach to target detection with human intervention; the human intervention is subsequently captured and then embedded into the receiver as a KB system.

In a surveillance scenario, radar performance is affected significantly by the unavoidable presence of interference. Typically, the interference is dominated by clutter (i.e. radar returns produced by undesired targets). Accordingly, to design a target tracker that embodies target detection, we need two kinds of information: one pertaining to the clutter acting alone, and the other pertaining to the target plus clutter.

2.3.1 Statistical Modeling of Statistical Representation of Clutter- and Target-Related Information

In order to describe how these two pieces of information can be addressed in specific terms, consider the case of a coherent radar dwelling on a particular patch of the ocean surface. With the radar being coherent, the radar returns contain amplitude as well as Doppler information on that patch. Correspondingly, the baseband version of the radar returns will be complex-valued. Now, the dwelling process can be of a long-term nature, in which case the nonstationary character of the radar returns becomes quite noticeable. In situations of this kind, we may be forced to avoid modeling the actual Doppler spectrum (i.e. plot of average power versus frequency) of the radar returns, and do so by exploiting the following intuitively satisfying observations:

> The Doppler spectrum of clutter by itself is relatively smooth, whereas the spectral content of the radar echo from a target appears essentially as a line component.

However, when the target cross-section is small and the target-to-clutter power ratio is therefore low, we need to enhance the line component due to the target. This enhancement may be achieved by performing the following transformation [2, 3]:

> Divide the average power in each Doppler bin of the spectrum (pertaining to the range-azimuth resolution cell of interest) by the mean of its neighboring bins, say k in number.

This transformation has the desired effect of accentuating the narrow peak of the line component due to the target and, at the same time, lowering the relatively wide peak of the clutter. Inspiration for the transformation, called a "peak filter," is traced to the "grouped periodogram test" described by Priestly [4], which was itself inspired by earlier work by Tukey in 1949. The statistics of the peak filter output, in the absence of a target, may now be evaluated under three assumptions [2, 3]:

1. None of the k neighboring Doppler bins in the power spectrum contains a target.
2. Inside a spectral window encompassing $(k + 1)$ Doppler bins, the continuous clutter power spectrum (that is always present) is approximately constant.
3. All $(k + 1)$ ordinates of the power spectrum are sampled independently.

Under these three assumptions, the individual ordinates of the actual power spectrum have a χ^2 distribution with two degrees of freedom [4]. Correspondingly, the peak-filter output, which divides each spectrum ordinate by k others, has a hypergeometric distribution, specifically an F-distribution with (2, 2k) degrees of freedom [2, 3]. On this basis, the clutter statistics are described by the distribution $F_{2,\ 2k}(z)$, where z is a random variable (i.e. average clutter power measurement). It is noteworthy that in reference 5, a similar observation is made using stochastic differential equation theory.

Turning next to the target, which is typically unknown, modeling its statistics is unfortunately not straightforward. For ease of implementation, and due to a lack of detailed knowledge about the target, it may be prudent to assume that the target has the same distribution that governs the clutter, but with a difference. (This assumption may hold in the case of a small target moving on an ocean surface, in which case the underlying dynamics of the clutter and the target are closely coupled.) Accordingly, if the clutter distribution is described by $F_{2,2k}(z)$, the target distribution is taken to be $\frac{1}{\gamma}F_{2,2k}\left(\frac{z}{\gamma}\right)$, where z is a power spectrum measurement and γ is the target-to-clutter power ratio [2, 3]; the scalar parameter z is not to be confused with the vector $\mathbf{z}$ introduced later.

In addition to the target statistics, the receiver needs to have a model that accounts for the motion of the target. To this end, we may assume that the target has a Gaussian-distributed acceleration with variance σ^2, which characterizes the agility of the target. For a low standard deviation σ, the target is seen by the radar when it is not accelerating. On the other hand, for a high σ, the task of target detection may become difficult due to possible confusion of the target with small clutter peaks, hence the likelihood of the radar making a decision error.

In summary, for an ocean environment under surveillance by a coherent radar, information on radar returns processed by the radar-scene analyzer for a particular range-azimuth cell may be modeled as follows:

1. *Clutter-statistics*, described by the F-distribution $F_{2,2k}(z)$, where z is a power spectrum measurement and k is the number of neighboring Doppler bins over which the measurement is averaged.
2. *Target-plus-clutter statistics*, described by the scaled F-distribution $\frac{1}{\gamma}F_{2,2k}\left(\frac{z}{\gamma}\right)$, where γ is the target-to-clutter power ratio.
3. *Target motion*, described by a Gaussian-distributed acceleration with a variance σ^2, which accounts for the target's agility.

It must be re-emphasized, however, that this model is appropriate for the specific case of a target moving on an ocean surface. For other environmental scenarios, the radar designer is challenged to develop appropriate statistical models to describe the information content of radar returns on clutter and targets.

2.4 BAYESIAN TARGET TRACKING

Previously, we mentioned that the Bayesian paradigm is a logical choice for coherent radar. We now describe a Bayesian strategy for the coherent radar detection of small targets in the presence of sea clutter. Unlike conventional tracking algorithms that perform intermediate detections (i.e. hard decisions) on the radar returns, the new algorithm processes the radar returns directly.[2] Specifically, the algorithm, referred to as a *direct tracking algorithm*, consists of three basic steps:

1. For a given search area, radar returns are collected over a certain period of time.
2. For each range-azimuth resolution cell in the search space, the probability that the cell contains a target is computed.
3. With the evolution of the target probability distribution resulting from the recursive computation of step 2 over time, target tracks are detected and corresponding hard decisions on possible targets are subsequently made.

In effect, the algorithm (formulated in probabilistic terms) may be viewed as a soft-decision procedure on target detection.

To set the stage for the Bayesian framework, let there be a total of R range-azimuth resolution cells in the search space S, and let $r \in S$ denote a resolution cell in question. Let ε_t^r denote the event of a single target occurring in resolution cell r at discrete time t. Let the vector $\mathbf{z}_t$ denote the frame that is made up of the spectral measurements for all R resolution cells at time t. The matrix

$$\begin{aligned}\mathbf{Z}_t &= [\mathbf{z}_t, \mathbf{z}_{t-1}, \ldots, \mathbf{z}_2, \mathbf{z}_1] \\ &= [\mathbf{z}_t, \mathbf{Z}_{t-1}]\end{aligned}$$

denotes the full set of all the available frames extending up to and including time t. Then, according to this notation, the vector $\mathbf{z}_t$ denotes the current frame and the remaining matrix $\mathbf{Z}_{t-1}$ denotes the combined set of all past frames. By the same token, $\mathbf{Z}_{t+1}$ denotes the combination of a future frame $\mathbf{z}_{t+1}$, the current frame $\mathbf{z}_t$, and all past frames $\mathbf{Z}_{t-1}$.

Following the traditional approach to state estimation, we may now identify three different forms of the Bayesian target-tracker:

1. *one-step predictor*, whose output is described by the conditional probability $\mathbf{P}(\varepsilon_t^r|\mathbf{Z}_{t-1})$;
2. *filter*, whose output is described by the conditional probability $\mathbf{P}(\varepsilon_t^r|\mathbf{Z}_t)$;
3. *smoother*, whose output is described by the expanded conditional probability $\mathbf{P}(\varepsilon_t^r|\mathbf{Z}_{t+1})$.

2. In reference 6, Bruno and Moura also describe a Bayesian approach to the tracking problem. Given a search space of R range-azimuth resolution cells and M possible targets, their algorithm is designed to track any of the targets. The algorithm does so by first computing the probability of each of the 2^M different target combinations. Specifically, the centroid of each target can be in any of the R resolution cells, or else be absent. The Bayesian tracking approach described in this chapter is however different, in that it is formulated in such a way that the algorithm can also operate in a smoothing mode, with the probability distribution of the smoothed output being conditional on both past and future observations.