Hard & Soft Fusion

Cornerstone of Information Processing and Management

An Introduction with Defence and Security Examples

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ABSTRACT

"Hard and Soft Fusion" is the process of combining incomplete and imperfect pieces of mutually complementary information from various sensor and non-sensor sources in such a way that a better understanding of an underlying real-world phenomenon is achieved. Typically, this insight is either unobtainable otherwise or a fusion result exceeds what can be produced from a single information source in accuracy, reliability, or cost.

Appropriate collection, registration, and alignment, stochastic filtering, logical analysis, space time integration, exploitation of redundancies, quantitative evaluation, and appropriate display are part of "Hard and Soft Fusion" as well as the integration of related context information. Today, "Hard and Soft Fusion" is evolving at a rapid pace and present in defence and security systems.

Although a vast research literature with specialized journals and conference proceedings, several handbooks, and scientific monographs deal with aspects of "Hard and Soft Fusion", it often seems difficult to find access to the underlying general methodology and to apply the inventory of various fusion techniques to solving individual application problems. To facilitate the transfer of notions and algorithms to problem solving is the is the over-all objective of the NATO STO Lecture Series ADVANCED ALGORITHMS FOR EFFECTIVELY FUSING HARD AND SOFT INFORMATION (IST-134).

This document comprises additional reading material to three lectures in this series that address selected aspects. Chapter 1 presents a more or less coherent methodological framework of "Hard and Soft Fusion" and is thus providing at least a selection of prerequisites for discussing applications in the defence domain (Chapter 2) and in security applications (Chapter 3) as well as the other lectures of this lecture series.

Contents

Hard & Soft Fusion – Cornerstone of Information Processing and Management

Fusion of "hard and soft" pieces of information is an omnipresent phenomenon that existed prior to its technological realization or the scientific reflection on it. In fact, all living creatures, including human beings, by nature or intuitively perform sensor data fusion. Each in their own way, they combine or "fuse" sensations provided by different and mutually complementary sense organs with knowledge learned from previous experiences and communications from other creatures. As a result, they produce a "mental picture" of their individual environment, the basis of behaving appropriately in their struggle to avoid harm or successfully reach a particular goal in a given situation.

1.1 Subject Matter

As a sophisticated technology with significant economic and defence implications as well as a branch of engineering science and applied informatics, modern information fusion aims at automating this capability of combining complementary pieces of information. Information fusion thus produces a "situation picture", a reconstruction of an underlying "real situation", which is made possible by efficiently implemented mathematical algorithms exploiting even imperfect data and enhanced by new information sources. Emphasis is not only placed on advanced sensor systems, technical equivalents of sense organs, but also on spatially distributed networks of homogeneous or heterogeneous sensors on stationary or moving platforms and on the integration of data bases storing large amounts of quantitative context knowledge. The suite of information sources to be fused is completed by the interaction with human beings, which makes their own observations and particular expertise accessible.

The information to be fused may comprise a large variety of attributes, characterized, for example, by sensor ranges from less than a meter to hundreds of kilometers, by time scales ranging from less than second to a few days, by nearly stationary or rapidly changing scenarios, by actors behaving cooperatively, incooperatively, or even hostile, by high precision measurements or sensor data of poor quality.

Besides observational data from technical sensors or collected by human observers, information fusion systems are fundamentally based on context information. It seems reasonable to distinguish between *physical context*, derived from natural sciences, *environmental context*, determined typically while operating the system, *partially known context*, often described by statistical models, and *language-encoded context*. In many cases, these categories of context information do not appear isolated from each other. Sensor models, for example, combine physical and partially known context for describing imprecise sensor measurements with environmental context, e.g. when a clutter background has to be estimated online.

In emerging informational assistance systems for defence and security applications, all forms of context information are of critical importance. The technological revolution is in particular driven by algorithms for extracting high-value information from sensor data streams of even poor quality. Due to the complexity of the real-world phenomena to be observed, however, and their inherently unpredictable nature, the role context information and its integration on various levels in systems engineering are crucial. In a sense, also legal and moral constraints can be viewed as context information shaping the very design of informational support for defence and security. We exemplary discuss data fusion methodologies having their roots in "classical" tracking and sensor data fusion applications and some more general design principles.

Information fusion systems emerging from this branch of technology have in effect the character of "cognitive tools", which enhance the perceptive faculties of human beings in the same way conventional tools enhance their physical strength. In this type of interactive assistance system, the strengths of automated data processing (dealing with mass data, fast calculation, large memory, precision, reliability, robustness etc.) are put into service for the human beings involved. Automated information fusion actually enables them to bring their characteristically "human" strengths into play, such as qualitatively correct over-all judgment, expert knowledge and experience, intuition and creativity, i.e. their "natural intelligence" that cannot be substituted by automated systems in the foreseeable future. The user requirements to be fulfilled in a particular application have a strong impact on the actual fusion system design.

1.1.1 Remarks on the JDL Model

Sensor data fusion systems have been developed primarily for applications, where a particular need for support systems of this type exists, for example in time-critical situations or in situations with a high decision risk, where human deficiencies must be complemented by automatically or interactively working data fusion techniques. Examples are fusion tools for compensating decreasing attention in routine and mass situations, for focusing attention on anomalous or rare events, or complementing limited memory, reaction, and combination capabilities of human beings. In addition to the advantages of reducing the human workload in routine or mass tasks by exploiting large data streams quickly, precisely, and comprehensively, fusion of mutually complementary information sources typically produces qualitatively new and important knowledge that otherwise would remain unrevealed.

The demands for developing such support systems are particularly pressing in defence and security applications, such as surveillance, reconnaissance, threat evaluation, and even weapon control. The earliest examples of large sensor data fusion projects were designed for air defence against missiles and low-flying bombers and influenced the development of civilian air traffic control systems. The development of modern sensor data fusion technology and the underlying branch of applied science was stimulated by the advent of sufficiently powerful and compact computers and high frequency devices, programmable digital signal processors, and last but not least by the "Stratecic Defence Initiative (SDI)" announced by US President Ronald Reagan on March 23, 1983.

After a certain level of maturity has been reached, the Joint Directors of Laboratories (JDL), an advisory board to the US Department of Defense, coined the technical term "Sensor Data and Information Fusion" in George Orwell's very year 1984 and undertook the first attempt of a scientific systematization of the new technology and the research areas related to it [1, Chapter 2, p. 24]. To the present day, the scientific fusion community speaks of the "JDL Model of Information Fusion" and its subsequent generalizations and adaptations [1, Chapter 3], [2]. The JDL model provides a structured and integrated view on the complete functional chain from distributed sensors, data bases, and human reports to the users and their options to act including various feed-back loops at different levels (Figure 1.1). It seems to be valid even in the upcoming large fields of civilian applications of sensor data fusion and computer security [3]. Obviously, the fundamental concepts of sensor data fusion have been developed long before their full technical feasibility and robust realizability in practical applications.

1.1.2 General Technological Prerequisites

The modern development of sensor data fusion systems was made possible by substantial progress in the following areas over the recent decades:

1. Advanced and robust *sensor systems*, technical equivalents of sense organs with high sensitivity or coverage are made available that may open dimensions of perception usually unaccessible to most living creatures.
2. *Communication links* with sufficient bandwidths, small latencies, stable connectivity, and robustness against interference are the backbones of spatially distributed networks of homogeneous or heterogeneous sensors.
3. Mature *navigation systems* are prerequisites of (semi-)autonomously operating sensor platforms and common frames of reference for the sensor data based on precise space-time registration including mutual alignment.
4. *Information technology* provides not only sufficient processing power for dealing with large data streams, but also efficient data base technology and fast algorithmic realizations of data exploitation methods.

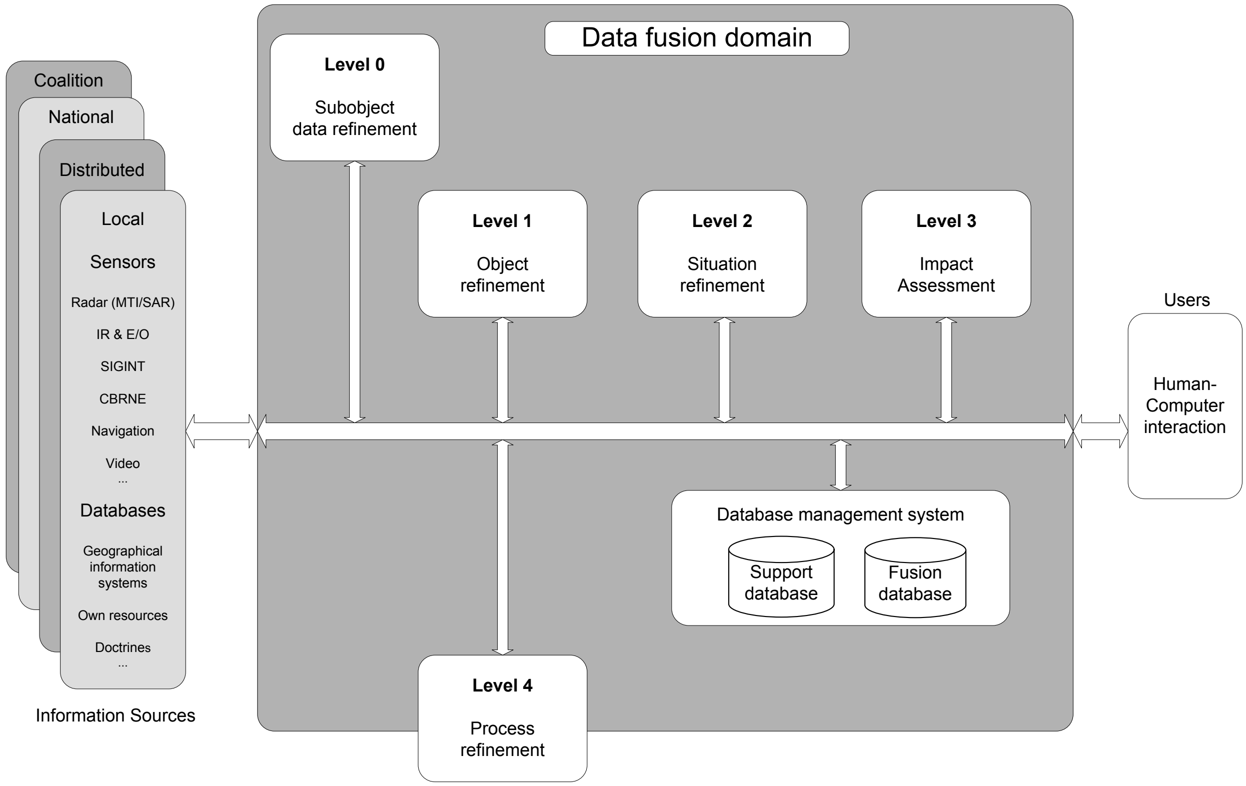


Fig. 1.1. Overview of the JDL-Model of Sensor Data and Information Fusion [1, Chapter 3], which provides a structured and integrated view on the complete functional chain from distributed sensors, data bases, and human reports to the users and their options to act including various feed-back loops at different levels.

5. *Technical interoperability*, the ability of two or more sub-systems or components to exchange and to information, is inevitable to build distributed "systems of systems" for sensor exploration and data exploitation [4].
6. Advanced and ergonomically efficient *Human-Machine Interaction (HMI)* tools are an integral part of man-machine-systems presenting the results of sensor data fusion systems to the users in an appropriate way [5].

The technological potential enabled by all these capabilities is much enhanced by integrating then in an overlay sensor data fusion system.

1.1.3 Relation to Information Systems

According to this technological infrastructure, human decision makers on all levels of hierarchy, as well as automated decision making systems, have access to vast amounts of data. In order to optimize use of this high degree of data availability in various decision tasks, however, the data continuously streaming in must not overwhelm the human beings, decision making machines, or actuators involved. On the contrary, the data must be fused in such a way that at the right instant of time the right piece of high-quality information relevant to a given situation is transmitted to the right user or component and appropriately presented. Only if this is the case, can the data streams support goal-oriented decisions and coordinated action planing in practical situations and on all levels of decision hierarchy.

In civilian applications, management information or data warehouse systems are designed in order to handle large information streams. Their equivalents in the defence and security domain are called C^4ISTAR Systems [4]. This acronym denotes computer-assisted functions for C^4 (Command, Control, Communications, Computers), I (Intelligence), and STAR (Surveillance, Target Acquisition and Reconnaissance) in order to enable the coordination of defence-related operations. While management information or data warehouse systems are primarily used to obtain competitive advantages in economic environments, C^4ISTAR systems aim at information dominance over potential opponents. The observation that more or less the same terminology is used in both areas for characterizing the struggle to avoid harm or successfully reach goals, is an indication of far-reaching fundamental commonalities of decision processes in defence command & control as well as in product development and planing, in spite of different accentuations in particular aspects.

A basic component of C^4ISTAR information systems, modular and flexibly designed as "systems of systems", is the combination of sensor systems and data bases with appropriate sensor data and information fusion sub-systems. The objective at this level is the production of timely, consistent and, above all, sufficiently complete and detailed "situation pictures", which electronically represent a complex and dynamically evolving overall scenario in the air, on the ground, at sea, or in an urban environment. The concrete operational requirements and restrictions in a given application define the particular information sources to be considered and data fusion techniques to be used.

A Characteristic Example

A particularly mature example of an information system, where advanced sensor data fusion technology is among its central pillars, is given by a distributed, coalition-wide C^4ISTAR system of systems for wide-area ground surveillance. It mirrors many of the aspects previously addressed and has been carried out within the framework of a multinational technology program called MAJIIC (Multi-Sensor Aerospace-Ground Joint ISR Interoperability Coalition) [4, Chapter 20]. By collaboratively using interoperable sensor and data exploitation systems in coalition operations, MAJIIC has been designed to improve situational awareness of military commanders over the various levels of the decision making hierarchy.

Based on appropriate concepts of deployment and the corresponding tactical procedures, technological tools for Collection, Coordination and Intelligence Requirements Management (CCIRM) are initiated by individual sensor service requests of deployed action forces. The CCIRM tools produce mission plans according to superordinate priorities, task sensor systems with appropriate data acquisition missions, initiate data exploitation and fusion of the produced sensor data streams in order to obtain high-quality reconnaissance information, and, last but not least, guarantee the feedback of the right information to the requesting forces at the right instant of time.

Under the constraint of leaving existing C^4ISTAR system components of the nations participating in MAJIIC unchanged as far as possible, the following aspects are addressed with particular emphasis:

1. The integration of advanced sensor technology for airborne and ground-based wide-area surveillance is mainly based on Ground Moving Target Indicator Radar (GMTI), Synthetic Aperture Radar (SAR), electro-optical and infrared sensors (E/O, IR) producing freeze and motion imagery, Electronic Support Measures (ESM), and artillery localization sensors (radar- or acoustics-based).
2. Another basic issue is the identification and implementation of common standards for distributing sensor data from heterogeneous sources including appropriate data and meta-data formats, agreements on system architectures as well as the design and implementation of advanced information security concepts.
3. In addition to sensor data fusion technology itself, tools and procedures have been developed and are continuously enhanced for co-registration of heterogeneous sensors, cross-cueing between the individual sensors of a surveillance system, the sensors of different systems, and between sensors and actuators, as well as for exploitation product management, representation of the "Coalition Ground Picture", for coordinated mission planning, tasking, management, and monitoring of the MAJIIC sub-systems.
4. MAJIIC-specific communications have been designed to be independent of network-types and communication bandwidths, making it adaptable to varying requirements. Commercially available and standardized internet- and crypto-technology has been used in both the network design and the implementation of interfaces and operational features. Important functionalities are provided by collaboration tools enabling ad-hoc communication between operators and exchange of structured information.
5. The central information distribution nodes of MAJIIC C^4ISTAR system of systems are so-called Coalition Shared Data servers (CSD) making use of modern database technology. Advanced Data Mining and Data Retrieval tools are part of all MAJIIC data exploitation and fusion systems.
6. From an operational point of view, a continuous interaction between Concept Development and Experimentation (CD&E process, [6]) by planning, running, and analyzing simulated and live C^4ISTAR

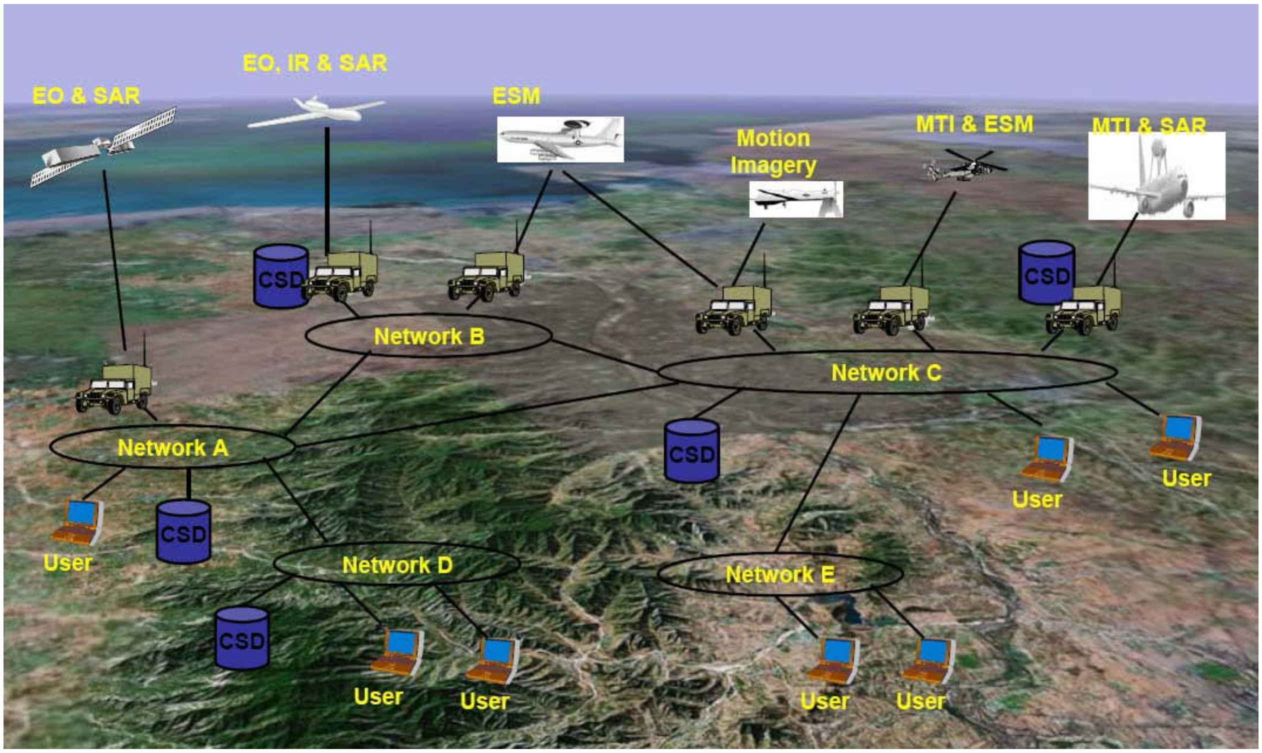


Fig. 1.2. MAJIIC system architecture emphasizing the deployed sensors, databases, and distributed sensor data fusion systems (Interoperable ISR Exploitation Stations).

experiments is an essential part of the MAJIIC program, fostering the transfer of MAJIIC capabilities into national and coalition systems.

Figure 1.2 provides an overview of the MAJIIC system architecture and the deployed sensor systems.

1.2 From Imperfect Data to Situation Pictures

Sensor data fusion typically provides answers to questions related to objects of interest such as: Do object exist at all and how many of them are moving in the sensors' fields of view? Where are they geolocated at what time? Where will they be in the future with what probability? How can their overall behavior be characterized? Are anomalies or hints to their possible intentions recognizable? What can be inferred about the classes the objects belong to or even their identities? Are there clues for characteristic interrelations between individual objects? In which regions do they have their origin? What can be said about their possible destinations? Are there observable over-all object flows? Where are sources or sinks of traffic? and many other questions.

The answers to those questions are the constitutive elements, from which near real-time situation pictures can be produced that electronically represent a complex and dynamically evolving overall scenario in the air, on the ground, at sea, under water, as well as in out- or in-door urban environments, and even more abstract spaces. According to the previous discussion, these "situation elements" must be gained from the currently received sensor data streams while taking into account all the available context knowledge and pre-history. Since situation pictures are fundamental to any type of computer-aided decision support, the requirements of a given application define which particular information sources are to be fused.

The sensor data to be fused are usually inaccurate, incomplete, or ambiguous. Closely-spaced moving objects are often totally or partially irresolvable. The measured object parameters may be false or corrupted by hostile measures. The context information is in many cases hard to formalize and even contradictory in certain aspects. These deficiencies of the information to be fused are unavoidable in any real-world application. Therefore, the extraction of 'information elements' for situation pictures is by no means trivial and requires a sophisticated mathematical methodology for dealing with imperfect information. Besides a precise requirement analysis, this is one of the major scientific features that characterizes and shapes sensor data fusion as branch of applied science.

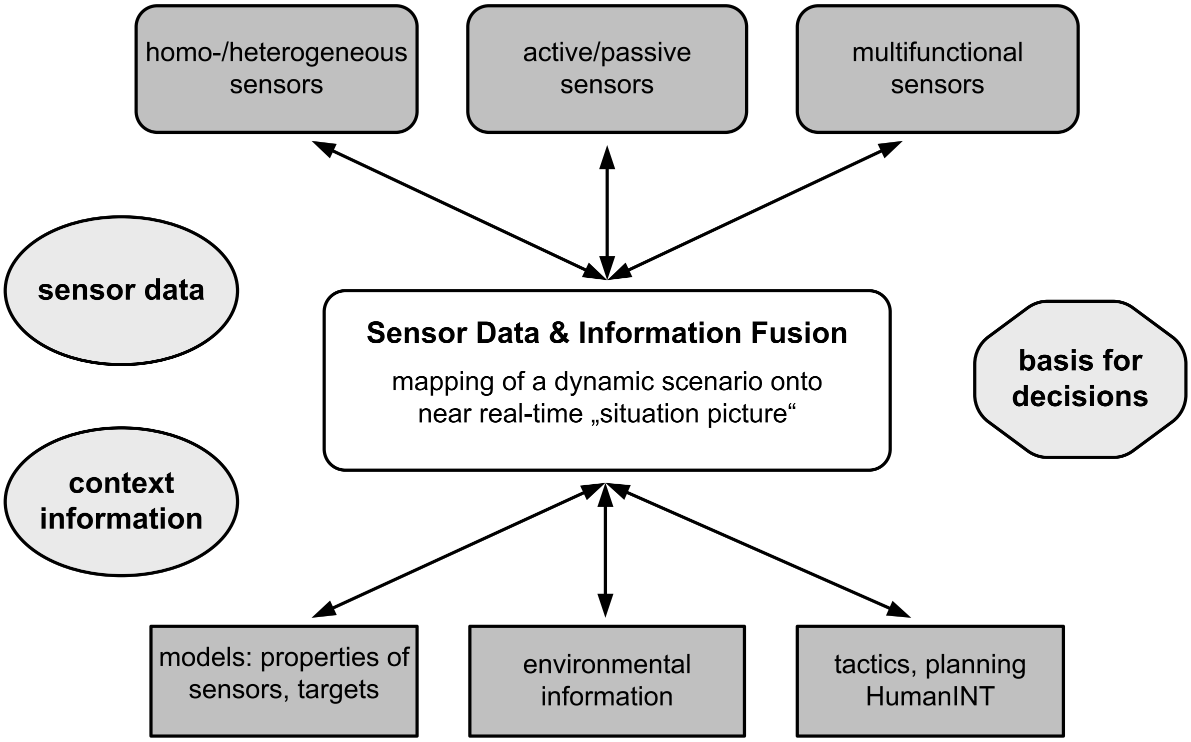


Fig. 1.3. Sensor data and information fusion for situation pictures: overview of characteristic aspects and their mutual interrelation.

1.2.1 Discussion of Characteristic Aspects

Figure 1.3 provides an overview of different aspects within this context and their mutual interrelation, which should be emphasized::

1. The underlying sensor systems can be located in different ways (collocated, distributed, mobile) producing measurements of the same or of different type. A multisensor system potentially increases the coverage or data rate of the total system and may help to resolve ambiguities.
2. Even by fusing homogeneous sensors, information can be obtained that is unaccessible to each sensor individually, such as in stereoscopic vision, where range information is provided by fusing two camera images taken from different viewpoints.
3. Fusion of heterogeneous sensor data is of particular importance, such as the combination of kinematic measurements with measured attributes providing information on the classes to which objects belongs to. Examples for measured attributes are Signal Intelligence (SIGINT), Jet Engine Modulation (JEM), radial or lateral object extension, chemical signatures etc.
4. Especially for defense and security applications, the distinction between active and passive sensing is important as passive sensors enable covert surveillance, which does not reveal itself by actively emitting radiation.

5. Multi-functional sensor systems, such as phased-array radar, offer additional operational modes, thus requiring more intelligent strategies of sensor management that provide feedback to the process of information acquisition via appropriate control or correction commands. By this, the surveillance objectives can often be reached much more efficiently.
6. Context information is given, for example, by available knowledge on sensor and object properties, which is often quantitatively described by statistical models. Context knowledge is also given by environmental information on roads or topographical occlusions and provided by Geographical Information Systems (GIS). Seen from a different perspective, context information, such as road maps, can also be extracted from real-time sensor data directly.
7. Militarily relevant context knowledge (e.g. doctrines, planning data, tactics) and human observer reports (HUMINT: Human Intelligence) is also important information in the fusion process. The exploitation of context information of this kind can significantly improve the fusion system performance.

1.2.2 Remarks on the Methods Used

Situation elements for producing timely situation pictures are provided by integratively and spatio-temporally processing various pieces of information that in themselves often may have only limited value for understanding the situation. Essentially, logical cross-references, inherent complementarity, and redundancy are exploited. More concretely speaking, the methods used are characterized by a stochastic approach (estimating relevant state quantities) and a more heuristically defined knowledge-based approach (modeling actual human behavior when exploiting information).

Among the data exploitation products of data fusion systems, object 'tracks' are of particular importance. Tracking faces an omnipresent aspect in every real-world application insofar as it is dealing with fusion of data produced at *different instants of time*; i.e. tracking is important in all applications where particular emphasis is placed on the fact that the sensor data to be exploited have the character of a time series.

Tracks thus represent currently available knowledge on relevant, time-varying quantities characterizing the instantaneous "state" of individual targets or target groups of interest, such as aircraft, ships, submarines, vehicles, or moving persons. Quantitative measures that reliably describe the quality of this knowledge are an integral part of a track. The information obtained by 'tracking' algorithms [9, 8, 10, 11] also includes the history of the targets. If possible, a one-to-one association between the target trajectories in the sensors' field of view and the produced tracks is to be established and has to be preserved as long as possible (track continuity). The achievable track quality does not only depend on the performance of the sensors used, but also on target properties and the operational conditions within the scenario to be observed. If tracks 'match' with the underlying real situation within the bounds defined by inherent quality measures being part of them, we speak of 'track consistency".

Tracking algorithms, including Bayesian multiple hypothesis trackers as particularly well-understood examples, are iterative updating schemes for conditional probability density functions representing all available knowledge on the kinematic state of the objects to be tracked at discrete instants of time t_l. The probability densities are conditioned by both, the sensor data accumulated up to some time t_k, typically the current data acquisition time, as well as by available context information, such as on sensor characteristics, the object dynamics, the environment, topographical maps, or on certain rules governing the object behavior. Depending on the time instant t_l at which estimates for the state $\mathbf{x}_l$ are required, the related estimation process is referred to as prediction ($t_l > t_k$), filtering ($t_l = t_k$), or retrodiction ($t_l < t_k$) [12, 13].

1.2.3 A Generic Sensor Data Fusion System

Figure 1.4 shows a generic scheme of functional building blocks within a multiple sensor tracking and data fusion system along with its relation to the underlying sensors. In the case of multi-functional sensors, there is feedback from the tracking system to the process of sensor data acquisition (sensor management). The following aspects should be emphasized:

Sensor Systems

After passing a detection process, essentially working as a means of data rate reduction, the signal processing provides estimates of parameters characterizing the waveforms received at the sensors' front ends (e.g. radar antennas). From these estimates sensor reports are created, i.e. measured quantities possibly related to objects

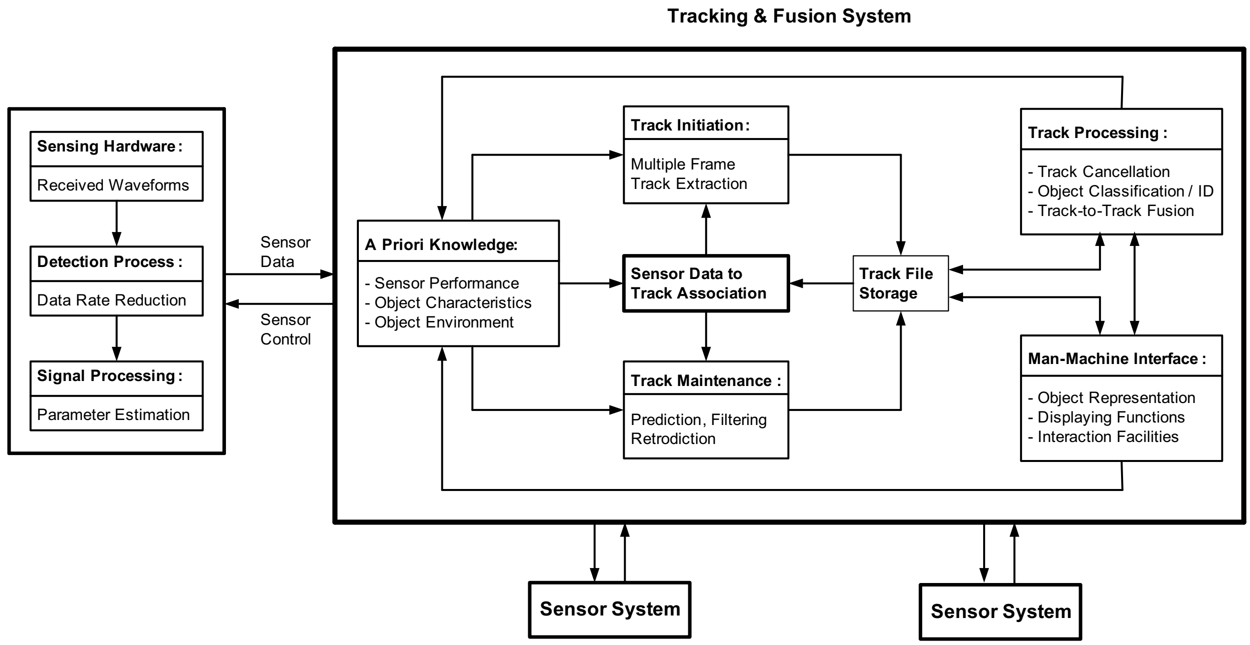


Fig. 1.4. Generic scheme of functional building blocks within a tracking/fusion system along with its relation to the sensors (centralized configuration, type IV according to O. Drummond).

of interest, which are the input for the tracking and sensor data fusion system. By using multiple sensors instead of one single sensor, among other benefits, the reliability and robustness of the entire system is usually increased, since malfunctions are recognized easier and earlier and often can be compensated without risking a total system breakdown.

Interoperability

A prerequisite of all further processing steps, which at first sight seems to be trivial, is technical interoperability. It guarantees that all relevant sensor data are transmitted properly, in a timely way, and completely including all necessary meta-data describing the sensor performance, the platform parameters, and environmental characteristics. This type of meta data is necessary to transform the sensor data into common frames of reference, to identify identical pieces of data, and to merge similar pieces of data into one single augmented piece of information. The process of combining data from different sources and providing the user with a unified view of these data is sometimes also referred to as data integration. Often interoperability acts as a bottleneck in designing real-world data fusion systems of systems [4, Chapter 20].

Fusion Process

All sensor data that can be associated to existing tracks are used for track maintenance (using, e.g., prediction, filtering, and retrodiction). The remaining data are processed for initiating new tentative tracks (multiple frame track extraction). Association techniques thus play a key role in tracking/fusion applications. Context information in terms of statistical models (sensor performance, object characteristics, object environment) is a prerequisite for track maintenance and initiation. Track confirmation/termination, classification/identification, and fusion of tracks related to the same objects or object groups are part of the track management functionalities.

Human-Machine Interface

The scheme is completed by a human-machine interface with display and interaction functions. Context information can be updated or modified by direct human interaction or by the track processor itself, for example as a consequence of object classification or road map extraction. For an introduction to the vast literature on the related problems in human factors engineering and on practical systems solutions see [5].

1.2.4 On Measuring Fusion Performance

In sensor data fusion, the underlying 'real' situation is typically unknown. Only in expensive and time-consuming experiments certain aspects of a dynamically evolving situation are monitored, sometimes even with questionable accuracy. For this reason, experiments are valuable for demonstrating the "proof of concept" as well as to understand the underlying physical phenomena and operational problems, for example. They are of limited use, however, in performance evaluation and prediction. This underlines the role of comprehensive Monte-Carlo-simulations in fusion system performance evaluation.

According to the previous discussion, sensor data fusion systems try to establish one-to-one relations between objects in the sensors' fields of view and identified object tracks in the situation picture. Strictly speaking, this is only possible under ideal conditions regarding the sensor performance and the underlying target scenario. It seems thus reasonable to measure the performance of a given tracking/fusion system by its characteristic deficiencies when compared to this ideal goal. In general, two categories of deficiencies can be distinguished that are either caused by mis-match regarding the input data or by non-optimal processing and unfavorable application constraints.

Selected Performance Measures

Selected performance measures or 'measures of deficiency' in the sense of the previous discussion, which have practical relevance in fusion systems design should be emphasized in the following.

1. Usually a time delay is involved until a track has been extracted from the sensor data. A corresponding performance measure is thus given by the 'extraction delay' between the first detection of a target by a sensor and a confirmed track.
2. False tracks, i.e. tracks related to unreal or unwanted targets, are unavoidable in the case of a high false return density (e.g. by clutter, jamming/deception). Corresponding 'deficiencies' are: mean number of falsely extracted targets per time and mean life time of a false track before its deletion.
3. Targets should be represented by one and the same track until leaving the field of view. Related performance measures are: mean life time of true target tracks, probability of an 'identity switch', and probability of a target not being represented by a track.
4. The track inaccuracy (given by the error covariance matrix of a state estimate, e.g.) should be as small as possible. Furthermore, the deviations between the estimated and actual target characteristics should correspond with the error covariance matrices produced (consistency). If this is not the case, 'track loss' usually occurs.

In a given application it is by no means simple to achieve a reasonable compromise between the various, competing performance measures and the user requirements. Optimization with respect to one measure may easily degrade other performance measures, finally deteriorating the entire system performance. This is especially true under more challenging conditions.

1.2.5 Tracking-derived Situation Elements

The primary objective of multiple sensor target tracking is to explore the underlying target kinematics such as position, velocity, or acceleration. In other words, standard target tracking applications gain information related to 'Level 1 Fusion' according to the well-established terminology of the JDL model of information fusion (see e.g. [1, Chapter 2] and the literature cited therein). Kinematic data of this type, however, are by no means the only information to be derived from target tracks. In many cases, reliable and quantitative higher level information according to the JDL terminology can be obtained. To be more concrete, wide-area air and ground surveillance is considered here as an important real-world example serving as a paradigm for other challenging tracking and fusion applications.

Inferences based on Retrodicted Tracks

The first type of higher JDL level information to be inferred from tracking data is based on a closer analysis of the histories of the kinematic object states provided by retrodiction techniques. The statements derived typically refer to object characteristics that are either time invariant or change with time on a much larger scale than kinematics quantities usually tend to do. This is the main reason why the gain in accuracy achievable by retrodiction techniques can be exploited.

- *Velocity History.* The analysis of precisely retrodicted velocity histories enables the distinction of objects belonging to different classes such as moving persons, boats, vehicles, vessels, helicopters, or jet aircraft. If the object speed estimated with sufficiently high accuracy has exceeded a certain threshold, certain object classes can be reliably be excluded. As an example, uncertainty whether an object is a helicopter or a wing aircraft can be resolved if in the track history a velocity vector 'Zero' exists. Depending on the context of the underlying application, classifications of this type can be essential to generate an alert report.
- *Acceleration History.* Similar considerations are valid if acceleration histories are taken into account: High normal accelerations, e.g., are a clear indication of a fighter aircraft. Moreover, one can safely conclude that a fighter aircraft observed with a normal acceleration $> 6\,g$, for example, is not carrying a certain type of weaponry (any more). In other words, conclusions on the threat level connected with the objects observed can be drawn by analyzing kinematic tracks.
- *Heading, Aspect Angle.* Precise reconstructions of the targets' heading vectors are not only important input information for threat evaluation and weapon assignment in themselves, but also enable estimates of the aspect angle of an object at a given instant of time with respect to other sensors, such as those producing high range or Doppler resolution spectra. Track-derived information of this type is basic for fusing spectra distributed in time and can greatly improve object classification thus providing higher-JDL-level information.
- *Rare Event Detection.* Analysis of JDL-level-1 tracks can be the key to detecting rare or anomalous events by fusing kinematic tracks with other context information such as annotated digital road maps and general rules of behavior. A simple example in the area of continuous-time, wide-area ground surveillance can be the production of an alert message if a large freight vehicle is observed at an unusual time on a dirt road in a forest region. There are analogous examples in the maritime or air domain.

Inferences based on Multiple Target Tracking

A second type of higher JDL level information related to mutual object interrelations can be inferred from JDL level 1 tracking data if emphasis is placed on the results of *multiple target* tracking.

- *Common History.* Multiple target tracking methods can identify whether a set of targets belongs to the same collectively moving group, such as an aircraft formation or a vehicle convoy, whose spatial extension may be estimated and tracked. If an aircraft formation has split off after a phase of penetration, e.g., the interrelation between the individual objects is to be preserved and provides valuable higher-JDL-level information that is important, e.g., when a former group target is classified as 'hostile' since this implies that all other targets originally belonging to the same group are likely to be hostile as well.
- *Object Sources and Sinks.* The analysis of large amounts of target tracks furthermore enables the recognition of sources and sinks of moving targets. By this type of reasoning, certain areas can be identified as air fields, for example, or an area of concentration of military forces. In combination with available context information, the analysis of multiple object tracks can also be used for target classification by origin or destination. A classification as hostile or suspect directly leads to an alert report.
- *Split-off Events.* By exploiting multiple target tracking techniques, certain split-off events can be identified as launches of air-to-air or air-to-surface missiles. The recognition of such an event from JDL-level-1 tracking information not only has implications on classifying the original target as a fighter aircraft, but can also establish a certain type of 'book-keeping', such as counting the number of missile launches. This enables estimates of the residual combat strength of the object, which has direct implications on countermeasures, e.g.
- *Stopping Events.* In the case of MTI radar (Moving Target Indicator), Doppler blindness can be used to detect the event 'A target under track has stopped.', provided this phenomenon is described by appropriate sensor models. If there is previous evidence for a missile launcher, e.g., missing data due to Doppler blindness may indicate preparation for launch with implications on potential countermeasures. In combination with other tracks, a stopping event may also establish new object interrelations, for example, when a target is waiting for another and then moving with it.

1.2.6 Selected Issues in Anomaly Detection

Anomaly detection can be regarded as a process of information fusion that combines incomplete and imperfect pieces of mutually complementary sensor data and context information in such a way that the attention of human decision makers or decision making systems is focused on particular events that are "irregular" or may cause harm and thus require special actions, such as exploiting more specialized sensors or initiating appropriate activities by military or security personnel [14]. Fusion-based anomaly detection thus improves situational awareness. What is actually meant by "regular" or "irregular" events is higher-level information itself that depends on the context of the underlying application. Here, it is either assumed to be a priori known or to be learned from statistical long-time analysis of typical situations.

In complex surveillance applications, we can often take advantage of context information on the sensing environment insofar as it is the stationary or slowly changing "stage" where a dynamic scenario evolves. Typical examples of such environmental information are digital road or sea-/air-lane maps and related information, which can essentially be regarded as spatial motion constraints (see Figure 1.5 as an illustration). In principle, this information is available by Geographical Information Systems (GIS). Another category of context information is provided by visibility models and littoral or weather maps indicating regions, where a high clutter background is to be taken into account, for example. Moreover, rather detailed planning information is often available. This category of information is not only important in mission planning or in the deployment and management of sensor systems, but can be used to decide whether an object is moving on a lane or leaving it, for example. In addition, ground-, sea- or air-lane information information can be used to improve the track accuracy of lane-moving vehicles and enhance track continuity.

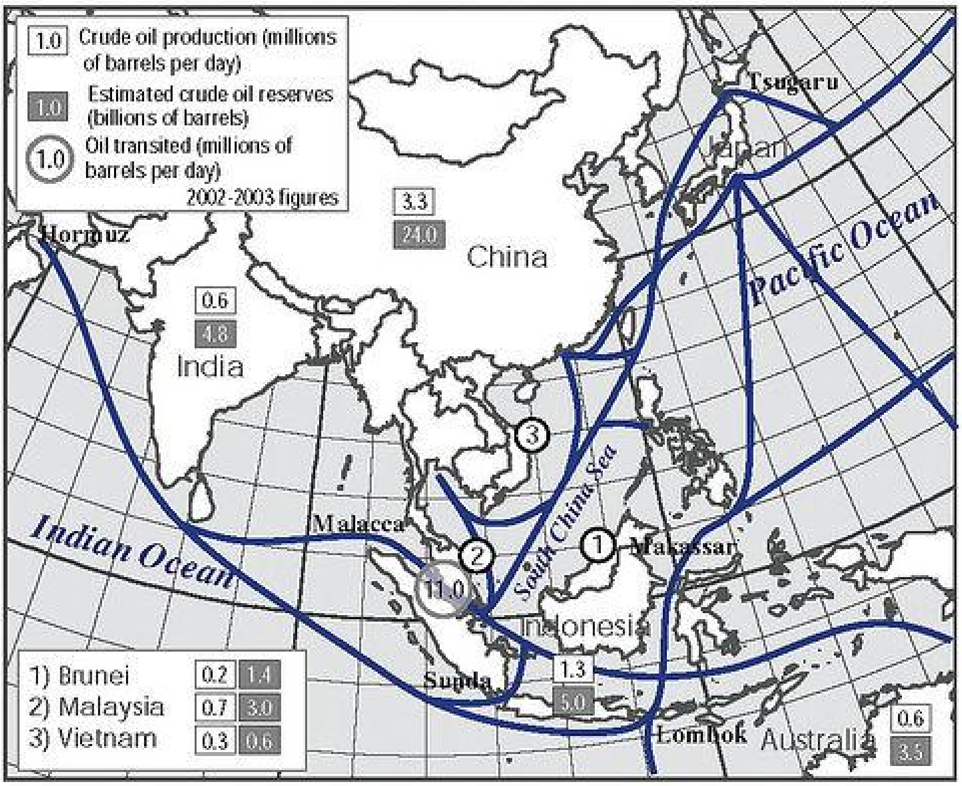


Fig. 1.5. Illustration of sea lanes and strategic passages in Pacific Asia.

Integration of Planning Information

In certain applications, rather detailed planning information is available, which provides valuable context knowledge on the temporal evolution of the objects involved and can in principle be incorporated into the tracking formalism. Planning information is often approximately described by space-time waypoints that have to be passed by the individual objects during a preplanned operation, i.e. by a set of position vectors to be reached at given instants of time and possibly via particular routes (roads, lanes) between the waypoints. In addition, we assume that the acceptable tolerances related to the arrival of the objects at the waypoints are characterized by known error covariance matrices, possibly individually chosen for each waypoint and object, and that the association between the waypoints and the objects is predefined.

The impact of waypoints on the trajectory to be estimated from future sensor data (under the assumption that the plan is actually kept) can simply be obtained by processing the waypoints as additional artificial 'measurements' via the standard Bayesian tracking paradigm, where the tolerance covariance matrices are taken into account as the corresponding 'measurement error covariances'. If this is done, the processing of sensor measurements with a younger time stamp are to be treated as "out-of sequence" measurements with respect to the artificial waypoint measurements processed earlier. According to these considerations, planning information can well improve both track accuracy and continuity as well as facilitate the sensor-data-to-track association problems involved, provided the plan is actually kept.

Detecting Regularity Pattern Violation

A practically important class of anomalies results from a violation of regularity patterns such as those previously discussed (motion on ground-, sea-, or air-lanes or following preplanned waypoints and routes). An anomaly detector thus has to decide between two alternatives:

- The observed objects obey an underlying pattern.
- The pattern is not obeyed (e.g. off-lane, unplanned).

Decisions of this type are characterized by decision errors of first and second. In most cases, it is desirable to make the decisions between both alternatives for given decision errors to be accepted. A "sequential likelihood ratio" test fulfills this requirement and has enormous practical importance. As soon as the test decided that the pattern is obeyed, the calculation of the likelihood ratio can be restarted since it is more or less a by-product of track maintenance. The output of subsequent sequential ratio tests can serve to re-confirm "normality" or to detect a violation of the pattern at last. The most important theoretical result on sequential likelihood ratio tests is the fact that the test has a *minimum decision length on average* given predefined statistical decision errors of first and second kind.

Tracking-derived Regularity Patterns

We have discussed moving targets that obey certain space-time constraints that are a priori known (roads/lanes, planned waypoints). A violation of these constraints was quite naturally interpreted as an anomaly. Seen from a different perspective, however, moving targets that are assumed to obey a priori *unknown* space-time constraints and to be observed by wide-area sensors, such as vehicles on an unknown road network, produce large data streams that can also be used for extracting the underlying space-time constraint, e.g. a road map. After a suitable post-processing, the produced tracks of motion-constrained targets simply define the corresponding constraints and can thus be extracted from tracking-based results. Extracted road-maps can be highly up-to-date and precise. A discussion where such ideas are used in wide-area maritime surveillance using AIS data can be found in [15] (AIS: Automatic Identification System).

1.3 Future Perspectives of "Hard and Soft" Fusion

Due to the increasing availability of inexpensive, but powerful sensor, communication, and information technology, its technical prerequisites, sensor data fusion, or more general, information fusion, increasingly emancipates from its roots in defense related applications. A commonplace example of this trend is the advent of navigation systems, which have developed a mass market by fusing military global navigation satellite system data with digital road maps in combination with an appealing graphical interface. We can therefore expect that information fusion will become a key technology driver for developing numerous innovative products penetrating everyone's daily life and changing it profoundly. In this context, many new research questions are expected to emerge that will foster the further evolution of information fusion as an also economically eminent branch of applied informatics.

1.3.1 Emerging New Applications

Even now, intelligent filtering, analysis, evaluation, and graphical presentation of multiple sensor information enable numerous products that make everyday life safer or more secure. For example, in intelligent car-driver assistance systems, image and video data from cameras and miniaturized automotive radar sensors are automatically fused in order to perceive road obstacles and pedestrians or to exclude "ghost objects". At airport security checks, assistance systems can be used, which directly take advantage of military surveillance technology. By fusing signatures of stand-off chemical sensors and miniaturized gamma-spectrometers, for example, with person trajectories, carry-on items contaminated with hazardous materials or explosives can be detected. This may be a contribution to avert threats or avoid terrorist attacks.

Other areas where information fusion based assistance systems will increasingly be important are medical and health care, process control, logistics, industrial production, precision agriculture, and traffic monitoring. A particularly stormy evolution can currently be observed for assistance systems, where physical activities and the health status of elderly or handicapped human beings can be monitored, allowing them to live in their usual everyday environment much longer than now. In the vast fields of fire, disaster, and pollution control, quick exploitation and fusion of complex data streams can be essential for safety analysis and designing corresponding concepts as well as for developing sophisticated emergency information and management systems.

Since sensor data fusion has actually evolved into a mature technology in major fields and provides a coherent and powerful inventory of methodologies and algorithms already proven in ambitious applications, the further realization of its inherent application potential is much alleviated by the very fact that R&D for new products can be done on a sound technology base that does not need to be created in a time-consuming and expensive way. For this reason, the expected development cycles for innovative products are short, while the development risks involved are calculable. Due to its traditional strengths in high-tech industries, such as system technology or software engineering, sensor or RFID technology, highly industrialized and research-intensive countries like Germany can use their potential especially in those branches where they are traditionally well-positioned – for example in automotive technology, automation and aerospace industries, in security, safety and medical technology, and last but not least, in information system technology in general.

1.3.2 Discussion of Large-scale Trends

More generally speaking, information fusion technology already provides mature results with profitable market opportunities, especially in those areas where physical or technical sensor data are to be fused with quantitative context information on the basis of well-understood mathematical algorithms, often making use of Bayesian reasoning.

Human Assistance Systems

Typically "human" fusion processes, however, characterized by associative reasoning, negotiating of reasonable compromises, or extrapolating incomplete information creatively and in an intuitive way, seem to be still unfit for automation. Nevertheless, technical data fusion systems can offer assistance functionalities also here, by which specifically human competencies of judgment are freed from routine or mass tasks, quite in the sense of a "cognitive tool" as discussed earlier. Moreover, highly promising research areas are and will increasingly be those that aim at modeling and formalizing this specific human expert knowledge and expertise of situation assessment and incorporate it into the process of automated multiple sensor data.

Context Data Integration

Furthermore, a large-scale technology tend to be highlighted is given by the large potential of quantitative non-sensor information available in comprehensive databases, such as Geographical Information Systems (GIS), which is still waiting to be integrated into multiple sensor data fusion systems. This is especially true in the vast area of ground, air, sea, and underwater robotics, but has also strong implications in guaranteeing high levels of air transportation security, even in the case of high traffic densities, and in advanced logistics support systems, such as container monitoring and tracking, topics with direct implications for global economy.

Network-centric Operations

A predominant trend in defence applications is given by the demand of supporting "Network-centric Operations", which will still be in effect for the next decade. Sensor data and information fusion technology is one of the major forces shaping this process of transformation from more standard operational doctrines. Especially for out-of-area operations and operations in an urban terrain, as well as for dealing with "asymmetric" opponents, distributed high-performance reconnaissance is inevitable. In particular, wide-area ground, sea, and underwater surveillance, belong to this field, specially by making use of unmanned reconnaissance robots (unmanned ground, aerial, or underwater vehicles). Moreover, intelligent security systems for harbors, critical infrastructure, or camp protection are likely to raise many research intensive data fusion problem.

Pervasive Passive Surveillance

A particularly exciting topic of recent research is advanced distributed signal and data fusion for passive radar systems, where radio, TV, or mobile phone base stations are used as sources for illuminating targets of interest. Even in remote regions of the world, each transmitter of electromagnetic radiation becomes a potential radar transmitter station, which enables air surveillance by passively receiving reflections of non-cooperatively emitted signals of opportunity. In this way, the reconnaissance process remains covert and is not revealed by actively transmitting radiation. Analogous considerations are valid for sub-sea surveillance.

Fusion-driven Communications

The communications sub-systems within a large sensor network are typically characterized by many internal degrees of freedom, which can be controlled and adapted. This opens the vast area of fusion-driven communications, where communications and the distributed data fusion system architectures are closely tied and optimized with respect to the particular surveillance goals to be reached [16]. In the focus are multi-component system consisting of sensors, data bases, and communication infrastructures that collectively behave as a single dynamically adaptive system. Important aspects are network scalability given a limited communication bandwidth, adaptive and optimal spectrum sharing protocols, sensor data against network objectives, and in-network information. In addition, the growing use and ubiquitous nature of sensor networks pose issues when networks deployed for multiple applications need to be combined or need to exchange information at the network level.

'Add-on' Research Efforts

Since a stormy evolution of civilian information fusion applications is to be expected in the near future, defence-related R&D on information fusion technology will increasingly show the character of "add-on" research, which adapts existing civilian problem solutions to specifically military requirements. This trend is analogous to the evolution in advanced communication systems, a technology that also had its roots in the military domain, before the civilian market opportunities became the predominant force driving its technological and scientific progress.

Hard & Soft Fusion – Military Applications

Advanced signal processing techniques exploit even sophisticated physical phenomena of objects of interest and are fundamental to modern sensor system design. In particular, they have a direct impact on the quantitative and qualitative properties of the sensor data produced and to be fused. This makes a more subtle modeling of the statistical characteristics of the sensor output inevitable. Via constructing appropriate sensor models based on a deeper insight into the physical and technical sensor design principles, the performance of tracking and sensor data fusion systems can be significantly improved.

This chapter is focused on selected physical and technical properties of sensor systems that are used in real-world ISR applications (Intelligence, Surveillance, and Reconnaissance), such as those discussed in [4, Chapter 20]. The analysis of characteristic examples shows that context information on particular performance features of the sensor systems involved is useful, in some cases even inevitable, to fulfill an overall ISR task. The well-established Bayesian methodology is wide and flexible enough to integrate more sophisticated, appropriately designed, but still mathematically tractable likelihood functions into the process of Bayesian Knowledge Propagation. The discussed examples cover finite Doppler blindness and main-lobe jamming.

The possibility to exploit even *negative sensor evidence* is a consequence that is directly connected with the use of more advanced sensor models. This notion covers the conclusions to be drawn from expected, but actually missing sensor measurements for improving the state estimates of objects under track. Even a failed attempt to detect an object of interest is a useful sensor output that is interpretable only if a consistent sensor modeling is available.

2.1 GMTI Radar: Doppler Blindness

Ground surveillance comprises track extraction and maintenance of single ground-moving vehicles and convoys, as well as low-flying objects such as helicopters or Unmanned Aerial Vehicles. As ground object tracking is a challenging problem, all available information sources must be exploited, i.e. the sensor data themselves, as well as context knowledge about the sensor performance and the underlying scenario.

2.1.1 Air-to-Ground Surveillance

For long-range, wide-area, all-weather, and all-day surveillance operating at high data update rates, GMTI radar proves to be the sensor system of choice (GMTI: Ground Moving Target Indication). By using airborne sensor platforms in stand-off ground surveillance applications, the effect of topographical screening is alleviated, thus extending the sensors' field of view. In [17] characteristic problems of signal processing related to GMTI tracking with STAP radar are discussed. In this context, the following topics are of particular interest:

- *Doppler-Blindness.* Ground moving vehicles can well be masked by the clutter notch of the sensor. This physical phenomenon directly results from the low-Doppler characteristics of ground-moving vehicles and causes interfering fading effects that seriously affect track accuracy and track continuity. The problems are even more challanging in the presence of Doppler ambiguities.
- *Collectively Moving Targets.* Collectively moving convoys consisting of individual vehicles are typical of certain applications and have to be treated as aggregated entities. In some cases, the kinematic states of the individual vehicles can be treated as internal degrees of freedom. In addition, the convoy extension can become part of the object state.

- *Road-Map Information.* Even military targets usually move on road networks, whose topographical coordinates are known in many cases. Digitized topographical road maps such as provided by Geographical Information Systems (GIS) should therefore enter into the target tracking and sensor data fusion process.
- *Multisensor Data.* Since a single GMTI sensor on a moving airborne platform can record a situation of interest only over short periods of time, sensor data fusion proves to be of particular importance. The data processing and fusion algorithms used for ground surveillance are closely related to the statistical, logical, and combinatorial methods applied to air surveillance.

2.1.2 A Model for Doppler Blindness

For physical and technical reasons, the detection of ground-moving targets by airborne radar, typically on a moving platform, is limited by strong ground clutter returns. This can be much alleviated by STAP techniques [17]. The characteristics of STAP processing, however, directly influence the GMTI tracking performance. Even after platform motion compensation by STAP filtering low-Doppler targets can be masked by the clutter notch of the GMTI radar. Let $\mathbf{e}_k^p = (\mathbf{r}_k - \mathbf{p}_k)/|\mathbf{r}_k - \mathbf{p}_k|$ denote the unit vector pointing from the platform position $\mathbf{p}_k$ at time t_k to the target at the position $\mathbf{r}_k$ moving with the velocity $\dot{\mathbf{r}}_k$. The kinematic object state is given by $\mathbf{x}_k = (\mathbf{r}_k^\top, \dot{\mathbf{r}}_k^\top)^\top$. Doppler blindness occurs if the radial velocities of the object as well as of the surrounding main-lobe clutter return are identical, i.e. if the function

$$h_n(\mathbf{r}_k, \dot{\mathbf{r}}_k; \mathbf{p}_k) = \frac{(\mathbf{r}_k - \mathbf{p}_k)^\top \dot{\mathbf{r}}_k}{|\mathbf{r}_k - \mathbf{p}_k|} \tag{2.1}$$

is close to zero. In other words, $h_c(\mathbf{x}_k; \mathbf{p}_k) \approx 0$ holds if the target's velocity vector is nearly perpendicular to the sensor-to-target line-of-sight. For this reason, the equation $h_c(\mathbf{x}_k; \mathbf{p}_k) = 0$ defines the location of the GMTI clutter notch in the state space of a ground target and as such reflects a fundamental physical/technical fact without implying any further modeling assumptions.

Qualitative Discussion

Any GMTI detection model for air-to-ground radar must thus reflect the following phenomena:

1. The detection probability P_D depends on the target state and the sensor/target geometry.
2. P_D is small in a certain region around the clutter notch characterized by the Minimum Detectable Velocity (MDV), an important sensor parameter that must enter into the tracking process.
3. Far from the clutter notch, the detection probability depends only on the directivity pattern of the sensor and the target range.
4. There exists a narrow transient region between these two domains.

GMTI models are adapted to STAP techniques in that the detection probability assumed in the tracking process is described as a function of the GMTI-specific clutter notch. While the current location of the notch is determined by the kinematical state of the target and the current sensor-to-target geometry, its width is given by a characteristic sensor parameter (MDV). In this way, more detailed information on the sensor performance can be incorporated into the tracking process. This in particular permits a more appropriate treatment of missing detections. In other words, information on the potential reasons that might have caused the missing detections enters into the tracking filter. We observed that by this measure, the number of lost tracks can significantly be reduced, while the track continuity is improved, finally leading to a more reliable ground picture. This qualitative discussion of the observed detection phenomena related to the GMTI clutter notch is similar in nature to that of resolution effects.

Quantitative Discussion

In a generic description of the detection performance of GMTI sensors it seems plausible to write $P_D = P_D(\mathbf{x}_k)$ as a product with one factor reflecting the directivity pattern and propagation effects due to the radar equation, $p_D = p_D(r_k, \varphi_k)$, the other factor being related to the clutter notch. To this end, let us consider functions of the following form:

$$P_D(r_k, \varphi_k, \dot{r}_k) = p_d(r_k, \varphi_k) \left(1 - \mathrm{e}^{-\frac{1}{2}\left(\frac{h_n(r_k, \varphi_k, \dot{r}_k)}{\mathrm{MDV}}\right)^2}\right). \tag{2.2}$$

In this expression the sensor parameter MDV has a clear and intuitive meaning: In the region defined by $|n_c(\mathbf{x}_k)| < \text{MDV}$ we have $P_D < \frac{1}{2}\, p_d$. The parameter MDV is thus a quantitative measure of the minimum radial velocity with respect to the sensor platform that a ground-moving target must at least have to be detectable by the sensor (Minimum Detectable Velocity). The actual size of MDV depends on the particular signal processor used.

For SWERLING I targets p_d is given by: $p_d(r, \varphi) = p_F{}^{1/[1+\text{snr}(r,\varphi)]}$ with the false alarm probability p_F and the signal-to-noise ratio $\text{snr}(r, \varphi) = \text{snr}_0\, D(\varphi)\, (\sigma/\sigma_0)\, (r/r_0)^{-4}$. Let the sensor's directivity pattern be described by $D(\varphi) = \sin^2(\varphi - \varphi_a)$.

After rearranging the terms in Equation 2.2, we can formally introduce Gaußian likelihood functions, where $h_n(\mathbf{x}_k)$ appears as a fictitious nonlinear measurement function:

$$P_D(\mathbf{x}_k; \mathbf{p}_k) = P_D - P_D^n\, \mathcal{N}\big(0; h_n(\mathbf{x}_k; \mathbf{p}_k), R_n)\big), \tag{2.3}$$

with a detection parameter P_D^n and a related 'variance' R_n given by a function of MDV.

Impact of Sensor-to-Object Geometry

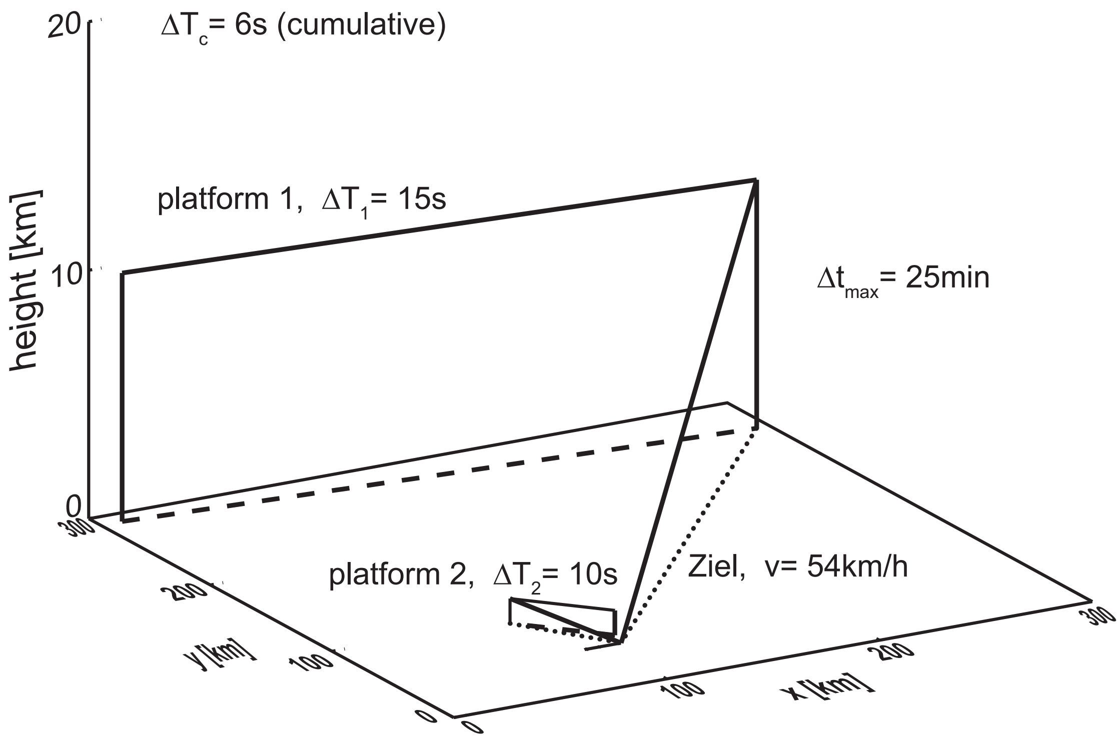


Fig. 2.1. Simplified ground target tracking scenario: two moving airborne GMTI radar platforms and a single ground moving target.

Assuming a flat earth, Figure 2.1 shows an idealized scenario with two airborne GMTI sensors observing a ground vehicle moving at a constant speed (15 m/s = 54 km/h) parallel to the x-axis for most of the time. This situation is typical of stand-off or gap-filling ground surveillance missions. In the second half of the observation period over $\Delta t_{\max} = 25$ min the target stops for 7 min. Then it speeds up again reaching its initial velocity. Finally, the target leaves the field of view of sensor 2. In Table 2.1 selected sensor and platform parameters are summarized. h_p, v_p denote the constant height and speed of the sensor platforms over ground. Δr, $\Delta\varphi$ are the range and azimuth regions covered by each sensor during observation. The revisit intervals are given by ΔT, while MDV denotes the Minimum Detectable Velocity, a GMTI-specific sensor parameter important to ground-moving target tracking. Unless appropriately handled, two phenomena in particular can cause problems in GMTI tracking:

Sensor	h_p [km]	v_p [m/sec]	Δr [km]	$\Delta\varphi$ [deg]	ΔT [sec]	MDV [m/sec]
1	10	200	[232, 292]	[-128, -67]	15	2
2	1	40	[22, 54]	[77, 172]	10	2

Table 2.1. Simplified GMTI tracking scenario: selected sensor and platform parameters.

1. Sensor-to-target geometries can occur where targets to be tracked are masked by the clutter notch of the sensor. This results in a series of missing detections until the geometry changes again.
2. As stopping targets are indistinguishable from ground clutter, the early detection of a stopping event itself as well as tracking of 'stop & go' targets can be important to certain applications.

The impact of these effects on the detection probability is shown in Figure 2.2 for the scenario previously introduced. For both sensors we observe deep notches (dashed line: platform 1, dotted line: platform 2). In the center of these notches the radial velocities of the target and the surrounding ground patch are very close to each other, thus making target discrimination by Doppler processing (STAP [17]) impossible. This is particularly true if the target stops.

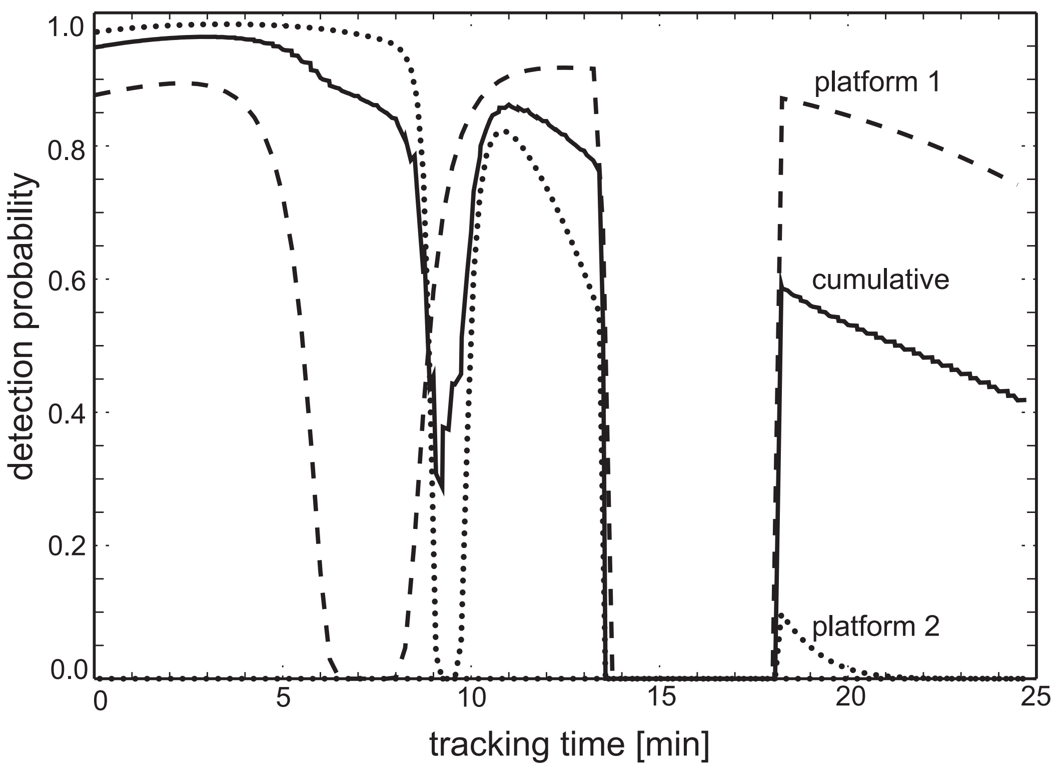


Fig. 2.2. GMTI tracking: detection probability of the individual sensors and the mean accumulated detection probability as a function of the tracking time.

The dashed and solid lines in Figure 2.3 denote the radial velocities of ground patches around the target and target returns, respectively. The area shaded in gray reflects the width of the clutter notches of the sensors, which is determined by the individual Minimum Detectable Velocities (MDVs). For each sensor, both curves are closely adjacent to each other, indicating that the target is moving at a much lower speed than the sensor platforms. We notice sliding intersections between the curves. They are responsible for the relatively long duration of Doppler-blind phases.

Assuming an idealized processing architecture (measurement fusion), the *mean cumulative revisit interval* ΔT_c results from the individual revisit intervals $\Delta T_1 = 15$ s, $\Delta T_2 = 10$ s, yielding $\Delta T_c = 6$ s. The *mean cumulative detection probability* P_D^c is shown in Figure 2.2 (solid line). The impact of the clutter notches is

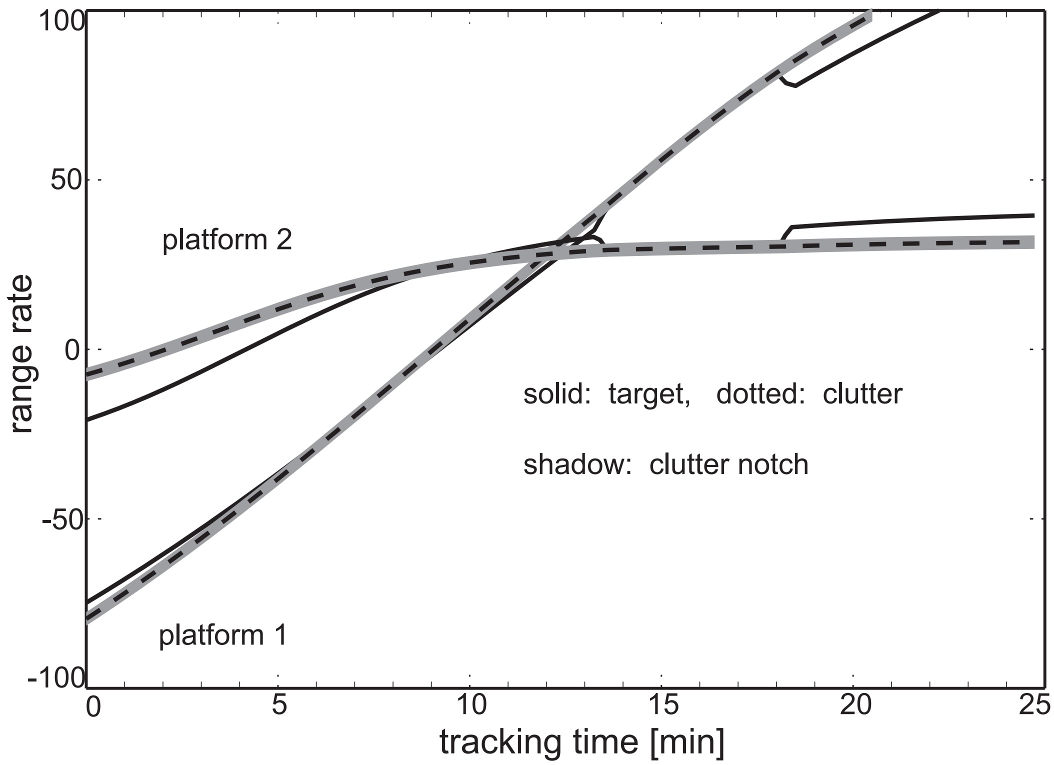


Fig. 2.3. GMTI tracking: range rate of the ground target and the surrounding ground patch relative to the moving GMTI sensors.

more or less compensated for. Due to the fact that P_D^c is related to the mean cumulative revisit interval ΔT_c = 6 s, being shorter than those of the individual sensors (ΔT_1 = 10 s, ΔT_2 = 15 s), P_D^c is smaller than the detection probability of the sensor dominating at that time.

On Convoy Resolution

Since in certain applications, ground traffic vehicles often move in convoys, at first view resolution phenomena seem to be typical of long-range ground surveillance. Due to the asymmetric effect of range and angle resolution, however, Doppler-blindness in many cases superimposes resolution effects. As soon as convoy targets cease to be resolvable, they are at the same time buried in the clutter notch and thus escape detection. Vice versa, resolvable convoy targets are rarely Doppler-screened. A separate modeling of the sensor resolution might therefore be omitted.

As an example we assume two targets moving in a row along a straight road with 30 km/h as typical of military applications. Their mutual distance is 50 m. The target/sensor geometry is as depicted in Figure 2.1. Let the sensor resolution be given by: α_r = 10 m (range), α_φ = 0.1° (azimuth), $\alpha_{\dot r}$ = 0.5 m/s (range-rate). Figure 2.4 shows the detection probabilities of both sensors (solid lines). The width of the notches is larger than in Figure 2.2 due to the smaller convoy speed. The dotted lines denote the resolution probabilities P_r of the sensors modeled:

$$P_r = 1 - e^{-\log 2(\Delta r/\alpha_r)^2}\, e^{-\log 2(\Delta\varphi/\alpha_\varphi)^2}\, e^{-\log 2(\Delta\dot r/\alpha_{\dot r})^2}. \tag{2.4}$$

Δr, $\Delta\varphi$, $\Delta\dot r$ are the distances between the targets in sensor coordinates. If P_r is dominated by the angular resolution (i.e. Δr and $\Delta\dot r$ are small), Doppler-blindness occurs. Outside of the notch the high range/range-rate resolution guarantees resolved returns.

2.1.3 Essentials of GMTI Tracking

The choice of a suitable coordinate system for describing the underlying sensor/target geometry, the sensor platform trajectory, and the available a priori information on the dynamical behavior of ground-moving targets

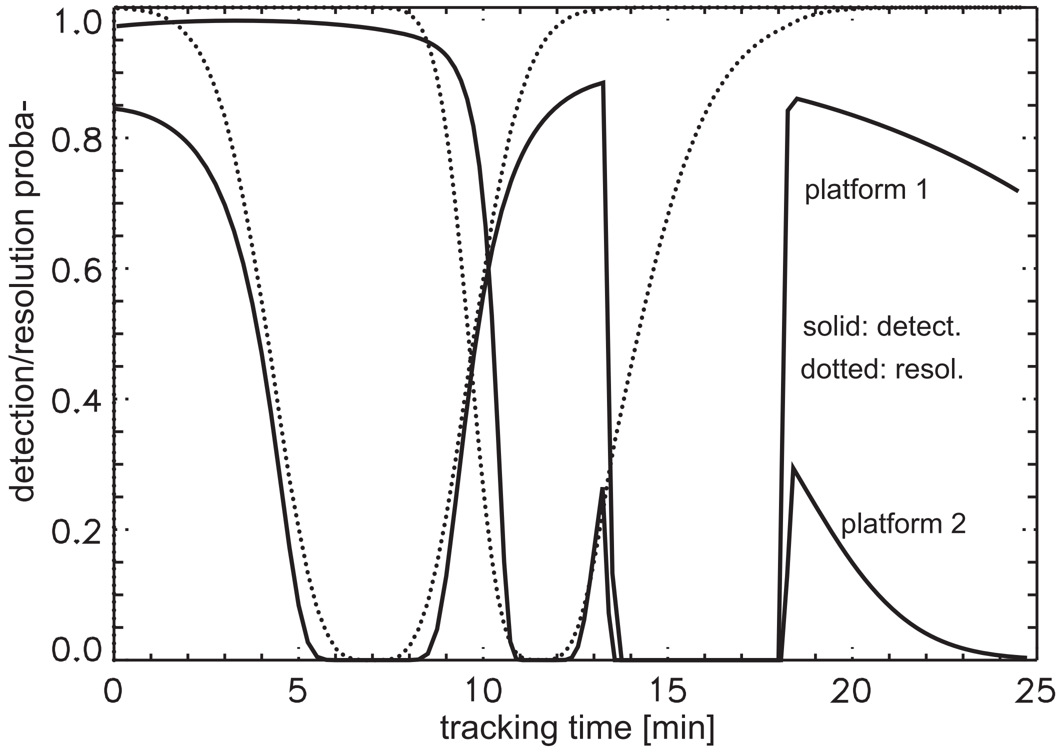


Fig. 2.4. detection and resolution probability

are prerequisites to target tracking. In wide-area applications a flat earth model is often not admissible. We consider three coordinate systems in which the underlying physical phenomena become transparent:

1. Appropriate *ground* coordinates, typically WGS84, where the description of the target and platform kinematics is of a particularly simple form,
2. the moving Cartesian *antenna* coordinate system, whose x-axis is oriented along the array antenna of the GMTI radar mounted on the airborne sensor platform,
3. the *sensor* coordinate system, in which the measurements of the kinematical target parameters are described (target range, azimuth, and range-rate).

The likelihood is given by the following expression (single vehicle, mild residual clutter density ρ_F, m_k plots in each sensor scan $Z_k = \{\mathbf{z}_k^j\}_{j=1}^{m_k}$):

$$\begin{aligned} p(Z_k, m_k|\mathbf{x}_k) &= \big(1 - P_D(\mathbf{x}_k; \mathbf{p}_k)\big)\rho_F \ + \ P_D(\mathbf{x}_k; \mathbf{p}_k) \textstyle\sum_{j=1}^{m_k} \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{h}(\mathbf{x}_k),\, \mathbf{R}\big) \\ &= p_0(Z_k, m_k|\mathbf{x}_k) + p_n(Z_k, m_k|\mathbf{x}_k) \end{aligned} \tag{2.5}$$

where $p_0 = p_0(Z_k, m_k|\mathbf{x}_k)$ denotes the standard likelihood without considering clutter notches:

$$p_0 = (1 - P_d)\rho_F + P_d \textstyle\sum_{j=1}^{m_k} \mathcal{N}(\mathbf{x}_k; \mathbf{h}(\mathbf{x}_k), \mathbf{R}), \tag{2.6}$$

$p_n = p_n(Z_k, m_k|\mathbf{x}_k)$ is the part of the overall likelihood function characteristic of the GMTI problem. For a generalization in case of Doppler-unambiguous measurements see [18, 19].

If the GMTI detection model is inserted into this expression, we immediately see that the effect of the GMTI-specific clutter notch on the likelihood function can formally be described by a fictitious measurements Zero of a fictitious quantity defined by pseudo measurement function $\mathbf{h}_k^n$, where the minimum detectable velocity plays the role of a fictitious measurements error standard deviation.

According to Bayes' rule, the processing of the new sensor data Z_k received at revisit time t_k is based on the predicted density $p(\mathbf{x}_k|\mathcal{Z}^{k-1})$ and the likelihood function $p(Z_k, n_k|\mathbf{x}_k)$. Assuming a Gaußian sum representation for $p(\mathbf{x}_k|\mathcal{Z}^{k-1})$, the Gaußian sum structure of the likelihood function guarantees that also $p(\mathbf{x}|Z^k)$ belongs to this family. According to Bayes Theorem we obtain up to a normalizing constant:

$$p(\mathbf{x}_k|\mathcal{Z}^k) \propto p(Z_k, n_k|\mathbf{x}_k)\, p(\mathbf{x}_k|\mathcal{Z}^{k-1}) \tag{2.7}$$

$$\propto \sum_i p_k^i\ \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k}^i,\, \mathbf{P}_{k|k1}^i\big). \tag{2.8}$$

The same type of mixture reduction techniques can be applied as in standard MHT tracking (pruning, local combining) in order to keep the number of mixture components under control. Simulations showed that even a representation by only two mixture components is sufficient in many practical cases and seems to mirror the underlying physics of the detection process quite well.

2.1.4 Effect of GMTI-Modeling

Figures 2.5 – 2.7 provide a qualitative insight into the effect of the refined sensor model on target tracking/data fusion. While a high adaptivity is evident near the clutter notch, far from the notch no difference to standard filters is observed.

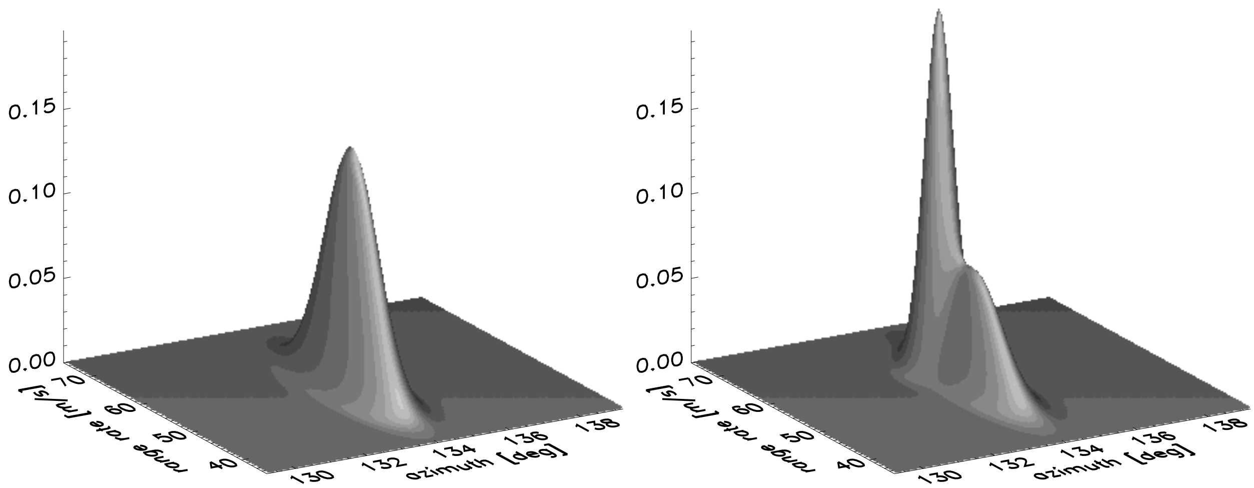


Fig. 2.5. Effect of GMTI modeling (missing detection near the clutter notch): (a) standard filter, (b) GMTI filter).

Figure 2.5 displays the probability density functions resulting from processing the event that a missing detection occurred near the notch. To show the most interesting features, the densities are projected on the azimuth/range-rate plane. While the probability density the standard tracker (Figure 2.5a) is identical with the corresponding predicted density, the refined sensor model leads to a bimodal structure (Figure 2.5b). The broader peak refers to the possible event that the missing detection has purely statistical reasons as in the case of standard filtering, while the sharper peak behind it reflects the hypothesis that the target was not detected because it is masked by the clutter notch.

The situation where the target is buried in the clutter notch for several revisits is represented in Figure 2.6. Obviously, the probability density of the standard filter totally faded away permitting no reasonable state estimation (Figure 2.6a). The refined filter, however, preserved a definite shape (Figure 2.6b). This can be explained as follows. Instead of actual sensor data, the very information that several successively missing detections occurred was processed. This event provides a hint to the filter that the kinematical target state probably obeys a certain relation determined by the clutter notch. Apparently, this piece of evidence proves to be as valuable as a measurement of one of the components of the target state.

Figure 2.7 refers to the event that a detection occurred near the clutter notch. While the standard filter produced a simple Gaußian, the refined filter shows a more complex structure. In fact, the probability density is a two-component mixture whose weighting factors differ in their sign (but sum up to one). The resulting shape permits an intuitive interpretation. The sensor model inherently takes into account the fact that the target state $\mathbf{x}_k$ does not lead to a small value of $n_c(\mathbf{x}_k)$; otherwise the target would not have been detected at all. For this reason, the sharp cut in the probability density simply indicates the location of the clutter notch.

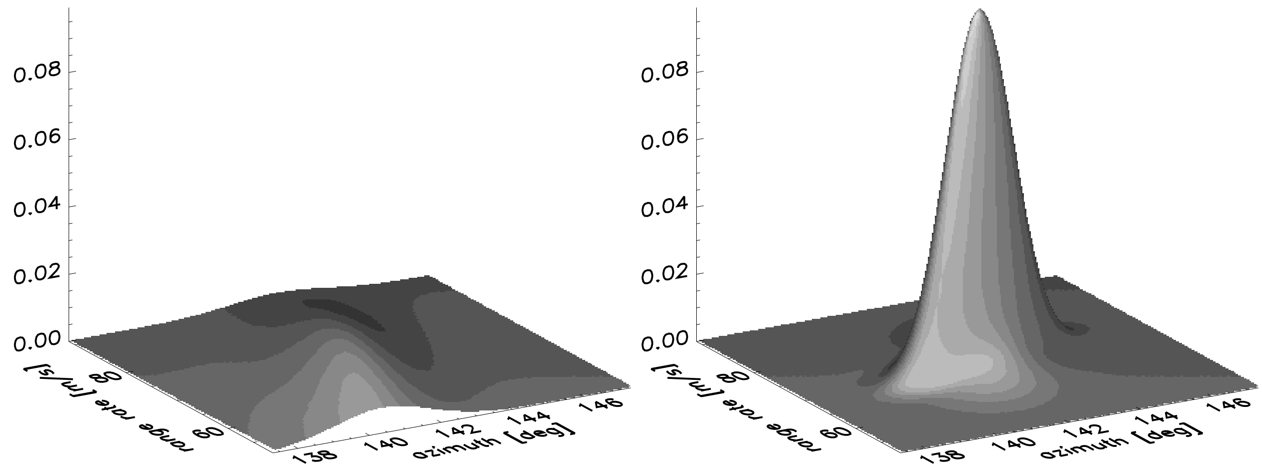


Fig. 2.6. Effect of GMTI modeling (target buried in the notch for several revisits): (a) standard filter. (b) GMTI filter.

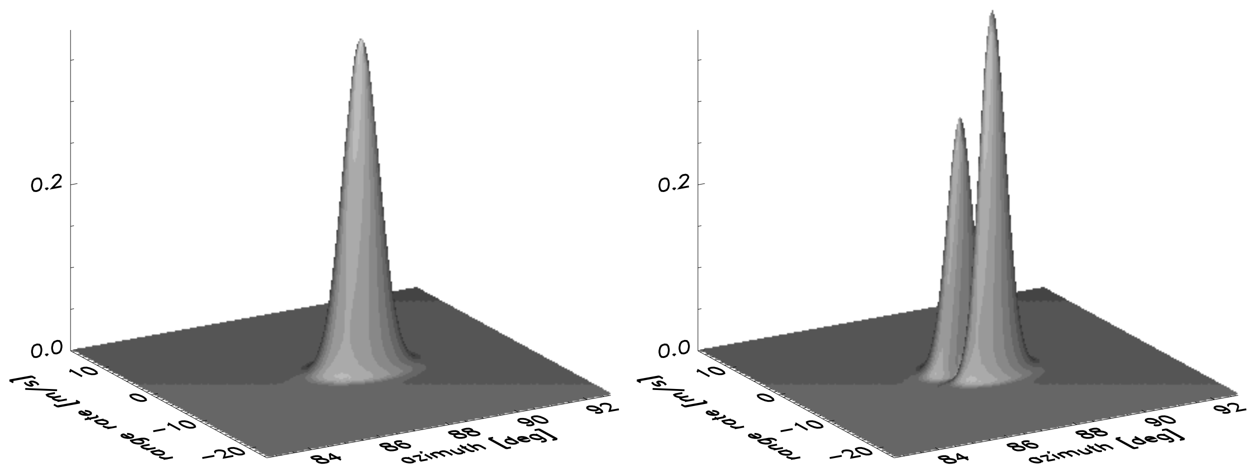


Fig. 2.7. Effect of GMTI modeling (detection occurs near the clutter notch): (a) standard filter. (b) GMTI filter.

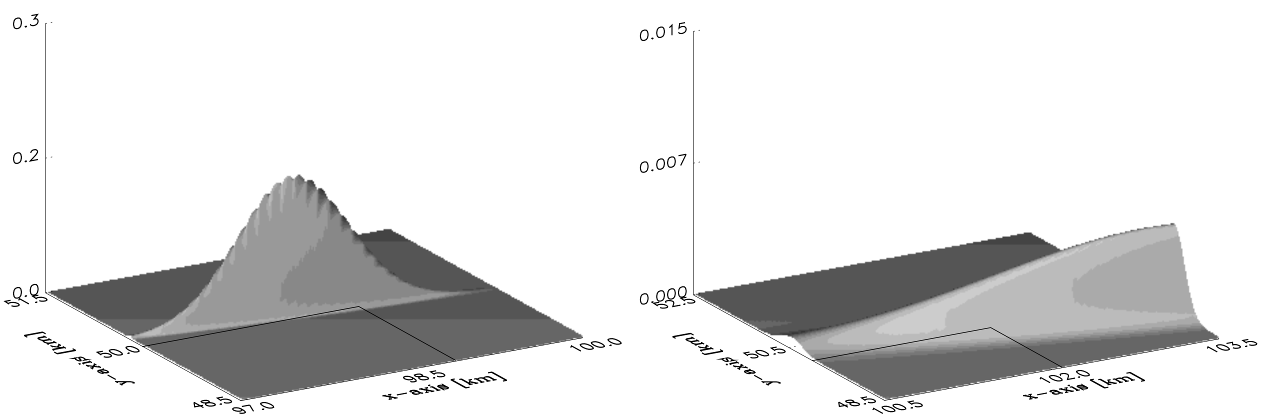


Fig. 2.8. Gain by processing GMTI data from sensor 1 only: (a) during tracking. (b) target stop.

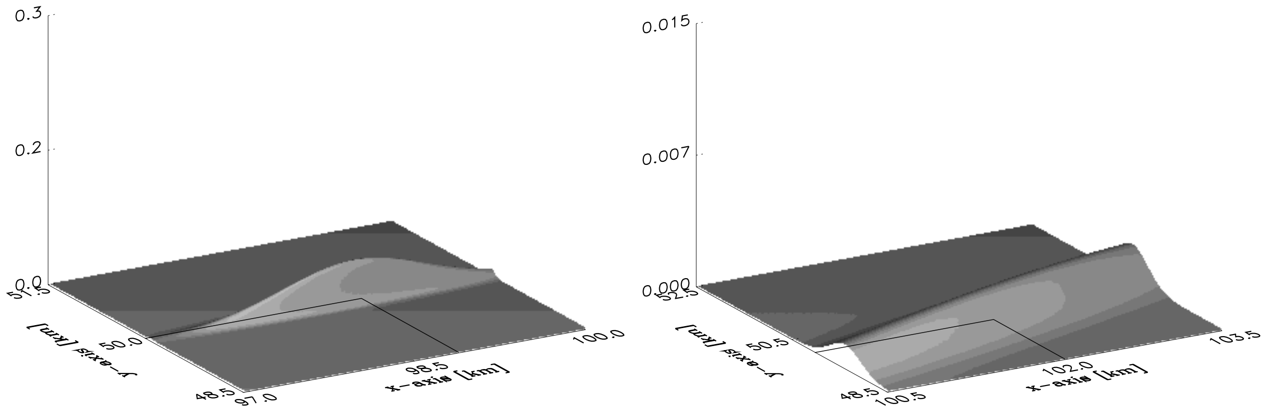


Fig. 2.9. Gain by processing GMTI data from sensor 2 only: (a) during tracking. (b) target stop.

Gain by Sensor Data Fusion

Figures 2.8 – 2.10 show the probability densities of the target position in Cartesian ground coordinates after filtering. The prolated structure of the probability densities mirrors the predominant impact of cross-range errors. Their shape is rotated with respect to each other due to the different sensor-to-target geometries. This effect can be much more pronounced in other situations. We indicated the true target position. Figures 2.8a – 2.10a refer to a regular tracking situation (after 10 min, see Figures 2.1, 2.2). Doppler-blindness occurred for sensor 2 during the previous revisits. The probability densities shown in Figure 2.8b – 2.10b have been calculated at a time when the target has stopped for 3 min. Evidently in Figures 2.8b, 2.9b the dissipation of the density functions is confined to a particular direction according to the GMTI sensor model.

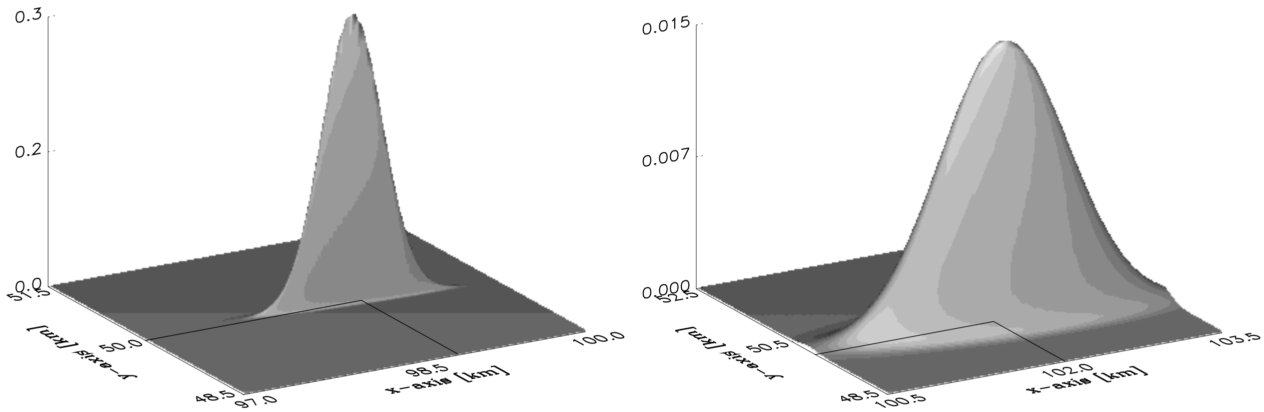


Fig. 2.10. Gain by fusing GMTI data from sensor 1 and 2: (a) during tracking. (b) target stop.

Gain by Sensor Data Fusion

Figures 2.8 – 2.10 show the probability densities of the target position in Cartesian ground coordinates after filtering. The prolated structure of the probability densities mirrors the predominant impact of cross-range errors. Their shape is rotated with respect to each other due to the different sensor-to-target geometries. This effect can be much more pronounced in other situations. We indicated the true target position. Figures 2.8a – 2.10a refer to a regular tracking situation (after 10 min, see Figure 2.1. Doppler-blindness occurred for sensor 2 during the previous revisits. The probability densities shown in Figure 2.8b – 2.10b have been calculated at a time when the target has stopped for 3 min. Evidently in Figures 2.8b, 2.9b the dissipation of the density functions is confined to a particular direction according to the GMTI sensor model.

Figure 2.10 shows the probability densities obtained by sensor data fusion. In both cases we observe a significant fusion gain. It is a consequence of the different orientation of the density functions and leads to improved state estimates. The result for the stopping targets is particularly remarkable. Though no sensor data are available from both sensors, the very fusion of the sensor output 'target under track is no longer detected' implies an improved target localization. This is a consequence of the different target/sensor geometries.

Key Publication

A detailed discussion of this approach has been published in:

- W. Koch and R. Klemm

  Ground Target Tracking with STAP Radar

  IEE Proceedings on Radar, Sonar and Navigation, Vol. 148, No. 3, p.173-185, June 2001 (Special Issue on: "Modeling and Simulation of Radar Systems, Ed.: S. Watts, invited paper).
  An extended version with results from various related conference papers of the author has been published as a handbook chapter in: W. Koch. Ground Target Tracking with STAP Radar: Selected Tracking Aspects. *Chapter 14 in: Klemm, R. (Ed.): Applications of Space-time Adaptive Processing. Institution of Electrical Engineers, IEE Press, 41 pages, London (2004).*

  Abstract
  The problem of tracking ground-moving targets with a moving radar (airborne, spaceborne) is addressed. Tracking of low Doppler targets within a strong clutter background is of special interest. The motion of the radar platform induces a spreading of the clutter Doppler spectrum so that low Doppler target echoes may be buried in the clutter band. Detection of such targets can be much alleviated by space-time adaptive processing (STAP) which implicitly compensates for the Doppler spread effect caused by the platform motion. Even if STAP is applied, low Doppler targets can be masked by the clutter notch. This physical phenomenon is frequently observed and results in a series of missing detections, which may seriously degrade the tracking performance. We propose a new sensor model adapted to STAP and discuss its benefits to tracking well-separated targets. By exploiting a priori information on the sensor specific clutter notch, the model in particular provides a more appropriate treatment of missing detections. In this context the Minimum Detectable Velocity (MDV) proves to be an important sensor parameter explicitly entering into ground-moving target indication (GMTI) tracking.

  Key words: air-/spaceborne radar, STAP, GMTI radar, GMTI tracking, minimum detectable velocity (MDV), Bayesian target tracking, probabilistic data association (PDA)

2.2 Main-lobe Jamming

The degrees of freedom available in applications with airborne phased-array radar enable suppression of so called main-lobe jammers that try to blind the radar by transmitting specially designed radiation directly into the main beam of the radar, by using adaptive array signal processing techniques [20]. Following the spirit of the discussions in the previous sections, the current position of the resulting jammer notch as well as information on the distribution of the related monopulse measurements can be incorporated into a more sophisticated sensor performance model of air-borne phased-array radar. The proposed model does not only improve object tracking in the vicinity of a jammer notch in terms of a shorter extraction delay, improved track accuracy/continuity. It also has strong impact on strategies for adaptive sensor control.

2.2.1 Modeling the Jammer Notch

Tracking of an approaching missile under mail-lobe jamming conditions is among the most challenging data fusion tasks [21]. Advance sensor models can contribute to their efficient and robust solution. An example is

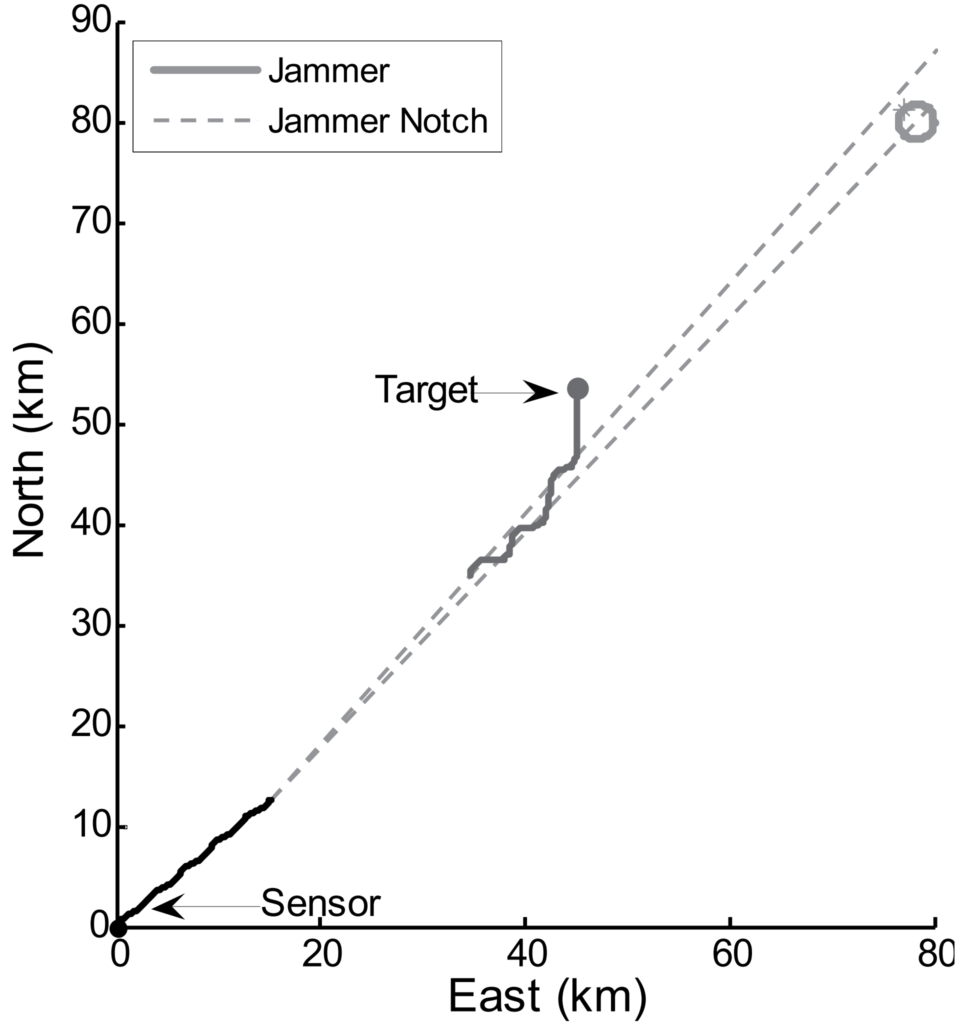


Fig. 2.11. Moving aircraft under mail-lobe jamming conditions: approaching missile near the shadow of the jammer notch

the simulated situation in Figure 2.11, which shows the trajectories of a sensor (AESA: Active Electronically Scanned Array) on a moving platform (black), of an object to be tracked (red), and the jammer (magenta).

By using adaptive digital beamforming techniques, AESA radars of modern interceptor aircraft are able to electronically produce a sector of vanishing susceptibility in their receive beam pattern. Excepting this "blind spot", also called jammer notch, the radar is operating more or less normally. A non-cooperative missile, however, is expected to approach the interceptor aircraft as long as possible in the shadow of the jammer notch. The dashed lines in Figure 2.11 characterize the spatial region of the blind spot depending on the current sensor-to-jammer geometry object.

The effect of the jammer is directly visible in the signal-to-noise-plus-jammer ration (SNJR) of the target, which is shown Figure 2.12 for the scenario discussed as a function of time. Only in the beginning can the missile be detected for a short time. Then it is masked for a long time by the radar's blind spot, until it becomes visible again in close vicinity of the sensor, where the reflected signal is very strong (Burn Through). Sophisticated signal processing provides estimates of the missile direction by using adaptive monopulse techniques [20] as well as the corresponding estimation error covariance matrix $\mathbf{R}(\mathbf{b}_k, \mathbf{j}_k)$ as an additional sensor output. $\mathbf{R}(\mathbf{b}_k, \mathbf{j}_k)$ depends on the current beam direction $\mathbf{b}_k$ of the AESA radar and the jammer direction $\mathbf{j}_k$ and describes in particular the mutual correlation of the estimated direction cosines in the vicinity of the jammer notch. It thus provides valuable context information on the sensor performance.

The sensor model is based on an expression for the signal-to-noise+jammer ratio (SNJR) after completing the signal processing chain. The following simple formula mirrors all relevant phenomena observed:

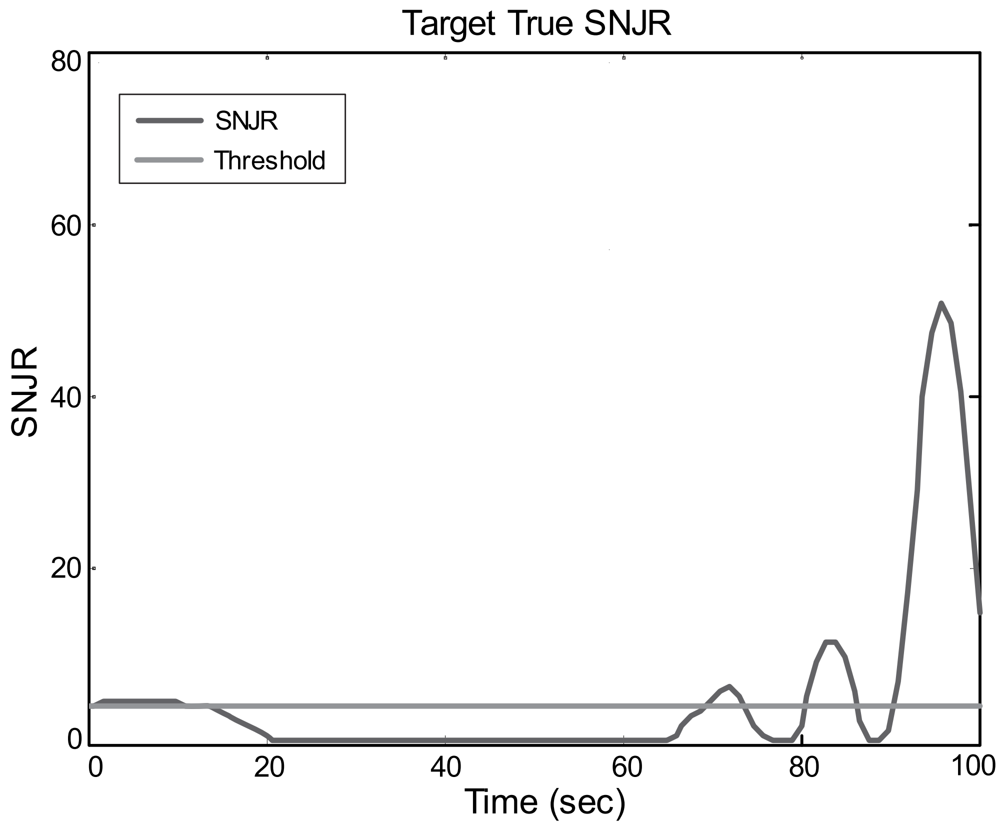


Fig. 2.12. Temporal variation of the signal-to-noise ratio under of an approaching missile under main-lobe jamming

$$\mathrm{SNJR}(\mathbf{d}_k, r_k; \mathbf{b}_k, \mathbf{j}_k) = \mathrm{SNR}_0 \left(\tfrac{r_k}{r_0}\right)^{-4} D(\mathbf{d}_k) \times \mathrm{e}^{-\log 2|\mathbf{d}_k - \mathbf{b}_k|^2/b^2} \left(1 - \mathrm{e}^{-\log 2|\mathbf{d}_k - \mathbf{j}_k|^2/j^2}\right).$$

The vectors $\mathbf{b}_k$ and $\mathbf{j}_k$ denote the angular position of the current beam and the jammer, respectively (assumed to be known). b is a measure of the beam width, while j indicates the width of the jammer notch produced by adaptive nulling, and r_0 is the radar's instrumented range. $\mathbf{d}_k$ is the object's direction vector and r_k its range from the sensor. $D(\mathbf{d}_d)$ reflects the antenna's directivity pattern. In the case of Swerling I fluctuations of the objects' radar cross section and for a simple detection model, the detection probability is a function of $\mathbf{d}_k$, r_k, $\mathbf{b}_k$, and $\mathbf{j}_k$:

$$P_D(\mathbf{d}_k, r_k; \mathbf{b}_k, \mathbf{j}_k) = P_F^{\frac{1}{1+\mathrm{SNJR}(\mathbf{x}_k;\mathbf{b}_k,\mathbf{j}_k)}}. \tag{2.9}$$

P_D can be approximated by using Gaußians linearly depending on the object state. Essentially, we enter this expression of the detection probability into the likelihood function, yielding a Gaußian sum type expression for it.

2.2.2 Tracking Filters Alternatives

According to the previous discussion, the signal-to-noise-plus-jammer is essential in the modeling of the detection probability and thus enters into the likelihood function ratio. After some approximations, the likelihood function can be represented by a Gaußian mixture, finally leading to a version of the Gaußian sum filter. Since the number of mixture components grows in each update step, adaptive approximation schemes must be applied. By using Monte-Carlo-simulations five competing approaches have been evaluated and compared with each other:

1. *Method 1 (Fixed EKF).* This tracking filter serves as a reference and uses no sophisticated sensor model. The impact of the jammer notch on P_D and the measurement error covariance matrix $\mathbf{R}$ are not taken into account.

2. *Method 2 (Variable EKF).* Here, only the monopulse error covariance $\mathbf{R}(\mathbf{b}_k, \mathbf{j}_k)$ is used as an improvement of the sensor model. The detection probability P_D is is assumed to be constant.
3. *Method 3 (Fixed Pseudo-bearing EKF).* This approach assumes a constant error covariance matrix $\mathbf{R}$, but uses the correct likelihood function, i.e. the jammer notch, in a second-order approximation.
4. *Method 4 (Variable Pseudo-bearing EKF).* In addition to the previous realization, here also the covariance matrix $\mathbf{R}(\mathbf{b}_k, \mathbf{j}_k)$ is part of the sensor model.
5. *Method 5 (Gaussian Sum Filter).* In this tracker the complete likelihood function and the monopulse covariance $\mathbf{R}(\mathbf{b}_k, \mathbf{j}_k)$ is used. The number of the mixture components involved to represent $p(\mathbf{x}_k|Z^k)$ is confined by three.

For the methods 3-5 the following is true: If the radar beam points to the vicinity of the blind spot and no detection occurs, a local search is performed. By this, probability mass is concentrated near the blind spot provided the target is actually there.

2.2.3 Selected Simulation Results

Figure 2.13 shows the mean track continuity averaged over 250 Monte-Carlo runs. The superiority of tracking methods that use context information on the spatial position of the blind spot is obvious. The use of the monopulse covariance matrix is necessary, but not sufficient for avoiding track loss. The methods 3, 4, and 5 can, using "negative" sensor evidence, bridge over the missing data in the jammer notch. In spite of the fact that method 5 is more computationally intensive than method 4, it shows deficiencies if compared with method 4. This is an indication for the fact that further performance improvements are possible by more advanced approximation methods.

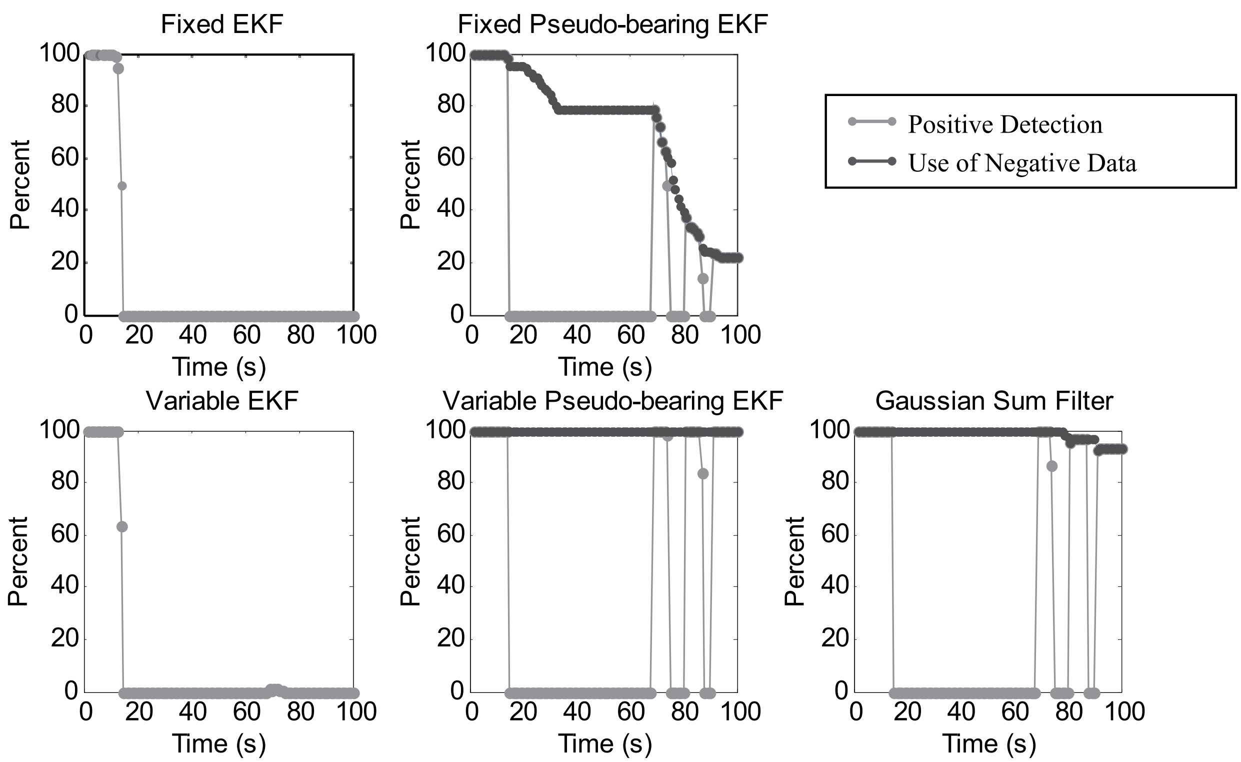


Fig. 2.13. Simulation results (250 runs) characterizing track continuity for different tracking filters.

Key Publication

A detailed discussion of this approach has been published in:

- W. Blanding, W. Koch , U. Nickel

  Adaptive Phased-Array Tracking in ECM Using Negative Information

  IEEE Transactions on Aerospace and Electronic Systems, vol. 45, nr. 1, p. 152-166, January 2009.

  Abstract
  Advances in characterizing the angle measurement covariance for phased array monopulse radar systems that use adaptive beamforming to null a jammer source allow for the use of improved sensor models in tracking algorithms. Using a detection probability likelihood function consisting of a Gaussian sum that incorporates negative contact measurement information, four tracking systems are compared when used to track a maneuvering target passing into and through standoff jammer interference. Each tracker differs in how closely it replicates sensor performance in terms of accuracy of measurement covariance and the use of negative information. Only the tracker that uses both the negative contact information and corrected angle measurement covariance is able to consistently reacquire the target when it exits the jammer interference.

  Keywords: Target tracking, adaptive beamforming, standoff jamming, Gaussian sum filter.

2.3 Negative Sensor Information

More advanced sensor models especially enable the exploitation of 'negative' sensor evidence. By this we mean the rigorous drawing of conclusions from expected but actually missing sensor measurements. These conclusions aim at an improvement of the position or velocity estimates for objects currently kept under track. Even a failed attempt to detect an object in the field of view of a sensor is to be considered as a useful sensor output, which can be processed by using appropriate sensor models, i.e. by background information on the sensors, with benefits for target tracking, sensor management, and sensor data fusion. The technical term chosen here for denoting such pieces of evidence, i.e. 'negative' information, seems to be accepted in the data fusion community (see, e.g. [22, 23]).

2.3.1 A Ubiquitous Notion

A very simple example illustrates that negative sensor information is an ubiquitous phenomenon, which often appears in disguise. The notion fits well into the Bayesian formalism. Assume a sensor producing at discrete time instants t_k mutually independent measurements $\mathbf{z}_k$ of a single object with Gaußian likelihood $\mathcal{N}(\mathbf{z}_k;\, \mathbf{H}\mathbf{x}_k,\, \mathbf{R})$. Absence of clutter is assumed ($\rho_F = 0$). The objects are detected with a constant detection probability $P_\mathrm{D} < 1$. We thus have classical Kalman filtering under the constraint that there exists not at each time a measurement. The likelihood function is thus given by:

1. In the case of a positive sensor output ($m_k = 1$), $\mathbf{z}_k$ is processed by Kalman filtering leading to $p(\mathbf{x}_k|\mathcal{Z}^k) = \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k}\big)$ with $\mathbf{x}_{k|k}$ and $\mathbf{P}_{k|k}$ given by:

$$\mathbf{P}_{k|k} = (\mathbf{P}^{-1}_{k|k-1} + \mathbf{H}^\top \mathbf{R}^{-1}\mathbf{H})^{-1} \tag{2.10}$$

$$\mathbf{x}_{k|k} = \mathbf{P}_{k|k}(\mathbf{P}^{-1}_{k|k-1}\mathbf{x}_{k|k-1} + \mathbf{H}^\top \mathbf{R}^{-1}\mathbf{z}_k). \tag{2.11}$$

2. For a negative sensor output ($m_k = 0$), the likelihood function is a constant $1 - P_\mathrm{D}$. By filtering the prediction density is not modified: $\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1}$, $\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1}$. According to 2.10 and 2.11 this result could formally be interpreted as the processing of a fictitious measurement with an infinite measurement error covariance $\mathbf{R}$, since $\mathbf{R}^{-1} = 0$.

2.3.2 Lessons Learned from Examples

The Bayes formalism and the likelihood function thus precisely indicate, in which way a negative sensor output, i.e. a missing detection has to be processed. This observation notion can be generalized and leads to the following conclusions:

1. Missing but expected (i.e. negative) sensor data can convey information on the current target position or a more abstract function of the kinematic object state. This type of negative evidence can be included in data fusion within the rigorous Bayesian structure. There is no need for recourse to ad hoc or empirical schemes.
2. The prerequisite for processing negative evidence is a refined sensor model, which provides additional background information for explaining its data. As a consequence, negative evidence often appears as an artificial sensor measurement, characterized by a corresponding measurement matrix and a measurement error covariance.
3. The particular form of the fictitious measurement equation involved is determined by the underlying model of the sensor performance, while the fictitious measurement error covariance is characterized by sensor parameters such as sensor resolution, radar beam width, or minimum detectable velocity.
4. Negative evidence implies well-defined probability densities of the object states that prove to be Gaussian mixtures with potentially negative coefficients summing up to one. Intuitively speaking, these components reflect that the targets keep a certain distance from each other, from the last beam position, or the clutter/jammer notch.
5. If the fictitious measurement depends on the underlying sensor-to-target geometry, we can even introduce the fusion of negative evidence.

Key Publication

A detailed discussion of this approach has been published in:

- W. Koch

  On exploiting 'negative' sensor evidence for target tracking and sensor data fusion

  International Journal on Information Fusion, Volume 8, Issue 1, p.28-39, Elsevier, January 2007 (Special Issue: "Best Papers of FUSION 2004", Eds: P. Svensson, J. Schubert, invited paper).

  Abstract
  In various applications of target tracking and sensor data fusion all available information related to the sensor systems used and the underlying scenario should be exploited for improving the tracking/fusion results. Besides the individual sensor measurements themselves, this especially includes the use of more refined models for describing the sensor performance. By incorporating this type of background information into the processing chain, it is possible to exploit 'negative' sensor evidence. The notion of 'negative' sensor evidence covers the conclusions to be drawn from expected but actually missing sensor measurements for improving the position or velocity estimates of targets under track. Even a failed attempt to detect a target is a useful sensor output, which can be exploited by appropriate sensor models providing background information. The basic idea is illustrated by selected examples taken from more advanced tracking and sensor data fusion applications such as group target tracking, tracking with agile beam radar, ground-moving target tracking, or tracking under jamming conditions.

  Keywords: Negative information/evidence, target tracking, sensor resolution, local search, adaptive beam positioning, GMTI sensor fusion

3

Hard & Soft Fusion – Security Applications

Before any further considerations on safety and security technology evolving from these roots, a look at the concise definition of public safety and security in juridical handbooks might provide some clarity: “The notion of public safety and security covers the integrity of the ... fundamental institutions ... of the state as well as the integrity of health, honor, freedom, property, and related objects of legal protection of its citizens. Defense against endangerment of public safety and security is the task of public safety and security authorities.âĂİ

3.1 Context-derived Design of Public Security Systems

In the domain of public security, multiple sensor security assistance systems are expected to play a role comparable to existing car driver assistance systems, i.e. contributing to the first, the technological pillar of a triple strategy.

Considering a concrete example, let us focus on detecting and preventing harm caused by hazardous materials in public infrastructures, e.g. by explosives or radioactive substances. The related events are contingent, uncertain, and rare, when happening, however, resulting in serious injuries of the “integrity of health, honor, and property” of a large number of citizens. Such events may even threaten “fundamental institutions of the state”. Typically, security contractors, a new and highly specialized profession, are responsible for countering such threats, thereby acting on behalf of public authorities. Let us consider a departure hall such as shown in Figure 3.1. Obviously, the security forces need support to fulfill their duty in such scenarios. Desirable are informational assistance systems that pinpoint potential threats, such shown in Figure 3.2, where a person is labeled as a potential threat, e.g. as carrying home made explosives similar to the London attacks in 2005. In a couple of minutes after this video sequence has been taken, the suspect may bring death to many citizens.

More generally speaking, automated recognition of security relevant features in public scenarios is a key functionality of security assistance systems. It has to fulfill several over-all requirements that need to cover a broader range of issues than conventional engineering standards such as:

1. Unburden from routine and mass tasks to gain room for human expertise and insight.
2. Focus human attention to potential threats, hazards, or anomalies as a key functionality.
3. Preserve dignity and informational self-determination by collecting threat-relevant data only.
4. Operate permanently without interfering with or annoying everyday public life.
5. Exploit sensors enabling apprehension beyond natural senses for threat recognition.
6. Indicate properly the possibly limited quality of inferences from inaccurate and incomplete data.
7. Profit from technology trends (sensors, communications, data bases, processors).
8. Fuse multiple sensor data and context information to the extent that is allowed.
9. Guarantee constant and standardized quality levels for any module used in public security applications.
10. Design scalable architectures to be adapted to large diverse networks of sensors and data bases.
11. Enable the utility-cost-privacy balance of each module be understood and its impact assessed.
12. Provide intuitive interfaces to human decision makers, adapted to their specific needs.

Essentially, multiple sensor security assistance systems that are designed along these lines combine the strengths of automated and human data exploitation by:

- real-time analysis of large streams of multiple sensor data and context data bases,

Fig. 3.1. A public infrastructure with security personnel (© by drp under CC BY-NC-ND 2.0).

- while enabling high decision competence in individual situations by expert knowledge.

Security assistance systems may thus be considered as "cognitive tools" for providing awareness of threats that enhance our natural mental capabilities of dealing with large amounts of security relevant sensor and context data in an analogous way as mechanical tools enhance our physical capabilities. Their development should be accompanied by considering technology-driven legal aspects and covering residual risks by properly designed insurance products. Moreover, by identifying fundamental technological limitations of preventive measures and quantitative performance analysis of modular and standardized security assistance systems, the residual risks and therefore even corresponding insurance premiums may become calculable, which would otherwise hardly be possible.

3.2 Hazardous Material Localization and Person Tracking

Returning to the 'London terrorist' example shown in Figure 3.2 âĂŞ what makes the labeled person suspicious? Is there a chance to sense the threat connected to him, to single him out in a crowd of non-suspects?

There is certainly little chance of threat recognition by video analytics alone. Probably, the suspect has not shown any type of individual behavior not being shared with many other persons. What makes him different, however, is the very fact of carrying a significant amount of explosives, homemade explosives that to a certain extent "smell", not to human noses, but to dogs' noses, for example, and olfactory chemical sensors. While in the biosphere "noses" are among the oldest of senses, their technical equivalents are still subject to a rapid technological development. Only recently, they have reached a level of maturity that making their operational use in open systems an option for a growing number of hazardous materials. Chemical sensors

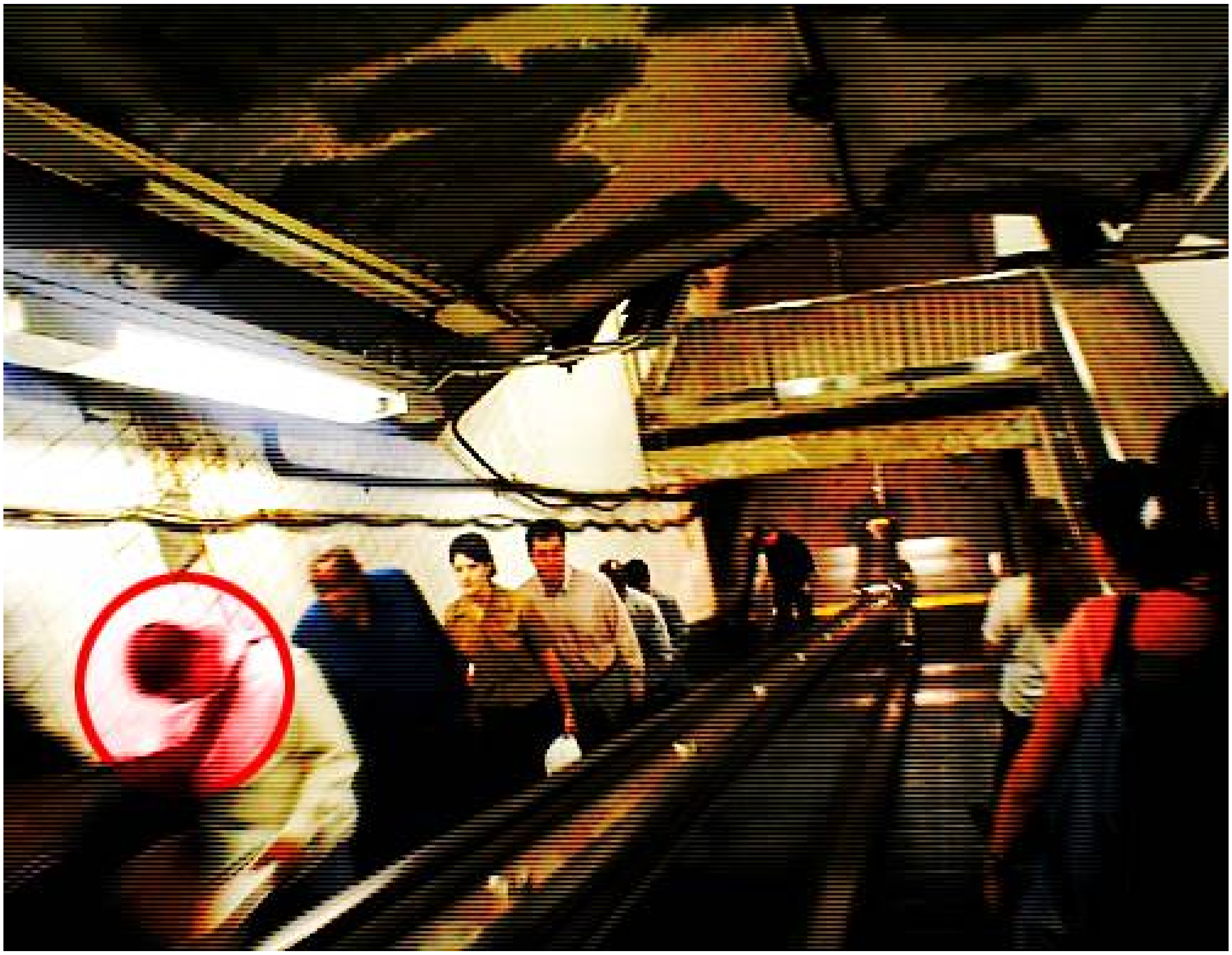


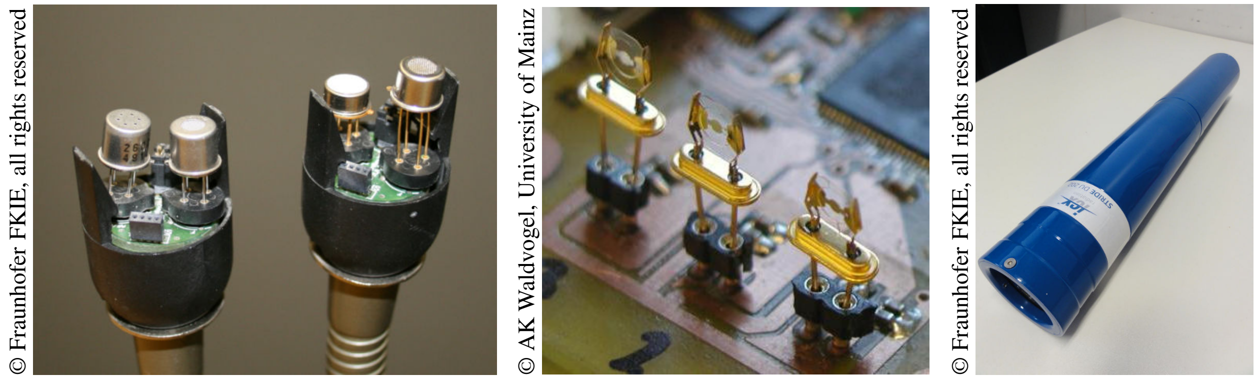
Fig. 3.2. Potential terrorist such as in the London tube attack 2005 (labeled red, © by drp under CC BY-NC-ND 2.0).

detecting even traces of popular explosives in open systems, however, are still in an experimental state and not yet available as stable products. In 3-5 years, however, this situation will have changed completely. System design considerations taking these new sensing options into account should thus start right now.

The design principle of a potentially inexpensive class of chemical sensors with enormous market potential, so-called quartz microbalances, is quite intuitive [24]. Basically, they consist of an oscillating quartz crystal coated with a macromolecular receptor substance that selectively absorbs particular substances to be detected. Even a few absorbed molecules cause an increase of mass attached to the oscillating crystal, which is sufficient for inducing a tiny, but measurable frequency shift. Quartz microbalances can thus be highly *sensitive*. By considering crystal arrays with different coatings, a significant *selectivity* can be reached as well. With this principle, even sensors for detecting biological agents are within reach, where enzymatic coatings are reversibly reacting with particular proteins, viruses, or even bacteria.

Apart from all physiological or chemical differences in olfactory senses or sensors, a fundamental commonality of all *attribute sensors* of this type can be identified, i.e. their *inherently limited space-time resolution capability*. While attribute sensors are able to detect the presence of a particular substance or classes of substances among a variety of alternatives, they on principle are unable to provide useful information on their location. They neither enable any association of the sensed signature to a particular carrier, nor any tracking of its position over time if the substance is carried-on. The same observation is valid for wider classes of attribute sensors such as radioactive sensors. Context information on these fundamental sensor properties is thus a highly critical component of system design.

Obviously, the situation in Figure 3.1 is by far too complex to provide any reasonable technological aid, at least in the foreseeable future. To enter public places like this, however, per-sons often have to pass well-defined



(a) MOx semi-conductor gas sensors (b) QMB array for gas sensing (c) Scintillation counter

Fig. 3.3. *Detection of gases and radiation in open systems.* The semi-conductor sensors in (a) adsorb molecules on a metal-oxide (MOx) coating. The sensor in (b) uses coated quartz micro balances (QMB). The scintillation counter in (c) counts gamma quanta from radioactive sources. (© by Fraunhofer FKIE)

access areas, skywalks or escalators such as shown in Figure 3.2, where the complexity of the surveillance task is much reduced. Tunnel-type areas, where persons enter, stroll along, and finally leave, enable a space-time approach for tracking-aided hazardous material localization. We may span a temporal basis to collect data over time and exploit 'space' by spatially distributing attribute sensors along the walls. The temporal dimension is used by video cameras or laser scanners for tracking each person. By fusing measurements of each chemical sensor over time with the tracking data of all potential carriers of hazardous materials, we get a chance to overcome the limited space-time resolution capability of attribute sensors. More abstractly speaking, we wish to learn from uncertain data, which time-varying object can be classified as suspect or non-suspect [25].

3.2.1 HAMLeT – Discussion of an Experimental Example

To illustrate tracking-aided multiple object, multiple sensor classification for informational security assistance systems, we discuss an experimental set-up called HAMLeT (Hazardous Material Localization and Person Tracking) [26]. A prototypical demonstration system like HAMLeT may serve as an example of how taking sensors plus associated system components, including a walkway, for example, creates a safety and security assistance module that conforms to the design principles identified earlier.

Firstly, relevant object properties are to be identified and modeled, e.g. by random vectors their kinematical characteristics, by random matrices their shape, by discrete random variables the class they belong to, such as "non-suspect" or "suspect" along with the potential type of threat. The collection of such quantities referring to a particular object at a given time defines the object state at this very time. For dealing with uncertain knowledge on objects states, appropriate functions of them are considered, mainly probability density functions, but also proper generalizations of this notion, such as probability hypothesis densities [27] or intensity functions [28]. Spiky functions of this type indicate precise information on the states, while multimodal or "broad" functions represent ambiguous or imprecise knowledge. Data-driven "learning" of object properties is essentially an iterative updating of such functions. For doing so, the relationships between sensor data and objects states are to be modeled, as well as possible errors and uncertainties attached to them. Formally, this is described by functions of the object states, measurements, and sensor parameters, called likelihood functions, which reflect the physical characteristics of the sensor data to be processed in the updating procedure. For initiating or terminating this learning iteration, statistical decision making is required.

A key problem in hazardous material localization is uncertainty on which position and attribute measurements are to be associated to which individual object. Among several solutions, *Expectation-Maximization* methods prove to be of particular value providing a unified and actually very beautiful framework. According to this methodology, each measurement is associated to all persons of interest with appropriate weighting factors. Ideally, measurements actually originating from a particular person have weight One, all other measurements Zero weight. Expectation-Maximization serves as a method to estimate the weighting factors from the measured data iteratively. In other words, joint estimation of objects states and data association weights is considered.

Chemical sensors are influenced by numerous external factors, i.e. context information, that is not easily modeled. Of strong impact on the data quality and time delays involved are the distances between potential carriers, their velocities, temperature, humidity and other environmental parameters such as the degree of turbulence, etc. For designing overall system parameters and quantitative performance predictions, experimental investigations are therefore inevitable. Figure 3.4 shows the experimental system HAMLeT, where in a corridor persons are entering and leaving. Three laser range scanners, four chemical sensors and three miniaturized gamma spectrometers are collecting data. For a detailed description of the mathematical methodology used (based on expectation maximization) and experimental results obtained see the dissertation [30]. Figure 3.5 provides an impression of the system's operation.

Of growing concern for public safety and security are so-called "dirty bombs", where radioactive materials, readily available for medical or commercial use, are combined with conventional explosives [31]. Their damage potential is high in view of contamination, health damage, and the psychological and societal impact in general [32]. There is also an ever increasing need for localizing radioactive materials in logistic chains or when deconstructing nuclear plants, where millions of tons of radioactively contaminated concrete and other debris have to be transported safely. A mobile version of the HAMLeT tunnel may be helpful even in case of catastrophes where incidents at chemical or nuclear plants are involved.

To sum up: by quantitatively analyzing the performance characteristics of an experimental system such as HAMLeT, it is in particular possible to assess the utility-cost-privacy balance, to define information needs and information outputs, to define the usual engineering interfaces and standards, and to define contractual interfaces. It also provides a means to measure or assess the marginal impact upon utility/cost/privacy of providing access to additional background, context, or historical information, or of providing additional output information. Systems like HAMLeT thus provide a means to test emerging architectures for security assistance systems.

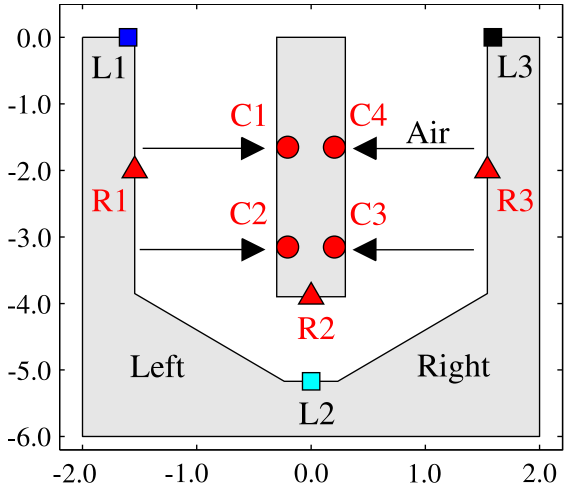
3.2.2 Context Integration: Law-Compliance by Design

Besides its use for system design considerations and quantitative performance prediction and evaluation, HAMLeT may also serve as a concrete example to raise societally relevant aspects of security assistance systems and to discuss "The Three Pillars of Public Safety and Security" on a more systemic level, i.e. the interrelations of their technological, legal and actuarial elements.

First of all and on principle, systems like HAMLeT do not collect any biometrically relevant parameters and therefore preserve the anonymity of the observed individuals by their very technical design. Only positional data in the corridor are collected for tracking-aided association of chemical or radio-active signatures to a distinct carrier. At least in the foreseeable future, chemical sensors are not capable to sense olfactory signatures characteristic of individuals. HAMLeT is thus "blind for normal people", i.e. for the vast majority of persons not carrying hazardous materials. Even though false alarms and manual inspection of a few remaining persons cannot be avoided, such systems may enable "normal" public life without extensive security checks at an ever increasing number of occasions that consider everybody as a "suspect". Moreover, multiple sensor security assistance systems may seamlessly be embedded in public infrastructures making them essentially "invisible". Since the airflow in public infrastructures, for example, can often be modeled fairly well, chemical sensors could be part of the air conditioning system of a public building.

There are, however, numerous procedurally and societally relevant questions in the context of security assistance systems that still have to be answered:

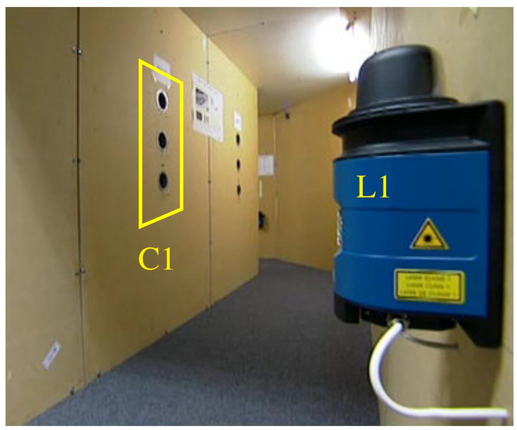
1. How to act when a threat is recognized? This task is by no means easy in cases as shown in Figure 3.2, where any open police action is likely to trigger an explosion. This question raises the problem of automated or semi-automated actions involving possibly even lethal effects and serious legal problems [33].
2. Which domains of life will be safe and secure? Security assistance systems are opening a "security umbrella", wherever the necessary investments are made. Will countering security threats remain the task of public authorities? Will living safely and securely remain an affordable public good?
3. How to certify security assistance systems? As demonstrated by systems such as HAMLeT, certain aspects of law-compliance are "in-built" technical features. Is this to be formalized to cover more features for wider classes of assistance systems? Are there procedures for certification and verification?



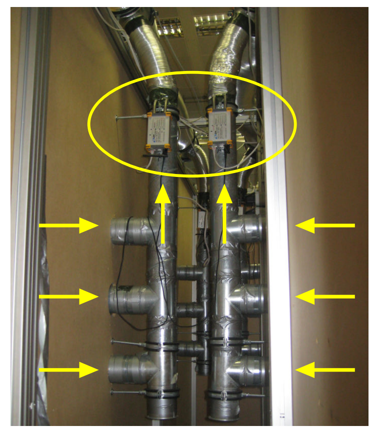
(a) Complete HAMLeT system setup

(b) System assembly with a U-turn in the middle

(c) Detector R3 in right part

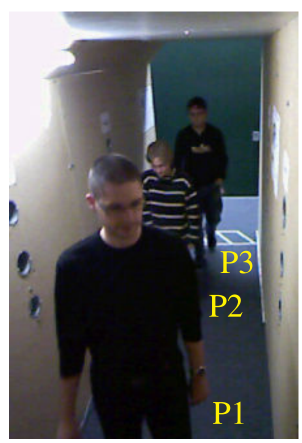


(d) Laser L1 and inlet tubes of platform C1



(e) Chemical platforms C1 and C4

(f) HAMLeT system with persons walking through



(g) Camera left part

(h) Camera right part

Fig. 3.4. *Views of the HAMLeT system.* In the upper row, (a) and (b) show the system plan and a photo of the system assembly. The middle row is dedicated to the sensors that are integrated with the system. In particular, (e) sketches the air stream which blows molecules towards the chemical sensors hooked into the tubes. The lower row shows people walking through the system corridor. (© by Fraunhofer FKIE).

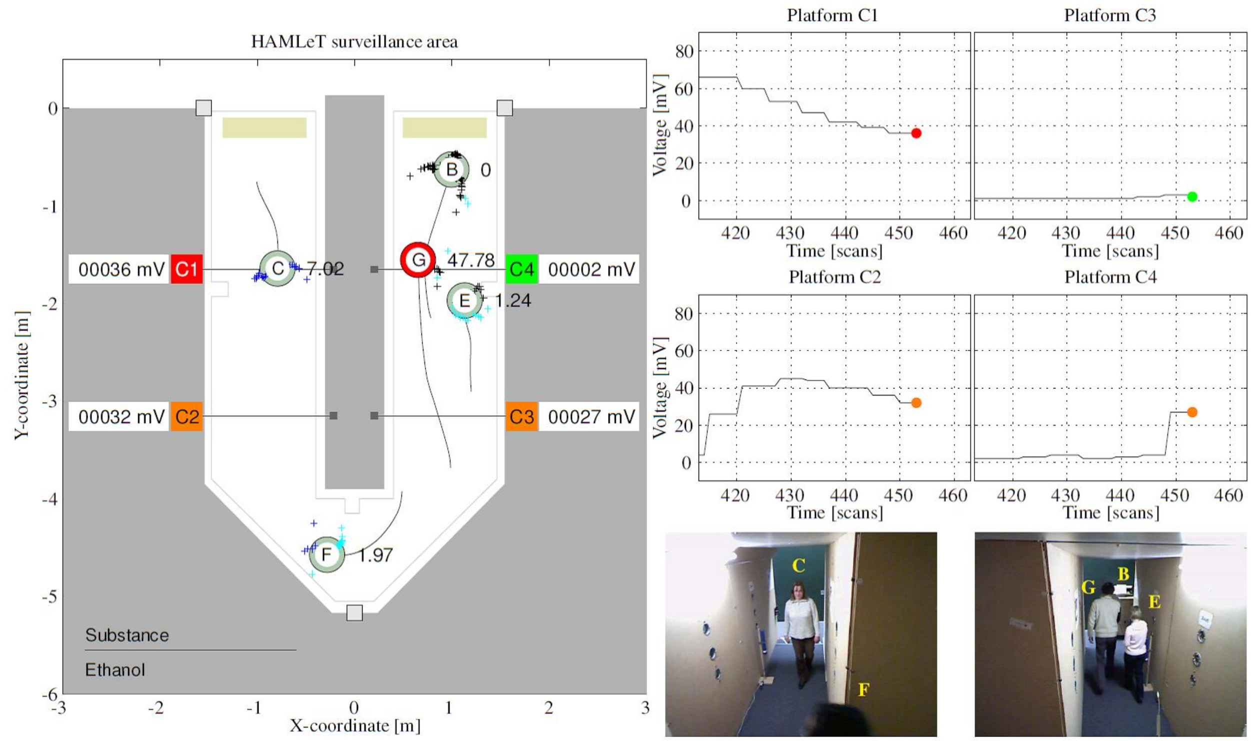


Fig. 3.5. Persons walking arbitrarily, carrier has a test-tube (snapshot 2). The left plot shows the surveillance corridor, the sensor placement, the signals of the chemical sensor platforms and the person tracks with their carrier potential. The four plots on the right visualize the development of the voltage signals over time. The video snapshots show the current person constellation. (© by Fraunhofer FKIE)

4. How to standardize security assistance systems? Calculation of residual risks and design of more intelligent legal measures for event prevention and actuarial residual risk compensation seem to become possible by standardized quality measures and quantitative performance evaluation for such systems.
5. What is the legal role of security contractors? New treat recognition technologies are likely to change traditional roles, since specialized technical under-standing and training are required. In which way do security contractors participate in “public authority”? Who is controlling and limiting them in their actions?
6. How to check system integrity? Security assistance systems cannot exist in hermetic environments and thus need a sort of “immune system”, since they are predictably targets in cyber-attacks or subject to varying and unpredictable conditions or malfunctions and must be capable to reconfigure themselves.

At any rate, such questions among others have a significant societal and political impact, they involve even psycho-emotional and cultural apprehension, interpretation and reaction patterns, and should therefore be discussed publicly. Interestingly enough, these topics are already present in early science fiction novels[34] and recent movies.

It seems worth mentioning that the technical term *Information Fusion* was coined in George OrwellâĂŹs very year 1984 in the defence domain, when the first attempt to scientifically systematize this emerging technology was made [35]. OrwellâĂŹs warning “DonâĂŸt let it happen!” may call us to think of potential threats to human society that may be related to this technology having reached a fairly mature level in the meantime. Attempts to identify and to counter undesirable developments will have to comprise interdisciplinary efforts by engineers, computer scientists, philosophers, sociologists, and, last but not least by lawyers and actuaries, “the engineers of ethics” that frame robust legal systems from more theoretical ethical insights and calculate residual risks based on statistical considerations.

3.2.3 Context Integration: Appropriate Sensor Models

So far, we have addressed context information that is language-encoded and even formalized to a certain degree in rule-based documents, e.g. basic legal notions on privacy etc., or even standardization and certification issues or rule of engagement that are crucial for the deployment and day-to-day operation of assistance systems for public security. According to our introductory discussion this type of context information may be called "soft". As we have shown, it is highly relevant for any systems design considerations and security systems engineering in general.

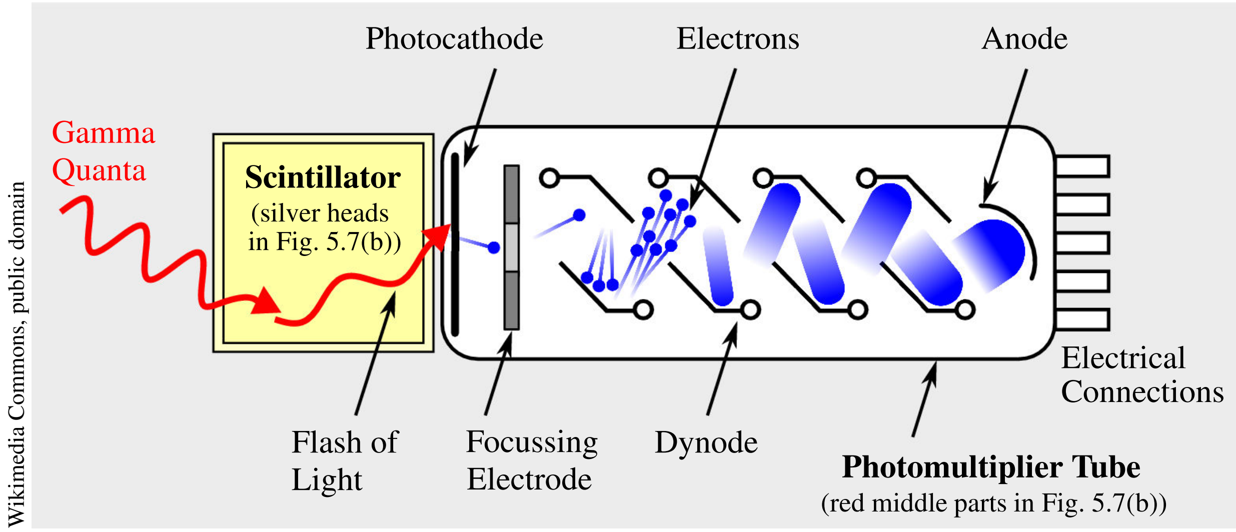
Of no less importance is "hard" context information at various levels. Let us define the "hardness" of such information by the possibility of describing it quantitatively. "Hard" information in this sense can thus be encoded in mathematical models and directly enters into the mathematically formulated data fusion algorithms for combining observational data produced by physical sensing devices. The complexity of the context information entering the design of appropriate sensor models to develop well-adapted likelihood functions may substantially vary for different sensor types.

In Figure 3.4, the placement of three scintillation sensors for detecting illicitly transported radioactive materials by their gamma radiation emitted is indicated by red triangles. Note that alpha and beta rays can be easily shielded: alpha rays are stopped by a sheet of paper and beta rays are stopped by a few millimeters of aluminum. Therefore, it is not possible to detect a shielded alpha or beta radiator within the HAMLeT concept. Gamma rays, in contrast, have the ability to penetrate matter and are merely attenuated. One of the aim of the HAMLeT system is thus to localize a person carrying a weak gamma radiation source.

"Scintillation counting" is a robust sensing principle that is illustrated in Figure 3.6. The device consists of a scintillator (yellow) and a photomultiplier tube (white). When gamma quanta of a radioactive source strike the scintillator, they are absorbed by the scintillation material. Due to the special characteristics of the material, this process causes small flashes of light: the scintillations. The number of flashes is proportional to the number of emitted gamma quanta. Counting the number of flashes over a certain period of time is therefore a means to estimate the source intensity. In Figure 3.6(a) the gamma quanta are represented by red arrows. Within a scintillation counter, the produced flashes of light are emitted towards a photocathode. The photocathode converts the flashes into electrons (blue), which are focussed by an electrode and then multiplied within a system of dynodes. At the end of the tube, the generated avalanche is strong enough to be registered as a signal. At the anode, the generated signals are collected and summed up. Figure 3.6(b) shows three devices without enclosure. The silver head of each device comprises the scintillator (with diameter 2âĂšâĂš and length 3âĂšâĂš), whereas the red part corresponds to the photomultiplier tube connected to the scintillator. A scintillation counter requires a computation and communication module to provide the data over an appropriate interface. Figure 3.6(c) shows a closeup view with the communication interface in the front. The component provides functions for digital signal processing and multi-channel analyzing. Therefore, in addition to the registered counts and the count rate, the device is also capable of deriving a spectrum from the measurements. The spectrum can be exploited to identify the detected radionuclide. The device is sensitive enough to detect a radioactive source of 220kBq while it is carried through the experimental corridor.

In view of sensor data fusion, this discussion of an advanced sensing device makes clear that non-sensor, "hard" context information is critically required at three different levels. 1) We need a clear statistical model of the underlying physics of radioactive decay (physical context). 2) We need an equally clear statistical model of the observable quantities that are related to the physical phenomena and of the errors involved in each measurement processes (partially known context). 3) We finally need a dispersion model of Gamma radiation when propagating though media (environmental context). Also here statistical approaches are needed to cover partially unknown effects. For a more detailed discussion see [30, p. 166 ff.].

While the dispersion of Gamma radiation within the HAMLeT system is not influenced by dynamically changing environmental factors, such as air turbulence, environmental context information is of critical relevance for chemical sensors. In open systems, molecules of the hazardous material to be detected and localized need gas as a carrier medium for being transported from their source towards the chemical sensor, where the detection is initiated. Therefore, an air ventilation system has been integrated. In Figure 3.4(a), the chemical sensor systems are indicated as red circles, i.e. they are placed in the center of HAMLeT, between the two halves of the U-shape. For each sensor system the ventilation system generates an air stream, which is represented by a black arrow. The air stream works like a barrier. When a person crosses the barrier, the streaming air immediately directs adhering molecules from the person towards the sensor triggering the



(a) Concept of a scintillation counter

(b) Three Stride™ detection units (not encased)

(c) Spectrometer interface

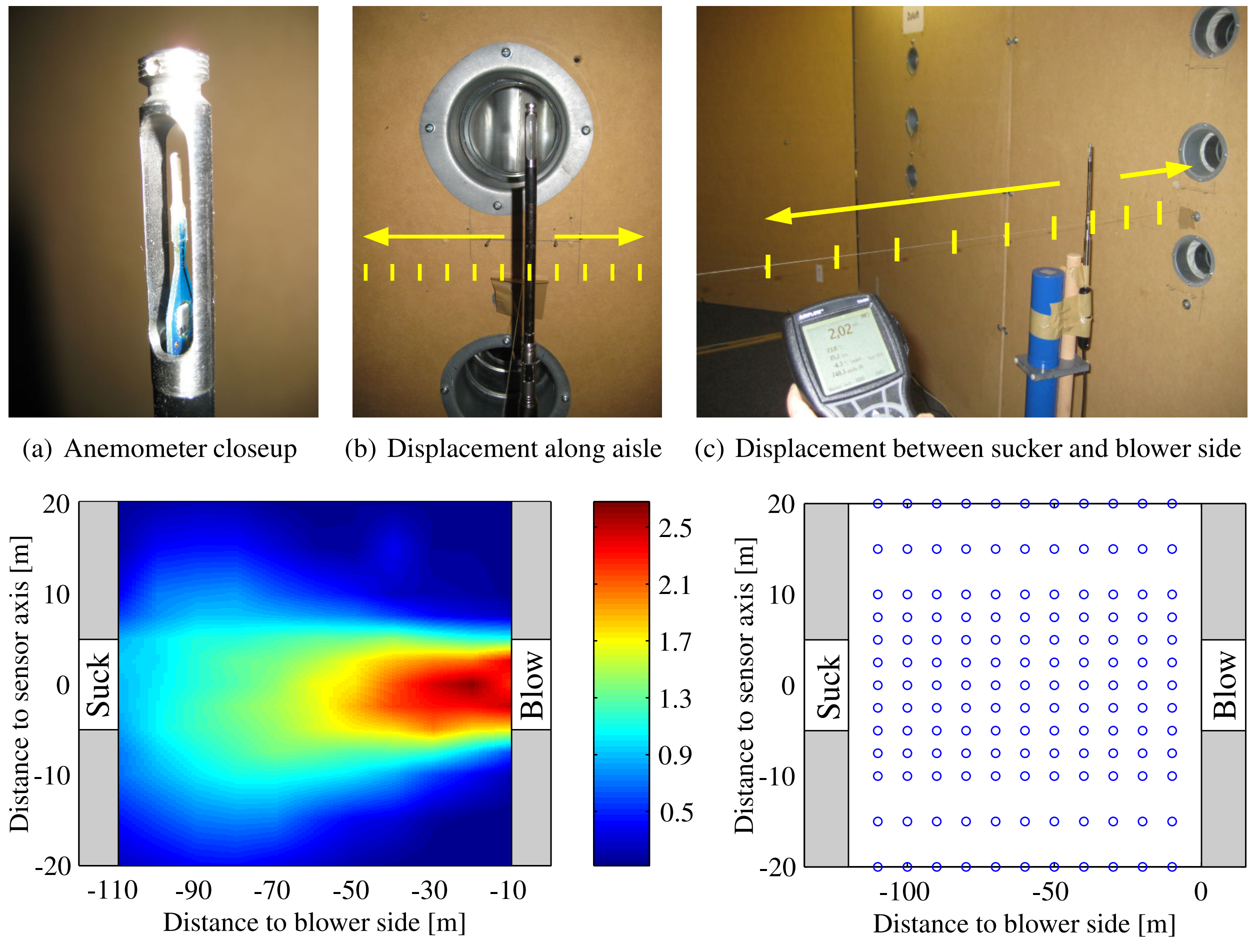
(d) Stride™ unit on the wall

Fig. 3.6. Radiation detectors used in the HAMLeT system. The radiation detection in the HAMLeT system is realized by gamma scintillation counters. The concept of this technology is explained by (a), while (b) âĂŞ (d) refer to the detection units integrated with the system. (© by Fraunhofer FKIE)

detection process with a relatively small time delay and estabishing a causal relation between the person movement and the sensor reaction.

The air barriers are generated by the combination of a sucking and a blowing component. In Figure 3.4(d) the inlet tubes of the chemical platform C1 are surrounded by a yellow rectangle. Figure 3.4(e) shows shows how the sensors C1 and C4 are installed. The air stream is indicated by yellow arrows. From this perspective, the sensors C2 and C3 are not visible. The exit of the ventilation system is on the top of the corridor. Molecules that have not been absorbed, leave the system via the roof tubes.

To provide context information for appropriate sensor models, anemometer measurements of the velocity of the air flow where carried out on a dense grid of measurement positions. The high density of the grid requires a high-precision instrument. The anemometer was shifted stepwise along a twine that was tautened between the sucker and the blower side of the air barrier. Figure 3.7(c) shows the experimental setup. At each measuring point the anemometer provides the magnitude of the wind velocity vector. In Figure 3.7(d) the measured and interpolated velocity distribution between the blower and the sucker side is depicted. The vertical extent of the area ranges from -20 cm to 20 cm. The visualization proves that the coaction of a sucking and a blowing component indeed generates an air barrier, which is able to remove molecules from a person and transport them to the sensor.



(a) Anemometer closeup (b) Displacement along aisle (c) Displacement between sucker and blower side

(d) Interpolated wind velocities [m/sec] (e) Grid of anemometer positions (blue circles)

Fig. 3.7. Visualization of the wind velocities at air barrier C1. (a) shows the anemometer, while (b) and (c) show the experimental setup according to the grid in (e) to provide environmental context information. In (d) the measured and interpolated velocity distribution between the blower and the sucker side is depicted. (© by Fraunhofer FKIE)

Since the air stream serves as a transportation medium for the molecules, the measured wind field can be used to estimate the travel time of molecules from the source to the sensor. Obviously, this is critical context information, since that the detection delay is essential for correctly associating chemical detections to person tracks, and thus for correctly localizing the source carrier. For a more detailed discussion see [30, p. 210 ff.].

3.2.4 Context Integration: Information on Person Flows

HAMLeT may serve a module in a larger over-all security assistance system that monitors person flows in public infrastructures. In a view, hazardous material localization is an example of the more general notion of *anomaly detection*. It can be regarded as a process of information fusion that combines incomplete and imperfect pieces of mutually complementary sensor data and context information in such a way that the attention of human decision makers or decision making systems is focused on particular events that require special actions [14]. Fusion-based anomaly detection thus improves situational awareness. What is actually meant by "regular" or "irregular" events is higher-level information itself that critically depends on the context of the underlying application. Here, it is either assumed to be a priori known or to be learned from statistical long-time analysis of typical situations. We thus may consider it as another example of environmental context information.

Integration of Regularity Patterns

In complex surveillance applications, we can often take advantage of context information on the environment to be insofar as it is the stationary or slowly changing "stage" where a dynamic scenario evolves. Typical examples of such environmental information are digital maps of roads, sea-/air-lane, or regions where people in a public infrastructure typically move. Context information of this type can essentially be regarded as spatial motion constraints. Another category of context information that be relevant in certain applications is provided by visibility models indicating regions, where sensor coverage is low. Moreover, rather detailed planning information or knowledge of prescribed motion is often available, e.g. for passengers after they have left the check-in counter. This category of information can be used to decide whether an object is moving on allowed path within a plausible time frame or leaving it, for example. In addition, map and behavior pattern information can be used to improve the track accuracy and enhance track continuity. See [11, p. 188ff.] for a more detailed discussion.

Often rather detailed information on the over-all behavior of person flows is available, which provides valuable context knowledge on the temporal evolution of their motion. In a sense, it is "hard" context information and can be incorporated into the tracking and classification algorithms. Person flow patterns can in certain situations approximately be described by space-time waypoints that have to be passed by the individual objects while reaching their destination, e.g. an airport gate. The waypoints are a set of position vectors to be reached at given instants of time and via particular routes between the waypoints within an infrastructure that are known in advance. In addition, we assume that the acceptable tolerances related to the arrival of the objects at the waypoints are characterized by known error covariance matrices, possibly individually chosen for each waypoint and object, and that the association between the waypoÃŋnts and the objects is predefined.

The impact of waypoints on the trajectory to be estimated from future sensor data (under the assumption that the regular pattern is actually preserved) can simply be obtained by processing the waypoints as additional artificial 'measurements' via the standard Bayesian tracking paradigm, where the tolerance covariance matrices are taken into account as the corresponding 'measurement error covariances'. If this is done, the processing of sensor measurements with a younger time stamp are to be treated as "out-of sequence" measurements with respect to the artificial waypoint measurements processed earlier. For dealing with out-of-sequence measurements see for example [11, p. 95ff.] and the literature cited therein. According to these considerations, planning information can well improve both track accuracy and continuity as well as facilitate the sensor-data-to-track association problems involved, provided behavior pattern is actually kept.

Detecting Regularity Pattern Violation

A practically important class of anomalies results from a violation of regularity patterns such as those previously discussed. An anomaly detector thus has to decide between two alternatives:

- The observed objects obey an underlying pattern.
- The pattern is not obeyed (e.g. passengers not aiming at the gate).

Decisions of this type are characterized by decision errors of first and second. In most cases, it is desirable to make the decisions between both alternatives for given decision errors to be accepted. A "sequential likelihood ratio" test fulfills this requirement and has enormous practical importance. For a more detailed discussion see [11, p. 199ff.]. As soon as the test decided that the pattern is obeyed, the calculation of the likelihood ratio can be restarted since it is more or less a by-product of track maintenance. The output of subsequent sequential ratio tests can serve to re-confirm "normality" or to detect a violation of the pattern at last. The most important theoretical result on sequential likelihood ratio tests is the fact that the test has a *minimum decision length on average* given predefined statistical decision errors of first and second kind.

We have discussed moving objects that obey certain space-time constraints that are a priorily known (paths, waypoints). A violation of these constraints was quite naturally interpreted as an anomaly. Seen from a different perspective, however, moving objects that are assumed to obey a priorily *unknown* space-time constraints and to be observed by appropriate sensors produce large data streams that can also be used for extracting the underlying space-time constraint. After a suitable post-processing, the produced tracks of motion-constrained objects define the corresponding constraints and can thus be extracted from tracking-based results. See [11] for a more detailed discussion.

3.3 Remarks on Extended Object Tracking

In several applications, it is necessary to learn more from the sensor data received than the time-varying geolocation of moving objects of interest. Rather, we wish to understand *what* the objects we observe are, i.e. we aim to learn as much as possible about their attributes in order to be able to classify or even identify them. Many relevant object attributes can be derived even from their purely kinematic properties such as speed, heading vector, and normal acceleration as well as from mutual interrelations inferable from multiple object tracks, as has been extensively discussed in the introductory chapter, Section 1.2.5.

In particular, the notion of an 'object extension' is introduced by symmetrical and positively dfinite random matrices serving as state quantities that complement the kinematic state vectors. In this way, matrix-variate analysis is brought into play, by which is is made possible to deal with collectively moving object groups and extended objects in a unified approach. This point of view is all the more appropriate, the smaller the mutual distances between the individual objects within a group are, or the larger an extended object is.

Due to the increasing resolution capabilities of modern sensors, there is an increasing need for recognizing extended objects as individual units, for initiating extended object tracks, and for extended object track maintenance. Extended objects typically involve a relatively large and often strongly fluctuating number of sensor reports originated by the individual scattering centers that are part of one and the same object. In this context, we usually cannot assume that in subsequent target illuminations the same scattering centers are always responsible for the measurements. The individual sensor reports can therefore no longer be treated in analogy to point object measurements produced by a group of well-separated targets.

Related problems arise if a group of closely-spaced objects is to be tracked. For sensors such as radar, the resolution capability in range is usually much better than in cross-range. As a consequence, two or more targets within the group can be irresolvable, depending on the current sensor-to-target geometry [36, 37, 38]. In addition, little is known about the measurement error of irresolved measurements produced by an unknown number of targets involved. Practically important examples are aircraft formations or ground moving convoys. Under these circumstances, it seems to be reasonable to treat the group as an individual object and to estimate and track its current extension from the sensor data.

The object extension should be considered as an additional 'internal degree of freedom' characterizing an extended object or a collectively moving object group (cluster) to be tracked. The object extension is thus a part of the object state and has to be estimated jointly with the kinematic properties involved. This paper section discusses a realization of this concept within a Bayesian framework. Temporally changing object extensions are tractable within the proposed framework. An extension increasing along a certain direction, e.g., can indicate that an object is beginning to separate into individual subgroups or parts, which then have to be tracked individually.

3.3.1 Generalized Formalism

In a Bayesian view, a tracking algorithm for an extended object or a collectively moving object group is an updating scheme for $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$ at each time t_k given the accumulated sensor data $\mathcal{Z}^k = \{Z_l, m_l\}_{l=1}^k$ and underlying models describing the object's temporal evolution and the sensor performance. Evidently the joint density

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k) = p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)\, p(\mathbf{X}_k|\mathcal{Z}^k) \tag{3.1}$$

can be written as a product of a vector-variate probability density $p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)$ and a matrix-variate density $p(\mathbf{X}_k|\mathcal{Z}^k)$ [39]. Furthermore, the probabilistic formalism indicates that the density $p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)$, describing the kinematical object properties in the product representation in Eq. 3.1, should show an explicit dependency on the current object extension $\mathbf{X}_k$. To the author's knowledge, random matrices were first introduced for describing physical phenomena by Eugene Wigner [41].

Extended target tracking, i.e. the iterative calculation of the joint density $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$, basically consists of two steps: prediction and filtering. This scheme is completed by the notion of retrodiction.

Prediction

Each update of the joint probability density $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$ of the extended target state $(\mathbf{x}_k, \mathbf{X}_k)$ is preceded by a *prediction* step,

$$p(\mathbf{x}_{k-1}, \mathbf{X}_{k-1}|\mathcal{Z}^{k-1}) \xrightarrow[\text{models}]{\text{evolution}} p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}), \tag{3.2}$$

based on the underlying evolution models. More precisely, we interpret the prediction density $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1})$ as a marginal density to be calculated by integration:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}) = \int d\mathbf{x}_{k-1} d\mathbf{X}_{k-1} \times p(\mathbf{x}_k, \mathbf{X}_k|\mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1})\, p(\mathbf{x}_{k-1}, \mathbf{X}_{k-1}|\mathcal{Z}^{k-1}). \tag{3.3}$$

For the (joint) transition density in the previous representation,

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1}) = p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1})\, p(\mathbf{X}_k|\mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1}), \tag{3.4}$$

we make use of natural Markov-type assumptions for its kinematical part, i.e. $p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1}) = p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})$, and assume that the object's kinematical properties have no impact on the temporal evolution of the object extension and previous measurements if $\mathbf{X}_{k-1}$ is given, i.e.:

$$p(\mathbf{X}_k|\mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1}) = p(\mathbf{X}_k|\mathbf{X}_{k-1}). \tag{3.5}$$

This restriction can be justified in many practical cases. We thus have:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathbf{x}_{k-1}, \mathbf{X}_{k-1}, \mathcal{Z}^{k-1}) = p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})\, p(\mathbf{X}_k|\mathbf{X}_{k-1}). \tag{3.6}$$

The probabilistic formalism clearly indicates that the evolution of the object kinematics, described by $p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})$, is affected by the current object extension $\mathbf{X}_k$ as well. This dependence cannot be ignored.

With the previous filtering update $p(\mathbf{x}_{k-1}, \mathbf{X}_{k-1}|\mathcal{Z}^{k-1})$ we obtain the following prediction formula:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}) = \int d\mathbf{x}_{k-1} d\mathbf{X}_{k-1} \times \underbrace{p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})\, p(\mathbf{X}_k|\mathbf{X}_{k-1})}_{\text{evolution model}}\; \underbrace{p(\mathbf{x}_{k-1}|\mathbf{X}_{k-1}, \mathcal{Z}^{k-1})\, p(\mathbf{X}_{k-1}|\mathcal{Z}^{k-1})}_{\text{previous update}}. \tag{3.7}$$

The transition densities $p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})$ and $p(\mathbf{X}_k|\mathbf{X}_{k-1})$ will be specified in Section III using suitable models that describe the temporal evolution of extended or group targets.

Further discussion is much simplified if we additionally assume that the *temporal change* of the object extension has no impact on the prediction of the *kinematical* object properties, i.e. if we are allowed to assume $p(\mathbf{x}_{k-1}|\mathbf{X}_{k-1}, \mathcal{Z}^{k-1}) \approx p(\mathbf{x}_{k-1}|\mathbf{X}_k, \mathcal{Z}^{k-1})$ or, in other words, to replace $\mathbf{X}_{k-1}$ by $\mathbf{X}_k$. Such an assumption seems to be justified in many practical cases. By this approximation, the predicted density

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}) = p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^{k-1})\, p(\mathbf{X}_k|\mathcal{Z}^{k-1}) \tag{3.8}$$

is given by two factors to be obtained by independent integrations:

$$p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^{k-1}) = \int p(\mathbf{x}_k|\mathbf{X}_k, \mathbf{x}_{k-1})\, p(\mathbf{x}_{k-1}|\mathbf{X}_k, \mathcal{Z}^{k-1})\, d\mathbf{x}_{k-1} \tag{3.9}$$

$$p(\mathbf{X}_k|\mathcal{Z}^{k-1}) = \int p(\mathbf{X}_k|\mathbf{X}_{k-1})\, p(\mathbf{X}_{k-1}|\mathcal{Z}^{k-1})\, d\mathbf{X}_{k-1}. \tag{3.10}$$

Filtering

The prediction is followed by a *filtering* step, in which the current sensor information Z_k at time t_k is to be processed:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}) \xrightarrow[\text{sensor model}]{\text{data: } Z_k, n_k} p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k). \tag{3.11}$$

More precisely, in the filtering step the sensor-specific likelihood function $p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k)$, defined by the current data and the underlying sensor model, is combined with the predicted density by exploiting Bayes' formula [11]:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k) = \frac{p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k)\, p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1})}{\int p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k)\, p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1})\, d\mathbf{x}_k d\mathbf{X}_k}. \tag{3.12}$$

3.3.2 Extended Object Prediction

The probability density $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$ of an extended or group target state is given by Eq. 3.12. The joint densities in this equation can be written as products:

$$\begin{aligned} p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k) &= p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)\, p(\mathbf{X}_k|\mathcal{Z}^k) \\ p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^{k-1}) &= p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^{k-1})\, p(\mathbf{X}_k|\mathcal{Z}^{k-1}) \\ p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k) &= p(Z_k|n_k, \mathbf{x}_k, \mathbf{X}_k)\, p(n_k|\mathbf{x}_k, \mathbf{X}_k). \end{aligned} \tag{3.13}$$

The kinematical state variable $\mathbf{x}_k$ at time t_k is given by $\mathbf{x}_k = (\mathbf{r}_k^\top, \dot{\mathbf{r}}_k^\top, \ddot{\mathbf{r}}_k^\top)^\top$ with the spatial state components $\mathbf{r}_k$. Let the dimension d of the vector $\mathbf{r}_k$ be also the dimension of the $d \times d$ SPD matrix $\mathbf{X}_k$ that describe the current ellipsoidal object extension (SPD: symmetrical and positively definite). $\dot{\mathbf{r}}_k$, $\ddot{\mathbf{r}}_k$ denote the corresponding velocity and acceleration. The dimension of the kinematical state vector $\mathbf{x}_k$ is thus $s \times d$, where $s - 1$ describes up to which derivative the object kinematics is modeled. Here we have $s = 3$.

Extended Object Evolution

The temporal evolution of an extended or collective object is modeled as usual in Kalman filtering theory: $\mathbf{x}_k = \boldsymbol{\Phi}_{k|k-1}\mathbf{x}_{k-1} + \mathbf{v}_k$, $p(\mathbf{v}_k) = \mathcal{N}(\mathbf{v}_k;\, \mathbf{0},\, \boldsymbol{\Delta}_{k|k-1})$. Using the Kronecker product [39], the evolution matrix $\boldsymbol{\Phi}_{k|k-1}$ can be written as:

$$\boldsymbol{\Phi}_{k|k-1} = \mathbf{F}_{k|k-1} \otimes \mathbf{1}_d, \tag{3.14}$$

where the $s \times s$ matrix $\mathbf{F}_{k|k-1}$ is given for example by van Keuk's model. The use of Kronecker products will prove to be very convenient in the subsequent calculations. For the dynamics noise covariance $\boldsymbol{\Delta}_{k|k-1}$, we postulate the following structure:

$$\boldsymbol{\Delta}_{k|k-1} = \mathbf{D}_{k|k-1} \otimes \mathbf{X}_k. \tag{3.15}$$

Model parameters describing the underlying dynamics are part of a $s \times s$ matrix $\mathbf{D}_{k|k-1}$, as given by van Keuk's model, for example. The $s \times s$ matrices $\mathbf{F}_{k|k-1}$, $\mathbf{D}_{k|k-1}$ also appear in this form in the 1D tracking problem. The system noise is thus a band limited Gaussian acceleration noise process with a covariance proportional to the extension matrix $\mathbf{X}_k$. This has the effect of directing the acceleration of the group (or object) centroid along the direction of the major axis of the ellipse.

The assumption of a dynamics covariance matrix $\boldsymbol{\Delta}_{k|k-1}$ depending on the current object extension $\mathbf{X}_k$, which is a consequence of the probability formalism, needs a discussion with more physical arguments:

1. The collective character of a group motion is the more pronounced the smaller the group is. The dynamical behavior of a smaller group is thus to a larger extent deterministic in nature ("‘maneuvering becomes dangerous"’).
2. For a group dissolving into subgroups, i.e. if its extension is increasing, the knowledge of its dynamical behavior decreases, and the motion of the group is not easily predictable, being expressed by the increasing dynamics noise covariance.
3. In addition, large extended or group objects will produce so many sensor measurements that the prediction part of the tracking process, i.e. exploitation of information on the object evolution, seems to be negligible if compared to the gain obtained in the filtering step.
4. In case of extended objects like submarines or ground moving convoys, which show a clear orientation, the proposed dynamics model provides a natural description of their actual movement along the major axes of the extension ellipse.

Besides these more or less physically motivated reasons, an important formal argument exists in favor of the model: A dynamics model of the proposed form implies a formal structure of the densities $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$, which enables a rigorous application of the Bayesian formalism under certain assumptions.

Structure of the Predicted Density

According to Eq. 3.13, the kinematics can be discussed separately from the extension estimation in the tracking process. Let us assume that the density of the kinematical state variable $p(\mathbf{x}_{k-1}|\mathbf{X}_k, \mathcal{Z}^{k-1})$ after filtering at time t_{k-1} is a Gaussian with the following special structure:

$$p(\mathbf{x}_{k-1}|\mathbf{X}_k, \mathcal{Z}^{k-1}) = \mathcal{N}(\mathbf{x}_{k-1};\, \mathbf{x}_{k-1|k-1},\, \mathbf{P}_{k-1|k-1} \otimes \mathbf{X}_k). \tag{3.16}$$

Then the previous evolution model guarantees that this structure is preserved by the prediction process (Eq. 3.9):

$$\begin{aligned} p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^{k-1}) = \int & \mathcal{N}(\mathbf{x}_k;\, (\mathbf{F}_{k|k-1} \otimes \mathbf{1}_d)\mathbf{x}_{k-1},\, \mathbf{D}_{k|k-1} \otimes \mathbf{X}_k) \\ & \times\ \mathcal{N}(\mathbf{x}_{k-1};\, \mathbf{x}_{k-1|k-1},\, \mathbf{P}_{k-1|k-1} \otimes \mathbf{X}_k)\, d\mathbf{x}_{k-1} & (3.17) \\ = & \ \mathcal{N}(\mathbf{x}_k;\, \mathbf{x}_{k|k-1},\, \mathbf{P}_{k|k-1} \otimes \mathbf{X}_k) & (3.18) \end{aligned}$$

according to the usual rules for Kronecker products with $\mathbf{x}_{k|k-1}$ and $\mathbf{P}_{k|k-1}$ given by:

$$\mathbf{x}_{k|k-1} = (\mathbf{F}_{k|k-1} \otimes \mathbf{1}_d)\mathbf{x}_{k-1|k-1} \tag{3.19}$$
$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k|k-1}\mathbf{P}_{k-1|k-1}\mathbf{F}_{k|k-1}^{\top} + \mathbf{D}_{k|k-1} \tag{3.20}$$

in close analogy to standard Kalman filtering.

Moreover, let us assume that the densities of the extension state variable $p(\mathbf{X}_{k-1}|\mathcal{Z}^{k-1})$ are given by Inverted Wishart densities [39] defined up to a factor independent of $\mathbf{X}_{k-1}$ by:

$$\begin{aligned} p(\mathbf{X}_{k-1}|\mathcal{Z}^{k-1}) &= \mathcal{IW}\big(\mathbf{X}_{k-1};\, \nu_{k-1|k-1},\, \mathbf{X}_{k-1|k-1}\big) & (3.21) \\ &\propto |\mathbf{X}_{k-1}|^{-\frac{1}{2}\nu_{k-1|k-1}}\ \mathrm{etr}\big[-\tfrac{1}{2}\mathbf{X}_{k-1|k-1}\mathbf{X}_{k-1}^{-1}\big]\,. & (3.22) \end{aligned}$$

d is the dimension of the measurement vectors $\mathbf{z}_k^j$ and $\mathrm{etr}[\mathbf{A}]$ an abbreviation for $\exp[\mathrm{tr}\mathbf{A}]$ with $\mathrm{tr}\mathbf{A}$ denoting the trace of a matrix $\mathbf{A}$. The expectation of $\mathbf{X}_{k-1}$ is given by $\mathbb{E}[\mathbf{X}_{k-1}] = \frac{\mathbf{X}_{k-1|k-1}}{\nu_{k-1|k-1}-2d-2}$.

In the prediction step, the parameters $\nu_{k|k-1}$, $\mathbf{X}_{k|k-1}$ defining $p(\mathbf{X}_k|\mathcal{Z}^{k-1})$ have to be calculated from $\nu_{k-1|k-1}$, $\mathbf{X}_{k-1|k-1}$ available after the previous filtering step according to appropriate modeling assumptions. In a first heuristic approach, we postulate that the expectation of the predicted density shall be equal to the expectation of the previous filtering step; i.e.: $\frac{\mathbf{X}_{k|k-1}}{\nu_{k|k-1}-2d-2} = \frac{\mathbf{X}_{k-1|k-1}}{\nu_{k-1|k-1}-2d-2}$. The degrees of freedom of an inverse Wishart density are related to the ‘precision’ of the corresponding expectation. The ‘precision’ of predictions, however, will decrease with increasing update intervals $\Delta t_k = t_k - t_{k-1}$. With a temporal decay constant τ as an additional modeling parameter, the following prediction update equations seem to be plausible:

$$\nu_{k|k-1} = \mathrm{e}^{-\Delta t_k/\tau}\, \nu_{k-1|k-1} \tag{3.23}$$
$$\mathbf{X}_{k|k-1} = \frac{\mathrm{e}^{-\Delta t_k/\tau}\nu_{k-1|k-1}-d-1}{\nu_{k-1|k-1}-d-1}\, \mathbf{X}_{k-1|k-1}. \tag{3.24}$$

$\tau = \infty$ represents a static object or group extension.

3.3.3 Extended Object Filtering

In the case of extended or group targets, the significance of a single measurement is obviously dominated by the underlying object extension. The sensor-specific measurement error that describe the precision by which a given scattering center is currently measured is the more unimportant, the larger the actual extension of the object is compared to the measurement error. The individual measurements must therefore rather be interpreted as measurements of the centroid of the extended or collective object, since it is unimportant for the extended object tracking task which of the varying scattering centers was actually responsible for the measurement.

We thus interpret each individual measurement produced by an extended object as a measurement of the object centroid with a corresponding ‘measurement error’ that is proportional to the object extension $\mathbf{X}_k$ to be estimated. By means of this ‘measurement error’, however, the object extension $\mathbf{X}_k$ becomes explicitly part of the likelihood function $p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k)$, which describes what the measured quantities Z_k, n_k can say about the state variables $\mathbf{x}_k$ and $\mathbf{X}_k$. As a consequence of this interpretation, the object extension $\mathbf{X}_k$ can also be estimated by exploiting the sensor data (besides the kinematical state vector $\mathbf{x}_k$).

By using the Kronecker product, we also assume that the measurement matrix has the following special structure:

$$(h_k^1 \mathbf{1}_d, h_k^2 \mathbf{1}_d, h_k^3 \mathbf{1}_d) = \mathbf{H}_k \otimes \mathbf{1}_d. \tag{3.25}$$

With $\mathbf{H}_k = (1, 0)$, e.g., scenarios with range and azimuth measurements are accessible after transforming them into Cartesian coordinates. According to the previous considerations, the corresponding measurement error covariance is given by the extension matrix $\mathbf{X}_k$ to be estimated.

Likelihood Function

In order to exploit Bayes' formula, a likelihood function factorized according to Eq. 3.13 needs to be defined. For the sake of simplicity, let us exclude false or unwanted measurements at present. In a first approximation, the number n_k of measurements in Z_k is assumed to be independent of the state variables $\mathbf{x}_k$, $\mathbf{X}_k$; i.e. $p(n_k|\mathbf{x}_k, \mathbf{X}_k)$ is assumed to be a constant. According to the the discussion in Section **??**, the joint density $p(Z_k|m_k, \mathbf{x}_k, \mathbf{X}_k)$ can be factorized:

$$p(Z_k|m_k, \mathbf{x}_k, \mathbf{X}_k) \propto \mathcal{N}\big(\mathbf{z}_k;\, (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_k,\, \tfrac{\mathbf{X}_k}{m_k}\big)\; \mathcal{LW}\big(\mathbf{Z}_k;\, m_k - 1,\, \mathbf{X}_k\big). \tag{3.26}$$

with a centroid measurement $\mathbf{z}_k$, a corresponding scattering matrix $\mathbf{Z}_k$, and a Wishart density in $\mathbf{Z}_k$ with $m_k - 1$ degrees of freedom.

Structure after Filtering

With these preliminaries, it is possible to exploit the Bayes formula Eq. 3.12. To this end, we have to calculate the product:

$$\begin{aligned} p(Z_k|n_k, \mathbf{x}_k, \mathbf{X}_k)\, p(\mathbf{x}_k, \mathbf{X}_k|\mathbf{Z}^{k-1}) \propto\; & \mathcal{N}\big(\mathbf{z}_k;\, (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_k,\, \tfrac{\mathbf{X}_k}{n_k}\big) \\ & \times\; \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k-1},\, \mathbf{P}_{k|k-1} \otimes \mathbf{X}_k\big) \\ & \times\; \mathcal{LW}\big(\mathbf{Z}_k;\, n_k - 1,\, \mathbf{X}_k\big)\; \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k-1},\, \mathbf{X}_{k|k-1}\big). \end{aligned} \tag{3.27}$$

By standard calculations (product formula for Gaussians and properties of Kronecker products, the product of the two Gaussians in the previous equation yields:

$$\begin{aligned} & \mathcal{N}\big(\mathbf{z}_k;\, (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_k,\, \tfrac{\mathbf{X}_k}{n_k}\big)\; \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k-1},\, \mathbf{P}_{k|k-1} \otimes \mathbf{X}_k\big) = \\ & \qquad \mathcal{N}\big(\mathbf{z}_k;\, (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_{k|k-1},\, S_{k|k-1}\mathbf{X}_k\big)\; \mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k\big) \end{aligned} \tag{3.28}$$

where the quantities $\mathbf{x}_{k|k}$ and $\mathbf{P}_{k|k}$ are given by

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + (\mathbf{W}_{k|k-1} \otimes \mathbf{1}_d)(\mathbf{z}_k - (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_{k|k-1}) \tag{3.29}$$

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{W}_{k|k-1} S_{k|k-1} \mathbf{W}_{k|k-1}^\top \tag{3.30}$$

with a scalar *innovation factor* and a gain matrix defined by

$$S_{k|k-1} = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^\top + \tfrac{1}{n_k} \tag{3.31}$$

$$\mathbf{W}_{k|k-1} = \mathbf{P}_{k|k-1} \mathbf{H}_k^\top S_{k|k-1}^{-1}. \tag{3.32}$$

The first factor on the right side in Eq. 3.26 does not depend on the kinematical state variable $\mathbf{x}_k$. It can be rewritten as

$$\mathcal{N}\big(\mathbf{z}_k;\, (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_{k|k-1},\, S_{k|k-1}\mathbf{X}_k\big) \propto |\mathbf{X}_k|^{-\frac{1}{2}}\; \mathrm{etr}\big[-\tfrac{1}{2}\mathbf{N}_{k|k-1}\mathbf{X}_k^{-1}\big] \tag{3.33}$$

up to a factor independent of the state variables and with an *innovation matrix* $\mathbf{N}_{k|k-1}$ defined by

$$\mathbf{N}_{k|k-1} = S_{k|k-1}^{-1}\big(\mathbf{z}_k - (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_{k|k-1}\big)\,\big(\mathbf{z}_k - (\mathbf{H}_k \otimes \mathbf{1}_d)\mathbf{x}_{k|k-1}\big)^\top. \tag{3.34}$$

The remaining two factors on the right side of Eq. 3.27 yield:

$$\begin{aligned} & \mathcal{LW}\big(\mathbf{Z}_k;\, n_k - 1,\, \mathbf{X}_k\big)\, \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k-1},\, \mathbf{X}_{k|k-1}\big)\, |\mathbf{X}_k|^{-\frac{1}{2}}\; \mathrm{etr}\big[-\tfrac{1}{2}\mathbf{N}_{k|k-1}\mathbf{X}_k^{-1}\big] \\ & \qquad \propto \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\big) \end{aligned} \tag{3.35}$$

with the simple update equations:

$$\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{N}_{k|k-1} + \mathbf{Z}_k \tag{3.36}$$

$$\nu_{k|k} = \nu_{k|k-1} + n_k. \tag{3.37}$$

Joint Density after Filtering

The probability density function of the joint state $(\mathbf{x}_k,\, \mathbf{X}_k)$ after processing the current sensor data Z_k at time t_k is thus given by:

$$p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k) = \mathcal{N}(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k)\; \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\big). \tag{3.38}$$

Important Remark: By means of the *innovation matrix* $\mathbf{N}_{k|k-1}$, it is possible to estimate an unknown measurement error covariance even in the case of point source targets or the extension of a completely irresolved target group, i.e. for $n_k = 1$.

3.3.4 Extended Object Kinematics

In many practical applications, we are interested in estimates of the kinematic state variables only, i.e. on the marginal density $p(\mathbf{x}_k|\mathcal{Z}^k)$ obtained by integrating the joint density $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$ over the random matrices $\mathbf{X}_k$:

$$\begin{aligned} p(\mathbf{x}_k|\mathcal{Z}^k) &= \int p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)\, d\mathbf{X}_k && (3.39)\\ &= \int \mathcal{N}(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k)\; \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\big)\, d\mathbf{X}_k. && (3.40) \end{aligned}$$

By lengthy but elementary algebraic calculations the integrand can be transformed into the following product:

$$\begin{aligned} &\mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k\big)\; \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\big) \propto \\ &\qquad |\mathbf{Y}_k(\mathbf{x}_k)|^{-\frac{(\nu_{k|k}+s-sd)+sd}{2}}\; \mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k}+s,\, \mathbf{Y}_k(\mathbf{x}_k)\mathbf{X}_{k|k}\big) \end{aligned} \tag{3.41}$$

with a matrix $\mathbf{Y}_k = \mathbf{Y}_k(\mathbf{x}_k)$ depending on the kinematical state variable $\mathbf{x}_k$ whose determinant is given by

$$|\mathbf{Y}_k| = 1 + (\mathbf{x}_k - \mathbf{x}_{k|k})^\top\, (\mathbf{P}_{k|k}^{-1} \otimes \mathbf{X}_{k|k}^{-1})(\mathbf{x}_k - \mathbf{x}_{k|k}). \tag{3.42}$$

With this representation of the integrand, integration over the random matrix $\mathbf{X}_k$ is trivial. We ultimately find that the marginal density with respect to the kinematical state variable $\mathbf{x}_k$ is given by a multivariate version of the Student density with $\nu_{k|k}$ degrees of freedom:

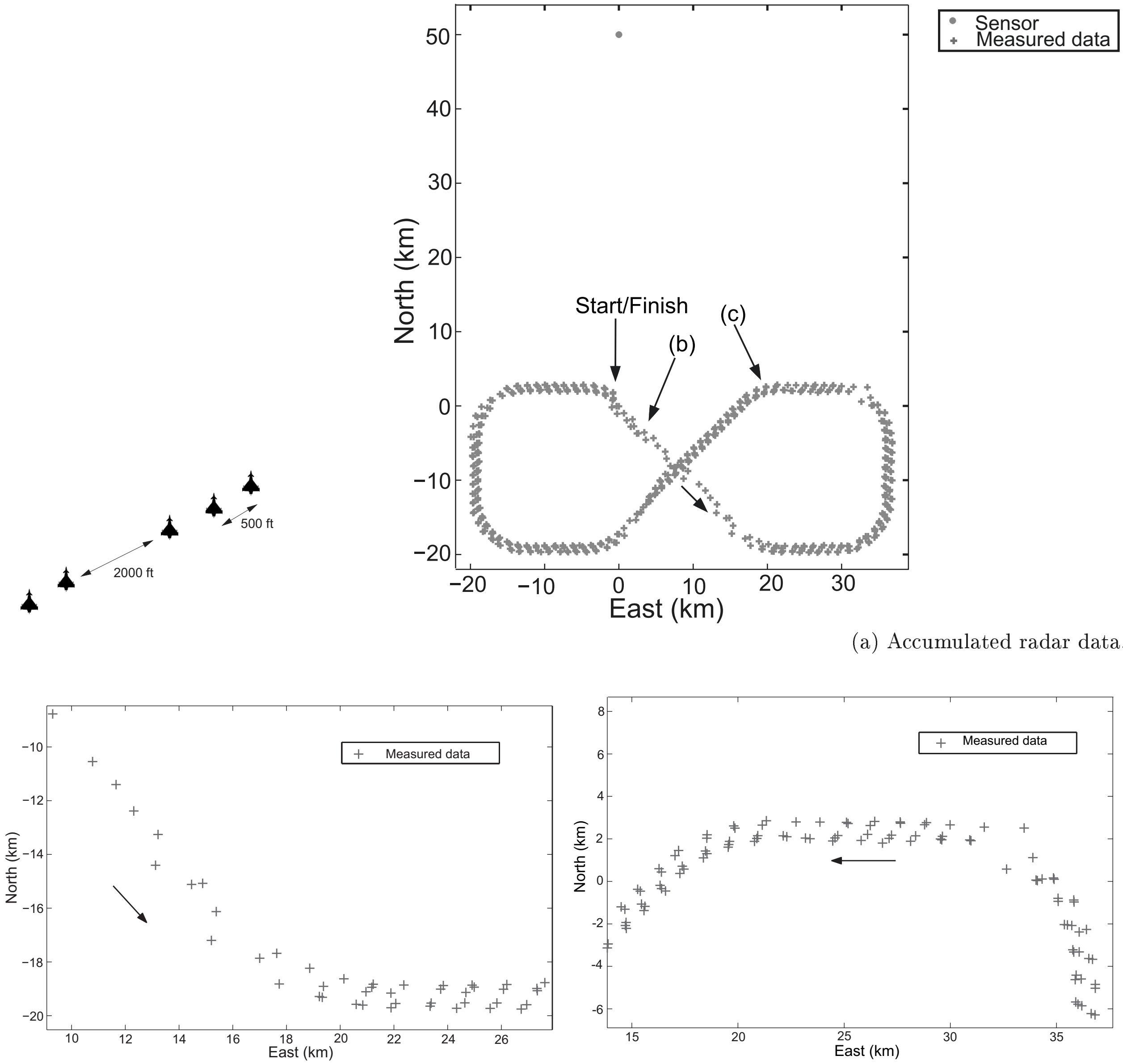
$$p(\mathbf{x}_k|\mathcal{Z}^k) = \mathcal{T}\big(\mathbf{x}_k;\, \nu_{k|k}+s-sd,\, \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_{k|k}\big). \tag{3.43}$$

By exploiting the multivariate t-density a 'gating' can be constructed that is simply a version of the Hotelling-t^2-test.

It is immediately clear that the marginalized prediction and retrodiction densities are also given by Student densities: $p(\mathbf{x}_l|\mathcal{Z}^{l-1}) = \mathcal{T}\big(\mathbf{x}_l;\, \nu_{l|l-1}+s-sd,\, \mathbf{x}_{l|l-1}, \mathbf{P}_{l|l-1} \otimes \mathbf{X}_{l|l-1}\big)$, $p(\mathbf{x}_l|\mathcal{Z}^k) = \mathcal{T}\big(\mathbf{x}_l;\, \nu_{l|k}+s-sd,\, \mathbf{x}_{l|k}, \mathbf{P}_{l|k} \otimes \mathbf{X}_{l|k}\big)$.

3.3.5 Selected Simulation Results

For the sake of simplicity, aircraft trajectories are simulated in a plane and partitioned into straight and circular segments where each aircraft is moving with a constant tangential speed as shown in Figure 3.8. In an echelon formation consisting of five aircraft, the leading aircraft is responsible for navigating, while the other aircraft try to preserve their relative position to the leading aircraft. The underlying radar sensor has a finite resolution capability (range resolution: 50 m, azimuth resolution: 1.0°). The corresponding measurement error standard deviations for resolvable objects are 10 m and 0.1°, respectively. The orientation of the aircraft formation varies as it moves around the trajectory. The update interval is 5 s. For the parameters of the Van-Keuk-evolution model, we chose $\Sigma = 1\ g$, $\theta = 40$ s. The normal acceleration during the maneuvers is 1 g, the speed is 250 m/s. The formation starts at the origin of the coordinate system.



(a) Accumulated radar data.

Detail (b)

Detail (c)

Fig. 3.8. Measurements of a Partly Unresolved Formation (resolution: 50 m, 1.0°, measurement error: 10 m, 0.1°)

Simulating a Partly Resolvable Formation

For the simulation of radar measurements, the corresponding measurements errors and the sensor resolution have to be taken into account. The generation of false returns is not considered here. For a group of two targets at positions (r_1, φ_1), (r_2, φ_2) in polar coordinates with respect to the sensor position, the probability of being unresolved, P_u, can be modeled by:

$$P_u(\Delta r, \Delta\varphi) = \mathrm{e}^{-\frac{1}{2}(\Delta r/\alpha_r)^2}\, \mathrm{e}^{-\frac{1}{2}(\Delta\varphi/\alpha_\varphi)^2} \tag{3.44}$$

with $\Delta r = r_2 - r_1$, $\Delta\varphi = \varphi_2 - \varphi_1$, where the sensor parameters α_r, α_φ characterize the radar's resolution capability in range and azimuth, respectively. According to this probability and for pairs of aircraft, it can be simulated whether an unresolved measurement occurs or not. In case of a resolution conflict the pair is replaced by a single unresolvable object at the centroid position. For large formations with more than two targets, a list is created containing all possible pairs of aircraft. A pair of this list is selected at random according to P_u and merged. In this case, one of the aircraft is to be removed the list, which thus has to be recalculated. If no resolution conflict occurs according to the probability $1 - P_u$, the pair is removed from the list. The previous reasoning is repeated for the remaining pairs. If the list is empty, the algorithm terminates.

We finally have to consider the effect of successive mergings on the simulated measurement errors of unresolvable objects. To this end, we assume that an unresolved measurement error resulting from m aircraft is to be simulated according to $\sigma^u_{r,\varphi} = m\sigma_{r,\varphi}$ where $\sigma_{r,\varphi}$ denote the standard deviations of resolvable range and azimuth measurements, respectively. It is reasonable to delimit the growth of the measurement error by the sensor resolution: $\sigma^u_{r,\varphi} \leq \alpha_{r,\varphi}$. In the same manner, missing detections can be simulated. We here assumed a detection probability $P^u_D = 1$ for unresolvable aircraft and $P^r_D = 0.9$ otherwise.

Impact of the resolution parameters

Figure 3.8 displays the radar data simulated according to these assumptions. The details in Figures 3.8b, c clearly reveal the impact of resolution phenomena and make it obvious that they depend heavily on the current sensor-to-target geometry. The discussed phenomena make it clearly evident that even a very regular target formation is very similar in appearance to an extended object producing a highly fluctuating number of measurements. There is no reasonable hope to be able to track the single components of such a formation individually.

Discussion of results

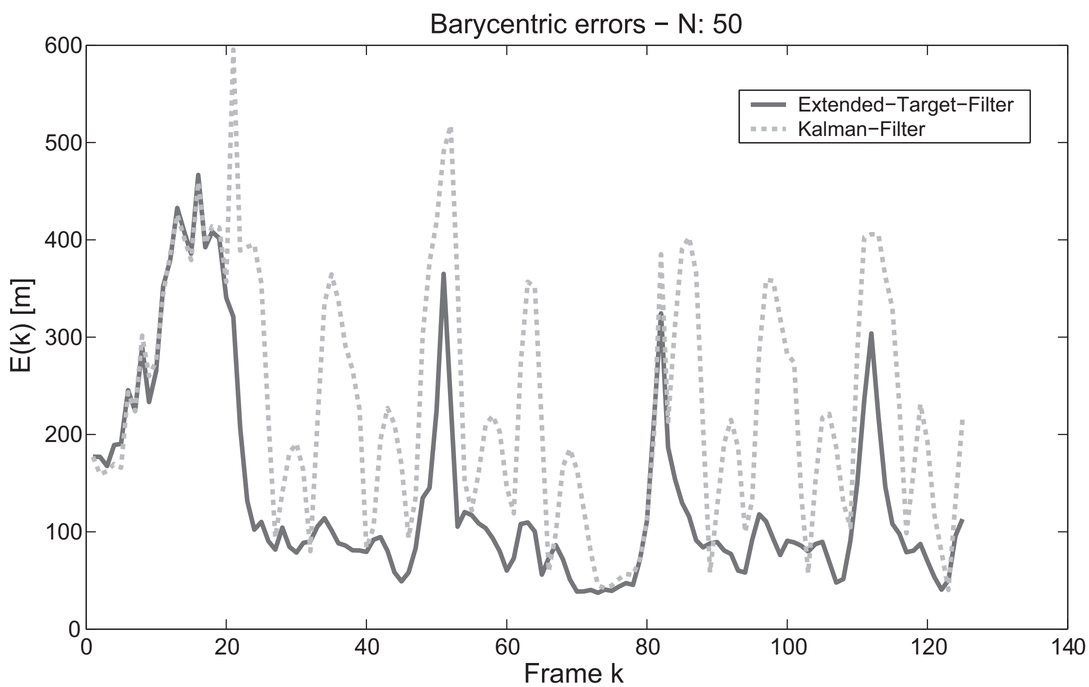


Fig. 3.9. Position error: extended target filter vs. standard Kalman filter

As before in the case of a totally irresolvable formation, in Figure 3.9 the root mean squared errors of the position estimates of the extended target filter are compared with the corresponding results produced by standard Kalman filtering. As the measurement error in the Kalman filter, we used the scattering matrix calculated from the true target positions within the formation and processed averaged measurements. The extended target filter shows significantly smaller estimation errors.

In Figure 3.10, the estimated major semi-axes are compared with the major semi-axes of the scattering matrix of the true target positions. The concordance seems to be fairly good. The peak in the middle of the time axis is due to the reorganization of the formation.

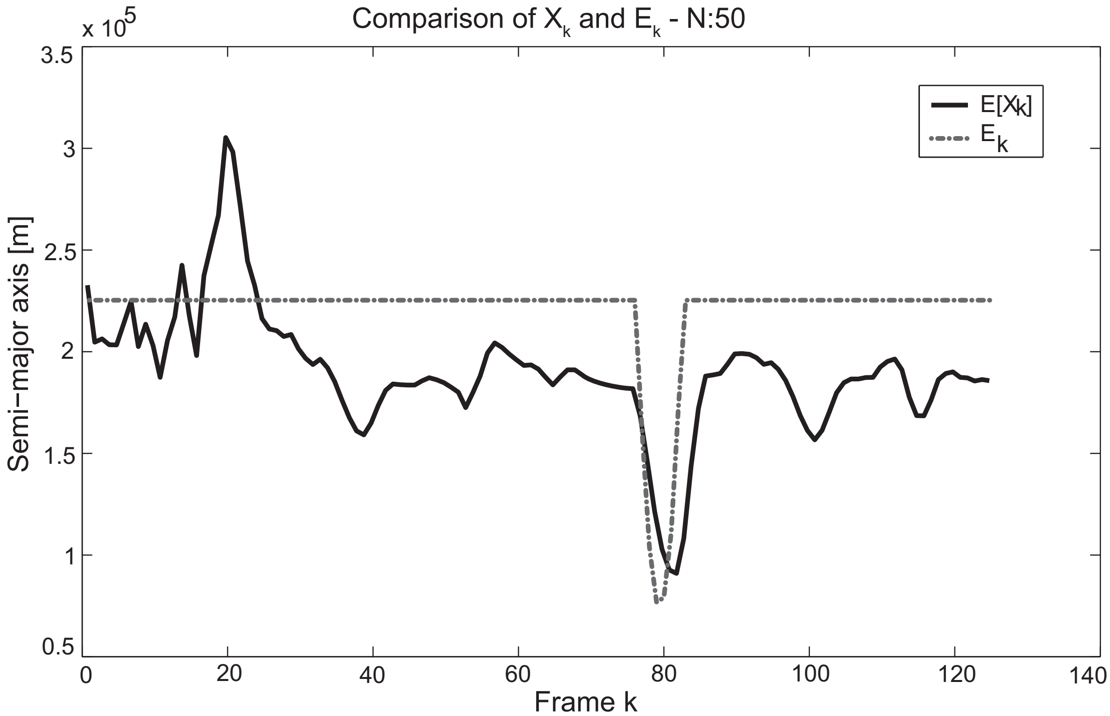


Fig. 3.10. Mean major semi-axes of $\mathbb{E}[\mathbf{X}_k|\mathcal{Z}^k]$ vs. $\mathbf{X}_k$

Figures 3.11 and 3.12 a 'split-off' maneuver that is clearly indicated by the increasing eccentricity of the estimated extension ellipse. As soon as the eccentricity exceeds a certain threshold, two extended object tracks are initiated and the sub-groups are tracked separately. The proposed filter thus provides a criterion of when a single extended object track has to be split into two extended object tracks. An analogous mechanism is possible in the case of a larger formation being created by merging two or more converging sub-groups.

3.3.6 Summary of Results

The essential theoretical result of this paper seems to be the insight that the Bayesian formalism can be applied to extended objects or collectively moving target clusters with approximations to be justified in many applications. Basically, the application of the Bayesian formalism relies on closure properties of matrix-variate Wishart and Inverted Wishart densities under multiplication.

In view of practical applications, the following aspects seem to be of particular relevance:

1. There exists a natural extension of the standard Kalman filter equations to objects whose spatial extension is approximately described by ellipsoids.
2. The object extension can be modeled by symmetrical, positive definite random matrices, whose statistical properties are described by well-known matrix-variate probability densities [39].
3. Due to the mild character of the approximations used, a representation of the probability densities involved by particle filtering techniques such as proposed in [43, 44], does not seem to be necessary. The densities are characterized by a finite parameter set.
4. Information on the objects' kinematic properties is represented by vector-variate Student densities. 'Gating', i.e. exclusion of unwanted measirements, is provided by a Hotelling test.
5. Tracking of point source targets with an unknown measurement error is a limiting case of the proposed method (e.g. tracking of an irresolvable formation).
6. With respect to the kinematical properties, the achievable filter performance is only slightly different from Kalman filtering with a known measurement error covariance matrix.
7. The estimated measurement error covariance matrix corresponds to the true measurement error covariance matrix (simulated) relatively well. This is an interesting side result, considering the small number of data in the case of a totally unresolved group.

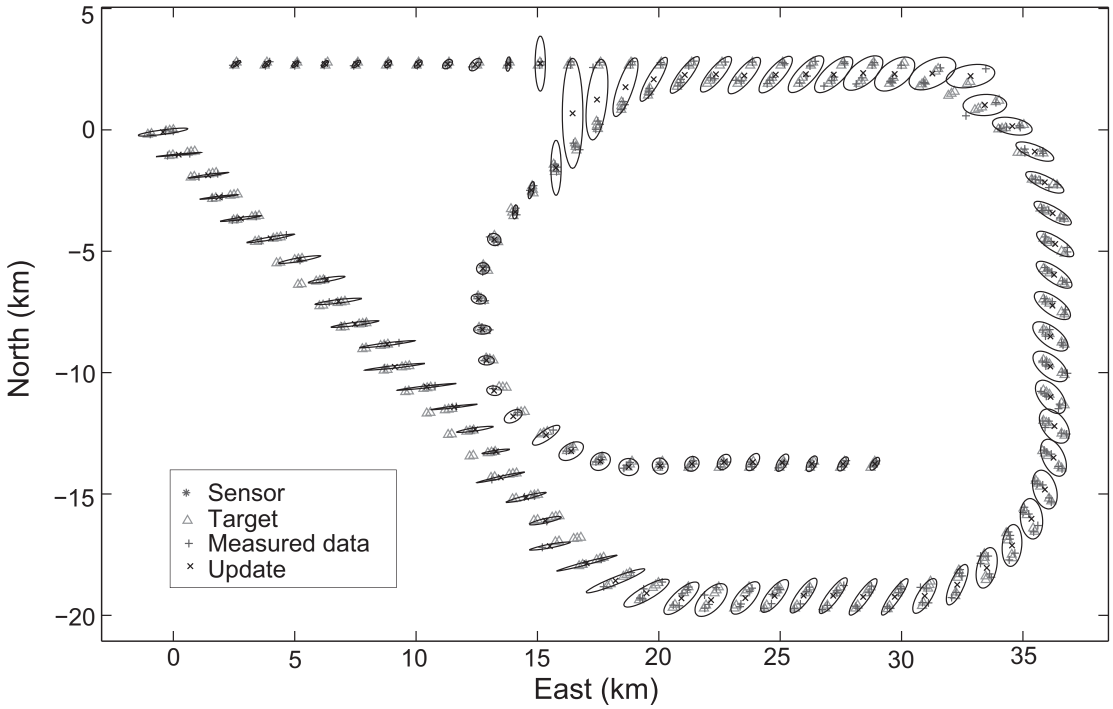


Fig. 3.11. Echelon formation: split-off maneuver

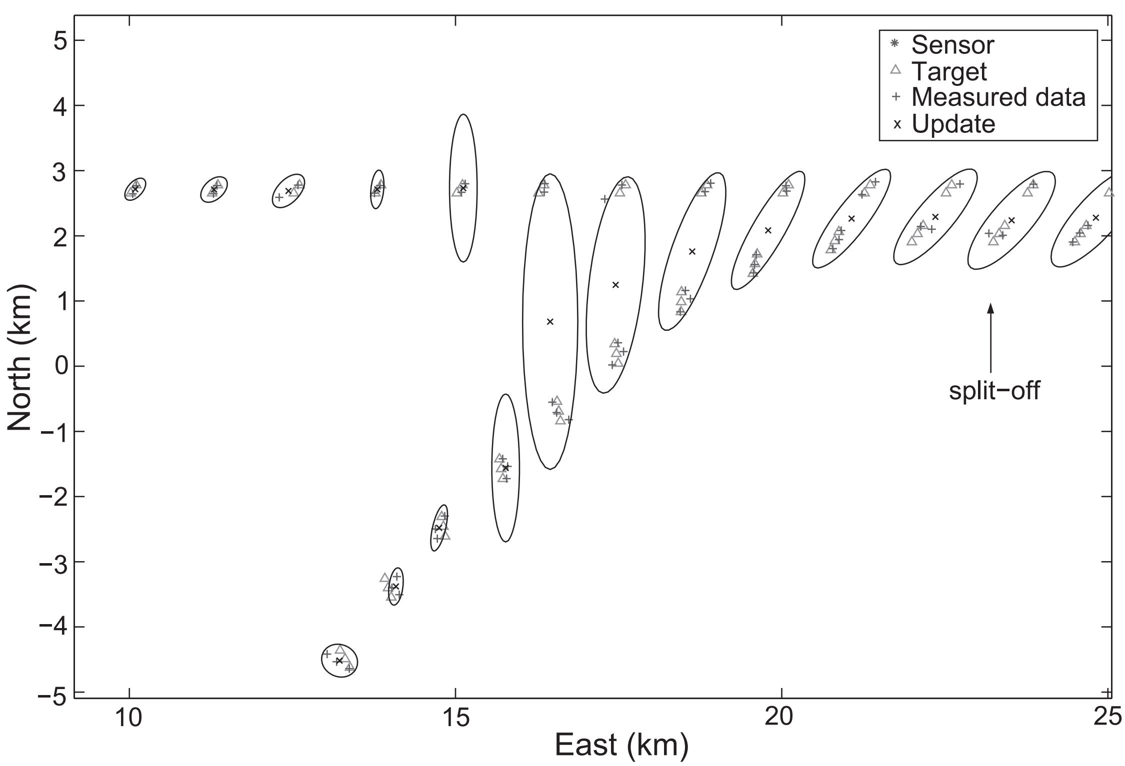


Fig. 3.12. Split-off maneuver (detail)

8. The proposed filter can successfully be applied to target formations, which are only partly resolvable depending on the underlying sensor-to-target geometry.
9. "Split-off" maneuvers, indicating that an object is beginning to separate into individual subgroups or parts, can be detected by analyzing the extension ellipsoid (e.g. by designing a test based on its eccentricity).

In principle, the proposed approximate Bayesian method for dealing with extended objects or collectively moving target clusters can be embedded into multiple-object, multiple-hypothesis tracking techniques and can also be combined with context information (e.g. road-map assisted convoy tracking). This opens an interesting field for further research.

Key Publication

A detailed discussion of this approach has been published in:

- W. Koch

  Bayesian Approach to Extended Object and Cluster Tracking using Random Matrices.

  IEEE Transactions on Aerospace and Electronic Systems, Vol. 44, Nr. 3, p. 1042-1059, July 2008.

  Abstract
  In algorithms for tracking and sensor data fusion, the targets to be observed are usually considered as point source objects; i.e. compared to the sensor resolution, their extension is neglected. Due to the increasing resolution capabilities of modern sensors, however, this assumption is often no longer valid, since different scattering centers of an object can cause distinct detections when passing the signal processing chain. Examples of extended targets are found in short-range applications (littoral surveillance, autonomous weapons, or robotics). A collectively moving target group can also be considered as an extended target. This point of view is the more appropriate, the smaller the mutual distances between the individual targets are. Due to the resulting data association and resolution conflicts, any attempt to track the individual objects within the group seems to be no longer reasonable.
  With simulated sensor data produced by a partly unresolvable aircraft formation, the addressed phenomena are illustrated, and an approximate Bayesian solution to the resulting tracking problem is proposed. Ellipsoidal object extensions are modeled by random matrices, which are treated as additional state variables to be estimated or tracked. We expect that the resulting tracking algorithms are also relevant for tracking large, collectively moving target swarms.

  Keywords: Target tracking, extended targets, group targets, target clusters, sensor resolution, random matrices, matrix-variate analysis

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