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Wolfgang Koch

Tracking and Sensor Data Fusion

Methodological Framework and Selected Applications

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To my beloved wife Dorothea who makes everthing possible

Foreword

Tracking and sensor data fusion have a long tradition in the Fraunhofer Research Institute for Communications, Information Systems, and Ergonomics (FKIE) and its predecessor FFM (FGAN Research Institute for Radio Technology and Mathematics). Established in 1963, mainly aspects of air traffic control have been the driving factors for applied research in these pioneering years. Radar digitization, distributed radar systems, fusion with background information such as flight plans or target tracking have been keywords describing the challenges at this time. Under Günther van Keuk—a young physicist from the University of Hamburg, student of Harry Lehmann and Lothar Collatz, joining FFM in 1965—these activities were related to distributed target tracking and data fusion in multiple radar networks for the German Agency of Air Traffic Security (DFS).

Over many years, active sensor management, tracking, and data fusion for the phased-array radar system ELRA (Elektronisches Radar, a dominating project over a long time) was an important focal point. Günther van Keuk was among the first, who proposed and realized a sequential track initiation scheme based on an optimal criterion related to state estimates. In this context, he developed a performance prediction model for phased-array radar, which has been called "Van-Keuk-Equation" in the tracking literature.

In summer 1990, another young physicist, Wolfgang Koch, joined van Keuk's department. Educated at the RWTH Aachen and a student of Gert Roepstorff, he began under van Keuk's mentorship to apply his fundamental theoretical knowledge to the application oriented world of sensor data fusion. He was a member of the team which has done pioneering work in multiple emitter tracking within networks of electromagnetic and acoustic sensors under the effect of hostile measures in challenging Cold-War reconnaissance scenarios.

In the following years—since 2002 as the successor of van Keuk as the department head of "Sensor Data and Information Fusion"—he contributed remarkable results to the field of sensor data fusion. He did it successfully and with passionate enthusiasm. So he became a well-known member of the world wide sensor data fusion community and the academic scene in Germany, especially at the University of Bonn. Today, the research activities at FKIE cover a wide range of topics in the area of sensor data fusion related to localization and navigation, wide-area surveillance, resource management, self protection, and threat recognition for defence and security applications.

The reader of this book will get both, a fairly comprehensive overview of the field of tracking and sensor data fusion and deeper insight in the specific scientific results, reached in the last two decades. I am very proud to have had the opportunity to follow this development and to be able to support these activities as the former director of FFM and FKIE, respectively, for almost 25 years. Enjoy reading this book as I did.

Adendorf, September 2013 Jürgen Grosche

Preface

Sensor Data Fusion is the process of combining incomplete and imperfect pieces of mutually complementary sensor information 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 sensor output 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 Sensor Data Fusion as well as the integration of related context information. The technical term "Sensor Data Fusion" was created in George Orwell's very year 1984 in the US defence domain, but the applications and scientific topics in this area have much deeper roots. Today, Sensor Data Fusion is evolving at a rapid pace and present in countless everyday systems and civilian products.

Although a vast research literature with specialized journals and conference proceedings, several handbooks, and scientific monographs deal with Sensor Data 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 of Sensor Data Fusion to problem solving in engineering and information systems design is the main objective of this book. The idea of it has grown from both the author's lecturing on Sensor Data Fusion at Bonn University since 2002 and extensive research work at Fraunhofer FKIE on improving defence- and security-related surveillance and reconnaissance systems by Sensor Data Fusion. The inner structure of the book directly follows from these considerations.

Sensor Data Fusion, as an information technology as well as a branch of engineering science and informatics, is discussed in an introductory chapter, put into a more general context, and related to information systems. Basic elements and concepts are introduced.

Part I presents a coherent methodological framework of Sensor Data Fusion, thus providing the prerequisites for discussing selected applications in Part II of the book in four chapters. The presentation reflects the author's views on the subject and emphasizes his own contributions to the development of particular aspects.

Based on a more general notion of object states, probabilistic models of their temporal evolution and the underlying sensors are discussed. Their proper combination within a Bayesian framework provides iterative update formulae for probability densities that represent the knowledge about objects of interest extracted from imperfect sensor observations and context information. Various data fusion algorithms appear as limiting cases and illustrate the more general Bayesian approach. Particular emphasis is placed on fusing data produced at different instants of times, i.e., on-time series of sensor data. The resulting multiple sensor tracking problem is a key issue in Sensor Data Fusion. A discussion of track initiation and fusion of locally preprocessed information, i.e., track-to-track fusion, concludes Part I.

Progress in fusion research is based on precise and methodical work on relevant, well-posed, but sufficiently specialized research questions. Besides answering them appropriately and evaluating the result in comparison to alternatives, the identification of such questions in itself is an essential part of scientific work and often far from trivial.

Following this observation, selected applications are discussed in Part II, where specific problems of Sensor Data Fusion are highlighted. Their solutions are based on the methods previously introduced, which are crucial for meeting challenging user requirements. At the same time, the application examples illustrate the inner structure and practical use of the underlying Bayesian formalism. The very success of Bayesian Sensor Data Fusion may serve as retrospective justification of the approach as well as a motivation to apply this formalism to an even broader field of applications.

The discussed examples are chosen from the author's own contributions to this area and are grouped around the following over-all topics:

1. *Integration of Advanced Sensor Properties*
2. *Integration of Advanced Object Properties*
3. *Integration of Topographical Information*
4. *Feedback to Acquisition: Sensor Management*,

which define the four chapters of Part II. The material discussed in the individual sections of these chapters is collected from journal publications and a handbook chapter by the author. Although the presentation of the key points with respect to specialized methodology and application aspects is self-contained on the methodological basis provided by Part I, a related publication of the author is displayed in each section, where more details and numerical results can be found.

The results of Part II are input for large ISR Systems (Intelligence, Surveillance, and Reconnaissance). Since the examples have been selected from sufficiently different, but mutually complementary areas in Sensor Data Fusion, the detailed analysis of the specialized problems involved and their individual solutions provide a fairly comprehensive overview of various aspects of Sensor Data Fusion for situation picture production. This type of "example-driven" discussion is perhaps better suited to stimulate research work and progress on analogous problems in different applications than a more abstract and generalizing presentation might do.

With some delay, Sensor Data Fusion is likely to develop along lines similar to the evolution of another modern key technology whose origin is rooted in the military domain, the Internet. It is the author's firm conviction that until now, scientists and engineers have only scratched the surface of the vast range of opportunities for research, engineering, and product development that still waits to be explored: the Internet of the Sensors.

This text book would not have been possible without two eminent scientists, who greatly formed the author's mind and apprehension over many years. Günther van Keuk, his teacher in tracking and Sensor Data Fusion and former department head, who died far too early in 2003, introduced him into the exciting field of Sensor Data Fusion and shaped his scientific habit. Jürgen Grosche generously accompanied the author's research as a Fraunhofer director with personal interest, valuable advice, and clear directions. In particular, Jürgen Grosche mediated the author's lecturing activities on Sensor Data Fusion at Bonn University and encouraged him to summarize his research results in this book.

Of course, the merits of many scientific colleagues should also be mentioned here, who contributed greatly through countless scientific discussions and joint work over the years, especially Klaus Becker, Richard Klemm, Martin Ulmke, and Ulrich Nickel. Furthermore, the author is indebted to Jane Stannus and Diana Dorau for their help in editorial and layout issues.

Since the inner strength for his professional life is given to the author by his family, his beloved wife Dorothea and his children Maria, Veronika, Theresia, Katharina, and Johannes, as well as by his parents and brothers, it might be appropriate to express his deep gratitude to them here as well.

Rolandswerth, September 2013 Johann WolfgangKoch

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Contents

Chapter 1
Notion and Structure of Sensor Data Fusion

Sensor data fusion 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 sensor data fusion aims at automating this capability of combining complementary pieces of information. Sensor data 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 a second to a few days, by nearly stationary or rapidly changing scenarios, by actors behaving cooperatively, in-cooperatively, or even hostile, by high precision measurements or sensor data of poor quality.

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Sensor data 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 sensor data 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 Origins of Modern Development

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 "Strategic 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, Chap. 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, Chap. 3], [2]. The JDL model provides a structured and integrated view on the complete functional chain from dis-

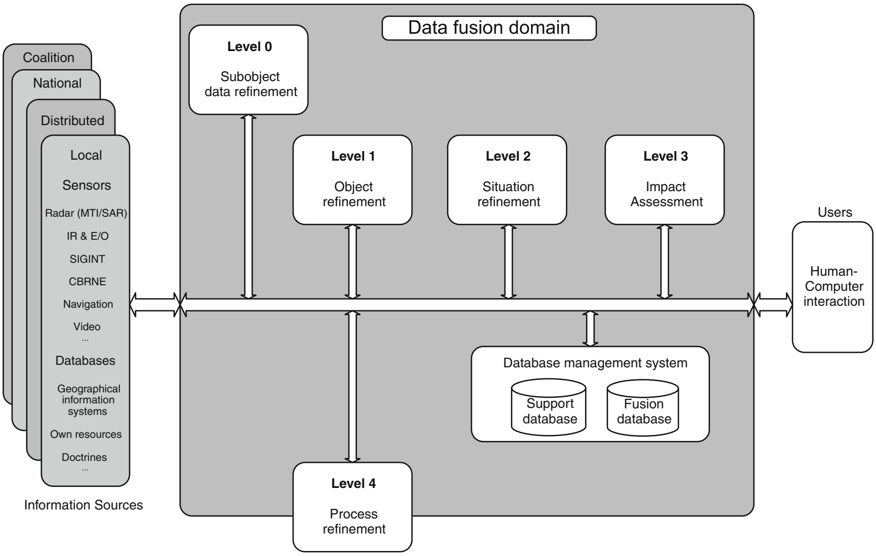

Fig. 1.1 Overview of the JDL-Model of Sensor Data and Information Fusion [1, Chap. 3], which provides a structured and integrated view on the complete functional chain from distributed sensors, data bases, and human reports to the users and their options to act including various feed-back loops at different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

tributed sensors, data bases, and human reports to the users and their options to act including various feed-back loops at different levels (Fig. 1.1). It seems to be valid even in the upcoming large fields of civilian applications of sensor data fusion and cyber 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.
5. *Technical interoperability*, the ability of two or more sub-systems or components to interact and to exchange and to information mutually understood, 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 them in an overall 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, the data streams can 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 military 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, Chap. 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 hetero-

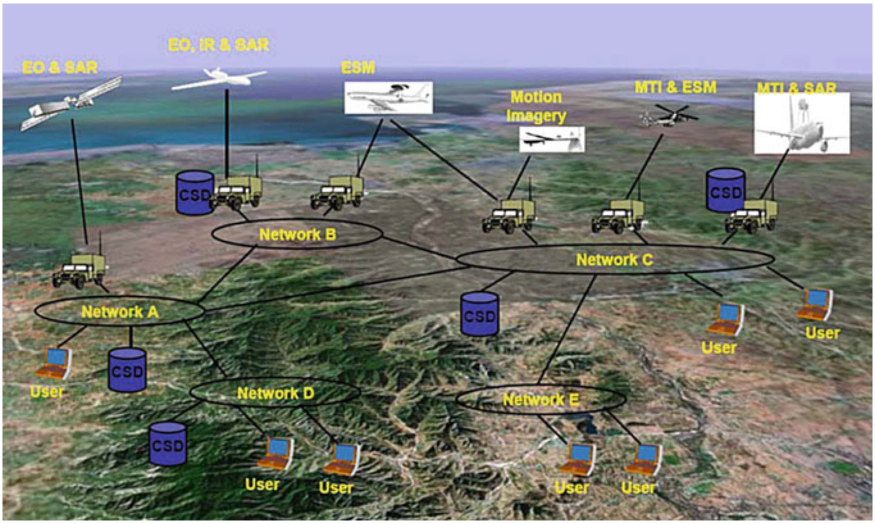

Fig. 1.2 MAJIIC system architecture emphasizing the deployed sensors, databases, and distributed sensor data fusion systems (Interoperable ISR Exploitation Stations)

geneous 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 the 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 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 Characterization as a Branch of Applied Science

The object of knowledge in sensor data fusion as a branch of applied science is sensor data fusion technology discussed previously. In other words, it aims at the acquisition of knowledge required to build automated sensor data fusion systems, often being part of larger information systems, by using appropriately developed scientific methodologies. This includes the elicitation, collection, analysis, modeling, and validation of this knowledge.

In order to reach this goal, scientific research in sensor data fusion is performed in an interdisciplinary way by applying fundamental results gathered from other sciences, such as natural sciences dealing with physical object properties perceptible by sensors and the underlying sensing principles, engineering sciences, mainly sensor engineering, metrology, automation, communications, and control theory, but also applied mathematics and statistics, and, last but not least, applied informatics. Two characteristic features of sensor data fusion can be identified.

1. The available sensor data and context knowledge to be fused typically provide incomplete and imperfect pieces of information. These deficiencies have manifold reasons and are unavoidable in real-world applications. For dealing with imperfect sensor and context data, sophisticated mathematical methodologies and reasoning formalisms are applied. Certain aspects of them are developed by extending the underlying methodology, thus providing contributions to fundamental research. Reasoning with uncertain information by using probabilistic or other formalisms is therefore a major scientific feature characterizing sensor data fusion.
2. As a branch of applied science, sensor data fusion is closely related to the practical design of surveillance and reconnaissance components for information systems. In implementing fundamental theoretical concepts, a systematic way of finding reasonable compromises between mathematical exactness and pragmatic realization issues as well as suitable approximation methodologies are therefore inevitable. System aspects such as robustness and reliability even in case of unforeseeable nuisance phenomena, priority management, and graceful degradation are of particular importance in view of practicability. This is equally true for comprehensive evaluation and prediction of fusion system performance and identification of relevant factors for system control and operation, based, for example, on extensive Monte-Carlo-simulations and the analysis of theoretical bounds [7].

1.2.1 Pioneers of Sensor Data Fusion

Since sensor data fusion can be considered as a branch of automation with respect to imperfect sensor data and non-sensor information, a historical reflection on its roots could identify numerous predecessors in automation engineering, cybernetics, and Bayesian statistics, who developed fundamental notions and concepts relevant to sensor data fusion. Among many other pioneers, CARL FRIEDRICH GAUSS, THOMAS BAYES and the Bayesian statisticians, as well as RUDOLF E. KALMAN have created the methodological and mathematical prerequisites of sensor data fusion that made the modern development possible.

Carl Friedrich Gauß

Many achievements in science and technology that have altered today's world can be traced back to the great mathematician, astronomer, geodesist, and physicist CARL FRIEDRICH GAUSS (1777–1855). This general tendency seems also to be true in the case of sensor data fusion. After finishing his opus magnum on number theory, GAUSS re-oriented his scientific interests to astronomy. His motive was the discovery of the planetoid Ceres by the Theatine monk GIUSEPPE PIAZZI (1746–1826) on Jan 1, 1801, whose position was lost shortly after the first astronomical orbit measurements. GAUSS succeeded in estimating the orbit parameters of Ceres from a few noisy measurements by using a recursively defined least-squares error compensation algorithm [8], a methodology, which can be interpreted as a limiting case of Kalman filtering, one of the most important backbone algorithms of modern target tracking and sensor data fusion. Based on his results, HEINRICH OLBERS (1758–1840) was able to rediscover Ceres on Jan 1, 1802. The discovery of three other planetoids followed (Pallas 1802, Juno 1804, Vesta 1807). Although until then, GAUSS was well-known to mathematical experts only, this success made his name popular, leading to his appointment at Göttingen University in 1807 as a Professor of Astronomy and Director of the Observatory. GAUSS' personal involvement in this new scientific branch of reasoning with imprecise observation data is indicated by the fact that he called his first borne child Joseph, after Father GUISEPPE PIAZZI [9, p. 15]. Three others of his children were named after the discoverers of Pallas, Juno, and Vesta.

Bayesian Statisticians

In sensor data fusion, the notion of "Bayesian probability" is of fundamental importance. It interprets the concept of probability as "a measure of a state of knowledge" (see [10], e.g.) and not as a relative frequency as in classical statistics. According to this interpretation, the probability of a hypothesis given the sensor data is proportional to the product of the likelihood function multiplied by the prior probability. The likelihood function represents the incomplete and imperfect information provided by the sensor data themselves as well as context information on the sensor performance and the sensing environment, while the prior probability the belief in the hypothesis before the sensor data were available (see Chap. 3 *Bayesian Knowledge Propagation* of this book).

The term 'Bayesian' refers to THOMAS BAYES (1702–1761), a British mathematician and Presbyterian minister, who proved a special case of this proposition, which is now called Bayes' theorem (published posthumously by his friend Richard Price (1723–1791) in 1763, [11]). The roots of 'subjective probability' can even be traced back to the great Jewish philosopher Moses Maimonides (1135/38-1204) and the medieval rabbinic literature [12, Chap. 10]. It was Pierre- Simon Laplace (1749–1827), however, who introduced a more general version of Bayes' theorem, apparently unaware of Bayes' work, and used it to approach problems in celestial mechanics, medical statistics, reliability, and jurisprudence [13, Chap. 3]. In the sequel, the foundations of Bayesian statistics were laid by many eminent statisticians.

Of particular importance is Abraham Wald (1902–1950, [14]), an Austro-Hungarian mathematician, who immigrated to the USA in 1938, where he created *Sequential Analysis*, a branch of applied statistical decision making, which is of enormous importance for sensor data fusion, especially in track management and consistency testing (see Chap. 4 *Sequential Track Extraction* of this book). In his influential work on *Statistical Decision Functions* [15], he recognized the fundamental role of Bayesian methods and called his optimal decision methods 'Bayes strategies'.

Rudolf E. Kalman and his Predecessors

The beginning of modern sensor data fusion is inextricably bound up with the name of Rudolf E. Kalman (*1930), a Hungarian-American system theorist, though he had many predecessors. The Kalman filter is a particularly influential example of a processing algorithm for inferring a time variable object state from uncertain data assuming an uncertain object evolution, which can elegantly be derived from Bayesian statistics. Among Kalman's predecessors, Thorvald Nicolai Thiele (1838–1910), a Danish astronomer, actuary and mathematician, derived a geometric construction of a fully developed Kalman filter in 1889 [16, Chap. 4]. Also Ruslan L. Stratonovich (1930–1997), a Russian physicist, engineer, probabilist, and Peter Swerling (1929–2000), one of the most influential RADAR theoreticians in the second half of the twentieth century [17, Appendix], developed Kalman-type filtering algorithms earlier using different approaches.

Stanley F. Schmidt (*1926) is generally credited with developing the first application of a Kalman filter to the problem of trajectory estimation for the NASA Apollo Spaceflight Program in 1960, leading to its incorporation in the Apollo navigation computer. The state-of-the-art until 1974 is summarized in the influential book *Applied Optimal Estimation*, edited by Arthur Gelb [18].

Contemporary Researchers

Independently of each other, Günther van Keuk (1940–2003) and Singer first applied Kalman filtering techniques to single air target tracking problems in multiple radar data processing [19, 20]. The foundations of multiple hypothesis tracking methods for dealing with data of uncertain origin related to multiple objects were laid by Robert W. Sittler, who first posed the problem [21], while Donald B. Reid published a method for solving it [22]. Van Keuk, Sam S. Blackman, and Yaakov Bar-Shalom were among the first, who transformed Reid's method into practical algorithms (see [23, 24] for an overview of the development until 2004).

In the vast research literature published since then, however, it is impossible to identify all important scientists and engineers. The following discussion of significant contributions is therefore by no means complete, reflects the author's personal point of view, and is related to methodological framework presented in Part 1 of this book.

In particular due to their monographs on target tracking and sensor data fusion issues, Yaakov Bar-Shalom [25], Sam S. Blackman [26], and Alfonso Farina [27] are highly influential researchers and have inspired many developments. Henk A. P. Blom introduced stochastic hybrid processes into data fusion [28], which under the name of "Interacting Multiple Models" still define the state-of-the-art in target dynamics modeling. He in particular applied Bayesian data fusion to large air traffic control systems under severe reliability constraints. Countless realization aspects in fusion systems design are covered by Oliver Drummond's contributions. Already in his PhD thesis [29], where he has addressed many important issues in multiple object tracking at a very early time. Larry Stone is a pioneer in Bayesian sonar tracking and data fusion in complex propagation environments [30]. Neil Gordon was among the first, who applied sequential random Monte-Carlo-techniques to non-linear tracking problems, known under the name of "Particle Filtering", and inspired a rapid development in this area [31]. Numerous contributions to problems at the borderline between advanced signal processing, distributed detection theory, and target tracking were made by Peter K. Willett. Xiao-Rong Li provided important solutions to radar data fusion. The integration of modern mathematical non-linear filtering to practical radar implementation is among the merits of Fred Daum. Numerous achievements in non-linear filtering, distributed sensing, and resources management were provided by Uwe D. Hanebeck. Hugh Francis Durrant-Whyte is generally credited with creating decentralized data fusion algorithms as well as with simultaneous localization and navigation. The stormy development of efficient multitarget tracking based on random set theory with Probabilistic Hypothesis Density Filtering (PHD) as an efficient realization has been developed by Ronald Mahler [32]. Finally, Roy Streit first introduced Expectation Maximization techniques to solve efficiently the various data association problems in target tracking and sensor data fusion and exploited the use of Poisson-point precesses in this area [33].

A well readable introduction to sensor data fusion was published by H. B. Mitchell [34]. The handbook "Advanced Signal Processing: Theory and Implementation for Sonar, Radar, and Non-Invasive Medical Diagnostic Systems" [35] deals with many advanced sensor data fusion applications. Martin E. Liggins, James Llinas, and David L. Hall edited the compendium "Handbook of Multisensor Data Fusion: Theory and Practice" [1]. An excellent introduction to more advanced techniques with emphasis on particle filtering is provided by Fredrik Gustafsson [36].

1.2.2 Organization of the Research Community

The interdisciplinary significance of sensor data fusion is illustrated by the fact that numerous institutions with different profiles are working world-wide on particular aspects of it. For this reason, the "International Society of Information Fusion (ISIF)" was founded in 1998 as a scientific framework organization. According to its constitution, it is "an independent, non-profit organization dedicated to advancing the knowledge, theory and applications of information fusion" [37]. Since that year, ISIF has been organizing the annual *International Conferences on Information Fusion*, the main scientific conference of the international scientific information fusion community.

1.2.3 Important Publication Platforms

To publish high-quality scientific papers on sensor data and information fusion, several well-established scientific journals are available, such as the *IEEE Transactions on Aerospace and Electronic Systems* and *on Signal Processing*, the most visible publication platforms, the *ISAF Journal of Advances in Information Fusion*, or the *Elsevier Journal on Information Fusion*. Besides the proceedings of the FUSION conferences, the annual SPIE Conference Series *Signal and Data Fusion of Small Targets (SPIE SMT)* organized by OLIVER E. DRUMMOND since 1989 in the USA, numerous special sessions at radar and automated control conferences as well as several national fusion workshops, such as the German IEEE ISIF Workshop Series *Sensor Data Fusion: Trends, Solutions, Applications (SDF)* [41], provide forums, where the latest advances and research results are presented and discussed among researchers and application engineers.

1.3 From Imperfect Data to Situation Pictures

Sensor data fusion typically provides answers to questions related to objects of interest such as: Do objects exist at all and how many of them are moving in the sensors' fields of view? Where are they located 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.

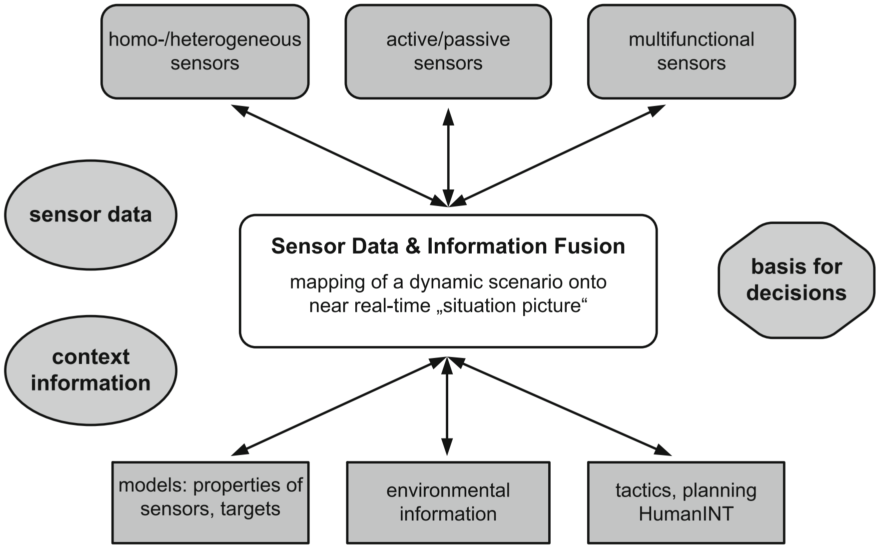

Fig. 1.3 Sensor data and information fusion for situation pictures: overview of characteristic aspects and their mutual interrelation

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.

1.3.1 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. 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.

1.3.2 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 [25, 26, 42] 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 on both, the sensor data accumulated up to some time t_k, typically the current data acquisition time, as well as on 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 ($t_l < t_k$) [43, 44].

1.3.3 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:

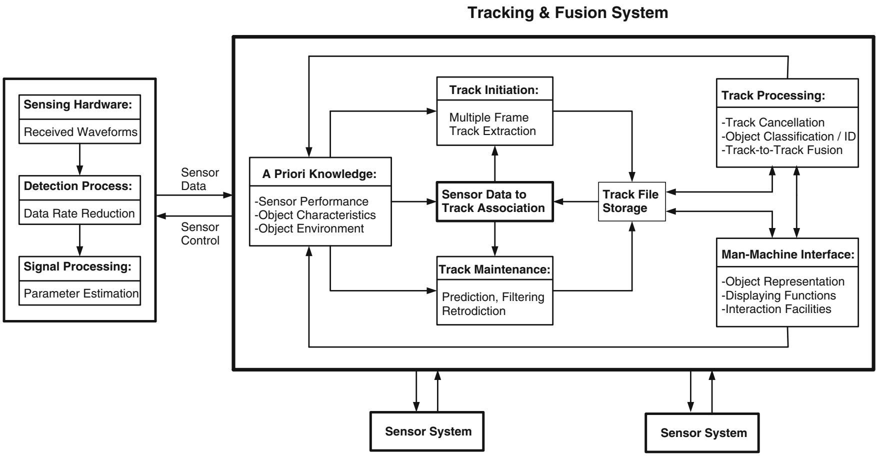

Fig. 1.4 Generic scheme of functional building blocks within a tracking/fusion system along with its relation to the sensors (centralized configuration, type IV according to O. Drummond)

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 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, Chap. 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 Ref. [5].

1.3.4 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 mismatch 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 density of false or unwanted data (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.

1.3.5 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, Chap. 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.

1.3.6 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 [45]. 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.

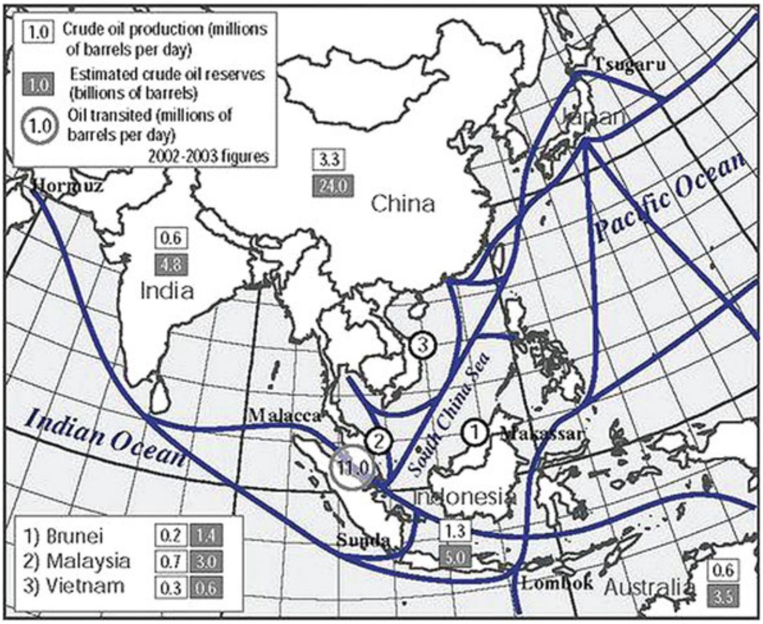

Fig. 1.5 Illustration of sea lanes and strategic passages in Pacific Asia

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 Fig. 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. See Sect. 9.1 for a more detailed discussion.

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 waypoínts 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. For dealing with out-of-sequence measurements see Sect. 5.1. 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 kind. 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 Chap. 9.2. 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. See Sect. 9.2 for a more detailed discussion. 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 [46] (AIS: Automatic Identification System).

1.4 Future Perspectives of Sensor Data 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.

1.4.1 New Everyday Life 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 research and development 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.

1.4.2 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, perhaps fundamentally unfit. 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 [48]. 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 research and development 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.

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Part I
Sensor Data Fusion: Methodological Framework

Chapter 2
Characterizing Objects and Sensors

In most cases, not all properties characterizing observed objects in a certain application have the same importance for producing a situation picture or can be inferred by the sensor systems involved. At the very beginning, we have to identify suitable object properties relevant to the underlying requirements, which are called *state quantities*. In the context discussed here, state quantities are completely described by numbers or appropriate collections of numbers and may be time-dependent. All relevant properties characterizing an object of interest at a certain instant of time t_k, $k \in \mathbb{N}$, are gathered in a collection X_k of state quantities, which is called *object state* at time t_k. Object states can also be composed of the individual object states of an object group.

2.1 Examples of State Quantities

1. As a first example, consider a vehicle moving on a road approximately modeled by a curve. If the vehicle's position or speed on the road at a time t_k only has interest, the corresponding object state is composed by two real numbers: the arc-length x_k of a point on the curve, representing its position, and its temporal derivative $\dot{x}_k$, representing its speed. The corresponding object state is thus given by a two-dimensional vector: $X_k = \mathbf{x}_k$ with $\mathbf{x}_k = (x_k, \dot{x}_k)^\top \in \mathbb{R}^2$.
2. Another practically important example is the kinematic state X_k of an object moving in the three-dimensional space at a given instant of time t_k, which is typically given by its position $\mathbf{r}_k$, velocity $\dot{\mathbf{r}}_k$, and acceleration $\ddot{\mathbf{r}}_k$ at this time. X_k is thus represented by a 9-dimensional vector $X_k = \mathbf{x}_k$ with $\mathbf{x}_k = (\mathbf{r}_k^\top, \dot{\mathbf{r}}_k^\top, \ddot{\mathbf{r}}_k^\top)^\top \in \mathbb{R}^9$.
3. A natural generalization of this concept is the notion of the joint state of two or more objects of interest that form an object group. If kinematic object characteristics are of interest, the corresponding object state X_k is given by a possibly high-dimensional vector $X_k = \mathbf{x}_k$ with $\mathbf{x}_k = (\mathbf{x}_k^{1\top}, \mathbf{x}_k^{2\top}, \dots)^\top$.

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4. The notion of object states, however, is broader and includes other characteristic state quantities. In certain applications, object attributes can be described by positive real numbers $x_k \in \mathbb{R}^+$, related to the object's backscattering properties, for example, such as its characteristic mean radar cross section. In this case, a relevant object state may be given by $X_k = (\mathbf{x}_k, x_k)$, where the individual state quantities $\mathbf{x}_k$ (e.g. kinematics) and x_k (e.g. cross section) are taken from different sets of numbers.
5. Stationary or moving objects may belong to distinct classes. Let the object property "object belongs at time t_k to class i_k" be denoted by $i_k \in \mathbb{N}$. Moving objects, for example, can be classified according to the dynamics mode currently in effect, or according to certain characteristic features indicating, e.g., their chemical signatures. Examples of object classes relevant to air surveillance are: *bird, glider, helicopter, sporting airplane, passenger jet, fighter aircraft, missile*. In this case, a characteristic object state is given by $X_k = (\mathbf{x}_k, i_k)$.
6. For describing spatially extended objects or collectively moving object clusters, the kinematic state vector $\mathbf{x}_k$ must be complemented by an additional state quantity characterizing their spatial extension. For the sake of simplicity and to deal with the extended object or cluster tracking problem as rigorously as possible, we confine the discussion to the practically important case of *ellipsoidal* object or cluster extensions. In this case, the current extension at time t_k can be described mathematically by a symmetric and positively definite matrix $\mathbf{X}_k$. According to this approach, the following object properties are covered:

   - *Size*: volume of the extension ellipsoid
   - *Shape*: ratio of the corresponding semi-axes
   - *Orientation*: direction of the semi-axes.

   The corresponding object state is thus given by $X_k = (\mathbf{x}_k, \mathbf{X}_k)$.

Since object states must be inferred from incomplete and imperfect information sources, the collection of state quantities such as

$$X_k = (\mathbf{x}_k, x_k, \mathbf{X}_k, i_k) \tag{2.1}$$

or some of them are interpreted as a *random variables*. The application of other, more general notions of uncertainty is possible (see [1], e.g.), but excluded here. According to the Bayesian interpretation of probability theory, all available knowledge on the objects of interest at time t_k is mathematically precisely represented by probability densities of their corresponding states $p(X_k)$. If only one state quantity is of interest, for example in $\mathbf{x}_k$, $p(\mathbf{x}_k)$ is given by a marginal density:

$$p(\mathbf{x}_k) = \sum_{i_k} \int \mathrm{d}x_k \mathrm{d}\mathbf{X}_k \; p(\mathbf{x}_k, x_k, \mathbf{X}_k, i_k). \tag{2.2}$$

Methods to calculate the probability density functions related to object states with at least approximate accuracy is the main goal in Bayesian sensor data fusion.