

Mathematical Engineering

Wolfgang Koch

# Tracking and Sensor Data Fusion

Methodological Framework and  
Selected Applications

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# Mathematical Engineering

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Methodological Framework and Selected  
Applications

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Wolfgang Koch  
Fraunhofer FKIE  
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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 Wolfgang Koch

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# 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.



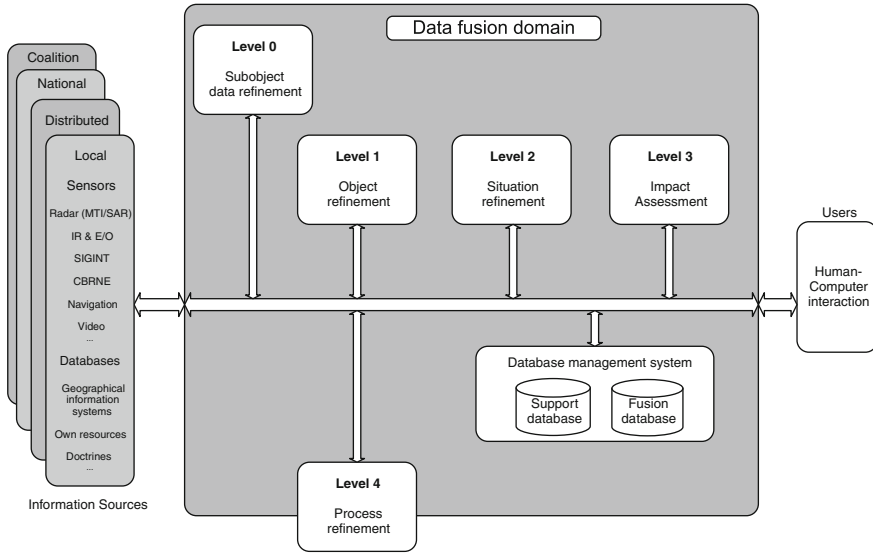
Sensor data fusion systems emerging from this branch of technology have in effect the character of “cognitive tools”, which enhance the perceptive faculties of human beings in the same way conventional tools enhance their physical strength. In this type of interactive assistance system, the strengths 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 inaccessible 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<sup>4</sup>ISTAR Systems [4]. This acronym denotes computer-assisted functions for C<sup>4</sup> (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<sup>4</sup>ISTAR 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<sup>4</sup>ISTAR 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.

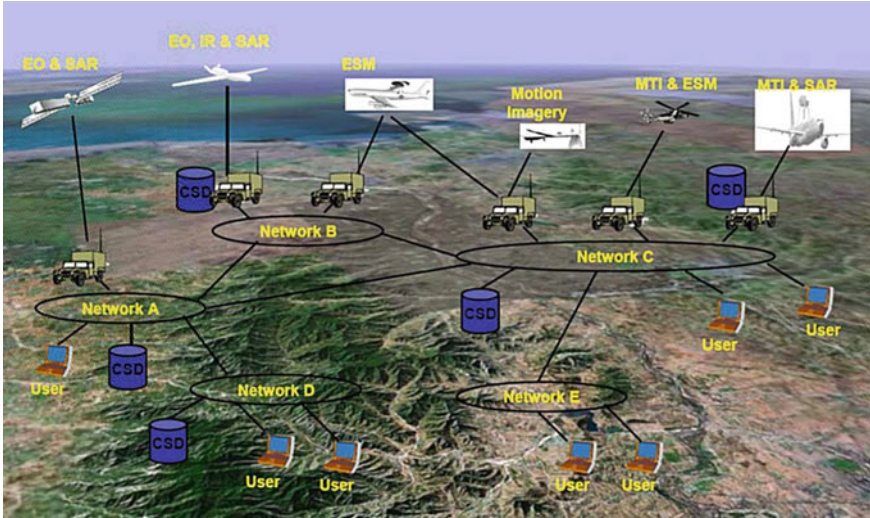
### *A Characteristic Example*

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<sup>4</sup>ISTAR 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 MAJIC (Multi-Sensor Aerospace-Ground Joint ISR Interoperability Coalition) [4, Chap. 20]. By collaboratively using interoperable sensor and data exploitation systems in coalition operations, MAJIC 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<sup>4</sup>ISTAR system components of the nations participating in MAJIC 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<sup>4</sup>ISTAR 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<sup>4</sup>ISTAR 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 processes 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***

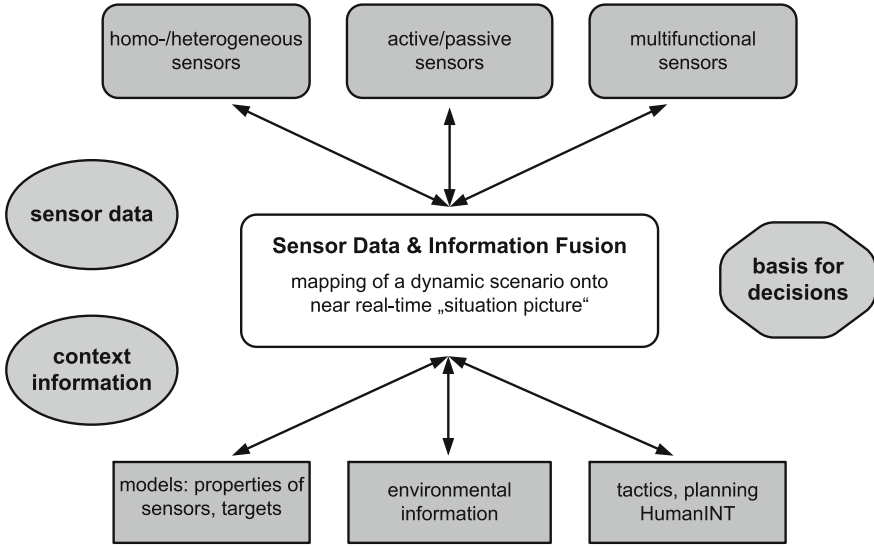
The interdisciplinary significance of sensor data fusion is illustrated by the fact that numerous institutions with different profiles are working world-wide on particular aspects of it. For this reason, the “International Society of Information Fusion (ISIF)” was founded in 1998 as a scientific framework 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.