Chapter 1

Introduction

Weather forecasting, battlefield assessment, target classification and tracking, transportation management—these are but a few of the many civilian and defense applications enhanced through the use of sensor and data fusion. The design of effective sensor and data fusion architectures involves optimization of size, cost, and performance of the sensors and associated data processing, which in turn requires a broad spectrum of knowledge. Accordingly, sensor and data fusion practitioners generally have an appreciation of (1) target and background signature-generation phenomena, (2) sensor design, (3) signal processing algorithms, (4) pertinent characteristics of the environment in which the sensors operate, (5) available communications, and (6) end use of the fusion products.

This book discusses the above topics, with major emphasis on signature-generation phenomena to which electromagnetic sensors respond, atmospheric effects, sensor fusion architectures, and data fusion algorithms for target detection, classification, identification, and tracking. The types of signatures and data collected by a sensor are affected by the following:

- The type of energy (e.g., electromagnetic, acoustic, ultrasonic, seismic) received by the sensor;
- active or passive sensor operation as influenced by center frequency, polarization, spectral band, and incidence angle;
- spatial resolution of the sensor versus target size;
- target and sensor motion;
- weather, clutter, and countermeasure effects.

Although this book focuses on phenomena that affect electromagnetic sensors, other sensors such as acoustic, ultrasonic, and seismic can also be a part of a sensor fusion architecture. This group of sensors has proven valuable in civilian applications, which include detection of vehicles on roadways, aircraft on runways, and geological exploration. Military applications of these sensors include the detection and classification of objects above and below ground. The information that nonelectromagnetic sensors provide can certainly be part of a data and sensor fusion architecture.

Once the signature-generation processes or observables are known, it is possible to design a multiple sensor system that captures their unique attributes. Sensors that respond to signatures generated by different physical phenomena can subsequently be selected and their outputs combined to provide varying degrees of immunity to weather, clutter, and diverse countermeasures. Oftentimes, the data fusion process produces knowledge that is not otherwise obtainable from a narrow wavelength-band sensor or is more accurate than information gathered from single sensor systems. An example of the former is the identification of vegetation on Earth through fusion of hyperspectral visible and infrared data from space-based sensors such as the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). The AVIRIS contains 224 detectors, each with a spectral bandwidth of approximately 10 nm that cover the 380- to 2500-nm band. Data fusion also improves the ability of missiles to track and defeat threats. In this case, accuracy is enhanced by handing off the guidance required for final missile impact from a lower resolution sensor, optimized for search, to a higher resolution sensor optimized to find a particular impact area on a target.

The discussion of data fusion that appears in this book is based on the definition derived from recommendations of the U.S. Department of Defense Joint Directors of Laboratories Data Fusion Subpanel, namely,

> *Data fusion is a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats and their significance.*

Data fusion consists of a collection of subdisciplines, some of which are more mature than others. The more mature techniques, such as classical, Bayesian, and Dempster-Shafer inference; fuzzy logic; pattern recognition using signal processing algorithms and artificial neural networks; and multisensor, multitarget tracking, draw on a theoretical apparatus that supports their application. The less mature techniques are dominated by heuristic and ad hoc methods.

The terms data fusion and sensor fusion are often used interchangeably. Strictly speaking, data fusion is defined as above. Sensor fusion, then, describes the use of more than one sensor in a multisensor system to enable more accurate or additional data to be gathered about events or objects present in the observation space of the sensors. More than one sensor may be needed to fully monitor the observation space at all times for a number of reasons: (1) some objects may be detected by one sensor but not another because of the manner in which signatures are generated, i.e., each sensor may respond to a different signature-generation phenomenology; (2) the signature of an object may be masked or countermeasured with respect to one sensor but not another; (3) one sensor may be blocked from viewing objects because of the geometric relation of the sensor to the objects in the observation space, but another sensor located elsewhere in space may have an unimpeded view of the object. In this case, the data or tracks from the sensor with the unimpeded view may be combined with past information (i.e., data or tracks) from the other sensor to update the estimated location of the object.

The fusion architecture selected to combine sensor data depends on the particular application, sensor resolution, and the available processing resources. Issues that affect each of these factors are discussed briefly below.

- Application: sensors supplying information for automatic target recognition may be allowed more autonomy in processing their data than if target tracking is the goal. Largely autonomous sensor processing can also be used to fuse the outputs of existing sensors not previously connected as part of a fusion architecture. Many target tracking applications, however, produce more reliable estimates of tracks when unprocessed multiple sensor data are combined at a central location to identify new tracks or to correlate with existing tracks.

- Sensor resolution: if the sensors can resolve multiple pixels (picture elements) on the target of interest, then the sensor data can be combined pixel by pixel to create a new fused information base that can be analyzed for the presence of objects of interest. In another method of analysis, features can be (1) extracted from each sensor or spectral channel within a sensor, (2) combined to form a new, larger feature vector, and (3) consequently input, for example, to a probability-based algorithm or artificial neural network to determine the object's classification.

- Processing resources: individual sensors can be used as the primary data processors when sufficient processing resources are localized in each sensor. In this case, preliminary detection and classification decisions made by the sensors are sent to a fusion processor for final resolution. If the sensors are dispersed over a relatively large area and high data rate, large bandwidth communications media are available to transmit unprocessed data to a central processing facility, then a more centralized data processing and fusion approach can be implemented.

The following chapter describes signature-generation phenomena and benefits associated with multiple sensor systems. The remaining chapters discuss sensor and data fusion signal processing architectures and algorithms suitable for automatic target recognition, target track estimation, and situation and threat assessment. The classical inference, Bayesian, Dempster-Shafer, voting logic, and fuzzy logic data fusion algorithms that are discussed in some detail have one characteristic in common. They all require expert knowledge or information from the designer to define the respective probability density functions, *a priori* probabilities and likelihood ratios, probability mass, confidence levels, or membership functions and production rules used by the algorithms. Other algorithms, such as knowledge-based expert systems and pattern recognition, also require the designer to assume rules or other parameters for their operation. Implementation of the data fusion algorithms is thus dependent on the expertise and knowledge of the designer, analysis of the operational situation, *a priori* probabilities or other probability data, and the types of information provided by the sensor data.

Summaries of individual chapter contents appear below.

Chapter 2 illustrates the benefits of multiple sensor systems in locating, classifying, and tracking targets in inclement weather, high clutter, and countermeasure environments. The attributes of the atmosphere, background, and targets that produce signatures detected by electromagnetic active and passive sensors are described, as are models used to calculate the absorption, scattering, and propagation of millimeter-wave and infrared energy through the atmosphere.

Chapter 3 explores sensor and data fusion architectures and examines the different classes of data fusion algorithms applicable to automatic target detection, classification, and track estimation. The methods used to categorize data fusion are described based on (1) where the sensor data are processed and fused and (2) the resolution of the data and the degree of processing that precedes the fusion of the data. The applications and implications of the taxonomies are also discussed.

Chapter 4 describes classical inference, a statistical-based data fusion algorithm. It gives the probability that an observation can be attributed to the presence of an object or event given an assumed hypothesis, when the probability density function that describes the observed data as a random variable is known. Its major disadvantages are: (1) difficulty in obtaining the density function for the observable used to characterize the object or event, (2) complexities that arise when multivariate data are encountered, (3) its ability to assess only two hypotheses at a time, and (4) its inability to take direct advantage of *a priori* probabilities. These limitations are removed, in stages, by Bayesian and Dempster-Shafer inference.

Chapter 5 presents a discussion of Bayesian inference, another probability-based data fusion algorithm. Based on Bayes' rule, Bayesian inference is a method for calculating the conditional *a posteriori* probability (also referred to as the posterior probability) of a hypothesis being true given supporting evidence. *A priori* probabilities for the hypotheses and likelihood functions that express the probability of observing evidence given a hypothesis are required to apply this method. A recursive form of Bayes' rule is derived for updating prior and posterior probabilities with multiple sensor data and applied to the fusion of data produced by multispectral sensors and a two-sensor mine detector.

Chapter 6 discusses Dempster-Shafer evidential theory, in which sensors contribute detection or classification information to the extent of their knowledge. Dempster's rules are exemplified with several examples, which show how to combine information from two or more sensors. One of the important concepts of Dempster-Shafer is the ability to assign a portion of a sensor's knowledge to uncertainty, that is, the class of all events that make up the decision space. Dempster-Shafer theory accepts an incomplete probabilistic model as compared with Bayesian inference. However, under certain conditions the Dempster-Shafer approach to data fusion becomes Bayesian as illustrated with a multiple target, multiple sensor example. Several modifications to Dempster-Shafer have been proposed to better accommodate conflicting beliefs and produce an output that is more intuitive. Some of these, including the pignistic transferable belief model, are explored in the chapter.

Chapter 7 examines artificial neural networks and the algorithms commonly used to train linear and nonlinear single and multilayer networks. The supervised training paradigms include minimization of the least mean square error between the known input and the learned output, perceptron rule, and backpropagation algorithm that allows the weights of hidden-layer neurons to be optimized. Other nonlinear training algorithms and neural networks that use unsupervised learning are described as well. Generalization through which artificial neural networks attempt to properly respond to input patterns not seen during training is illustrated with an example.

In Chapter 8, a voting algorithm derived from Boolean algebra is discussed. Here each sensor processes the information it acquires using algorithms tailored to its resolution, scanning, and data processing capabilities. The outputs from each sensor are assigned a confidence measure related to how well features and other attributes of the received signal match those of predetermined objects. The confidence-weighted sensor outputs are then input to the fusion algorithm, where series and parallel combinations of the sensor outputs are formed and a decision is made about an object's classification.

Chapter 9 describes fuzzy logic and fuzzy neural networks. Fuzzy logic is useful when input variables do not have hard boundaries, or when the exact mathematical formulation of a problem is unknown. Fuzzy logic may also decrease the time needed to compute a solution when the problem is complex and multi-dimensional. In fuzzy set theory, an element's membership in a set is a matter of degree and an element may be a member of more than one set. Fuzzy logic permits control statements or production rules, also called fuzzy associative memory, to be written to accommodate the imprecise states of the variables. Several types of defuzzification operations are discussed, which convert the output fuzzy values into a fixed and discrete output that is used by the control system. The balance of an inverted pendulum and track estimation with a Kalman filter are two examples used to illustrate the wide applicability of fuzzy logic. Adaptive fuzzy neural systems are also discussed. These rely on sample data and neural algorithms to define the fuzzy system at each time instant. Two techniques are described that extend fuzzy set theory to fuse information from multiple sensors: one uses combinatorial relationships and a measure of confidence attributed to subsets of available sensor data, while the other is based on an evidence theory framework that incorporates fuzzy belief structures and the pignistic transferable belief model.

Chapter 10 examines three fusion architectures suitable for fusing passively acquired data to locate and track targets that are emitters of energy. This material was written, in part, by Henry Heidary of Hughes Aircraft Company, now Raytheon Systems Company. In theory, any form of emitted energy (microwave, infrared, visible, acoustic, ultrasonic, magnetic, etc.) can be located with the proper array of passive receivers. These three approaches permit the range to the emitters to be estimated using only the passively received data. Two of the architectures use centralized fusion to locate the emitters. One of these analyzes the unprocessed received signal waveforms, while the other associates azimuth and elevation angle measurements to estimate the location of the emitters. The third architecture uses a distributed processing concept to associate the angle tracks of the emitters that are calculated by the individual sensors. Factors that influence the signal processing and communications requirements imposed by each of the methods are discussed.

Chapter 11 contains retrospective comments that summarize the knowledge, probabilities, confidence levels, rules, or other information needed to apply the detection, classification, and identification algorithms discussed in detail in previous chapters.