An Introduction to Data Fusion

W. Elmenreich

Institut für Technische Informatik
TU Vienna, Austria
wil@vmars.tuwien.ac.at

December 19, 2000

Abstract

In general, a fusion system is composed of sources of data, of means of acquisition of this data, of communications for the exchange of data, of intelligence to process data, update a dynamic model of the world and make decisions about further actions.
In this paper, a definition of data fusion and sensor data fusion is worked out based on former publications. Four existing data fusion models, the JDL model, the intelligence cycle, the Boyd control loop and the Dasarathy model are discussed and a general purpose fusion model with three ordered stages of fusion is introduced. Based on this model the paradigm how the human brain processes vision data is explained.

Keywords: multi-sensor, multi-source, data fusion, data fusion model.

1 Introduction

An animal recognizes its environment by the evaluation of signals from multiple and multifaceted sensors. Nature has found a way to integrate information from multiple sources to a reliable and feature-rich recognition. Even in case of sensor deprivation, systems are able to compensate for lacking information by reusing data obtained from sensors with an overlapping scope. Humans for example combine signals from the five body senses (sight, sound, smell, taste, and touch) with knowledge of the environment to create and update a dynamic model of the world. Based on this information the individual interacts with the environment and makes decisions about present and future actions [Gro98].

This natural ability to fuse multi-sensory data has evolved to a high degree in many animal species and is in use for millions of years. Now the application of fusion concepts in technical areas leads to a new discipline, that spans over many fields of science. The basic concepts of data fusion are not new. According to [BC99] data fusion first appeared in the literature in the 1960s when mathematical models for data manipulation like the Bucy-Kalman filter [Kal60] have been developed and has been implemented in the next two decades in the field of robotics [Gra86] and defense industries [Nah80, Cha83].

While first data fusion methods where developed primarily for military applications, today, multi-sensor data fusion is applied in many fields, e.g., maintenance engineering [Edw93], robotics [Gra86], pattern recognition [Bar94], remote sensing [But92], and aerospace systems [Bla90].

Traditionally, researchers dealing with data fusion have assumed that the communication, storage, and processing subsystems are highly reliable. They focused on algorithms for integrating data from homogeneous or heterogeneous collections of potentially faulty/incaccurate sensors. Researchers dealing with redundant or replicated computations have, for the most part, assumed that input data is perfect and that the only sources of errors or inaccuracies are faults in the data communication, storage or processing subsystems and the numerical characteristics of the algorithms used (e.g., roundoff errors) [Par95].

It is the objective of this paper to define a model of an integrated system composed of methods, communication and control that is able to process incomplete data over a network with unreliable communication sources.

The paper is structured as follows: Section 2 states a definition of the terms data fusion and multi-sensor fusion.

Section 3 compares the advantages of a multi-sensor system over sensing with a single sensor.

Section 4 compares existing sensor fusion models and proposes a sophisticated version of the three-stage model.

Section 5 maps the three-stage model presented in section 4 onto a biological example for data fusion.

The paper gives an outlook on further areas of work and is summarized in section 6.

2 A Definition of Data and Sensor Fusion

In the literature, several definitions of the term *data fusion* can be found. In [Dod98] data fusion is defined as "the process of combining data in such a way that the result provides more information than the sum of the individual parts". This definition puts the accent on data processing methods. Lucien Wald [Luc99] analyzes some definitions of the term data fusion and concludes "data fusion should be seen as a framework, and not merely as a collection of tools and means". In my paper the term data fusion will be used to describe a whole system composed of

- Data sources,
- Means of acquisition of this data (not all sources must be sensory)

- Data communications
- Intelligence to process data
- at least one output of data with improved quality

The data sources to a data fusion process are not specified to be sensory data of identical sensors. Gerard T. McKee [McK93] distinguishes direct fusion, indirect fusion and fusion of the outputs of the former two. Direct fusion means the fusion of sensor data from a set of heterogeneous or homogeneous sensors, soft sensors and history values of sensor data, while indirect fusion uses information sources like a priori knowledge about the environment, human input.

This paper is concerned with the fusion of sensor data, which usually is referred to as multi-sensor data fusion:

Multi-sensor Data Fusion Multi-sensor data fusion (MSDF) is the integration and extraction of desired information from data obtained by two or more sensors or by one sensor operating in two or more modes [Smi91].

3 Comparison of Distributed Sensing over Individual Sensing

Drawbacks of Individual Sensors

The following problems occur with single physical sensors:

Sensor Deprivation The breakdown of a sensor element causes a loss of perception on the desired object.

Limited Spatial Coverage An individual sensor normally covers only a restricted region, for example a boiler thermometer reading provides only a prediction of the temperature near the thermometer and may fail to render the average water temperature in the boiler.

Limited Temporal Coverage Some sensors need a certain set-up time to perform and transmit a measurement, thus limiting the maximum frequency of measurements.

Imprecision Measurements from individual sensors depend on the precision of the employed sensing element.

Uncertainty Uncertainty, in contrast to imprecision, depends on the object being observed rather than the observing device. Uncertainty arises when features are missing (e.g. occlusions), when the sensor cannot measure all relevant attributes of the percept, and when the observation is ambiguous [Mur96]. A single sensor system is unable to reduce uncertainty in its perception, because of its limited view of the object [Foo95].

The problem of sensor deprivation can only be solved by implementing redundancy. The traditional approach builds a fault-tolerant unit of three identical units with a voter [vN56] or two fail-silent units [Kop90]. A fail-silent unit produces either correct results or, in case of failure, no results at all. In a sensor fusion system robust behaviour against sensor deprivation can be achieved by using sensors with overlapping views of the desired object, which works as well with identical replications of a sensor but also with a suite of heterogeneous sensors.

Benefits on Distributed Sensing

Potential advantages that can be expected from the fusion of a set of heterogeneous or homogeneous sensors are described in [Bos96] and [Gro98]:

Robustness and Reliability Multiple sensor suites have an inherent redundancy which enables the system to still provide information even in case of partial failure.

Extended Spatial and Temporal Coverage One sensor can look where others cannot and can perform a measurement while others cannot.

Increased Confidence A measurement of one sensor is confirmed by measurements of other sensors covering the same domain.

Reduced Ambiguity and Uncertainty Joint information reduces the set of ambiguous interpretations of the measured value.

Robustness against interference By increasing the dimensionality of the measurement space (e.g. measuring the desired quantity with optical sensors and ultrasonic sensors) the system becomes less vulnerable against interference.

Improved Resolution When multiple independent measurements of the same property are made, the resolution of the fused value is better than a single sensor's measurement.

In [Rao98] the performance of sensor measurements obtained from an appropriate fusing process are compared to the measurements of the single sensor. According to this work, an optimal fusing process can be designed, if the error distributions of the sensors are precisely known. This optimal fusing process performs at least as well as the best single sensor.

A further motivation for sensor fusion is reducing of system complexity. In a traditionally designed system the sensor measurements are fed into the application, which has to cope with a lot of imprecise, ambiguous and incomplete data streams. In a system where sensor data is preprocessed by fusing methods the input to the controlling application can be standardized independent of the employed sensor types, thus facilitating application implementation and providing the possibility of changes in the sensor system regarding number and type of employed sensors.

4 Data Fusion Model

Existing Data Fusion Models

Due to the fact that data fusion models depend heavily on the applications, there is no general model of data fusion until today [Bed00].

The JDL Model

In 1985 the US Joint Directors of Laboratories (JDL) proposed a data fusion model under the guidance of the Department of Defense (DoD). This *JDL model* [Wal90] consists of five levels of fusion processing and a database, which are all interconnected by a bus. The five levels (pre-processing, single object refinement, situation refinement, implication refinement, and process refinement) are not meant to have a strict ordering. The JDL model is very popular for data fusion systems, but is not always appropriate for other than defense data fusion systems [Bed00].

The Intelligence Cycle

Another approach to model a data fusion application is to line out its cyclic character. Representatives of such an approach are the intelligence cycle [Shu91] and the Boyd control loop [Boy87].

The *Intelligence Cycle* comprises the following stages:

Planning and Direction: Determinate intelligence requirements

Collection: Gather appropriate information

Collation: Line up collected information

Evaluation: Fuse and analyze information

Dissemination: The fused intelligence is distributed to users

The Boyd Control Loop

John Boyd [Boy87] has proposed a cycle of observation–orientation–decision–action (see Figure 1). The *Boyd control cycle* or *OODA loop* represents the classic decision-support mechanism in military information operations. Because decision-support systems for situational awareness are tightly coupled with data fusion systems [Bas00], the Boyd loop has also been used for data fusion.

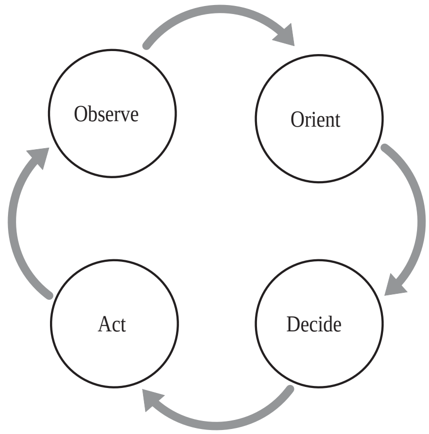

Figure 1: The Boyd (or OODA) Loop

The Three-Level Characterization and the Dasarathy Model

A characterization of data fusion, that is common in the literature is based on three ordered levels of detail. In [Luo99] these are named data level (low level), feature level and decision level (high level), in [Bas99] a three-level abstraction is given by data level, information level and knowledge level. Based on a three-level characterization of data, feature and decision, Belur Dasarathy [Das97] identified five different types of fusion depending on the level of input and output data: Data-In – Data-Out, Data-In – Feature-Out, Feature-In – Feature-Out, Feature-In – Decision-Out, and Decision-In – Decision-Out.

A Model Based on the Three-Level Characterization

Most data fusion models emphasize a rather high level of abstraction of the data. For systems with a main focus on low level sensor fusion, these models are not very adequate. In addition most models have been developed especially for military applications. Therefore, I selected an extended version of the three layer model, that was used by [Das97, Luo99, Bas99].

Figure 2 depicts the model with three stages of fusion and an ordered data flow from the upper left to the lower right. A suite of sensors performs measurements on an real world object. The data obtained is passed through individual sensor algorithms that can be performed locally and cover tasks for signal preprocessing like amplifying, smoothing, timestamping or Fast Fourier Transformation (FFT). The next process is sensor fusion where the measurements are combined with respect to a priori knowledge about the sensor properties. This sensor fusion process provides virtual sensor data, which represents a more complete data structure than physical sensor data. Thus reducing the complexity of the following task, the feature extraction, where a mapping of the (soft) sensory inputs to a real world image is performed. Based on this real world image, control decisions are made by the next stage.

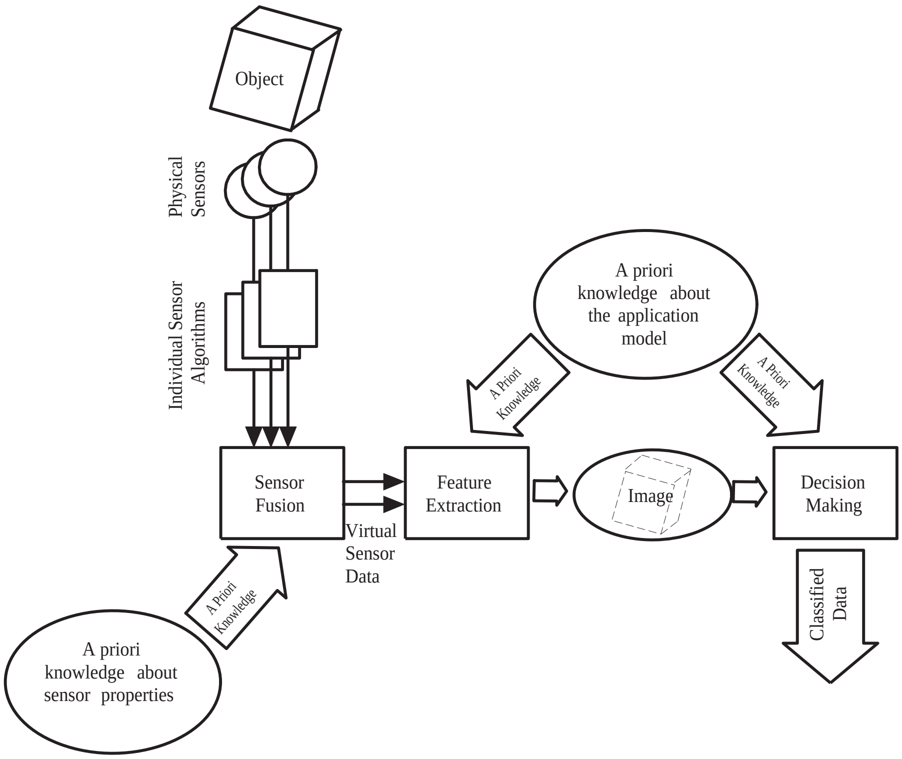

Figure 2: A Fusion Model based on Data/Feature/Decision Level

Instead of constructing a closed loop model like the Boyd loop or the intelligence cycle approach, loops are introduced via feedback paths. Feedback paths can be applied at various fusion stages. Figure 3 depicts feedback as a sensor adjustment at the individual sensor algorithms or as algorithm adjustment on the fusion stages where the physical sensor data is already fused. The feedback sources can be data from the sensor fusion process, feature data, or decisions. To give an example, imagine a process supervision system employing a swivel-mounted stereoscopic camera. The sensors are the pixels of the camera images. At sensor fusion level the brightness and contrast could be adjusted by a sensor adjustment feedback. At feature level the object distances are derived from the two camera images, so the camera focus can be adjusted. Furthermore, instead of swaying the camera simply from left to right, the system could be run by a decision process, at which objects the camera should be aimed.

5 Man's Vision: a Biological Example for Data Fusion

The human brain paradigm is certainly applicable at all three levels, for example in optical vision: The eyes contain a suite of receptors, the cones and the rods. The cones gather color information. An individual mechanism detects color contrasts for a local set of cones. These are connected to the corpus geniculatum

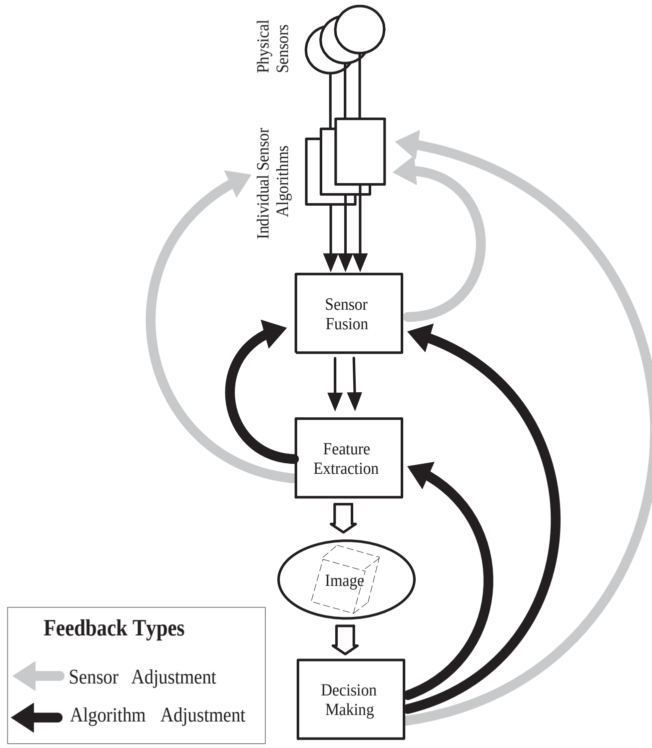

Figure 3: Feedback Paths in the Fusion Model

laterale via the ganglions. Here sensor fusion takes place, the information from many ganglions gets fused and reduced. Although the human eye provides only a sharp shot in the center of sight, the sensor fusion process produces an image which appears to be sharp over the whole scope. In the visual cortex features like horizontal and vertical edges, blobs (color perception), movement detection and stereopsis is derived from the available data [Hub98, Eys98].

Stereopsis is the visual estimation of three dimensions via stereoscopic vision. Although it is necessary to have two images of the same scene from two slightly different angles to provide true three-dimensional vision, the human vision system provides a workaround for situations, where only one eye's view is available: In case of a deprivation of one sensor, three dimensional information is retrieved by combining world knowledge about size of objects, distance to horizon, perspective or color-shift to blue due to the atmosphere. Based on this information sources, the brain learns to guess about distances [Bre77].

Based on the output of the feature fusion in the visual cortex, the brain makes aware and unaware decisions about present and future actions. The greatest dominance of the human capabilities over a machine is mainly at this decision level, whereas the machine is most effective at sensor data level because of its ability to process large amounts of data in a short time [Das97].

6 Outlook and Conclusion

Data Fusion offers a great opportunity to overcome physical limitations of sensing systems. An important point will be the reduction of software complexity, if the properties of the physical sensors get hidden behind a sensor fusion module. Most data fusion models, that come from military applications lack of ordered fusion stages with defined interfaces, so the simple three stage characterization sensor level–feature level–decision level is apt best for a basic model in many cases.

References

[Bar94] M. Bares, D. Canamero, J. F. Delannoy, and Y. Kodratoff. XPlans: Case-based Reasoning for Plan Recognition. *Applied Artificial Intelligence*, 8(4):617–643, Oct.-Dec. 1994.

[Bas99] T. Bass. Multisensor Data Fusion for Next Generation Distributed Intrusion Detection Systems. *Invited Paper, IRIS National Symposium on Sensor and Data Fusion, The Johns Hopkins University Applied Physics Laboratory*, pages 24–27, May 1999.

[Bas00] T. Bass. Intrusion Detection Systems and Multisensor Data Fusion: Creating Cyberspace Situational Awareness. *Communications of the ACM*, 43(4):99–105, May 2000.

[BC99] P. Bryanston-Cross, M. Burnett, D. D. Udrea, R. Marsh, B. H. Timmerman, A. Starr, and J. Estabon. INTErSECT: The Application of Data Fusion to a Multi Sensored Intelligent Engine. *IEE Colloquium on Intelligent and Self-Validating Sensors*, pages 6/1–6/11, June 1999.

[Bed00] M. Bedworth and J. O'Brien. The Omnibus Model: a new model of data fusion? *IEEE Aerospace and Electronics Systems Magazine*, 15(4):30–36, April 2000.

[Bla90] S. S. Blackman and T. J. Broida. Multiple Sensor Data Association and Fusion in Aerospace Applications. *Journal of Robotic Systems*, 7(3):445–485, June 1990.

[Bos96] E. Bosse, J. Roy, and D. Grenier. Data Fusion Concepts Applied to a Suite of Dissimilar Sensors. *Canadian Conference on Electrical and Computer Engineering, 1996*, 2:692–695, May 1996.

[Boy87] J. R. Boyd. A Discourse on Winning and Losing. *Unpublished set of briefing slides available at Air University Library, Maxwell AFB, Alabama*, May 1987.

[Bre77] H. G. Bredemeyer and K. Bullock. *Orthoptik*. Walter de Gruyter, Berlin/New York, 1977.

[But92] F. Butini, V. Cappellini, and S. Fini. Remote Sensing Data Fusion on Intelligent Terminals. *European Transactions on Telecommunications and Related Technologies*, 3(6):555–563, Nov.-Dec. 1992.

[Cha83] S. P. Chaudhuri and R. D. Ferrante. Object Identification in a Simulated Battlefield Using Artificial Intelligence Techniques. *Proceedings of the 1983 IEEE Military Communications Conference*, 3:673–677, 1983.

[Das97] B. V. Dasarathy. Sensor Fusion Potential Exploitation-Innovative Architectures and Illustrative Applications. *Proceedings of the IEEE*, 85:24–38, Jan. 1997.

[Dod98] Tony Dodd. An Introduction to Multi-Sensor Data Fusion. ISIS research group, Department of Electronics & Computer Science, University of Southhampton, http://www.isis.ecs.soton.ac.uk/research/projects/khepri/tjd96r/, March 1998.

[Edw93] I. Edwards, X. E. Gross, D. W. Lowden, and P. Strachan. Fusion of NDT Data. *The British Journal of Non Destructive Testing*, 35(12):710–713, Dec. 1993.

[Eys98] U. Eysel. *Klinische Neuroopthalmologie*, chapter Zentrale Anteile der Sehbahn, pages 10–21. Georg Thieme Verlag, Stuttgart, New York, 1998.

[Foo95] K. E. Foote and D. J. Huebner. Error, Accuracy, and Precision. Technical report, The Geographer's Craft Project, Department of Geography, University of Texas at Austin, 1995.

[Gra86] J. H. Graham. An Evidential Approach to Robot Sensory Fusion. *Proceedings of the 1986 IEEE International Conference on Systems, Man, and Cybernetics*, 1:492–497, 1986.

[Gro98] P. Grossmann. Multisensor Data Fusion. *The GEC journal of Technology*, 15:27–37, 1998.

[Hub98] A. Huber. *Klinische Neuroopthalmologie*, chapter Periphere Anteile der Sehbahn, pages 2–9. Georg Thieme Verlag, Stuttgart, New York, 1998.

[Kal60] R. E. Kalman. A New Approach to Linear Filtering and Prediction Problems. *Transaction of the ASME, Series D, Journal of Basic Engineering*, 82:35–45, March 1960.

[Kop90] H. Kopetz, H. Kantz, G. Grünsteidl, P. Puschner, and J. Reisinger. Tolerating Transient Faults in MARS. *20th. Symposium on Fault Tolerant Computing, Newcastle upon Tyne, UK*, June 1990.

[Luc99] Wald Lucien. Some Terms of Reference in Data Fusion. *IEEE Transactions on Geoscience and Remote Sensing*, 37(3), May 1999.

[Luo99] R. C. Luo and K. L. Su. A Review of High-level Multisensor Fusion: Approaches and Applications. *Proceedings of the 1999 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, pages 25–31, 1999.

[McK93] G. T. McKee. What can be fused? *Multisensor Fusion for Computer Vision, Nato Advanced Studies Institute Series F*, 99:71–84, 1993.

[Mur96] R. R. Murphy. Biological and Cognitive Foundations of Intelligent Sensor Fusion. *IEEE Transactions on Systems, Man and Cybernetics*, 26(1):42–51, Jan. 1996.

[Nah80] P. J. Nahin and J. L. Pokoski. NCTR Plus Sensor Fusion Equals IFFN or Can Two Plus Two Equal Five? *IEEE-Transactions-on-Aerospace-and-Electronic-Systems*, AES-16(3):320–337, May 1980.

[Par95] B. Parhami. Multi-Sensor Data Fusion and Reliable Multi-Channel Computation: Unifying Concepts and Techniques. *Conference Record of the Twenty-Ninth Asilomar Conference on Signals, Systems and Computers*, 1:745–749, Act.-Nov. 1995.

[Rao98] N. S. V. Rao. A Fusion Method That Performs Better Than Best Sensor. *Proceedings of the First International Conference on Multisource-Multisensor Information Fusion*, pages 19–26, July 1998.

[Shu91] A. N. Shulsky. *Silent Warfare: Understanding the World of Intelligence.* Brassey's, New York, 1991.

[Smi91] C. R. Smith and G. J. Erickson. Multisensor Data Fusion: Concepts and Principles. *IEEE Pacific Rim Conference on Communications, Computers and Signal Processing*, 1:235–237, May 1991.

[vN56] J. von Neumann. Probabilistic Logics and the Syntheseis of Reliable Organisms from Unreliable Components. In C. E. Shannon and J. McCarthy, Editors, *Automata Studies*, pages 43–98. Princeton University Press, 1956.

[Wal90] E. Waltz and J. Llinas. *Multisensor Data Fusion.* Artech House, Norwood, Massachusetts, 1990.