An Architectural Selection Framework for Data Fusion in Sensor Platforms

by

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ABSTRACT

The role of data fusion in sensor platforms is becoming increasingly important in various domains of science, technology and business. Fusion pertains to the merging or integration of information towards an enhanced level of awareness. This thesis provides a canonical overview of several major fusion architectures developed from the remote sensing and defense community. Additionally, it provides an assessment of current sensors and their platforms, the influence of reliability measures, and the connection to fusion applications.

We present several types of architecture for managing multi-sensor data fusion, specifically as they relate to the tracking-correlation function and blackboard processing representations in knowledge engineering. Object-Process Methods are used to model the information fusion process and supporting systems. Several mathematical techniques are shown to be useful in the fusion of numerical properties, sensor data updating and the implementation of unique detection probabilities.

Finally, we discuss the importance of fusion to the concept and operation of the Semantic Web, which promises new ways to exploit the synergy of multi-sensor data platforms. This requires the synthesis of fusion with ontology models for knowledge representation. We discuss the importance of fusion as a reuse process in ontological engineering, and review key lifecycle models in ontology development. The evolutionary approach to ontology development is considered the most useful and adaptable to the complexities of semantic networks. Several potential applications for data fusion are screened and ranked according to the Joint Directors of Laboratories (JDL) process model for information fusion. Based on these predetermined criteria, the case of medical diagnostic imaging was found to offer the most promising applications for fusion, on which future product platforms can be built.

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Nomenclature

ACDS: Advanced Combat Direction System

AESA: Active Electronically-Steered Array

AI: Artificial Intelligence

ASW: Antisubmarine Warfare

ATR: Automatic Target Recognition

COS: Class of Supply

CCART: Cargo Category Allocation Rates Table

C^4ISR: Command, Control, Communications, Computers
Intelligence, Surveillance and Reconaissance

DARPA: Defense Advanced Research Projects Agency

EIA/IS: Electronic Industries Association / Interim Standard

EM: Electro-Magnetic

EO: Electro-Optical

ESM: Electronic Support Measures

FOV: Field of View

GPS: Global Positioning System

HMM: Hidden Markov Model

IFFN: Identify-Friend-Foe-Neutral

IFOV: Instantaneous Field of View

INS: Inertial Navigation System

IR: Infrared

ISS: International Space Station

JDL: Joint Director of Laboratories

KBS: Knowledge-Based Systems

MMW: Millimeter Wave

MW: Microwave

NATO: North Atlantic Treaty Organization

NMR: Nuclear Magnetic Resonance

OPD: Object Process Diagram

OPM: Object Process Methodology

PRM: Perceptual Reasoning Machine

RF: Radio Frequency

SAR: Synthetic Aperture Radar

SE: Systems Engineering

SRL: Sense and Respond Logistics

SWL: Semantic Web Language

T&E: Test and Evaluation

UAV: Unmanned Aerial Vehicle

URI: Universal Resource Identifier

UV: Ultraviolet

WSN: Wireless Sensor Network

CHAPTER 1: INTRODUCTION

1.1 Data Fusion Defined

Data fusion is interpreted widely depending on the applications, technologies and

communities of interest. It refers in a broad sense to the processing and distribution of

data from two or more sources to obtain a property of an environment or object.

Common sensor devices include video cameras, range finders, tactile sensors and sonar.

Environments may include oceanic or terrestrial surfaces, airborne or ground-based

combat zones, warehouse facilities and web-based retail (e.g. Fig.1-1). The list of

stakeholders grows as new forms of sensors are developed and applied to data-rich

environments. The following definitions are culled from the remote sensing community,

where fusion concepts and nomenclature have been matured over several decades.

> *"Image fusion is the combination of two or more different images to form a new image by using a certain algorithm" [Pohl and Van Genderen, 1998]*

> *"...techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone" [Hall and Llinas, 1990]*

> *"...a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources" [US Department of Defense, 1991]*

In recent years, fusion has been extended beyond the process-centered view, to reflect a

more holistic methodology for information management. For instance, Buchroithner and

Wald (1998) advanced the following definition:

> *"Data Fusion is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining*

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information of greater quality; the exact definition of 'greater quality' will depend upon the application."

Figure 1-1 Data fusion example:
Image Superposition from 3 data sources

Overview of Data Fusion Models

Models are used to represent specific patterns of behavior or form (Maier and Rechtin, 2002). They capture the diverse, and often conflicting, architectural views of a product or process. Different models can help bring specific problems to bear in complex system engineering and architecting. In Table 1-1, these views are related to notions of stakeholder value and system success. Many of these views can then be fitted to some level of quantitative or qualitative model, which might help guide policy or manage assets in interrelated political, technical or economic systems.

Perspective or View	Description
Purpose / objective	What the client wants
Form	What the system is
Behavioral or Functional	What the system does
Performance objective / requirements	How effectively the system does it
Data	The information retained in the system and its interrelationships
Managerial	The process by which the system is constructed and managed

Table 1-1 Representation Models and their Objectives

Representation Models. Various representation models have been developed to help illustrate, on both behavioral and predictive terms, the commonly accepted stages of data fusion. The focus of this work will be on the form, functional and data models needed to implement state-of-the-art fusion systems. Performance-related or technology policy issues will not be investigated in depth in this research.

Purpose and Function Models. An inference, according to Webster's dictionary, is defined as a deduction made on the basis of a set of hypotheses. The Joint Directors of Laboratories (JDL) published a model in 1992 that extends conventional single-source methods to a multi-level, multi-source inference hierarchy. It is the most widely used method for categorizing data fusion functionality in the US. In 1998, the JDL model was revised to provide a framework for investment in automation, among other things. Fusion objectives can be expressed by the system problem statement:

> *"To align, associate, predict and infer...[in order] to produce identity estimates and situational refinements...in support of a diverse mission environment which operates on processed and referenced sensor data."*

In later sections, various concept fragments in the JDL model, such as threat assessment, will be reinterpreted and evolved to serve commercial requirements for data fusion needs.
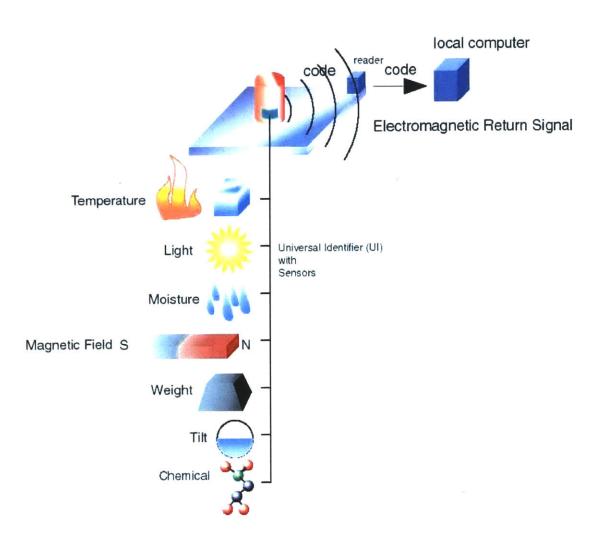
Figure 1-2 The Sensor-to-Signal Value Chain.

The data fusion functions are defined according to the hierarchy in Table 1-2 (Hall, 2002)

Level 0	*Sub-Object Data Association and Estimation*: pixel/signal level data association and characterization
Level 1	*Object Refinement*: observation-to-track association, continuous state estimation (e.g. kinematics), discrete state estimation (e.g. target type & ID), prediction (Kalman filter)
Level 2	*Situation Refinement*: object clustering and relational analysis, to include force structure and cross force relations, communications, physical context, etc.
Level 3	*Impact Assessment*: [Threat Refinement]; threat intent estimation, [event prediction], consequence prediction, susceptibility and vulnerability assessment
Level 4	*Process Refinement*: adaptive search & processing (element of resource management)

Table 1-2 Function Hierarchy

In level 0, association addresses the problem of sorting and correlating observations into common groups. This grouping, by entity, makes it easier to characterize the observations for refinement at the next stage. It also makes the determination, if any, of a relationship between source data and entity. An example algorithm used to perform association in Level 1, object refinement, adds the step of tracking to the cycle. Tracking refers to the estimation of position and velocity of the entity and can be implemented by Kalman filters, Hidden Markov Models and dynamic Bayesian nets (Wald, 2002). Level 2 situation refinement fuses the spatial and temporal relationships between entities and forms an abstracted interpretation of patterns on the order of battle data. Finally, level 3 focuses on the prediction algorithms to infer intentions and perform threat assessment. Level 4 extends the adaptive search and processing steps to include regulation of data that is acquired. In other words new data is acquired in a way that is directly influenced by the processing and interpretation of data obtained at previous time steps. Level 4 is also known as the 'meta-manager' where decisions are represented and fused.

The object-process refinement cycle in Figure 1-3 maps to the representation models described in Table 1-1. It also approximates the holistic framework posited by Crawley (2005) for product and operator attributes.[1] However, while Crawley's framework focuses exclusively on the global architecture issues related to product attributes, the JDL model considers a more granular definition. This suggests two ways to approach fusion analysis; one which tailors each activity to the available set of models (the 'model-

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[1] An attribute, here, is meant to denote the form, function, needs, goals, and timing of a system. This is different from notion of attribute fusion, through which sensor data is translated into decisions.

centric' view), and another that captures all fusion activity into a single model (the

'system-generic' view). The model-centric view might be thought of in terms of the

physical model based on the physical characteristics of the object (Hall, 1992), whereas

the system-generic view might be considered in light of the monitoring system described

by level 4.

	where	what	when	who	why	how	how well

Level 0: Association & Estimation	Level 1: Object Refinement	Level 2: Situation Refinement	Level 3: Threat Refinement	Level 4: Process Refinement

DATA FUSION PROCESSING

physical objects
individual   organizations

events
specific   aggregated

environment & enemy tactics
local   global

enemy doctrine objectives & capability
local   global

friendly vulnerabilities & mission
options   needs

friendly assets
local   global

effectiveness
battle   theatre

resource management
local   global

Figure 1-3 DF Cycles Span
(Courtesy: Llinas, DF Working Group)

Form Models. Form is the ultimate object of design (Alexander, 1964). A form model is

closely tied to the function model, and both are unified in an overarching system concept.

Form represents a level of physical abstraction that accommodates the working principles

of the system concept, which must allow for the execution of all functions (Crawley,

2005). In data fusion, a form model is directly related to domain-specific notions of

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space and connectivity. That is, an electromechanical device which fuses data to deliver value adopts different form aspects than does a C^4ISR defense system. Therefore, diverse products need to be assessed at roughly the same architectural level and order of complexity to draw meaningful inferences from system concepts.

Data Models. The drive for increasing levels of automation in corporate and governmental information systems has created a requirement for innovative data models. One of the functional objectives in data systems is to establish structure- and elicit learning- from complex and disparate sources. Solutions are increasingly being manifested in computer database systems, but the principles of data modeling apply equally to paper-based methods. This work will attempt to expand the reference case models from remote sensing systems to other domains. Here, we can take lessons from commercial retailing operations, where companies such as Wal-Mart have invested in sophisticated data warehouses to manage their inventory using new technologies such as RFID (Cebrowski and Garstka, 1998). These self-synchronizing networks have emerged from the co-evolution of organization. This data becomes valuable when it extracts marketplace trends and gets coupled with real-time transaction information about local retail operations. The core elements of fusion, then, have already been successfully deployed in some commercial settings.

1.2 Literature Review

<u>Origins</u>

The concept of data fusion goes back to the defense research community of the 1980's.

Specifically, three models were borne out of military applications in radar, missile and

surveillance technologies. Much of the lexicon developed in the data fusion community

is designed to support intelligence cycles (Bedworth and O'Brien, 2000). In the UK, the

defense establishment considered this to be a process – comprised of collection, collation,

evaluation and dissemination. Note that there is not a specific planning and direction

phase, as articulated in the American cycle concept. A brief description of activities in

the various phases is given below:

- **Collection**- Information from electronic or human sources is gathered and reported.
- **Collation**- Adjacent reports are combined or compressed for next stage fusion.
- **Evaluation**- Intelligence is fused, either through some form of automation or via human interpretation, to make informed decisions at the next stage.
- **Dissemination**- Distribution of intelligence reports to commanders for asset deployment.

The UK Intelligence Cycle organizes methods and tasks (data collection) toward some

concrete deliverable (asset deployment), without prescribing tools. An even higher level

of abstraction can be achieved with Boyd's four-phase action loop: Observe, Orient,

Decide and Act (Boyd, 1987). Although semantically, this model is rooted in the military

command process and is somewhat analogous to the JDL model, it introduces the notion

of iteration and feedback. This distinguishes it from the JDL sequence, which is a linear

'bus' of information inflows and outflows. By adding a dimension of control, Boyd

recasts fusion as a systems-theoretic problem that can be described by all three

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mathematical formalisms: continuous time, sampled data and discrete event analysis.

Random set measurement models extend single-sensor single target point-variate

statistics to describe a variety of multi-sensor, multi-target scenarios. They do this by

incorporating ambiguous evidence (natural language reports, rules) in multi-sensor and

target estimation.

The Waterfall Model proposed by Bedworth (1994) was endorsed by the UK Technology

Foresight Data Fusion Working Group. It focuses on lower-level sensing capabilities and

divides the fusion levels more finely than others. Since there is no control loop, the

interactions to decision making are linear. The Dasarathy Model (1997) likens the five

levels of fusion to an input-output paradigm. In Table 1-3, a feature refers to the property

or target attribute of an object. Features can be mathematical attributes (measurements)

or image attributes (color).

Input	Output	Notation	Analogues
Data	Data	DAI-DAO	Data-level fusion
Data	Features	DAI-FEO	Feature selection and feature extraction
Features	Features	FEI-FEO	Feature-level fusion
Features	Decisions	FEI-DEO	Pattern recognition and pattern processing
Decisions	Decisions	DEI-DEO	Decision-level fusion

Table 1-3 Dasarathy Model

The data is injected to the input pipeline and returns output data at the first level.

In subsequent levels, it feeds data and returns features, which in turn yield decisions.

These processes correspond to the feature extraction, pattern recognition and decision

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selection stages. The Omnibus Model (Bedworth and O'Brien, 1999) in Figure 1-4

attempts to unify the above views in a single, iterative decision loop. The primary

architectural merit of Omnibus is that it captures – in one graphic – the respective

zooming by previous models.
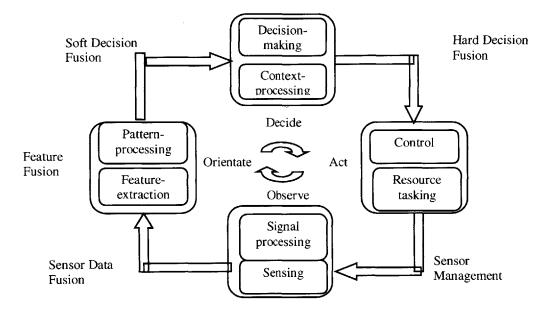
Figure 1-4 Omnibus Model

Current Research Agenda

System Engineering and Data Fusion. The research agenda in the Data Fusion

Community is broad and deep. The problems can be seen as either classification-based,

relating to sensor deployment, placement, behavior and coordination in networks (Luo,

2002). The problems can also be stated as methodological, which take a decision-

theoretic approach to resolving system trades. This view of data fusion would employ

utility-oriented concepts that seek to quantify the value of information to stakeholders. It

takes an analytic approach to problems via qualitative tools for reasoning abstractly about

the fusion process. Some of the quantitative research methods apply Bayesian statistics, Dempster-Schafer theory, Hough transforms and combinatoric set theory (Hall, 2002). Finally, beyond the logical and physical questions, there are real management and policy issues at stake, such as: how best to inject information fusion during various system development activities; how to create a secure, replicable base for applications, and what is the correct competitive space for fusion systems?

The Information Systems Office at the Defense Advanced Research Projects Agency (DARPA) allocates the issues according to operational and technical challenges. Key barriers to implementing fusion systems – the operational challenge- include data overload and interoperability. According to Flank (1998) over 80% of information is either never usefully processed or is deposited in some remote database and rendered obsolete. Real-time processing of information is then an important problem in the design of fusion systems. So too are the notions of sensor reliability and availability. This is also a technical challenge. Flank advocates performance metrics for characterizing and aggregating entity-level fusion. Speed and cost of algorithm development further drain management resources, for which Flank has suggested common fusion infrastructures to launch new products. He also cites the need to use emerging object-oriented modeling and wrapping techniques to make fusion 'engines' more interoperable. A diverse application context requires data structures that are robust to changes in semantic representations.

The systems engineering (SE) discipline focuses on the frameworks and tools related to design processes for multi-faceted products or services. It provides more than a set of methods to deal with complexity in product development. Rather, it offers strategic and tactical concepts for managing phases across a system's lifecycle. A generic lifecycle would include ideation and requirements planning, design-build, integration and test, maintenance and disposal. Specific design objectives render some processes more critical than others; the emphasis should be a function of relative maturity and hardware/software content. The Data Fusion Engineering Method (Project Correlation, 1997) presents a successful heuristic application of system engineering to fusion design. The framework in Figure 1-5 divides the development task between functional partitioning and point designs. Performance is evaluated at progressive levels of complexity from high- level architecture to detailed design.
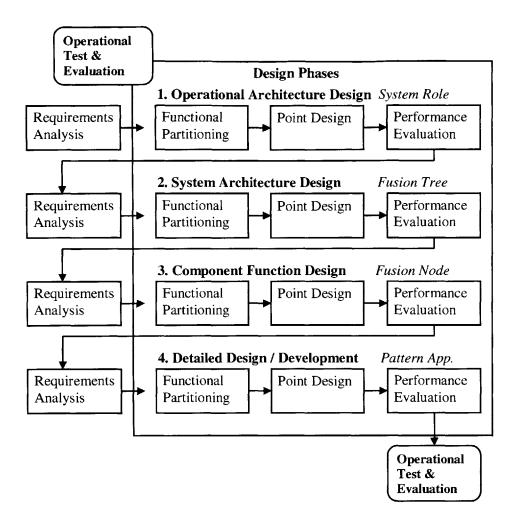
Figure 1-5 Data Fusion Systems Engineering Process

Steinberg (2000) identified three systems engineering challenges in data fusion.

Firstly, how should uncertainty be modeled, both in sensory observations and in the

phenomenon which produce those observations? Secondly, how should systems

aggregate non-commensurate sensory data (i.e. imagery, text and signals)? Finally, how

should multiple observations (under single- and multi-source conditions) be correlated,

processed and maintained? Steinberg elaborates on the notion of data visibility with an

analogy to resource management. Both resource management and data fusion rely on a

certain level of granularity for effect. The former technique results in action, the latter in

estimation. As sensor design is pushed beyond conventional measures of estimation, so too will the expected impact of fusion data. It is thus critical that the synergies between data fusion and neighboring domains be leveraged.

At its core, data fusion is an information-theoretic process enabled through hardware and software products and systems. Subjects such as quality assurance and risk assessment are less developed in the information domain, relative to traditional hardware fields like aerospace or nuclear engineering. This provides a unique opportunity for the practitioner community to extend the Data Fusion knowledge base (and taxonomy) across all phases of system engineering. When held to similar notions of reliability and utility as mechanical components, sensor data might codify a more holistic framework for specifying product requirements or mission objectives.

System Architecture and Sensor Networks. System architecture has broad

interpretations depending on the domain of interest. It is both an early phase in systems

engineering, and an artifact of that process. Crawley (2005) provides the following

definition:

> *"The embodiment of concept, and the allocation of physical/informational*
> *function to elements of form, and definition of structural interfaces among*
> *the elements and with the surrounding context."*
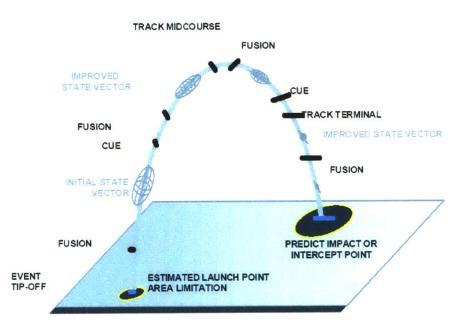
**Figure 1-6 Fusion Improvement of State Vector,
Launch to Intercept (Alberts et al., 2000)**

Figure 1-6 demonstrates the increase in battle space awareness through progressive

fusing of the state vector. The improvement is measured as an enlargement of intercept

area from initial event tip-off.

Varshney (1997) elaborates on the system architecture issues related to distributed sensor

networks. Sensor suites can be configured in parallel, so that multiple sensors make

observations concurrently. Likewise, they can be arranged in serial, or tandem, contributing sequential observations. The effects of spatial and temporal aggregation can drive the mission and performance outlook for a system. In the network of Figure 1-7, various sensors are strategically placed throughout the building to monitor structural health.
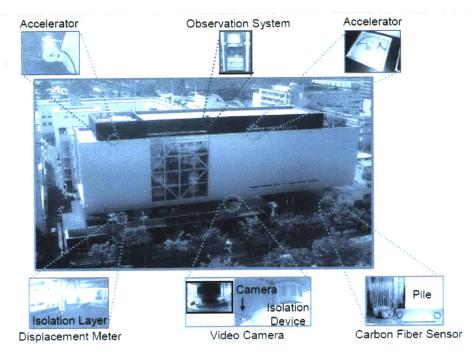
Figure 1-7 Sensor Network in a Civil Structure

The level at which fusion occurs is another architectural checkpoint of interest to practitioners. It is widely accepted that data can be combined at three levels: data, feature, and decisions. The attributes and requirements of these three modes are summarized in the Hierarchical Classification Scheme of Table 1-4.

Attribute-Level	*Data-level fusion*	*Feature-level fusion*	*Decision-level fusion*
Data Source	Raw observations	State vectors	Combination of raw data and state vectors
Source Compatibility	Commensurate (i.e. similar units/source)	Commensurate	Non-commensurate
Bandwidth needs	High	Low	Reduced
Accuracy (resolution)	High (resolution has inverse relation to wavelength)	Medium	Low
Timeline	Front-end processing	Mid-stage processing	Late-stage processing
System architecture	Centralized	Distributed	Hybrid
Examples	Multi-spectral pixels of data, typically based on signal processing, spanning the electromagnetic spectrum	Imaging sensors with stereo vision that provide depth, range information	Event identification or object confirmation based on the observation of some common phenomena

Table 1-4 Hierarchical Classification Scheme

Table 1-4 assumes that the input/output (I/O) transform is restricted to a specific level. If, within a fusion process, the I/O is selected from non-commensurate sets of raw data and feature vectors, it results in a combinatorial explosion of outcomes. An example cited by Varshney is the data gathered by two human eyes; when processed, it returns depth perception (data in-feature-out fusion). Similarly, the pattern recognition process interpolates features and selects a decision (feature-in, decision-out fusion). Complex fusion processing is more likely to draw on these kinds of multi-source, non-commensurate and differential I/O regimes.

System architecture is not limited to topology or processing. It also involves setting system goals, refining context, decomposing function, and planning for change. These deliverables have been cast in the Conceive-Design-Implement-Operate framework for

interpreting product development. Crawley (2005) groups architectural responsibility

under the conception phase. See Figure 1-8 below.

Generic PDP

Conceive		Design		Implement		Operate	
Mission	Conceptual Design	Preliminary Design	Detailed Design	Element Creation	Integration, System Test	Life Cycle Support	Evolution
• Business Strategy • Functional Strategy • Customer Needs • Competitors • Program plan • Business case	• Goals • Function • Concepts • Regulation • Technology • Platform plan • Supplier plan • Architecture • Commitment	• Requirements definition • Model development • Requirements flowdown • Detail decomposition • Interface control	• Design elaboration • Goal verification • Failure & contingency analysis • Validated design	• Sourcing • Implementation ramp-up • Element implementation • Element testing • Element refinement	• Product integration • Product testing • System testing • Refinement • Certification • Market positioning • Delivery	• Sales, Distribution • Operations • Logistics • Customer support • Maintenance, repair, overhaul • Upgrades	• Product improvement • Family expansion • Retirement
Envision		*Design*		*Develop*		*Deploy*	

Primary Domain of the Architect

Figure 1-8 Architecture tasks in Product Development (Crawley, 2005)

The programmatic and business decisions made at this stage will significantly impact the

evolution of the system. Robust architectures should leave the vision of the architect

intact, well beyond his or her direct involvement with the project.

Finally, something should be said about architecting for multiple stakeholders and

enterprises. This is relevant to the data fusion challenge and addressed by Jackson

(2005). Architecture, he says, lends more than concept structure to a system. It is, rather,

a fundamental ontology, or vocabulary of terms, which can be applied across domains.

Bridging the Platform-Network Divide. Information fusion is enabled by a variety of

sensor technologies. Luo *et al.* (2002) classified these technologies according to

operating principles:

- Mechanical parameter variation (e.g. pressure gauges, optical encoders)
- Material parameter variation (e.g. resistance thermometers, strain gauges)
- Direct signal generation (e.g. microphones, accelerometers, proximity sensors (laser or eddy current))
- Ionization based (photo detectors, photomultipliers)
- Quantum mechanical (magnetometer)

These technologies span a range of application areas, from structural health monitoring and medical diagnostics to supply chain management. As new applications are discovered, traditional electro-mechanical sensors are being supplanted by embedded circuits and optical devices. Such miniaturization techniques can improve overall package density and increase performance, as well as lower power consumption. More recently, many sensors are equipped with wireless transceivers, allowing them to be placed in new environments, or not having to be physically connected, thus forming so called wireless sensor networks (WSN). Finally, software tools have significantly enhanced controllability and communications between sensor hosts. Jackson (2005) discusses the importance of problem framing in both process and product development. He goes on to recommend that solutions for software be considered in implementation rather than structural terms.

The concept of product platforms presents some novel approaches to the design and integration challenges that arise in data fusion (Simpson, 2005). The current lack of information reuse, standardization and benchmarking motivates practitioners across industry to seek unified and controllable development techniques. Platforms help to bridge this gap through architecture and supply chain management. More importantly,

they can help position a firm for cost and scale efficiencies throughout the lifecycle. This is a pre-requisite for growth and sustainability of product lines.

The concept of product lines and families are relatively new to the software engineering domain (Weiss, 2005). The motivation for platform thinking in software systems is similar to that of hardware systems. In systems that undergo long durations/exposures, the involvement of multiple contractor organizations and budgetary restrictions justifies the use of platforms in order to develop "core assets." Weiss uses the example of the Exploration Initiative by NASA, where software-dominant platforms can be used in the development of large, spacecraft control software. At United Technologies Research Center, information platforms need the same rationalization, model-based analysis and evolution plan which influence hardware strategy (Bailey, 2005). The firm Design Continuum finds that platforms make it difficult to reach alignment on future requirements, but they can nevertheless improve time-to-market, service and reliability (Merle, 2005). The up-front planning costs must be weighed against back-end delivery objectives in determining the extent to which a firm decides to platform its technology. The parallels only go so far, however; a fusion system will have radically different specifications and constraints, which interleave its function and architecture. Such constraints include the effects that disparate sensor location and information sources might have on system design. These constraints influence both how the system is decoupled and the extractable value from a platform strategy.

1.3 How to Think about Data Fusion

The problems associated with data fusion have been laid out. How should we think about

the data fusion itself? Is it a product, a process, a system or a capability? The answer, of

course, is all of the above. It is a function of the value attached to the information,

capability or hardware which depends on data fusion.

Figure 1-9 places data fusion within the greater context of system terminologies. It

encompasses sensor fusion, with reference to defense applications; adjacent to this is a

commercial (IT) equivalent, information fusion. Though multi-sensor integration

overlaps with data fusion, it does not feature the Correlation and Estimation activity.

Similarly, resource management is an ancillary function extraneous to the whole system

but includes collection (data) management. Though fusion-related processes are set in a

holistic context, the diagram is not an adequate semantic decomposition. Nor does it

convey the spectrum of capability and infrastructure required to support product-systems.

Such a framework is necessary for integrating models with applications. They will be

developed in later chapters.

```
┌─────────────────────────────────────────────────────────────┐
│                      Data Fusion                            │
│  ┌──────────────────────┐  ┌──────────────────────┐         │
│  │ Information Fusion    │  │   Sensor Fusion      │         │
│  │       Data           │  │       ATR            │         │
│  │      Mining          │  │     Tracking         │         │
│  └──────────────────────┘  └──────────────────────┘         │
│                                                             │
│               Correlation Estimation                        │
└─────────────────────────────────────────────────────────────┘
```

Data Fusion

Information Fusion
Data
Mining

Sensor Fusion
ATR
Tracking

Correlation Estimation

Level 0: SubObject Data Association

Multi-sensor Integration

Collection Management

Resource Management

Level 1: Object Refinement

Level 2: Situation Refinement

Level 3: Impact Assessment

Level 4: Process Refinement

Figure 1-9 A Context for Data Fusion
(adapted from Bowman et al., 1998)

For the system architect, there are significant multi-disciplinary issues which need to be brought together under a single and robust fusion framework. While fusion techniques have been employed since the development of radar and associated technology, the concepts of detection, estimation and monitoring have taken hold in other sensory domains. It is a multi-disciplinary specialty, drawing on the sciences of pattern and feature recognition, artificial intelligence, operations research and signal/image processing. And it is largely *user*-driven; depending on system stakeholders for concept refinement and implementation. As the demand for fusion applications broadens, there is an increased need to better evolve and integrate system design into complex network and

platform architectures. This challenge can be met if the data fusion community continues to develop the field, formally, as a scientific or engineering field of inquiry.

Commercial Transfer. An important challenge which must be addressed is how best to transfer innovative DF technologies to the commercial realm. The success of data fusion processes in civilian and defense C^4ISR systems has promising applications for medical diagnostics equipment, failure detection systems, condition-based maintenance and supply chain management- using RFID and rule-based analytics- among others. The community is currently trying to construct a generic taxonomy which can extend fusion methods beyond its defense systems or earth science applications bias. The need to establish such a lexicon of data fusion terms, measurements and performance models is widely accepted among numerous national and international stakeholders. This is evidenced by the establishment of Data Fusion working groups, both in government and academia which have been collaborating for several years. The relation of ontology working groups toward the development of comprehensive Semantic Web services will be discussed in Chapter 5.

In Table 1-5, Wald (1999) presents various views on the key design and implementation issues related to sensor fusion.

Topological (Design)	Processing (Implementation)
Spatial distribution of sensors	How to fuse the data
Communications network	Select performance measures
Bandwidth	Determine relevance of data to objectives
Analytic Redundancy	Artificial creation of signals based on synthesis of other partially correlated sensor signals
Global Architecture	Select fusion methods and architectures

Table 1-5 Sensor Fusion Challenges

Steve Flank (1998) of the Information Systems Office views Data Fusion as a set of strategy-oriented goals. These can be divided between operational and technical objectives:

Operational Goals
- Reduce information overload
- Overcome barriers to interoperability
- Improve speed, cost, and reusability of development

Technical Goals
- Context and Performance Characterization
- Intelligent Fusion Strategist
- Fusion Engine Encapsulation

Composing a Solution. Developing the frameworks and taxonomy for complex fusion design is a critical task for the system architect. As data environments become more complex and interconnected, the role of the architect is to manage the ambiguity and interaction of fusion and related-systems. These challenges are no longer the purview of electrical or mechanical engineers, because their effects touch almost every conceivable domain of innovation. Consequently, holistic solutions will synthesize all factors in direct and indirect fields. Other benefits include the expansion of industrial capacity

(factory automation), and defense capability (intelligence and surveillance). This thesis is therefore motivated on a number of different levels, including business, organizational, technical and societal. It will not address the sensor characterizations relating to various applications, such as sensitivity, voltage and current levels, linearity, impedances, gain, offset and drift. Rather, this thesis will address sensor applications in the 'macro' (in the large), investigating design and development challenges in the integration and implementation of data fusion technology onto sensor networks and platforms.

1.4 Thesis Objectives

In summary, this thesis seeks to address the global issues related to fusion design, and the guidelines for selecting a specific architecture given an implementation task. The objectives are defined as follows:

- To review current models of data fusion which are actively utilized in various scientific/engineering communities (Chapter 1)

- To relate the concept of fusion to the operation of different types of sensors and sensor platforms (Chapter 2)

- To provide a brief overview of current fusion algorithms and methods (Chapter 3)

- To present basic fusion processes as they occur in a C^4ISR system (Chapter 4)

- To model an information fusion ontology using Object-Process Methodology and to discuss its relevance to the Semantic web (Chapter 5)

- To elaborate a set of fusion engineering and management architectures in support of complex system design (Chapter 6)

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CHAPTER 2: SENSORS AND SENSOR PLATFORMS

2.1 Sensor Categories

The value of data fusion lies in the breadth of sensor categories available to the designer. The traditional applications normally cull these sensors from the electromagnetic spectrum. For instance, in data fusion through remote sensing, electro-magnetic energy reflected or emitted from objects is measured and reported. However the energy from acoustic, ultrasonic, magnetic and seismic waves all offer potentially rich sources of information on which to design fusion system architectures.

2.2 Single Sensor Systems

A sensor is comprised of a transducer which converts energy entering an aperture into lower frequencies from which targets and background information may be discerned through a data processor. Digital sensors, actuators and low power RF radios all help to enable the functionality of a single sensor system (NSF, Directorate for Computer and information Science and Engineering) through integration of a single chip in a processor's memory. Figure 2-1 illustrates the basic components of a typical sensor system. Examples of sensor apertures include antennas (for RF energy), optics (for IR-UV-visible light energy) and microphones/hydrophones (for acoustical energy).
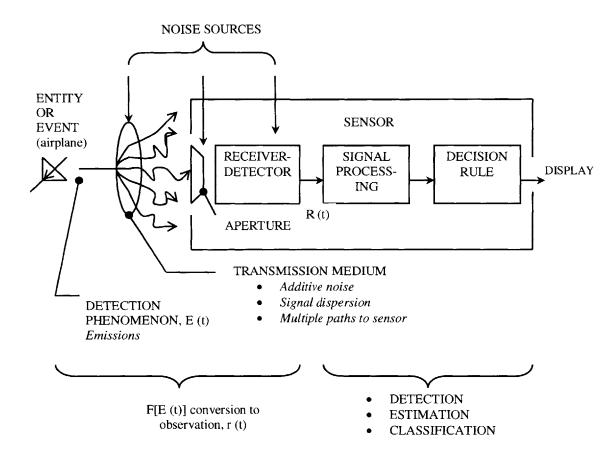
NOISE SOURCES

ENTITY
OR
EVENT
(airplane)

SENSOR

| RECEIVER-DETECTOR | SIGNAL PROCESS-ING | DECISION RULE |

DISPLAY

R (t)

APERTURE

TRANSMISSION MEDIUM
- *Additive noise*
- *Signal dispersion*
- *Multiple paths to sensor*

DETECTION
PHENOMENON, E (t)
Emissions

F[E (t)] conversion to
observation, r (t)

- DETECTION
- ESTIMATION
- CLASSIFICATION

**Figure 2-1 A sensor system
(adapted from Waltz and Llinas, 1990)**

There are significant limitations due to single sensors that should be mentioned. For instance, weather, clutter and noise may interfere with the recognition of an object by a single sensor system. A key determinant to the success of a single sensor system is the orientation of the mission, and whether there are sufficient data processing resources that are localized in each sensor (Klein, 1999).

2.3 Multi-Sensor Systems

Multi-sensor systems offer numerous advantages over single sensors when it comes to the

fundamental tasks of utilizing and delivering information toward a specific objective. For

instance, Landsat-1, the first earth observation satellite launched in 1972, was a historical

program designed to obtain information on agricultural and forestry resources, geology

and mineral resources, hydrology, pollution, oceanography and marine resources, among

other objectives. The system acquired visible light and near infrared earth photos, as well

as radiometric Earth images, through a multi-sensor vidicon and multi-spectral scanner.

The data was processed and stored in wide-band video tape recorders which offered

'near-global' coverage capability[2] .The combination of microwave, millimeter wave,

infrared and visible sensors has also been used in daily weather forecasting.

Furthermore, the collection of ground-based and aerial sensor data has been useful for

characterizing the targets which are being imaged by these sensors.

The relative performance of multiple sensors over single sensor systems can be illustrated

through the graph in Figure 2-2, below, on detection probability. If performance is

measured over some nominal signal-to-noise ratio, the profile shows the improvement of

a tri-sensor suite (with MMW and IR sensors) over a single millimeter wave sensor.

When the system false alarm rejection is divided equally among three sensors, there is a

marked increase in false alarm probability 10^{-2} (versus 10^{-6} for a single sensor system).

More importantly, the voting fusion algorithm used here combines the signal processing

in series and parallel combinations that increases the detection probability for both

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[2] Retrieved from Wikipedia.com

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nominal and suppressed target signature levels. When detection probability is the priority, the tradeoff in false alarm sets versus detection probability clearly favors the multiple sensor system- 63% compared to 27% for the reduced-signature target. False alarm sets indicate that the measurement is unreal and to be ignored.
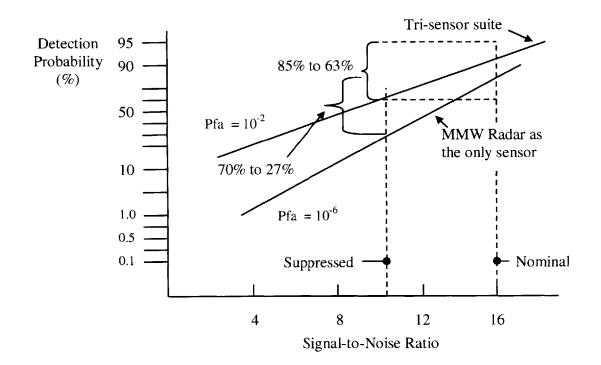

Figure 2-2 Multiple sensor versus single sensor performance with suppressed target signatures (adapted from Klein, 1999)

In addition to the improved detection performance noted above, multiple sensors offer:

- Improved system reliability through redundant sensor suites
- Increased dimensionality of the measurement space
- Enhanced spatial and temporal coverage
- Enhanced confidence about the measurement sets.

However, one major challenge when measuring the same object or phenomenon with multiple sensors at the same time is that of calibration. In large scale sensor networks, manual, single sensor calibration does not work. Complexities from scaling, limited

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access to sensors in the field and sensor drift require alternative measures to be utilized.

Each sensor has its own calibration and the multiple sensors may not agree. This

problem has been resolved through a process of collaborative calibration that

systematically corrects errors (biases) in sensor readings. One scheme proposed

(Bychkovsky et al, 2003) relies on redundancy in measurements due to over-deployment

of sensor assets. This scheme first derives functions relating to the output discrepancies

of neighboring sensors, and then uses a heuristic method to address pair-wise

inconsistencies in the network.
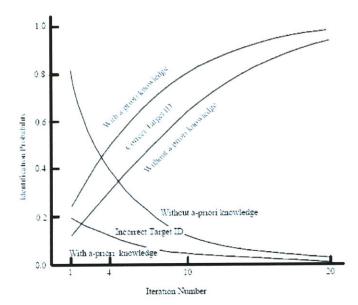
Figure 2-3 Identification probability convergence

Finally, another way to interpret the detection-false alarm tradeoff is through target

identification "correctness." Figure 2-3 (Kadar, 2001) shows that correct target ID is

improved with a priori knowledge, both in terms of the detection probability as well as

the number of iterations required for detection. The monotonic increase in probability to

1 for the correct ID, and to 0 for the incorrect ID, is known as ID convergence.

2.4 Active versus Passive Sensors

Sensors are often classified as either active or passive depending on their signal conditioning. An active sensor requires external sources of excitation, while passive sensors generate their own electrical output (without requiring external voltages or currents). The need then, for external active circuitry to produce electrical output signals from the sensor determine whether, structurally, a sensor should be classified as active or passive.

In the microwave spectrum, these definitions take on a slightly different meaning. Active microwave sensors provide their own source of radiation to illuminate a target, as in RADAR imaging. They use radio waves to detect objects and determine their position, range, or shape. Active sensors tend to provide more information than passive sensors, at the cost of increased power consumption and interference when other active sensors are in operation and easier detectability of the sensor. For instance, active MMW radars operate in mono-static and bi-static configurations. In the former, the transmitter and receiver are collocated on the same platform so that the receiver processes energy that is backscattered from objects in the FOV. In the bi-static mode, the transmitter and receiver are spatially disconnected, reducing the type and versatility of applications.

Passive microwave sensors record energy emitted by the atmosphere or surface, reflected by the surface or transmitted from the subsurface. Another example of a purely passive sensor is an electro-optical sensor, which in military applications can offer stealthy (non-detectable) operation. Since passive sensors depend on naturally occurring energy, they are limited in the location and timing of their operation. For instance, the

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amount of solar radiation at polar latitudes is insufficient for visible light sensors (during

the polar night), and limits the use of passive detectors to low latitudes. The Thematic

Mapper on Landsat satellites is an important exception to this design limitation, as it taps

into seven different sensor bands. These bands are sensitive to numerous ranges of the

electromagnetic spectrum, from the visible to thermal infrared portions of the spectrum.

The Landsat is therefore launched at strategic times to ensure that the satellite will make

passes during optimal periods of solar radiation (sun-synchronous orbits).

2.5 Sensor Platforms

A sensor platform is a vehicle or system used to carry the sensor. Example platforms are shown in Figure 2-4 (a-b). Typical sensor platforms in the C^4ISR arena include satellites and aircraft (manned or unmanned), but can also include balloon kits for low-level surveillance (remote sensing), ladder trucks and a host of other mobile or stationary devices. The fundamental selection factor is the altitude that determines the ground resolution in turn sets the IFOV (Instantaneous field of view) of the sensor on board[3].
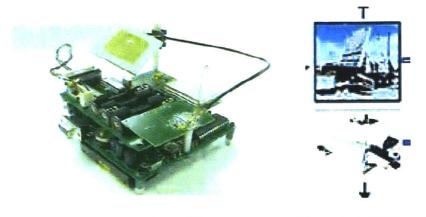

Figure 2-4 (a) Wireless reconfigurable Platform at Dartmouth

Figure 2-4 (b) Truck mount ground-based phased array

Ground-based sensors offer some cost advantages in terms of maintenance and operation compared to aerial platforms. They can be placed on structures in buildings, towers or on board terrain vehicles. The complexity and maintenance of the ground-based sensor is dependent on the design involved. For instance, highly complex phased array antennas are ground-based sensors with thousands of apertures array elements, see Figure 2-4 (b). The advent of AESA (Active Electronically Steered Arrays) has replaced the need for

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[3] Retrieved from The GIS Development Portal.

mechanical turntables that require maintenance of bearings, hydraulics and auxiliary components.

Aerial platforms are used to elevate the sensor above the earth's surface for better coverage. Cameras mounted on aircraft constitute a type of aerial sensor that is used to monitor land use practice, locate fires and produce high resolution mapping of remote or inaccessible regions. Airborne scanning devices are becoming generally available, and can record radiation over a wider spectral range than photographic devices. They also offer the advantage of providing data in multi-channel digital format (Harrison and Jupp, 2000). They are considered easier to reuse than satellite or air platforms whose design objective might be based on remote data and image sensing. An exception to this category is the Unmanned Aerial Vehicle (UAV) which has shown to be a considerably less expensive platform for communications, intelligence and surveillance information gathering.

CHAPTER 3: OVERVIEW OF FUSION ALGORITHMS & METHODS

3.1 Fusion of Numerical Properties: The Kalman Approach[4]

State representation of a model is an important element in the fusion of numerical

properties. In 1960, R.E. Kalman's "New Approach to Linear Filtering and Prediction

Problems" laid forth the groundwork for fusion of numerical properties.

The state of a system is represented by the dynamic world model, M(t), whose list of

primitives describe a state at time t.

$$M(t) \equiv \{P_1(t), P_2(t), \ldots, P_m(t)\}$$

Each primitive P_i in the system model above is identified by unique identifier, or label, as

well as a confidence factor.

$$P(t) \equiv \{ID, \dot{X}(t), CF(t)\}$$

Where,

P(t) is the local descriptor of the world model M(t);

ID is the label by which the primitive may be identified and recalled;

$\dot{X}(t)$ is a state estimate; and

CF(t) is the confidence factor.

We add an element of random noise to the observation Y(t), denoted by N(t).

$$Y(t) = {}^Y\mathbf{H}_{\dot{X}} X(t) + N(t).$$

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[4] This section is adapted from Crowley and Demazeau.

The actual world state is estimable from the collection of the set of primitives of N properties,

$$\hat{X}(t) \equiv \{ \hat{x}_1(t), \hat{x}_2(t), \dots \hat{x}_n(t) \}.$$

Incorporating uncertainty into this model can be represented by the expected deviation between the estimated and true vector. It is approximated with the covariance matrix between the estimated and actual system state:

$$\dot{C}(t) \equiv E\{[X(t) - \dot{X}(t)] \, [X(t) - \hat{X}(t)]^T\}$$

The key result from Kalman's work is the development of the weighting matrix known as the Kalman gain, defined using the prediction uncertainty, $C^*_y(t)$.

$$K(t) := C^*_x(t) \, {}^Y H_x{}^T [\, C^*_y(t) + C_y(t)]^{-1}$$

Where,

$^Y H_x{}^T$ is matrix transformation of the coordinate space of the estimated state $X(t)$.

$^Y H_x{}^T$ is an observation process that projects onto the world an observation vector $Y(t)$. This relative weighting between the prediction and observation leads to the ability to update the estimated properties and derivatives via the difference between predicted and observed properties.

$$\hat{X}(t) := X^*(t) + K(t) \, [Y(t) - Y^*(t)]$$

3.2 Bayesian Methods

In this section[5], we present Bayesian methods for data fusion. Whereas the Kalman approach to data fusion focuses on the updating of properties, Bayesian methods focus on updating probabilities.

The Bayesian form is derived from the conditional probability of the intersection of two events.

$$P(BC \mid A) = p(C \mid AB)\, p(B|A)$$

This can be rewritten as,

$$P(C|AB) = p(BC|A)\, /\, p(B|A).$$

When C is interpreted as a set of mutually exclusive and collectively exhaustive set of outcomes, we can derive the following,

$$P(C_i|AB) = \frac{p(B \mid C_iA)\, p(C_i \mid A)}{\sum P(B \mid C_jA)\, p(C_j \mid A)}$$

Where,

$p(C_i \mid A)$ is an a priori (or prior) probability of Ci, based upon the state of information A;

$p(C_i \mid AB)$ is the a posteriori (or posterior) probability of Ci, given the data B and the prior state A;

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[5] This section is adapted from Waltz and Llinas.

$p (B \mid C_i A)$ is the likelihood function, which is the likelihood of observing the

data B given C_i and the prior state of information.

$\sum_j P(B \mid C_jA) \, p \, (C_j \mid A)$ is the pre-posterior or probability of the data occurring

given the state of prior information, conditioned on all possible outcomes of C_j.

An influence diagram for Bayesian identification fusion is presented in Figure 3-1.

Various sensor reports are converted in a given time period to likelihood functions. We

adapt an example (Waltz and Llinas, 1990) regarding IFFN and ESM sensors.

Sensor Report	Type ID Given Report	Joint Sensor Report	Previous Period Posterior	Current Period Posterior

IFF → IFF/T

RAID → RAID/T

"A" → "A"/T

"B" → "B"/T
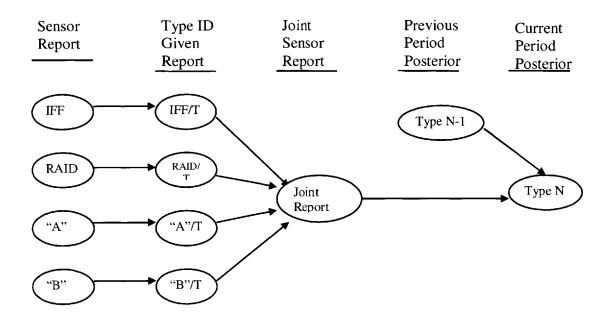
Joint Report

Type N-1

Type N

Figure 3-1 Influence Diagram

The interrogation chain requires that sensor response be represented in the form of some

sort of hypothesis or declaration, for later probabilistic combining. The IFFN sensor

responds with a "Friend" declaration, p_{IFFN} (Data | FRD) when it receives a valid

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response to its query. Similarly, the electronic support measure would make a positive

identification based on the type of aircraft it detects P_{ESM} (data | T_k).   This results in the

following equations:

$$P_{IFFN} \text{ (data } | T_k) = P_{IFFN} \text{ (data } | FRD) \cdot p \text{ (FRD} | T_k)$$
$$+ P_{IFFN} \text{ (data } | FOE) \cdot p \text{ (FOE} | T_k)$$
$$+ P_{IFFN} \text{ (data } | NEU) \cdot p \text{ (NEU} | T_k)$$

When there is no neutrality measure, then we can eliminate the final term.

$$P_{IFFN} \text{ (data } | T_k) = P_{IFFN} \text{ (data } | FRD) \cdot p \text{ (FRD} | T_k)$$
$$+ P_{IFFN} \text{ (data } | \text{ not FRD }) \cdot p \text{ (not FRD} | T_k)$$

Now that we have derived the type ID given report, the joint sensor report can be

computed. This example concerns non-commensurate sensors, i.e. they rely on different

phenomena (IFFN and ESM). Therefore, the probabilities are considered independent

and the joint likelihood values are:

$$P \text{ (data } | T_k) = \prod p_i \text{ (data } | T_k)$$

For all k, or types of aircraft.

We can confirm this result numerically as follows:

$$P_{IFFN} \text{ (data } | T_k) = P_{IFFN} \text{ (data } | FRD) \cdot p \text{ (FRD} | T_k)$$
$$+ P_{IFFN} \text{ (data } | FOE) \cdot p \text{ (FOE} | T_k)$$
$$+ P_{IFFN} \text{ (data } | NEU) \cdot p \text{ (NEU} | T_k)$$

where the likelihoods, P_{IFFN} (data |) is based on some *a priori* test measurement,

$$P_{IFFN} \text{ (data | FRD)} = 0.6 \qquad P_{ESM} \text{ (data | FRD)} = 0.3$$

$$P_{IFFN} \text{ (data | FOE)} = 0.2 \qquad P_{ESM} \text{ (data | FRD)} = 0.4$$

$$P_{IFFN} \text{ (data | NEU)} = 0 \qquad P_{ESM} \text{ (data | FRD)} = 0$$

To calculate the likelihoods based on type of aircraft T_k , we can multiply the above likelihoods by the binary probabilities of p (FRD | T_k) =1, p (FOE | T_k) =0 and p (NEU | T_k) = 0. Thus, when there is no neutrality measure, for a scenario in which only one side has a given type of aircraft,

$$P_{IFFN} \text{ (data | } T_k \text{)} = P_{IFFN} \text{ (data | FRD)} \cdot \text{p (FRD | } T_k\text{)}$$
$$+ P_{IFFN} \text{ (data | not FRD)} \cdot \text{p (not FRD | } T_k\text{)}$$

$$P_{IFFN} \text{ (data | } T_k \text{)} = (0.6) \times (1) + (0.2) \times (0) = \textbf{0.6} \qquad \text{and}$$
$$P_{ESM} \text{ (data | } T_k \text{)} = (0.3) \times (1) + (0.4) \times (0) = \textbf{0.3}$$

So that the joint likelihoods are

$$P \text{ (data | } T_k \text{)} = \prod \text{ p}_i \text{ (data | } T_k\text{)} = 0.6 \times 0.3 \quad => \quad \textbf{0.18}$$

where 0.18 is the probability of a joint sensor report for all k, or types of aircraft.

Finally, the last link of the influence diagram is satisfied by Bayes's Rule

$$P(T_k \mid data) = \frac{p\,(data \mid T_k) \cdot qT\,k}{p\,(data)}$$

Where,

qT_k = previous period's value of $p(T_k \mid data)$;

$p\,(data) = \sum p\,(data \mid T_k) \cdot q\,T_k.$

The level of updating is a function of the number of detections during a given time period. The last step in Bayesian fusion is to calculate the friend, foe, or neutral identification, as well as any class membership issues. This requires the posterior probabilities for type and the scenario defined.

$$P(FRD \mid data) = \sum p(\,T_k \mid data) \cdot p\,(FRD \mid T_k)$$
$$P(FOE \mid data) = \sum p(\,T_k \mid data) \cdot p\,(FOE \mid T_k)$$
$$P(NEU \mid data) = \sum p(\,T_k \mid data) \cdot p\,(NEU \mid T_k)$$

3.3 Voting Fusion

Voting fusion[6] is a powerful approach to sensor fusion that uses Boolean methods to estimate a system's detection and false alarm probability. In this section, we derive the basis of this approach and then extend it to an example using nested confidence levels.

Nesting refers to the level of dependence of a confidence level for a sensor. Non-nested confidence levels are based on the disjoint assumption of probability theory, so that the system detection probability can be expressed as follows

$$P_d \{A1 \ U \ A2\} = P_d\{A1\} + P_d \{A2\}$$

And $P_d \{A1 \cap A2\} = 0$

The number of confidence levels required for system functioning is proportional to the number of sensors in the system. From a performance viewpoint, this requires an understanding of how confidence intervals are related to detection and false alarm probabilities.   The Venn diagram in Figure 3-2 (a) (Klein, 1999) illustrates the detection / classification space for a tri-sensor configuration suite.
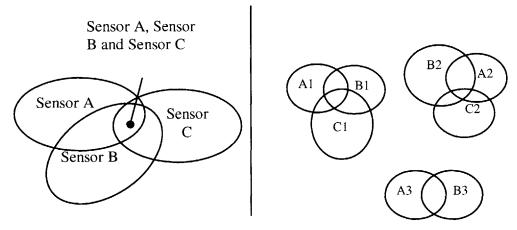
Sensor A, Sensor
B and Sensor C

Sensor A

Sensor
C

Sensor B

A1 B1

C1

B2 A2

C2

A3 B3

Figure 3-2(a) Detection modes   **Figure 3-2(b) Confidence levels**

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[6] This section is adapted from Klein.

Due to the null set intersection equation described above, the non-nested confidence

levels allow false alarm probabilities to be optimized for each sensor's confidence level.

The 3 sensor suite is chosen because it has the least likelihood of false alarm detection,

compared to the probability of single sensor false alarm detection. Having at least 3

sensors, even with lower confidence levels, provides better assurance against false target

identification under non-commensurate conditions, where the sensors are responding to

different signal phenomena.

The system detection probability equation is derived from three dual sensor modes and a

single tri-sensor suite mode as follows. The first term, with all 1's as subscripts,

represents the lowest level output combination. The next two terms represent

intermediate confidence outputs, and the fourth term, A_3 B_3 requires the highest-level

confidence output. The following equation is an exhaustive set with no confidence mode

overlap.

$$\text{System } P_d = P_d \{ A_1\ B_1\ C_1 \ \text{ or } A_2\ C_2 \text{ or } B_2\ C_2 \text{ or } A_3\ B_3 \}$$

This can be reduced using the following Boolean expansion

$$P \{ X \text{ or } Y \} = P\{X\} + P\{Y\} - P\{XY\}$$

to the result

$$\text{System } P_d = P_d \{ A_1\ B_1\ C_1 \} + P_d \{A_2\ C_2\} + P_d \{B_2\ C_2\} + P_d \{ A_3\ B_3\}$$
$$-\ P_d \{A_2\ B_2\ C_2\}$$

When the sensors are responding to different signal generation phenomena, then the probabilities are independent of each other. The following two expressions relate this for both detection and false alarm probability for the system.

System P_d = $P_d\{A_1\}$ $P_d\{B_1\}$ $P_d\{C_1\}$ + $P_d\{A_2\}$ $P_d\{C_2\}$ + $P_d\{B_2\}$ $P_d\{C_2\}$
$\qquad$ + $\quad$ $P_d\{A_3\}$ $P_d\{B_3\}$ - $P_d\{A_2\}$ $P_d\{B_2\}$ $P_d\{C_2\}$ $\qquad\qquad$ [detection]

System P_{fa} = $P_{fa}\{A_1\}$ $P_{fa}\{B_1\}$ $P_{fa}\{C_1\}$ + $P_{fa}\{A_2\}$ $P_{fa}\{C_2\}$ + $P_{fa}\{B_2\}$ $P_{fa}\{C_2\}$
$\qquad$ + $\quad$ $P_{fa}\{A_3\}$ $P_{fa}\{B_3\}$ - $P_{fa}\{A_2\}$ $P_{fa}\{B_2\}$ $P_{fa}\{C_2\}$ $\qquad\qquad$ [false alarm]

When detection probabilities are not independent of each other, we use the nested sensor confidence levels. These are represented pictorially by Figure 3-3
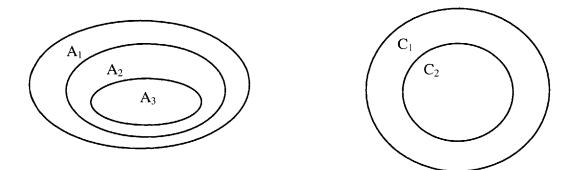
Figure 3-3 Nested Confidence levels

where the confidence levels are embedded or dependent on each other. The union and null intersection rules do not apply in this situation so that the areas of overlap need to be discounted.

This results in the following equation,

$$\text{System } P_d = P_d\{A_1\}\, P_d\{B_1\}\, P_d\{C_1\} + P_d\{A_2\}\, P_d\{C_2\} + P_d\{B_2\}\, P_d\{C_2\}$$
$$+ \quad P_d\{A_3\}\, P_d\{B_3\} - P_d\{A_2\}\, P_d\{B_1\}\, P_d\{C_2\}$$
$$- \quad P_d\{A_1\}\, P_d\{B_2\}\, P_d\{C_2\} - P_d\{A_3\}\, P_d\{B_3\}\, P_d\{C_1\}.$$

[detection]

Similarly,

$$\text{System } P_{fa} = P_{fa}\{A_1\}\, P_{fa}\{B_1\}\, P_{fa}\{C_1\} + P_{fa}\{A_2\}\, P_{fa}\{C_2\} + P_{fa}\{B_2\}\, P_{fa}\{C_2\}$$
$$+ \quad P_{fa}\{A_3\}\, P_{fa}\{B_3\} - P_{fa}\{A_2\}\, P_{fa}\{B_1\}\, P_{fa}\{C_2\}$$
$$- \quad P_{fa}\{A_1\}\, P_{fa}\{B_2\}\, P_{fa}\{C_2\} - P_{fa}\{A_3\}\, P_{fa}\{B_3\}\, P_{fa}\{C_1\}$$

[false alarm]

By plugging in terms for A_1-A_3, B_1-B_3, and C_1-C_3, we can see that nested confidence levels results in a lower probability of detection and false alarm rate than non-nested confidence intervals.

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CHAPTER 4: MODEL OF A C⁴ISR SYSTEM

4.1 Scenario Profile

The Command, Control, Communications and Computers paradigm of a (C^4ISR) system present a variety of fusion challenges for the system engineer. The high-level system functions can be broken down as follows (Waltz & Llinas, 1990):

- Sensing: Methods used to search, acquire, identify, and track targets including one's own and opposing forces
- Communications: The links between one's own forces to communicate the location and status of each other's forces as well as the transmission of sensor and intelligence data
- Processing: The fusion of sensor and source data to create an accurate assessment of the combat environment in real time.
- Commanding: The assessment of the possible meanings of the situation.
- Controlling: The development and dissemination of the tasking orders under control.

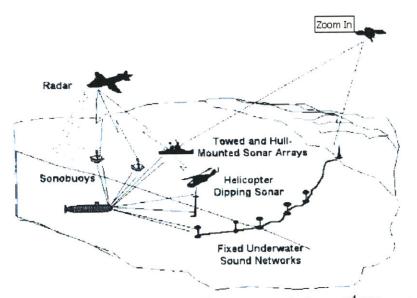One such specific application is in Figure 4-1, an ocean surveillance system (Hall, 1997).

Figure 4-1 Ocean Surveillance scenario for a C⁴ISR system

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4.2 System Concept

The mission of an ocean surveillance system is to protect, defend and warn against future threats and scenarios. The system above uses multiple sensor platforms (hull-mount and dipping sonar, airborne radar etc.) to act upon primary observable data, such as EM signals, acoustics signals, or derived observations (wakes) over a predetermined surveillance volume. The system concept for ocean surveillance is presented in Figure 4-2, and it follows the generic, analytic model. The architecture is constructed from position/entity nodes in a search volume, and value is delivered in the form of a threat analysis.
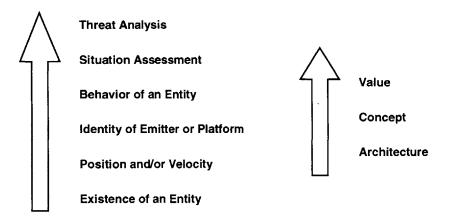
Threat Analysis

Situation Assessment

Behavior of an Entity

Identity of Emitter or Platform

Position and/or Velocity

Existence of an Entity

Value

Concept

Architecture

Figure 4-2 Inference hierarchies: Specific and generic models

The C^4ISR system was chosen because it provides a powerful framework for not only analyzing the fusion objective but also all other intermediate processing and ancillary functions, i.e. level 1 through level 3 (Refer to Table 1-2). These correspond to alignment, association, correlation, classification, situation and threat assessment.

4.3 Mission-level Decomposition

Decomposition, according to Crawley (2005) is the division of things. In this section, we conduct form- and process-level decomposition in order to zoom in on various sensor families as a function of the anti-submarine warfare mission.
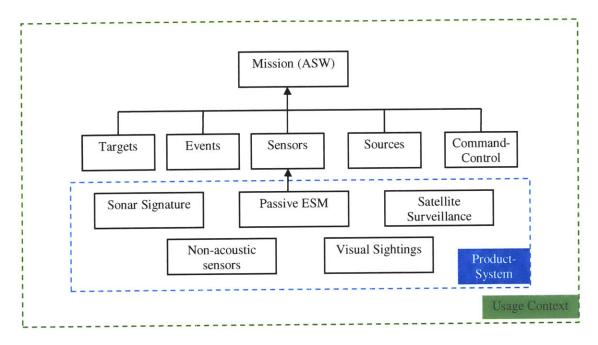

Figure 4-3 The Place of Sensors in ASW

The advantage of hierarchically decomposing a system, Figure 4-3, is that it aggregates various elements of the mission in an understandable way (i.e., it sets the usage context). Inherent complexity in this system is borne from the fact that the sensors are spatially distributed and may not process data in a known operational sequence. We need, therefore, to further evaluate this structure to take into account specific discriminating categories that may, among other things, highlight the sensor data effects timeline. Object-Process Methodology can help us with such a transformation.

4.4 Object-Process Modeling of the ASW Mission

We begin by documenting the functionality of the system architecture. Let us reorder the core processes outlined in Section 4.1 to deliver some sense of parallelism with the JDL model. In Figure 4-4, boxes constitute both human and physical objects whereas ovals define the processes. The text inside each of the boxes is known as a command sentence and the level of functionality is derived from a host of sensor output categories.
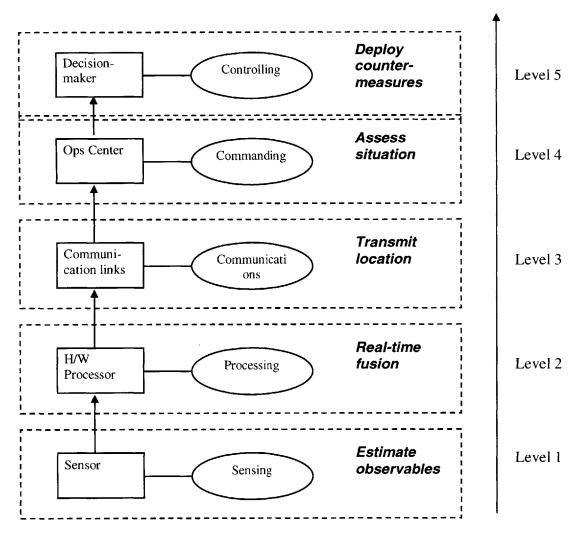

Figure 4-4 Function hierarchy

Structural relations of the observables.

The breadth of targets and events which arise in the C4ISR scenario can be modeled based on the principle of exhibition-characterization, one of 4 fundamental OPM structural relation links. Hall has developed 3 levels of discrimination, based on the following set of attributes:
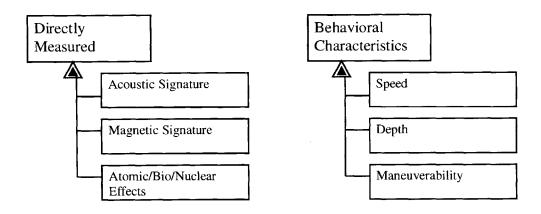

Figure 4-5 Attribute Representation in OPM

Finally, the third discrimination category which can be added to Figure 4-5 is contextual information, related to the origin of the mission, and its locations.

A typical antisubmarine warfare mission (ASW) is comprised of a battle group commander, a surveillance volume of 2000 x 2000 km, 4 surveillance aircraft, 12 ASW ships and 2 ASW submarines. The maximum targets in track are between 100-200, and the number of reports/minute, between 1,000-5,000. This translates to 1-5 C2 decisions/minute. The non-commensurate data is compiled from the multitude of active and passive sensor systems being deployed by land-based surveillance centers, (sub) surface platforms and patrolling aircraft. The detection and monitoring activity is occurring within an integrated air-land-ocean environment.

The concept of a triggering event in OPM is one that initiates some type of process in a system. In ASW, let us consider this event to be a surface activity or torpedo launch. Upon detection of an enemy launch, there is uncertainty about the processing state of the torpedo which needs to be resolved. The fixed underwater sonar network will report transgression of the torpedo along its wake, but only after that trigger event has occurred. Through the fusion nodes, this can trigger a state of engagement, or awareness, and cue up anti-submarine systems along the outer ocean periphery. Depending on the frequency of the tracks, the ASW contingent will be able to respond through appropriate countermeasures prior to the torpedo exit event (target kill). The rapidity of response will not only be a function of the target mobility and velocity; it is very much dependent on the synchronization of fusion nodes in the sensor network. The use of real-time object and process links in OPM can help simply the requirements for an ASW scenario design.

Multi-sensor systems have supported the automation of data fusion processes through multi-spectral methods such as Radio Frequency (RF), infrared (IR) and electro-optical (EO) emissions and reflections (Waltz and Llinas, 1990). This automation is further enabled by the deployment of theatre-wide data links and networks which support intra-sensor cueing, and hand-off, as well as the exchange of target detection tracks for cross-correlation and association. Finally, the redundant and complementary use of low-observable weapons such as passive ESM, IR, and EO sensors has provided automation advantages over active single sensor systems such as Active Electronically-Steered Array (AESA) radars.

4.5 Integration

Integration, or fusion, of the observables toward some stakeholder objective is the next step and a main driver of complexity in the system. Integration is more than a mathematical combining of state and feature vectors. It refers to the broader assemblage of hardware and software components which need to function cohesively in order to deliver value. The risk in this process is that integration might not enhance but could actually reduce the quality of the fused data. Processing by non-commensurate sensors needs to be carefully managed in order to prevent the emergence of inferior data that cannot be adequately utilized. We have presented Bayesian methods in Chapter 3 to show that this approach enables non-commensurate processing for event prediction and detection.

The notion of timing features highly among the design specifications of a fusion system. Time can be analyzed along multiple dimensions – the sampling rate of sensor, as listed above, the alignment- or registration- with other sensors, and delays due to data filtering.

Registration refers to the process of making sensors commensurate in both spatial and temporal dimensions, which means that measurements correspond to data from the same location and time period. Geometrical transformation is one of many methods used to make sensor output commensurate. When this does not occur, the system may revert to separate operation of the sensors, or enact a guiding or cueing type of sensory processing function. The example often cited is that of a vision-sensor which helps to guide the movement of a tactile array at the end of manipulators (Luo and Kay, 1990).

Filtering, or smoothing, is used to increase the signal-to-noise ratio. According to the

matching filter theorem, the filter that gives the optimum resolution of a signal from

noise is a filter that is matched to the signal.

Finally, modular system design eases the integration challenge through distributed

processing of sensors across a system. Distributed and smart sensors help to create

standardized digital interfaces that can be easily adapted to requirements of a branch or

field network. In this scheme, smart sensors are effectively plugged into nodes along a

device network based on the sensory processing requirements.

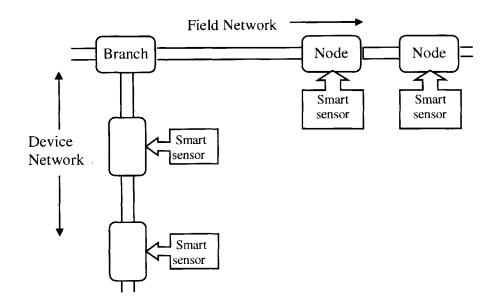**Figure 4-6 Network Integration of Smart Sensors (Kester, 1998)**

The C^4ISR example presented in this chapter illustrates some of the key issues

facing the fusion system designer. The high-level system functions were synthesized into

a unified concept for an anti-submarine warfare mission. This was then decomposed by

form and function into constituent parts according to the product-system and overall

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usage context. Core operations were matched to the JDL hierarchy for information fusion and elaborated on using definitions from Object-Process methodology. The final step in the system analysis involved re-integration of both the data and physical processes which constituted the model. Sensor registration, filtering and integration across distributed or wireless networks are becoming important design issues as C^4ISR systems increase in both scale and complexity.

CHAPTER 5: FUSION AND THE SEMANTIC WEB

5.1 Motivation

An ontology is a "specification of a conceptualization." (Gruber, 2000). It is a

description, often a program, of conceptual and relational links that exist between an

agent and community of agents. In practical terms, an ontology can therefore help to

specify various levels of knowledge representation – and therefore knowledge sharing –

in complex information systems where data fusion occurs. Promoting a common

understanding of domain helps to facilitate interoperability among disparate information

sources. Ontologies can range from controlled vocabularies to highly expressive

domain models, integrated data dictionaries, structured data models and computational

models (Bourey-Brisset, 2003). The interest in ontological engineering has increased due

to the need for improved knowledge management, organization, electronic commerce and

informational retrieval and extraction (Pinto & Martins, 2004). These attributes feature

highly in both intelligent transportation systems as well as supply chain management.

5.2 Ontologies and the Semantic Web

Van Heist (1997) and Guarino (1998) identify three general classes of ontologies based on existing frameworks:

- **Representation**- defining class, instance, superclass [Frame ontology]
- **General or Upper Level**- defining general concepts that are reusable across domains such as a time, time point, time interval, time overlap [Time ontology]
- **Domain**- defining concepts from a specific subject area, such as chemistry, which lays out classes of reactive chemical elements, and the electronic configuration of each chemical element (Chemical-Element Ontology]

The complexity of developing an ontology is based on the need to be both specific enough for particular applications while offering the representational breadth that can reach multiple disciplines.

The Semantic Web, in the words of Tim Berners Lee (Chair, Worldwide Web Consortium) is the application of weblike design to data. "Its structure will foster environments where software agents roam from page to page to readily carry out sophisticated tasks for users."[7] The Semantic web adds identification tags to information and then links them so that computers can discover data more efficiently and form new associations. In his "stack of specifications" Berners-Lee talks about three stages of evolution in the identifiers which are used for concepts: 1) numbers or strings, 2) Universal Resource Identifiers (URIs) – identify the same thing in all contexts, and 3) dereferencable URIs.

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[7] Retrieved from Scientific American.com, 2001

What does this evolution mean for the data which gets generated in a complex C^4ISR system as described in Chapter 4? Firstly, it highlights the inadequacy of single sensor systems that might only call on binary vector string data (for instance IFFN sensors). Indeed, the profile of missions is increasingly complicated with multi-objective, multi-source data that needs to be interwoven in context, behavioral and directly measured features (Table 5-1).

Discriminating Categories	ASW Mission
Directly Measure Features	• Acoustic signatures, • Magnetic signatures, • Diesel fume spectra, • Bio-nuclear effects
Behavioral Characteristics	• Speed • Sustained speed • Depth • Maneuverability • Hostile act
Contextual Information	• Origin of mission • Location relative to friendly vessels

Table 5-1 Target Discrimination Attributes

Secondly, URI protocols enable new applications to be defined so that friendly source data can be received and integrated to an allocated domain space. Finally, the third stage of concept evolution in the Semantic Web relates to the notion of metadata processing. That is, an automated agent can pick up data "on the fly" and then use that metadata to enhance processing in a specific ontology. The machine analogy made by Berners-Lee is applicable here; if there is a semantic 'web machine', then it is a proof validator, not a

theorem prover. For instance, sensor data should be validated using a combination of a priori and posterior data to validate observations, not to prove particular theories.

5.3 The Ontological Lifecycle

The development of ontology follows an evolving prototype lifecycle, Figure 5-1 (Martins and Pinto, 2004). It requires constant iteration within and between the fundamental steps in development: namely, specification, conceptualization, formalization, implementation and maintenance. The evolving lifecycle for ontology is different from the sequential waterfall approach or the a priori planning in iterative development. It is inherently more flexible by allowing the designer to return to any component at any point in time. But because there is no predetermined metric of quality, it is more all the more challenging to ascertain when the ontology is complete.
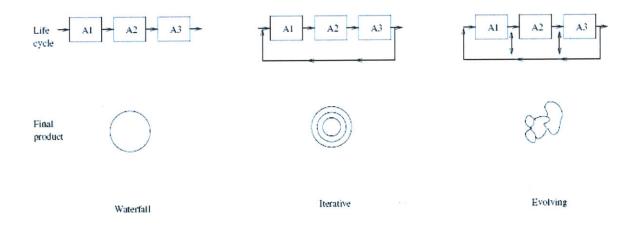

Figure 5-1 Lifecycle Development Models

Ontologies must confer both structure and flexibility in order for the Semantic Web to function. They can be used to enhance web searches, based on precise rather than

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ambiguous concepts. But they also must tailor to the decentralized nature of the web and web services. For this arrangement to work, we propose that a knowledge representation system has a degree of hierarchy to it. The syntactic problems have begun to be addressed in developing the web through Semantic Web Language (SWL). Formal ontologies and models for their development can play an important role in resolving the semantic issues, i.e., giving names to the basic concepts of the data and writing rules to take advantage of their connections. In managing this process, the source ontologies require periodic updating in order to refresh the cycle of evolution which takes place.

Automatic Target Recognition (ATR) from the C^4ISR example from Chapter 4 offers an opportunity for testing this ontology development model (Waltz and Llinas, 1990). The formalization process was completed with a system concept description. The implementation of the ontology requires some formal knowledge representation scheme, in this case the OWL Web Ontology language.

Classes

    Database Classification:

        ➤ **Syntactic: pattern grammar structures that relate target features in time, space or spectrum**

        ➤ **Parametric: probability distributions for each (sub)class**

        ➤ **Non-Parametric: vector coordinates of each (sub)class in feature space for computation of distance to each target feature vector**

        ➤ **Distribution-free: non-statistical discriminant functions that partition feature space into class regions.**

    Processes

        ➤ **Preprocessing: removal, reduction of noise, bias, gain and geometric distortions**

        ➤ **Detection: computational reduction of candidate targets using criteria such as contrast relative to background, intensity, closed boundary, shape, size**

        ➤ **Segmentation: boundary identification and target extraction**

        ➤ **Feature Extraction: feature characterization from picture element segmentation**

> Classification:
  o non-statistical partitioning of feature space into decision regions
  o statistical (parametric) methods
  o syntactic classifiers parse components of target class using grammatical techniques
> Contextual and High-level Classification
  o Global classification for relationships within scene
  o Temporal classification for changes recognized by successive sensor frames
  o Knowledge-based classification to reinforce global and local scene data

Attributes
  Product-System
    > Sonar signature
    > Passive ESM
    > Satellite surveillance
    > Non-acoustic sensors
    > Visual sightings

Figure 5-2 OWL Ontology for C^4ISR Mission

Figure 5-2 lays the foundation for ontology of a complex ASW mission with Automatic Target Recognition processing. Like the OWL language, it subdivides the mission into classes, subclasses and properties that have restrictive elements or attributes. For instance, reduction occurs in both pre-processing and detection, but these classes co-exist within a very different set of criteria. This is one of the outcomes of an effective ontology- to define the elements of a complex system or domain without overlapping intent or meaning.

5.4 Fusion as a Reuse Process

Ontology re-use is a common way to propagate the knowledge gained in various fields without having to "reinvent the wheel." There are two commonly accepted modes of

reuse in ontological engineering: fusion/merging and composition/integration (Martins

and Pinto, 2004). In fusion re-use, the ontology is built by bringing together knowledge

from different source ontologies from the same subject. These are not revisions or

improvements but rather unique ontologies that have been developed from similar subject

material. In composition/integration, ontologies are built through assembling source

modules from various subjects. This is appropriate when ontologies have gone through

extensive modification, adaptation or specialization over time.

Lucien Wald (1999) has developed terms of reference in data fusion that can be

repurposed toward various fusion ontologies. Wald derives most of his terms from the

remote sensing and defense system applications, but we will demonstrate their extension

to other fields through domain, goal-based and mathematical reasoning. The following

Object-Process diagram is an explicit representation of the semantic decomposition of

these terms for generalized fusion. Its overarching premise is the treatment and origins of

raw information, which can take several forms, from measurement and signal to

observations and verbal reports. The code in Figure 5-3 demonstrates the relation links

that constitute the OPD of Figure 5-4.

→	• "Is a". is the same as
→	• A code. surrogate. address of symbol for
▲	•Decomposes to. aggregates to
⚠	•Is characterized by. exhibits
△	•Specializes to. generalizes to
⚠	•Instantiated to. belongs to the class of

Figure 5-3 Relational links in OPM

Although fusion is the central process in this diagram, it is helpful to include aspects of the supporting system, as well as supporting processes, which act on the information. It is worth noting that there are many types of raw information which can be refined over various processes and environments. The hardware elements of the supporting system have been simplified to represent a simple sensor arrangement. In reality, complex fusion systems are comprised of multiple, distributed platforms with thousands of apertures and waveforms. Similarly, there are many more supporting processes which enable data fusion; these hierarchical classification schemes will be discussed later.
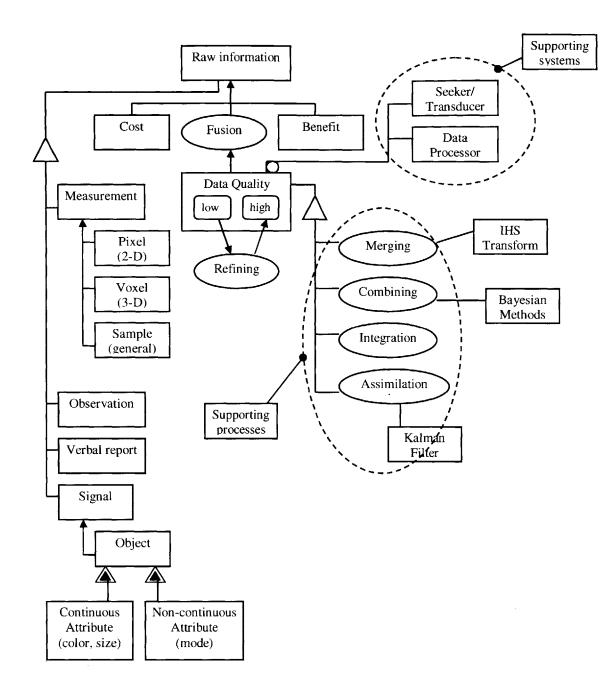
Figure 5-4 Object-Process Diagram for Information Fusion

5.5 Parallelism and Other Taxonomies

Rule-based analytics in knowledge-based systems (KBS) have benefited tremendously from the advent of parallel computers. For instance, the rules highlighted in Figure 5-4 under supporting processes can be subjected to rule-level partitioning, where classes such as correlation, combination or association rules are generated.

Class-based rule partitioning forms another aspect of ontology development, namely one based on fusion algorithm. Whereas the Object-Process Diagram above took an information-based approach to ontology design, the class methods utilize a hierarchical scheme which imparts a specific decompositional logic, or organization. Hall develops taxonomy for level 1 processing that is extensible to other levels of fusion. This is derived from algorithms- both statistical and heuristic- which are based on level 1 fusion, object identification. Level 1 is specialized into 3 classes: positional, identity and ancillary support algorithms. These are further decomposed by technique or method. Positional fusion, for instance, involves parametric association and estimation of data. Identity fusion uses physical models, cognitive models and feature-based inference. Ancillary support systems, which often comprise more than 80% of the fusion effort, include numerical libraries, data alignment, preprocessing, database management and man/machine interfaces. These are only one instance of a larger class of items.

The following taxonomy of identity-classification algorithms was developed (Waltz and Llinas, 1990) and incorporates techniques described in Chapter 3, as well as other methods.
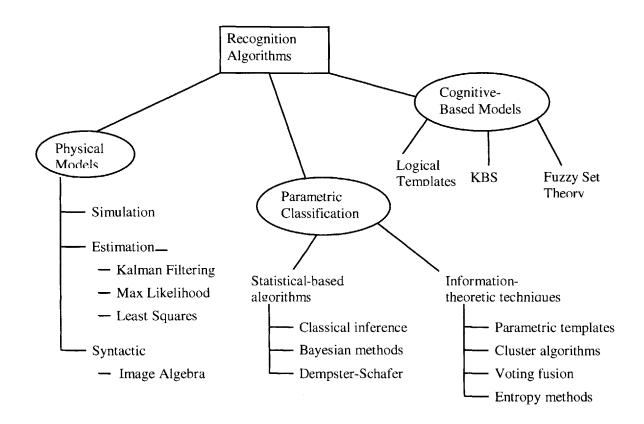
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**Figure 5-5 Class-Based Ontology for
Identity Classification Algorithms**

The purpose of Figure 5-5 is not to delve into the particular implementation aspects of

specific fusion algorithms, but rather to show another way in which ontology can be

constructed and indexed in the Semantic Web. A portion of the Semantic Web reference

card is given in Figure 5-6.

Figure 5-6 Classes in the OWL Ontology

Finally, parallelism can play an important role in developing ontology for semantic networks. MacRae and Byrne (1987) studied the use of connectionist parallel architectures for real-time data fusion applications for the Royal Navy. Their architecture uses objects and relationship links as in OPM, but takes on a very different representation scheme. Objects are identified by nodes and connected via links of inheritance. Sensor data is processed at local active node centers, and then propagated along to parallel nodes as further attribute data is generated. Figure 5-7 is the layout of connectionist architecture from MacRae's research.
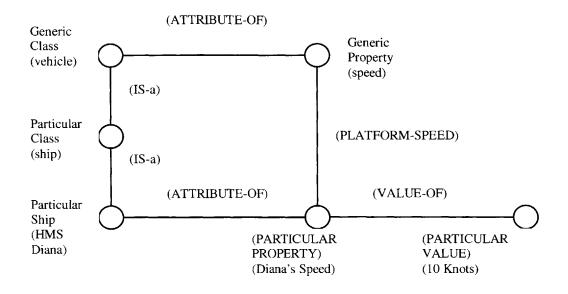
Figure 5-7 Semantic Network Example

The semantic network example above illustrates the potential of ontology-based fusion

for the Semantic web. Like the wireless reconfigurable hardware platform developed at

Dartmouth (see Figure 2-4(a), Chapter 2), a web-based semantic network can enable

sensor networks to be "dynamically discovered, composed and integrated with distributed

fusion services" to support new and challenging missions. An easily evolvable ontology

will be a key facet to support rapid propagation of sensor data through the Semantic Web

value chain, from source providers to end users.

CHAPTER 6: SYSTEM ENGINEERING FOR DATA FUSION

6.1 Implementation Challenges

Information quality and assurance discussed in the previous chapter are two elements of the lifecycle which drives system design. The Electronic Industries Association / Interim Standard 632 (EIA/IS 632) lifecycle in Figure 6-1 builds on the progression from requirements and functional analysis to form allocation and synthesis. The lifetime is indeed a function of the system architecture. In single sensor systems, it may be driven by the dominant material and physical constraints, whereas multi-sensor nodes are more likely to factor in attributes of the larger network in which they reside.

What drives the design of C^4ISR? This is best understood in terms of mission-level requirements, a key component in systems engineering methodology.

Requirements Analysis
Analyze Markets & Environments
Identify Functional Requirements
Define / Refine Performance
Design Constraint Requirements

Requirements Loop

Functional Analysis / Allocation
Decompose to lower level functions
Allocate performance to lower levels
Define / Refine functional interfaces
Define / Refine / Integrate functional

Design Loop

Synthesis
Transform architecture (functional to physical)
Define configuration items & elements
Define / Refine Physical Interfaces
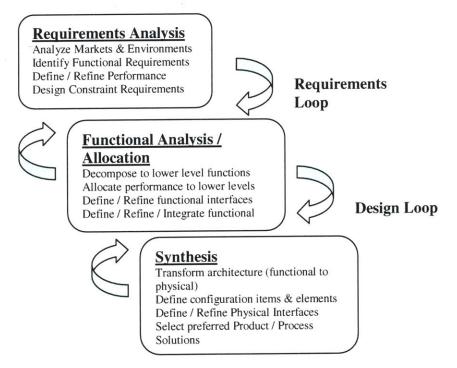Select preferred Product / Process Solutions

Figure 6-1 EIA/IS 632 System Lifecycle Standards

The requirements loop. The market for C⁴ISR has been evolving since the Second

World War. Projected 2010 spending is $29.01 billion, with a base year U.S. C⁴ISR

budget of $19.03 billion. These segments can be roughly broken up as follows:
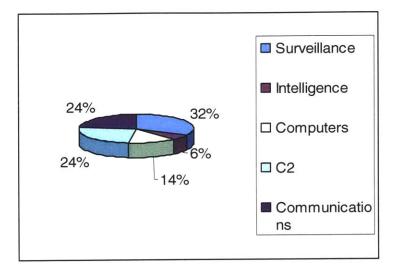
Figure 6-2 DoD C⁴ISR Segment Funding (Frost & Sullivan, 2004)

Some of the major constraints in this first loop (for current operations) include a

congressional shift from technology to protection of troops, a prevalence of immature

technologies and the trend toward joint projects with more requirements.

Among the many challenges in data fusion, there are two which can be addressed by the

systems framework highlighted above. The first is the basis for selection of mathematical

techniques. This process must take into account the perspectives of various system

stakeholders, including the user, numerical analyst, operations researcher and system

engineer. The specific algorithms available include association methods, positional

estimation (Kalman filtering), identity fusion (templating, voting, D-S methods, classical

Bayesian inference) and pattern recognition techniques (adaptive neural nets and cluster

methods), (Klein, 1999). Another challenge is the provisioning of data, a priori.

Increasingly, this requires the need for experiential models of cognition and situational

assessment in order for the fusion system to provide accurate and meaningful results.

The partitioning of data fusion into two problem domains is a reflection of this evolving

requirement for cognitive models. The first domain is based on whether any given entity

– signals, physical objects, aggregates or structures- are of interest in its attributes,

characteristics or behavior. The second domain is based on the assemblage of

components whose 'interrelations' are of interest, where the targets themselves are such

situations. This most closely relates to Level 2 data fusion concerning the implications

context.

Cognitive models for situation assessment can have an indeterminate number of

entities, depending on the reasoning of the agents. According to Situation Theory,

abstract situations, or infons, are represented by the form

$$(P, x_1, \ldots, x_n, h, k, p)$$

Where P is an m-place relation ($m \geq n$);

            $x_1, \ldots, x_n$ are entities;

            h and k are a location and time (which may be points or an

                       extended region;

            p is a polarity, or truth-value.

Real and abstract situations can be distinguished by their polarity. A real situation is a set

of facts with polarity equal to 1 (Bowman, 2004). Figure 6-3 illustrates Bowman's

cognitive model for a perceptual reasoning machine (PRM), based on the concept of

reinforcement learning.
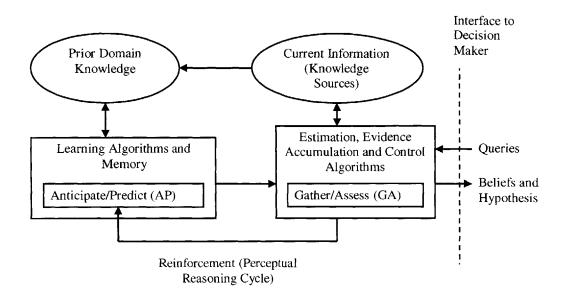
**Figure 6-3 Perceptual Reasoning Machine (PRM)
for Cognition & Situational Awareness**

The closed loop PRM provides situational feedback to a human perceptual system which optimizes the decision-making process. This is viewed as a "meta-level" information management system for resource control that continuously updates domain knowledge as it is acquired.

The implementation challenges related to data fusion are often specific to the platform on which the system is integrated. Some of the many platforms choices include satellites, manned aircraft, unmanned vehicles, surface ships, submarines, fixed land systems, mobile land systems and man-pack systems. These systems are driven by their own physical and information constraints and therefore need to be accommodated for in this manner. In any functional analysis of a given platform, due consideration need be given to the lowest-level notions of form and objective.

Calibration
Corrections

Optics
and
Detectors

Gain
Compensati
on,
A/D
conversion

Signal
Processing
-Adaptive
Thresholding-
Spatial/Tempo
ral filtering

Automatic
Target
Recognition
-2D Feature
Extraction
-Classification
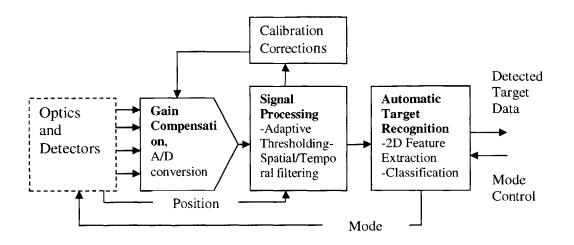
Detected
Target
Data

Mode
Control

Position

Mode

Figure 6-4 IR Sensor, Functional Decomposition

The system above has been decomposed to the lower-level, base functions such as gain compensation, signal processing and automatic target recognition, per the design loop of Figure 6-4. This type of analysis offers the advantage of allocating function at the sub-system level, where performance can be more directly measured.

Test and evaluation (T&E) is a key element of the implementation process. Along with simulation, it offers the designer a reduction of costs compared to military exercises, flight test programs and operational evaluations. Furthermore, it enhances overall security (data is analyzed in a controlled environment). Hall and Llinas (1997) have constructed a framework for Test & Evaluation which prioritizes roles based on pertinent mission, function, platforms, geographies and customer organizations. This model is further refined by evaluating how fusion performs over the platform "space," i.e. from single-platforms to multi-platforms, under highly-controlled, loosely managed and fully autonomous scenarios.

6.2 Process Selection: Comparing Fusion Levels

Table 6-1 (adapted from Luo and Kay, 1990), sets forth criteria that can be used in selecting a fusion level for a given application. These characteristics form part of the selection process that can be used in screening for an appropriate concept. The table is divided among four levels of data that approximately correspond to the JDL fusion levels. The criteria are based on the type of sensory information being generated -individual signals, images, features, etc. The table goes on to characterize the content of such information. The degree and means of registration are also important factors, as the spatial position of sensors determines their ultimate footprint and target-detection space. Overlapping footprints ensure that time-dependent phenomena such as a target motion are observed by all sensors at the same time. The criteria in Table 6-1 can then be used to select the type of architecture which factor into the fusion system design, i.e., central or sensor-level processing. The main difference between these two is that the former processes sensor reports directly, and in one place, requiring a more complex fusion processor. This helps to achieve better accuracy when the multi-sensor data is not generated by independent phenomena. Sensor-level fusion is preferred when the signatures are independent. There is more cueing of sensors with others in the suite, where the optimization of each sensor's signal is specific to the transducer design. Since discrimination among targets occurs locally, before data entry, it reduces the load on the fusion processor (Klein, 1999).

The next step in concept selection is known as the down-select phase. During down-select, potential applications are screened according to their "fit" with the JDL processing criteria. This method was developed by Stuart Pugh in the 1980's and helps

design teams to decide on optimal strategies for their product goals. A Pugh concept

selection matrix is provided in the Appendix. It ranks applications based on the

processing requirements of the data.

Characteristics	Signal Level	Pixel Level	Feature Level	Symbol Level
Type of Sensory information	Single or multi-dimensional signals	Multiple images	Features extracted from signals and images	Symbol representing decision
Representation level of information	Low	Low to Medium	Medium	High
Model of sensory information	Random variable corrupted by uncorrelated noise	Stochastic process on image or pixels with multidimensional attributes	Non-invariant geometrical form, orientation, position and temporal extent of features	Symbol with associated uncertainty measure
Degree of registration				
• *Spatial*	High	High	Medium	Low
• *Temporal*	High	Medium	Medium	Low
Means of registration				
• *Spatial*	Sensor co-alignment	Sensor co-alignment or shared optics	Geometrical transformations	Spatial attributes of symbol Temporal attributes
• *Temporal*	Synchronization or estimation	Synchronization	Synchronization	
Fusion method	Signal estimation	Image estimation or pixel attribute combination	Geometrical and temporal correspondence, and feature attribute combination	Logical and statistical inference
Improvement due to fusion	Reduction in expected variance	Increase in performance of image processing tasks	Reduced processing, increased feature measurement accuracy, and value of additional features	Increase in truth or probability values
Type of Architecture	Central-level fusion	Central-level fusion	Central-level or sensor-level (decentralized)	Hybrid-level fusion (combines both central and decentralized)

Table 6-1 Comparison of Various Fusion Levels

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6.3 Tracker-Correlator Architectures

There are currently 3 general synthetic architectures for data processing which

exist today, centralized, decentralized (autonomous) and hybrid architectures. Refer to

Figures 6-5 through 6-7, (Hall and Llinas, 1997).

A. CENTRALIZED FUSION
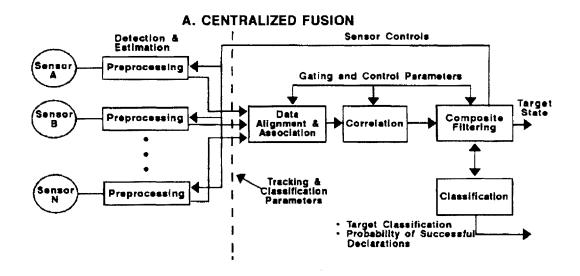
Figure 6-5 Centralized Fusion Architecture

The advanced combat direction system (ACDS) is an example of the centralized fusion

architecture (Waltz and Llinas, 1990). The system has external interfaces with existing

sensors which maintain different reporting protocols and data links. Acoustic, IFF, ESM

and Radar send sensor-level tracks and target reports to the track management processor

(indicated by the dashed line in Figure 6-5). These reports are fed into the ACDS

database which contains tactical status, intelligence, maps, doctrine and tracks. Each

track-to-track association or identification from the arrival of new observations requires

retrieval of the data from a central decision support processor (not shown).

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The common thread underlying these location-driven architectures is the notion of a progressive data flow from sensor set (A, B...N) through detection, classification and end-state. Under the centralized scheme, the preprocessed output is collected into the data alignment / association through coordination transformation. Raw data from a multi-target environment is correlated and then transmitted to the central processing facility. A variant of this type of fusion is centralized fusion of feature vector data. This construct drives ambiguity out of the system by extracting feature vectors from an image. The feature-based method is one of many types of approaches to the object recognition problem.

In autonomous or decentralized fusion architecture, Figure 6-6, individual tracking and classification functions are assigned to each sensor output.

B. AUTONOMOUS FUSION

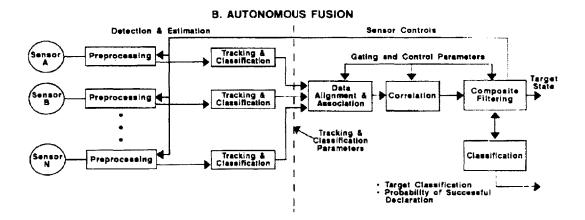**Figure 6-6 Decentralized Fusion Architecture**

This effectively removes the fusion process (the track management processor) further downstream. Rather than performing sequential estimation at the *data* level (as in the centralized case), this architecture provides *state* vector estimation of position and velocity for an object. Although they cull from single-source data, decentralized systems

tend to degrade the output because there is information loss between the sensor and fusion process. An example of a decentralized system is a robot navigation system that can autonomously navigate through a continuous state-space through selective switching between sensors, actuators and their effectors (legs, wheels, joints and grippers). Intelligent agents such as robots might be designed factoring some goal-state into its decentralized architecture.

The third generic tracker / correlator architecture is a hybrid system, Figure 6-7, which combines state-vector and data-level fusion processes. This confers more flexibility than the previous two cases but imposes a switching cost. For instance, a dense target environment or complex signal propagation may require centralized fusion for a more accurate assessment of identity. The availability of sensors may constrain the user to select autonomous fusion; any changeover between the two will impose selection and monitoring costs, as well as communication requirements which need to be carefully weighed against the expected benefit. In the domain of robotic software architectures, the hybrid tracker/correlator would be used to combine elements of reactive and deliberate control. Reactive control refers to sensor-driven control that may be used for low-level decision making processes, whereas deliberate (path planning) control refers to global, executive decision-making. Both are necessary for the operation of unmanned land or air vehicles as well as planetary rovers (Russell & Norvig, 2003).
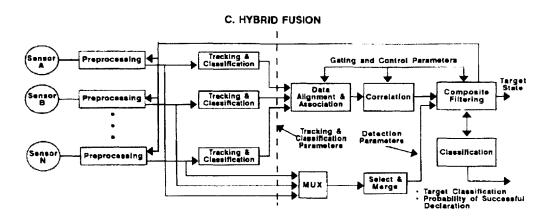
C. HYBRID FUSION

Figure 6-7 Hybrid Fusion Architecture

What makes these three architectures unique? Firstly, they can be considered ontologies of function. That is, these three arrangements represent a taxonomy of tracker-correlator functions. In the language of OPM, the operand in these architectures are the raw data or measurement sets (centralized fusion), locally fused data (track file, or decentralized approach) and raw/preprocessed data (hybrid approach).

The advantages of the three architectures are summarized below (Waltz and Llinas, 1990). Centralized fusion requires high bandwidth buses to pass the high-rate raw data and powerful central processing capability. The autonomous approach tailors the track and classification functions to individual sensor outputs, at the expense of an accurate position estimate. Finally, the hybrid approach selectively transitions between the central and autonomous processes as the situation requires.
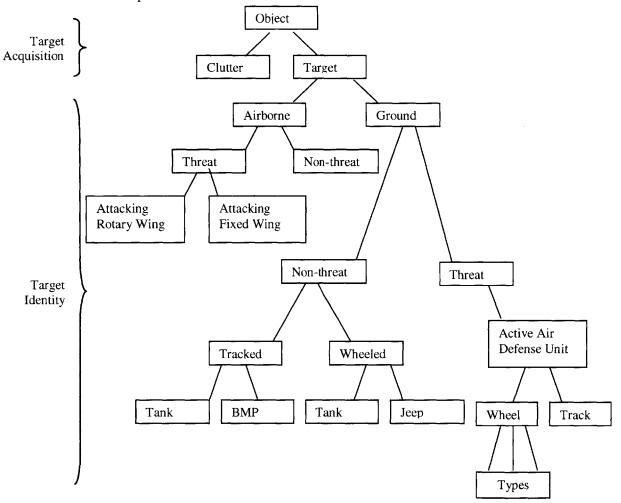
Real world architectures are designed to incorporate more than just the tracker-correlator aspect highlighted above, which represents only 20% of the software development effort for a fusion system, based on lines of code as a metric (Waltz & Llinas, 1990). Other

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representations exist for the identity component of Level 1 fusion. Levels 2 and 3 fusion

adopt, among others, the blackboard approach described in the following section.

Finally, Level 4 fusion models functions pertaining to communication, database

management, human factors and executive control.

6.4 Hierarchical Architectures

A blackboard description of an object hierarchy is an excellent model for building

semantic knowledge databases and networks. Categories are the building blocks of any

large scale knowledge representation scheme (Russell & Norvig, 2003). The blackboard

adaptation in Figure 6-8 (Waltz and Llinas, 1990) illustrates the potential precursor to a

semantic network for target identification.

The blackboard approach uses categorical reasoning to relay the notion of

inheritance and parallelism.

Figure 6-8 Blackboard Processing Architecture

The blackboard approach presents L2 (Situation) or L3 (Threat) assessments for an air-land battle. It confers flexibility to the designer through static and dynamic representation models that are based on independent, modular knowledge sources. As rule-based expert systems, they are a useful construct for exploratory research and incremental development of a problem. Finally, hierarchical decompositions help deal with the problem of complexity in mission design by reducing the number of activities through progressive levels of detail. Object-oriented representations in action decomposition are stored in plan libraries- or databases- that can be accessed to fit the needs of the mission. However, hierarchical methods such as blackboard architectures do not always decompose problems correctly. In artificial intelligence (AI), the inability to capture everything in a set of logical rules is known as the qualification problem (Russell and Norvig, 2003). Consequently, blackboard architectures can be expensive to build, modify and operate.

6.5 Applications

Command, Control, Communications, Computers and Intelligence Surveillance & Reconnaissance systems (C^4ISR) provide mature, highly evolved examples of data fusion, but they are not the only systems which make use of data fusion concepts. The objective of a C^4ISR system is to provide a comprehensive view of the tactical and strategic battle space through a variety of technology- and intelligence-based media. The systems are composed of software, hardware and human elements which work in concert to support decision-making processes. Fulfillment of C^4ISR objectives draws heavily on the utilization of sensor data. Increasingly, fusion design needs to account for the transition from platform-based systems to network-centric operations.

Sense & Respond is an emerging domain in military and commercial logistics with powerful implications for the fusion paradigm. It is a managerial framework that was originally proposed by researchers at IBM (Lin *et al*, 2005), based on the dynamic of change in business, security and technology. It is comprised of a "value net" of self-synchronizing partnerships which form and dissolve to adapt to demands in the environment. Elements of this value net have been evolved, specifically the triumvirate known as operational, logistics and intelligence command, for military and defense scenarios. SRL almost mirrors the data fusion process itself, by observing patterns, detecting issues, and performing root-cause analysis.

Finally, data fusion in robotics plays an important role in factory automation processes, such as material handling, part fabrication and assembly. This can appear in the form of cooperative systems, dexterous hands, and tele-operation for mining and manufacturing.

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Biometrics offers interesting case applications of data fusion principles. Biometrics are used in the security or identification sectors, where the systems draws on an attribute database to make comparisons and declarations about ownership or identity. This is characterized by a subset of the processes used in the JDL model of data fusion: object identification (collection), collation and evaluation. The final stage of processing uses relatively simple decision rules, to either accept or reject the user based on the attribute data on record.

The Haughton-Mars expedition to the Canadian Arctic, conducted by MIT in 2005, synthesizes some of these and other considerations in a complex data fusion system design. Among other objectives, the team set out to determine the efficacy of RFID technology for intelligent agent and asset tracking in support of exploration logistics (de Weck and Simchi-Levi, 2006). The International Space Station (ISS) is currently dominated by manual tracking and barcodes, so the hypothesis was that automated, web-accessible systems could offer potential savings in time and effort for inventory management.

Though the concept of RFID tagging was simple, it led to complications with respect to optimal antenna installation, and tracking of liquids and metallic items. The system was equipped with both passive battery-run and active tagging, leading to interference in the 915 MHz and 2450 MHz bands. This implied that the range data could be reliable under more powerful, strictly active RF sensors. This would, of course, require the proper level of EMI shielding of the agents, containers and ATVs being tracked.

In a separate part of the experiment, the team developed functional Class of Supply (COS) ontologies to supplement the Cargo Category Allocations Rates Table (CCART) used by NASA as well as supply classifications used by NATO and the US Military. This was borne out of the need to capture all major items for the new space exploration initiative not already listed in the CCART, such as categories for propellant, fuels and surface transportation vehicles needed for remote science stations.

Dynamically indexing these remote logistics categories to a generic, upper level ontology that is web-enabled could vastly improve the tracking operation. The sensor data being fused could help teams to not only make operational adjustments to the expedition (for instance, regarding ATV usage), but also improve the quality and relevance of the experiments. For instance, an asset library that is hyperlinked to the web could inform agents of similar expeditions with results/findings openly accessible to the participants. Semantic web links would ensure that there is no violation in naming conventions as new logistics applications are discovered. Connectionist architectures would enable the Class of Supply and other ontologies to optimally evolve with remote science networks, catering to the diversity of exploration missions around the world. Table 6-2 adapted below (Hall and Llinas, 1997) lists some relevant domains for data fusion, including applications pertaining to RFID / asset management.

Application	Inferences Sought by Data Fusion Process	Primary Observables	Surveillance Volume	Sensor Platform
Condition-based maintenance	• Detection, characterization of system faults • Recommendations for corrective actions	• EM signal • Acoustic • Magnetic • Temperature • X-Ray • Vibration	Microscopic to hundreds of feet	• Ships • Aircraft • Factory
Robotics	• Location, ID of obstacles, and objects to be manipulated	• TV • Acoustic • EM • X-Rays	Microscopic to tens of feet	• Robot body
Medical diagnostics	• Location, ID of tumors and disease	• X-Rays • NMR • Temperature • IR • Visual inspect • Chem/bio data	Human body volume	• Lab • Equipment
Environmental monitoring	• Location, ID and evolution of natural phenomena	• SAR • Seismic • EM radiation • Core samples	Hundreds of miles (site monitoring)	• Satellite • Aircraft • Ground • Subsurface
Intelligent Transportation Systems	• Location of position, state estimation / ID	• Acoustic • Vibration • Optical • Range	Tens of feet to miles	• Satellite • Doppler • GPS • INS
RFID Systems	• Location of agents, assets, and manually kept inventory	• RF • Range	Dozens of feet (30-60 ft)	• Human • Warehouses • Trucks • All-terrain vehicle

Table 6-2 Applications for Data Fusion

CHAPTER 7: CONCLUSIONS

This thesis has introduced some of the formal process models for data fusion which have been developed by the remote sensing and defense communities. An overview of sensor and sensor platforms was described, as they relate to the concepts and challenges of multi-sensor data fusion.

The C^4ISR example demonstrated some of the major processes and constituents of a data fusion system. The data fusion development cycle can be matched to that of other similar system engineering cycles, beginning with clearly defined mission requirements, functional objectives and sensor requirements analysis. The inputs are brought together during the design synthesis phase, and result in detailed specifications of the fusion system.

Multi-sensor systems were compared to single sensor systems, and shown to offer improved detection performance, especially under suppressed target signatures. Some mathematical techniques for data fusion were also presented in this thesis. For instance, the Kalman approach to linear filtering is applicable to the fusion of numerical properties, Bayesian methods were demonstrated for the updating of detection probabilities and Boolean algebra was used to illustrate that nested sensor confidence levels result in a lower detection probability than non-nested confidence levels in multi-sensor systems.

The role of fusion in ontological engineering was also discussed, specifically as it relates to knowledge databases for fusion. Ontology reuse can be a major facilitator for creating blackboard architectures for knowledge representation.

Systems engineering processes can play an important role in structuring and implementing complex fusion designs, beginning with concept selection. A Pugh Concept Screening Matrix was developed (See Appendix) which ranked several potential application areas for their adaptability to C^4ISR-type fusion. The medical diagnostics domain was found to be the most strongly correlated with the JDL data processing criteria. The data may be simply gathered through visual observation, thermometers, etc, or processed using sophisticated sensor machines, based on nuclear magnetic resonance, acoustic imaging and X-ray imaging. In either case, there is a clear demand for the high-tech application of fusion software algorithms and hardware sensing devices in this expanding and important field.

Future research in data fusion can address how Object-Process Methodology can be used to better understand problems related to concurrency control in localized sensors and distributed sensor networks. It may also include an application of the fusion models developed for commercial implementation in vehicle health monitoring, marketing science and logistics or supply chain management. Additional research is required into designing data fusion test-beds so that some of the tracker-correlator architectures discussed in this thesis can be evaluated and verified for performance. Finally, research can be undertaken in developing robust ontologies that will enable the benefits of multi-sensor fusion to be more widely accessible through the Semantic Web.

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Appendix

Selection Criteria	Concepts				
Processing	C⁴ISR (reference)	Remote Sensing	Medical Diagnostics	Intelligent Transportation Systems	Condition Monitoring
Level 1					
Detection	0	0	+	+	+
Orientation	0	0	0	+	-
Classification	0	+	+	-	+
Identification	0	+	+	+	+
Level 2					
Object Aggregation	0	+	+	-	+
Event & Activity Aggregation	0	0	+	-	0
Contextual Interpretation & Fusion	0	+	0	-	0
Level 3					
Capability Estimation	0	-	0	-	-
Prediction of Enemy Intent	0	-	0	-	-
Identification of Threat	0	0	+	-	+
Multiperspective Assessment	0	+	0	0	+
Offensive & Defensive Analysis	0	0	-	-	0
Level 4					
Evaluations	0	+	+	+	+
Fusion Control	0	0	0	+	0
Source Requirements Processing	0	+	0	+	+
Mission Management	0	0	0	+	0
Sum +'s	0	7	7	7	8
Sum 0's	16	7	8	1	5
Sum -'s	0	2	1	8	3
Net Score	0	5	6	-1	5
Rank	3	2	1	4	2
Continue?	Yes	Yes	Yes	No	Yes

This Pugh Concept Selection screen is designed to weight application areas against the processes in the JDL implementation model. The baseline, reference case is the C⁴ISR system; all other selection criteria are comparatively ranked against the reference case (+ or -).

The method was developed to help narrow concepts quickly and to improve them

in a structured manner. As we can see, it is an imperfect approach – according to the ranking, the selection matrix above would not have us develop a fusion system for an intelligent transportation system. However, all indicators point to this being a worthy implementation of data fusion. Kobayashi *et al.* (1994) proposed the Kalman approach for fusing measurement data from differential GPS, wheel speedometer and optical fibre rate gyro. And Mirabadi and Schmid (1996), evaluated train speed and measurement through a combination of GPS, INS and tachometers.

Medical diagnostics features highest as a JDL implementation option, which means that it is best suited to leverage the algorithms and processes from the C^4ISR reference case. The example cited from Luo *et al.* (2002) is the case-based data fusion methods used to support clinical decision support. The detection and classification process might involve a cardiac event including ventricular and atrial activity. The process being controlled referred to automatic rhythm monitoring through integration of electrocardiogram and hemodynamic signals.

Although it is a quantitative tool for comparing concepts, there is inherent subjective error in Pugh methods. In the example above, sources of error have mainly to do with the bias of the selection criteria to the remote sensing and defense lexicon of data fusion. This highlights the importance of developing upper-level ontologies which can grasp the concepts and processes that underpin the widest possible range of fusion applications.