2

Revisions to the JDL Data Fusion Model

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2.1 Introduction

The data fusion model, developed in 1985 by the U.S. Joint Directors of Laboratories (JDL) Data Fusion Group*, with subsequent revisions, is the most widely used system for categorizing data fusion-related functions. The goal of the JDL Data Fusion Model is to facilitate understanding and communication among acquisition managers, theoreticians, designers, evaluators, and users of data fusion techniques to permit cost-effect system design, development, and operation.[1,2]

This chapter discusses the most recent model revision (1998): its purpose, content, application, and relation to other models.[3]

2.2 What Is Data Fusion? What Isn't?

2.2.1 The Role of Data Fusion

Often, the role of data fusion has been unduly restricted to a subset of the relevant processes. Unfortunately, the universality of data fusion has engendered a profusion of overlapping research and development in many applications. A jumble of confusing terminology (illustrated in Figure 2.1) and ad hoc methods in a variety of scientific, engineering, management, and educational disciplines obscures the fact that the same ground has been plowed repeatedly.

*Now recharted as the Data and Information Fusion Group within the Deputy Director for Research and Engineering's Information System Technology Panel at the U.S. Department of Defense.

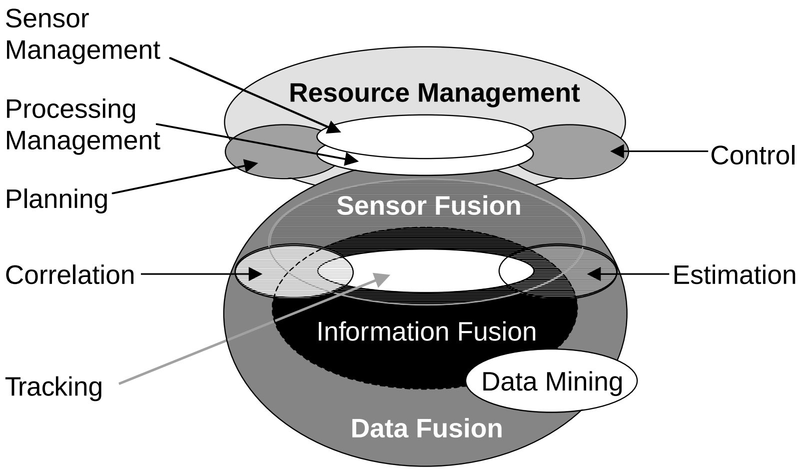

FIGURE 2.1 (Con)fusion of terminology.

Often, the role of data fusion has been unduly restricted to a subset of processes and its relevancy has been limited to particular state estimation problems. For example, in military applications, such as targeting or tactical intelligence, the focus is on estimating and predicting the state of specific types of entities in the external environment (e.g., targets, threats, or military formations). In this context, the applicable sensors/sources that the system designer considers are often restricted to sensors that directly collect data from targets of interest.

Ultimately, however, such problems are inseparable from other aspects of the system's assessment of the world. In a tactical system, this will involve estimation of one's own state in relation to the relevant external entities: friends, foes, neutrals, and background. Estimation of the state of targets and threats cannot be separated from the problems of estimating one's own location and motion, of calibrating one's sensor performance and alignment, and of validating one's library of target sensor and environment models. The data fusion problem, then, becomes that of achieving a consistent, comprehensive estimate and prediction of some relevant portion of the world state. In such a view, data fusion involves exploiting all sources of data to solve all relevant state estimation/prediction problems, where relevance is determined by utility in forming plans of action.

The data fusion problem, therefore, encompasses a number of interrelated problems: estimation and prediction of states of entities both external and internal to the acting system, and the interrelations among such entities. Evaluating the system's models of the characteristics and behavior of all of these external and organic entities is, likewise, a component of the overall problem of estimating the actual world state.

Making the nontrivial assumption that the universe of discourse for a given system can be partitioned into an unknown but finite number of entities of interest, the problem of consistently estimating a multi-object world state can be defined as shown in Figure 2.2.[4] Here, $x_1 \ldots, x_k$ are entity states, so the global state estimation problem becomes one of finding the finite set of entity states X with maximum *a posteriori* likelihood.

The complexity of the data fusion system engineering process is characterized by difficulties in

- representing the uncertainty in observations and in models of the phenomena that generate observations;
- combining noncommensurate information (e.g., the distinctive attributes in imagery, text, and signals);
- maintaining and manipulating the enormous number of alternative ways of associating and interpreting large numbers of observations of multiple entities.

Find Most Likely Multiobject State:

$$\hat{X} = \arg\max \int \lambda(X)\delta X$$

$$= \arg\max \sum_{k=0}^{\infty} \frac{1}{k!} \int \lambda(\{x_1,\ldots,x_k\})dx_1,\ldots,dx_k$$

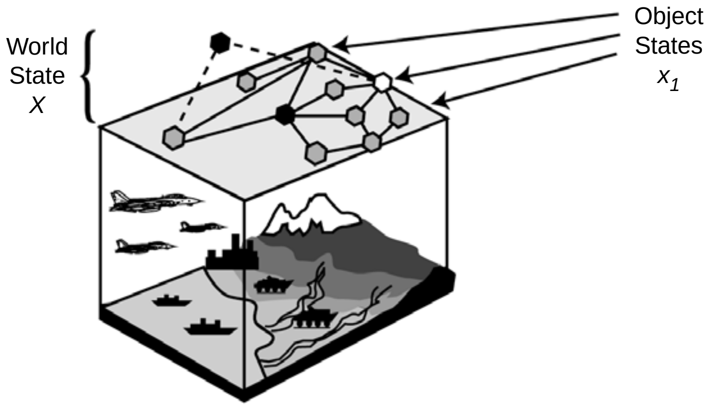

FIGURE 2.2 Global state estimation problem.

Deriving general principles for developing and evaluating data fusion processes — whether automatic or manual — will help to take advantage of the similarity in the underlying problems of data association and combination that span engineering, analysis, and cognitive situations. Furthermore, recognizing the common elements of diverse data fusion problems can provide extensive opportunities for synergistic development. Such synergy — enabling the development of information systems that are cost-effective and trustworthy — requires common performance evaluation measures, system engineering methodologies, architecture paradigms, and multispectral models of targets and data collection systems.

2.2.2 Definition of Data Fusion

The initial JDL Data Fusion Lexicon defined data fusion as:

> A process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of its estimates and assessments, and the evaluation of the need for additional sources, or modification of the process itself, to achieve improved results.[1]

As the above discussion suggests, this initial definition is rather too restrictive. A definition is needed that can capture the fact that similar underlying problems of data association and combination occur in a very wide range of engineering, analysis, and cognitive situations. In response, the initial definition requires a number of modifications:

1. Although the concept *combination of data* encompasses the broad range of problems of interest, *correlation* does not. Statistical correlation is merely one method for generating and evaluating hypothesized associations among data.
2. Association is not an essential ingredient in combining multiple pieces of data. Recent work in random set models of data fusion provides generalizations that allow state estimation of multiple targets without explicit report-to-target association.[4-6]

3. *Single or multiple sources* is comprehensive; therefore, it is superfluous in a definition.
4. The reference to *position and identity estimates* should be broadened to cover all varieties of state estimation.
5. *Complete* assessments are not required in all applications; *timely*, being application-relative, is superfluous.
6. *Threat assessment* limits the application to situations where threat is a factor. This description must also be broadened to include any assessment of the cost or utility implications of estimated situations. In general, data fusion involves refining and predicting the states of entities and aggregates of entities and their relation to one's own mission plans and goals. Cost assessments can include variables such as the probability of surviving an estimated threat situation.
7. Not every process of combining information involves collection management or process refinement. Thus, the definition's second sentence is best construed as illustrative, not definitional.

Pruning these extraneous qualifications, the model revision proposes the following concise definition for data fusion:[3]

Data fusion is the process of combining data or information to estimate or predict entity states.

Data fusion involves combining data — in the broadest sense — to estimate or predict the state of some aspect of the universe. Often the objective is to estimate or predict the physical state of entities: their identity, attributes, activity, location, and motion over some past, current, or future time period. If the job is to estimate the state of people (or any other sentient beings), it may be important to estimate or predict the individuals' and groups' informational and perceptual states and the interaction of these with physical states (this point is discussed in Section 2.5).

Arguments about whether *data fusion* or some other label best describes this very broad concept are pointless. Some people have adopted terms such as *information integration* in an attempt to generalize earlier, narrower definitions of data fusion (and, perhaps, to distance themselves from old data fusion approaches and programs). However, relevant research should not be neglected simply because of shifting terminological fashion. Although no body of common and accepted usage currently exists, this broad concept is an important topic for a unified theoretical approach and, therefore, deserves its own label.

2.3 Models and Architectures

The use of the JDL Data Fusion Model in system engineering can best be explained by considering the role of models in system architectures in general. According to the IEEE definition,[7] an *architecture* is a "structure of components, their relationships, and the principles and guidelines governing their design and evolution over time." Architectures serve to coordinate capabilities to achieve interoperability and affordability. As such, general requirements for an architecture are that it must

1. Identify a focused purpose,
2. Facilitate user understanding/communication,
3. Permit comparison and integration,
4. Promote expandability, modularity, and reusability,
5. Promote cost-effective system development,
6. Apply to the required range of situations.

The JDL Model has been used to develop an architecture paradigm for data fusion[8-10] (as discussed in Chapter 18); however, in reality, the JDL Model is merely an element of an architecture. A model is an abstract description of a set of functions or processes that may be components of a system of a particular type, without indication of software or physical implementation. That being the case, the previous list of architectural virtues applies, with the exception of item (1), which is relevant only to specific system architectures.

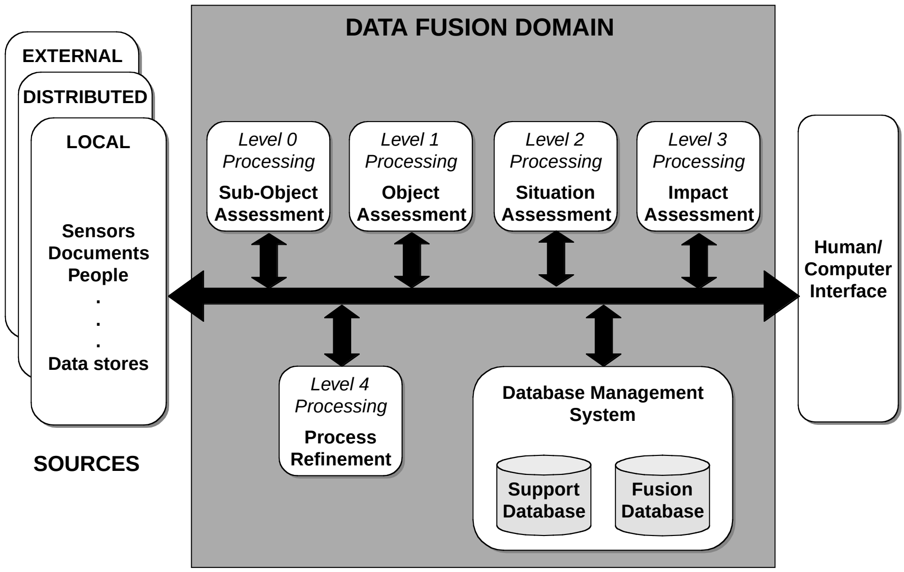

FIGURE 2.3 Revised JDL data fusion model (1998).[3]

The JDL Model was designed to be a *functional* model — a set of definitions of the functions that could comprise any data fusion system. Distinguishing functional models from *process* models and other kinds of models is important. Process models specify the interaction among functions within a system. Examples of process models include Boyd's Observe, Orient, Decide and Act (OODA) loop, the Predict, Extract, Match and Search (PEMS) loop, and the UK Intelligence cycle and waterfall process models cited by Bedworth and O'Brien.[11]

Another type of model is a *formal* model, constituting a set of axioms and rules for manipulating entities. Examples are probabilistic, possibilistic, and evidential reasoning frameworks.*

A model should clarify the elements of problems and solutions to facilitate recognition of commonalities in problems and in solutions. Among questions that a model should help answer are the following:

- Has the problem been solved before?
- Has the same problem appeared in a different form and is there an existing solution?
- Is there a related problem with similar constraints?
- Is there a related problem with the same unknowns?
- Can the problem be subdivided into parts that are easier to solve?
- Can the constraints be relaxed to transform the problem into a familiar one?[12]

2.3.1 Data Fusion "Levels"

Of the many ways to differentiate types of data fusion functions, the JDL model has gained the widest usage. The JDL model's differentiation of functions into fusion levels (depicted in Figure 2.3) provides a useful distinction among data fusion processes that relate to the refinement of "objects," "situations," "threats," and "processes."[2]

* This is seen as equivalent to the concept of *framework* as used in Reference 11.

TABLE 2.1 Characterization of the Revised Data Fusion Levels

Data Fusion Level	Association Process	Estimation Process	Entity Estimated
L.0 — Sub-Object Assessment	Assignment	Detection	Signal
L.1 — Object Assessment		Attribution	Individual Object
L.2 — Situation Assessment	Aggregation	Relation	Aggregation (Situation)
L.3 — Impact Assessment		Plan Interaction	Effect (situation, given plans)
L.4 — Process Refinement	Planning	(Control)	(Action)*

* Process Refinement does not involve estimation, but rather control. Therefore, its product is a control sequence, which — by the duality of estimation and control — relates to a controlled entity's actions as an estimate relates to an actual state.[15]

Nonetheless, several concerns must be raised with regard to the ways in which these JDL data fusion levels have been used in practice:

- The JDL levels have frequently been misinterpreted as specifying a *process* model (i.e., as a canonical guide for process flow within a system — "perform Level 1 fusion first, then Levels 2, 3, and 4…).
- The original JDL model names and definitions (e.g., "threat refinement") seem to focus on tactical military applications, so that the extension of the concepts to other applications is not obvious.
- For these and other reasons, the literature is rife with diverse interpretations of the data fusion levels. The levels have been interpreted as distinguishing any of the following: (a) the kinds of association and/or characterization processing involved, (b) the kinds of entities being characterized, and (c) the degree to which the data used in the characterization has already been processed.

The objectives in the 1998 revision of the definitions for the levels are (a) to provide a useful categorization representing logically different types of problems, which are generally (though not necessarily) solved by different techniques and (b) to maintain a degree of consistency with regard to terminology. The former is a matter of engineering; the latter is a language issue.

Figure 2.3 shows the suggested revised model. The proposed new definitions are as follows:

- Level 0 — Sub-Object Data Assessment: estimation and prediction of signal- or object-observable states on the basis of pixel/signal-level data association and characterization.
- Level 1 — Object Assessment: estimation and prediction of entity states on the basis of inferences from observations.
- Level 2 — Situation Assessment: estimation and prediction of entity states on the basis of inferred relations among entities.
- Level 3 — Impact Assessment: estimation and prediction of effects on situations of planned or estimated/predicted actions by the participants (e.g., assessing susceptibilities and vulnerabilities to estimated/predicted threat actions, given one's own planned actions).
- Level 4 — Process Refinement (an element of Resource Management): adaptive data acquisition and processing to support mission objectives.

Table 2.1 provides a general characterization of these concepts. Note that the levels are differentiated first on the basis of types of estimation process, which roughly correspond to the types of entity for which state is estimated.

2.3.2 Association and Estimation

In the common cases where the fusion process involves explicit association in performing state estimates, a corresponding distinction is made among the types of association processes. Figure 2.4 depicts assignment matrices that are typically formed in each of these processing levels. The examples have the form of two-dimensional matrices, as commonly used in associating reports to tracks.

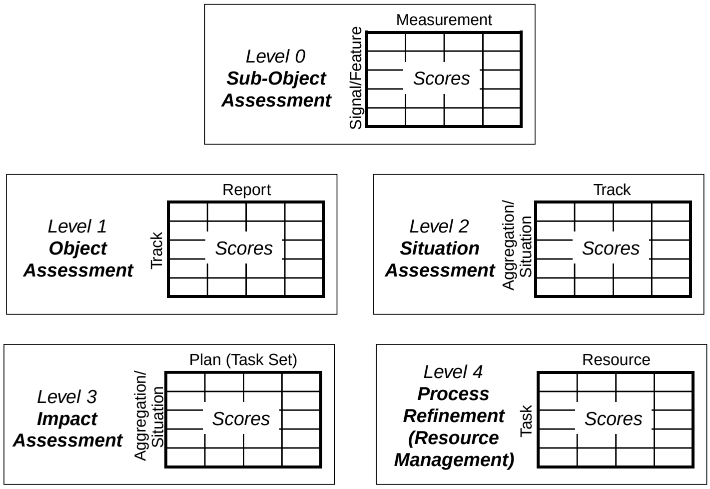

FIGURE 2.4 Assignment matrices for various data fusion "levels."

Level 0 association involves hypothesizing the presence of a signal (i.e., of a common source of sensed energy) and estimating its state. Level 0 associations can include (a) signal detection obtained by integrating a time series of data (e.g., the output of an analog-to-digital converter) and (b) feature extraction from a region in imagery. In this case, a region could correspond to a cluster of closely spaced objects, or to part of an object, or simply to a differentiable spatio-temporal region.

Level 1 association involves selecting observation reports (or tracks from prior fusion nodes in a processing sequence) for inclusion in a track. Such a track is a hypothesis that a certain set of reports is the total set of reports available to the system referencing some individual entity. Global Level 1 hypotheses map the set of observations available to the system to tracks. For systems in which observations are assumed to be associated with only one track, this is a set-partitioning problem; more generally, it is a set-covering problem.

Level 2 association involves associating tracks (i.e., hypothesized entities) into aggregations. The state of the aggregate entity is represented as a network of relations among aggregation elements. Any variety of relations — physical, organizational, informational, and perceptual — can be considered, as appropriate to the given information system's mission. As the class of estimated relationships and the numbers of interrelated entities broaden, the term *situation* is used to refer to an aggregate object of estimation. A model for such development is presented by Steinberg and Washburn.[14]

Level 3 association is usually implemented as a prediction, drawing particular kinds of inferences from Level 2 associations. Level 3 fusion estimates the impact of an assessed situation (i.e., the outcome of various plans as they interact with one another and with the environment). The impact estimate can include likelihood and cost/utility measures associated with potential outcomes of a player's planned actions.

Because Level 2 has been defined so broadly, Level 3 is actually a subset of Level 2. Whereas Level 2 involves estimating or predicting all types of relational states, Level 3 involves predicting some of the relationships between a specific player and his environment, including interaction with other players' actions, given the player's action plan and that of every other player. More succinctly, Level 2 concerns relations in general: paradigmatically third-person, objective relations. Level 3 concerns first-person relations — involving the system or its user — with an attendant sense of subjective utility.

Level 4 processing involves planning and control, not estimation. As discussed by Bowman,[15] just as a formal duality exists between estimation and control, there is a similar duality between association and planning. Therefore, Level 4 association involves assigning resources to tasks.

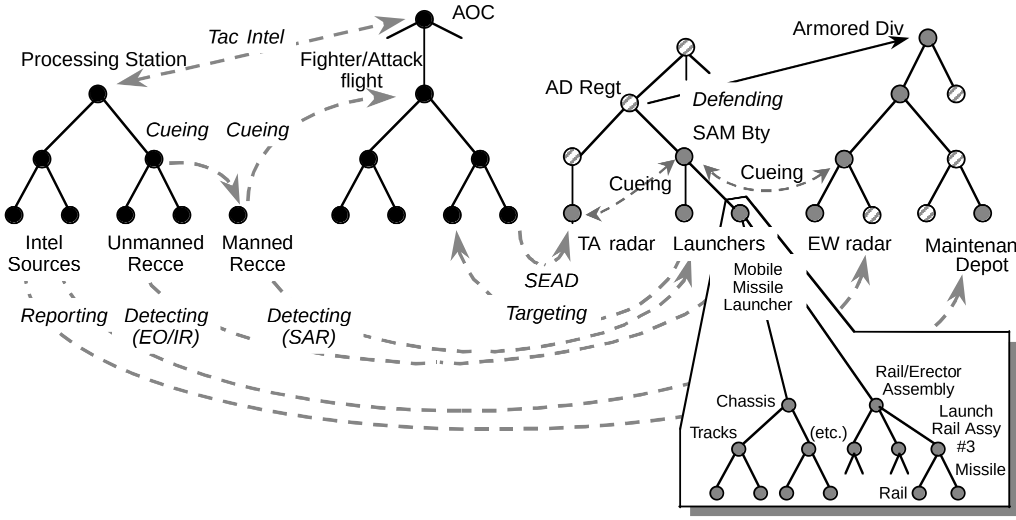

FIGURE 2.5 A Level 2 hypothesis with imbedded Level 1 hypotheses.

2.3.3 Context Sensitivity and Situation Awareness

Once again, the JDL model is a functional model, not a process model. Therefore, it would be a mistake to assume that the information flow in data fusion must proceed strictly from Level 1 to Level 2 to Level 3. Such a mistake has, unfortunately, been common with system designers. A "bottom-up" fusion process is justified only under the following conditions:

- Sensor observations can be partitioned into measurements, each of which originates from, at most, one real entity.
- All information relevant to the estimation of an entity state is contained in the measurement of the individual entity.

Neither of these conditions is necessarily true, and the second is usually false.

The value of estimating entity states on the basis of context is becoming increasingly apparent. A system that integrates data association and estimation processes of all "levels" will permit entities to be understood as parts of complex situations. A relational analysis, as illustrated in Figure 2.5, permits evidence applicable to a local estimation problem to be propagated through a complex relational network.

Note that inferencing based on hypothesized relationships among entities can occur within and between all of the data fusion levels. Figure 2.6 depicts typical information flow across the data fusion levels. Level 0 functions combine measurements to generate estimates of signals or features. At Level 1, signal/feature reports are combined to estimate the states of objects. These are combined, in turn, at Level 2 to estimate situations (i.e., states of aggregate entities). Level 3, according to this logical relationship, seems to be out of numerical sequence. It is a "higher" function than the planning function of Level 4. Indeed, Process Refinement (Level 4) processes can interact with association/estimation data fusion processes in a variety of ways, managing the operation of individual fusion nodes or that of larger ensembles of such nodes. The figure reinforces the point that the data fusion levels are not to be taken as a prescription for the sequencing of a system's process flow. Processing partitioning and flow must be designed in terms of the individual system requirements, as discussed in Chapter 16.

2.3.4 Attributive and Relational Functions

Table 2.1 shows that association within Levels 0 and 1 involves assignment, while Levels 2 and 3 association involves aggregation. This can be modeled as the distinction between

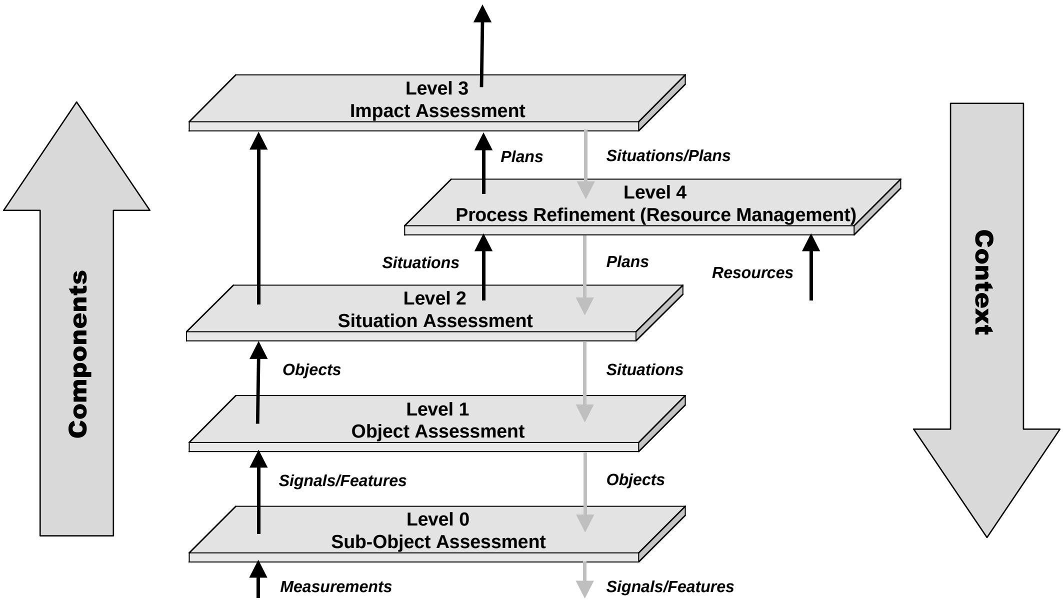

FIGURE 2.6 Characteristic data flow among the "levels."

- estimation on the basis of observations: $(x|Z)$ or $(X|Z)$ for entity or world states, given a set of observations, Z, and
- estimation on the basis of inferred relations among entities: $(x|R)$ or $(X|R)$, where R is a set of ordered n-tuples $<x_1,\ldots,x_{n-1},r>$, the x_i being entity states and r a relational state

Figure 2.5 provides an example of the relationship of Level 1 and 2 hypotheses. A Level 2 hypothesis can be modeled as a directed graph, the nodes of which may correspond to entity tracks and, therefore, to Level 1 hypotheses. More precisely, a node in a Level 2 hypothesis corresponds to a perceived entity. The set of observations associated directly with that node can be considered to be a Level 1 hypothesis imbedded in the Level 2 structure. Of course, entities can be inferred from their context alone, without having been observed directly. For example, in the SA-6 battery of Figure 2.6, the estimation of the presence of launchers at three corners of a diamond pattern may support the inference of a fourth launcher in the remaining corner. The figure further illustrates the point that hypotheses regarding physical objects (e.g., the mobile missile launcher at the lower right of Figure 2.5) may themselves be Level 2 relational constructs.

2.3.4.1 Types of Relationships

Assembling an exhaustive list of relationships of interest is impossible, which is one reason that Level 2 fusion (Situation Assessment) is generally more difficult than Level 1 fusion. Level 2 problems are generally more difficult than Level 1 problems. The process model for aggregate entities — particularly those involving human activity — is often poorly understood, being less directly inferable from underlying physics than Level 1 observable attributes. For this reason, automation of Situational Awareness has relied on so-called cognitive techniques that are intended to copy the inference process of human analysts. However, knowledge extraction is a notoriously difficult undertaking. Furthermore, Level 2 problems often involve a much higher dimensionality, corresponding to the relations that may be part of an inference. Finally, no general metric exists for assessing the relevance of data in these unspecified, high-dimension spaces, unlike the simple distance metrics commonly used for Level 1 validation gating. Relationships of interest to particular context exploitation or situation awareness concerns can include:

- Spatio-temporal relationships;
- Part/whole relationships;

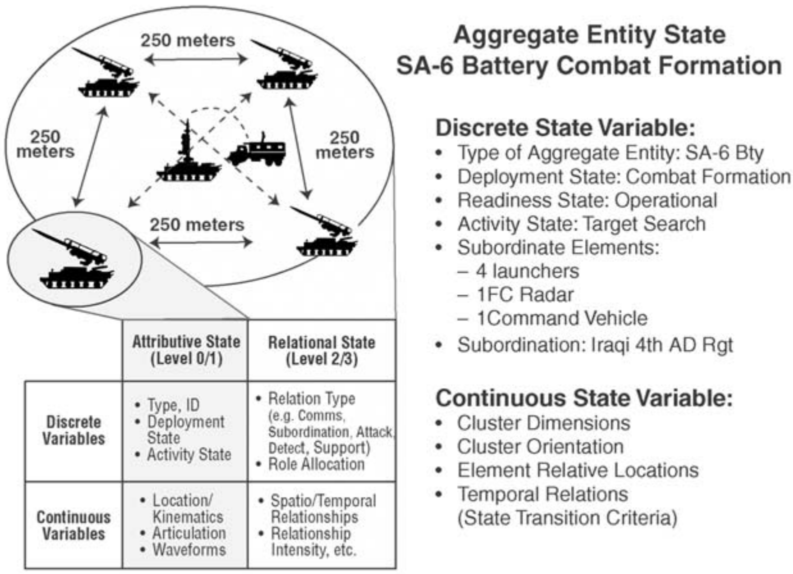

FIGURE 2.7 Attributive and relational state example.

- Organizational relationships (e.g., *X* is a subordinate unit to *Y*) and roles (e.g., *X* is the unit commander, company clerk, CEO, king, or court jester of *Y*);
- Various causal relations, whereby *X* changes the state of *Y*:
  - Physical state (damaging, destroying, moving, invading, repairing)
  - Informational state (communicating, informing, revealing)
  - Perceptual or other mental state (persuading, deceiving, intimidating)
  - Financial or legal state (paying, fining, authorizing, forbidding, sentencing)
  - Intentional relationships, whereby *X* *wishes* to change the state of *Y* (targeting, jamming, cajoling, lying to);
- Semantic relationships (*X* is of the same type as *Y*);
- Similarity relationships (*X* is taller than *Y*);
- Legal relationships (*X* owns *Y*, *X* leases *Y* to *Z*);
- Emotional relationships (love, hate, fear);
- Biological relationships (kinship, ethnicity).

2.3.4.2 Attributive and Relational Inferencing Example

Figure 2.7 provides an example of the attributive and relational states within and among the elements of an aggregate entity. Steinberg and Washburn[14] discuss formal methods for inferring relational states to refine entity-level and aggregate-level state estimates. A Bayesian network technique is used to combine

- the estimate of an entity state, X_i, based on a set of observations, Z_i, in a Level 1 hypothesis (track) and
- the estimate of an entity state, X_i, based on a set of relations, R_i, among nodes (tracks) in a Level 2 hypothesis (aggregation).

The distribution of discrete states, x_d, for *X*, *given its assignment to the given node in a Level 2 hypothesis*, ζ, will be determined by this "evidence" from each of these sources:

$$p_{L2}(x_d,\varsigma) = \frac{p_{L1}(x_d)\Lambda_\varsigma(x_d)}{\sum_{x_d} p_{L1}(x_d)\Lambda_\varsigma(x_d)} \tag{2.1}$$

where $p_{L1}(x_d)$ is the probability currently assigned to discrete state, x_d, by Level 1 data fusion of observations associated with node X, and $\Lambda(x_d)$ is the evidence communicated to X from the tracks related to Y in a Level 2 association hypothesis.

The evidence from the nodes communicating with X will be the product of evidence from each such node Y:

$$\Lambda_\zeta\left(x_d\right) = \prod_{\langle X,Y\rangle\in\zeta} \Lambda_Y\left(x_d\right) \tag{2.2}$$

The factors $\Lambda_Y(x_d)$ are interpreted in terms of relational states among entities as follows. Ordered pairs of entities are hypothesized as having *relational states*, $r_i(X,Y)$. A given track, Y, may be involved in several competing relations relative to X with probability distributions $p[r_i(X,Y)]$.*

Updating a track, Y, contributes information for evaluating the probability of each state, x, of a possible related entity, X. As with attributive states, relational states, r, can be decomposed into discrete and continuous components, r_d and r_c (as exemplified in Figure 2.6). Then this *contextual evidence* is given by

$$\begin{aligned}\Lambda_Y\left(x_d\right) &= \sum_{y_d} p_{L1}\left(y_d\right) p\left[y_d \middle| x_d\right] = \int \sum_{y_d} p_{L1}\left(y_d\right) p\left[y_d \middle| r x_d\right] p\left[r \middle| x_d\right] dr \\ &= \sum_{y_d} p_{L1}\left(y_d\right) \sum_{r_d} p\left[y_d \middle| r_d, x_d\right] p\left[r_d \middle| x_d\right] \int p\left[r_c \middle| r_d, x_d\right] dr\end{aligned} \tag{2.3}$$

Inferences can be drawn about a hypothesized entity denoted by track X_i, given the Level 2 hypothesis that the entity corresponding to X_i stands in a particular relationship to another hypothesized entity corresponding to a track X_j. In the example shown in Figure 2.8 (based on sets of relationships as illustrated in Figure 2.7), it is assumed that an entity — elliptically referred to as X_1 — has been estimated to have probabilities $p(x_1)$ of being an entity of types and activity states x_1 on the basis of Level 1 association of sensor reports z_1 and z_2. Then, if X_1 and X_2 meet the criteria of particular relationships for any states x_1 and x_2 of X_1 and X_2, respectively, inferences can be drawn regarding the probabilities as to the type and activity of X_2.

For example, given the estimate that X_1 and X_2 stand in certain spatio-temporal and other relationships, as listed in Figure 2.7, there is a mutual reinforcement of pairs of Level 1 state estimates $\langle x_1,x_2\rangle$ that are consistent with this relationship (e.g., that X_1 is a Straight Flush radar and X_2 is an SA-6 surface-to-air missile battery) and suppression of nonconsistent state pairs. Conditioned on this association, the estimate of the likelihood of track X_2 can be refined (i.e., the hypothesis that the associated observations — z_3 in Figure 2.8 — relate to the same entity). Furthermore, likelihood and state estimates to other nodes adjoining X_2 can be further propagated (e.g., to infer the battery-association and the type and activity of a missile launcher, X_3, hypothesized on the basis of observations z_4 and z_5). As noted above, the presence, identity, and activity state of entities that have not been observed can be inferred (e.g., the presence of

* For simplicity, the present discussion is limited to binary relations. In cases where more complex relations are relevant, a second order can be employed, whereby entities can have binary links to nodes representing n-ary relations.[16]

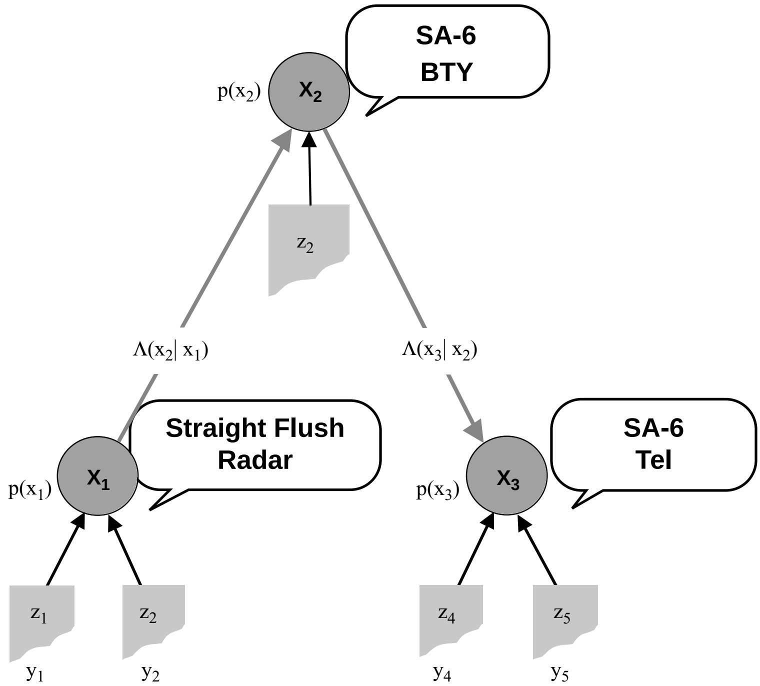

FIGURE 2.8 Attributive and relational inferencing example.

a full complement of launchers and other associated equipment can be inferred, conditioned on the assessed presence of an SA-6 battery).

Each node in a Level 2 hypothesis combines the effects of evidence from all adjacent nodes and propagates the updated probability distributions and likelihood (i.e., association confidence) regarding an entity state to the other nodes. Loops in the inference flow occur; however, methods have been defined to deal with them.

2.3.4.3 A Generalization about the Levels

Level 1 data fusion involves estimating and predicting the state of inferred entities based on observed features. Level 2 data fusion involves estimating and predicting the state of inferred entities on the basis of relationships to other inferred entities. Because of their reliance on these inference mechanisms, Levels 0 and 3 are seen as special cases of Levels 1 and 2, respectively (as illustrated in Figure 2.9):

- Level 0 is a special case of Level 1, where entities are signals/features.
- Level 3 is a special case of Level 2, where relations are first-person relations.

Earlier, this chapter asserted that Level 4 fusion is not fusion at all, but a species of Resource Management; therefore, only two super-levels of fusion remain, and these are partitioned by type of data association. A secondary partitioning by type of entity characterized distinguishes within these super-levels. Section 2.5 presents the case for an even finer partitioning within the JDL levels.

2.4 Beyond the Physical

In general, then, the job of data fusion is that of estimating or predicting the state of some aspect of the world. When that aspect includes people (or any other information systems, for that matter), it can be relevant to include a consideration of informational and perceptual states and their relations to physical states. *Informational state* refers to the data available to the target. *Perceptual state* refers to the target's own estimate of the world state.[17] (See Chapter 15.)

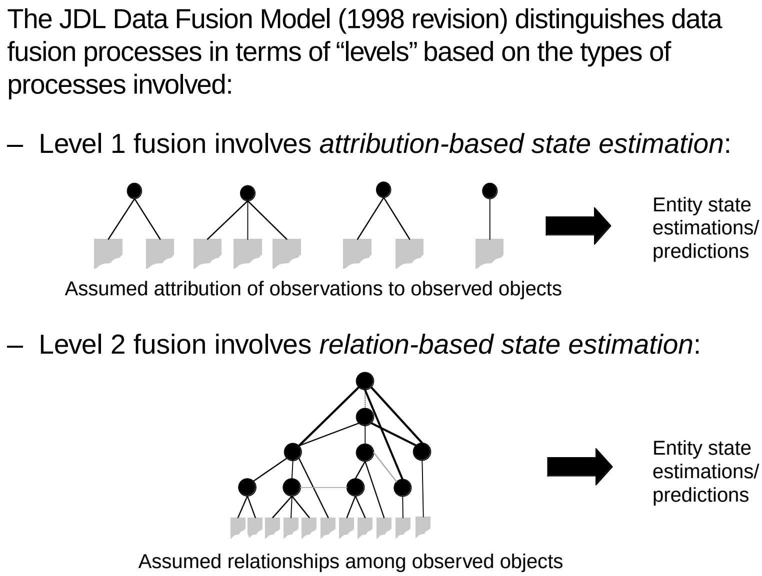

FIGURE 2.9 Attributive and relational inferencing.

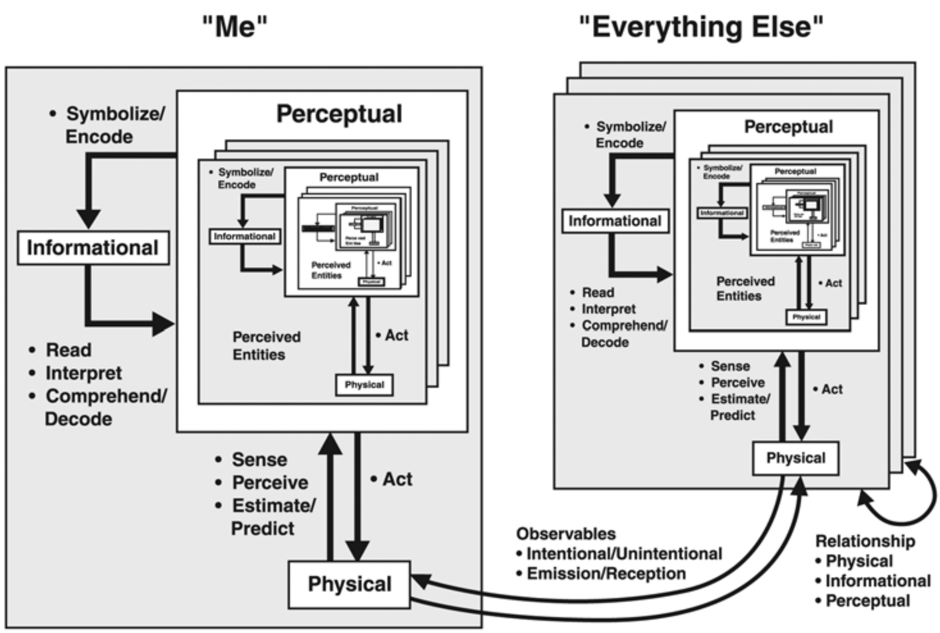

FIGURE 2.10 Entity states: three aspects.

A person or other information system (represented by the box at the left of Figure 2.10) senses physical stimuli as a function of his physical state in relation to that of the stimulating physical world. These include both stimuli originating outside the person's body and those originating from within.

The person can combine multiple sensory reports to develop and refine estimates of perceived entities (i.e., tracks), aggregations, and impacts on his plans and goals (Levels 1–3 fusion). This ensemble of perceived entities and their interrelationships is part of the person's *perceptual state*. As depicted in the figure, his perceptual state can include an estimation of physical, informational, and perceptual states and relations of things in the world. The person's perceptions can be encoded symbolically for manipulation, communication, or storage. The set of symbolic representations available to the person is his *informational state*. Informational state can encompass available data stores such as databases and documents. The notion of informational state is probably more applicable to a closed system (e.g., a nonnetworked computer) than to a person, for whom the availability of information is generally a matter of degree. The tripartite view of reality developed by Waltz[17] extends the work of philosopher Karl Popper. The status of information as a separable aspect of reality is certainly subject to discussion. Symbols can have both a physical and a perceptual aspect: they can be expressed by physical marks or sounds, but their interpretation (i.e., recognizing them orthographically as well as semantically) is a matter of perception.

As seen in this example, symbol recognition (e.g., reading) is clearly a perceptual process. It is a form of context-sensitive model-based processing. The converse process, that of representing perceptions symbolically for purpose of recording or communicating them, produces a physical product — text, sounds, etc. Such physical products must be interpreted as symbols before their informational content can be accessed. Whether there is more to information than these physical and perceptual aspects remains to be demonstrated. Furthermore, the distinction between information and perception is not the difference between what a person *knows* and what he *thinks* (cf. Plato's *Theatetus*, in which knowledge is shown to involve true opinion plus some sense of understanding). Nonetheless, the notion of informational state is useful as a topic for estimation because knowing what information is available to an entity (e.g., an enemy commander's sources of information) is an important element in estimating (and influencing) his perceptual state and, therefore, in predicting (and influencing) changes.

The person acts in response to his perceptual state, thereby affecting his and the rest of the world's physical state. His actions may include comparing and combining various representations of reality: his network of perceived entities and relationships. He may search his memory or seek more information from the outside. These are processes associated with data fusion Level 4.

Other responses can include encoding perceptions in symbols for storage or communication. These can be incorporated in the person's physical actions and, in turn, are potential stimuli to people (including the stimulator himself) and other entities in the physical world (as depicted at the right of Figure 2.10). Table 2.2 describes the elements of state estimation for each of the three aspects shown in Figure 2.10. Note the recursive reference in the bottom right cell.

Figure 2.11 illustrates this recursive character of perception. Each decision maker interacts with every other one on the basis of an estimate of current, past, and future states. These include not only estimates of who is doing what, where, and when in the physical world, but also what their informational states and perceptual states are (including, "What do they think of *me*?").

If state estimation and prediction are performed by an automated system, that system may be said to possess physical and perceptual states, the latter containing estimates of physical, informational, and perceptual states of some aspects of the world.

TABLE 2.2 Elements of State Estimation

	Attributive State		Relational State	
Object Aspect	Discrete	Continuous	Discrete	Continuous
Physical	Type, ID Activity state	Location/kinematics Waveform parameters	Causal relation type Role allocation	Spatio-temporal relationships
Informational	Available data types Available data records and quantities	Available data values Accuracies Uncertainties	Informational relation type Info source/ recipient role allocation	Source data quality, quantity, timeliness Output quality, quantity, timeliness
Perceptual	Goals Priorities	Cost assignments Confidence Plans/schedules	Influence relation type Influence source/recipient role allocation	Source confidence World state estimates (per this table)

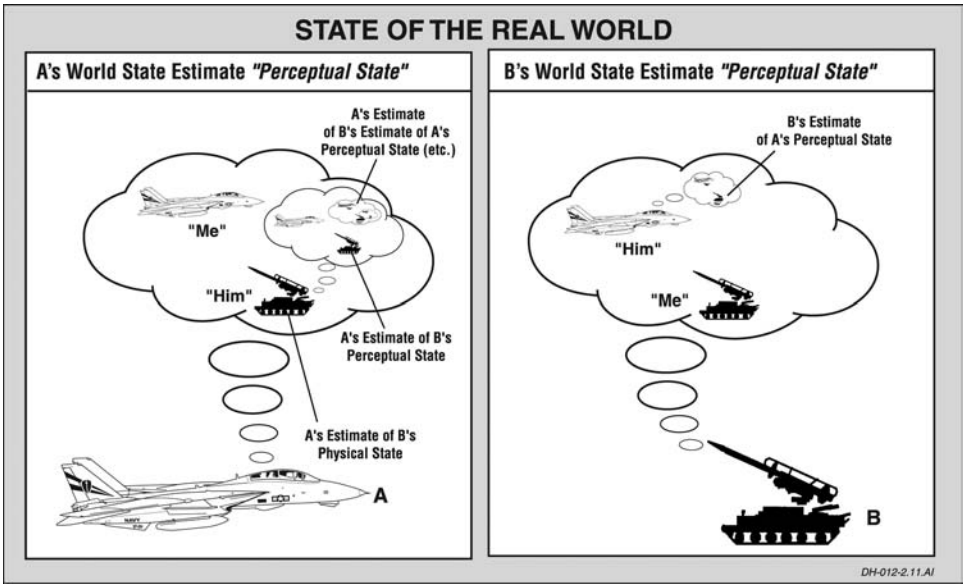

FIGURE 2.11 World states and nested state estimates.

2.5 Comparison with Other Models

2.5.1 Dasarathy's Functional Model

Dasarathy[18] has defined a very useful categorization of data fusion functions in terms of the types of data/information that are processed and the types that result from the process. Table 2.3 illustrates the types of inputs/outputs considered. Processes corresponding to the cells in the highlighted diagonal X region are described by Dasarathy, using the abbreviations *DAI-DAO, DAI-FEO, FEI-FEO, FEI-DEO*, and *DEI-DEO*. A striking benefit of this categorization is the natural manner in which technique types can be mapped into it.

TABLE 2.3 Interpretation of Dasarathy's Data Fusion I/O Model

INPUT \ OUTPUT	Data	Features	Objects
Data	Signal Detection DAI-DAO	Feature Extraction DAI-FEO	Gestalt-Based Object Characterization DAI-DEO
Features	Model-Based Detection/ Feature Extraction FEI-DAO	Feature Refinement FEI-FEO	(Feature-Based) Object Characterization FEI-DEO
Objects	Model-Based Detection/ Estimation DEI-DAO	Model-Based Feature Extract DEI-FEO	Object Refinement DEI-DEO
	Level 0	*Level 0*	*Level 1*

TABLE 2.4 Expansion of Dasarathy's Model to Data Fusion Levels 0–4

		OUTPUT					
		Data	Features	Objects	Relations	Impacts	Responses
INPUT	Data	Signal Detection *DAI-DAO*	Feature Extraction *DAI-FEO*	Gestalt-Based Object Extract *DAI-DEO*	Gestalt-Based Situation Assessment *DAI-RLO*	Gestalt-Based Impact Assessment *DAI-IMO*	Reflexive Response *DAI-RSO*
	Features	Model-Based Detection/ Feature Extraction *FEI-DAO*	Feature Refinement *FEI-FEO*	Object Characterization *FEI-DEO*	Feature-Based Situation Assessment *FEI-RLO*	Feature-Based Impact Assessment *FEI-IMO*	Feature-Based Response *FEI-RSO*
	Objects	Model-Based Detection/ Estimation *DEI-DAO*	Model-Based Feature Extraction *DEI-FEO*	Object Refinement *DEI-DEO*	Entity-Relational Situation Assessment *DEI-RLO*	Entity-Based Impact Assessment *DEL-IMO*	Entity-Relation Based Response *DEI-RSO*
	Relations	Context-Sensitive Detection/Est *RLI-DAO*	Context-Sensitive Feature Extraction *RLI-FEO*	Context-Sensitive Object Refinement *RLI-DEO*	Micro/Macro Situation Assessment *RLI-RLO*	Context-Sensitive Impact Assessment *RLI-IMO*	Context-Sensitive Response *RLI-RSO*
	Impacts	Cost-Sensitive Detection/Est *IMI-DAO*	Cost-Sensitive Feature Extraction *IMI-FEO*	Cost-Sensitive Object Refinement *IMI-DEO*	Cost-Sensitive Situation Assessment *IMI-RLO*	Cost-Sensitive Impact Assessment *IMI-RLO*	Cost-Sensitive Response *IMI-RSO*
	Responses	Reaction-Sensitive Detection/Est *RSI-DAO*	Reaction-Sensitive Feature Extraction *RSI-FEO*	Reaction-Sensitive Object Refinement *RSI-DEO*	Reaction-Sensitive Sit Assessment *RSI-RLO*	Reaction-Sensitive Impact Assessment *RSI-RLO*	Reaction-Sensitive Response *RSI-RSO*
		Level 0		*Level 1*	*Level 2*	*Level 3*	*Level 4*

We have augmented the categorization as shown in the remaining matrix cells by adding labels to these cells, relating input/output (I/O) types to process types, and filling in the unoccupied cells in the original matrix.

Note that Dasarathy's original categories represent constructive, or data-driven, processes in which organized information is extracted from relatively unorganized data. Additional processes — FEI-DAO, DEI-DAO, and DEI-FEO — can be defined that are analytic, or model-driven, such that organized information (a model) is analyzed to estimate lower-level data (features or measurements) as they relate to the model. Examples include predetection tracking (an FEI-DAO process), model-based feature-extraction (DEI-FEO), and model-based classification (DEI-DAO). The remaining cell in Table 2.3 — DAO-DEO — has not been addressed in a significant way (to the authors' knowledge) but could involve the direct estimation of entity states without the intermediate step of feature extraction.

Dasarathy's categorization can readily be expanded to encompass Level 2, 3, and 4 processes, as shown in Table 2.4. Here, rows and columns have been added to correspond to the object types listed in Figure 2.4.

Dasarathy's categories represent a useful refinement of the JDL levels. Not only can each of the levels (0–4) be subdivided on the basis of input data types, but our Level 0 can also be subdivided into detection processes and feature-extraction processes.*

Of course, much of Table 2.4 remains virgin territory; researchers have seriously explored only its northwest quadrant, with tentative forays southeast. Most likely, little utility will be found in either the northeast or the southwest. However, there may be gold buried somewhere in those remote stretches.

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* A Level 0 remains a relatively new concept in data fusion (although quite mature in the detection and signal processing communities); therefore, it hasn't been studied to a great degree. The extension of formal data fusion methods into this area must evolve before the community will be ready to begin partitioning it. Encouragingly, Bedworth and O'Brien[11] describe a similar partitioning of Level 1-related functions in the Boyd and UK Intelligence Cycle models.

TABLE 2.5 Bedworth and O'Brien's Comparison of Data Fusion-related Models[11]

Activity being undertaken	Waterfall model	JDL Model	Boyd Loop	Intelligence Cycle
Command execution			Act	Disseminate
Decision making process	Decision making	Level 4	Decide	
Threat assessment		Level 3	Orient	Evaluate
Situation assessment	Situation assessment	Level 2		
Information processing	Pattern processing	Level 1		Collate
	Feature extraction			
Signal processing	Signal Processing	Level 0		
Source/sensor acquisition	Sensing		Observe	Collect

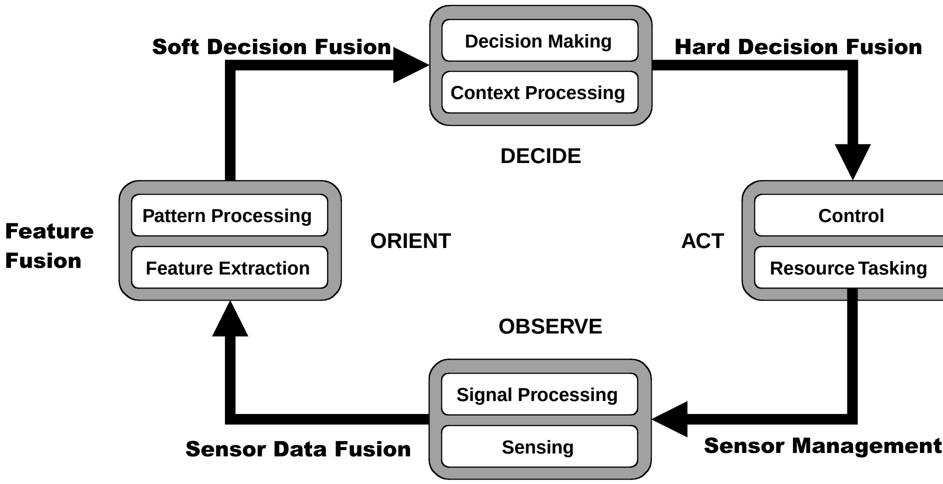

FIGURE 2.12 The "Omnibus" process model.[11]

2.5.2 Bedworth and O'Brien's Comparison among Models and Omnibus

Bedworth and O'Brien[11] provide a commendable comparison and attempted synthesis of data fusion models. That comparison is summarized in Table 2.5. By comparing the discrimination capabilities of the various process models listed — and of the JDL and Dasarathy's *functional* models — Bedworth and O'Brien suggest a comprehensive "Omnibus" *process* model as represented in Figure 2.12.

As noted by Bedworth and O'Brien, an information system's interaction with its environment need not be the single cyclic process depicted in Figure 2.12. Rather, the OODA process is often hierarchical and recursive, with analysis/decision loops supporting detection, estimation, evaluation, and response decisions at several levels (illustrated in Figure 2.13).

2.6 Summary

The goal of the JDL Data Fusion Model is to serve as a functional model for use by diverse elements of the data fusion community, to the extent that such a community exists, and to encourage coordination and collaboration among diverse communities. A model should clarify the elements of problems and solutions to facilitate recognition of commonalties in problems and in solutions. The virtues listed in Section 2.3 are significant criteria by which any functional model should be judged.[12]

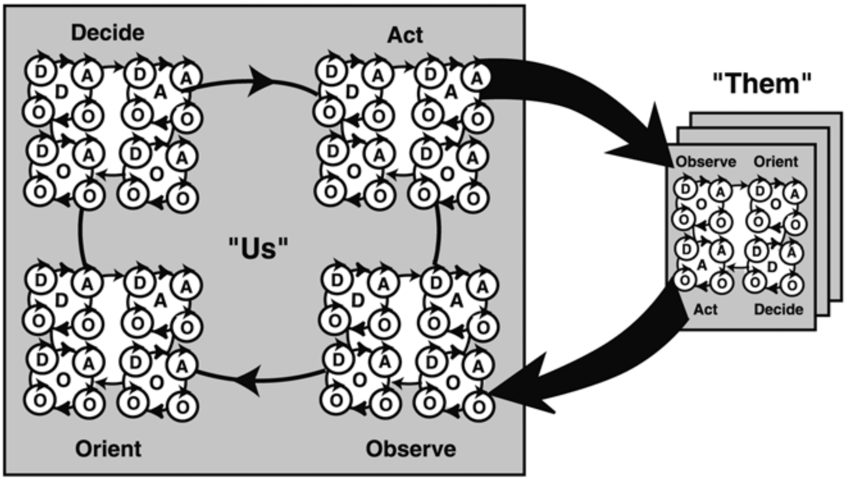

FIGURE 2.13 System interaction via interacting fractal OODA loops.

Additionally, a functional model must be amenable to implementation in process models. A functional model must be compatible with diverse instantiations in architectures and allow foundation in theoretical frameworks. Once again, the goal of the functional model is to facilitate understanding and communication among acquisition managers, theoreticians, designers, evaluators, and users of data fusion systems to permit cost-effect system design, development, and operation.

The revised JDL model is aimed at providing a useful tool of this sort. If used appropriately as part of a coordinated system engineering methodology (as discussed in Chapter 16), the model should facilitate research, development, test, and operation of systems employing data fusion. This model should

- Facilitate communications and coordination among theoreticians, developers, and users by providing a common framework to describe problems and solutions.
- Facilitate research by representing underlying principles of a subject. This should enable researchers to coordinate their attack on a problem and to integrate results from diverse researchers. By the same token, the ability to deconstruct a problem into its functional elements can reveal the limits of our understanding.
- Facilitate system acquisition and development by enabling developers to see their engineering problems as instances of general classes of problems. Therefore, diverse development activities can be coordinated and designs can be reused. Furthermore, such problem abstraction should enable the development of more cost-effective engineering methods.
- Facilitate integration and test by allowing the application of performance models and test data obtained with other applications of similar designs.
- Facilitate system operation by permitting a better sense of performance expectations, derived from experiences with entire classes of systems. Therefore, a system user will be able to predict his system's performance with greater confidence.

References

1. White, Jr., F.E., *Data Fusion Lexicon*, Joint Directors of Laboratories, Technical Panel for C^3, Data Fusion Sub-Panel, Naval Ocean Systems Center, San Diego, 1987.
2. White, Jr., F.E., "A model for data fusion," *Proc. 1st Natl. Symp. Sensor Fusion*, vol. 2, 1988.
3. Steinberg, A.N., Bowman, C.L., and White, Jr., F.E., "Revisions to the JDL Data Fusion Model," *Proc. 3rd NATO/IRIS Conf.,* Quebec City, Canada, 1998.
4. Mahler, R.. "A Unified Foundation for Data Fusion," *Proc. 1994 Data Fusion Sys. Conf.*, 1994.

5. Goodman, I.R., Nguyen, H.T., and Mahler, R., *New Mathematical Tools for Data Fusion*, Artech House, Inc., Boston, 1997.
6. Mori, S., "Random sets in data fusion: multi-object state-estimation as a foundation of data fusion theory," *Proc. Workshop on Applications and Theory of Random Sets,* Springer-Verlag, 1997.
7. *C4ISR Architecture Framework, Version 1.0*, C4ISR ITF Integrated Architecture Panel, CISA-0000-104-96, June 7, 1996.
8. *Data Fusion System Engineering Guidelines*, SWC Talon-Command Operations Support Technical Report 96-11/4, vol. 2, 1997.
9. *Engineering Guidelines for Data Correlation Algorithm Characterization*, TENCAP SEDI Contractor Report, SEDI-96-00233, 1997.
10. Steinberg, A.N. and Bowman, C.L., "Development and application of data fusion engineering guidelines," *Proc. 10th Natl. Symp. Sensor Fusion*, 1997.
11. Bedworth, M. and O'Brien, J., "The Omnibus model: a new model of data fusion?", *Proc. 2nd Intl. Conf. Information Fusion*, 1999.
12. Polya, G., *How To Solve It*, Princeton University Press, Princeton, NJ, 1945.
13. Antony, R., *Principles of Data Fusion Automation,* Artech House, Inc., Boston, 1995.
14. Steinberg, A.N. and Washburn, R.B., "Multi-level fusion for Warbreaker intelligence correlation," *Proc. 8th Natl. Symp. Sensor Fusion*, 1995.
15. Bowman, C.L., "The data fusion tree paradigm and its dual," *Proc. 7th Natl. Symp. Sensor Fusion*, 1994.
16. Curry, H.B. and Feys, R., *Combinatory Logic*, North-Holland, Amsterdam, 1974.
17. Waltz, E., *Information Warfare: Principles and Operations*, Artech House, Inc., Boston, 1998.
18. Dasarathy, B., *Decision Fusion*, IEEE Computer Society Press, 1994.