Levels?

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***Abstract* — *This paper challenges the familiar hierarchical partitioning of data fusion problems into "levels". The JDL data fusion model and its variants are seen as a method to partition a problem space in a way that tends to support different types of solutions. The layered view of fusion presented in these models is a rough engineering-based representation of a domain that has been addressed in analytically- and empirically-based models developed over centuries by philosophers and cognitive scientists. These ontological and cognitive models involve distinctions that are not all necessarily hierarchical or sequential. A hierarchical partitioning – while often convenient in characterizing fusion problems – should not be an impediment to fusion solutions that span the levels. A more flexible and comprehensive partitioning scheme is suggested.*

Keywords: epistemology, JDL data fusion model, problem modeling, model-based recognition, anomaly-based detection, abductive learning, context-based feasibility

I. Dedication

This paper is dedicated to the memory of Otto Kessler: colleague, mentor and friend; a pioneer of the data fusion community in the United States and worldwide. Otto played a leading role in establishing the U.S. Joint Directors' of Laboratories (JDL) Data Fusion Group and the group's data fusion model that is the topic of this paper.

II. Models

The well-known JDL Data Fusion model [1,2] has served as a paradigm for much subsequent discussion of data and information fusion. Although there have been many revisions and rivals, nearly all of them differ in the definition of fusion "levels"; tacitly presuming that the problems, approaches or issues in Information Fusion are layered: that some sort of discrete hierarchy exists that, among other things, imposes problems of information or control flow across the boundaries.

In [3] we surveyed several alternative models for data fusion, considering their various purposes and corresponding effectiveness. As David Hall has quipped regarding the best known of these models, "the JDL model doesn't actually exist." We take this to mean that, while the model of course exists within the realm of models, it does not necessary correspond to structures that are fundamental in the universe of discourse to which the model is intended to apply.

We need to be clear as to the reason for having a data fusion model. Models have been developed and used for a variety of purposes. Metaphysicians have developed *Ontological Models* of the kinds of entities that exist. Philosophers from Aristotle [4] to Kant [5] and Hegel [6] and cognitive scientists from Piaget [7], Chomsky [8] and Minsky [9] to Pinker [10] and Endsley [11] have developed *Epistemic Models* that, among other things, define categories of sensing, perceiving and knowing. *Management Models* are used to represent methods for problem-solving in many disciplines: mathematics, the sciences, engineering, business, government, the arts, etc. Among Management Models are *Engineering Models*, such as the IDEF series of system engineering models [12] (we'll revisit IDEF at the end of this paper).

To assess competing fusion models, we need to make distinctions among distinctions: ontological, epistemic, engineering. Various fusion models (including various versions of the JDL model) are based on one or another of these, and sometimes straddle the distinctions (e.g. "Level 5"). Not all such distinctions are hierarchical and most are really not fusion-specific distinctions, in the sense of fusion as combining multiple "pieces" of information.

Ontological distinctions occur independent of any fusion process and epistemic distinctions can be made even when considering the perception, cognition or knowledge of a single "piece" of information.

To the extent that it is meant to support system design and evaluation, a Data Fusion model is a Management Model and, specifically, an Engineering Model. As such, it should partition the problem space in a way that tends to support different types of solutions. For example, the stated objectives of [13] were (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 the mainstream of technical usage.

We propose the following measures of effectiveness for Engineering Models, to include Data Fusion models:

a) A clear distinction of problems that tend to require different solution methods (clustering metrics);
b) Generality of applicability to facilitate technology re-use and to facilitate deeper understanding;
c) Well-defined relationship of the modeled domain to related disciplines; in the case of data fusion, this should include learning, pattern discovery, pattern generalization, theory and model-building, pattern explanation, resource management: planning and control, system engineering: design/development and analysis.

We find it useful to define *Data Fusion* as the process for combining data to estimate entity states, where an entity can be any aspect of reality at any degree of abstraction [13].

As such, data fusion is a particular topic of Epistemology: learning on the basis of multiple pieces of data.[1] That is to say, fusion is concerned with both the general learning problem and specific data fusion problems. We can define the *General Learning Problem* is that of discovering entity states, relationships and expectations (contingent states). The *Specific Data Fusion Problem* is that of determining what data are relevant to a state estimation/expectation problem and determining how relevant data are to be combined in deriving state estimates/expectation; with the particular problem of accounting for uncertainty in determining data relevance, data accuracy and inference technique performance.[2]

An examination of the JDL model in its many incarnations shows it to be a model of the General Learning Problem (not the Specific DF Problem): a partitioning scheme of types of knowledge acquisition problems.

III. "LEVELS"

The notion of "levels" of data fusion originated in the late 1980s with the U.S. Joint Directors of Laboratories (JDL) Data Fusion Subgroup [1,2]: a body of level-headed individuals.

The partitioning criteria in the early versions of the JDL model were easily blurred: do we differentiate "levels" based on types of input, types of processes or types of outputs? None of these criteria is absolutely right or wrong but they may serve different needs.

In [13,18-22] we successively proposed refinements to the early definition of levels. The explicit goals of these refinements were to clarify the criteria for partitioning into levels and to broaden the applicability beyond the original tactical military domain. We suggested partitioning according to fusion products. State estimation functions differ broadly according to the types of state variables to be estimated; target states of interest being distinguished in terms of "levels" corresponding to the levels described in various versions of the JDL model.

Also in the 1980s, Bowman discovered a strong formal and functional duality between data fusion and resource management functions, arguing that concepts and techniques for both should be developed together for cost-effective and efficiently coordinated "DF&RM" systems [13]. This duality is evident in the symmetry of the DF and RM nodal functions seen in Figure 1. We extended the DF&RM duality and by defining a set of corresponding RM levels [19-22].

These "levels" of data fusion and resource management processes map into a categorization of entity state variables which a DF system is tasked to estimate or which an RM system is tasked to control. Examples of such problem variables are given in Table 1. The third and fourth columns distinguish continuous-valued and discrete-valued variables at each level. The fifth and sixth columns respectively list the traditional data fusion and resource management levels with modestly revised labels [3,13,18-22].

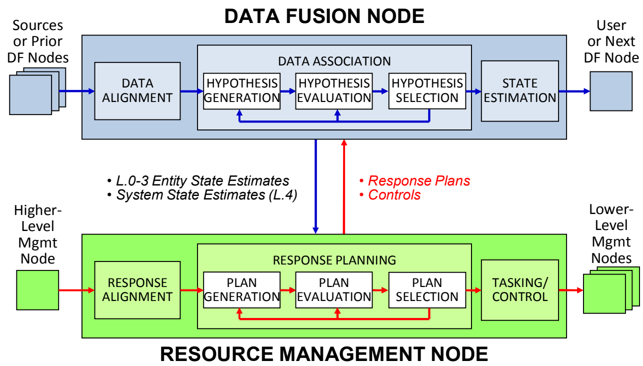

Figure 1. Dual Data Fusion and Resource Management Nodes [18]

It seems to make more sense to distinguish inference problems on the basis of types of entity state variables rather than by type of entity:

- A given entity can be addressed at more than one level. For example, a vehicle can be the "target" of a level 1 data fusion process if level 1 states – e.g. its location, velocity, size, weight, type, identity or activity – are being estimated;
- That same vehicle can be the "target" of a level 2 data fusion process if it is considered as a complex or a structure, such that level 2 states – e.g. the relationships among its components or its subassemblies – are being estimated;
- It could also be the subject of a level 3 data fusion process if it is considered as a dynamic process, such that level 3 states – e.g. its course of action and outcome states – are being estimated;
- It could even be the subject of a level 4 data fusion process if it happens to be the system performing the estimation and level 4 states – e.g. the operating conditions and performance relative to users' objectives – are being estimated.[3]

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[1] Fusion is generally restricted to learning facts (*wissen*), not learning behaviors (*können*); the latter being a topic important to planning and executing responses to estimated world states. Under Bowman's Data Fusion and Resource Management Dual Node Architecture [13-17], these are Resource Management functions. However, learning how to respond is a modeling problem. As discussed in Section IV, model development, evaluation and refinement are arguably data fusion processes.

[2] What it is to combine data or information: a) we can think of a "piece of information" simply as a value of a random variable; so the General Learning Problem is that of evaluating variables of interest; and b) combining can involve i) filtering of multiple measurements (or estimates) of given variable or ii) inference of the value of a variable from estimates of values other variables, $p(x|Z)$.

[3] Such shifting in the ways in which we consider a given entity is called "semantic reconstrual" or "Gestalt shift" in linguistics and cognitive science [10]. Consider the difference in meaning between 'Ann slapped Bob on the face' and 'Ann slapped Bob's face'. In the former sentence, the face is construed as an aspect of Bob, who is treated as an individual, a level 1 entity (i.e. he is described in terms of level one state variables). In the latter sentence, the face is a construed as a distinct entity separable from Bob (although not quite in the manner of the film Face-Off) and Bob is conceived as a complex of constituent parts (i.e. he is described in terms of level 2 state variables).

Analogously, the same vehicle can be the "target" of Resource Management processes at any level, depending on which of its aspects are being managed:

- Level 0: signals/observables;
- Level 1: individual resources;
- Level 2: a coordinated set of resources;
- Level 3: the system's mission goals; or
- Level 4: its design or configuration.

A data fusion process has the role of estimating entity states of interest within a problem domain. It may operate at one or more of the "data fusion levels" shown in Table 1; generating corresponding estimates of patterns, individuals, situations, scenarios/outcomes or of the state of the system itself. The latter may include states of sensors, data repositories and other information sources; of weapons and other effectors; of fusion, resource management and other processes; and of any other system resources.

Information can flow within and across the data fusion and resource management levels. Looking at the data fusion "levels" as depicted in Figure 2, we find a natural upward flow from measurements to extracted signals/features to detected and characterized individual entities; to inferred relationships among such entities and characterizations of networks of relationships (situations); to inferred courses of actions, scenarios and outcomes; and thence to an assessment of system performance.

Table 1. Entity State, Data Fusion and Resource Management "Levels" [22]

Level	Entity Class	Example Continuous State Variables	Example Discrete State Variables	Data Fusion (Inference) Level	Resource Management Level
0	Patterns; e.g. features or signals	Temporal/ spatial/ spectral extent, amplitude and shape/ modulations	Signal/feature class, type, attributes	Signal/ Feature Assessment	Signal/ Feature Management
1	Individuals; e.g. physical objects or events	Location, velocity, size, weight, event time	Object class, type, identity, activity or attributes	Individual Entity Assessment	Individual Resource Management
2	Structures; e.g. relationships and situations	Distance, force/energy/ information transfer	Class, type, identity or attributes of relations, slots, arguments, situations	Situation Assessment	Resource Relationship Management (coordination)
3	Processes; e.g. courses of action, scenarios and outcomes	State utility, duration, transition conditions	State transitions; Class, type, identity, attributes of processes, scenarios or impacts	Scenario/ Outcome Assessment	Mission Objective Management
4	System resources	(all of the above, applied to system resources)	(all of the above, applied to system resources)	System Assessment	System Management

Table 2. Downward flow of contextual information across the fusion "levels" [22]

Data Fusion Level	Downward Flow of Contextual Information
4 ↓ 3	Estimates of the state of the system's own resources and, specifically, of its goals and utility valuation across outcomes, provide expectations for the utility/cost of potential scenarios and outcomes
3 ↓ 2	Estimates of a course of action or scenario provide expectations for the states of constituent situations (stages of the evolving course of action or scenario)
2 ↓ 1	Estimates of a situation provide expectations for the states of constituent entities
1 ↓ 0	Estimates of the state of an individual provide expectations for the states of observable signals/features

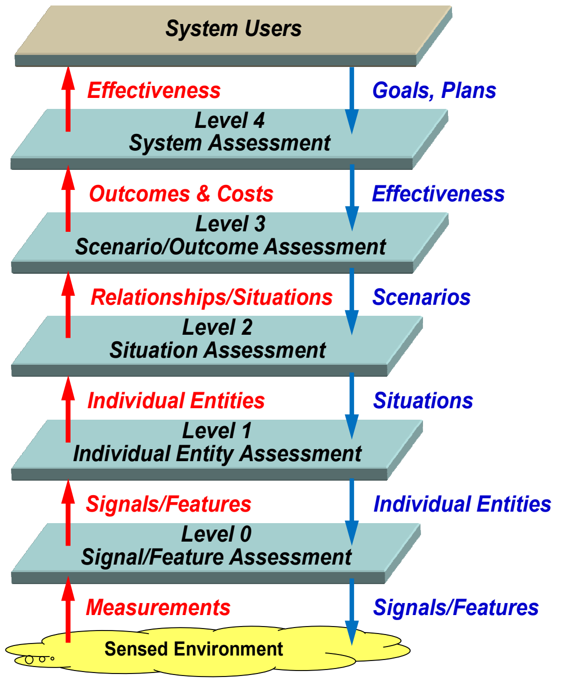

Figure 2. Characteristic information flow across the "levels"[19][4]

There is, however, an equally natural downward flow, whereby estimated scenarios provide expectations for situation states, which in turn provide expectations for constituent object states, which provide expectations for the signal/feature environment and, therefore, for expected measurements.

Information flowing downward across the data fusion levels can often be used as a context for the lower-level inference problems, as depicted in Table 2: estimates of higher-level states may be used to condition entity states for example by determining prior probabilities. An example is in group tracking, in which level 1, 2 and 3 processes function synergistically. This type of "multi-level" approach has been discussed in [33], integrating "low level" sensor data and semantically rich "high-level" information in a holistic manner, thus effectively implementing a multi-level processing architecture and fusion process.

It should be noted that the flow does not necessarily pass through all the levels. Imagine the case of a radar operator's screen going abruptly blank (no radar signal, Level 0), which could lead almost directly to high level products: is the radar malfunctioning (Level 4) or being jammed, thus foretelling an imminent attack (Level 3)?

[4] Figure 2 distinguishes system "user(s)" standing outside the system *per se* from various functions that human operators may perform within the system at any or all levels. As discussed in Section IV, relative to "Level 5" fusion, human/machine interfaces that facilitate human inference and control *within* the system are considered functionally no different than analogous interfaces between automated functions. For simplicity, the figure does not show other system aspects, such as resource management processes sensors, data stores or communications.

An adaptive fusion/management process may involve retrieval and exploitation of information within or across levels in response to evolving information needs. Relevant contexts for inference are often not self-evident or unique, but must be discovered and selected as a means to problem-solving. System implications for such an integrated adaptive process are discussed in [22,24,[34].

IV. LEVELING THE LEVELS

Human cognition is commonly conceived as a sequential process: sensing, then perceiving, then knowing [6,8,9]. This seems to be the principal metaphor guiding the fusion "levels". Sentient creatures are generally quite adept at moving information across this sequence. It is easy to formalize such a sequential process in engineering data fusion systems. However, not all ontological distinctions are hierarchical nor are all epistemic distinctions sequential. Consider the traditional data fusion levels:

Level 0

Defining a "level" in terms of "signals" and "features" is not sufficiently broad. For one thing, other types of information involve other types of primitive entities: bits, lexemes, sememes, musical notes, quarks, genes, …

Even within the domains of signals and features, we can distinguish among:

a) sensing/ sense impressions/ measurements considered as individuals (e.g. single pixel);
b) features, loosely defined as aggregates or structures of measurements (etc.) which can be further distinguished as spectral, spatial, or temporal (i.e. dynamic) features; we can also distinguish between literal features and induced features such as shadows, wakes and contrails;[5]
c) "plots" (a naval term meaning something like an association of measurements), perhaps more primitive than features, being tracks without state estimates (we can also have measurements aggregated analogously in other dimensions: spatial regions and spectral channels);

Note that this distinction corresponds rather neatly to the above distinction of entity levels 0, 1, and 2.

Level 1

As noted, this level – concerning entities considered as individuals – blurs with level 2, which can consider the same entities as aggregates, structures, organizations, organisms or systems. Individuals are paradigmatically physical objects, but can also be abstractions: a number, word, corporation, or other moral, theological, or scientific (etc.) concept. We can make further distinctions: monolithic versus fragmented individuals (e.g. Switzerland *vs* Indonesia); and individual objects *vs* individual events.

Events themselves can be distinguished much as in level 0: momentary *vs* temporally extended events (e.g. a meal, a

5 Of course, we will want to distinguish features in the sense of attributes of the observed entity from features in the sense of attributes of observations that entity [5].

battle). An event may be localized (Dirac impulse events) not only temporally, but also in spatial and spectral (etc.) dimensions. Events may be simple or complex, involving the interactions of multiple actors; thereby becoming a topic for level 2 and/or level 3 fusion.

Level 2

The products of level 2 data fusion are estimates of relationships (each defined as a relation and a set of arguments) and situations (defined as structures of relationships) [21,25].

Level 2 data association involves assigning an entity as an argument of a relationship or assigning a relationship as an element of a situation.

Level 2 state estimation involves characterizing instantiated relations, related entities and situations in terms of the types of relations and arguments involved (e.g. logical, causal spatial, spectral and temporal, part/whole, grammatical, social, legal, relations). Structures can be distinguished as relatively closed causal systems (e.g. the solar system or an urban area), organism, purpose-build structures (a building, nest or country), etc. Arguments can be distinguished as above as measurements, features, tracks, objects, events, etc.

There are numerous examples of processes that span the levels, such as group tracking or warm track initiation, in which information about an individual is used in refining the state estimate of others, and in which the coordinated motion is used to infer the state of relationships and of the group situation.

Level 3

In the earliest versions of the JDL model, level 3 fusion was labeled "Threat Assessment"[1,2] Subsequent researchers have concentrated on one or another aspect of threat assessment in defining "level 3" data fusion:

a) Temporal aspect: predicting future states [3,4];
b) Contingency/ causality aspect: projecting states (past, present, future) [5]; estimating and predicting scenarios and outcomes, vice observed situations [6];
c) Utility aspect: estimating cost of (future) situations [3,7].

We argued in [11,21] that the concept needed to be broadened to include the great variety of situations that don't involve threats. At the time, we recommended the label "Impact Assessment", focusing on the outcomes of hypothesized scenarios. We now prefer Lambert's [26] suggestion of "Scenario Assessment"; a scenario being a dynamic situation or the dynamic evolution of situations (if there is a distinction to be made between these alternatives), capturing all three of the above aspects.

Types of level 3 fusion inferences include

- *Conditional Event/Situation Prediction*: "If *x* were to follow this course of action, what would be the outcome?" This involves a reactive environment (one that responds differentially to actions) and often involves one or more responsive agents; often assumed to be capable of intentional activity. In Military Threat Assessment, the reactive element consists of "our" forces, concerned with intentional actions and reactions of hostile agents;
- *Counterfactual Event/Situation Prediction*: "If *x* had followed this course of action, what would have been the outcome?" Inferencing includes estimation of (conditional/counterfactual) outcome and cost, which may be performed using Bayesian cost analysis. Once again, the focus is usually on outcomes of "our" alternative courses of action;
- *Forensic Projection*: "What past scenario caused the present evidence?"

Clearly, threat assessment can have elements of level 1 fusion (e.g. estimation of agents' capabilities); of level 2 fusion (relationships with various assets of concern that might present opportunities for attack or desires to attack); and of level 3 fusion (e.g. prediction of evolving interactions, to include attacks).

More generally, we can distinguish topics relating to threat or scenario/impact assessment that map into the other "levels":

- signals in the sense of time-series or dynamic features (which are topics of level 0 fusion, as are "plots" in the special sensed described above);
- processes that are courses of action of an individual (as in level 1 recursive target tracking);
- scenarios, involving the interactions of multiple individuals over time (more or less, tracking of level 2 entities); b) outcomes (level 1 or level 2 events);
- impacts; i.e. effects on individual entities (distinguished from level 1 or level 4 states only in being contingent outcomes); and
- costs/utilities of outcomes (which can be level 4 attributes or level 1 attributes, depending on whether the entity in question is me).

Level 4

Level 4 concerns the states of one peculiar entity: the "me" mentioned above. This is the "ego" of the system performing the estimation or for whom the estimation is performed. The boundary conditions and the sets of resources whose states are to be estimated, are often not easy to specify (this is a concern not only for level 4, but for the other levels, which all presume to estimate the states of individuated entities).

Table 2 exposes the dissimilarity in the flow from level 4 to level 3 relative to the other inter-level flows; suggesting that the pattern that defines the sequence of "levels" does not actually extend to level 4. In other cases, an entity at a given level may be viewed as comprising one or more entities at the next lower level. That is not the case for level 4. Rather, as evident from Table 1, level 4 state variables are distinguished from variables at any level 0-3 only by virtue of referring to the system itself. Level 0-3 DF & RM are "third-person" processes, involving estimation and control of entity states outside the given DF&RM system; level 4 DF & RM are "first person" processes, involving self-estimation and self-control.

This is not the only reason that the inclusion of a DF&RM level 4 is problematical: a system's boundary conditions are often fuzzy, allowing various degrees of ownership or control.

The peculiar entity that is the concern of level 4 fusion is also the concern of interesting problems in philosophy, religion, cognitive science and law to define what is meant by one's self. At what point do fetuses cease to be part of a person? When does the person come into being or cease being? For an engineered system – such as a "data fusion and resource management system" – the system boundaries might defined legally: by specifications and contracts. Nonetheless, the degree of ownership, accessibility, controllability of such resources may be quite varied and ambiguous; governed by convention and convenience. When I sit in a restaurant, a particular chair, table, knife and fork are "mine" but only to a degree and for a while.

Level 4 entities span all the other levels: the states of the "system's" own signals/ features, individual resources, relationships among resources and courses of action of the same sorts as those of other "systems", except for the matter of ownership. This has an effect on the dualism between data fusion and resource management levels. A suggestion would be to redefine the latter to refer, not to various classes of organic entities (as in Table 1), but to the same classes as distinguish the data fusion levels, independent of ownership. If so, System Assessment and System Management are seen not as processes at a different level, but at processes that cut across levels 0-3 as they concern entities that happen to "belong" more or less to the inference system itself. Table 3 suggests broader concepts for Resource Management that better match the Data Fusion levels.

Table 3. Metabolizing level 4

Level	Data Fusion (Inference) Level	Resource Management Level (and examples)
0	Signal/ Feature Assessment	Signal/ Feature Management (what to do about the neighbor's noisy stereo?)
1	Individual Entity Assessment	Individual Entity Management (what to do about the noisy neighbor?)
2	Situation Assessment	Relationship/Situation Management (what to do about the marriage?)

Another issue concerning level 4 is that of generating and refining the predictive models that are used in inferencing and planning and executing responses. These are models that predict the characteristics and behaviors of "target: and background entities of concern at any fusion level. They also include models of the organic system resources (sensor performance models, etc.). The Data Fusion/Resource Management distinction, together with the seminal estimation/control distinction, is not at all obvious in model building and refinement.

Whereas the familiar data fusion processes itemized in Table 1 generate estimates of the states of particular entities at given times, a predictive model is an estimate of the distribution of possible *states* of an entity or of a class of entities. A second-order process, model assessment, may produce estimates of model fidelity, consistency, generality and efficiency (Occam's razor). Is model generation is an estimation process. Or is it a management process? More generally, is hypothesis generation an estimation process (hypothesizing) or a management process (*building* an hypothesis)?

Level 5 and beyond

We need to be clear as to the reason for having a data fusion model. As an engineering model its purpose is to partition the problem space in a way that tends to support different types of solutions. The definitions of level 5 by Blasch [27], Hall [28] and others [29] in terms of human involvement, certainly capture an important dimension of data fusion solutions; but it is a different dimension than the above, which differentiates "levels" in terms of types of output, not by type of process or by type of user.

On the other hand, a level 5 could be defined as a conversion of information to human-exploitable formats (visual, audible, haptic, olfactory) [28]. Our concern is that such definition does not capture the rich variety of possible human-machine roles and interactions: people can serve as system information sources, processors, managers, and product recipients. Such a "level 5" also smacks at anthropocentrism: what's so special about people? What about fusion in other animals? Furthermore, many human-engineered fusion systems have no person "in the loop": consider a missile seeker, a Mars rover or Siri®. As biologic and artificial processes blur – with the possibility of implanted sensors, cyborgs or real machine cognition – the interface blurs as well.

We would rather say that people can perform or participate in data fusion and resource management processes at any of levels 0-4 (if there is a 4) and that data formatting, conditioning and alignment for presentation to a person is functionally no different than formatting, conditioning and alignment for presentation to an automatic process.

V. A Better Mousetrap, or Gonzago's Revenge

The JDL data fusion model and its variants are seen as examples of *Engineering Models*; i.e. methods to partition a problem space in a way that tends to support different types of solutions. Such partitioning should not be seen as barriers to solutions that span the partitions.

It is shown that data fusion problems involve distinctions that are not all necessarily hierarchical or sequential.

By formulating the Specific Fusion Problem and the General Learning Problem in terms of random variables to be estimated, rather than by types of target entities, the issue disappears. Reasoning across attributive, relational and dynamic variables – roughly, the topics of the traditional levels 1-3 data fusion and resource management – involves no mysteries. Rather, consistent processes can be used for data alignment, data association and state estimation within and across the traditional data fusion "levels".

The JDL model and its progeny partition the fusion problem by type of *output*. Other partitioning schemes may also be useful. Dasarathy argued for a partitioning scheme by *input* as well as output [30].

Data fusion problems can also be partitioned in terms of the *metrics* used in inferencing: a decision may be unqualified, or stated as a discrete modality, quadratic distance, entropy, likelihood, probability, evidence mass, *ad hoc* confidence, etc.

Yet another partitioning alternative – proposed in [22,31], based on a taxonomy by Waltz [32] – distinguishes categories of inference problems by the way they use *predictive models*:

Category 0 involves the classic methods used in most fusion systems, in which high-confidence models of target characteristics and behaviors are available, allowing targets to be recognized by model matching.

Category 1 encompasses problems where normal background activities are sufficiently understood that anomalies can be detected and diagnosed as potential entities and activities of interest.

Both categories 0 and 1 use prior models that have been validated in one way or another: in category 0 these are models of target entities or activities; in category 1 these are models of normal or background activities.

In contrast, categories 2 and 3 are used to overcome deficiencies in prior models or in observable data, respectively. In category 2 new models are composed to explain observed data. In category 3, activities of interest might not be observable; rather their prior feasibility is determined on the basis of contextual information.[6]

In Category 2, training data is assumed to be insufficient to develop predictive models; therefore the process is one of abductive reasoning: building and testing models to best explain available data. An analyst, or possibly an automated process, constructs a hypothesized situation or scenario in an attempt to account for observed data. As in the classical scientific method, the hypothesis is evaluated to predict further observables that could either confirm, or refute the hypothesis. By acquiring such data as available, explanatory, predictive models of the observed situation or scenario are refined, selected or rejected.

Finally, Category 3 involves problems in which activities of interest may not be detectable or discriminable at all. Rather, contextual cues cause concern for general classes of activities: domain constraints, adversary capability developments, strategic planning, etc. [35].

Oftentimes, an inference problem is best addressed using multiple methods across categories. Figure 3 depicts such a system that integrates processing across the categories as information states and information needs evolve.

For example, the process can begin by detection of anomalies relative to normal background activity (detected by category 1 processes). This can trigger category 0 processing to attempt to recognize that activity. If the data matches no models, or matches ambiguously, category 2 processes could be triggered in an attempt to explain the anomalous data.

[6] We might want to add a "Category -1" to Waltz' list to capture model-free estimation methods; e.g. by parametric filtering. This shows the risk inherent in starting a numbering sequence with 0.

Alternatively, contextual factors alone may engender worries about the possibility of activities of concern; say, hidden developments of advanced weapons. If these contextual factors indicate that such activities are feasible (level 3 inferencing), a search for confirmatory indicators will be undertaken. Depending on the detectability of such indicators and the availability of predictive models, category 0 and category 1 methods might be employed to recognize the activity of concern or, at least, suspicious anomalies.

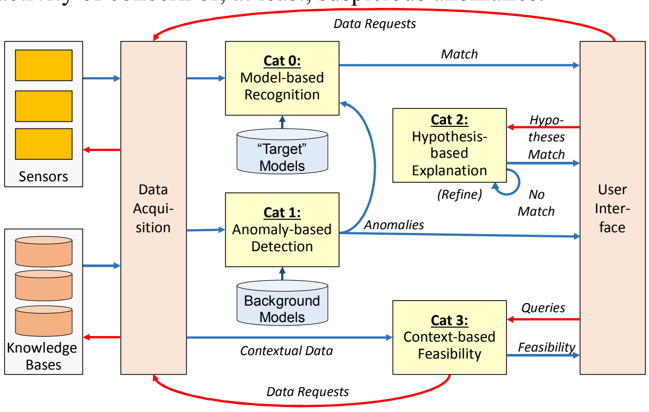

Figure 3. Adaptive data fusion across categories

Figure 4 sketches a partitioning of fusion problems in these four dimensions, taking the form of an IDEF0 process diagram. Such diagrams have been useful in characterizing a wide diversity of system design approaches; identifying implementation alternatives in terms of input, method, output and goals. They should be equally useful in designing data fusion and resource management systems.

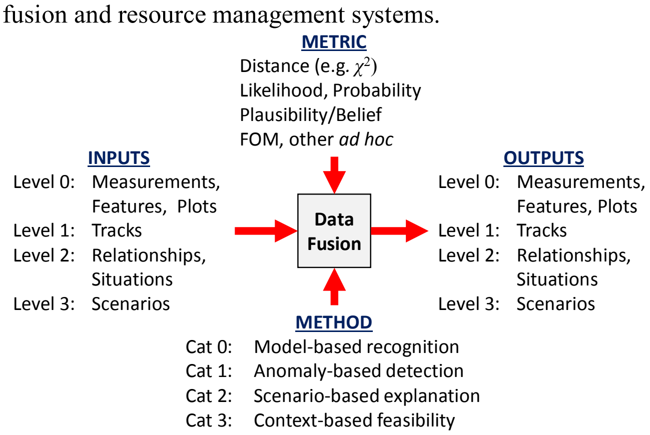

Figure 4 (Some) dimensions of inference problems

VI. SUMMARY

As proposed several times in the literature, there are many ways to partition data fusion problems. Partitioning by desired type of output as in JDL-derived fusion models is one way. A partitioning of problem spaces either by outputs, inputs, methods or metrics alone should not be allowed to restrict the flexibility of solutions appropriate to diverse and dynamic information needs, or to the qualities of available data or prior models. We here discuss how a partitioning based on categories of inference problems can better help address, among other aspects, recent challenges posed by multi-level fusion and context integration approaches.

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