Evolution of the JDL Model

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Dedication—This paper is dedicated to the memory of Chris Bowman: brilliant colleague and close friend; a pioneer of the data fusion community in the United States and worldwide. Chris played a leading role in refining the JDL data fusion model that is the topic of this paper. He died unexpectedly before we could complete this article.

MODELS

The well-known Joint Directors of Laboratories (JDL) Data Fusion model has served as a paradigm for much of the subsequent discussion and development of data and information fusion.

The model was conceived in the late 1980's by the JDL Data Fusion Subgroup, consisting of prominent fusion experts and representatives from various US Government agencies [1], [2], [3]. The model was formulated as a scheme for clearly defining and differentiating concepts concerning the then-new field of data fusion. The model gained considerable influence by its articulation in Waltz and Llinas's landmark book, *Multisensor Data Fusion* [4].

Developments in the succeeding decades in applications and in applicable methods–in problem spaces and solution spaces–have strained the taxonomy, boundary assumptions, and partitioning scheme assumed in the early model. This has prompted numerous revisions and alternatives to the model.

Concepts and terms have been broadened to apply data fusion methods beyond the JDL's initial tactical military domain. Data fusion itself, initially defined 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]*

was defined more simply and comprehensively as:

> *the process of combing data to estimate or predict the state of some aspect of a world state [5].*

With the wisdom of age, we now prefer to define *Data Fusion* in even simpler and broader terms as:

> *the process of combining data to estimate entity states;*

where an entity can be any aspect of a universe of discourse at any degree of abstraction. To maximize breadth of applicability, we forgo distinctions of sensor fusion, data fusion, information fusion, knowledge fusion, etc.; considering "data fusion" as the encompassing term.

A data fusion process has the role of estimating entity states of interest within a problem domain on the basis of multiple data. As such, data fusion is a particular topic of epistemology: learning on the basis of multiple pieces of data. The specific data fusion problem is that of determining what data are relevant to a state estimation problem and using such data in deriving estimates; accounting for uncertainty in data relevance, data accuracy and in the performance of the inference method.

The JDL model introduced the notion of fusion "levels" as in Figure 1, distinguishing classes of fusion processing methods as applicable to major distinguishable classes of problems: processes that relate to the refinement of estimates or understanding of "objects" (Level 1), "situations" (Level 2), "threats"(Level 3), and "processes" (Level 4) [2], [3], [4].

The JDL model and its progeny have had to confront issues of the semantics of such terms. When the initial JDL model was used in for integrating across US Navy C4I and Combat systems, the issue arose as to the use of the terms "entity" and "object". Although commonly used interchangeably, the software community takes an entity to be a real world "thing" and an object to be a machine representation thereof (we'll see that clarification of usage in later revisions to the model). There's no space here either to describe common usage or to prescribe preferred usage. However, a fusion model will need an ontology and taxonomy to clarify such terms as:

- attribute//property//feature//signal//observable
- entity//object//individual//target

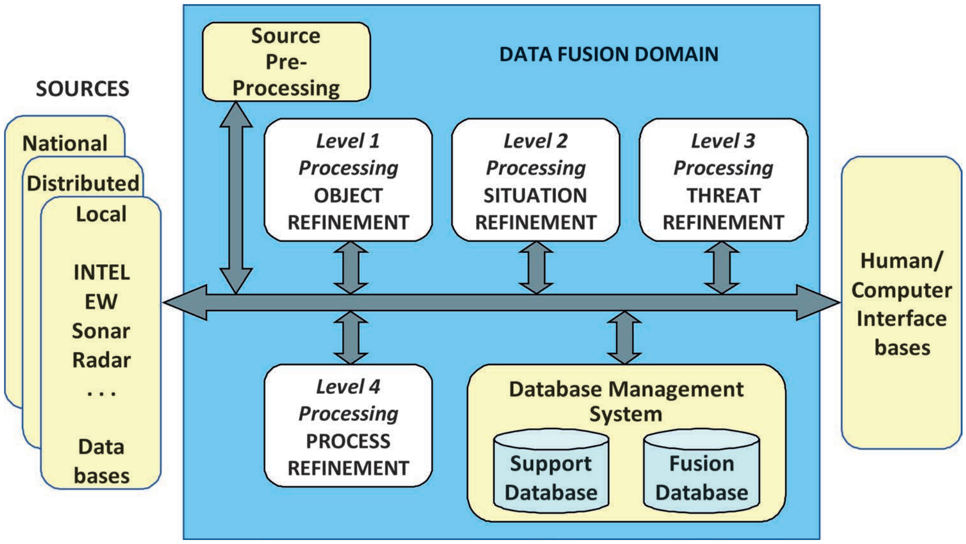

Figure 1
Early JDL data fusion model, 1990 [4].

- relation//relationship
- structure//complex//situation//scenario
- detection//contact//perceived entity//track (*vide* [7])

The original JDL model depicts levels as interacting via a bus architecture, such that processing sequences and access to data are free design variables. The prominence of 'threat" and the illustrative list of "sources" reveal the initial military focus. Later refinements generally had the purpose of broadening this perspective. After all, the very purpose of data fusion is inclusivity: to exploit *all* available information pertinent to a given problem. This motivates the broadest possible generalization and abstraction of problems and of solutions. It should be appreciated that significant research and development has occurred across the widest range of application, far beyond those of a military nature.

Challenges and refinements to the model are to be expected and welcomed to meet changing needs and perceptions. The model was not revealed to the JDL Data Fusion Subgroup on tablets from Mount Sinai. We made it up.

Ongoing developments in various technologies have obliged consideration of the relationship and role of data fusion in respect to new forms of knowledge representation and of uncertainty management, of data mining, cloud-based information retrieval, multimedia information exploitation, artificial intelligence and machine learning, joint human/machine problem-solving, etc.

A reexamination of the model was undertaken in the late '90s to clarify terms, broaden the model as much as possible from its initial focus on tactical military applications, refine the partitioning scheme, and explore relationships of data/information fusion with resource management, data mining, human situation awareness, and decision-making [5]. Source pre-processing was ennobled as Level 0 fusion to encompass data association and estimation at the feature/signal level (e.g., calibration, filtering, pulse train deinterleaving, modulation characterization). Level 4 fusion was divorced from resource management to clarify and exploit the distinction and duality of fusion/estimation vs management/control functions:

- *L0, Feature/Signal Assessment*: estimation of patterns: paradigmatically signal or feature modulations in 1, 2, or more dimensions; but can extend to most any abstract pattern: numeric or geometric patterns; musical or literary themes; rhyme schemes, etc.
- *L1, Individual Entity Assessment*: estimation of states of entities considered as individuals
- *L2, Situation Assessment*: estimation of relational states and of complexes of relationships
- *L3, Scenario/Impact Assessment*: predictive or forensic estimation of courses of action, scenarios, and outcomes
- *L4, System Assessment*: estimating states of the system itself: e.g., sensor and data alignment, estimation or control performance, fidelity of predictive models

Blasch has led the examination of several alternative approaches over the years [8–12]. As a recognition of the characteristic role that human cognition plays in understanding information, he and his colleagues introduced a DF Level 5, "User Refinement", similarly proposed by Hall and Mullen as "Cognitive Refinement" [13].

These ideas were incorporated in 2004–05 in a significant variant developed by the ISIF Data and Information Fusion Group (DIFG) [9]. As depicted in Figure 2, the DIFG model distinguishes fusion levels as transforming information between entities of various types. It effectively partitions fusion processes on the basis of *agency*, in terms of classes of entities providing and receiving the data. This is an *information*

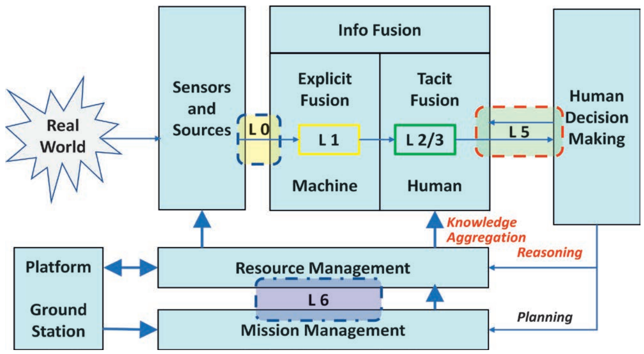

Figure 2
DIFG model, 2005, redrawn from [9].

exploitation model in that it includes planning and control at its Levels 4 and 5.[1]

Other model variants [11], [12], [14] similarly distinguish high-level from low-level information fusion (HLIF vs. LLIF), both in terms of types of processes and in types of products:

> *The low-level functional processes support target classification, identification, and tracking, while high-level functional processes support situation, impact, and fusion process assessment. LLIF concerns numerical data (e.g., target locations, kinematics, and attribute types). HLIF concerns abstract symbolic information (e.g., threat, intent, and goals) [12].*

This seems an unnecessarily constraining and perhaps forced marriage. Symbolic methods are certainly applicable to "low level" target classification, numerical methods (e.g., belief networks) to relational and situational assessment and to process assessment. Recognition and prediction of relational, situational, and system states are clearly akin to low-level individual state recognition and prediction. Similar classification, characterization, and tracking methods may apply. HLIF can provide context for predicting and understanding LLIF state and HLIF states can provide context for one another.

BUT WHICH MODEL IS RIGHT?

How then, to select among the multitude of JDL model variants and alternatives? These models tend to differ either:

- in scope: do they include control as well as estimation processes? Do they encompass human as well as machine techniques?
- in partitioning scheme: are elements differentiated by type of input, processes, output, or agencies (i.e., who or what does the fusing)? or
- in purpose: is it an ontological, epistemic, management, or engineering model?

Many fusion models, including various versions of the JDL model, are based on one or another of these distinctions, and sometimes straddle the distinctions.

We need to be clear as to the reason for having a data fusion model. 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, we would like it to partition the problem space in a way that tends to support different types of solutions. For example, the stated objectives of [5] were (a) to provide a useful categorization representing logically different types of problems, which are commonly solved by different techniques; and (b) to maintain a degree of consistency with the mainstream of technical usage.

Let us propose three desired qualities for engineering models, to include data fusion models:

- ***Avoid Confusion*** with a clear distinction of problems that tend to require different solution methods
- ***Constrain Profusion*** of models and methods by generalizing concepts and constructs so as to apply across a wide range of problem domains, facilitating integration, technology re-use and deeper understanding
- ***Mitigate Diffusion*** of communities of practice by clearly defining the relationships of the modeled domain to other domains, promoting coordination and synergy. As in international politics, a data fusion model shouldn't erect borders that impede the useful flow of goods and services, either internally between fusion levels or with neighboring domains: planning, data mining, machine learning, etc.

In short, practitioners desire clear and comprehensive modeling of fusion problems, solutions, and problem domains. Internal and external synergy is facilitated by a common representational framework across fusion functions and with neighboring disciplines, as discussed in [19], and a comprehensive functional architecture [18], [20].

Although there have been many revisions and rivals to the JDL model, nearly all of them partition the fusion domain in terms of fusion "levels". 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 necessarily right or wrong but they may serve different needs.

In [5], [6], [15–18] we successively proposed refinements to the early definition of levels (e.g., Figure 3). The explicit goals were to clarify the partitioning and to broaden applicability beyond the original tactical military domain. We suggested partitioning levels according to fusion products: specifically,

[1] The DIFG model's distinction between "Explicit Fusion", performed by machines, from "Tacit Fusion", performed by humans, is a bit anthropocentric. There's no fundamental reason why machines can't perform higher-level (L2/3) fusion or people–or animals for that matter–can't perform lower level (L1) fusion. Perhaps we should view the reference to "human" agency as an exemplar for internal or external processes by sentient beings. Developments in AI, not to mention SF, blur that distinction. Also, the boxes labeled "Platform" and "Ground Station" in the figure can be viewed merely as examples of model instantiation.

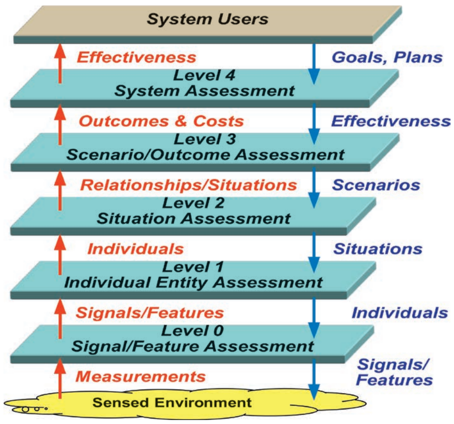

Figure 3
1999 revision [5].

the types of state variables to be estimated. In this way states of interest can be distinguished in terms roughly corresponding to the levels described in earlier versions of the JDL model.[2]

We also extended the formal and functional duality between data fusion and resource management functions by defining a set of corresponding management levels [17–20]. This extension helps clarify the role of data fusion within the broader field of information exploitation. Bowman applied this broader purview to formulate a dual-node network architecture, comprised of paired data fusion/management nodes, each pair acting as a quasi-autonomous agent that acquires and processes data to meet its evolving objectives in the system context [20].

These DF and RM levels 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.

But how do the traditional fusion "levels" fare given this insight? Levels 0 through 2 clearly can be distinguished by types of variables: signal/feature parameters vs. individual metric and kinematic variables vs. relational variables.

Level 3 fusion estimates or predicts courses of action, events, and impacts. As these generally concern projected entity states and relationships, many versions of fusion models refer to a blended "Level 2/3" (as in Figure 2). We can broaden the earlier label "Impact" to "Outcome", which may include impacts on various entities, including on "our" system and mission.

As for Level 4, we have indicated the importance of differentiating estimation from control and, therefore, fusion from management [20]. *System Assessment* is therefore preferable as a fusion level to the original model's *Process Refinement*. However, L4 fusion is still an awkward fit. The distinction of L4 from other fusion levels is more a matter of ownership than of type of process or product. In L4, a system assesses its own signal/feature parameters, individual metrics and kinematics, and relationships; i.e., its own L0–3 variables. However, because system boundaries and ownership can be partial, mutable, and uncertain, so can the distinction between system assessment and assessment of external variables. Therefore, L4 challenges our preference for clear boundaries and partitioning criteria.

The original fusion Level 4, Process Refinement, as well as the proposed Levels 5 and 6, relates to the resource management side of data exploitation. Indeed, the original JDL documentation addressed these concerns as Level 4 machine control, Level 5 user control, and Level 6 control of the data collection and processing. These "levels" reflect the multi-dimensionality of data exploitation.

Even within the single dimension that distinguishes data fusion Levels 0 through 3, the term "levels" can be misleading. The sequential numbering of levels (or depictions as in Figure 3) should not be construed as a constraint. Fusion/management processes must be free to employ data types and sources within or across levels as needed [20].[3]

Figure 4 presents the original, non-hierarchical JDL model, refined and extended to improve clarity and breadth in modeling fusion problems, solutions, and problem domains:

a. clearer partitioning scheme, based on classes of variables to be evaluated or managed (*to avoid Confusion*)

b. generalization of concepts to extend to all applications, both in leveling the levels in a bus configuration and expanding their scope (*to constrain Profusion*)

c. expanding the model to include resource management to encompass all aspects of information exploitation (*to mitigate Diffusion*)

The notional agent bus architecture–as in the original model of Figure 1–allows data to flow unconstrained by the model within and among the data fusion and resource management levels, enabling flexible, opportunistic data exploitation and response. System users external to the fusion processes are shown, with the proviso that people can perform any of the functions internal to data fusion.

SUMMARY

The JDL model was developed to define the concepts and structure of the data fusion problem: that of estimating entity states of interest within a problem domain. The model has been refined over the years (a) to extend as broadly as possible across diverse problem domains to facilitate common solutions to common problems and (b) to recognize synergies with other disciplines related to information understanding and information exploitation. A testament to the contribution of the model has been in the wide use of its structure and taxonomy not only by researchers and practitioners, but also in data fusion product specifications for acquisition and deployment.

[2] As argued in [17], [18], [19], generality is improved by partitioning inference problems on the basis of types of entity state variables rather than by type of entity. A given entity–say, an aircraft–can be addressed at more than one level: as an individual (at Level 1) or as a complex (Level 2) such that the relationships among its components or subassemblies are being estimated. The aircraft may also be addressed at Level 3 as a dynamic process; or at Level 4, if it happens to be the system performing the estimation.

[3] Machine learning methods may operate across non-adjacent levels, inferring situations directly from measurements. Conversely, states of individuals may be inferred from situations or courses of action.

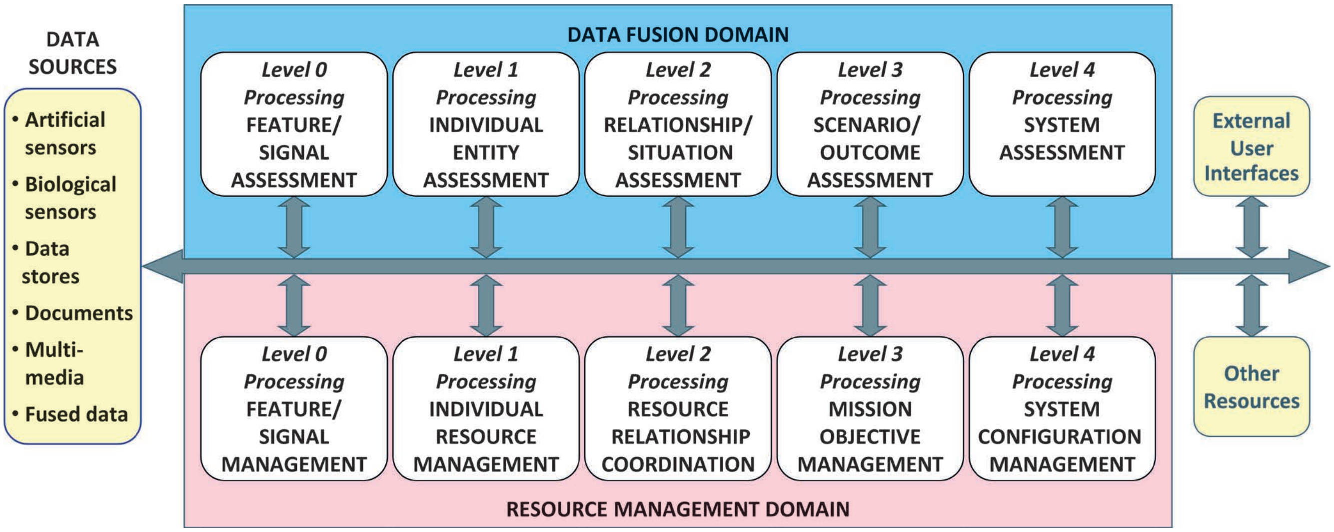

Figure 4
Candidate data fusion process model [18].

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