Multi-Hypothesis Structures, Taxonomies and Recognition of Tactical Elements for Combat Identification Fusion

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Abstract

One of the greatest difficulties in developing a fusion process is determining the type, quantity, and quality of the information provided. Even when this is accomplished, the utility (*relationship*) of the information is often difficult to establish. For the problem of combat identification (Combat ID or *Combat ID*) this is especially taxing. Often numerous sources provide information, but relationship guidelines are not well developed, or are ambiguous or inconsistent. This deficiency leads to poorly constructed fusion architectures and methodologies because information is either ignored or improperly combined in the fusion process. Using the Joint Directors of Laboratories (JDL) information fusion model as a guide, this paper will address the movement of attribute information across multiple hypothesis classes as it relates to developing the identification of different objects, and how it can be combined both within and between JDL fusion levels. The result of this analysis will lead to an information architecture that is naturally adaptive to information regardless of quality, level, or specificity. Such a full Combat ID architecture must be able to facilitate a broad range of information at various levels. In this paper we provide examples for taxonomies, multiple hypotheses, and the recognition of tactical elements to illustrate the relevant issues and present an architectural model. Further, implementation of such an architecture may facilitate a *power to the edge* approach to decision-making when edge units are provided with Combat ID information at the level of recognizable "tactical elements" for which decisions are made.

I. INTRODUCTION

The Joint Directors of Laboratories (JDL) information fusion model provides an excellent basis for parsing information according to discrete levels. For the combat identification

(Combat ID or Combat ID) problem encountered by military forces, a straightforward mapping into the JDL model exists. From this, an additional mapping of Combat ID categorizations can be gleaned from various operational specifications (such as Operational Specification (OS) 516) to further refine information categories for each JDL level. However, the relationship between information categories both within each JDL level and between JDL levels must be defined in order to maximize information available for a fusion process. This paper explores an architecture definition process that represents Combat ID information movement between hypotheses within an individual JDL level and between JDL levels 1, 2, and 3. Defining this architecture will involve an investigation into detailed *taxonomic relationships* between information sets and their subsequent canonical mappings. From this a definition of a *response mapping*, which allows the interpretation of elements from one taxonomy in terms of another taxonomy, can be made. Concepts are then tied into multi-hypothesis structures based on the JDL model. This model of Combat ID fusion is constructed in the context of Situational Awareness (SA). Of particular interest is the relationship of level 3 information and its complexities. For the purposes of this paper, the problems associated with Combat ID for air objects provide an instructive example, although the model is fully extensible to the general Combat ID problem.

To maximize the agility of the fighting forces (*edge units* as described by Alberts & Hayes [1]), there exists a critical need to provide these units with Combat ID at the intent level (Level 3). This Combat ID discernment capability requires a situational understanding of opposing units at the decision level rather than the observable individual platforms. This results in a need for a distributed Combat ID architecture to support modeling of upper echelon intent. Implementation of such an architecture may facilitate a *power to the edge* approach to decision-making when edge units are provided with Combat ID information at the level of recognizable *tactical elements* for which decisions are made.

II. TAXONOMIC RELATIONSHIPS DEFINED

A *taxonomy* is a classification scheme for objects of interest, which parallels the study of *ontologies*. It is a set of mutually exclusive labels. An example is the classic *Combat ID* (*Combat ID*) taxonomy {Friend, Assumed Friend, Neutral, Pending, Unknown, Suspect, and Hostile}. The *Nationality* taxonomy is {US, Russia, UK, France, Iraq, Iran, Zimbabwe, …}. Other examples are the *Category* taxonomy {Space, Air, Surface, Subsurface, Land}, the *Platform* taxonomy {Fighter, Bomber, Transport, …}, the *Type* taxonomy {F-14, F/A-18, F-22, Typhoon, Viggen, E-3, …}, and the *Class* taxonomy {F-14A, F-14B, F-14D, F/A-18A, F/A-18B, F/A-18C, F/A-18D, …}. The Category, Platform, Type and Class taxonomies are successive refinements of predecessor taxonomies. Given a Class label, a Type label can be inferred, given a Type label, a Platform label can be inferred, and given a Platform label, a Category label can be inferred. (There are some exceptions, for example a C-130 might be an attack aircraft or a transport.) More precisely, taxonomy *A* is an *f-refinement* of taxonomy *B* if *f* is a function $f : A \rightarrow B$ such that if $b_1 \neq b_2$ then $f^{-1}(b_1) \cap f^{-1}(b_2) = \varphi$, where φ = empty set. An example is given in figure 1, in which it can be seen that $f^{-1}(F-16) \cap f^{-1}(F/A-18) = \varphi$. If *f* is an obvious function, as it is for example for the taxonomies Type and Class, we say simply that taxonomy *A* is a *refinement* of taxonomy *B*. Other collections of taxonomy do not show such a relationship—an F/A-18 might have any of a dozen or more Nationalities, and each Nationality can have many different aircraft Types.

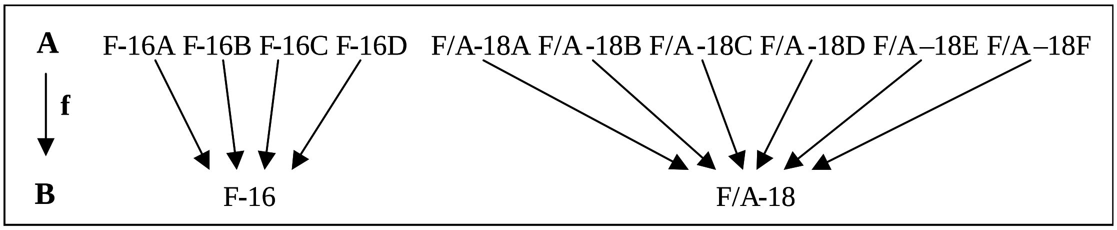

Figure 1. f-refinement Taxonomy Example

If a taxonomy *A* is an *f-refinement* of taxonomy *B* and $a \in A$, $b \in B$, and $f(a) = b$, we say that *a* is an *f-refinement* of *b*. If *f* is an obvious function, we say simply that *a* is a refinement of *b*. For example, F/A-18A in the Class taxonomy is a refinement of F/A-18 in the Type taxonomy.

Given a set *S* of objects, a taxonomy imposes a partition on the set. Each element of the partition is the set of all elements of *S* for which a single element of the taxonomy is the appropriate name. An example of an element of the partition imposed on aircraft by the Type taxonomy is the set of all F-15s. Another is the set of all 747s. A taxonomy T_1 is a refinement of another taxonomy T_2 if the partition imposed by T_1 is a refinement of the partition imposed by T_2. Figure 2 shows the f-refinement of figure 1 as a partition refinement.

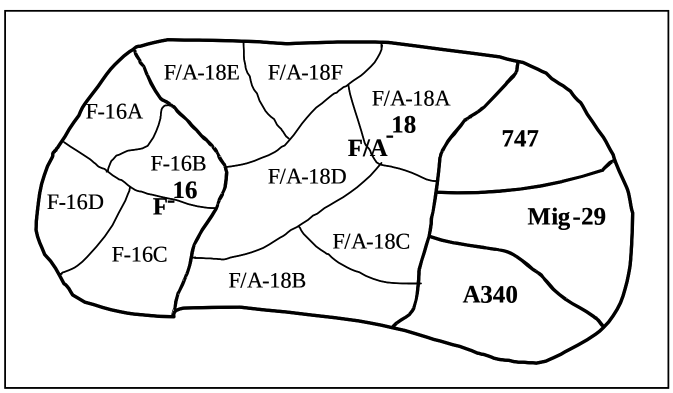

Figure 2. An f-refinement as a Partition Refinement

A *taxonomic refinement series* is a set of taxonomies, $\{T_i\}_{i=1}^{n}$, such that T_{i+1} is a refinement of T_i. An example is the series Category, Platform, Type, and Class. The problem of interest is how to use information about an object from different taxonomies to categorize the object in one of those taxonomies, or in another, completely different, taxonomy. It is a practical problem since some sensors categorize an object in the context of one or more taxonomies. For example, an ELINT sensor might be able to discern that the object might be an F-14 or an F/A-18D on the basis of emission characteristics. The information is from both the Type and Class taxonomies. It can be used to infer that, in the Type taxonomy, the object is either an F-14 or an F/A-18. It can be used to infer that the object is an Air object in the Category taxonomy, and that it is not a Chinese aircraft in the Nationality taxonomy. Canonical mappings provide a way to exploit these taxonomic relationships.

III. CANONICAL MAPPINGS

As can be seen in figure 3, two taxonomies might be related through mappings in more than one way. Figure 3 shows how sets T_6 and T_3 are related through both the mapping m_3 and the composite mapping m_2*m_1. Since these mappings in general will not be equal for any particular application, a set of canonical mappings must be defined between any two related taxonomies (the canonical mapping from a taxonomy to itself is, of course, the identity mapping). In the case of a collection of taxonomies that are successive refinements, the canonical mappings reflect the hierarchical nature of the taxonomies themselves.

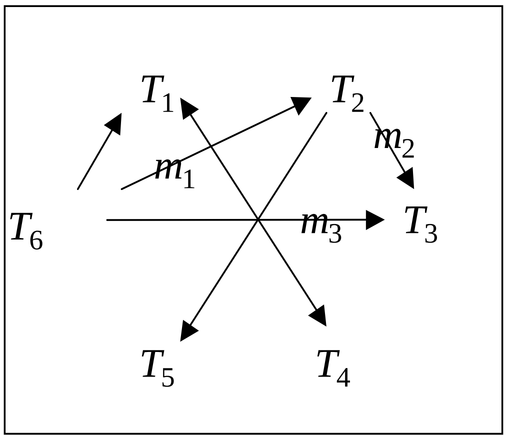

Figure 3. Non-Canonical Mapping Example

It is conceivable to have multiple canonical mappings between two sets, and to maintain parallel state information for both. This may allow better quality results by combining the two states, since each mapping is an expression of domain information. Thus a state arrived at with one canonical mapping encapsulates background information that the other lacks. More significantly, it is conceivable that the two states might be in conflict. This might indicate an inconsistency in the sensor inputs used to infer the two states, but it also could reflect varying uses or ambiguous interpretations of the observations. The gain from using more than one canonical mapping might or might not be worth the extra complexity.

IV. RESPONSE MAPPING

Response mapping is a way to interpret a response with elements from one taxonomy in terms of another taxonomy. It also provides a means of interpreting a response with elements from more than one taxonomy in the various referenced taxonomies. Level expansion, which is a case of response mapping among the taxonomies, is of particular interest because of existing sensors that yield a response with elements from both the

Type and Class taxonomies. The objective is to make it possible to maintain parallel states in multiple taxonomies. As each response is received, it is interpreted in the taxonomies of interest. The state for each taxonomy is then updated.

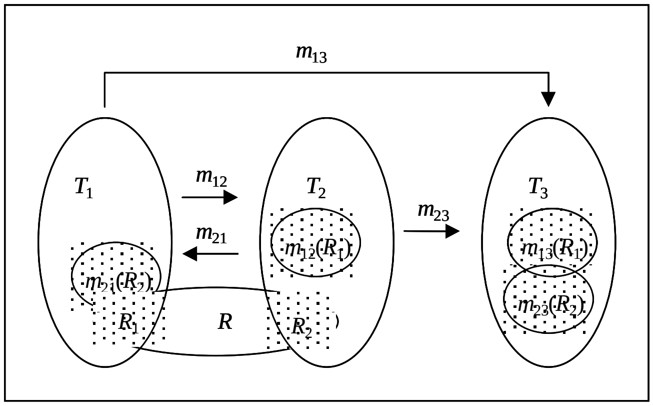

Figure 4. Response Mapping in a Refinement Series

Referencing figure 4, let R be a response from a source of information. It is composed of a set of attributes, potentially from several different taxonomies. Let the canonical mapping from taxonomy T_i to taxonomy T_j be m_{ij}. Each taxonomy potentially has elements that are part of the response (R_1 and R_2 in the figure), as well as elements that are the images, under a canonical mapping, of elements in other taxonomies ($m_{12}(R_1)$, $m_{21}(R_2)$, $m_{13}(R_1)$, $m_{23}(R_2)$ in figure 4).

V. JDL BACKGROUND

For the purpose of brevity, we assume the reader has some familiarity with the JDL model. However, a purposeful description is needed here to clarify some concepts. An excellent resource for further information on the JDL information fusion model is found in Hall and Llinas [2] and Steinberg, et al. [3]. Figure 5 provides a graphical description of the model.

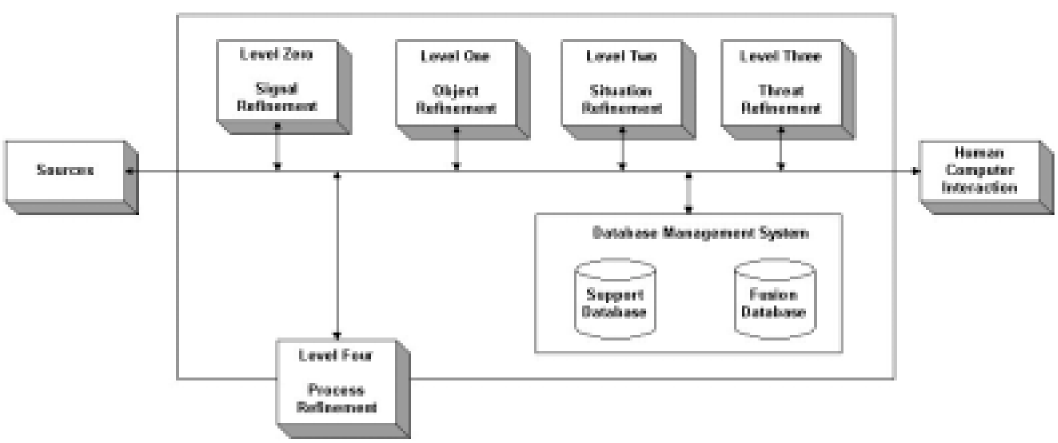

Figure 5. JDL Fusion Process Model

The problem of parsing and fusing Combat ID information falls within JDL levels 1, 2, and 3. Level 0 information includes such operations as coherent signal processing of measurement data, centroiding and filtering of kinematic data, IFF code degarbling, emitter classification, association and tracking, etc. This level of processing is generally performed entirely within individual sensors. Level 4 processing is a *metaprocess*, which is a process that monitors and optimizes the overall data fusion performance via planning and control, not estimation as in JDL levels 1 through 3. In the context of Combat ID, the following discussion defines the type of information processed by the remaining JDL categories.

JDL Level 1 – Object Refinement. This processing level combines information from the results of level 0 processing within sensors. Level 1 fusion combines information about the location and attributes of objects so as to detect, locate, characterize, track, and identify these objects. This level of processing involves information assignment/correlation, determination of position and what is defined as *taxonomic Combat ID*. The OS 516.2 designations for this are category, platform, type, class, unit, and nationality – although nationality is often considered as a level 3 category. Examples of level 1 declarations include tank, M-1 Abrams, fighter, DDG, 737-300, etc. The goal therefore of JDL level 1 processing is to determine exactly what an object is, not its relationship to the identifying platform. Three specific areas that taxonomic Combat ID processing embodies include: (1) Information alignment such as time synchronization, and gridlock and bias removal (2) Information correlation (platform-platform, type-platform, class-type, etc., according to OS 516.2 object categories), and (3) Probabilistic/evidential attribute estimation (Bayesian, Dempster-Shafer, etc.). Generally speaking, in order to fuse information at this level, multiple hypotheses must be tracked. This is because taxonomic Combat ID information from Intelligence-Surveillance-Reconnaissance (ISR) sources will be available at many different levels. Automating the fusion and declaration decision process flexibly across these levels, as information is available, without throwing away valuable information and context is challenging.

JDL Level 2 – Situation Refinement. This processing level includes the ability to establish contextual relationships of objects declared in level 1 processing with their environment. This includes situation refinement using some sort of assessment to declare an object as (1) Friend, (2) Assumed Friend, (3) Neutral, (4) Suspect, (5) Hostile, and (6) Unknown. The taxonomic identification produced by the level 1 process generally does not imply the state of an object. Level 2 processing uses some sort of decision methodology such as if-then logic, or voting fusion to *derive* the object state and establish the Combat ID. As an example, if an object is determined to have a high confidence taxonomic Combat ID of an F-16, this in itself offers no information on whether it is friendly towards the platform performing the identification. However, inserting a level 2 assessment decision will enable the proper Combat ID declaration to occur based on such rules as country-of-origin, flight profile, intelligence information, etc. In this example, doctrine could derive a Combat ID of *Assumed Friend* if no hostile entities were known to have any F-16s in their inventories. Some sensor/source information may also be *directly fused* at this level such as secure Identification Friend-or-Foe (IFF) modes and data link associations, if available. The presence of this type of secure information can be directly associated with the existence of a *Friend*, although the lack of it does not normally imply a *Hostile* or *Unknown* designation. It is important to note that level 2 categories are drawn from a single taxonomy, so the structures for fusion will be different from the ones best suited for the multiple taxonomies of level 1.

JDL Level 3 – Threat Refinement. This processing level attempts to interpret a situation from a dynamic behavior point-of-view and involves evaluating hypotheses concerning the future actions of an object and the potential consequences of those actions. This includes threat analysis and the assessment of intent. Conceptually, this is similar to a mind reading exercise to determine what the object will do, under what circumstances will it happen, and with what motivation. For Combat ID, this processing level can take the results of levels 1 and 2, in addition to independently processing information, and will determine if the identified object is a candidate for engagement. For example, using a self defense scenario, if an object is positively identified as a *Hostile*, but is flying away from any defended assets and poses no threat, then the object's intent may not be threatening and the identifying platform may choose not to engage it. Depending on the refinement in the level 1 processing, if platform type, class, unit, nationality, and/or activity are known, then this may be used along with the Combat ID for level 3 processing. As an example, if an object is identified as *Hostile*, with a taxonomic identification of a military reconnaissance aircraft on a surveillance mission, then that object may not qualify for engagement because it has no offensive weapons capability (again depending on doctrine and situation). Bayesian and neural networks are two methods of fusing information at this level.

VI. MULTI-HYPOTHESIS STRUCTURES

An information model for multi-hypothesis structures is shown in figure 6.

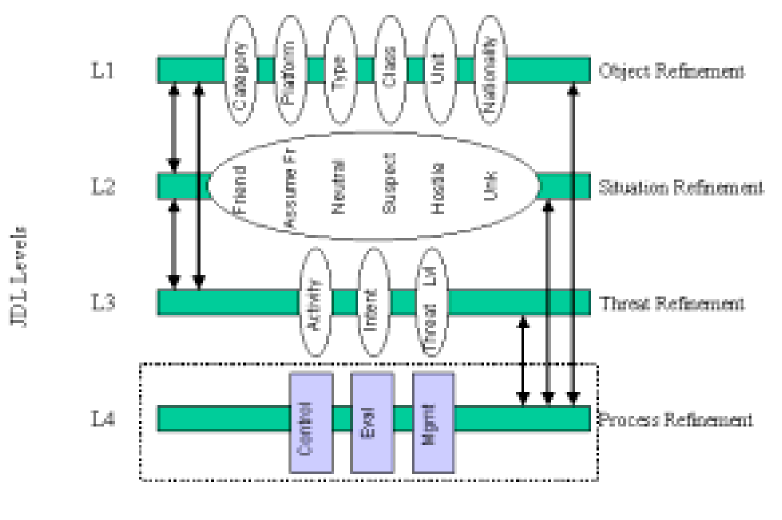

Figure 6. Multi-Hypothesis Structures with JDL Levels

This figure stipulates that there are six hypothesis categories for level 1, one for level 2 (that has six possible states), and three for level 3. The level 4 structure is included for completeness, but will not be referenced in this discussion. Each of these hypotheses is populated from various possible fusion methods, some of which were discussed in section 2. Not all hypotheses will be populated all the time. This will be determined by the amount and type of information present for every object associated with a track store (or file). Figure 6 represents the following:

- Each hypothesis category has an associated probability distribution that is derived as a function of the observed sensor/source parameters. Information primarily moves between hypotheses within an individual level (horizontal bars) with some information moving between levels 1, 2, and 3. Level 4 primarily accepts requests for optimization and provides feedback to levels 1, 2, and 3.
- Each hypothesis category has a unique threshold value for declaration that is dictated by mission, doctrine, and available information. Some means to automate a decision threshold is required which is the subject of future work. A good level 2 example is the decision between a declaration of *Hostile* or *Neutral*. Obviously the *Neutral* ID hypothesis will require less information to declare than the life-critical *Hostile* ID, so a higher decision threshold for a *Hostile* declaration will probably be required.
- Each hypothesis structure requires decision logic to determine how to arrive at a decision given a set of observed sensor/source parameters.
- Each hypothesis declaration is made taking into account the probability of a wrong decision (or non-decision) and its consequences.

JDL Level 1 Structures

The Level 1 structure is quite different from the level 2 and 3 variants. The level 1 hypothesis structures of *category*, *platform*, *type*, *class*, form a taxonomic refinement series, while *unit* and *nationality* are related to all four of the taxonomies in the series. Figure 7 illustrates this example.

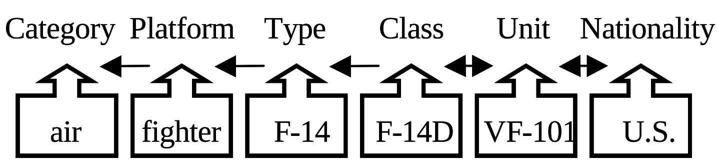

Figure 7. CID Level 1 Information Flow

Every sensor type that produces information will provide information that spans both the three JDL levels and the hypothesis categories within these levels. As an example, suppose we receive the following sets of level 1 information from two very good sensors:

- Sensor 1: F-14, F-15, F/A-18
- Sensor 2: F-14A, F-15E, F/A-18C, F/A-18D

Sensor 1 is providing *type* information while sensor 2 is providing *class* information. However, both sensors are proving information that will help all the hypothesis structures, especially sensor 2, which is providing specific subsets of objects declared by sensor 1. Sensor 2 has defined one instance of object F-14, one instance of object F-15, and two instances of object F/A-18 related to sensor 1. So that both hypothesis structures can be supported, object mappings can be performed between them.

Table 1. Sensor Type vs. Class Reporting

TYPE	POSSIBLE CLASS	CLASS ELEMENTS
F-14	F-14A	3
	F-14B	
	F-14D	
F-15	F-15A	5
	F-15B	
	F-15C	
	F-15D	
	F-15E	
F/A-18	F/A-18A	6
	F/A-18B	
	F/A-18C	
	F/A-18D	
	F/A-18E	
	F/A-18F	

For the case of sensor 1 *type* information table 1 represents the possible maps to the *class* information provided by sensor 2. So sensor 1 provides 3 objects to the hypothesis structure of sensor 2 for F-14, 5 objects for F-15, and 6 for F/A-18. The probability of each new possible *class* element is the probability of the class as reported (or derived) from the sensor divided by the number of possible objects (i.e. 3, 5, and 6 in this case) available in the *a priori* database. Since sensor 1 can only report to the *type* level in this case, in the absence of additional information, entropy requires that all classes within that type be equiprobable. For the opposite case where sensor 2 can contribute to a *type* hypothesis, a mapping can occur between the declared aircraft highlighted in table 1, and their respective *type*. So F-14A with its associated probability confidence (which is equiprobable to F-15E, F/A-18E, and F/A-18F) can be mapped to F-14 and processed with the type hypothesis. Both of these cases will occur *regardless* of whether there are common elements between the hypothesis structures or sensors.

A more comprehensive relationship between level 1 object structures can be seen in the following Bayesian network example in figure 8 from Paul [4] built using the Netica® software package from Norsys. In figure 8, the relationships between the various level 1 structures are immediately clear. The relationships between entities in this network were constructed from various open sources and entered into the model, which is how the discrete probabilities were obtained. Figure 8 therefore represents the *a priori* state of the universe for F-14, F-16, F/A-18, and Boeing 737 aircraft. The assumption in this example is that a series of aircraft object classes are returned by a set of unbiased attribute sensors. For this example, we have a high quality, complex Bayesian sensor that returns information that an object is a fighter (0.85) or a commercial aircraft (0.15); and that it is

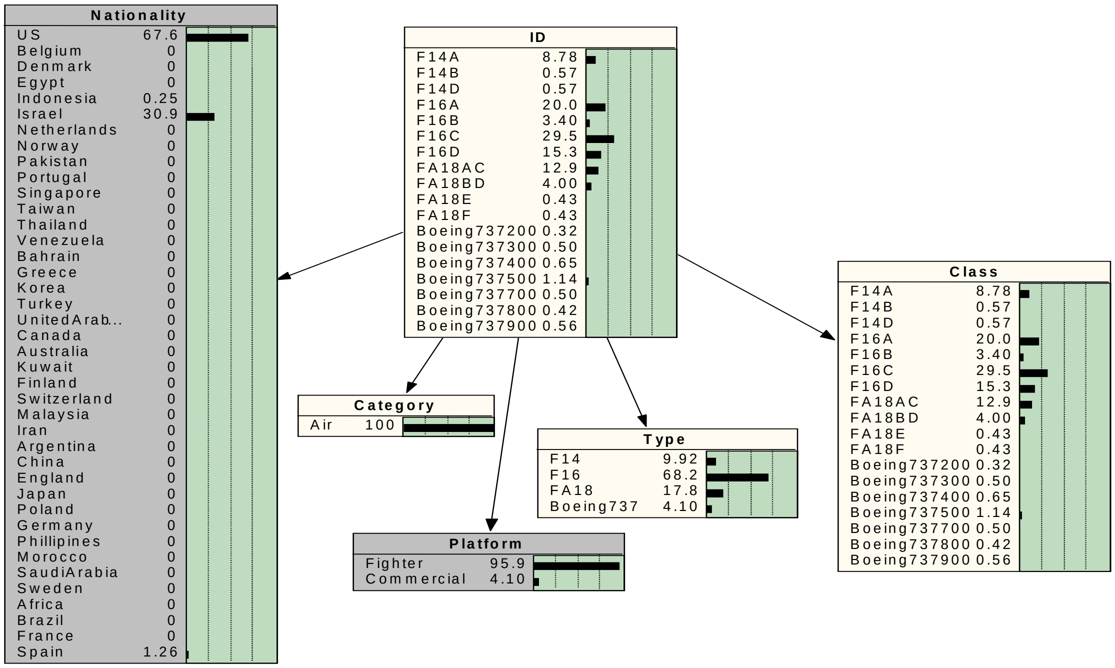

Figure 8. Taxonomic ID Bayesian Network After Information Processing

either from Israel (0.7), the US (0.1), Indonesia (0.1), or Spain (0.1). The resulting Bayesian network is shown in figure 9.

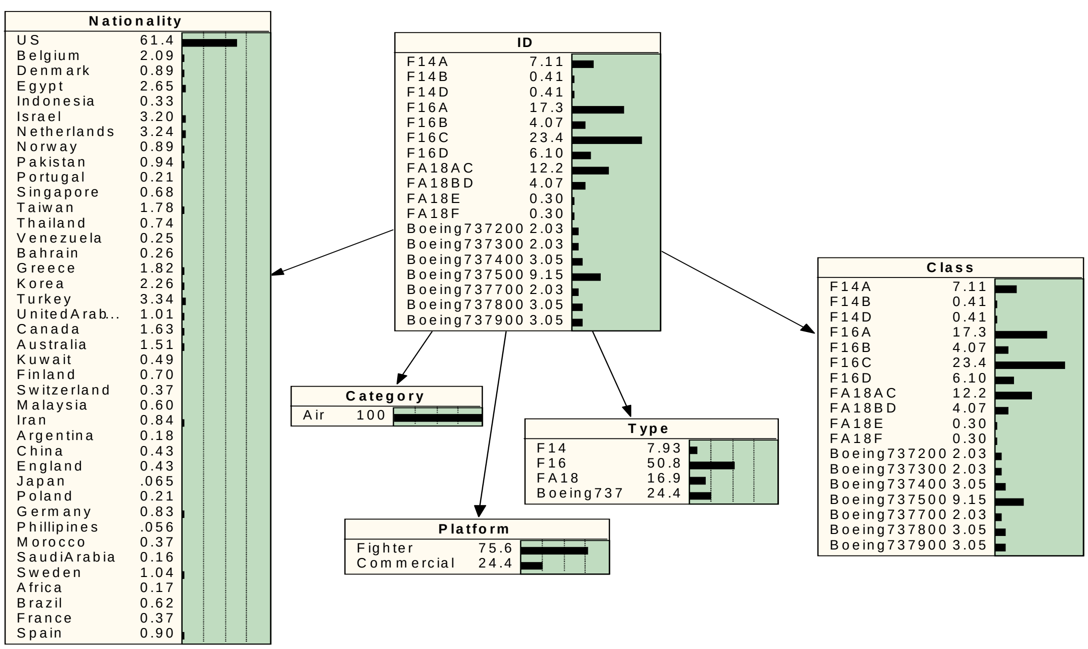

Figure 9. JDL Level 1 Taxonomic ID Bayesian Network

The shaded areas of Nationality and Platform in figure 8 represent where the new sensor information was read. The *ID* node in both figures 8 and 9 is a mirror of the *class* node in this example, however it can reflect any node of interest. There are many complexities with building a tactical Bayesian network for air object taxonomic ID that are beyond the scope of this paper. This includes assigning probabilities to large amounts of information and handling ambiguous or corrupted information. However, this example demonstrates the necessity of developing relationships between JDL level 1 information structures in order to minimize information loss.

JDL Level 2 Structures

Unlike level 1 constructs, each level 2 entity has little (or no) relationship to other level 2 entities because level 2 information is really contained within a single hypothesis category. If an object were declared *Hostile* via level 2 hypothesis, this hypothesis would have no contribution to a level 2 Friend hypothesis, other than to test for conflicts. Referring to figure 6, level 2 information is both measurement based and derived from level 1 information. Measurement based level 2 information is only provided from secure sources of information that usually involve cryptologic methods to convey trusted information that is resilient against spoofing and compromise. Regardless, only direct evidence of a *Friend* is possible with these systems. No other Combat ID declaration is "directly" measurable. So the Combat ID declarations of *Assumed Friend, Neutral, Suspect, Hostile, Unknown, and Pending* are all derived states, because no positive measurement information exists beyond a perfectly cooperating friendly object via secure information transfer.

Derived level 2 information providers include all level 1 information sources. The level 1 information discussed in the previous section can be used to declare an ID of *Friend, Hostile*, etc., after the application of doctrine or equivalent processing techniques. For example, a detected emitter that is correlated to an adversary's platform would be a candidate for refinement to *Suspect* or *Hostile* after application of ID doctrine.

Table 2. JDL Level 2 Transition Matrix

	Fr	As Fr.	Neut	Sus	Hos	Ukn
Fr	0	2	2	2	-	-
As Fr.	1	0	2	2	-	-
Neut	2	2	0	2	2	-
Sus	2	2	2	0	1	-
Hos	-	-	2	2	0	-
Unk	1	1	1	1	1	0

One way to view the internal relationships of JDL level 2 information is to construct a biased Combat ID transition matrix. An example of this matrix is shown in table 2. The numbers in this matrix represent the number of hypothesis transitions that are required to go from one Combat ID state to another in this taxonomy. For example, to move from *Friend* (Fr) to *Assumed Friend* (As Fr.) requires two state transitions – one to go to *Unknown* (Unk) and one to go to *Assumed Friend*. Downgrades of hypotheses like this generally require two transitions. Some upgrades, notably *Assumed Friend* to *Friend* and *Suspect* to *Hostile* only require a single hypothesis transition while all others must first be downgraded to *Unknown*. Some state transitions are not allowed such as the movement from *Friend* to *Hostile* due to the ramifications of making this type of designation. Generally, the object of interest must be completely re-evaluated before this transition is allowed.

JDL Level 3 Structures

Referring to figure 6, level 3 information is both measurement based and derived from level 1 and 2 information. Level 3 information consists of an object's *activity* (ASW, Intel, CAP, etc.), *intent* (threat, non-threat, etc.), and *threat level* (lethality). The capability to estimate with accuracy the future actions of an opponent and the possible consequences of those actions is the primary goal of an application of the JDL level 3 structures. As discussed previously, this is similar to a mind reading exercise that, on the basis of recent literature on the subject, has had problematic development at best. The JDL level 3 *Threat Refinement* structures provide more than a means to look at hostile forces, but also provide for a clear assessment of all theater forces including those that are friendly and neutral. Therefore it is the goal of this level to provide the following capabilities, derived from Hall [5]:

- Estimation of aggregate force capabilities – includes hostile, friendly, and neutral forces as determined by level 2 processes
- Identification of threat opportunities – includes the mission planning process, force vulnerabilities, and probable hostile force actions and scenarios.
- Prediction of hostile intent – includes analysis of information, actions, events, and communications.
- Estimation of implications – For every hypothesized force (friendly and hostile) action, estimates of timing, prioritization, and opportunities can be made.

This task as described above represents a classical fusion of inferences drawn from dissimilar sources based upon direct observation. As the taxonomy addressed for Combat ID is fused based on both the physical characteristics of the target itself as well as its behavior (including actions, missions, and apparent intent), there exist essentially two basic forms of reasoning and information available for situational awareness (SA) for JDL level 3 threat refinement. These two forms are:

- <u>Observation Driven SA Reasoning</u> provides an evaluation of the situation based upon direct observation. This represents situational awareness based upon what a potential threat is doing.
- <u>Mission Driven SA Reasoning</u> provides an evaluation of the situation based upon how well it matches to a specific anticipated threat mission.

Level 3 fusion requires both activities to be performed in concert.

VII. COMBAT ID IN SITUATIONAL AWARENESS

Combat ID in the context of SA is invariably referenced, but far less often is implemented into Combat ID algorithms as an explicit taxonomic process. Hanson and

Harper [6] demonstrate that situation assessment (for threat refinement) is strongly related to data fusion. A general definition of SA from Endsley [7] is: *Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.* In terms of levels, this definition can be structured in a way analogous to the JDL hierarchy:

- **Level 1 SA:** Perception of the environmental elements – The identification of key elements of "events" that, in combination, serve to define the situation. This serves to semantically tag key situational elements for higher levels of abstraction in subsequent processing.
- **Level 2 SA:** Comprehension of the current situation – This combines level 1 events into a comprehensive holistic pattern (or tactical situation). This serves to define the current status in operationally relevant terms to support rapid decision-making and action.
- **Level 3 SA:** Projection of future status: projection of the current situation into the future, so as to predict the course of an evolving tactical situation. Time permitting, this supports short-term planning and option evaluation.

A direct comparison of these three levels of SA and JDL data fusion show that the functions are clearly distinct at level 1, since JDL data fusion focuses on the *numeric* processing of tactical elements to provide identification and tracking, whereas SA focuses on the *symbolic* processing of these entities, to identify key "events" in the current situation. At level 2, the definitions are virtually identical, to yield the conventional definition of SA (that of generating a holistic pattern of the *current* situation). At level 3, the SA definition is more general than a pure data fusion definition, since the former also includes projection of ownship/aircraft/battalion/etc. and friendly intent, and capability in addition to threat intent and impact assessment.

Although Mission Driven Awareness focuses on Level 3 Situational Awareness, due to the desirability of a concurrent multi-layered data fusion/situational awareness approach, mission driven awareness can be used to accelerate level 2 SA and hence focus the fusion process more quickly. Such a benefit may be crucial in the common case of time critical targets of interest.

VIII. RECOGNITION OF TACTICAL ELEMENTS

Mission Driven Awareness allows us to infer from the results of lower level knowledge fusion the *mission* (or *activity*) component of Combat ID as specified in the Combat Identification Capstone Requirements Document [8]. Such identification of the *mission* or *activity* implies a situational awareness of the decisions made by both sides of an adversarial encounter. This Combat ID capability is not only essential to generate a needed Predictive Situational Awareness (PSA) to minimize fratricide, but is also broadly characteristic of the class of fusion algorithms which can recognize behaviors and project from those behaviors the intent and probable Courses of Action (CoAs) available to hostile commanders. In short, these fusion algorithms may be represented in the familiar

JDL Fusion Model (Figure 5) as Level 3 Fusion to address *Threat Refinement* (Impact Assessment) both predictively and deductively:

- Predictive Situational Awareness projects CoAs to determine potential impacts (evaluate utility of CoAs to a hostile commander in terms of the impact achieved), and
- Determination of Intent deduces the hostile commander's intent from the evaluation of the CoAs that best corroborate observed behaviors.

However, these decisions are not generally made at the level of the unit observed (typically a platform such as an 'aircraft', 'vehicle', etc.), but rather at a higher *decision element* that is tasked to perform a given tactical mission. Therefore, to enable *decision fusion* at an actionable level, recognition of the tactical elements that represent the decision-level, units (often an organizational entity such as an 'armored column', 'flight of aircraft', 'convoy of vehicles', 'terrorist cell', etc.) becomes essential.

This suggestion is based on the observation that although newly developed Combat ID algorithms show great promise for target identification and classification, their utility for determination of intent is limited by their focus on track fusion (JDL levels 1 & 2). Use of a Combat ID architecture structured hierarchically helps implementation of inference processing for Level 3 fusion (figure 10 as modified from the 2000 Data & Information Fusion Group [9]).

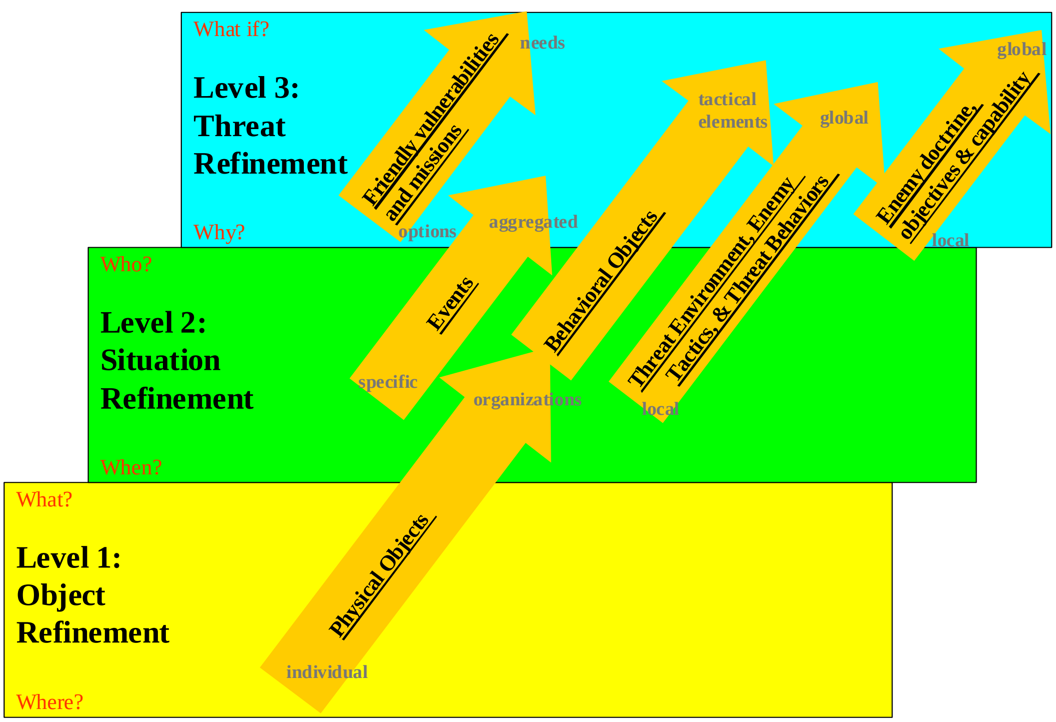

Figure 10. Tactical Elements Employed by Fusion Level

As may be suggested from Figure 10, to reproduce the decision-making process, it is desirable for the decision-fusion to be able to recognize and characterize not only individual physical objects (bottom of figure), but also the organizations, events, tactics, objectives, missions and capabilities (middle to top of figure). Most of these recognition schemes are domain specific and typically either require or at least benefit from use of a-priori information (i.e., 'intelligence').

Accordingly, the JDL model is reorganized in Figure 11 to show information flow with the inference level increasing from bottom up. This corresponds loosely to the techniques typically used as discussed in this paper and shown on the right side of the figure.

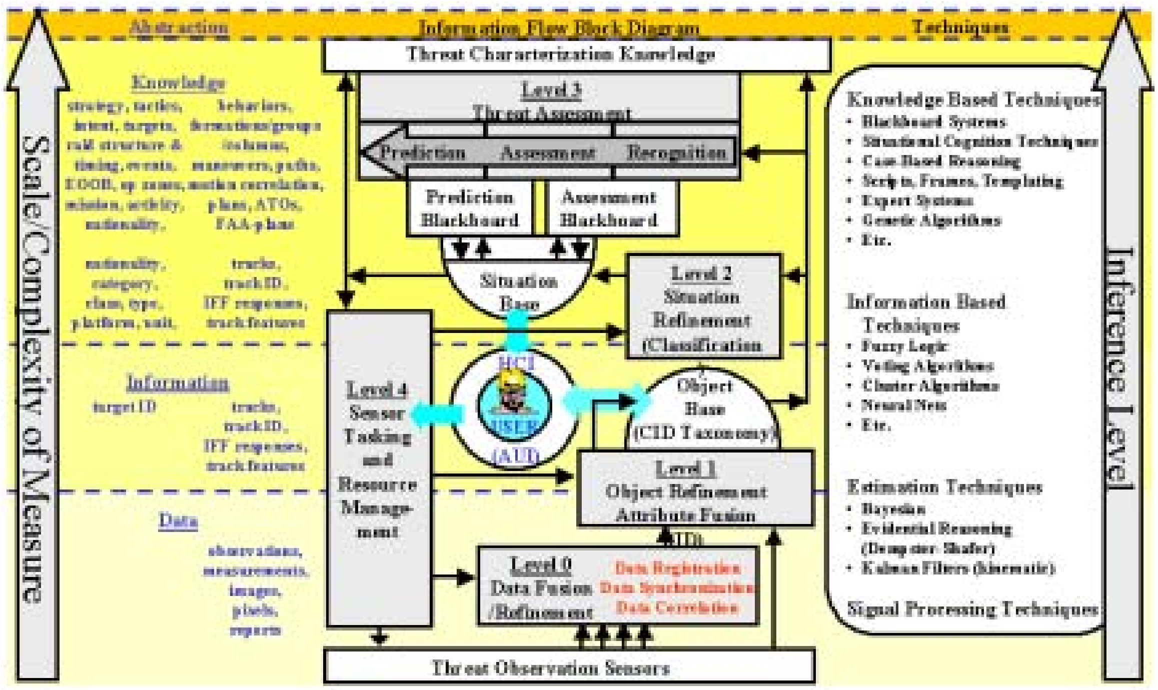

Figure 11. Aggregate of Proposed Level 0 – 4 Fusion Methodologies

Data structures are displayed on the left side of Figure 11. Data structures representative of knowledge fusion as identified in the upper left of the figure include the tactical elements with raid structure and timing, missions, activities and operational zones. The critical process of generating a *situation base*, as shown in the center of the figure, represents *recognition of tactical elements*. The purpose of this paper is not to characterize this process so much as to identify the architectural characteristics of a Combat ID structure that would support such a capability.

Implementation of such an aggregative recognition of tactical elements is facilitated by use of the corresponding architectures for multi-hypothesis structures and taxonomies for Combat Identification. Use of such an architecture may in turn then facilitate a *power to the edge* [1] approach to decision-making which enables edge units by providing these units with the Combat ID information structured, traceable, and displayed to the level of recognizable tactical elements for which decisions are made.

The *power* that would be provided to *edge units* would be in the form of enhanced Combat ID, earlier Combat ID when contextual cues can discriminate between alternative Combat ID hypotheses, and integration of CoA assessments to evaluate the Combat ID of various threatening elements with the generation of CoAs for mission planning. This information can enable a *self-synchronization* as described by Alberts & Hayes [1] as well as the more obvious support of Effects Based Operations as described by Smith [11].

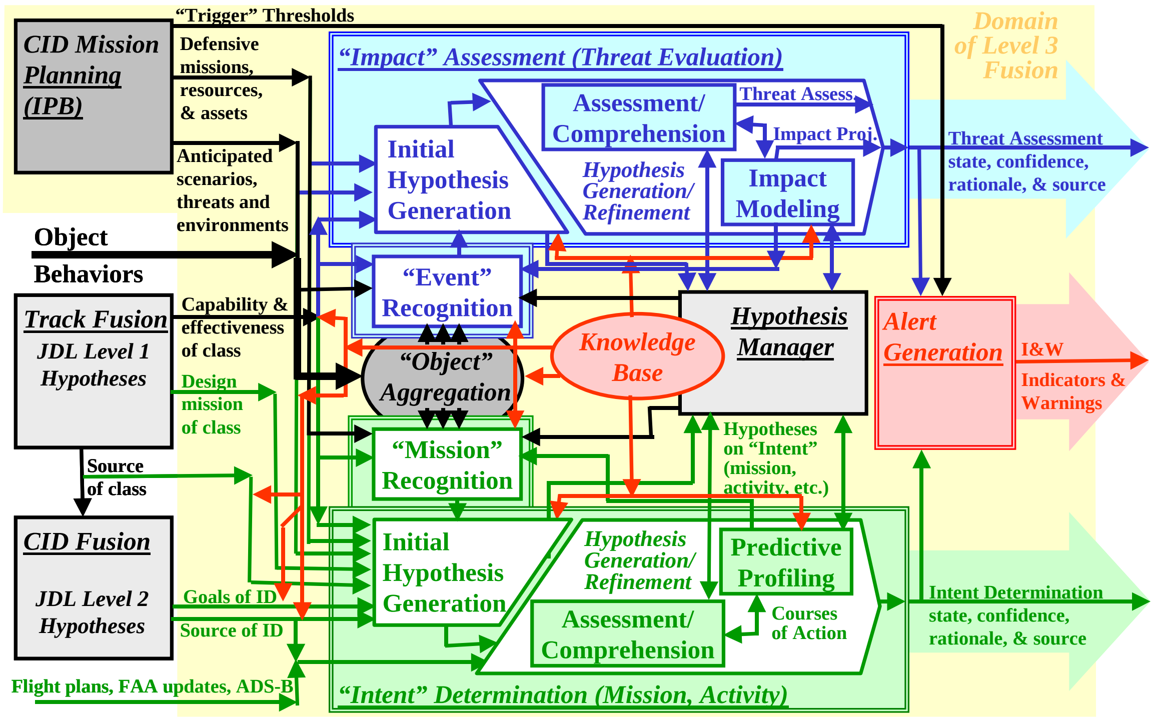

Figure 12: Potential Functional Flow for a Proposed Threat Evaluation Tool for Combat Identification

Determination of a hostile commander's intent typically requires the representation of his decision-making process. By returning to the dual-view characterized previously that addresses impact assessments in both a predictive and deductive form, one can propose a functional flow as shown in Figure 12. In this example, a Recognition-Primed Decision-making (RPD) process is employed as described by Klein [10]. As a result, for both forms we observe the familiar Recognition/Assessment/Evaluation model. For the predictive form at the top of the figure, the system recognizes threatening tactical elements and generates threat assessments and impact predictions. For the deductive form at the bottom of the figure, the system recognizes potential threat intents and generates assessments of intent and their associated Courses of Action (CoAs). Acting in tandem, the dual activity model thus proposed provides a useful tool for the determination of intent coupled with the recognition of the critical tactical elements that can be integrated with existing Combat ID assessment tools.

IX. CONCLUSIONS AND FUTURE WORK

This paper stresses the importance of understanding the contextual relationship of information available from sensors and sources in order to properly incorporate all information into a fusion process, especially in the context of Combat ID.

Regardless of the method used to fuse information across the JDL levels, the numerical result of the fusion process (or the confidence in the declaration of *Neutral*, as an example) doesn't necessarily provide all of the information necessary to make a decision. This is especially critical for Combat ID where a wrong answer can have disastrous effects. The *USS Vincennes* incident in July 1988, Black Hawk shoot-down in 1994, and the Patriot Missile battery misidentification in 2003 are all reminders that the context, type, timeliness, quantity, and quality of information must be understood prior to making a decision. For expansion of work in this area, we have developed measures of information value, completeness, and decision cost that complement this multi-taxonomic approach for information fusion. Other future work of interest includes contextual reasoning approaches with extensibility beyond a given domain, realization of the recognition of tactical elements, multi-objective collaborative mission planning and decision-making under uncertainty, and predictive situational awareness integration approaches.

In this paper we deliberately avoided the use (except briefly in the beginning) of the word *ontology*. The word "ontology" seems to generate a lot of controversy, probably from its origins in artificial intelligence (AI). An ontology is an explicit specification of a conceptualization. The term is borrowed from philosophy, where an ontology is a systematic account of existence. For AI systems, what "exists" is that which can be represented. Thus, in the context of AI, we can describe the ontology of a program by defining a set of representational terms. In such an ontology, definitions associate the names of entities in the universe of discourse (e.g., classes, relations, functions, or other objects) with human-readable text describing what the names mean, and formal axioms that constrain the interpretation and well-formed use of these terms. Formally, an ontology is the statement of a logical theory (see http://www-ksl.stanford.edu/kst/1). Pragmatically, a common ontology defines the vocabulary with which queries and assertions are exchanged among agents. Ontological commitments are agreements to use the shared vocabulary in a coherent and consistent manner. In this case, our use of the term "taxonomy" is consistent with "ontology" and the two can be considered synonymous.

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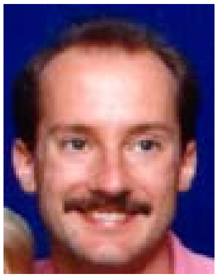
BIOGRAPHIES



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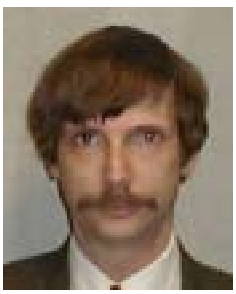

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