Resource Management Coordination with Level 2/3 Fusion Issues and Challenges

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ABSTRACT

Information fusion system designs require sensor and resource management (SM) for effective and efficient data collection, processing, and dissemination. Common Level 4 fusion sensor management (or process refinement) inter-relations with target tracking and identification (Level 1 fusion) have been detailed in the literature. At the ISIF Fusion Conference, a panel discussion was held to examine the contemporary issues and challenges pertaining to the interaction between SM and situation and threat assessment (Level 2/3 fusion). This summarizes the key tenants of the invited panel experts. The common themes were:

1) **Addressing the user in system control,**

2) **Determining a standard set of metrics,**

3) **Evaluating fusion systems to deliver timely information needs,**

4) **Dynamic updating for planning mission time-horizons,**

5) **Joint optimization of objective functions at all levels,**

6) **L2/3 situation entity definitions for knowledge discovery, modeling, and information projection, and**

7) **Addressing constraints for resource planning and scheduling.**

INTRODUCTION

Since the advent of information fusion (IF) theory, the duality between estimation (fusion) and control (sensor management) are functionally related in the 1990 Joint Directors of the Labs (JDL) and the updated 2004 Data Fusion Information Group (DFIG) models. As IF designs increase in complexity, there is an imperative need to understand the interactions among Level 4 (L4) process refinement for (L1) object refinement and (L2/3) situation and impact assessment (SA/IA). In order to explore, elicit, and summarize the contemporary issues and challenges in resource management (RM) interactions with SA/IA, an invited panel discussion was organized by Ivan Kadar at the annual Fusion conference. This serves as a summarized view

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of the panel discussions, highlighting the key issues, and challenges addressed.

Another panel discussion, entitled *"Issues and Challenges in Resource Management with Applications to Real-World Problems"* [SPIE-Proc. V6235, April 2006] addressed related areas such as: [1]

1) formulating utility functions,

2) distributed attention,

3) net-centric network and service management bandwidth allocation for L1/2/3,

4) distributed algorithms with adaptive platforms and sensors,

5) off-line learning combined with real-time optimization, and

6) performance metrics.

In 1997, Hall and Llinas [2] overviewed various approaches for sensor management including surveillance volumes for sensors on platforms. In L4, they address Measurement of evaluation, Measures of performance, and Utility theory as optimization techniques and presented some issues and challenges listed below.

Current Status	Challenges and Limitations
Robust system for single-sensor systems	**Incorporation of mission objectives/constraints**
Operations research formulation	**Environmental context for sensor utilization**
Limited approximate reasoning app.	**Conflicting objectives (e.g., detection vs. accuracy)**
Focus on MOP and MOE	**Dynamic algorithm selections/modification Diverse sensors**

The key challenges expressed were: 1) limited communications bandwidth for data aggregation; 2) context-based approximate reasoning for L3 understanding; and 3) knowledge representation for L2 processing, which were similar issues of the ISIF panel discussion for SA processing [3]. The interplay between RM and the various

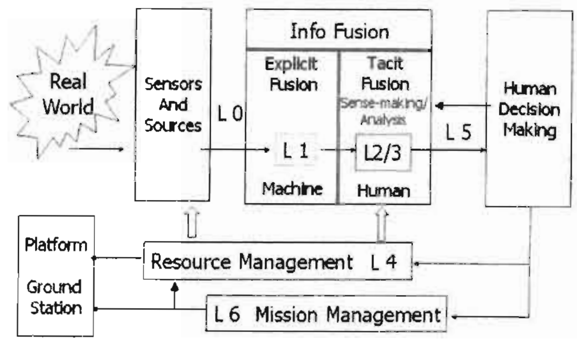

Fig. 1. DFIG 2004 Model

fusion process levels are still evolving as more data becomes available, increasing attention to IF designs, and globalization [1].

In what follows, we address the issues associated with resource management for L2/3 (SA/IA) interaction [4]. As stated above, while SA/IA are less well researched, even further removed is the SA-RM and IA-RM interdependencies. Developments for tracking and control (L 1-4) have been addressed [5, 6], and communication issues [7, 8]. Also, utility and risk assessments [9] have been posed for SA/IA interactions that could be used in an objective function.

DFIG FUSION MODEL

To set the stage, we show the DFIG[1] model (as the upgrade to the JDL [10, 11, 12] model) in Figure 1. What is needed is a pragmatic design interface that captures the various management functions coupled to estimation needs. The DFIG model differentiates control functions based on the spatial/temporal/frequency needs and availabilities between sensors, platforms, and users. The spectral needs are based on the type of sensor. The temporal needs are based on the user's requests for timely information to afford action. Finally, the spatial needs are based on the mission goals.

In this model, the goal was to separate the IF and RM functions. RM is divided into sensor control, platform placement, and user selection to meet mission objectives. L2 (SA) includes tacit functions which are inferred from L1 explicit representations of object assessment. Since the unobserved aspects of the SA problem cannot be processed by a computer, user knowledge and reasoning is necessary. [13 - 16] L3 (IA) sense-making of impacts (threats, course of actions, game-theoretic decisions, intent [17], etc.) help refine the SA estimation and information needs for different actions [18]. The current DFIG definitions include:

- **Level 0 -**
  Data Assessment: estimation and prediction of signal/object observable states on the basis of

[1] Frank White, Otto Kessler, Chris Bowman, James Llinas, Erik Blasch, Gerald Powell, Mike Hinman, Ed Waltz, Dale Walsh, John Salerno, Alan Steinberg, Dave Hall, Ron Mahler, Mitch Kokar, Joe Karalowski, Richard Antony

pixel/signal level data association (e.g., information systems collections);

- **Level 1 -**
Object Assessment: estimation and prediction of entity states on the basis of data association, continuous state estimation, and discrete state estimation (e.g., data processing);

- **Level 2 -**
Situation Assessment: estimation and prediction of relations among entities, to include force structure and force relations, communications, etc. (e.g., information processing);

- **Level 3 -**
Impact Assessment: estimation and prediction of effects on situations of planned or estimated actions by the participants; to include interactions between action plans of multiple players (e.g., assessing threat/intent actions to planned actions and mission requirements, performance evaluation);

- **Level 4 -**
Process Refinement (an element of Resource Management): adaptive data acquisition and processing to support sensing objectives (e.g., sensor management and information systems dissemination, command/control).

- **Level 5 -**
User Refinement (an element of Knowledge Management): adaptive determination of who queries information and who has access to information (e.g., information operations) and adaptive data retrieved and displayed to support cognitive decision-making and actions (e.g., human computer interface).

- **Level 6 -**
Mission Management (an element of Platform Management): adaptive determination of spatial-temporal control of assets (e.g., airspace operations) and route planning and goal determination to support team decision-making and actions (e.g., theater operations) over social, economic, and political constraints.

The RM tradeoffs, design attributes, and challenges for instantiating this model include:

Issues for level 2/3 analysis with L4 control include:

1) Level 2/3 tradeoffs in information quantity (throughput),

2) Timeliness of process refinement to control sensing needs,

3) Level 3 domain knowledge context use to predict future needs,

4) Multiple users have differing levels of process needs in a distributed fashion from the same situation, and

5) Varying fidelity of confidence reporting of impending threats and situations based on uncertainty calculus [19].

The IF challenges includes the development of:

1) Pedigree analysis to backtrack through associations to capture the impending threat,

2) Time Horizons of control actions from IA to update the SA (i.e., priority schemes),

3) Performance models of L1 analysis to afford L2/3 information needs satisfaction and level 4 RM,

4) Hierarchical cost functions that include risk and utility analysis of L4 processes, and

5) Unified set of metrics that afford SA/IA processing that can be optimized in a RM 4 objective function.

Coordinated complementary and orthogonal actions are needed over differing timelines and geographical areas. Mission management necessitates a global control function to determine which sensors, resources, and users are activated in for local control responsibilities and action approval.

ADAPTIVE & AUTOMATIC IF RM

Ivan Kadar advocated the need for both: 1) adaptive (implies a behavior, which results in reinforcing outcome by optimizing a specific objective function and the ability to modify behavior); and 2) automatic (implies self-acting requiring minimum or no human supervision) attributes of resource management. Both attributes are also part of human perceptual reasoning and control to maximize the expected value of perceived information [20 - 22].

In order to examine the issues and challenges of explicit, implicit, or desired interactions among the "Levels" of IF, with focus on L2/3, functional elements are decomposed at each fusion level. Specifically, utilizing representational and modeling constructs, objective functions, optimization, and RM control effects on interacting levels identifies future research directions to realize adaptive and automated interacting levels of RM.

Decomposing Functional Elements

Data or Information fusion is the process of combining data to refine state estimates and predictions [11, 23]. It can be implied from the words "refine" and "estimate," that this process is, in part, distributed decision-making under uncertainty with a control mechanism objective to minimize uncertainty in estimates and predictions, and maximize the information value gathering in a real-time environment with time constraints.

Issues

1) *What models and methods are appropriate, such as influence diagrams [24], to represent relationships, uncertainty, decisions, and values to optimize objective functions (in commensurate units and same scale, e.g., entropy) at each fusion level or globally to achieve desired performance measures-of-merits (MOMs)?*

2) RM controls fusion levels either individually or jointly to optimize a global objective function with a desired performance MOM. The issue of formulation of commensurate unit objective functions, as well as the relationship of individual level control affecting the performance of other levels by their interactions vs. joint optimization of objective functions with low computational complexity needs to be addressed. Potential solutions include game theoretic approaches with multiple players with or without knowing individual players' objective functions.

3) L1 processes under RM control may optimize kinematic and identity (ID) states of entities, but do not necessarily optimize performance at L2/3 (wherein the individual levels have interrelated but necessarily commensurate objectives). Thus individual "Level" or joint optimization is needed at each iteration step.

Perspectives and Metrics

The measure of effectiveness of situation/threat systems is measured by the ability to rapidly and reliably answer questions such as: *What?, Who?, Whose?, Which?, Where is it going?,* and *What is its intent? What resource to use?* The shorter the response time of the system in accomplishing these functions, the more time is available to formulate effective response strategies. Therefore, response time should be included in objective functions.

These observations usher in a host of issues relating to selection of commensurate objective functions as we seek to optimize the performance at each level while satisfying the global composite objective (utility function) of RM with respect to mission goals, subject to decision-making under uncertainty. With several potentially non-commensurate variables involved the utilities can be based on well-known information theoretic measures of relative Shannon entropy, Kullback-Leibler, Renyi and Csiszar divergences [24] to serve as a common denominator. However, it has been shown that [25] the very notion of entropy is non-universal and purpose-dependent in both relative information measures and in divergences. Nevertheless entropy-based "relative performance" is unaffected by the non-universal property, which only effects alternative formulations.

Challenges

1) Most research has focused on sensor and platform management at L1 to optimize kinematic and ID objective functions based on commensurate information measures, which necessitates non-commensurate utility functions.

2) Many RM systems operate in open loop (e.g., cross cueing sensors) to improve kinematic and ID MOMs. The resultant interaction with L2/3 do not necessarily yield improved MOMs. What is needed is a closed loop design.

3) There has been minimal research in managing L2/3, and selecting SA and IA specific objective functions. Possible approaches could be based upon fuzzy-sets based models, mapping fuzzy outcomes to probabilities to compute commensurate entropy-based objective functions providing a common framework for interactions among levels. Issues include model representation fidelity, mapping accuracy, response time dependence, and computational complexity.

4) A related general issue with optimizing at each level separately is the possibility of conflicting objectives and not achieving a global optimum with respect to system mission objectives.

Model for Planning, Interactions Modeling, and Decision-Making

Operators need the ability to control L1-4 processes for optimum L1 processing and for knowledge capture at L2/3. In addition, L2/3 is to establish relationships (not necessarily hierarchical) and associations among entities, it should anticipate with a priori knowledge in order to rapidly assess, interpret, and predict what these relationships might be; it should plan/pre-plan, predict, anticipate with updated knowledge, adaptively learn, and control the fusion processes via RM for optimum information-knowledge capture and decision-making. These attributes are similar to the characteristics of human perceptual reasoning embodied in an adaptive anticipatory closed loop feedback information control mechanism known as the Perceptual Reasoning Machine (PRM) paradigm [20-22], information flow is shown in Figure 2. Viewed as a "meta-level information management system," PRM consists of a feedback planning / resource management system whose interacting elements are: "assess," "anticipate," and "preplan/act." That is:

- Gather/Assess current, Anticipate future (hypotheses), and Preplan/Act (predict) on information requirements and likely threats,

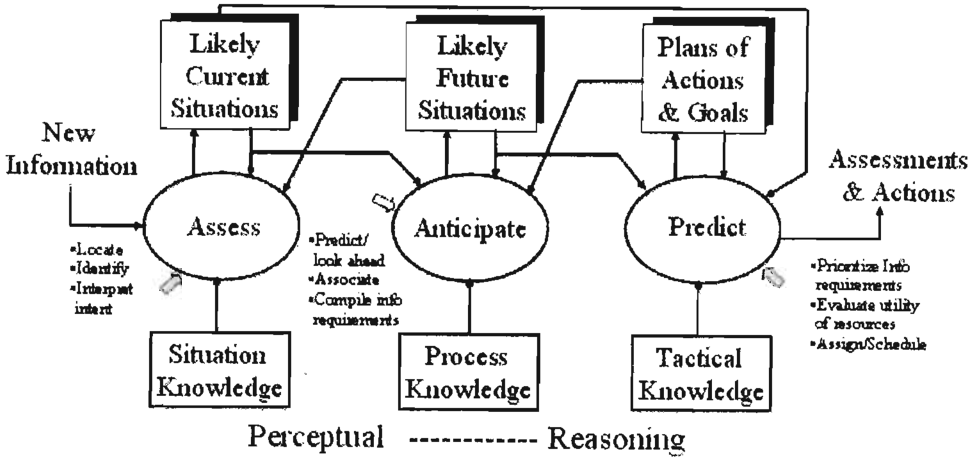

Fig. 2. Information Flow among PRM Elements

- Plan the allocation of resources and acquisition of data through the control of a separate distributed multisource sensors/systems RM,
- Interpret and Act on acquired (sensor, spatial, and contextual) data in light of the overall situation by interpreting conflicting/misleading information.

The PRM construct also highlights the issue of the expected effects of RM on input/output changes at each Level, and local objective function optimality changes effecting RM control itself in a human perceptual reasoning framework [20-22]: in order to perceive one needs to: 1) sense and deliver stimuli to the "system;" 2) the "system" when "properly stimulated" delivers a feedback ("reinforcement") to the "system" in order to modify its output and optimize objectives.

Additional Issues Include:

- Current IF designs do not incorporate human thought processes, perceptual reasoning under uncertainty, and time responses,
- RM systems minimally anticipate (short planning horizons) and thus not able to plan far ahead,
- RM systems do not adaptively update world models,
- Imply use of limited a-priori information, and
- At most, imply potential for new knowledge capture to maximize knowledge of current and future events.

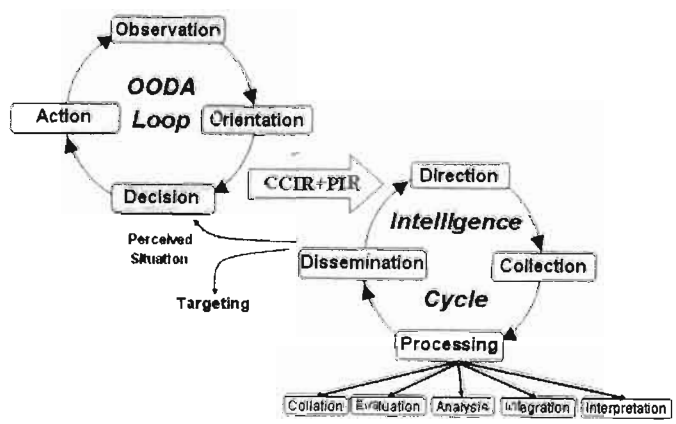

Fig. 3. Intelligence Cycle interfacing with OODA Loop

INFORMATION ACQUISITION AND FUSION

Ken Hintz details multiple types of information that can be extracted from sensor actions which affect sensor data fusion. Some information can be anticipated in the form of predicting which information will maximally reduce the uncertainty about a random variable. Some information is after-the-fact and can be used to change the quality of fusion by, for example, selecting different state estimator process models. The next level of improving fusion is by actively determining which information for a sensor system [26] to obtain and therefore taking a proactive role in the fusion process, rather than simply performing the best fusion of data that is provided.

The general problem of resource allocation in a heterogeneous, multi-sensor sensor system is closely tied to its requirements to be adaptive, operate in real-time, as well as to assess and estimate processes in a non-cooperative environment [27]. It is easy to associate data rate with information rate and think that because we meet a sample rate requirement, that we are maximizing the information flow into our state estimate. It should be remembered that the primary objective of a sensing system, and hence the associated fusion process, is to minimize the valued uncertainty about our platform's situation. Valued uncertainty has two components. One component is the reduction of uncertainty which is calculable in the form of information gain. The second component is the mission information value of the sensing platform. Process refinement should include the acquisition of information, namely a reduction in our uncertainty about a process.

Sensor Information

It is a common misconception that sensor information applies only to target kinematics however this is far from being true. There are at least five types of sensor-based computable information about a process:

Kinematic state information is based on the reduction of the norm of its associated error covariance matrix. While the amount of this reduction is of interest by itself, it is often the derived products of this state estimation that are of more interest and value to the mission. The target's intent can often be inferred from target temporal and spatial behavior.

Search information which is based on the entropy reduction of the search probability mass function represents the uncertainty of where targets are as a function of spatial position. By populating a search PMF with a priori target location probabilities and then updating this representation as a result of all searches and tracking dwells one can maintain a map of the axis to point a sensor which will yield the highest probability of detecting a target based on their expected locations and the uncertainty reduction through sensor actions.

Target Identification differentiates one target from among a set of possible target types. Various signal processing methods can be used to determine target type or class and it is a simple calculation to determine the amount of information gained.

Cuer information is gained by detecting a target with one type of sensor or operating mode and handing that detection off to a more capable sensor or sensor operating mode. Combinations of sensors are usually required to provide an effective all-weather capability and special processing modes can determine the presence of a target even though it may take another mode or sensor to localize it.

Situation information reduces our uncertainty about the "intent" of an adversary which may include non-traditional information types.

Issues and Challenges

The fundamental purpose of a sensing system is to acquire information about a process in order to infer something about the process intent or the entity that is directing it [28]. L2 is a vital component of data fusion since it allows us to decide what information we need and how to best allocate our resources to obtain that information. In a non-stressing environment, resource allocation is not a problem as there usually are adequate resources to effectively search for new targets while maintaining tracks on targets already detected and of interest. As the complexity of the situation and threat environment becomes stressing that a sensor manager must decide how to most effectively use its assets.

1) Data fusion should not be considered independently of the data acquisition process, but rather it should be thought of as the binding element of the fusion process since it is the need to search to detect target which starts the sensing process. Resource allocation is what starts the process; it is not merely a function which needs to be applied after the fact.

2) It is not enough to do the best job of fusing data since it is as important, to the overall operation of the sensing system to decide what information to acquire (L4).

3) While one can directly see the state uncertainty reduction of a process being estimated, there are second level effects which can further enhance the process of information acquisition. There is inferential information which can be obtained by analyzing the results of a sensing action. For example, an analysis of track data and the target's kinematic state can infer target intention and produce situation information based on whether the target is inbound or outbound or maneuvering to get into an offensive position relative to platform (Level 2).

4) It is also common for a target to be detectable with one type of sensor but not trackable with the necessary degree of precision. This may be a function of not only sensor type but also the mode in which a sensor is operating. Cuer information can allow us to improve tracking of a target by handing it off to other sensors which can provide reduced kinematic error covariance or add feature aided tracking to allow us to differentiate among merging or crossing targets and continue to track them as independent tracks even though they may not be resolvable in space.

5) Proper situation information assessment can allow resources to be allocated to more valued

data acquisition. Of significant importance in SRM is the best use of the sensors to insure early detection since early detection yields the longest lead time within which to deal with a potential adversary. Longer dwell times can yield this increased sensitivity based on signal to noise improvement, but this result is at the cost of coverage. Information based management is independent of particular scenarios.

Acquisition of some types of information can affect the other components of the data acquisition process, therefore we need to start treating the sensor and the information acquisition as part of the fusion process itself. Fusion should go beyond the best processing of data and the associated state estimation and data association but also be performed with the interest in maximum information extraction.

RM OF INTELLIGENCE INFORMATION

Joachim Biermann addresses the role of intelligence. Up to now, the intelligence processing is uncoupled from its sources and their underlying information collection and data acquisition processes. L2/3 fusion procedures which are based on knowledge (e.g., about the behaviour of an adversary) should be used to improve the tasking of the collection efforts initiated by a changing environment feeding RM processing for intelligence gathering.

Intelligence Cycle

Intelligence processing is an important part of Command and Control (C2) in defense and security because the provision of the most accurate situational awareness and commander understanding is an essential prerequisite for all decision-making in conjunction with other activities. Within network centric operations and the global information environment of asymmetric threats, the growing challenge is to rapidly manage the large volumes of data and information that are available and to portray the results in a timely and appropriate manner. A wide variety of information produced by the full spectrum of sensors and human sources has to be collected, filtered, processed, and disseminated. This is normally done in a structured and systematic series of operations which is called the "Intelligence Cycle" (IC).

The Processing phase within the Intelligence Cycle is the series of actions where the information, which has been collected in response to the commander's directions, is converted into intelligence products. The representation of the military intelligence process in Figure 3 shows the interrelation between the Command and Control Cycle and the Intelligence Cycle [29]. The decision process of the Observe, Orient, Decide, Act (OODA) Loop interfaces with the Direction phase of the IC.

RM used for the production of intelligence has to take into account concurrency requests from mission planning and operation procedures. An improved, direct interaction between L2/3 intelligence fusion functions and information management acquisition is required for these procedures.

Collection and Planning

A collection plan is established and maintained by the intelligence staff to coordinate information gathering. It involves:

- Developing information requirements from individuals or groups and tasking of organic and attached sources and agencies.
- Forwarding of requests for information to sources and agencies that are not organic or attached.

The *Collection Coordination & Intelligence Requirements Management (CCIRM)* methodology supports plan development. The making of an effective collection plan is the key to answering the Commander's Critical information requirements (CCIR) and priority information requests (PIR). A plan is accomplished by the sources and agencies. A source is defined as "a person from whom, or a thing from which, information can be obtained" whilst an agency is "an organization or individual engaged in collecting and/or processing information." Sources and agencies are normally grouped as:

- *Controlled.* Intelligence staff tasks collection assets to answer questions, such as ISTAR;
- *Uncontrolled.* Not under the control of the intelligence staff and which cannot be tasked; and
- *Casual.* Produce information from an unexpected quarter [30].

The above mentioned notion of "control" only means that the respective source or asset is organic to the unit the intelligence staff is part of itself. It does not mean that the operational tasking is actually done by the command of this staff.

Fusion to Support RM

Taking into account how collection planning and CCIRM are organized, it is obvious that, as regards content, the commander's requirements (CCIR and PIR) are the main factors for the initiation and control of all these processes. Caused by the existing processing flow, commander questions are only based on the previously disseminated finished intelligence product which is presented to him. No internal aspect of the intelligence production will directly cause a new request for information, the tasking of assets, and RM. Because of the unawareness of intermediate results and hypotheses of knowledge-based fusion procedures their potential to improve intelligence RM for better production of intelligence is unused.

In order to task collection assets, the intelligence staff has to identify the indicators which address particular IR. The ID of significant facts is what is done during the analysis step of the processing phase of the IC [29, 31]. These indicators, which are defined as *"Items of information which reflect the intention or capability of a potential adversary to adopt or reject a course of action"* [32], are grouped as:

- *Alert or Warning Indicators* relate to preparations for aggression carried out by an adversary, some of which will give early warning of the fact that hostilities are imminent.

- *Tactical or Combat Indicators* reveal the type of operation that the belligerent is on the point of conducting. Each type of operation across the spectrum of operations will require specific and characteristic preparations.

- *Identification Indicators.* ID indicators and signature equipment are those that enable the identity and role of a formation, unit or installation to be determined from the recognition of its organisation, equipment, or tactics.

In conventional processing, the selection of indicators that are appropriate to the operational situation will depend on the abilities of the Intelligence staff. The nature of the indicators that they select will drive the choice of sources and agencies which will be tasked to collect the information and intelligence they require. For template-based IF, these indicators are part of the underlying world model and incorporated into the fusion procedures.

Issues and Challenges

1) Specific mental models and domain knowledge, e.g., about the intention and typical behavior of opposing forces and hostile factions, which is fundamental to the L2/3 fusion template based fusion methods [31], should be used to detect deficiencies in the provided information (e.g., not precise enough or not comprehensive enough information) causing inabilities to make sufficient deductions in analysis and integration for SA/IA.

2) The detection of revealing gaps in the available information and knowledge should be designs. For example, the unification method, a generally applicable fusion method from computer science which can be combined with Feature-Valued-Matrices. These matrices are not only a standard representation form in the field of computational linguistics, they also have at least two additional advantages. First, they can be easily notated in XM L (allowing for L2 interoperability). Second, they can store incomplete information [33].

3) It will be necessary to investigate how L2/3 fusion procedure should interact with the tasking and management of conventional resources of the intelligence process to focus the collection efforts on revealing gaps in information quality and availability to extend the understanding of the notion of "resources" to analyse the benefit of L2/3 fusion results.

4) Besides these advantages, taking into account the information inundation which has to be processed in intelligence cells, automatic support in defining information requests not only is more comprehensive and faster than human information processing, it also is more unbiased and impartial. Human SA/IA depends on subjective aspects. Knowledge-based information fusion relying on accepted models of the operational domain (schemata or templates) is unprejudiced in its detection of lacking information and alternatives of possible situation development (estimated future situation).

This RM would establish a changed RM not in respect to optimizing the planning for the allocation and scheduling of resources but would improve the definition of tasks to be scheduled in an integrated decision support system.

DECISION-THEORETIC SENSOR RM

Chee Chong advocates that sensor resource management (SRM) is usually formulated as an optimization problem under uncertainty. A decision-theoretic model shows that the objective function should not be just tracking or target ID performance. Instead, it should represent the expected outcome value from the collected data. This outcome depends on how the collected data and fusion results are used in making other RM decisions such as action-to-target assignment. As an example of action-to-target assignment, RM should consider the integrated weapon-to-target management problem and propose a decomposition to make the solution feasible.

The SRM goal is to support better decisions, and not just better sensor data or fusion results because information by itself has no intrinsic utility. Since IF results are used to action or other decisions that impact outcome such as the survival of own assets or destruction of threat, we need a framework for representing the relationship between decisions, uncertainty, and utility. Decision theory provides such a framework.

Decision-Theoretic Model

In a decision-theoretic formulation of SRM, sensor decisions are selected to optimize an expected utility in the presence of uncertainty. Figure 4 shows an influence diagram for such a model for the first two time steps.

The threat state may represent the position/velocity and type of multiple targets as well as their intent. Own state includes the location and status of the assets. Outcome includes both status of threat and own assets. Thus the value to be maximized may reflect either threat destruction or own asset survival. The threat estimate is generated by L1/2 fusion. Predicting the outcome given the own state and threat estimate is impact assessment (L3). However, predicting outcome requires more than just own state and threat estimates. One also needs to know how the threat estimate is used to generate other response decisions (e.g., weapon) that affect the threat state and own state and eventually the outcome. Weapon decisions affect the threat state while moving away from a threat affects the own state. Figure 4 shows an influence diagram that includes the response decision. It is similar to the sensor influence diagram in [34]. In order to solve the SRM problem, the response decision has to be provided by an external algorithm (weapon resource manager) or an approximation computed internally by the sensor resource manager.

Problem Decomposition

The sensor and response RM problems are tightly coupled as seen in Figure 4. Consider weapons as the main response resource. Weapon management prioritizes targets and decides which targets to shoot at and the weapons to use. SM does not need to observe targets that are not of interest to the weapon manager. Similarly, the weapon manager needs to know future sensor data availability in order to plan weapon actions. Thus, the optimal approach to SM is to solve the integrated sensor/ weapon RM problem. However, each problem by itself is difficult enough to be solved exactly [4, 26, 35, 36]. Thus, we need a way of providing an approximate coupling between the two problems. One approach is to assume that nominal policies are available at each planning interval. A nominal weapon policy specifies the mapping of threat estimates (and own states) into weapon decisions. This is equivalent to specifying the weapon decisions in Figure 4. Similarly, a nominal sensor management policy specifies the sensor decisions. Given the nominal policies, the integrated RM problem decomposes into independent sensor and weapon management problems.

Finding good approximate nominal policies is crucial in making this approach work. Since the nominal policies have to be updated at each planning time, they should be efficient to compute. One approach is take the weapon manager's output as the reference and use sensitivity analysis to look at the benefit of getting additional information for tracking and

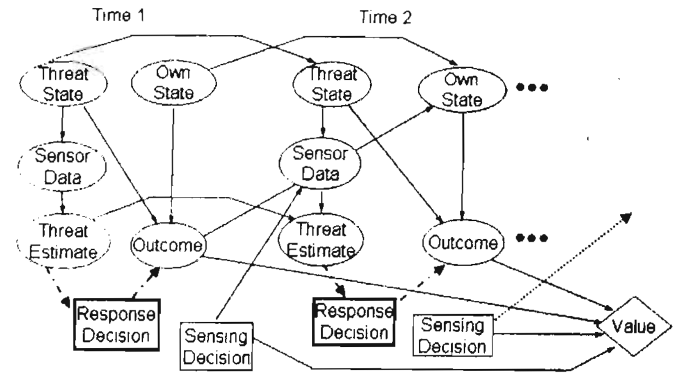

Fig. 4. Influence diagram with response decisions

target ID. This information value will be provided to the sensor manager as the optimization problem objective. Note that this objective is different from just information gain because the latter is not related to the expected value of the outcome.

Similarly, the current SM policy can be used to compute the predicted track quality and target identity probability in the future. This information is provided to the weapon manager to specify the nominal data that will be available. Figure 5 shows the information exchange between the weapon and sensor RM. Basically, the weapon resource manager provides an objective function for the SM problem while the sensor manager specifies the available information for the weapon management problem.

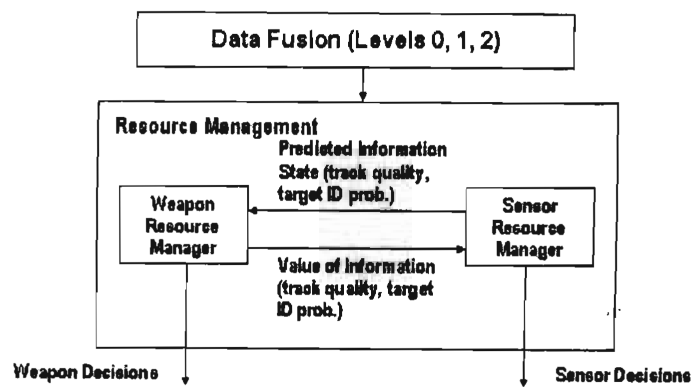

Fig. 5. Influence between sensor and weapon RM

Sensor RM Issues and Challenges

SRM requires knowing the value of the information generated by fusion from the collected data. This information value is generally different from information-theoretic measures since it depends on how the information is used to make response decisions such as assignment of weapons to targets, or taking other defensive actions. The decision-theoretic approach models the relationship between information, decision, and value and involves both sensor and response RM. While the integrated RM is difficult to solve exactly, it is possible to decompose the problem into sub-problems by defining appropriate interfaces. In addition to techniques of solving the decomposed weapon and RM problems, research issues for SM include how to compute the information value efficiently, and predicting the performance of sensor decisions.

Issues and Challenges

1) Tighter integration of sensor and action-based resource management to support resource responsiveness.

2) Use of nominal policies or strategies to decompose the sensor/response problems for approximate solutions are needed.

3) Outcome-based value metrics to support sensor-to-action assignments.

COUPLING RM TO L2/3 CAPABILITIES

John Salerno advocates that RM is a necessary and an integral component to any L2/3 capability and presents a cyber fusion example. Process Refinement or feedback is a key component of any closed loop system. It is important to explore what process refinement means in terms of the higher levels of fusion. In doing so, we further refine the existing definitions of the various levels and based on these definitions, we discuss how each of these levels interacts with the other.

Addressing Level 2/3 Fusion

There continues to be a debate as to what Levels 1 (L1) and L2 represent. One belief is that L1 deals only with the tracking and ID of individual objects while L2 is the aggregation of the objects into groups. For example, L1 objects could be various equipments (tanks, APCs, missiles, etc.). At L2, equipment along with personnel can be aggregated into a unit or division based on time and space. But if we consider this separation then several questions arise; *How do we account for concepts or non-physical objects and can't we track a group or activity like an object? What is a situation? How does the system acquire the necessary a priori knowledge (or relationships) to perform aggregation? What is the difference between models to identify an object, group, or activity?* To begin to answer these questions we must address definitions and then use them to refine what we mean by L1/L2.

> An entity as *"something that has a distinct, separate existence, though it need not be a material existence. In particular, abstractions and legal fictions are usually regarded as entities. In general, there is also no presumption that an entity is animate. The word entity is often useful when one wants to refer to something that could be a human being, a non-human animal, a non-thinking life-form such as a plant or fungus, a lifeless object, or even a belief."*
>
> An object is *"a physical entity; something within the grasp of the senses" "something perceptible by one or more senses, especially by vision or touch"* (***The Free Dictionary***). *What if the entity is not a physical object?* Generally speaking, an abstract entity still can be associated with a time or existence of an abstract concept.
>
> A group is *"a number of things (entities, to include individuals) being in some relation to each other,"* while an event is *"something that takes place; an occurrence at an arbitrary point in time."*
>
> Both entities and groups can be associated with a specific event or a series of events. An activity is *"something done as an action or a movement."* Activities are composed of entities/groups related by one or more events over time and/or space. (***Wikipedia***) [37].

By definition, an event, group, and activity can be considered as a more complex entity and can be tracked and identified. Activities and activity aggregation (which we refer to as the situation) is both a part and a result of L1. Models or a priori knowledge is necessary for L1 to be capable of identifying the object, group, or activity. The a priori knowledge (i.e., the relationships or associations) can be learned through Knowledge Discovery and validated by an operator or provided directly. Note: Knowledge Discovery techniques can only learn statistically relevant occurrences. As such, new or novel ideas cannot be learned and require knowledge elicitation.

L2 is then the SA at a snapshot in time. L2 includes the interpretation or meaning of what is happening with respect to context and time while L3 is the determination of whether there exists a threat or impact: *Is there an entity, group, event, or activity that we should care about?* Specifically, situation assessment is a quantitative evaluation of the situation that has to do with the notions of judgment, appraisal, and relevance. Roy [38] provides a description of a number of questions/products that are developed under what they call Situation Analysis. In our case, we believe a number of these products are created at L1 while others are L2. L1 attempts to answer such questions as Existence and Size Analysis (*How Many?*), Identity Analysis (*What?/Who?*), Kinematics Analysis (*Where?*), and *When?*, while L2 provides: Behavior Analysis (*What is the object doing?*), Activity Level Analysis (*Build up?, draw down?*), Intent Analysis (*Why?*), Salience Analysis (*What makes it important?*), and Capability/Capacity Analysis (*What could they/it do?*). We can also argue that L2/3 are a result of analysis of current data. After this assessment, the next step would be to forecast or project the current situation and threat into the future. We specifically call this function a projection (as defined by Endsley [39]) which takes the situation and projects or forecasts it to time t + n, where n is some number of time steps. Figure 6 summarizes what we have presented thus far.

Process Refinement Meaning for L2/3

Process Refinement covers two separate but integrated capabilities: external and internal process. Externally, we are concerned with providing sensors or collections with positioning information based on forecasted or anticipated movement of objects/entities or groups. The classical example here is the tracking of an object using a Kalman Filter. Theoretically, a similar approach can be done with concepts and groups. Also, since models are typically used to define relationships, one can also use these models for projection. Models that describe activities not only describe how entities, groups, and events are related, they also provide knowledge as to what might happen next, and thus, can provide positional information for sensor collection.

Level 2/3 is concerned with current situation ID, adversary's capabilities, strengths, and weaknesses. This understanding of the adversary is packaged into what is called an adversarial model or adversary's mental model [40]. In today's environment, models as defined by current doctrine consist of: 1) Doctrinal Templates (illustrate the employment patterns/dispositions preferred by an adversary when not constrained by the operational environment effects); 2) Description of Adversary Tactics and Options (a written description of an opponent's preferred tactics); and 3) High-Valued Target IDs (those assets that the adversary commander requires for successful mission completion).

Projection, Anticipation, or Forecasting, shown in Figure 6, is accomplished by the analyst and supports the development or analysis of possible 1) adversary intent; 2) Courses of Action (COA) – to include a prioritize list identifying the most likely and most dangerous; and 3) a set of collection requirements. As part of the process that an analyst performs while developing their SA/IA, they may develop a collection of requirements and identify new relationships (and, in turn, update their model(s) of the world).

Internal processes also need to be monitored to ensure that the information processing system is performing as designed. At the object level one can suggest, possibly based on environmental inputs, which source is "better" at that time for tracking or identifying the object or sending the same sensor data to multiple algorithms (running in parallel), coming up with possibly different answers and combining the results in some manner. Similar concepts can be used at the activity level. As previously mentioned, a second area is the update of a priori knowledge or models. As new information comes in and new knowledge is developed through the assessment and projection process, the analyst may update existing models or add/create new models (regardless of whether it is a new/modified object, group, or activity).

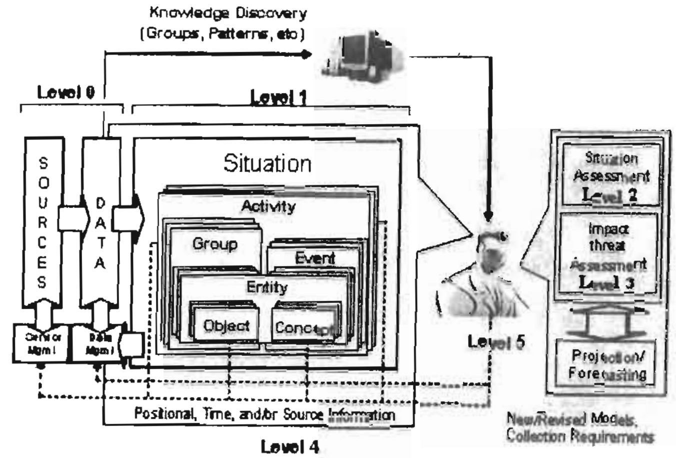

Fig. 6. Proposed Refinement of JDL Model

Issues and Challenges

1) Better understand the definitions and interactions between Levels 4 and 2/3.

2) Establish definitions of Levels 1 and 2 in hopes to better clarify each of their roles.

3) Level 2/3 concepts such as projection, forecasting, and situation/threat assessment and how they can jointly exist.

RM FOR NET-CENTRIC ENVIRONMENTS

Subrata Das utilizes constraint programming (CP) to address RM and L2/3 processing. The military RM problem involves timely distribution and placement of materiel, personnel, and sensor assets to accommodate mission requirements. Moreover, the problem is highly dynamic in nature in the sense that requirements are constantly evolving at every moment due to changing situations in the underlying missions. The traditional solution using mass-based hierarchical distribution of resources. This modern RM problem needs to be considered within a network centric environment (NCE), and hence the term "sense and respond logistics" (S&RL) [41]. Given this paradigm, issues of effective node communication and coordination within a NCE replace the complexity of a centralized and monolithic search problem for traditional RM.

RM is intimately related to the problem of planning and scheduling of tasks, that is, one cannot effectively reason with resources in isolation. In the data fusion domain, this view translates to consideration of the collection management process during SA/IA and COA generation processes. Within a NCE, a node must proactively determine mission requirements based on the current situation and threat, and then coordinate with other nodes to meet those requirements via some communication mechanism (e.g., publish and subscribe) on the underlying infrastructure. The specific algorithmic approach advocated for dynamically managing resources is essentially based on CP techniques, where constraints are declaratively stated and placed on the types and quantities of resources at hand, dynamically added or retracted from the system, and amendable for dynamic RM environments. The approach distinguishes between consumable and non-consumable resources. Here, we illustrate the CP approach to RM in NCE in terms of two examples. The first example is related to surveillance asset management and the second is related to logistics.

Constraint Programming

CP offers a declarative and flexible modeling environment with complex constraints, and incorporates dynamic changes through constraint propagation. A constraint is simply a logical relation among several unknowns (or variables), each taking a value in a given domain. For instance, the constraint "air sensor asset A can use only runway R" relates two objects temporally without precisely specifying their working time intervals, which are variables taking values from the time interval domain. Now, working time intervals of A for data dissemination or tracking will be restricted by the working time intervals of R due to the constraint. From an analytical perspective, CP is about solving problems by stating constraints which must be satisfied by the solution. This is an effective software technology for declarative description and solution of combinatorial problems with complex constraints, especially in areas of planning and scheduling. A constraint satisfaction problem (CSP) [42, 43] consists of:

- A set of variables $X = \{x_1, \ldots, x_n\}$,
- For each variable x_i, a finite set D_i of values (its domain),
- A set of constraints restricting the values that the variables can simultaneously take.

A solution to a CSP is an assignment to every variable of a value from its domain in such a way that every constraint is satisfied. It is usually preferable to determine an optimal solution, according to some objective function defined in terms of some or all of the variables.

Solutions to CSPs can be found by searching systematically through the possible assignments of values to variables. For example, the generate-hypothesize-and-test method systematically generates each possible assignment and then it tests to see if it satisfies all the constraints. A more efficient approach uses the backtracking method that incrementally attempts to extend a partial solution toward a complete solution, by repeatedly choosing a value for an unsolved variable. The major disadvantage of these search methods is their late detection of inconsistencies.

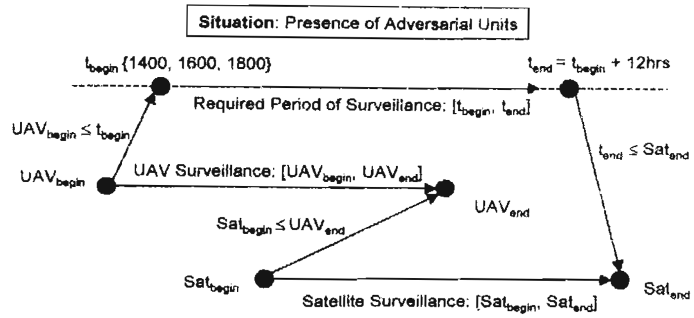

Fig. 7. Constraint Network for Sensor Asset Management

An important feature of CP that helps to detect inconsistency at an early stage is constraint propagation over finite domain variables. Intuitively, CP is a deductive activity that allows the extraction of new information from a constraint, which may reduce the search space that needs to be explored. A very simple example of constraint propagation is the handling of disequalities like *"air asset A cannot be assigned to runway R2."*

Various constraint propagation techniques that work on binary constraint networks (i.e., all constraints relate two variables) of variables and constraints have been introduced to prune the search space. These range from simple node-consistency to popular arc-consistency to complete but expensive path-consistency. It is possible to convert a CSP with n-ary constraints to another equivalent binary CSP. A binary CSP can be depicted by a constraint graph in which each node represents a variable, and each arc represents a constraint between variables represented by the end points of the arc. A unary constraint is represented by an arc originating and terminating at the same node. An example binary constraint network is shown in Figure 7. The network represents one possible scheduling of two air and space surveillance assets (UAV and Satellite) for a tactical area known to have been interdicted by some adversarial units. The required surveillance will take place for a period of at least 12 hours starting at the time point t begin and ending at t end.

Each node of the network in the figure is a variable representing either the start time or the end time of the scheduling of an asset. Each arc represents a constraint involving the two nodes joining the arc.

Constraint networks can be built from hierarchical representations of tasks [44, 45] where each such representation of a task consists of precondition which needs to be satisfied before the task can be executed, the subtasks or atomic actions that constitute the task, and finally, effects after the task is executed. These representations are unfolded during the resource planning and scheduling process.

Net-Centric Environments

RM within an NCE can be effectively realized via Sense and Respond Logistics (S&RL), which is different from the classic, mass-based approach to logistics. S&RL identifies

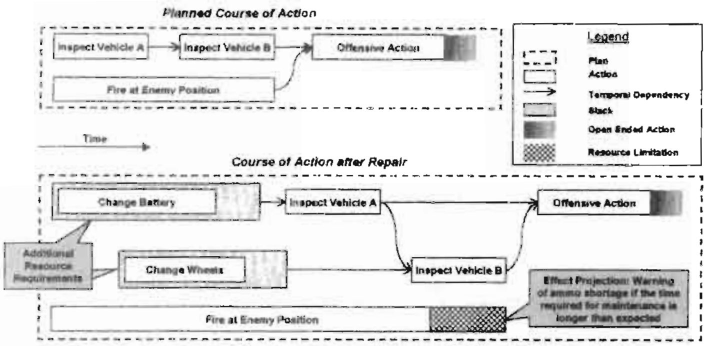

Fig. 8. Logistics Replanning in Net-Centric Environment

relevant operational evolutions that are likely to affect the logistics status, projects changes at the operational level onto the logistic level to assess and prepare for any resource requirements, and finally compares the projected requirements with currently allocated resources to determine additional logistic needs. Figure 8 illustrates a small-scale scenario explaining the functioning of S&RL.

Two armored vehicles, A and B, that are to be used as part of the operation must be fully functional for the mission, and thus, need to be inspected before the offensive action begins. The two vehicles' inspection must be done in sequence as there is only one inspector. The inspector recommends changing the battery and the wheels in vehicles A and B, respectively. These two changes can be made in parallel as there is more than one mechanic available at the base, but the inspection that will follow the repair still has to be done in sequence. The recommended repairing process thus prolongs the expected time interval. Consequently, there will be a shortage of ammunition from this extended firing; this will be recognized early and project additional resource requirements.

The CSP paradigm can effectively implement the above line of reasoning. The planned course of action is represented in a constraint network, and additional constraints are inserted as soon as the inspector discovers faults. The network is then transformed to another network by adding the new repair tasks and their dependencies to the existing inspection tasks. As a result, the new network becomes inconsistent due to the additional resource requirements. Existing constraints must be relaxed (e.g., results in accumulating more ammunition) to generate a feasible schedule of the actions and resources.

Issues and Challenges

1) net-centric environment and service management bandwidth allocation for L1/2/3,

2) Communication and timely ordering of information, and

3) Addressing constraints for resource planning and scheduling.

SUMMARY OF PANEL DISCUSSION

The purpose of this paper is to summarize the results of panel discussion on resource management interaction with L2/3 situation and impact fusion. Thus cognizance of the interactions facilitates user desired information needs presentation, control, and satisfaction to support effective and efficient proactive decision-making. RM issues, are: 1) designing for users, 2) determining a standard set of metrics for cost function optimization, 3) optimizing/evaluating fusion systems to deliver timely information needs, 4) dynamic updating for planning mission time-horizons, 5) joint optimization of objective functions at all levels, 6) L2/3 situation entity definitions for knowledge discovery, modeling, and information projection, and 7) addressing constraints for resource planning and scheduling.

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