

Fusion 2012 Panel Discussion Topic 3

Issues of Uncertainty Analysis in High-Level Information Fusion

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Abstract— High-Level Information Fusion (HLIF) utilizes techniques from Low-Level Information Fusion (LLIF) to support situation/impact assessment, user involvement, and mission and resource management (SUM). Given the unbounded analysis of situations, events, users, resources, and missions; it is obvious that uncertainty is manifested by the nature of application requirements. In this panel, we seek discussions on methods and techniques to intelligently assess the problem of HLIF uncertainty analysis to alleviate high-performance statistical computational optimizations, unrealizable mathematical assumptions, or rigorous modeling and problem scoping which lead to time delays, brittleness, and rigidity, respectively. Given the various methods of LLIF and the complexity of HLIF, an interest to the ISIF community is to utilize diverse methods (such as those from other communities) that bridge the LLIF-HLIF gap of uncertainty analysis. To get a qualified and diverse viewpoint, we present a summary of HLIF uncertainty processes towards developing a multisource ontology of uncertainty to support HLIF modeling, methods, and management and systems design.

Keywords: Fusion, Uncertainty Reasoning, Resource/Sensor Management, Cognitive Systems, Bayesian, Evidential Reasoning, Probabilistic Ontologies

I. PANEL MOTIVATION

High-level Information Fusion (HLIF) has been of considerable interest to the fusion community ever since the development of the fusion process models. The low-level versus high-level distinction was made evident in the seminal text on the subject by Waltz and Llinas, *Multisensor Data Fusion*, in “Figure 1.1 Elements of a basic data fusion system.” [1] The low-level functional processes support target classification, identification, and tracking, while high-level functional processes support situation, impact, and user fusion process refinement. LLIF concerns numerical data (e.g., locations, kinematics, and attribute target types). HLIF concerns abstract symbolic information (e.g., threat, intent,

and goals). Research is needed in uncertainty analysis over modeling, representations, reasoning, cognition, management, hard-soft integration, and relevance of HLIF processes.

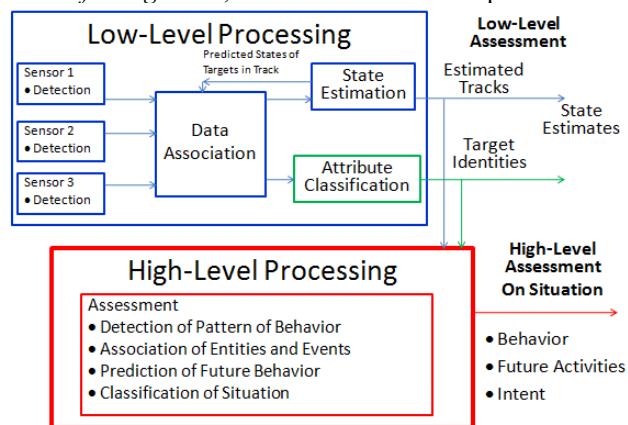


Figure 1 Elements of a basic data fusion system. [1]

While HLIF discussions at the International *Conference on Information Fusion* (referred to as *FusionNN*), including other panel discussions, detailed contemporary challenges, the Evaluation of Techniques for Uncertainty Representation (ETUR) working group sought to address uncertainty issues in HLIF. Recent HLIF texts include: *Mathematical Techniques in Multisensor Data Fusion* [2], *Concepts, Models, and Tools for Information Fusion* [3], *High-Level Fusion* [4], *High-Level Information Fusion Management and Systems Design* [5], and *Handbook of Multisensor Data Fusion*, [6-7]. The need for HLIF uncertainty analysis is important for measures of performance and measures of effectiveness [8].

A. Panel Organization and Discussion Overview

For this panel, experts were compiled based on various research thrusts and their Fusion12 papers:

Methods: Costa, Laskey, Stampouli [9],
Cognitive Designs: Blasch, Nagi, Ng [10],
Systems Design: Blasch, Nagi, Schubert [11],
Decision Support: Costa, Ng, Valin [12, 13], and
Evaluation: Laskey, Schubert, Stampouli [14].

The HLIF panel discussion’s goal is to highlight the unsolved problems and concerns to motivate the information fusion community towards systems-level solutions. The panelists’ expert perspectives are based on three areas: (1) previous panel discussions and summaries, (2) an integrated list of HLIF challenges, and (3) companion papers presented at the *Fusion2012* conference (note we switch to *Fusion12* to refer to the conference).

Panel 2012 Questions

- What are *methods* of Uncertainty Representation (UR)?
- Can multiple methods coexist and act synergistically?
- Are preferable techniques of UR for LLIF and HLIF?
- How to bridge the LLIF and HLIF uncertainty evaluation gap?
- What techniques are of interest from other communities for ISIF applications?
- What is future of HLIF ETUR methods or top unsolved challenges?

Answers to these questions were formulated in the companion *Fusion12* papers [9-14].

B. Previous Related Panel Discussions

Panel discussions provide a valuable resource to the community to overview the current techniques and provide areas of concern for future research. Previous Fusion Conference panel discussion papers related to HLIF include knowledge representation (*Fusion05*) [15], resource management coordination with situation and threat assessment (*Fusion06*) [16], agent-based design (*Fusion07*) [17], HLIF research (*Fusion08*) [18], intent modeling (*Fusion09*) [19], and HLIF challenges [20]. Dale Lambert [21] posed some grand challenges for the Information community including: semantic, epistemic, paradigm, interface, and systems. Added to the grand challenges were decision support process [22] and *evaluation challenges* [23]. Evaluation challenges include uncertainty reasoning, measurement, and context-dependent testing.

C. High-Level Information Modeling

Following [1], the Joint Directors of Laboratories (JDL) model was proposed and subsequent revisions were proposed by the Data Fusion Information Group (DFIG). The DFIG model [7] supports the original JDL goals while highlighting pragmatic design issues by coupling resource management (RM) functions with information fusion (IF) estimation needs. The DFIG model supports differing control functions based on the spatial/temporal/ spectrum differences. The *spectral* needs drive sensor selection. The *temporal* needs are based on the user’s need for timely information to afford action. Finally, the *spatial* needs are based on the mission goals. The current team diagrammed the current process model, shown in Figure 2, while maintaining the structure of the JDL model.

The current DFIG levels include:

- | | |
|--------------------------------|------------------------------|
| Level 0 – Data Assessment | Level 4 – Process Refinement |
| Level 1 – Object Assessment | Level 5 – User Refinement |
| Level 2 – Situation Assessment | Level 6 – Mission Management |
| Level 3 – Impact Assessment | |

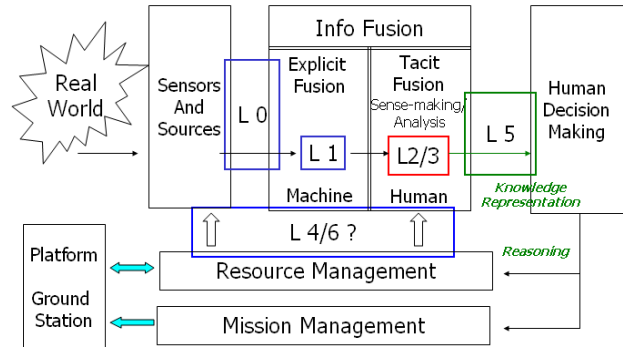


Figure 2. Data Fusion Information Group (DFIG) model.

In the DFIG model, the goal was to separate the information fusion (IF) (L0-L3) and resource management (RM) functions (L4-L6). IF provides uncertainty assessment while RM seeks to reduce uncertainties. High-level information fusion (as referenced to levels beyond the DFIG Model Level 1) is the ability of a fusion system, through knowledge, expertise, and understanding to: *capture* awareness and complex relations for perception [24], *reason* over past and future events for decision makers [25], *utilize* direct sensing exploitations and tacit reports, and *discern* the usefulness and intention of results to meet system-level goals based on contextual information [26]. The Information Fusion community has coined the term “high-level fusion” however this implies that there is a low-level / high-level distinction when in reality they are coupled. Designs of real-world information fusion systems imply distributed information source coordination (network), organizational concepts (command), and environmental understanding (context). There is a need for automated processes that provide uncertainty analysis in support of cognitive decision processes and information management particularly at higher levels requiring reasoning and inference.

The rest of this paper includes panel discussions topics: Section II (Bayesian Semantics), Section III (Evidential Methods), Section IV (Computational Cognitive Systems), Section V (Information Management), Section VI (Hard and soft fusion and uncertainty), and Section VII (HLIF Uncertainty Measures). Section VIII concludes the paper with a summary of the panel discussion.

II. FIRST-ORDER BAYESIAN SEMANTICS FOR UNCERTAINTY ANALYSIS IN HLIF

Paulo C. G. Costa, Kathryn B. Laskey: Analytical methods for Low-Level Information Fusion (LLIF) Systems have become well established. Probabilistic methods are common for managing uncertainty when fusing data at JDL levels 0 and 1. JDL levels 2 and above (High-Level Information Fusion –

HLIF) bring a new set of challenges requiring sophisticated approaches to fusing information and managing the associated uncertainty. There is as yet no consensus on a general methodology for managing uncertainty in HLIF. In this panel presentation, we argue that any solution for HLIF must connect the semantics of the information being fused with its associated uncertainty. We present first-order Bayesian semantics as one alternative that addresses this requirement in a sound and efficient way, providing a promising alternative for HLIF systems that must perform uncertainty analysis.

A. Introduction

In a typical LLIF system, the information being fused is tied closely to the basic physics of the problem. Phenomena of interest are well understood and standard engineering models exist. The underlying semantics is rarely made explicit, usually being implicitly encoded in data structures. A prototypical example is the fusion of radar returns with overlapping error ellipses to output a fused track. This approach works because information is represented and processed at a low level of abstraction and standard data structures can be “hardwired” into systems. However, integrating information at JDL levels 2 and above involves representing and reasoning with entities at higher levels of abstraction (e.g. aircraft, formation, enemy intention, etc.). More sophisticated representations are required to capture the meaning of the information being fused. “Hardwiring” of semantics is unfeasible, as different HLIF sources capturing the same entity might be based on distinct conceptual understandings of a given entity and thus represent it in diverse ways.

B. Ontologies: Making Semantics Explicit

As recognition has grown that syntax-based LLIF solutions are inadequate to meet the demands of HLIF, semantics has been viewed as a silver bullet to address the need. As a result, ontology engineering has become a major aspect of HLIF research. Since its adoption in the field of Information Systems, the term ontology has been given many different definitions. For the purposes of this discussion, a computational ontology is defined as any explicit, formal representation of knowledge about a domain of application.

Early computational ontologies (e.g., [27]) were essentially just type hierarchies. The need soon became apparent to represent additional relationships, such as parthood, as well as attributes of entities. Formalized logical semantics for ontology languages enabled the development of logical reasoners that could deduce logical consequences of the encoded domain knowledge. The most common semantics for ontology languages is description logic, a decidable fragment of first-order logic. Two formal ontologies are considered equivalent if there is a truth-preserving mapping between expressions expressed in their respective languages. Automated deductive inference is employed both to determine type inclusion relations and to determine equivalence. Wielinga [28] gave early work on computational ontology a sounder mathematical foundation by defining an ontology as an equivalence classes of language/implementations in an algebra of ontology-transformations. Standardization efforts [29] led to the OWL web ontology language and formal specification [30] which

supports implementation, extension, comparison, evolution and reuse of ontologies.

Existing computational ontological theory and implementations support many of the requirements for complex systems. However in practice applications of such schemes are typically updated by humans or by simple overwriting of previous knowledge with new “finished” knowledge. This underutilizes capabilities of existing automation, over-utilizes scarce human expertise, and leaves users with an increasing glut of data without information, or perhaps at best, relevant information without actionable knowledge (*cf.* [31]).

C. Semantics and Uncertainty in HLIF

Current ontology formalisms lack a principled, standardized means to represent uncertainty, which is a major aspect of Information Fusion. For instance, HLIF applications, among other tasks, must be able to:

- hypothesize the existence of an entity;
- declare a relationship between one entity and another;
- declare that another entity is one of several potential participants in a given relationship;
- observe evidence about an attribute of an entity;
- assert potential membership of an element in a set;
- prune unlikely hypotheses.

All the above tasks require representing and reasoning with uncertain, incomplete information. Ontologies alone do not provide a standard approach to this. As a result, engineers have turned to palliative solutions in which probabilities are inserted in an ontology as annotations (e.g. marked-up text describing some details related to a specific object or property). Such solutions address only part of the information that needs to be represented. Too much information is lost due to the lack of a representational scheme that captures structural constraints and dependencies among probabilities. A true probabilistic ontology must be capable of properly representing these nuances.

In previous work (e.g., [32, 33, 34]) we have presented the concept of probabilistic ontologies as a means to address these issues in a principled way. Probabilistic ontologies (POs) provide a principled, structured, sharable formalism for describing knowledge about a domain and the associated uncertainty. POs could serve as a formal basis for representing and propagating fusion results in a distributed system. They expand the possibilities of standard ontologies by introducing the requirement of a proper representation of statistical regularities and uncertain evidence about entities in a domain of application.

PR-OWL (Probabilistic OWL) [33] extended OWL to have a formal semantics and practical computation of probability distributions over class instances, enabling a mathematically consistent method to declare hypotheses and update their probabilistic support with inductive Bayesian inference. PR-OWL in turn is based on the theory of Multi-Entity Bayesian Networks (MEBN) [35], which was developed with the purpose of meeting the representational and computational challenges inherent in higher-level multi-source fusion and situation awareness. Specifically, MEBN can represent any hypothesis that can be expressed in first-order logic. Its basis in directed graphical models gives it a natural representation for

cause and effect relationships. Its built-in capability for context-specific independence provides a natural way to represent contextual factors that facilitate hypothesis management (HM), such as conditions under which a hypothesis can be pruned because it has little or no impact on conclusions of interest. MEBN also supports a natural representation for essential categories of uncertainty for general situation awareness, such as uncertainty about entity existence (i.e., is a report a false alarm); uncertainty about the type of entity; and uncertainty about functional relationships (e.g., which entity gave rise to a report). Its basis in Bayesian theory provides a natural theoretical framework for learning with experience. Its graphical representation supports an intuitive interface for specifying probabilistic ontologies. Finally, its modular representation formalism supports adaptability, by allowing changes to be made to parts of an ontology without affecting other parts or other ontologies, and composability, by allowing problem-specific models to be constructed “on the fly,” drawing only from those resources needed for the specific problem.

As such, PR-OWL provides a promising alternative for HLIF systems, as it combines both an explicit representation of semantics of a system and a principled account of its underlying uncertainty. The challenge remains of developing solutions that implement the above-cited concepts within a scalable, efficient framework.

D. The Future

Despite recent advances in multi-source fusion, the need remains for principled way of representing and reasoning with uncertainty in HLIF systems. A successful approach not only must enable explicit representation of semantics but also must be built upon a sound mathematical foundation. A first-order Bayesian approach provides both and, as research on scalable and computationally efficient algorithms evolves, will be a strong contender to address the current limitations in uncertainty analysis in HLIF systems.

III. EVIDENTIAL METHODS

Dafni Stampouli, Gavin Powell: Evidential methods are used extensively for fusing data in LLIF scenarios and offer a range of means to represent and evaluate uncertainty. For HLIF fusion however, the existing combination rules are not adequate to address the challenges of the task.

Defining the frame of discernment is not a straight forward task. There might be no clear boundary between the differing hypotheses. It is difficult to define exhaustive and mutually exclusive hypotheses in complex problems and environments. Some sets with cardinality larger than one might not be as meaningful as in LLIF. At the same time, assigning initial belief to the frame of discernment is not a simple task. In HLIF tasks there might be need for dynamic change in the frame of discernment. Furthermore, the curse of dimensionality is still evident and evidential methods are limited by the size of the frame of discernment.

The existing combination rules have difficulty dealing with the temporal nature of evolving situations, and can be plagued by issues related to commutivity and associativity. Combination rules need to be able to deal with information that is ordered over time, but also where ordering shouldn't

matter, such as receiving information from a number of sensors looking at the same target at the same instance in time. Such a dual fusion type situation is common but is very difficult to model given current combination rules.

HLIF requires subjective and qualitative analysis and the existing quantitative methods are not adequate. HLIF includes both textual and numeric variables and concepts. There is need for semantic representation of the input information and the situation at hand. This creates more uncertainty and ambiguity, and the representation of these is not currently adequate. At the same time, there are not any adequate distance measures to define similarity between concepts or non-numeric attributes. For example, police intelligence analysis relies on interpretation and processing of witness statements. As with all HUMINT information, these are subject to biases, imprecision, and omissions. Interpreting and fusing this information requires the deduction of semantic meaning from them. Previous work has tried to address these issues but further work and refinement is still required [36, 37].

Vagueness and uncertainty is more relevant in HLIF tasks. The benefits of evidential methods are that they already have some tools in place to represent and model vagueness, uncertainty and conflict, such as the empty set. However, interpreting the empty set is not well defined within HLIF scenarios. Evidential method support both closed-world and open-world cases. In a closed-world scenario it is possible to indicate conflict of the input sources, while in an open-world scenario a high value at the empty set might indicate that the answer is outside of the current frame of discernment. In current studies, this distinction was implemented [38] only in small and relatively simple scenarios, which however fail to represent the challenges of HLIF. The work indicated that the current combination rules cannot adequately represent open world scenarios and more work is required to expand or enhance them.

Another challenge is that it is difficult to adequately describe a HLIF scenario and breakdown the tasks and expected performance. Data to support such scenario and sufficient evaluation metrics are yet to be defined.

IV. COMPUTATIONAL COGNITIVE SYSTEM

Gee Wah NG: Computational Cognitive System *Computational Cognitive System (CCS)* is one way of achieving the goal of high level fusion i.e. impact assessment, situation assessment and addressing uncertainty. CCS takes inspiration from the human brain. This short paper will discuss a method of bringing the various concepts and design principles from understanding of the brain to build a CCS that achieve the goal of high level information fusion for adaptive decision making.

A. Introduction – Cognitive Architecture

The CCS involves the design of an architecture which is termed the Cognitive Architecture (CA). CA specifies a computational infrastructure that defines the various regions/functions working as a whole to produce human-like intelligence [39, 40]. It also defines the main connectivity and information flow between various regions/functions, and also models information processing in the human brain. The

classes of functions in the CA are modeled after the five core regions of the brain. They are:

- A) **Prefrontal cortex (Executive Function)** – Prefrontal cortex (PFC) involves in decision making, planning complex cognitive behaviors, predict outcome, orchestration of thought and actions in accordance to internal goals.
- B) **Perception** - Perception is the process of acquiring, interpreting, selecting, and organizing sensory information.
- C) **Limbic System (Affective Functions)** - The limbic system is a term for a set of brain structures that supports a variety of functions including emotion, behavior and formation of long term memory.
- D) **Association Cortex (Integrative Functions)** - Higher-order cortices are termed the association areas, associating sensory inputs to motor outputs and performing mental task mediating between sensory inputs and motor outputs.
- E) **Motor Cortex (Motor Control)** - Regions of the cerebral cortex involved in the planning, control, and execution of voluntary motor functions.

The following subsections will further discuss the key components essential in executive function to achieve the high level information fusion. At high level information fusion, the system will need to have the prior knowledge database and perform reasoning given the observation to infer situation, impact and intention. The executive function achieves this through its ability to representation different knowledge in terms of semantic, episodic and procedural knowledge. The reasoning processes are encapsulated in the following 3 components, namely the dynamic reasoner, the associative reasoner and the anticipatory reasoner.

B. Dynamic Reasoner

The biological brain encapsulate information in chunks i.e. mass of neurons (thousand of neurons) storing information in many small quantities distributed in the brain [41]. Neurons are “fired” to connect to other neurons via synapses. This enables small chunks of neurons connection to build a complete picture dynamically as new information stimulates the change in the neuron’s firing. This process enables the pre-frontal cortex to make its reasoning and inference. Similarly, we build in the executive function, a dynamic reasoner based on this principle. We encapsulate small chunks of knowledge in Bayesian fragment or any small semantic network. When an observation is received from the perception module, the dynamic reasoner will start to combine the various relevant fragments into the big knowledge network that can aid in its reasoning process [42, 43]. We call this dynamic reasoner the D’Brain. This D’Brain engine resides in the CCS. Figure 3 show an example of the dynamic reasoner. The reasoner is dynamic because the instantiated situation network is not precompiled and it evolves as new evidence is received. The decision output is dynamically adjusted in line with the unfolding of events.

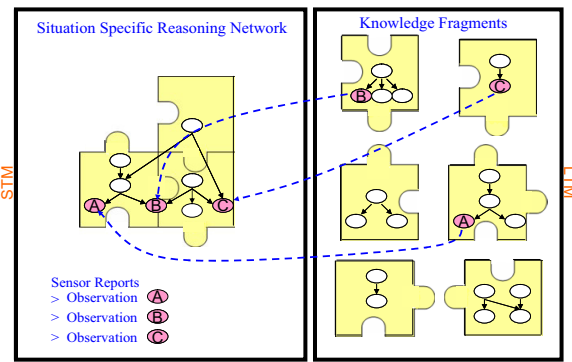


Figure 3. Schematic diagram of D’Brain

C. Associative Reasoner

The Associative Reasoner is an associative reasoning engine where knowledge is represented in the form of semantic network. Semantic network is a powerful and natural graphical form of knowledge representation where concepts are represented as nodes and relations represented as links between nodes. A modified PageRank [44] algorithm is used as the inference mechanism to perform associative connection. The idea is to propagate relevancy using a variant of PageRank’s algorithm given an initial set of observed nodes to discover which are the most relevant unobserved nodes in the semantic network. The PageRank is then interpreted as a measure of relevancy of the other unobserved nodes given the initial set of observed nodes.

D. Anticipatory Reasoner

The Anticipatory Reasoner takes the principle of the mirror neurons in the human brain. The mirror neuron is a neuron that fire when one observes a similar action performed by another i.e. the neuron “mirrors” the behaviour of the other, as though the observer were itself acting [45]. Using this principle, a computational anticipatory module (Figure 4) was built which contains a Self and Other person. Self refers to the entity making the inference. Within the Self, there exists an Own model and a mirrored model of the Other person. The Own model represents the mechanism for actual Self decision making and behaviour selection, and may include beliefs, desires, preferences, etc. The mirrored model is a simulated model used to represent the Other person within the Self, i.e., for inference of the Other person’s actions.

The models receive perception inputs from the environment. Before the inputs are used for inference in the mirrored model, reference changing or perspective changing is required. This maps the Other person’s states as own and vice versa, i.e., putting oneself in the other person’s shoes.

Initially, the mirrored model of the Other person is mapped from the Own model (assuming no prior knowledge or little information about the Other). Over time, as actions of the Other person are viewed, updates would be made to the mirrored model, and hence the mirrored model should converge towards the Other person’s model given enough updates.

The framework is based on the assumption that both the Self and the Other person are rational individuals and thus there should be some consistency in the actions.

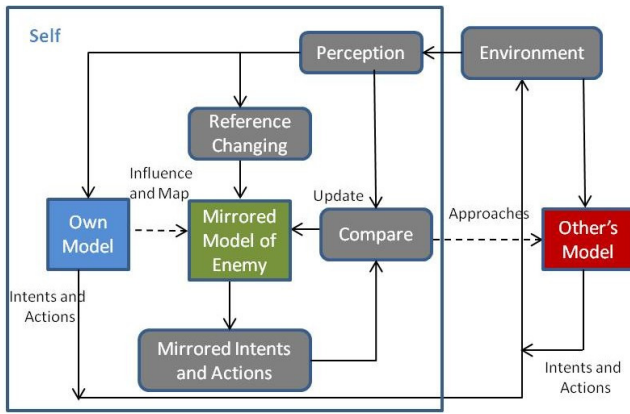


Figure 4. Computational Anticipatory Module.

E. Conclusions

A CCS that is designed using the concepts and principle from understanding of brain are presented. We elaborated the 3 components used in the executive function that could help in high level information fusion.

V. INFORMATION FUSION MANAGEMENT

Johan Schubert: Numerous information management issues are involved in information fusion. Information arriving from different sources may be mixed-up and referring to different problems, possibly concerning different issues with different frames and may be highly conflicting [46].

When conflict is higher than measurement errors it is a sign that something is wrong. It should be noted that there is at least three possible sources of conflict other than measurement errors. We may have modeling (representation) errors, mixed-up pieces of information, or faulty sources. Faulty sources are corrected by appropriate discounting, modeling errors are corrected by adopting an appropriate frame of discernment and mixed-up information concerning different problems can be managed by clustering. These issues are discussed in this section within the scope of Dempster-Shafer theory [47, 48].

A. Managing Subproblem

We developed a method for handling belief functions that concern multiple events. This is the case when it is not known *a priori* to which event each belief function is related. The belief functions are clustered into clusters that should be handled independently.

1) *Clustering consonant belief functions:* In [49] a method for clustering belief functions based on their pairwise conflict was developed. This method was extended into a method capable of also handling pairwise attractions [50].

When we are reasoning under uncertainty in an environment of several different events we may find some pieces of evidence that are not only uncertain but may also have propositions that are weakly specified in the sense that it may not be certain to which event a proposition is referring. We must then make sure that we do not by mistake combine pieces of evidence that are referring to different events.

In order to handle several belief functions regarding different events independently we arrange them according to which event they are referring to. We partition the set of belief functions into clusters where belief functions within the cluster

are all assumed to refer to the same event. However, if the belief functions are not labeled as to which event they are referring to, it is uncertain whether two different belief functions are referring to the same event and not possible to differentiate between them using only their propositions. We then use the conflict of Dempster's rule when the two belief functions are combined as an indication of whether they belong together. This is the basis for separating belief functions into clusters. A high conflict between the two belief functions is an indication that they do not belong to the same cluster. The higher the conflict is, the less credible that they belong to the same cluster.

For each cluster we may create a new belief function on a metalevel stating that we do not have an "adequate partition." These belief functions do not reason about the original problems. Rather they reason about the partitioning of the other belief functions into different clusters.

In [51], we established a criterion function of overall conflict for the entire partition called the metaconflict. It was derived as the plausibility of having an adequate partitioning for all subsets. The function is minimized by neural clustering. In Figure 5, we observe the convergence of two clustering processes. Each line is a path traveled by a belief function from the center of the circle at the first iteration of the neural network towards one of twelve cluster positions at the edge of the circle.

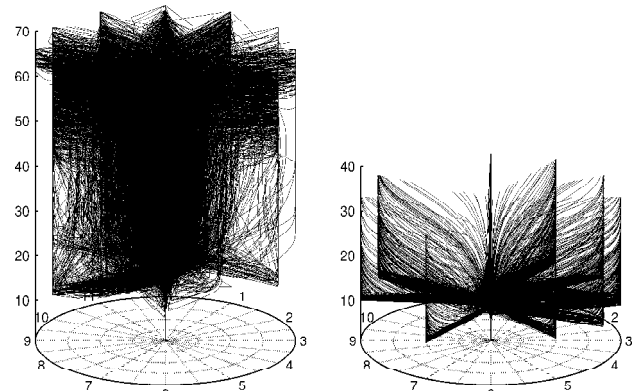


Figure 5. The clustering process of 4095 belief functions into twelve clusters. Left using conflicts only. Right using attractions and conflicts.

2) *Clustering non-consonant belief functions:* We have developed a method for managing non-consonant belief functions concerning different events where the belief functions are mixed up [52]. This method is based on the extension introducing attractions [50] and a decomposition method for belief functions [53].

The method can be described as first decomposing all belief functions into a set of simple support functions (SSFs) and inverse simple support functions (ISSFs) [53]. Secondly, all SSFs and ISSFs are clustered, taking account of both conflicts as well as information regarding which SSFs and ISSFs were decomposed from the same belief function.

3) *Estimating the number of clusters:* We may use particle filter methods for estimation of number of clusters. We have developed a sequential approach for grouping observations into an unspecified number of clusters [54].

A potential clustering with a specified number of clusters is represented by an association hypothesis. Whenever a new belief function arrives, a posterior distribution over all hypotheses is iteratively calculated. A set of hypotheses is maintained by Monte Carlo sampling. At each time-step, the posterior distribution is projected into a distribution over the number of clusters. This method solves the same problem as [49] except that it handles the reports sequentially and does not need to be given the number of clusters.

B. Managing the Event Space

In order to find an appropriate framing of the problem we construct alternative frames from input belief functions [55]. The problem we are facing can be summarized as: We have some uncertain information about several different aspects of some phenomenon. However, we do not know the frame of discernment. Instead we try to construct the frame from the cores of the belief functions at hand. Here, we do not make any assumption that the cores are sets of atomic elements. Instead we assume that they may belong to different homogeneous subframes whose cross product is the frame representing all possibilities of the whole problem.

As there may be several different alternative frames at any moment in time we want to find the most appropriate frame. We define appropriateness in such a way as it fulfills two different aspects simultaneously. Shafer [48], p. 280, proposed that an ideal frame should simultaneously let our evidence “interact in an interesting way” without “exhibit too much internal conflict”. We interpret “interesting” as having an as sharp distribution as possible. The best way to measure how focused the distribution is on as few focal elements as possible is using the generalized Shannon entropy. The best way to measure how focused the distribution is on as small focal elements as possible is using the generalized Hartley information measure. Together they make up the aggregated uncertainty measure (AU). Finding a frame that minimizes AU for the combined distribution is our answer to finding the frame that best let our evidence “interact in an interesting way”. At the same time we like the conflict of the combination of all belief functions to be as small as possible as any conflict larger than measuring errors is a sign that something (possibly the framing of the problem) is wrong. Finding a frame that minimizes the conflict is our answer to not “exhibit too much internal conflict”. To see both considerations achieved simultaneously we minimize their probabilistic sum.

C. Managing Sources

We develop a method for conflict management where it is assumed that all belief functions are referring to the same problem or alternatively that they are false [56]. In general a high degree of conflict is seen as if there is a representation error in the frame. One type of representation error resulting in high conflict is when belief functions concerning different subproblems that should be handled independently are erroneously combined. When this is the case the assumption that all belief functions combined must refer to the same problem (*not* different subproblems) is violated.

We interpret the conflict as metalevel evidence stating that at least one piece of evidence in the combination should not be part of that combination. By temporarily removing (and replacing) each belief function from the combination, one at a

time, we induce a drop in conflict. This is used to derive metalevel evidence regarding each individual belief function indicating that this particular belief function does not belong to the problem in question [57]. When assuming that there is only one problem at hand, such metalevel evidence must be interpreted as a proposition about the falsity of this belief function. A normalization of the drop in conflict will be shown to be the degree of falsity of that belief function.

We investigate how to manage the conflict on an individual case-by-case basis using the degree of falsity. We would then like to pay less regard to a piece of evidence the higher the degree is that it is false, pay no attention to it when it is certainly false, and leave it unchanged when there is no indication as to its falsity.

However, instead of directly discounting each piece of evidence to its individual degree of falsity we take an incremental step in that direction. Based on these initial discounts we recalculate conflict and update all degrees of falsities. The process is performed sequentially until a predefined level of maximal acceptable conflict is reached. With this sequential approach we obtain a smooth discounting process (compared to if we would have fully discounted each belief function to its degree of falsity) and we are able to exactly match any level of acceptable conflict without risk of overshooting.

It is important to observe that different measures may measure different types of distances. Some distance measures measure the degree to which two bodies of evidence are different, while conflict measures the degree to which they are incompatible. For example, two propositions “a red car” and “a fast car” are different, but may be fully compatible if there is a red fast car in the frame.

VI. HARD+SOFT FUSION AND UNCERTAINTY

Rakesh Nagi This panel presentation is focused on the uncertainty modeling and analysis in Hard+Soft Information Fusion. When fusing “soft” human-based observation information with “hard” physics-based sensor reports an important issue of uncertainty representation and analysis comes up. Hard sensors are typically based on scientific principles from physics, demonstrate repeatability, and can be well characterized by probabilistic error rates. The classical probabilistic representation of uncertainty seems to be an accepted framework.

On the other hand, human reports are laden with various forms of uncertainty. First, human perception and cognitive processing is self referential and learning-based. Its accuracy depends on the level of training, but is still prone to bias and improper error characterization. Heuer states [58], “the mind is poorly ‘wired’ to deal with (uncertainty).” Second, humans convey information in linguistic form and the choice of word(s) or symbol(s) they might choose are mappings of their internal neuro-cognitive estimates. There is symbolic uncertainty. In their FUSION 2008 paper, Auger and Roy [59] describe some of the underlying fundamental issues in the ambiguity of language and the issues involved in assigning degrees of uncertainty to linguistic expressions and words. Harras [60] describes two basic aspects of linguistic ambiguity: referential ambiguity (ambiguities between linguistic signs and the reality they depict in the world) and

linguistic ambiguity (different variations between a symbol and its associated meaning). Finally, humans use qualitative terms like "a lot," "very unlikely," and "much more likely," which require formal uncertainty characterization in quantitative terms. Zadeh [61] discusses similar issues and argues for the use of fuzzy methods for *computing with words*. We concur and adopt the possibilistic or fuzzy representation of uncertainty for soft information.

Thus, the hard+soft domain demands multiple uncertainty representation frameworks, and their fusion requires that we work with them simultaneously. Let us recap that while possibility theory and probability theory both provide approaches to the representation and manipulation of uncertain information they are used to model different aspects of uncertainty. Generally probability theory is used for the representation of randomness and variability while possibility theory is useful in cases of imprecision, vagueness, and incompleteness. Nevertheless attempts have been made to provide transformations between these two measures of uncertainty. At times, these transformation can be useful in situations where we have information in both formats and we need to provide a basis for the fusion function of Common Referencing or normalization of disparate representations of some information [62].

There yet seems to be no single best way to execute these transformations – the statistical/mathematical literature indicates that some transformational framework is needed that constrains the formalism of the transformation. Some principles that have been used are the following: Probability/Possibility Consistency, Insufficient Reason, Information Invariance, Preference preservation, Symmetry preservation, and Ignorance preservation. These principles provide a basis to “preserve” something across the transformation – each one provides a different approach. Essentially, the result of a transformation from one representation to another is a type of “best estimate” of the alternate representation for a given value of the input form – an estimate consistent with or framed by the “Principle” applied (see [63, 64], for example).

Significant research is needed in uncertainty representation of soft information and its correlation with probabilistic hard information, in our opinion. Further, the accurate characterization of the human’s ability to sense and report accurately on observations of interest is a much needed multidisciplinary area of research. A recent paper [65] studies approximately 300 references that address one or more of 67 categories of human observation in counter insurgency and which provide empirical evidence of a qualifying variable (contextual or environmental factor) that has potential to influence an individual’s ability to make an accurate observation in a respective category. Much research is needed in the “source characterization” of the human observer.

VII. HLIF UNCERTAINTY MEASURES

Pierre Valin: Issues in uncertainty analysis of an information fusion system have been a topic of discussion at the fusion conferences [available at www.isif.org]. Key issues include process models, user assessment, context and meaning, and metrics with associated challenges in evaluation, control, and visualization. For example, *control* in resource management

requires uncertainty metrics that are processed to guide future sensor actions and the need for estimation-like capabilities for HLIF relations. Contemporary interests are issues between low-level (signal processing, object state estimation and characterization) and high-level fusion (control and relationships to the environment). Specific areas of interest include *modeling* (situations, environments), *representations* (semantic, knowledge, and complex), *systems design* (scenario-based, user-based, distributed-agent) and *evaluation* (measures of performance/effectiveness, and empirical case studies). The goal is to address the operational and strategic issues in pragmatic information Fusion system designs.

Fusion03 incorporates differing HLIF issues and solutions to situation assessment [66, 67, 68], intent estimation [69], and ontology representations [70, 71]. *Fusion04* HLIF research includes situational presentations [72, 73] of context dependent attributes.

In 2005, Schubert and Svensson provide a first of a kind literature review of robust high level fusion performance [74]. At *Fusion05*, user refinement [75] issues are presented for uncertainty refinement and further research expands on these topics in *Fusion06* [76, 77]. Between 2007-2008, HLIF design tradeoffs [78] and threat assessment evaluation [79, 80, 81] was the focus.

During 2009, with the already mentioned numerous panels calling out the needs for HLIF, numerous papers are presented. Solutions are presented for HLIF L2 situation assessment [82, 83] and L3 threat assessment [84]. The scenario issues of context [85, 86] and culture [87] are addressed. Various L5 user refinement decision support techniques are proposed [88, 89, 90 91].

With the panel discussion in HLIF in *Fusion10*, areas addressed were formal theories for HLIF SA modeling [92, 93], situation and knowledge representations [94, 95], HLIF system design [96, 97], decision support [98], and evaluation [99]. Common themes from the Fusion10 panel in HLIF include:

- (A) *Situational awareness* support,
- (B) Layered set of adaptive *process control loops*, and
- (C) Understanding the *role of human intelligence*.

For example, an element for situational awareness includes the use of *information relevance* (IR) as a quality of service (QOS) or information quality (IQ), that aid human intelligence in working with sensor management control loops. From 25 IR criteria, these were categorized as:

- **Usefulness**: Relevance values are dependent on potential applications (4): *Timeliness Relative to an Operation*, Request Completion, Utility in Decision Making, and Utility in Fusion;
- **Extrinsic relevance**: Determination of relevance values requires comparison of considered knowledge with current knowledge state (5): *Degree of Synchronicity of Time-Stamped Knowledge Set*, *Novelty*, External Consistency, Time-Stamping Relative to a Fact (Event), and Variation Rate Compared to Current State;
- **Intrinsic relevance of content**: Determination of relevance values is content-dependent, but can be considered context independent (8): Completeness,

Consistency with General Rules, Domain Membership of Physical Values, Domain Membership of Qualitative Values, Existing Reference Theme, Expiry Date, Internal Consistency, and Precision;

- **Complexity:** The information usefulness is evaluated using measurements on the information format (2): Density, and Volumetry;
- **A priori (metadata):** Determination of relevance values is achieved using the metadata attached to the information (7): *A Priori Credibility*, *A Priori Thematic Classification*, *Existing Reference to a Request*, *Measurement Date*, *Priority*, *Collection Protocol Compliance*, and *Security*.

From subject matter experts reviewing textual content, nine variables were deemed feasible and of interest to subject matter experts. Of the nine (listed in italics), *extrinsic relevance* and *a priori (metadata)* composed most of the set of measures. These measures relate to the information fusion QOS metrics of timeliness, confidence (credibility), and accuracy (existing reference to a request) [8]. These variables support previous HLIF discussions on situation assessment, uncertainty refinements, culture, and situation and knowledge representation.

VIII. SUMMARY OF PANEL DISCUSSION

High-level information fusion *situation/impact assessment*, *user involvement*, and *mission and resource management (SUM)* requires analysis of uncertainties for the transition of information fusion designs. There are numerous ongoing challenges that the Fusion community can discuss towards a common understanding and coordination for uncertainty analysis. Current panel thoughts have highlighted these challenges for HLIF uncertainty analysis:

- 1) **HLIF Modeling** (situations, environments, processes),
- 2) **Ontology Representations** of HLIF Information (probabilistic, semantic, knowledge, and complex),
- 3) **Evidential Reasoning** (temporal, vagueness, and decomposition of a scenario),
- 4) **Cognitive Modeling** (reasoning, inference, and relationships), and
- 5) **Information Management** (clustering, events, and sources),
- 6) **Hard-Soft Fusion** (physics-based and human-based uncertainty representations, sources, and integration), and
- 7) **Information Relevance** (HLIF measures, decision support, situational analysis).

Developing a multisource ontology of uncertainty [9] is important to support in HLIF modeling, methods, and management, as shown in Figure 6.

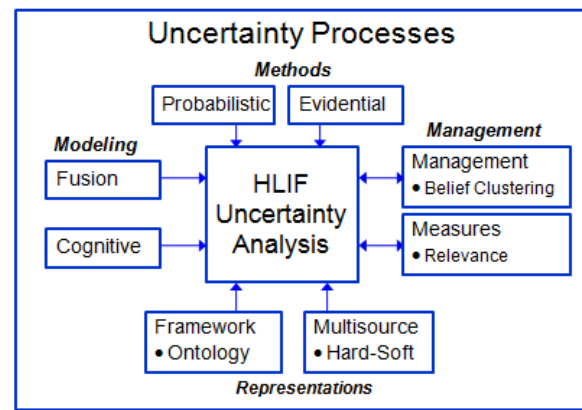


Figure 6. Uncertainty Processes.

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Kathryn B. Laskey is Associate Professor of Systems Engineering and Operations Research at George Mason University and Associate Director of the Center of Excellence in Command, Control, Communications, Computing and Intelligence (C4I Center). She teaches and performs research on computational decision theory and evidential reasoning. Professor Laskey's research involves extending traditional knowledge representation methods to represent uncertainty, eliciting knowledge from human experts, and applying probability theory to draw conclusions from evidence arising from multiple sources. Her applied work includes modeling the emplacement of improvised explosive devices, predicting aircraft delays, managing terrorist risk at public facilities, judicial reasoning, and planning military engagements. Dr. Laskey developed multi-entity Bayesian networks (MEBN), a language and logic that extends classical first-order logic to support probability. She was a key contributor to the development of PR-OWL, an upper ontology that allows MEBN theories to be represented in OWL ontologies. As an invited expert to the World Wide Web Consortium (W3C), Dr. Laskey co-chaired the Uncertainty Reasoning for the World Wide Web Experimental Group (URW3-XG), which investigated aspects of uncertainty that need to be standardized for web-based applications. She is co-organizer of the Uncertainty Reasoning for the Semantic Web series of workshops at the International Semantic Web Conference. Dr. Laskey served on a National Academy of Sciences committee to assess the statistical validity of the polygraph and has served on several boards and committees of the National Academy of Sciences.



Dr. Dafni Stampouli holds a BEng degree in Electronic Engineering and a PhD in segmentation of medical images. She studied for a Masters in Data in Information Fusion in the University of Cardiff, in Wales, and since undertook the role of fusion research engineer in the corporate research department of EADS. Her work is the area of information fusion, uncertainty representation and situation assessment in security and civil applications. She is a member of the IEEE and the IET.



Dr. Gee Wah Ng received his PhD from University of Manchester Institute of Science and Technology (UMIST), UK, in 1996. In 2006 and 2007, he is research associate in MIT and visiting scholar at Boston University. He is currently a programme director in DSO National Laboratories for Information Exploitation Programme. Concurrently he is an Adjunct Associate Professor in National University of Singapore, Engineering Science Programme. He authored three technical books and published many technical papers in International Conferences and Journals. The three technical books are namely "Application of Neural Networks to Adaptive Control of Nonlinear systems" (John Wiley and Sons Inc. ISBN: 0 471 97263 0), "Intelligent Systems - fusion, tracking and control" (Research Studies Press and Institute of Physics Publishing. ISBN: 0 86380 277 X) and "Brain-Mind Machinery" (World Scientific Publishing Co. ISBN: 978-981-279-025-5). His current R&D interest include data and information fusion, computational cognitive system (brain-inspired technology), target tracking, large scale data mining and analytics, and computational intelligence techniques for information processing.



Johan Schubert (Ph.D., 1994) is a Deputy Research Director with the Division of Information and Aeronautical Systems at the Swedish Defence Research Agency. He received an M.Sc. in Engineering Physics in 1986 and his Ph.D. in Computer Science in 1994, both from the Royal Institute of Technology, Stockholm. He has conducted research in Information Fusion and Decision Support for 25 years and published 16 journal articles, four book chapters and 40 conference papers. He was the technical program chair of the Seventh International Conference on Information Fusion (FUSION 2004), co-editor of the conference proceedings and guest co-editor of a double special issue of the journal Information Fusion on FUSION 2004. He is a board member of the Belief functions and Applications Society (BFAS) and member of the editorial board of the Information Fusion Journal (INFFUS). His current research interests include theoretical and applied aspects of Soft Computing, Neural Networks, Evolutionary Algorithms, Modeling and Simulation, Data Farming, Management of Uncertainty and Dempster-Shafer Theory, military applications of high-level Information Fusion and Artificial Intelligence for Situation and Threat Assessment and its use in Decision Support Systems.



Dr. Nakesh Ragi is the Chair and Professor of Industrial and Systems Engineering at the University at Buffalo (SUNY). He received his Ph.D. (1991) and M.S. (1989) degrees in Mechanical Engineering from the University of Maryland at College Park, while he worked at the Institute for Systems Research and INRIA, France, and B.E. (1987) degree in Mechanical Engineering from University of Roorkee (now IIT-R), India.

He is a recipient of Institute of Industrial Engineers (IIE) Fellow Award (2010), University at Buffalo's "Sustained Achievement Award" in recognition of outstanding achievements in scholarly activity (2009), Business First of Buffalo's "40 under Forty" award (2004), SME's Milton C. Shaw Outstanding Young Manufacturing Engineer Award (1999), IIE's Outstanding Young Industrial Engineer Award in Academia (1999), and National Science Foundation's CAREER Award (1996). His papers have been published in journals including *Information Fusion*, *Journal of Advances in Information Fusion*, *IIE Transactions*, *International Journal of Production Research*, *Journal of Manufacturing Systems*, *International Journal of Flexible Manufacturing Systems*, *Journal of Intelligent Manufacturing*, *Computers in Industry*, *Computer Integrated Manufacturing Systems*, *Management Science*, *Operations Research*, *Naval Research Logistics*, *European Journal of Operational Research*, *Annals of Operations Research*, *Computers and Operations Research*, *Computers and Industrial Engineering*, and *ASME and IEEE Transactions*. Dr. Nagi's major research thrust is in the area of high-level information fusion, data intensive analytics, graph association and matching, production systems and applied/military operations research. He is the principal investigator of an ARO MURI on Network-based Hard and Soft Information Fusion.



Dr. Pierre Valin taught and conducted research in theoretical physics (elementary particles) for over 12 years at various universities after graduating from Harvard University with a Ph.D. in 1980. He then spent over 10 years at Lockheed Martin Canada as a Senior Member of Engineering R&D, acquiring expertise in data/information fusion, reasoning under uncertainty, imagery classifiers and their fusion, etc. He joined Defence R&D Canada at Valcartier in 2004, where he has been Group Leader for 3 research areas over the years: Situation

Analysis and Information Fusion, Decision Analysis and Collaborative Planning, and now Future Command and Control Concepts and Structures, while also an adjunct professor at Université Laval and at McMaster University for the supervision of graduate students. He is Thrust Leader for Air Command at DRDC. Dr. Valin has been involved in information fusion research from its early stages, and was President of the International Society of Information Fusion (ISIF) in 2006 and is now its VP Membership.

His main interests are in Multi-Sensor Data Fusion requirements and design, benchmarking, use of a priori information databases, imagery classifiers and their fusion, reasoning frameworks, neural networks, fuzzy logic, reasoning techniques for identification (Bayes, Dempster-Shafer, and Dezert-Smarandache), SAR image processing, situation, threat and intent assessment, distributed information fusion and dynamic resource management, information relevance, amongst others.