High-Level Fusion: Issues in Developing a Formal Theory

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***Abstract** - Network-centric operations demand an increasingly sophisticated level of interoperation and information fusion for an escalating number and throughput of sensors and human processes. The resulting complexity of the systems being developed to face this environment render lower level fusion techniques alone simply insufficient to ensure interoperability, as they fail to consider subtle, but critical, aspects inherent in knowledge interchange. A fundamental mathematical theory of high-level information fusion is needed to address (1) the representation of semantics and pragmatics, (2) the mathematical framework supporting its algorithmic and computing processes, and (3) scalability of products such as common and user-defined operational pictures. We argue that there is no silver bullet for addressing these elements, and therefore any successful approach to the problem of high-level fusion must be systemic. In this paper, we propose the development of mathematical foundations that systemically address this problem from a decision theoretic perspective, and might seed the development of such fundamental theory. As a case study illustrating these techniques we present our current development of PROGNOS, a HLF system focused on the maritime domain.*

Keywords: Bayesian reasoning, probabilistic ontologies, multi-entity Bayesian networks.

1 Introduction

Research on the subject of information fusion has focused primarily on specific application areas. The bulk of research effort has concentrated on lower-level data alignment (e.g. multi-sensor data fusion, syntactic protocols, distributed simulation, etc), on semantic mapping solutions (e.g. Semantic Web approaches, specialized semantic mapping solutions, etc), or other topics that do not fully address the fundamentals of high-level knowledge integration. This gap has been recognized and there have been some efforts to address it (e.g. [1]). However, in spite of recent advances in the problem of merging knowledge from different sources, there is still a lack of a fundamental theory of high-level information fusion (HLF). Whatever the elements of such a theory might be, we argue that any successful approach to the problem of high-level fusion must be systemic in nature, requiring a sound mathematical foundation.

In the next section, we focus on the general problem of HLF and its major issues, while arguing that simply applying one or a combination of low-level fusion (LLF) approaches is insufficient to ensure proper exchange of knowledge among complex systems. We illustrate our ideas through a case study that emphasizes the need for proper knowledge exchange in a real world scenario, introduced in section 3. Our approach to the HLF is laid out in sections 4 and 5. Section 4 focuses on the representational gap and how to address it in a general theory of HLF. Section 5 presents our vision for addressing scalability, the nemesis of HLF approaches. We conclude with a discussion on future avenues for research, reinforcing the need for both mathematical foundations and a systems engineering process to ensure synergy among the innovative technologies being developed for HLF.

2 Fusing Knowledge

Complexity in networked systems increases not as an end in itself, but as a side effect of success. New capabilities are implemented, new technologies are added, scope is broadened, specialization increases, larger problems are tackled -- and complexity grows. Because of complexity creep, success can be a mixed blessing. An intricate but capable system is a blessing in its ability to support complex user operations, but it can become a curse when the need arises to interoperate with other equally complex systems. In such an environment, a synergistic and effective use of diverse systems can only be achieved by addressing the challenges of: (1) enabling interoperability among diverse systems and data repositories; (2) incorporating a wide variety of traditional and non-traditional types of data coming from geographically dispersed sources; and (3) providing the ability to process massive volumes of noisy, incomplete and uncertain data in a timely manner. Advances in connectivity and computation alone are insufficient to meet the challenge. The sheer volume of data creates informational and cognitive bottlenecks. Incompatible formats and semantic mismatches necessitate tedious and time-consuming manual processing at various points in the decision cycle. As a result, massive amounts of potentially relevant data remain unexploited, narrow processing stovepipes continue to provide stop-gap solutions, and decision makers' cognitive resources are too often focused on low-level manual data integration rather than high-level reasoning about the situations to be addressed. We illustrate the above points with a case study intended to show the demands posed to HLF systems in the context of a standard net-centric military product: the Common Operational Picture.

3 Common Operational Picture

A Common Operational Picture (COP) is intended to provide timely and accurate information, enabling shared situational awareness across multiple commands [2]. The more recent notion of user-defined operational picture (UDOP) provides tailored, decision-focused information for individual users. Traditionally, a COP or UDOP is defined as a display of relevant items such as friendly and enemy troop locations, terrain and cultural features, and infrastructure [3]. This display-centric definition encourages a focus on algorithms for data processing and visualization, and tends to downplay the need for computational representations of the underlying phenomena giving rise to the data. The recent emphasis on ontology in the DoD Net-Centric Data strategy [4] points to a growing recognition that computation without representation cannot meet the needs of today's commander. Robust, mathematically rigorous, and faithful representation of the battlespace is a key enabler for shared situation awareness.

The COP of the future requires the capabilities to:

- Represent entities including conventional and irregular units and their constituent components;
- Represent ambient "green, gray and pink" populations as well as their cultural and military relations;
- Represent past and projected future tracks of individuals and aggregate entities over time and space;
- Represent interactions, events and situations;
- Aggregate observations to entities, and lower-level entities to higher-level entities;
- Represent reports from sensors and other information sources, and their relationship to the objects and entities reported upon;
- Fuse multi-source intelligence data to hypothesize instances of the above;
- Capture uncertainty and alternative hypotheses regarding all of the above;
- Facilitate efficient and scalable hypothesis management and uncertainty reasoning;
- Enable applications to consistently operate on the COP to support experimentation and simulation to infer missing information and project/predict possible futures;
- Support various views, targeted to different echelons, missions, and users, of decision-relevant aspects of the COP.

Addressing the above capabilities clearly requires devoting attention to structuring knowledge, in contrast to a pure focus on merging data. New approaches are needed to bridge the gap from data interchange to knowledge interchange, to free human decision-makers from information overload and low-level manual tasks, and to provide them with actionable, decision-relevant information.

4 Filling the Ontological Gap

As recognition grew that syntax-based LLF solutions were not enough to satisfy the increasing need for interoperable systems, semantics came to be viewed as a silver bullet to address the need. As a result, ontology engineering became a major aspect of research on interoperability. Since its adoption in the field of Information Systems, the term ontology has been given many different definitions. For the purposes of this work, a computational ontology is defined as any explicit, formal representation of knowledge about a domain of application.

Early computational ontologies (e.g., [5]) 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 ontologies so constructed were considered equivalent if there was a truth-preserving mapping between expressions expressed in their respective languages. Automated deductive inference was employed both to determine type inclusion relations and to determine equivalence. Wielinga [6] 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. Further refinements by many researchers [7] led eventually to the OWL web ontology language and formal specification [8] which added many mathematical constraints to enable consistent object-oriented implementations, ontology extension, comparison, evolution and re-use.

Existing computational ontological theory and implementations support many of the requirements for complex systems such as the traditional COP. Examples include representing entity types, composition and parthood relationships, and attributes of entities. Reasoners are available to perform deductive inference to derive logical consequences of the knowledge represented by the ontology. 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, overutilizes scarce human expertise, and leaves users with an increasing glut of data without information, or perhaps at best, relevant information without actionable knowledge (*cf.* [9]).

4.1 The COP Revisited

To avoid the above shortcomings, overcome intelligence processing stovepipes, enable net-centric warfare, and admit interoperation of intelligence over the battlespace enterprise, the COP of the future must be attended by a massively concurrent set of automated and semi-automated agents that share a common, mathematically well-founded and mathematically consistent computational ontology that enables them to continuously perform the following functions while maintaining a mathematically consistent COP that respects their shared ontology.

- Update/Evolve the COP by fusing new intelligence with the current COP.
- Repair the COP by correcting or replacing previous intelligence now overcome by events.
- Identify critical missing information for intelligence pull requests.
- Identify conflicts in entities, events and situations.
- Resolve or clarify conflicts.
- Explain inductive and deductive inferences.

Note that such COP maintenance agents would necessarily follow a divide-and-conquer approach to the COP by dividing the COP at least by levels of granularity or abstraction, and by space-time region. Strong mathematical foundations are required to assure that boundary effects in the division of processing can provably be avoided or straightforwardly ameliorated by other COP agents.

These capabilities in turn require significant research and development in application of the mathematical and computational sciences. For example, the following capabilities are likely to prove necessary:

- Automatic first order scoping for types of classes to enable ontologically consistent aggregation of entities into higher level entities, such as observations into tracks and individuals and equipment into paramilitary (e.g. insurgent) units;
- Automated resolution of type to part-of relations in order to infer entity types from observed or inferred individuals or groups and equipment;
- Consistent use of multiple granularity or abstraction of representation from observations to tracks, from individuals to units, and from interactions to events;
- Transformations of units or groups by attrition of other interactions and events;
- Evidential reasoning to rigorously perform inductive inference in order to fuse observations into higher level intelligence;
- Efficient and scalable computational inference to support real time or semi-real time situational hypothesis management and forensic analysis;
- Formal semantics for interactions vice events, such as shooting that leads to riot vice a skirmish;
- Comparability of signal-to-symbol processing transformations via ontological understanding of evidence extracted from signals by different means, e.g. infrared moving-blob detection vice infrared human detection both in of types/classes, and in terms of the semantics associated to the signal-to-symbol processing transformations; and
- Scientifically consistent signal-to-symbol processing and inference, requiring an ontology of signal-specific features extracted by processing, such as projected surfaces and boundaries in visual imagery.

To meet the needs of the future COP, mathematical foundations for DoD computational ontologies need:

- Class representation that unifies first order logic with ultra filters and other set-theoretic consistent mathematics (e.g. partial orders, lattices, semi-groups Boolean algebras) that inherently clarifies the distinctions between type and composition of entities from components [10];
- Rigorous evidence-to-hypothesis ontological foundation consistent with the scientific method; such that it supports rigorous experimentation;
- Experimentation links to ontologically encoded measures of performance and effectiveness;
- Ontology supporting extraction/transformation of signals to symbols [11];
- Semi-groups or other algebraic representations of aggregations of forces in order to automatically, consistently perform type recognition from components;
- Formal representation of entity attributes that condition inference such as attributes representing allegiance and cultural affinities;
- Representation of agent interactions and movements – i.e. tracks and events in an evidentially confirmable fashion;
- Ontological representation of terrain and tracks in terrain as a mathematically consistent representation at multiple levels of granularity [12];
- Ontological representation of classes-as-processes in order to rigorously capture COP agent semantics;
- Compatibility with application of processes embodying theories of representation, adaptation, evolution, projection and prediction (e.g., hypothesis testing, agent interaction/simulation, game theoretic projection).
- Scalable and mathematical rigorous computational methodologies for managing large amounts of data in a general graphical architecture [13] to support COP (e.g., computing data to entity and entity to tracks association likelihoods, formulating and evaluating situational hypothesis nominations, and reasoning with scalable inference in distributed information networks).

4.2 Mathematical Support for Representation and Reasoning

A careful assessment of the above needs exposes three aspects that must be addressed for a representational and reasoning framework in support of effective higher-level knowledge fusion:

1) A rigorous mathematical foundation,
2) The ability to represent intricate patterns of uncertainty, and

3) Efficient and scalable support for automated reasoning.

Current ontology formalisms deliver a partial answer to items 1 and 3, but their lack of a principled, standardized means to represent uncertainty prevents a complete solution to complex applications such as COP. This has spurred the development of palliative solutions in which probabilities are simply inserted in an ontology as annotations (e.g. marked-up text describing some details related to a specific object or property). These solutions address only part of the information that needs to be represented, and too much information is lost to the lack of a good representational scheme that captures structural constraints and dependencies among probabilities. A true probabilistic ontology must be capable of properly representing those nuances. More formally:

Definition 1 (from [14]): A probabilistic ontology is an explicit, formal knowledge representation that expresses knowledge about a domain of application. This includes:

- Types of entities that exist in the domain;
- Properties of those entities;
- Relationships among entities;
- Processes and events that happen with those entities;
- Statistical regularities that characterize the domain;
- Inconclusive, ambiguous, incomplete, unreliable, and dissonant knowledge related to entities of the domain; and
- Uncertainty about all the above forms of knowledge;

where the term entity refers to any concept (real or fictitious, concrete or abstract) that can be described and reasoned about within the domain of application. ■

Probabilistic ontologies (POs) provide a principled, structured, sharable formalism for describing knowledge about a domain and the associated uncertainty and 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 the statistical regularities and the uncertain evidence about entities in a domain of application.

PR-OWL (Probabilistic OWL) [15] 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) [16], 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. One example in which POs written in PR-OWL format are used as a representational framework can be found in the PROGNOS project [17], which aims to provide a COP for the maritime domain. Figure 1 depicts a model developed in UnBBayes-MEBN, an open source, Java-based graphical editor for probabilistic ontologies being developed as a collaborative effort between the University of Brasilia and George Mason University [18].

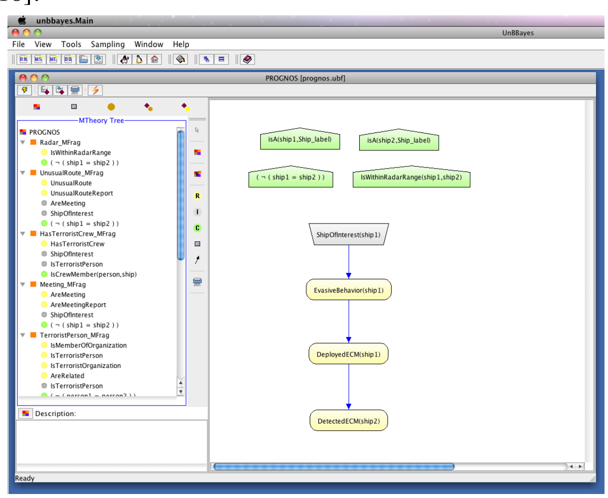

Figure 1 A MEBN Fragment of the "Ship of Interest" MTheory

In a MEBN setup, domain knowledge is stored in the form of MEBN Fragments (MFrags), which are small graphs that convey causal and statistical relationships describing specific characteristics of the domain. An MFrag represents a conditional probability distribution of the instances of its resident random variables (RVs) given the values of instances of their parents in the fragment graphs and given the context constraints. RVs are graphically represented in an MFrag either as resident nodes, which have distributions defined in their home fragment, or as input nodes, which have distributions defined elsewhere. Context nodes are the third type of MFrag nodes, and represent conditions assumed for definition of the local distributions. In response to accruing data, the system reacts by assembling Situation Specific Bayesian

Networks (SSBNs), which are used to assess the likelihood of the diverse hypotheses being analyzed. The right pane of Figure 1 above shows an MFrag, which can be thought of as a template that can be instantiated as many times as needed to build a SSBN. The left pane of Figure 1 shows an MTheory tree (named as PROGNOS), which is a set of MFrags (with just some of their nodes explicitly depicted) that satisfies consistency constraints ensuring the existence of a unique joint probabilistic distribution (JPD) over the RVs mentioned in the theory.

Typically, MFrags are small, because their main purpose is to model "small pieces" of domain knowledge that can be reused in any context that matches the context nodes. This is a very important feature of the logic for modeling complex, intricate situations and is one that can be seen as the knowledge representation version of the "divide and conquer" paradigm for decision-making, which breaks a hard, complex decision problem into a set of smaller ones. That is, MEBN allows for a similar decomposition approach to characterize intricate, complex military situations as a collection of small MFrags, each representing some specific element of a simpler situation. The additional advantage of MEBN modelling is the ability to reuse these "small pieces" of knowledge, combining them in many different ways in different scenarios. In this example of a PR-OWL/MEBN application in a COP scheme, the MFrags within the MTheory contain domain specific information that is represented in a modular format so only the necessary modules to answer a specific query are instantiated. Figure 2 shows the SSBN generated from a query posed against the MTheory depicted in Figure 1 .

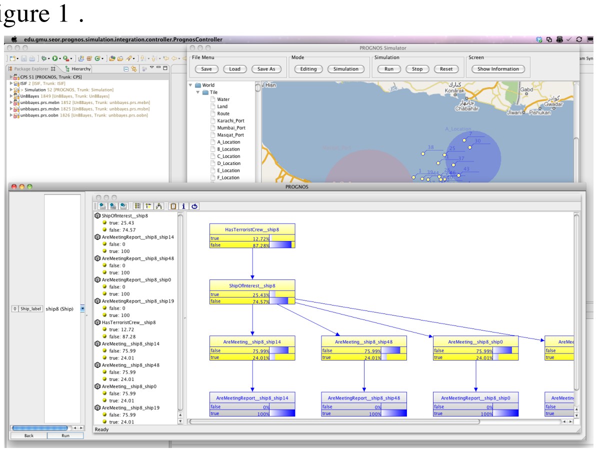

Figure 2 A SSBN derived from the "Ship of Interest" MTheory

The right panel of the lower window shows the nodes of the SSBN, which can be analyzed as any usual Bayesian network. The flow of events happening in PROGNOS when providing a maritime COP can be summarized in the following process: 1) A collection of MFrags is stored as a set of POs in PR-OWL format, some are domain-specific (e.g. task-related ontologies), some convey aspects of general knowledge (e.g. probabilistic mappings between ontologies); 2) upon receiving a query (e.g. a request for information about a given vessel), the system starts a SSBN construction algorithm, which will look for existing information and define which sensors (or systems) should be queried to provide extra knowledge; 3) after receiving this extra information, an SSBN is instantiated to provide the best possible answer to the original query. Clearly, this is an oversimplification of all the processes happening before the final output as a SSBN, yet it provides a good picture of how a modular, composable COP system can be built using the mathematically supported representational framework of PR-OWL/MEBN.

As a full integration of first-order logic (FOL) and probability, MEBN allows for: (1) a means of expressing a globally consistent joint distribution over models of any consistent, finitely axiomatizable FOL theory; (2) a proof theory capable of identifying inconsistent theories in finitely many steps and converging to correct responses to probabilistic queries; and (3) a built in mechanism for adding sequences of new axioms and refining theories in the light of observations. Therefore, the principled mathematical support from its MEBN foundations ensures that PR-OWL addresses the above-stated requirements for a HFL representational framework.

5 Addressing Scalability

Performing multi-source data merging from a huge body of data demands not only that knowledge be aggregated consistently, but also that inference is scalable. Performing plausible reasoning in support of complex decisions typically requires examining a numerous entities with many dependent indicators. These include occurrence of related activities, pointers to a common plan of action, similar spatio-temporal evolution within a situation map, etc. Portraying repeatable patterns within a target group with a non-fixed number of common parameters requires the expressivity of first-order logics, which PR-OWL POs can provide in a flexible yet consistent fashion. However, for higher-level fusion problems such as the one illustrated in our case study, the concept of a track must be generalized to a complex spatio-temporal entity that is related to and interacts in various ways with other evolving spatio-temporal entities. This can lead to exponential growth in the number of hypothesis, to the point at which considering all of them explicitly would be intractable. To address this problem, we are developing automated techniques to construct and manage hypotheses using MEBN models to assess the impact of incoming evidence and identify hypotheses to enumerate. Hypothesis management in PROGNOS is achieved through various techniques. From a systems engineering point of view, it employs a HM control architecture, which manages resource allocation for keeping track of hypothesis as well as supporting the hypothesis discovery process. From a technological point of view, two key methods are employed: suggestors, which provide initial processing to eliminate unrelated or improbable hypothesis, and Spatio-Temporal HM algorithms, which ensure that the system can handle the computational demands of the HM process.

5.1 Hypothesis Management

Suggestors are small and fast functions that under the constraints of the run-time specific information apply domain-specific reasoning to specify model construction actions. The idea is analogous to the gating function in a tracker. Suggestor computation is lightweight, and is followed up with more intense Bayesian reasoning only when hypotheses pass a threshold. Suggestors provide a modeling and inference environment that allows modelers to make compact, intuitive specifications for model construction actions.

Modelers can construct suggestors that, for instance, filter which variables to attach as parents to a given resident variable in an MFrag, out of all possible parents that meet the context constraints specified in its home MFrag. This allows the modeler to control the model construction process, in contrast to the naive bottom-up construction algorithm, which will just attach all parents that meet the context constraints. The model construction actions within this framework include:

- hypothesizing the existence of an entity;
- declaring a relationship between one entity and another;
- declaring that another entity is one of several potential participants in a given relationship;
- observing evidence about an attribute of an entity;
- asserting potential membership of an element in a set;
- pruning unlikely hypotheses.

Suggestors encapsulate rules for performing assembly of situation-specific models; thus, they take a particular state of the model and transform it into another state. For instance, a modeler can specify that if an instance of a pattern has an unfilled slot for one of its events or activities, then the suggestor should trigger to fill the slot.

In other words, suggestors are responsible for identifying which MFrags to instantiate and how many of them should be instantiated. In order to do so, a suggestor compares incoming evidence with existing patterns that might fit it and "suggests" which fragments should be instantiated given that data. Therefore, one key aspect of the current development is to employ efficient assembly algorithms to ensure the SSBN construction will provide timely and accurate answers.

Stochastic suggestors can be incorporated as a proposal distribution into a Markov Chain Monte Carlo hypothesis management (MCMCHM) approach [21]. Markov Chain Monte Carlo Data Association (MCMCDA) is a new approach for recursive hypothesis formation and management [21]. It has a strong theoretical grounding as an approximation to the optimal Bayesian solution, and has been shown to work well in practice. In PROGNOS, we are developing a MCMC hypothesis management (MC2HM) module based on this promising approach.

The second key approach for HM being developed in PROGNOS is the Spatio-Temporal HM methodology [22],[23], which generalizes traditional HM technology from multiple-hypothesis tracking to support the more expressive representations required for higher-level fusion. In PROGNOS, this representational flexibility is essential to provide adequate means for applying HM to guide the SSBN construction algorithm, as well as to allow for prediction and impact assessment, all being key issues for establishing a maritime COP.

5.2 Hybrid Inference

So far the query process that led to the SSBN in Figure 2 involves only discrete variables. However, prediction and impact assessment entails reasoning in space and time, and requires hybrid discrete, continuous, and possibly nonlinear and non-Gaussian models to describe complex spatio-temporal entities. To achieve that, PROGNOS employs recent research on efficient approximate inference for hybrid probabilistic networks to deal with this challenging computational problem. The method is based on message passing mechanism and uses unscented transformation to approximate any nonlinear transformations of arbitrary continuous distributions [24].

It is well known that for a general hybrid BN with nonlinear and/or non-Gaussian RVs, there is no existing method that could produce exact posterior distributions. Hence, one has to rely on approximate methods in that case. Because of the heterogeneity of variables and arbitrary functional relationships in the models, approximate methods usually produce errors due to functional transformation, distribution approximation, discretization, and/or structure simplification. To minimize the approximation error while ensure scalability, in PROGNOS, we are particularly interested in the message passing framework because of its simplicity of implementation and good empirical performance. Pearl's message passing algorithm [25] is the first exact inference method originally proposed for polytree discrete Bayesian networks. For pure continuous networks, similarly, Pearl's algorithm is applicable with continuous message represented in appropriate forms such as the first two moments of Gaussian. However, in general hybrid models, the message representation and manipulation for arbitrary continuous variable and message propagation between different types of variables are non-trivial [13].

In PROGNOS, we employ a novel approach called direct message passing (DMP) to compute, propagate, and integrate messages for hybrid models [19]. The complexity of hybrid inference is essentially determined by the size of the joint state space of all discrete parent nodes. It is easy to prove that, in a connected CLG, all discrete parents will end up in one clique with at least one continuous node [26]. DMP has a similar computational issue when exact inference is required. This is because for each state of a discrete parent node, its continuous child has to compute messages according to their functional relationships. Therefore, messages sent by a continuous node with a hybrid CPD will be in the form of a Gaussian mixture in which the components are weighted by probabilities passed from its discrete parents. As an example, Figure 3 shows a typical hybrid model involving a continuous node X with a discrete parent node D and a continuous parent node U. In the model, messages sent between these nodes are: (1) π message from D to X, denoted as $\pi_X(D)$; (2) π message from U to X, denoted as $\pi_X(U)$; (3) λ message from X to D, $\lambda_X(D)$; and (4) λ message from X to U, denoted as $\lambda_X(U)$.

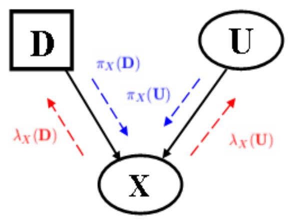

Figure 3 A typical hybrid model

In general, for a polytree network, any node X d-separates evidence into $\{\mathbf{e}^+, \mathbf{e}^-\}$, where $\mathbf{e}^+$ and $\mathbf{e}^-$ are evidence from the sub-network "above" X and "below" X respectively. The λ and π message maintained in each node are defined as,

$$\lambda(X) = P(e_x^- \mid X) \tag{1}$$

and

$$\pi(X) = P(X \mid e_x^+) \tag{2}$$

With the two messages, it is straightforward to see that the belief of a node X given all evidence is just the normalized product of λ and π values, namely,

$$BEL(X) = P(X \mid e) = P(X \mid e_x^+, e_x^-) = \alpha\lambda(X)\pi(X) \tag{3}$$

where α is a normalization constant.

In [19], a recursive formula for computing direct messages between mixed variables was derived. The hybrid messages, $\pi_X(U)$ and $\lambda_X(U)$ as shown in Figure 3 , are mixtures of Gaussians with the number of components equal to the size of the state space of its discrete parent D. When a mixture message propagates to another continuous node with discrete parents, the message size will increase again exponentially. However, as mentioned before, while the Junction Tree (JT) algorithm has to deal with this intractability, DMP has a choice to approximate the original Gaussian mixture with a reduced one. With a pre-defined error bound, Gaussian mixture reduction methods such as the one proposed in [20] can be applied to find a good approximate mixture with a smaller number of components. It is straightforward to incorporate these methods into DMP to make the algorithm scalable with an acceptable accuracy trade-off.

In addition, instead of only the first two moments as produced by the Junction Tree algorithm, DMP provides full density estimates for continuous variables and can be extended with unscented transformation [24] for the general hybrid models with nonlinear and/or non-Gaussian distributions. Since DMP is a distributed algorithm utilizing only local information, there is no need to transform the network structure as required by the Junction Tree algorithm. In addition, the algorithm does not require prior knowledge of the global network topology, which could be changing dynamically as in the PROGNOS scenarios. This is a major advantage of the algorithm and is particularly important to ensure scalable and reliable message exchanges in a large information network where computations can be done locally.

5.3 PROGNOS HM Module

The PROGNOS Hypothesis Management Module [27] leverages the preceding techniques and interacts with the rest of the PROGNOS system primarily through the query process.

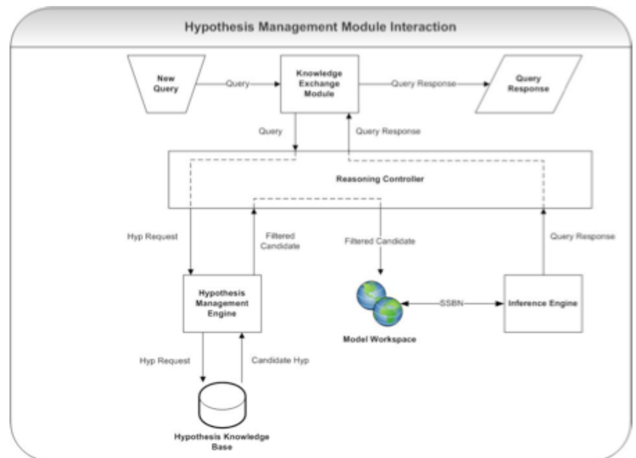

Figure 4 HM Module Interaction with PROGNOS (from [27])

The simplified flow outlined in Figure 4 begins with a New Query to PROGNOS initiated by the System Operator at a GUI. This flows through the Knowledge Exchange Module to the Reasoning Controller where it is converted to a Hypothesis Request. The request is sent to the HM Engine of the HM Module, which coordinates with the Hypothesis Knowledge Base to select one or more Candidate Hypotheses. Before exiting the HM Engine, the Candidate Hypotheses are filtered and pruned to maintain computational viability before transfer to the Model Workspace via the Reasoning Controller. The Model Workspace and Inference Engine work to create the SSBN and perform inferences to obtain a Response to the query. The Response is returned to the System Operator through the Reasoning Controller and Knowledge Exchange Module. Without introduction of a query by a System Operator, the HM Module continuously performs three major functions on incoming data. It processes incoming data, proposes, and discovers hypotheses.

6 Conclusion

Despite recent advances in multi-source fusion, the need remains for a fundamental theory of HLF. A successful theory requires a systemic approach built upon a sound mathematical foundation. Because exact inference will be intractable in complex situations, scalable approximations with consistent and reliable performance are needed. A case study was presented for PROGNOS, a proof-of-concept HLF system focused on the maritime domain.

Acknowledgments

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