Abstract: This panel position paper discusses advantages and challenges of multi agent fusion systems (MAS) with respect to the modeling flexibility and fusion reliability. We argue that the MAS paradigm in combination with rigorous modeling and inference methods can facilitate design of theoretically and technically sound fusion systems. This is illustrated with the help of a MAS approach to Bayesian fusion which supports robust and efficient situation assessment in crisis management settings. However, the MAS paradigm might be ill-suited for certain domains and information fusion theories. In addition, implementation of multi agent fusion systems for real world applications can be theoretically as well as technically very challenging. We identify several research topics which address these challenges.

Keywords: distributed fusion, heterogeneous information, multi agent systems, Bayesian networks.

1 Introduction

Multi agent systems (MAS) paradigm can facilitate development of theoretically and technically sound fusion systems which can cope with very challenging domains. We illustrate this in the context of increasingly relevant situation assessment problems in crisis management, such as detection of toxic gases, disease outbreaks, fires, etc. In such settings, critical hidden events must be inferred through interpretation (i.e. fusion) of large quantities of uncertain and very heterogeneous information. The information can be accessed via static sensors or ad-hoc sensor networks formed at runtime as sensors are delivered to the area of interest via mobile platforms (e.g. unmanned aerial vehicles). In addition, in crisis situations we might be able to obtain valuable information from humans in the field by using the existing communication and storage infrastructure, such as fixed and mobile phone networks, WWW, databases, etc. In fact, the information originating from humans might be prevalent due to insufficient coverage and density of sensor networks.

Interpretation of different types of information requires adequate domain models which provide mapping between heterogeneous observations and hypotheses of interest. However, situation assessment in crisis management settings introduces several substantial challenges:

- Domains are often complex, which means that models are inevitably abstractions associated with significant uncertainties.
- Information sources are heterogeneous and noisy. The heterogeneity of observations implies complex domain models.
- Constellations of information sources are often not known prior to the operation and they change at runtime.

It turns out that probabilistic causal models facilitate design of fusion systems which can cope with these challenges. Namely, monitoring processes can often be viewed as causal stochastic processes, where hidden events cause observations with certain probability. Such processes can be modeled with the help of Causal Bayesian networks (BN) [1], [2], which provide a theoretically rigorous and compact mapping between hidden events of interest and observable events.

However, BNs describing monitoring processes must capture every information source and observation explicitly. Thus, each fusion process requires a specific domain model which maps observations from the current constellation of information sources to the hypotheses of interest. In addition, often it is very difficult or impossible to obtain BNs which precisely capture the true distributions between the modeled events. The impact of modeling inaccuracies can be mitigated through processing of inputs from many heterogeneous information sources. However, large
numbers of information sources require large BNs which, in turn might require significant communication and processing resources.

In the following discussion we show that, in certain domains, we can effectively cope with these challenges by using a MAS approach implementing modular Bayesian fusion systems. Such a modular approach can facilitate design of very flexible and robust fusion systems. However, the MAS paradigm might be ill-suited for certain fusion problems and it introduces substantial challenges with respect to development and testing of real world systems.

2 Flexibility through Modularity

By using modular fusion systems, adequate causal domain models can be assembled out of basic fusion modules as information sources become available. In addition, a modular approach supports distribution of partial fusion processes throughout networks of processing devices. In this way communication and processing bottlenecks can be avoided. Beside theoretically sound inference, basic fusion components must also support complex communication and cooperation protocols to autonomously organize into meaningful distributed fusion systems. Modules should also be able to analyze the overall fusion performance and have the capabilities to improve the fusion performance with the help of learning techniques. In order to be able to systematically deal with such functional complexity we make use of the multi agent systems (MAS) paradigm [3]; agents are cooperating processing nodes with limited fusion capabilities based on local BNs (i.e. limited domain knowledge). A probabilistic multi agent fusion system must be able to compute correct (exact) posterior probabilities over certain variables of interest by using evidence obtained from different cooperating agents.

We assume that fusion agents are used as assistants to human decision makers [4]; they observe the environment, distill the relevant information and supply it to the decision makers. Such a fusion system typically does not influence its environment significantly; most actions are limited to self-organization and sensor management of a fusion system as well as control of different fusion processes.

We view the MAS paradigm primarily as a means for efficient implementation of sound information fusion approaches. However, the MAS paradigm might not be suitable for certain problems and theories, since adequate domain models or inference algorithms simply cannot be implemented in distributed frameworks efficiently. For example, many dependencies between the modeled phenomena result in severe dependencies between the fusion modules; such systems can be difficult to implement and can be very inefficient due to massive messaging required for the coordination of the processes in different modules. In addition, fusion processes based on certain types of models cannot be distributed efficiently without significant approximations; in such cases we might not be able to preserve all crucial properties of the fusion algorithms, which makes analysis of fusion systems more difficult.

A. Distributed Fusion Based on Causal Bayesian Networks

It turns out that BNs often support efficient distribution of models and fusion processes. By considering the locality of causal relations in BNs we can derive design and organization rules for multi agent systems, which implement exact belief propagation in distributed fusion systems without any centralized configuration and fusion control [5]. These principles are used in Distributed Perception Networks (DPN) [6]. DPN agents are basic building blocks which cooperate to form arbitrarily large distributed fusion systems. DPN systems are in essence distributed self organizing classifiers, which consist of agents with very heterogeneous domain expertise. Agents wrap information sources and provide uniform communication and fusion protocols. In contrast to other approaches to distributed inference in BNs [4], [7], the DPN framework supports theoretically correct fusion which does not require any compilation of secondary fusion structures (e.g. junction trees [4], [8]) that span several modules. As new information sources wrapped by DPN agents enter the scene, the domain models of fusion systems are adapted on the fly, without any centralized control. DPN agents wrapping mobile sensor suites supply local BNs, arbitrarily sophisticated sensor models, which are plugged into the overall system as the agents join the fusion organization. In other words, each agent contributes a local model which relates agent’s observations with the rest of the distributed causal model. In addition, DPN agents exploit causal models to generate meaningful queries which are communicated to the people via SMS or WWW and can be replied by simple yes/no; we obtain only information which can be processed by the fusion system and parsing of natural language is avoided. In this way DPN agents facilitate efficient acquisition of very heterogeneous information from humans in the field. This is very relevant for crisis management applications where humans can be viewed as omnipresent and often the only available information sources. Clearly, sound fusion of such information is very challenging, since we cannot obtain precise sensor models for human reports. However, we
can show that this is possible if we use BNs (see the following section).

3 Reliability

A very challenging aspect of real world applications is reliability. Fusion results should be delivered on time and must not be misleading. Reliability can be achieved through a combination of inherently robust fusion techniques, self-diagnosing methods as well as sound development processes (i.e. design, implementation and verification/validation).

A. Robust Modeling and Inference

In many real world domains it is virtually impossible to obtain completely accurate models. Thus, the systems should be robust against modeling inaccuracies. With the help of the recently introduced theory of Inference Meta Models [9], we can show that certain types of BN topologies support very accurate estimation with asymptotic properties even if we use parameters that deviate from the true distributions significantly. This is the case if (i) the domain models feature many conditionally independent fragments and (ii) the modeling parameters correctly capture very simple greater-than/smaller-than relations between the probabilities in the true distributions. We can assume that such relations can easily be identified by experts or extracted from relatively small data sets with the help of machine learning techniques. This is especially relevant for a broad class of real world applications, where it is often very difficult or even impossible to obtain precise domain/sensor models; e.g. what is the true probability of obtaining certain types of reports from humans given some critical events? However, the experts might know with a high certainty that the probability of obtaining a correct report of a certain type is greater than 0.5. The Inference Meta Models theory implies that in such settings we could obtain high-quality detection systems by using many heterogeneous reports from humans. This is very relevant for applications, where dense networks of high-quality sensors are not available, but we can easily access large quantities of information via the existing communication infrastructure, such as GSM, phones, Internet, etc.

In addition, domain models are abstractions which do not support correct estimation in all possible cases.

Therefore, the system should be able to diagnose its own fusion processes at runtime and signal potentially misleading results. By using probabilistic causal models, we can derive simple reject mechanisms whose effectiveness grows with increasing number of modeling fragments which are conditionally independent given the variables of interest [9].

Both robust fusion and effective rejection of potentially misleading results require large models and many information sources. In such settings a MAS framework can be useful, since a modular approach facilitates acquisition of large quantities of relevant information as well as efficient communication and processing in large BNs; fusion can be distributed throughout several networked devices.

An interesting research question is how the robustness and fusion performance of systems based on other theories (e.g. Dempster-Shafer, Fuzzy sets, etc.) improves as the quantity and heterogeneity of observations grow. Also, agents should be able to gradually adapt their domain knowledge as they are exposed to new situations. This requires research on different aspects of robust learning in distributed systems; e.g. runtime learning without making overall behavior instable, types of suitable training data and their acquisition, etc.

B. Reliability Through Structured Life Cycles

Development of reliable MAS fusion systems requires novel approaches to well structured life cycles. Namely, beside the inherent software complexity, a life cycle must address challenges introduced through model-based reasoning techniques (see for example [10]).

As it was argued in [1], causal BNs facilitate design of good domain models, since humans tend to reason in causal terms. In addition, to a certain extent the MAS paradigm can support technically sound designs, which facilitates development and maintenance of complex fusion systems. On the other hand, however, distributed designs can introduce substantial challenges with respect to the verification and validation (V&V), which are indispensable activities in development of mission critical systems. Namely, in a MAS fusion system each agent has its own thread of control and partial fusion processes are distributed over a system of networked machines. Such asynchronous distributed systems can be very difficult to test and debug.

This requires research on principled approaches to V&V which are economical and cover all relevant aspects of the operation. The emphasis should be on the exploitation of rigorous fusion theories for improved V&V. By using theory we can predict correct system output given certain inputs. In addition, theory

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2 A special case are causal models featuring tree topologies with great branching factors

3 For example, assume the true conditional probabilities over binary variables E and C: P (e|c)=0.7, P (e|c)=0.3, P (e|c)=0.4 and P (e|c)= 0.6. We say that a conditional probability table correctly captures relations between these probabilities if its parameters (i.e. conditional probabilities P(E|C)) satisfy very simple relations: P'(e|c) > 0.5 and P'(e|c) < 0.5
can facilitate development of fault models, which expose inherently brittle parts of the code and domain models. In this way the development as well as V&V activities can be focused on critical parts of the system (see [9] for an example of a model describing causes of faulty inference with BNs).

References


