FILTERING AND VISUALIZING UNCERTAIN BATTLEFIELD DATA USING BAYESIAN NETWORKS

Ole J. Mengshoel and David C. Wilkins

Beckman Institute
University of Illinois at Urbana-Champaign
1304 West Springfield Avenue
Urbana, IL 61801

Serdar Uckun

Rockwell Science Center
444 High Street
Palo Alto, CA 94301

ABSTRACT

Filtering, interpreting, and visualizing massive amounts of uncertain data is a core challenge of battlefield reasoning. Another challenge is the fact that knowledge about enemy and even friendly forces is uncertain and incomplete. This paper presents a Bayesian network approach to meet these challenges. We present Bayesian networks, and describe how they can be used for battlefield reasoning, in particular intelligence analysis. We emphasize how Bayesian networks can be used for intelligent information processing in the form of filtering, fusion, and selection of information.

INTRODUCTION

Bayesian networks (BNs) are an important knowledge representation technique in artificial intelligence and related areas [Pearl 1988]. Substantial progress has been made over the last ten years in all areas of BN research. However, there are still important issues to be addressed. In this paper, we take as starting point the domain of battlefield reasoning, and present how BNs can be utilized in this area. Furthermore, we discuss research directions being pursued that should pave the way for more efficient, heuristic BN inference for battlefield reasoning as well as in other domains.

Battlefield reasoning is a complex reasoning task where uncertain and incomplete data and knowledge is pervasive, in particular with respect to the enemy's operations. A Bayesian network can be used to address these issues, and this paper discusses preliminary results in the domain of battlefield reasoning.

The battlefield reasoning domain and task are presented, emphasizing intelligence analysis. We discuss the domain and task characteristics that are of interest: uncertainty, incompleteness, dynamics, and sensing. An initial Bayesian network for the domain is presented, and we discuss how it is a representative of a class of Bayesian networks. We investigate the use of genetic algorithms (GAs) [Holland, 1975] [Goldberg, 1989] for heuristic BN inference. GAs are robust function optimizers that employ stochastic, instance-based (or population-based) search. Since a BN represents a function, it is natural to consider using GAs to search in the space of instantiated BNs, and in that way construct a heuristic algorithm for BN inference.

The rest of this paper is organized as follows. First, Bayesian networks are briefly presented. Second, a scenario for military intelligence analysis is given. Third, we discuss how to formally represent this scenario as a Bayesian network. Fourth, we present how this network can be used for filtering, fusion, and intelligent selection of information. Finally, we conclude and outline directions for future research.

BAYESIAN NETWORKS

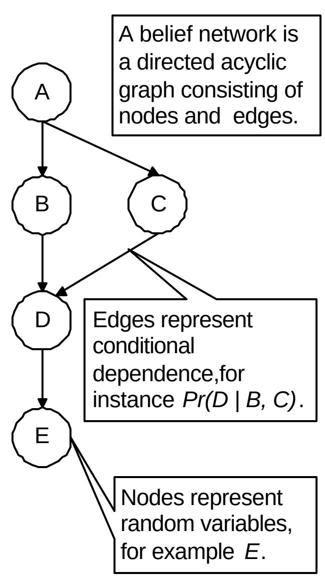


Figure 1. Example Bayesian network.

*Prepared through collaborative participation in the Advanced and Interactive Displays Consortium. Consortium sponsored by the U.S. Army Research Laboratory under the Federated Laboratory Program, Cooperative Agreement DAAL01-96-2-0003. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation thereon.

Bayesian networks are used for reasoning and learning under uncertainty [Kim & Pearl, 1983] [Pearl, 1988] [Lauritzen & Spiegelhalter, 1988]. Bayesian networks are also known as causal networks, belief networks, or influence diagrams. Probability theory and graph theory form their basis: random variables are nodes and conditional dependencies are edges in a directed acyclic graph. Edges typically point from cause to effect. Temporal Bayesian networks can be used in dynamic environments [Mengshoel & Wilkins, 1997a]. A simple Bayesian network consisting of the five nodes *A*, *B*, *C*, *D*, and *E* is shown in Figure 1. In addition to the graph, there are conditional probability tables associated with each node *V* and its parents *pa(V)*, expressing the conditional probability $Pr(\mid pa(V))$. For Figure 1, assuming discrete binary nodes with values {0,1}, $Pr(D=0 \mid B=1, C=0))$ is one of the entries in *D*'s conditional probability table.

Inference in Bayesian networks is one focus of our research. The inference task of belief updating amounts to the following: Given evidence at node *E* and query node *Q*, infer posterior probability $Pr(Q \mid E=e_i)$. Any nodes in the network can be evidence or query nodes. For the example BN, this leads to different types of inference: (i) diagnostic – as in $Pr(A \mid E=e_i)$; (ii) causal - as in $Pr(E \mid A=a_j)$, and (iii) mixed – as in $Pr(D \mid E=e_i, A=a_j)$. A variety of approaches to Bayesian network inference have been investigated [Kim & Pearl, 1983] [Pearl, 1988] [Henrion, 1988] [Lauritzen & Spiegelhalter, 1988] [Horvitz et al., 1989][Lin et al., 1990] [Rojas-Guzman & Kramer, 1996] [Welch, 1996]. These inference algorithms vary in many respects – they are exact, approximate, or heuristic; work on singly or multiply connected graphs; and are used for different inference tasks. Computational hardness has been shown both for belief updating [Cooper, 1990] and belief revision [Shimony, 1994]. Research into non-exact algorithms for solving these tasks approximately or heuristically is therefore important, and is presented in more detail below.

INTELLIGENCE ANALYSIS SCENARIO

The purpose of intelligence analysis is to understand enemy activity and in particular to answer priority intelligence requests (PIRs). There is a doctrinal one to one mapping between PIRs and decisions that are executed during battle, so PIRs play an important part in battlefield reasoning. The central component of the intelligence analysis task is abduction, therefore intelligence analysis is similar to medical diagnosis: PIRs correspond to diagnoses, intelligence reports correspond to symptoms. Intelligence analysis takes as input reports concerning enemy activity and produces

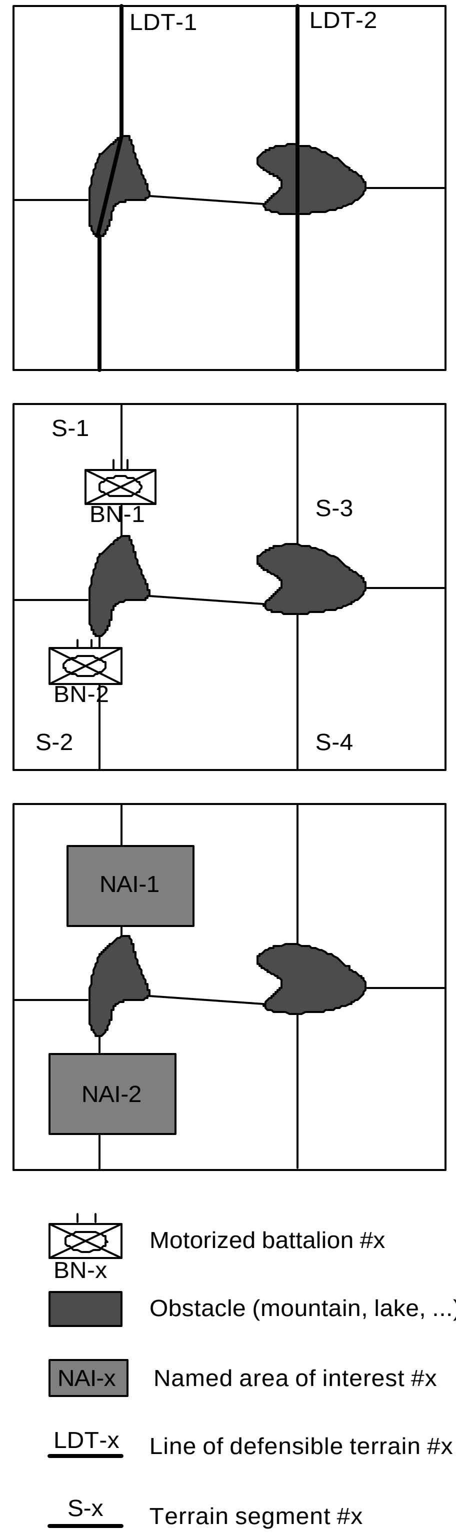


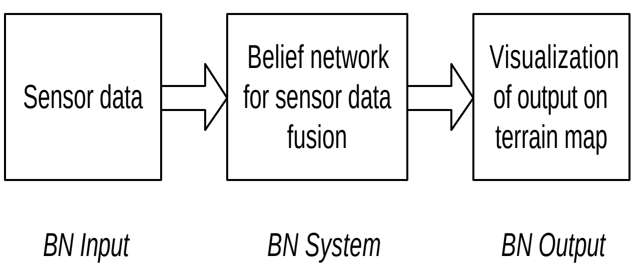
Figure 2. Maps at different levels of abstraction for intelligence analysis scenario.

PIRs with associated measure of confidence (or posterior probabilities, beliefs). An intelligence analysis BN can be used to perform this filtering task automatically.

As an example, consider the scenario shown in Figure 2. (This scenario is adapted from [Schlabach, 1997].) The highest abstraction level is shown at the top, the lowest abstraction level at the bottom in this figure. At the highest level of abstraction, the commander is interested in lines of defensible terrain (LDTs), and in particular which LDT the enemy has chosen to defend. In this case there are two LDTs - LDT-1 and LDT-2. At the middle level of abstraction, we find the enemy forces, in this case BN-1 and BN-2. Finally, at the lowest level of abstraction we find map locations and named areas (NAIs) in particular.

REPRESENTATION USING BAYESIAN NETWORKS

The battlefield reasoning challenge is twofold: First, sensor data is low-level, high-volume, and uncertain. Second, model knowledge is uncertain and incomplete. The Bayesian network approach, as illustrated in Figure 3, is to perform data fusion and filtering using a Bayesian network and output and visualize the results.



We will distinguish between two classes of scenarios. In defensive enemy scenarios, the enemy is defending, friendly is attacking. The scenario presented above is of this type. Here, a non-temporal belief network is used to model the enemy and to filter uncertain information. In offensive enemy scenarios, the enemy is attacking, friendly is

Figure 3. Bayesian network (BN) system for filtering battlefield data.

defending. Temporal belief networks are used to model the enemy and to filter uncertain information in these situations [Mengshoel & Wilkins, 1997a]. In the following we will focus on the defensive enemy scenario from the previous section, however the approach generalizes to other scenarios.

A partial Bayesian network model for battlefield reasoning, the RAVEN BN, is shown in Figure 4. This network con-

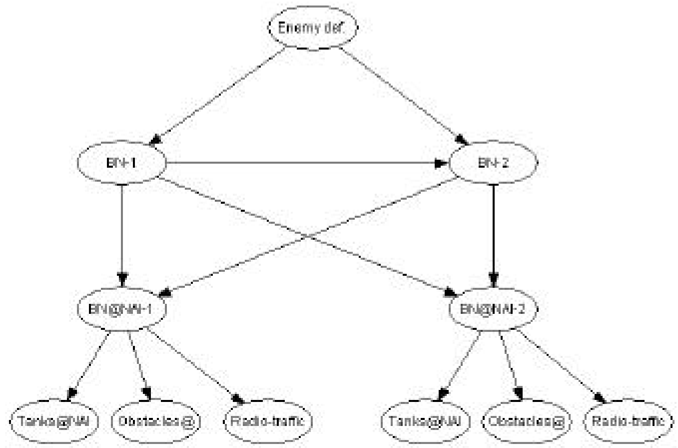


Figure 4. The RAVEN Bayesian network for filtering battlefield data.

sists of three main layers, which can be mapped to the military intelligence community's terminology [Schlabach, 1997]. Starting from the top of Figure 4, the layers are as follows. First, the diagnosis layer corresponds to priority intelligence requests (PIRs). Second, the filtering layer corresponds to specific intelligence requests (SIRs). Third, the message layer corresponds to observable SIRs. Also notice the correspondence to the three levels of abstraction visualized in Figure 2.

Due to space limitations, the conditional probability tables of the RAVEN BN are not shown here. The states of the nodes are presented in Figure 5 – the numbers in this figure may be ignored for now. The PIR in this BN is the node Enemy-def., which ranges over states {LDT-1, LDT-2}. This node describes the enemy's two possible LDTs – see Figure 2. The nodes BN-1 and BN-2 in the filtering layer model where the two battalions are, so they both range over the line segments {S-1, S-2, S-3, S-4}. The nodes BN@NAI-1 and BN@NAI-2 describe the allocation of enemy BNs to map locations, and in particular to NAIs. Finally, the six nodes in the message layer represent whether certain signatures are or are not observed in a particular NAI. For example, Radio-traffic@NAI-1 has states {Yes, No} and represents whether or not there is radio traffic in NAI-1.

INFERENCE USING BAYESIAN NETWORKS

The BN model described above can be used to draw probabilistic inferences. First, consider the probabilities (or confidences) over the node Enemy-def. based on prior knowledge - before any messages arrive. LDT-1 is the most probable line of defense, as can be seen to the left in Figure 5. Note that probabilities are given in percentages rather than on the usual [0,1] scale. So based on prior knowledge, there is an 80% chance that Enemy def. is LDT-1, while there is a 20% chance that it is LDT-2.

Now suppose three messages arrive: "No obstacles at NAI-1", "Radio traffic at NAI-1", and "No tanks at NAI-1". To reflect these messages, the corresponding three nodes are clamped to the appropriate values as shown to the right in Figure 5. Because of these updates of the BN, the inference procedure updates the probabilities over the other nodes in the network as shown to the right in Figure 5. In particular, the Enemy-def. state LDT-2 is now the most probable, with 60.42% chance. The chance of LDT-1 is 39.58%. This is consistent with the intuition that not seeing tanks or obstacles in any NAI on LDT-1 makes LDT-2 more probable - see Figure 2.

The inference algorithm of the BN tool used above, HUGIN, is an exact algorithm known as clustering [Lauritzen & Spiegelhalter, 1988]. For sparse BNs this algorithm works well, however for large and strongly connected BNs it doesn't. For this reason, a heuristic approach to belief revision in BNs is investigated [Mengshoel, 1997] [Mengshoel & Wilkins, 1998]. More specifically, we assume that the GA fitness function is a joint probability density function represented as a BN. This is a restriction on the fitness function, but probability theory in general and BNs in particular have proven sufficiently rich to make this an interesting restriction. Using a GA has three advantages: simplicity, robustness, and efficiency. First, a GA is a relatively simple algorithm. Second, the search provided by a GA should give robust inference across a spectrum of BNs. Third, there might be BNs where the GA is more efficient than other inference algorithms, in particular compared to stochastic simulation algorithms when there is low-probability evidence [Welch, 1996].

Building on previous research [Lin et al., 1990] [Rojas-Guzman & Kramer, 1996] [Welch, 1996], our research has so far focused on GA selection and BN abstraction in the context of GAs [Mengshoel, 1997] [Mengshoel & Wilkins, 1997b] [Mengshoel & Wilkins, 1998]. Concerning selection in GAs, our research has shown empirically that combining the GA techniques of scaling and niching [Goldberg & Richardson, 1987] [Goldberg, 1989] improves GA-based belief revision significantly [Mengshoel & Wilkins, 1998].

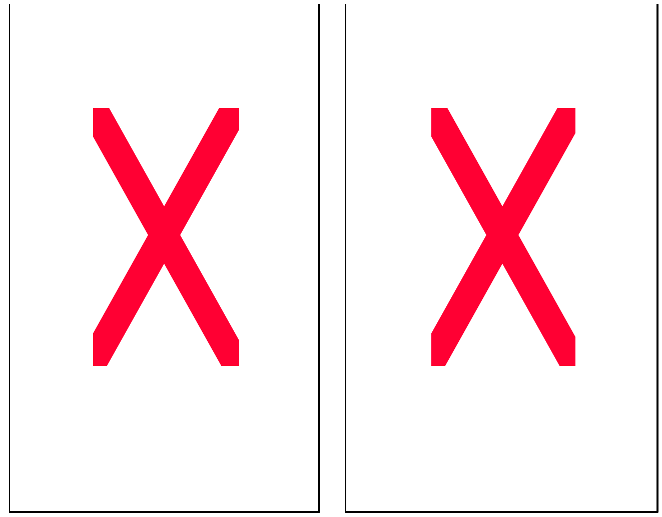


Figure 5. Probabilities over nodes in the RAVEN BN before and after processing of messages.

CONCLUSION AND FUTURE WORK

This paper has presented an approach to filtering and visualizing battlefield data using Bayesian networks. In particular, the approach addresses two of the main challenges associated with battlefield reasoning, namely the uncertainty associated with the data as well as the uncertain and incomplete knowledge of the process generating that data, be it enemy or friendly forces. Current research using genetic algorithms for Bayesian network inference has also been described.

There are several directions of future work. First, the prototype Bayesian network RAVEN presented here needs to be extended and generalized, including generalizing the approach to encompass other scenarios. Second, there is need for research on improving the efficiency of BN inference. Third, there is a need for improving the user interface, including visualization and sonification that would allow for cooperation between many experts in military analysis working on essentially the same Bayesian network.

Acknowledgements: Thanks to MAJ J. L. Schlabach for his help in constructing the RAVEN network.

REFERENCES

[Cooper, 1990] Cooper, G. (1990). The computational complexity of probabilistic inference using Bayesian belief networks. Artificial Intelligence, 42(2-3):393 - 405.

[Deb & Goldberg, 1989] Deb, K. and Goldberg, D. E. (1989). An investigation of niche and species-formation in genetic function optimization. In Schaffer, J. D., editor, *Proceedings of the Third International Conference on Genetic Algorithms*, Arlington, Virginia. Morgan Kaufman.

[Goldberg, 1989] Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization & Machine Learning*. Addison-Wesley, Reading, MA.

[Goldberg & Richardson, 1987] Goldberg, D. E. and Richardson, J. (1987). Genetic algorithms with sharing for multimodal function optimization. In Grefenstette, J. J., editor, *Proceedings of the Second International Conference on Genetic Algorithms*, pages 41 - 49, Hillsdale, New Jersey. Lawrence Erlbaum Associates.

[Henrion, 1988] Henrion, M. (1988). Propagating uncertainty in Bayesian networks by proabilistic logic sampling. In Lemmer, J. F. and Kanal, L. N., editors, *Uncertainty in Artificial Intelligence 2*. Elsevier.

[Holland, 1975] Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. University of Michigan Press, Ann Arbor, MI.

[Horvitz et al., 1989] Horvitz, E. J., Suermondt, H. J., and Cooper, G. F. (1989). Bounded conditioning: Flexible inference for decisions under scarce resources. *In Proceedings of the Fifth Conference on Uncertainty in Artificial Intelligence (UAI-89)*, pages 182 - 193, Windsor, Ontario. Morgan Kaufmann.

[Kim & Pearl, 1983] Kim, J. H. and Pearl, J. (1983). A computational model for combined causal and diagnostic reasoning in inference systems. In *Proceedings of the Eighth International Joint Conference on Artificial Intelligence (IJCAI-83)*, pages 190 - 193, Karlsruhe, Germany. Morgan Kaufmann.

[Lauritzen & Spiegelhalter, 1988] Lauritzen, S. and Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems (with discussion). *Journal of the Royal Statistical Society series B*, 50(2):157 - 224.

[Lin et al., 1990] Lin, R., Galper, A., and Shachter, R. (1990). Abductive inference using probabilistic networks: Randomized search techniques. Technical Report KSL-90-73, Knowledge Systems Laboratory, Stanford.

[Mengshoel, 1997] Mengshoel, O. J. Belief Network Inference in Dynamic Environments. In *Proceedings of the Fourteenth National Conference on Artificial Intelligence (AAAI-97)*, Providence, RI. Morgan Kaufman.

[Mengshoel & Wilkins, 1997a] Mengshoel, O. J. and Wilkins, D. C. Visualizing Uncertainty in Battlefield Reasoning Using Belief Networks. In *Proceedings ARL Advanced Displays and Interactive Displays Fed. Lab. First Annual Symposium*, pages P-15 - P-22, Jan. 1997, Adelphi, MD.

[Mengshoel & Wilkins, 1997b] Mengshoel, O. J. and Wilkins, D. C. Abstraction and Aggregation in Bayesian Networks. In Geib, C., editor, *Abstractions, Decisions, and Uncertainty: Papers from the 1997 AAAI Workshop*, pages 53 - 58, Providence, RI. Technical Report WS-97-08, AAAI Press.

[Mengshoel & Wilkins, 1998] Mengshoel, O. J. & Wilkins, D. C. Genetic Algorithms for Belief network inference: The Role of Scaling and Niching. *Submitted for publication.*

[Pearl, 1988] Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.* Morgan Kaufmann, San Mateo, California.

[Rojas-Guzman & Kramer, 1996] Rojas-Guzman, C. and Kramer, M. A. (1996). An evolutionary computing approach to probabilistic reasoning on Bayesian networks. *Evolutionary Computation*, 4(1):57 - 85.

[Schlabach, 1997] Schlabach, J. L. (1997). *The Illinois architecture: A framework that provides new opportunities for applications in battlefield reasoning.* Master's thesis, University of Illinois at Urbana-Champaign, 1997.

[Shimony, 1994] Shimony, E. (1994). Finding MAPs for belief networks is NP-hard. *Artificial Intelligence*, 68:399 - 410.

[Welch, 1996] Welch, R. L. (1996). Real time estimation of Bayesian networks. In *Proceedings of the Twelfth Annual Conference on Uncertainty in Artificial Intelligence (UAI - 96)*, pages 533 - 544, Portland, Oregon.

---

*The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied of the Army Research Laboratory or the U.S. Government.