An Intelligent Design System for Military Situation Assessment

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Abstract

Maintaining an accurate assessment of military situation assessment is essential to prevention, containment and effective response to military conflicts of all kinds. This research developed an intelligent decision support system for military situation assessment, which would be extremely useful for military decision makers. High uncertainty and the dynamics of the environment is a crucial problem for military situation assessment. In this research, Bayesian network models which have the ability to model and reason under uncertainties are employed as decision models. A new approach for constructing a decision model from knowledge base according to the changes in environment is proposed. An example from domain-littoral threats assessment is used to demonstrate this system's capability to construct situation-specific Bayesian network decision models from the domain knowledge base dynamically. The generated Bayesian network for situation assessment can be changed as the situation evolves.

1. Introduction

A military decision maker faces some of the most difficult and high-stakes decision problems known to humanity. There is a centuries old volume of literature on principles of effective military decision making. The complexity of military decision making has been growing with increasing communication and offensive capabilities. Situation assessment is the process of evaluating a situation to support decision-making. One theory proposes that experienced decision makers base most of their decisions on situation assessments [1]. Shortly, situation assessment is to create relevant relations between objects in the environment. Military situation assessment consists of integrating information from different parts and different elements of the battlefield to form the current total picture, and predict future trends. Military situation assessment helps to analyze enemy's intent and to suggest the best defense posture to adopt. Maintaining an accurate assessment of military situation is essential to prevention, containment and effective response to military conflicts of all kinds. It is clear that an intelligent decision support system that supports effective and timely situation assessment and mission selection would be extremely useful for military decision makers.

A crucial problem for military situation assessment is the problem of high uncertainty and the dynamics of the environment. The flexibility of Bayesian networks (BN) for representing probabilistic dependencies and the relative efficiency of computational techniques for performing inference over them makes Bayesian networks an extremely powerful tool for solving problems involving uncertainty. Therefore, Bayesian networks have gained widespread use in decision support systems.

In recent years, many knowledge representation schemes have been developed for the dynamic construction of probabilistic and decision models. These include first-order logic [2, 3, 4], similarity network [5], network fragments [6], time-critical dynamic influence diagrams [7], sequential influence diagrams [8], object-oriented Bayesian networks (OOBN) [9,10], interactive dynamic influence diagrams [11] and so on. All these methods can facilitate the dynamic construction of probabilistic and decision models. However, these knowledge representation schemes are not suitable for our decision support system.

This paper presents a new knowledge representation framework. Bayesian network models are employed as decision models. We developed an intelligent decision

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system for military situation assessment using Java programming language. This system uses the proposed knowledge representation framework which supports model construction during runtime from a domain knowledge base.

A case from domain-littoral threats assessment is used to demonstrate this system's capability of constructing situation-specific Bayesian network models from the domain knowledge base dynamically. The generated Bayesian network can be employed for littoral threats situation assessment.

2. Intelligent decision support system

In our work, an intelligent decision support system was developed for military situation assessment. This intelligent decision system provides explicit representation of expert knowledge; deals with uncertain and incomplete information and dynamically responds to the changes in environment. This section describes the system architecture, knowledge base representation, model construction and system implementation.

2.1. System architecture

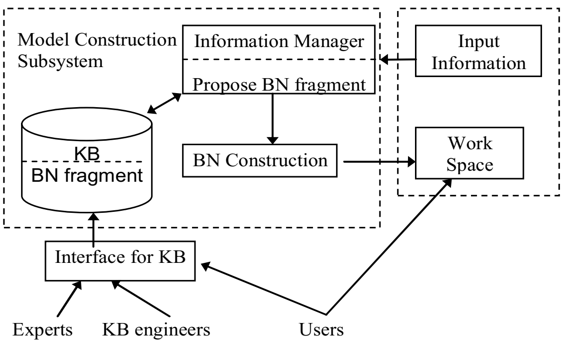


Figure 1. System architecture

The functional architecture of the intelligent decision prototype system is shown in Figure 1. The system is architecturally composed of model construction subsystem, an interface for information input and the resulting decision model display, and an interface for the knowledge input and maintenance.

The information, which user inputs on the interface – input information, serves as the inputs to the model construction subsystem. Based on these external inputs, Model construction subsystem retrieves sub-models from the domain knowledge base, constructs a BN model from the Bayesian networks in the selected sub-models and attaches evidence to the BN. The resulting BN model is shown on the interface -work space. Experts, knowledge base engineers and users input and maintain knowledge on the interface for KB.

The component input information provides a graphic interface for user to input information which includes events, conditional information and evidences. And it also provides a mechanism for mapping those inputs to structure information which includes hypotheses, conditional information and evidences. The structure information is used to trigger the model construction subsystem. Each hypothesis is triggered by one or multiple events. Bayesian network is used to represent the relationships between these events and hypotheses. In other words, Bayesian network is used to implement the mapping of hypotheses. The mapping for conditional information and the mapping for evidences are direct mappings from the external inputs to structure information.

Model construction subsystem includes three components: information manager, knowledge base and BN construction. The knowledge base stores a large amount of sub-models and the relationships among these sub-models. In Section 2.2, the knowledge base representation will be discussed in details. The major function of Information manager is knowledge base retrieval. The inputs to the information manager are structure information that is used for sub-models selection and BN construction. Based on hypotheses and conditional information, Information manager accesses the knowledge base, gets corresponding sub-models and sends these sub-models for BN construction. Given the selected sub-models, the BN construction combines the Bayesian networks in the selected sub-models. The combination result is a BN model. Evidences are attached to the BN model. In Section 2.3, the model construction process will be discussed in details.

The component work space provides a graphic interface for user to monitor, modify and inference the constructed BN model. Work space displays the BN model. Given a BN model, users can modify the probability distributions or the BN structure according to their preference. If the BN model is modified, work space displays the updated model. Work space also provides some algorithms to perform inference on the BN model

The component interface for KB provides a friendly interface for the expert or KB engineer to input and maintain sub-models and the relationships among those sub-models.

2.2. Knowledge representation

In our knowledge representation framework, three classes are defined and their instances are used to represent knowledge and knowledge base structure. These classes are called BN fragment, net fragment and basic fragment.

A BN fragment instance is an instance of BN Fragment class. It is a sub-model that is used to represent probabilistic knowledge for some part of the domain. Larger situation specific models tend to include these sub-models. Our representation framework takes BN fragment instances as its basic units, which consists of a set of attributes and a specific Bayesian network.

Net fragment and basic fragment are two classes whose instances are used to represent the relationships among theses BN fragment instances. In a domain knowledge base, these BN fragment instances are organized in a hierarchy and partition structure. Basic fragment instances organize BN fragment instances in a partition structure. A basic fragment instance has a set of BN fragment instances, which represent similar problem under different conditions. When composing a partition, we place each distinguished BN fragment instance into one and only one set. In other words, all BN fragment instances in a basic fragment instance are different and each BN fragment instance belongs to one and only one set. Given the specific condition, only one BN fragment instance is selected from the set of BN fragment instances. Given different conditions, the same BN fragment instance may be selected. The partition structure allows the knowledge engineer or expert to compare similar problems and provide accurate information. Net fragment instances organize BN fragment instances in a hierarchy structure. A net fragment instance has a set of net fragment instances or basic fragment instances. The set of net fragment instances or basic fragment instances are at the next level of the hierarchy. The hierarchy structure allows the knowledge engineer or expert to represent the same knowledge in different hierarchy structures according to their preferences.

Given a specific domain, a large set of BN fragment instances and the relationships among theses BN fragment instances are stored in the domain knowledge base. The knowledge engineer or expert encodes BN fragment instances and the relationships among these BN fragment instances in the form of net fragment instances and basic fragment instances.

2.3. Model construction

In the previous section, we proposed a knowledge representation framework in which the domain knowledge base stores a large set of BN fragment instances in a hierarchy and partition structure.

In this section, a model construction approach is proposed. Based on external inputs, the proposed approach retrieves BN fragment instances from the domain knowledge base, combines the Bayesian networks in the selected BN fragment instances and attaches evidence to the combination result.

The steps for model construction are:

Map the possible inputs (e.g. events) to hypotheses, conditional information and evidences according to the mapping information.

Based on hypotheses and conditional information, select BN fragment instances from the domain knowledge base.

Given the selected BN fragment instances, combine the Bayesian networks in the selected BN fragment instances. The combination result is a Bayesian network model. Then, evidences are attached to the corresponding nodes of the Bayesian network model.

The proposed approach here takes the bottom-up construction approach. For a specific domain, the domain knowledge base stores a large number of BN fragment instances. For a specific problem, a Bayesian network model is generated based on the domain knowledge base and external inputs. The possible external inputs from user must be mapped to hypotheses, conditional information and evidences. Each hypothesis is triggered by one or multiple events. Bayesian network is used to implement the mapping of hypotheses. The mapping for conditional information and the mapping for evidences are direct mappings from the external inputs to conditional information and evidences. A graphic interface is provided for users to encode the mapping information. Hypotheses and conditional information are used for BN fragment instances selection. Each hypothesis corresponds to a net fragment instance or a basic fragment instance in the domain knowledge base. Given hypotheses, the corresponding net fragment instances or basic fragment instances can be obtained by retrieving the domain knowledge base. Given the corresponding net fragment instances or basic fragment instances and conditional information, the BN fragment instances can be selected. After the BN fragment instances are selected, the Bayesian networks in the selected BN fragment instances are combined. The combination result is a Bayesian network model. Evidences are attached to the corresponding nodes of the Bayesian network model. When the external inputs change, the hypotheses, conditional information and evidences may be changed or updated. These changes will lead to the changes in the generated Bayesian network model. Therefore, the generated Bayesian network model may be constantly updated as the situation evolves.

2.4. System implementation and knowledge base implementation

Based on the proposed methods, the intelligent decision system had been developed using Java programming language. In this system, the major component is Model Construction Subsystem. The component provides an Application Programming Interface (API), which is a series of functions. The major functions are reading knowledge and verifying knowledge in the knowledge base and constructing a Bayesian Network model according to external information.

Using the API, we develop the intelligent decision system, in which an interface for information input and the resulting decision model display and an interface for the knowledge input and maintenance are developed.

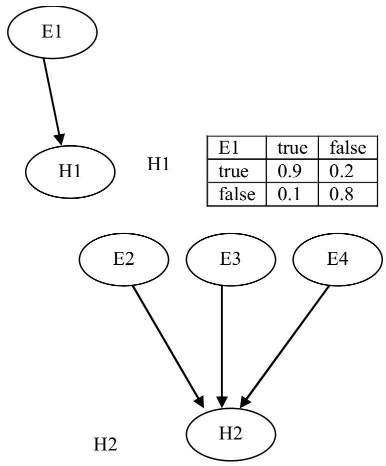
On the interface for information input and the resulting decision model display, user inputs external information on the graphic interface. To construct decision model, the system will call the API that constructs a Bayesian Network decision model according to external inputs, and then the generated decision model will be shown on the interface. Users can modify the decision model according to their preference on the interface. The system also provides some algorithms to perform inference on the decision model.

On the interface for the knowledge input and maintenance, the knowledge engineer, expert or user encode all knowledge. OilEd is an ontology editor allowing the user to build ontologies using DAML+OiL. We use the tool-OilEd to input BN fragment instances, net fragment instances and basic fragment instances. A domain knowledge base stores a lot of BN fragment instances, net fragment instances, and basic fragment instances. The interface also provides some functions to verify the inputted information. One of the major functions is to check loops in the combination of Bayesian networks in the selected net fragment instances.

3. Example

The implemented system is capable of constructing a decision model during runtime from a domain knowledge base. In this section, we will use an example from domain-littoral threats assessment to demonstrate how the system is employed for military situation assessment.

We developed a knowledge base of the domain - littoral threat assessment. The domain knowledge base stores a lot of BN fragment instances, net fragment instances and basic fragment instances. All instances are encoded by the knowledge engineer, expert or user on the interface for KB.



E1	true	false
true	0.9	0.2
false	0.1	0.8

E2	true				false			
E3	true		false		true		false	
E4	true	false	true	false	true	false	true	false
true	0.99	0.9	0.86	0.8	0.85	0.8	0.8	0.1
false	0.01	0.1	0.14	0.2	0.15	0.2	0.2	0.9

Figure 2.Hypotheses Mapping

Figure 2 shows the mapping information of hypotheses. There are four events and two hypotheses. The four events are E1-"foreign officer come by ship", E2-"suspicious boat", E3-"terrorist arrest around regional countries" and E4-"recent terrorist attacks during period". Two hypotheses, which are hypothesis1 –"attack on sector blue" and hypothesis 2- "terrorist attack", may be triggered by the four events. The Bayesian network shown in Figure 2 is used to represent the relationships between these events and hypotheses. In this example, it is assumed that, the hypothesis is triggered when the probability of a hypothesis being true is greater than 0.7. For the event "foreign officer come by ship", hypothesis H1 is triggered when the probability (0.9) of the hypothesis H1 is greater than 0.7 after assigning the event as true.

In this example, there are two kinds of conditional information, namely "aggressive" and "conservative".

On the interface for information input and the resulting decision model display, input the hypothesis – H1, and select conditional information – aggressive, the system generates a Bayesian network model in Figure 3 based on the domain knowledge base and external inputs (H1, aggressive). The generated Bayesian network shown on the interface can be used for littoral threats assessment.

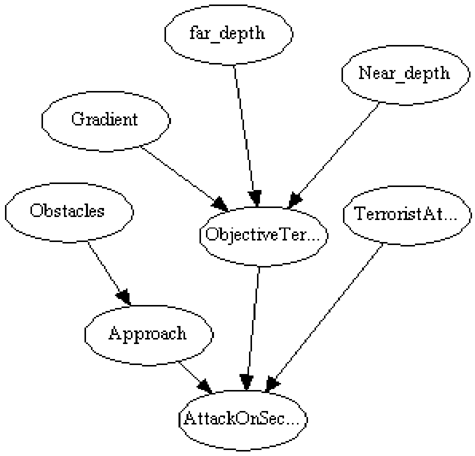


Figure 3. Bayesian network model generated based on the hypothesis – H1, the conditional information – aggressive

Figure 2 shows the mapping information of hypotheses after a new event "suspicious boat" arrives. The probability of the hypothesis H2 being true is 0.8 which is greater than 0.7 after assigning the event as true, therefore hypothesis H2 is also triggered. In other words, when the two events (E1, E2) are true, the two hypotheses are triggered.

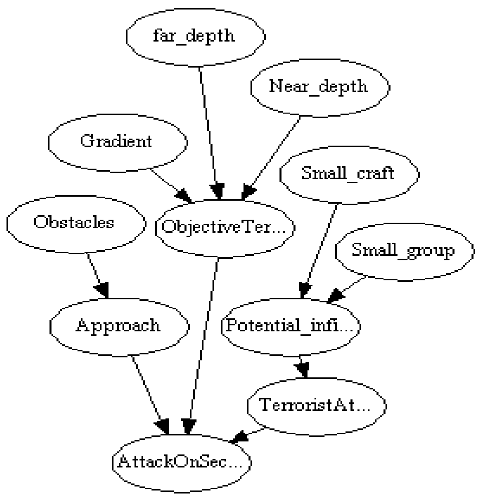


Figure 4. Bayesian network model generated based on the hypotheses – H1 and H2, the conditional information – aggressive

On the interface for information input and the resulting decision model display, input the hypotheses - H1 and H2, and select conditional information – aggressive, the system generates a new Bayesian network model in Figure 4 according to the new situation. The new generated Bayesian network is quite different from the old one as shown in Figure 3. The military decision makers can use the new resultant model to re-analyze littoral threats.

In this example, when a new event- "suspicious boat" arrives, the Bayesian network model will be generated according to the new situation. Therefore, the generated Bayesian network model for assessing littoral threat can be dynamically updated.

The example from domain-littoral threats assessment shows that the system is capable of constructing situation-specific Bayesian network models during runtime from a domain knowledge base to reason about littoral situations.

4. Discussion

Our work here is related to a number of previous work as well as some on going ones. Most work on automated network construction takes a set of probabilistic influences on a single variable as the unit of knowledge [2, 3, 4]. Laskey and Mahoney [6] present a knowledge representation framework that takes as its basic unit the network fragment, which consists of a set of related variables together with knowledge about the probabilistic relationships among the variables. Our proposed knowledge representation framework permits the knowledge base engineer to specify knowledge in sub-model, and the relationships among sub-models according to their preference. A sub-model is used to represent probabilistic knowledge for some part of the domain. It is clearly, our framework focuses on knowledge acquisition and organization.

There are currently two OOBN frameworks. Bangsø's OOBN[10] have several advantages over Koller and Pfeffer's OOBN [9]including a more intuitive definition of inheritance, the capability of compactly representing dynamic situations and more efficient inference algorithms. The classes of OOBNs allow automatic generation of a model from external input. Whenever external inputs indicate a new object in the domain, an instance of an appropriate class can be added to the domain. We provide a practical approach to generate Bayesian network from external information. In an OOBN class, the interface encapsulates the internal variables of the class, dseparating them from the rest of the network. Our sub-models can be considered as a normal BN. Our proposed knowledge representation allows the KB engineer or the expert to represent knowledge flexibly, and facilitates knowledge acquisition. In order to avoid loop in the Bayesians Network combination, our system provides a guideline for avoiding loops and a function for checking loops [12]. In model construction process, An OOBN can be considered as a BN, a part of which is refined according to external information. Our work proposes Hypotheses Mapping. Given hypotheses and conditional information, a group of sub-models can be selected. Those selected sub-models can combine into a Bayesian network successfully. Therefore, my approach provides a practical and general method for dynamic model construction. However, in our approach, more work need to be done in building a knowledge base.

5. Conclusion

Decision support system for military situation assessment is very useful for military decision makers. A crucial problem for military situation assessment is the problem of high uncertainty and the dynamics of the environment. In our research, Bayesian network model is employed as decision model because of its capability to solve problems involving uncertainty. To deal with the dynamical problem, we propose a new approach for constructing a decision model from knowledge base according to the changes in environment.

Based on this proposed approach, this research develops an intelligent decision support system for military situation assessment. This intelligent decision system provides explicit representation of expert knowledge; deals with uncertain and incomplete information and dynamically responds to the changes in environment.

A case from domain-littoral threats assessment is used to demonstrate this system's capability to construct situation-specific Bayesian network models from the domain knowledge base dynamically. The generated Bayesian network used to assess littoral threat can be changed as the situation evolves. The system has been used to deal with different problems on military situation assessment.

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