Combat State Assessment Based on Improved Structure-Variable Dynamic Bayesian Network

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Abstract. Variable structure dynamic Bayesian network can effectively evaluate the combat state and be able to adapt to the sudden battlefield environment, but there is still a problem in the transformation between stages. Aiming at the problem of redundant information transmission in the variable structure dynamic Bayesian network, an improved variable structure dynamic Bayesian network is proposed to filter the information of the transfer network. The method determines whether the nodes are redundant by the conditional independence of the nodes in adjacent time slices under the condition of the completion of the known phase, and then filters the redundant information. The experimental results show that the proposed method can effectively eliminate the redundant information and enhance the perceived sensitivity of the effective information.

1. Introduction

The status of the combat unit is an important part of the military intelligence decision-making system. With the continuous application of high-tech, the uncertainty and complexity of the battlefield environment are increased, and the higher requirements of the combat status assessment are put forward. As a powerful method of uncertain reasoning, dynamic Bayesian network is an effective method to solve the problem of operational state assessment. However, the operation process is usually a non-steady state process, and the impact of the combat forces is different at different stages of the operation, and the traditional dynamic Bayesian network can not analyze the rapid changes of the environment. The solution to this problem is to allow the Bayesian network structure and the parameters to change to get a structure-variable dynamic Bayesian network (SVDBN). In the literature, the structure-variable dynamic Bayesian network was used to predict the traffic flow, and better results were obtained than the traditional methods. Document uses structure-variable dynamic Bayesian network to distinguish target in Air to Air Combat. The above literatures do not consider the problem that redundant information will be transmitted with hidden nodes when using the structure-variable dynamic Bayesian network.

2. Structure-Variable Dynamic Bayesian Networks

Definition: variable structure dynamic Bayesian networks can be represented by $(B_t, B_{t+1})$, $B_t$ uses a static Bayesian network to describe the probability distribution $P(X_{[n]})$ in the initial state.

$$P(X_{[n]}) = P(X^1_{[n]}, X^2_{[n]}, \ldots, X^n_{[n]}) = \prod_{i=1}^n P(X^i_{[n]} \mid Pa(X^i_{[n]}))$$

$B_{t+1}$ is a Bayesian network containing two adjacent time slices, it describes the state change of a time slice to the next time slice by conditional probability.
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\[ P(X_{\{i\}} | X_{\{i-1\}}) = \prod_{i=1}^{N} P(X_{\{i\}} | \text{Parent}(X_{\{i\}})) \]  
\[ X_{\{i\}} \text{ represents the } i\text{-th node } X_i \text{ on the time slice } t; \text{ Parent}(X_{\{i\}}) \text{ represents the father node of } X_{\{i\}}, \text{ and } N \text{ is the number of nodes on the time slice } t. \]

3. Simulation Evaluation of Combat State based on Variable Structure Dynamic Bayesian Network

In combat simulation, the combat mission is usually divided into several stages, such as standby, maneuver, troops deployment, strike and so on. At different stages, the factors that the commander needs to consider are usually different, but the factors that need to be considered in the same phase are basically the same. This situation provides a basis for the evaluation of dynamic Bayesian networks using variable structure. Each phase of the combat mission is considered a steady-state, and the dynamic Bayesian network is built on this basis for each phase. When the troops complete a certain phase of the task is completed and into the next stage, with the action and the target changes, will have an impact on the combat status of the various factors also changed, which resulted in Bayesian network structure mutation. The transition network between the last time slice of the previous stage and the first time slice in the latter stage is different from the transfer network in the phase, reflecting the sudden change of the structure. The next stage is regarded as another steady state. The latter phase is viewed as another steady state, establishing dynamic Bayesian networks for evaluation, repeating the above behavior until complete the evaluation of the operational status in the whole mission.

3.1. Information Redundancy Defects

There are redundant information accumulation in the simulation evaluation of troops carrying out multi-stage combat mission by using SVDBN. The following example is illustrated with a simplified operational state evaluation network.

![Figure 1 Two-stage Operational Status Assessment Network](image)

As can be seen from the diagram, there is a channel in the transfer network of the third time slice to the fourth time slice \( X_1^3 \rightarrow X_2^4 \rightarrow X_2^4 \). It can be seen that the message of \( X_1^3 \) can be passed along the path \( X_1^3 \rightarrow X_2^4 \rightarrow X_2^4 \) to \( X_2^4 \), which in turn affects all the evaluation results of \( X_2^4 \) and subsequent. However, in the actual situation, in the case where the maneuver phase has been completed, phase II does not need to be maneuvered, and the road conditions will not have an impact on the combat status of the troops. This kind of message delivery is not realistic, and therefore, in the phase transformation must eliminate the redundant information...
brought about by the wrong impact.

3.2. The Cause of Redundant Information Dissemination
In combat simulation, the combat task of the army is usually divided into several stages, and the next stage task B must usually be carried out in the pre phase task A:

\[ P(B | A = 0) = 0 \]  \hspace{1cm} (3)
\[ P(B | A = 1) = P(B) \]  \hspace{1cm} (4)

In the form, A=0 indicates that the pre-task A is not completed, and A=1 indicates that the pre-task A has been completed. In phase A and stage B intermediate adding the nodes describing the completion of the A phase, and the following structure can be obtained:

\[ \text{completion of the A phase} \]

Figure 2 Conditional independence between stages

From the knowledge of graph theory, when we obtain the evidence that task A has completed, node A and node B are separated by the completion node, and task A and task B are conditional independent, so the factors that affect the state of the force in task A can not directly affect the combat status of the forces in task B through the relationship between tasks A and B. In the evaluation network, however, the evaluation node of the last time slice of the previous task stage A and the first time slice of the latter task stage B have a direct causal relationship between the evaluation nodes in the two time slices (As shown in Figure 1 \( X^1_i \rightarrow X^1_i \)). The evaluation nodes in stage A contain the information of all the evidence nodes in the stage A, so the redundant evidence information will be transmitted through the causal relationship in the next stage.

4. Improved Variable Structure Dynamic Bayesian Networks

4.1. Finding redundant information paths
On the basis of the previous analysis, the transfer network in the stage change is improved, the path through which the valid information is transmitted is retained, and the path of the redundant information is blocked to filter the influence of the redundant information. The completion of the previous task is added to the transfer network, and obtaining a new network through structural learning. It is judged whether the path between the two time slices is separated by the node to distinguish whether the node on the path transmits the redundant information.

4.2. Eliminating redundant information paths
1) Delete all directed edges in the transfer network.
2) Introduce the pre-stage task completion node \( X' \).
3) Obtain a new network structure by learning the structure of the existing nodes through the sample data.

Figure 3 Eliminating the paths of information dissemination (1)
4) Delete the nodes in previous time which don’t have path between the nodes in the next time.
5) Delete the nodes in previous time whose path connecting to the latter part all through the $X'$.  
6) Divide x and all its directed edges.
7) Connect the remaining nodes according to the original structure.

![Figure 4 Eliminating the paths of information dissemination(2)](image)

5. numerical experiment

5.1. Evaluation network model

The operation plan is divided into three stages: maneuver stage, equipment preparation stage and implementation strike phase (As shown in Figure 5).

![Figure 5 Network model](image)

The observation node for Special Warfare Sabotage (SS), sabotage the Enemy Reconnaissance (ER), rain (R), wind (W). The road conditions (L), Communication Situation (CS), the State Army (ST) for hidden nodes, State of Troops (ST) is divided into four states: good (to finish the task timely and accurate), general (to complete the task, but slightly delayed) and poor (delay too long, finish quality not high), poor (failed).

Two improved transfer networks are shown in Figure 6.

![Figure 6 Two improved transfer networks](image)

In this experiment, there are four kinds of combat operations in the army, in order to facilitate the analysis, the probability of a good state for comparative analysis.

5.2. The ability to assess the changes in conditional evidence

Scenario 1: imaginary rain, breeze, invincible, invincible party special warfare sabotage reconnaissance, 1 to 9 time slice for mobile phase, 10 to 18 time slice preparation stage for weapons, 19 to 27 time slices for the implementation of the combat phase, the 3 phase of the task was completed successfully.

Scenario 2: imaginary rain, breeze, special warfare invincible sabotage, 1 to 9 phase motor phase, 10 to 18 stages of preparation stage for weapons, 19 to 27 stages for the implementation of the combat phase, the 3 phase of the task was completed successfully. The seventh time node causes the enemy to
be alert because of poor camouflage. Enemy reconnaissance increased from very little to less. Eighth, ninth, tenth time slice increased to frequent, then the troops strengthened camouflage, 11, 12 time slice reduced to less, 13 to 20 time slice reduced to very few. The SVDBN and the improved SVDBN were evaluated in both scenarios and the results of the same method were compared.

Figure 7 The probability of good condition for the comparisons with two methods

It can be seen from Fig.7 that the probability of good assessment of the SVDBN method and the improved SVDBN method is greatly reduced when the enemy reconnaissance activity increases in the 7, 8, 9, 10 time slice. Indicating that both methods can respond to changes in evidence.

5.3. The filtration of redundant information

Scenario: Light rain, medium wind, less enemy reconnaissance. Maneuver stage: in the 7th, 8th and 9th time the film against the enemy, causing road damage. By changing the driving route in the 9th time node to reach the destination, complete maneuver. 9-18 time film successfully completed the weapons preparation; 19-27 time film successfully completed the implementation of combat missions.

Figure 8 The effect of redundancy information filtering

It can be seen from Figure 6 that the road condition is redundant information. The result of SVDBN method is affected by the motorized road conditionsthe due to the lack of redundant information filtering. The results of the initial phase of the weapons preparation phase show that the troops are in a poor operational state. And then gradually weaken the impact of the wrong message, the evaluation results in the combat state gradually improved. Because the improved SVDBN method uses information filtering to eliminate the erroneous effects of road conditions, the results of the SVDBN are closer to the end of the second phase, and the impact of the redundant information is effectively eliminated. After accepting multiple observations in the second stage, the results of the two approaches tend to be consistent, demonstrating that the information that is being eliminated in the improved SVDBN method is redundant. The experimental results show that the SVDBN algorithm needs a long time to weaken the influence of redundant information, which has a great influence on the evaluation results. The improved SVDBN method can effectively eliminate the influence of redundant information.
5.4. Awareness of effective information

Scenario: The scenario is the same as scenario 2 in experiment 4.2.

![Figure 9 Awareness of effective information](image)

It can be seen from Fig. 6 that the reconnaissance activity is valid information for the transition from the maneuver phase to the weapon preparation phase. It can be seen from Figure 8, 6, 7, 8, 9 time film, due to the intensification of the enemy reconnaissance activities, the two methods of combat status of the assessment results are consistent decline, indicating that the improved method will not eliminate the effective information. At the same time, the improved SVDBN method is more sensitive to the effective information than the SVDBN method.

6. Conclusion

In this paper, an improved variable structure dynamic Bayesian network method is proposed for the defects of the redundant information in the traditional variable structure dynamic Bayesian network method which will be spread by hiding the nodes. The experimental results show that the improved method eliminates the influence of redundant information, retains the effective information, and is more sensitive to the change of the effective information, which provides a more effective method for the combat state evaluation.

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