Evaluation of Intelligent Air Defense algorithm based on Machine Learning

Jiayuan Guo1,*, Zirui Zhao2, Jinghao Zhou3

1Southwest Jiaotong University•University Of Leeds, Chengdu, Sichuan, 611756
2Shandong University of Science and Technology, Jinan, Shandong, 250000
3College of Computer Science and Technology, Harbin Engineering University, Harbin, Heilongjiang, 150000

*Corresponding author: guojiayuan@swjtu.edu.cn

Abstract. In the complex and rapidly changing combat environment, the enemy interference and sensor performance limitations and other factors lead to insufficient battlefield information. In order to make the UAV have the ability to carry out threat assessment under the condition of insufficient information, a Bayesian network (BN) threat assessment modeling method based on small data sets is proposed in this paper. Starting with the two problems of BN structure learning and parameter learning under the condition of small data set, using the constraint matrix obtained by Bootstrap method as the constraint item added to the score function, a BN structure learning algorithm based on small data set is proposed, and the BN parameter learning algorithm based on interval prior constraint is adopted. The simulation results show that, compared with the traditional BN learning algorithm, the BN learning algorithm proposed in this paper has higher accuracy and availability in UAV threat assessment modeling under the condition of small data set.

Keywords: Bayesian network; small data set; matrix constraint; UAV; threat assessment

1. Introduction
At present, among the many different methods to solve the threat assessment problem of unmanned aerial vehicle (UAV), Bayesian Network (BN) has become an effective tool to solve this kind of problem by vividly simulating the characteristics of human thinking. However, in the above literature, the traditional BN structure learning and parameter learning algorithms are applied to solve the threat assessment problem of UAV under the condition of complete data set, but in the actual battlefield environment, on the one hand, due to the limitation of sensor performance and the enemy's interference and deception, the amount of UAV sampling information is often insufficient, on the other hand, sometimes for the tactical purpose of "first enemy decision, first enemy strike". Decisions have to be made as soon as possible. At this time, the traditional BN learning algorithm is difficult to guarantee the requirements of learning accuracy, has a great impact on the reasoning of the network, and can not obtain threat assessment results that meet the requirements.
In this paper, a threat assessment method of UAV based on small data set BN learning is proposed. Firstly, the matrix constraint of BN structure is obtained by using Bootstrap method, and then the BN structure learning algorithm based on matrix constraint and the BN parameter learning algorithm based on prior constraint are proposed. Finally, the proposed algorithm is used to solve the problem of UAV threat assessment under the condition of small datasets.

2. Task description
UAV threat assessment is a sub-module of autonomous reconnaissance mission. UAV takes all the battlefield situation information as input, according to the real-time acquisition of enemy location information, enemy confrontation information and enemy type information, and integrates offline domain expert knowledge to complete the threat assessment of the current battlefield situation. Figure 1 is a schematic diagram of the battlefield background of UAV threat assessment.

3. BN structure Learning algorithm based on Matrix constraint
Bootstrap sampling is a new statistical method of computer simulation put forward by Efron, a professor of statistics department of Stanford University in the United States, on the basis of summarizing the previous research results. In statistics, this method is often used to deal with the problem of small data sets. Based on the given observation data, it does not need other assumptions and additional information to simulate and infer the distribution of statistics.

Bootstrap sampling is applied to the learning process of BN structure. The main purpose of this method is to resample the given small data set D randomly and put back. Under the condition of not
changing the network information, m sample sets of n nodes \( D^* = \{D_1, D_2, ..., D_m\} \), are obtained so as to expand the small data set and facilitate further BN structure learning.

The BN structure represents the qualitative relationship between nodes and nodes. In this paper, the BN structure is expressed in the form of mathematical matrix. The following is expressed in the matrix mathematical form of the classical Asia network in BN to describe BN, as shown in figure 3:

![Matrix expression of BN structure](image)

**Figure 3** Matrix expression of BN structure

4. **Parameter Learning algorithm based on Prior constraint**

The prior information of parameters is usually given in the form of continuous intervals. For example, according to the domain knowledge or expert experience, the prior parameter estimation interval "12" can be given. First, the prior information is described by the uniform distribution, then the prior parameter is taken as the variable, the mean value is taken as the constraint, and the variance is taken as the target. The Beta distribution closest to the uniform distribution is obtained by using the optimization method. The mean and variance of uniform distribution can be expressed as follows:

\[
E_u(\theta) = \frac{\theta_1 + \theta_2}{2}
\]
\[
\text{Var}_u(\theta) = \frac{(\theta_1 - \theta_2)^2}{12}
\]

The convex optimization method under constraints is used to solve two prior parameters of Beta distribution.

\[
\begin{align*}
\min (\text{Var}_u - \text{Var})^2 \\
\text{s.t} \{E = E_u, \alpha > 0, \beta > 0\}
\end{align*}
\]
By combining the above two formulas, the prior parameters $\alpha$ and $\beta$ which can more accurately describe domain knowledge and the corresponding Beta distribution $B[\alpha, \beta]$ can be solved by convex optimization model [20] under constrained conditions. The prior distribution is sampled and the virtual samples under prior conditions are obtained, thus the domain knowledge is transformed into sample data by using the prior parameters under constrained conditions, and the amount of network data information is increased. The learning accuracy of BN parameters under the condition of small data set is improved.

The specific steps of the BN parameter learning algorithm based on prior constraints under the condition of small data sets are given below, and the algorithm flow is shown in figure 4.

5. Simulation and analysis

5.1. Algorithm simulation
In this paper, the Asia network is used to verify the algorithm, and the sample size is increased from 10 to 100. The K2 algorithm proposed in this paper after adding the score function to the constraint matrix $S$ obtained by Bootstrap resampling is compared with the original K2 algorithm. In order to avoid the randomness caused by data sampling, each algorithm is run 10 times, and finally the average value is obtained as the final result. The algorithm comparison results are shown in figure 5-figure 8.
Figure 5 The total BIC of this algorithm and K2 algorithm

Figure 6 Average BIC of this algorithm and K2 algorithm
Figure 7 The total hamming distance between this algorithm and K2 algorithm

Figure 8 The average hamming distance between this algorithm and K2 algorithm

From figure 5 and figure 6, we can see that when the amount of data is small, the BIC score of the BN structure obtained by the proposed algorithm is better than that of the original K2 algorithm. As can be seen from figures 7 and 8, when the sample size is greater than 35, the hamming distance of the BN structure obtained by this algorithm is smaller. It is proved that the K2 algorithm can also get a better learning effect in small data sets because of the additional constraints in this paper.

Through the above simulation results of learning threat assessment network under the condition of different data sample size, when the sample size is greater than 40 groups, the network structure tends to be stable and does not change with the increase of sample data. At this time, the threat assessment network model can be determined, as shown in figure 9 below:
The structure of the threat assessment network model has been stable. At this time, the BN parameter learning algorithm based on prior constraints is used to learn the network parameters of the model. The parameter learning results under the condition of 40 groups, 50 groups and 60 groups of data samples are given below, as shown in Table 1, Table 2.

The above parameter learning results and KL-divergence results show that both the BN learning algorithm under the condition of small data set and the traditional BN learning algorithm will continuously improve the accuracy of the network parameters learned with the continuous increase of the sample size, and the KL-divergence will continue to decrease and approach to 0, and the parameters of the real threat assessment network model will continue to approach. However, the parameter KL-divergence score result of this algorithm under the condition of 40 groups of samples is similar to that of the traditional BN learning algorithm when the sample size is 70 groups, which fully reflects that this algorithm has the advantages of less dependence on the number of samples and high learning accuracy than the traditional BN learning algorithm. These advantages make this algorithm have the ability to deal with UAV threat assessment modeling under the condition of small data set.

Next, using the same data samples, the real network parameters, the network parameters obtained by this algorithm and the network parameters obtained by traditional BN learning algorithm are used to complete the network reasoning of the threat assessment model, and the change curve of sample data and threat assessment results is obtained, which shows the threat degree information under different data quantities, as shown in figure 10 below.

**Table 1** 40 groups of data the model parameters obtained by the algorithm in this paper

| Target threat | Target type  | Target confrontation | target location |
|---------------|--------------|----------------------|-----------------|
| (T1:low, T2:high) | (I1: Warning radar, I2: AAP) | (K1:yes, K2:no) | (L1:far, L2:near) |
| T1(low) | 0.5173 | (0.4841,0.5159) | (0.7866,0.2134) | (0.5086,0.4914) |
| T2(high) | 0.4827 | (0.9008,0.0992) | (0.2240,0.7760) | (0.6405,0.3595) |

**Table 2** 60 groups of data the model parameters obtained by the algorithm in this paper

| Target threat | Target type  | Target confrontation | target location |
|---------------|--------------|----------------------|-----------------|
| (T1:low, T2:high) | (I1: Warning radar, I2: AAP) | (K1:yes, K2:no) | (L1:far, L2:near) |
| T1(low) | 0.4657 | (0.4583,0.5417) | (0.8146,0.1854) | (0.4484,0.5516) |
| T2(high) | 0.5343 | (0.8866,0.1134) | (0.2380,0.7620) | (0.5069,0.4931) |
Figure 10 The relationship between the amount of data and threat probability

The above simulation results show that with the increase of the number of samples, the probability of high threat obtained by the BN learning algorithm and the traditional BN learning algorithm under the condition of small data sets continues to increase, and both of them continue to approach the reasoning results obtained by the real parameters. However, when the number of samples is 40 groups, the BN learning structure learning algorithm under the condition of small data sets has learned the real threat assessment model network, and then begins to learn parameters, and when the number of samples reaches 50, the reasoning result is similar to that of 60 groups of traditional BN learning algorithms. Because the traditional BN structure learning K2 algorithm can not learn the stable BN structure of threat assessment and then can not learn the BN parameters in the process of data sample size from 40 groups to 60 groups, there is no inference result of threat assessment between 40 groups and 60 groups of data samples. When the data sample size increases from 60 to 80 groups, the traditional BN learning algorithm plays a role and gradually approaches the reasoning results of the BN learning algorithm and real parameters under the condition of small data sets.

6. Conclusion

Aiming at the threat assessment of UAV under the condition of small data set, this paper proposes a matrix constrained BN structure learning algorithm, and then combines the BN parameter learning algorithm based on prior constraints to complete the structure learning and parameter learning of BN. Compared with the traditional BN learning algorithm, the simulation results show that the traditional algorithm needs at least 60 sets of data to get reasoning results. This algorithm only needs 40 sets of data to solve the problem of UAV threat assessment, which verifies the superiority of this algorithm. The deficiency of this paper is that the approximate learning algorithm is used in BN structure learning, and the learned structure is the local optimal solution, which affects the final reasoning accuracy. The next step is to introduce another constraint to improve the approximate learning algorithm of BN.
structure or directly adopt the improved accurate learning algorithm (limited by the number of nodes, up to 26 nodes) to improve the accuracy of reasoning results.

Reference
[1] Wang Yi, Liu Sanyang, Zhang Wen, Wang Yanan. Threat assessment method for intuitionistic fuzzy multi-attribute decision making with uncertain attribute weights [J]. Acta Electronica Sinica, 2014 42 (12): 2509-2514.
[2] Yang Jian, Gao Wenyi, Liu Jun. A threat assessment method based on Bayesian network [J]. Journal of PLA University of Science and Technology (Natural Science Edition), 2010, 11 (1): 43-48.
[3] Ruohai, Gao Xiaoguang, Guo Zhigao. Bayesian network structure learning based on improved BIC score [J]. Systems Engineering and Electronic Technology, 2017, 39 (2): 437-444.
[4] Zhou Lin, Liu Xianjiang, Fang Yongjun, etc. System deviation estimation method based on Convex Optimization under Bayesian Framework [J]. Journal of Detection and Control, 2019 (4).
[5] Zhang Zhe. Research on non-convex optimization algorithm for UAV path planning problem [D]. Shanghai Jiaotong University, 2019.