A Structure-variable Bayesian Network Model for Vehicle Threat Assessment

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Abstract—In driving assistant system and automated driving system, accurate and real-time threat assessment is necessary to improve the safety. Besides moving targets, the influence factors of safety also include environment and driver. To evaluate the threat level of host vehicle, a modified Bayesian network (BN) model is proposed in this paper. In addition to objects' state and environment condition, the driver’s subjective factor is also considered to structure a more adequate model and assess a more accurate threat level, including physical factor and psychological factor. Because of the rate of change of various factors is different greatly, the structure-variable Bayesian network (VBN) model is proposed to increase the computational efficiency. Finally, simulation is designed to verify the availability of two kinds of network models, and it verifies that the VBN is better in computational efficiency than static BN.

1. INTRODUCTION
The threat assessment is a crucial technology to obtain the high level of information fusion system and estimate the threat level of environment accurately, which processed the data from multiple sensors and information source [1]. It has been widely applied in the automatic driving path planning and the auxiliary driving system. The threat assessment method can be divided into two basic categories. One is based on trajectory prediction method of vehicle motion model, the other is the threat assessment model based on knowledge [2].

Considering uncertainty of the vehicle motion state and the measurement at the next time, the threat assessment model based on knowledge makes these uncertainties to probability to get the predicted trajectories of probabilistic description [3]. For example, Michael L. Hinman described a series of innovative artificial intelligence algorithm to calculate situation assessment and threat prediction [4]. Yanli Lu developed the relationship between fuzzy approximation operator and fuzzy reasoning, and build a model for threat assessment [5]. Jie Lu proposed intelligent multi-criteria fuzzy group decision-making to deal with inconsistent assessment, incomplete information and inaccurate opinions [6].
Galina L. Rogova described a mixed-initiative model which includes arguments with beliefs [7]. Hui Chen established a indicators system which includes three levels to depict the cause and effect relationship, and proposed the assessment model based influence nets [8].

BN model is used to infer and judge the incomplete, imprecise or uncertain knowledge and information [9]. It can be used to calculate threat assessment. For example, Mohsen Naderpour presented a fuzzy dynamic BN based on situation assessment approach [10]. Keyvan Golestan proposed a comprehensive framework to address the road safety problem which relied on the BN to handle uncertainty [11]. In the literature [12], the author developed a vehicle collision threat assessment model basing on BN. The threat level in this model is affected by vehicle motion parameters and environmental factors. The condition probability (CPT) is acquired by parameter learning method, and the threat level is inferred by Message Passing algorithm. The simulation results show that the collision threat assessment model based on BN can reflect the vehicle collision threat level accurately, and be in good real-time performance.

But in the static BN (SBN), the influence of the driver’s subjective factor on the threat assessment is not fully considered to make the network have weak adaptability. So, this study adds the driver’s subjective factors into the network to get accurate threat assessment. On the other hand, considering the rate of change of model variables is different greatly and avoiding calculating the probability of influencing factors repeatedly in the continuous time which have no change, the VBN is proposed to increase the computational efficiency.

2. MODIFIED STATIC BAYESIAN NETWORK MODEL

2.1. Modified SBN Model

In general, there are many factors that affect the driving safety of vehicles, they all can be used as threat factors in BN model to assess threat level. In order to meet the requirements of real-time and accuracy, only the main factors which is closely related to the traffic safety can be used to infer in BN model.

![Modified SBN model](image)

In the traditional collision warning system, threat factors can be classified into two categories, including object vehicle factor (TC) and environmental factor (EF). TC includes relative velocity (RV), relative distance (RD) and the type of objective vehicle (VT). EF includes road condition (RC) and visibility condition (VC). In order to calculate threat level (TL) accurately, this paper adds the driver’s influence (DF) into the original SBN. DF includes psychological state (PS) and physical state (PH). The modified SBN is shown in Figure 1.

2.2. Creating Membership Function

The variables of nodes in BN model are discrete, but the relative distance and relative velocity are continuous variables. So, before calculating the threat level, these two nodes should be fuzzed. The triangle membership function model for these factors is shown in Figure 2. L, M and H are the corresponding values of the continuous variable divided into three levels of low, medium and high. Each continuous variable can use the same method for variable membership to calculate.
2.3. LCPT Determination
After establishing the BN model, we need to determine LCPT of each node. There are two methods to
determine the LCPT, one is using the knowledge of domain expert, the other is through lots of tests and
parameters learning [13]. Because the parameter learning in BN is not the focus of this study, the LCPT
in this paper is obtained through the original LCPT [12] for simplicity.

TL is classified into high threat (HT), moderate threat (MT) and low threat (LT). Taking TC as an
example, the influence of TC is divided into high condition (HC), medium condition (MC) and low
condition (LC). According to the parameter correction process in literature [12], the initial conditional
probability table of the network model is finally determined. It is given in Table 1.

| TL   | TC   |
|------|------|
| HC   | 0.97 | 0.03 |
| MC   | 0.01 | 0.98 |
| LC   | 0    | 0.99 |

RV is divided into fast velocity (HS), medium velocity (MS) and low velocity (LS). RD is classified
into far distance (HD), medium distance (MD) and near distance (LD). VT is classified into heavy
vehicle (BC), mid-size vehicle (MC) and small vehicle (SC). EF is classified into high influence (HE),
medium influence (ME) and low influence (LE). RC is classified into ice road (IR), wet road (RR) and
dry road (DR). VC is classified into far visibility (HV), medium visibility (MV) and poor visibility
(LV). DF is classified into good influence (HF), medium influence (MF) and bad influence (LF). PS is
classified into good state (HP), medium state (MP) and bad state (LP). PH includes high level (HH),
medium level (MH) and low level (LH). The other threat factors can be added to the threat model
similarly to obtain complete LCPT with high reliability.

3. STRUCTURE-VARIABLE BAYESIAN NETWORK

3.1. Construction of Structure-variable BN Model
The evidence nodes of the SBN include visibility, road condition, relative velocity, relative distance and
type of objective vehicle. According to practical experience, we can see that slippery degree of road
surface and visibility of the environment remain stable. So, the SBN is modified in this chapter. The
structure variable of the VBN is drove by evidence event to improve the computational efficient. The
process of structure variable is shown in Figure 3.

When the road condition or the visibility is changed, the method reasoning the threat assessment for
the VBN is same to the one for SBN, and the state of the node EF is retained. When the road condition
and visibility remain unchanged during periods, the node EF is as an evidence node. It’s state saved
before is as evidence input.
3.2. Calculating in Structure-variable BN Model

In exact inference algorithms, Message Passing algorithm has some characteristics like simple principle, high computational efficiency[14]. So, the Message Passing algorithm is chosen in this chapter. It can satisfy real-time requirements of vehicle collision warning algorithm for VBN.

In this paper, \( \pi \) and \( \lambda \) are evident information from subset of parent nodes and subset of child nodes respectively. \( \tau_L \) represents the state of TL that objective vehicle to host vehicle, and the evident information from subset of parent nodes and subset of child nodes are represented to \( \tau_L^+ \) and \( \tau_L^- \). So the posterior probability after updating evidence information is represented to \( p(\tau_L|\tau_L^+,\tau_L^-) \).

According to the definition of conditional independence and topological model, equation (1) is expressed as:

\[
p(TL|\tau_L^+,\tau_L^-) = \frac{p(D_{\tau_L}^+,\tau_L^-|TL) \cdot p(D_{\tau_L}^-|TL) \cdot p(\tau_L|\tau_L^+,\tau_L^-)}{p(D_{\tau_L}^+,\tau_L^-)}
\]

Where \( \alpha \) is the normalized constant. The derivation process is shown in the literature [12], (| )

\[
\text{nodes } \{RV, RD, VT, RC, VC, PS, PH\} \text{ are all evident nodes. According to the literature [12], the molecular equation in equations (1)-(4) are reduced as equations (5)-(11).}
\]

\[
\begin{align*}
\lambda_{\delta T}^+(TC_i) &= \lambda(HS) \cdot P(HS|TC_i) + \lambda(MS) \cdot P(MS|TC_i) \\
&\quad + \lambda(LS) \cdot P(LS|TC_i) \\
\lambda_{\delta T}^-(TC_i) &= \lambda(HD) \cdot P(HD|TC_i) + \lambda(MD) \cdot P(MD|TC_i) \\
&\quad + \lambda(LD) \cdot P(LD|TC_i) \\
\lambda_{\delta T}^+(VC_i) &= \lambda(BC) \cdot P(BC|TC_i) + \lambda(MC) \cdot P(MC|TC_i) \\
&\quad + \lambda(SC) \cdot P(SC|TC_i) \\
\lambda_{\delta T}^+(EF_i) &= \lambda(IR) \cdot P(IR|EF_i) + \lambda(RR) \cdot P(RR|EF_i) \\
&\quad + \lambda(DR) \cdot P(DR|EF_i) \\
\lambda_{\delta T}^+(DF_i) &= \lambda(HH) \cdot P(HH|DF_i) + \lambda(MH) \cdot P(MH|DF_i) \\
&\quad + \lambda(HP) \cdot P(HP|DF_i) \\
\lambda_{\delta T}^+(DE_i) &= \lambda(HH) \cdot P(HH|DE_i) + \lambda(MH) \cdot P(MH|DE_i) \\
&\quad + \lambda(LP) \cdot P(LP|DE_i) \\
\lambda_{\delta T}^+(DF_i) &= \lambda(HH) \cdot P(HH|DE_i) + \lambda(MH) \cdot P(MH|DE_i) \\
&\quad + \lambda(LP) \cdot P(LP|DE_i)
\end{align*}
\]

Because node TL is the root node, \( p(TL|\tau_L^+,\tau_L^-) \) in equation (1) can be transformed to equation (12).

\[
\pi(TL) = P(TL|\tau_L^+,\tau_L^-) = P(TL)
\]

Combining with equations (1)-(12), the threat level of objective vehicle after updating evidence information is shown as follows:

\[
p(TL|\tau_L^+,\tau_L^-) = \alpha \cdot \lambda_{\delta T}^+(TC_L) \cdot \lambda_{\delta T}^+(TL) \cdot \lambda_{\delta T}^-(TL) \cdot \pi(TL)
\]

Finally, three possible values must be weighted and normalized. The threat level is:

\[
\text{Threat level} = \frac{P(TL|\tau_L^+,\tau_L^-)W_T + P(MT|\tau_L^+,\tau_L^-)W_M + P(LT|\tau_L^+,\tau_L^-)W_L - W_T}{W_T - W_L}
\]
According to equations (3), (8) and (9), when the states of the evident nodes \{VC, RC\} is stable, the evident information \(\lambda_{\text{VC}}(EF_C)\), \(\lambda_{\text{RC}}(EF_R)\) of environment condition will be stable. The value of \(\lambda_{\text{EF}}(TL_E)\) is also stable. Thus it can be seen, the VBN will not reduce the accuracy relative to SBN, but it can improve the computational efficiency.

4. SIMULATION

4.1. Simulation of Modified SBN

In order to verify the effectiveness of modified SBN, two scenes are designed. Each scene includes three conditions. In scene 1, the RD of condition 1, 2 and 3 is set to three different levels: far, middle and near. Other threat factors are all in good shape. In scene 2, the PS of condition 1, 2, and 3 is set to three different levels: good, common and bad, respectively.

| Network       | RD         |
|---------------|------------|
|               | Far        | Medium     | Near        |
| Original SBN  | 0.0026     | 0.010      | 0.065       |
| Modified SBN  | 0.0011     | 0.0072     | 0.062       |

| Scene         | PS         |
|---------------|------------|
|               | Good      | Common    | Bad         |
| Scene 1       | 0.0011    | 0.0072    | 0.062       |
| Scene 2       | 0.0011    | 0.0256    | 0.478       |

The comparisons of simulation results are shown in Table II and Table III. From Table II, it can be concluded that the threat level from modified SBN is consistent with the one from the Original SBN. Table III shows that when the driver’s psychological value gets worse, the threat level will be higher. The results coincide with the fact and the validity of the improved SBN is verified.

4.2. Simulation of VBN

In order to verify VBN is correct, scene 3 based on scene 2 is designed. In scene 3, the RC of condition 1, 2, and 3 is set to three different levels: dry, wet and ice. At the same time, the VT of condition 1, 2, and 3 is set to three different levels: small, midsize and heavy.

Figure 4 and Figure 5 are the simulation results. In these figures, (0, 33] is the threat level inferred in condition 1, (34, 64] is the threat level inferred in condition 2, and (65, 100] is the threat level inferred in condition 3.
Figure 4 is the threat level of VBN model in scene 3. It shows the threat level from modified SBN is the same to the one from VBN. So VBN is effective. The time performance between the modified SBN and VBN is compared in Figure 5. It verifies the time performance of VBN is better than that of SBN in the same environment.

5. CONCLUSION
In terms of the effectiveness, real-time and accuracy of vehicle assessment, this paper establishes a new model to improve the original SBN. Basing on the modified SBN model, the VBN model is proposed to improve the time performance. Firstly, the driver’s subjective factor is considered into the original SBN model to improve the network. Secondly, basing on the modified SBN model, the rate of change of variable is considered in model to propose the VBN model, and the VBN model is reasoned with the Message Passing algorithm.

In this paper, the effectiveness of the modified SBN model and the VBN model is verified, and the computational efficiency of the VBN model is better than that modified SBN model.

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