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A NEW RISK ESTIMATION MODEL OF BAYESIAN NETWORK FOR ADAPTING TO DRIVING ENVIRONMENT CHANGING

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Abstract. *In recent years, research on automated driving of automobiles is being promoted, and accidents caused by human error by driving support systems are also expected to decrease. However, most of the accidents occur because the risk that the driver feels subjectively is too small. Therefore, to reduce the number of traffic accidents, it is necessary to raise danger perception while driving. There are two kinds of risk in the driving environment: the subjective risk felt by the driver and the objective risk existing in the driving environment. In this research, we construct a model to estimate each risk value by using two pieces of information: traffic environment information obtained from the front image of the vehicle and driving operation information of the driver. Furthermore, by combining them the risk of adapting to the driving environment is determined, and acts to raise drivers' perception of danger.*
Keywords: Driving support, Hazard estimation, Objective risk, Subjective risk, Bayesian network

1. **Introduction.** In recent years, along with the development of automatic driving technology [1], the development of a system that prevents the occurrence of car accidents, especially automobile manufacturers, has attracted attention. The most widely practiced system, called a pre-crash safety system, adds assistance such as braking to the vehicle immediately before a contact accident occurs, to mitigate the damage of the accident [2].

On the other hand, about 77% of safe driving duty violations are included in the number of traffic accidents by law violations, where safe driving duty violations include safety non-confirmation, inattentive driving, dozing driving, inappropriate driving operation, and so on [3]. As shown in Figure 1, a driver generally performs driving behavior by repeating the cycle of recognition, judgment, and operation in a driving situation [4]. In the case of the pre-crash safety system, assistance is added to the vehicle against the action of the operation. Therefore, the pre-crash safety system can avoid car accident severity caused by violation of safe driving obligations, but it is almost impossible to prevent accidents themselves from occurring by this system. However, if recognition and judgment are accurately performed, it is possible to prevent accident occurrence itself. For that reason, a study of Driver Psychology Evaluation System Based on Driving Operation Information has been carried out [5].

In this research, therefore, in order to give drivers the support of recognition and judgment, we try to develop a danger level estimation model by a Bayesian network using the traffic environment information of the front video of the vehicle obtained from the video of the Drive Recorder (DR) and the driving behavior information obtained from the Car Area Network (CAN). As an applicational example to demonstrate the

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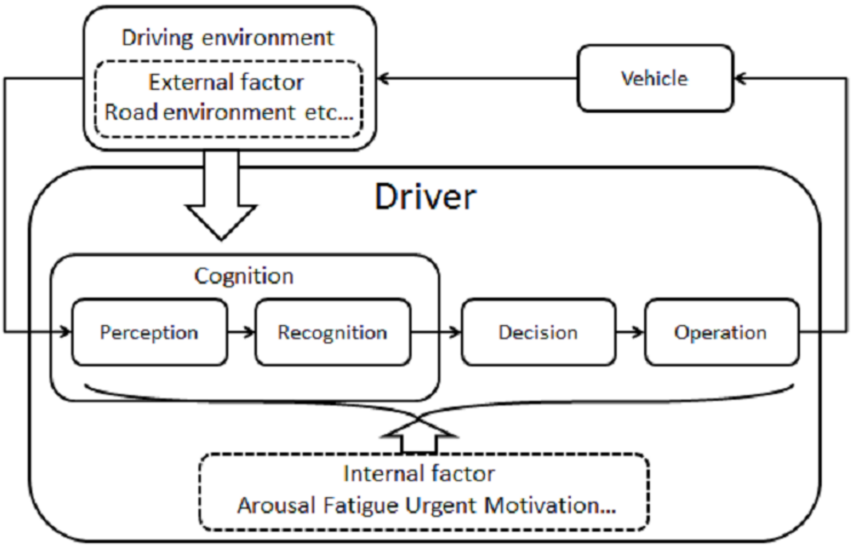


Figure 1. Driver operation model

usefulness of this method, the danger level estimation model is applied to representative traffic environments such as tracking vehicles, overtaking and encounters.

The remainder of the paper is organized as follows. In the next section, hazard definition and risk perception are introduced. And then, construction of risk estimation models by using Bayesian network is presented in Section 3. Furthermore, in Section 4, driving situation estimated by using the risk estimation models is demonstrated and good performance of our technique is obtained. Finally, in Section 5, we state the conclusions of this paper.

2. **Hazard Definition and Risk Perception.** In the field of traffic safety science, hazards are defined as environmental scenes, events, and factors that increase the possibility of accidents occurring in different traffic conditions. In other words, it can be said that they are the external driving environment factor shown in Figure 1. Specifically, in addition to traffic participants such as cars and pedestrians, signboards, intersections and curves are also defined as hazards. However, the types of these hazards are not clearly classified. In addition, it is speculated that perception characteristics to hazards greatly differ even in the same environment depending on the driver's driving experience, driving skill, driving aptitude, etc. [6]. This subjective evaluation of the hazard, which is different for each driver, is called subjective risk. Opposite to this, objective evaluation of hazards is called objective risk. Here, in a state where the subjective risk is smaller than the objective risk, there is a high possibility that the driver will fall into a belief, and it may lead to an accident.

The overall conceptual diagram of the risk estimation model is shown in Figure 2. In this research, we first built a subjective risk evaluation model that shows how the driver perceives hazards by using driving operation information, and an objective risk estimation model of hazards based on traffic environment information. And then, a current driving situation risk with the two values obtained from the subjective risk evaluation model and objective risk evaluation model is defined to evaluate the risk of the current.

3. **Construction of Risk Estimation Model.**

3.1. **Bayesian network.** The Bayesian network is a directed acyclic probabilistic model consisting of random variables as nodes and connecting arcs (unidirectional arrows) to represent the dependency relationship between the node variables [7]. The dependency

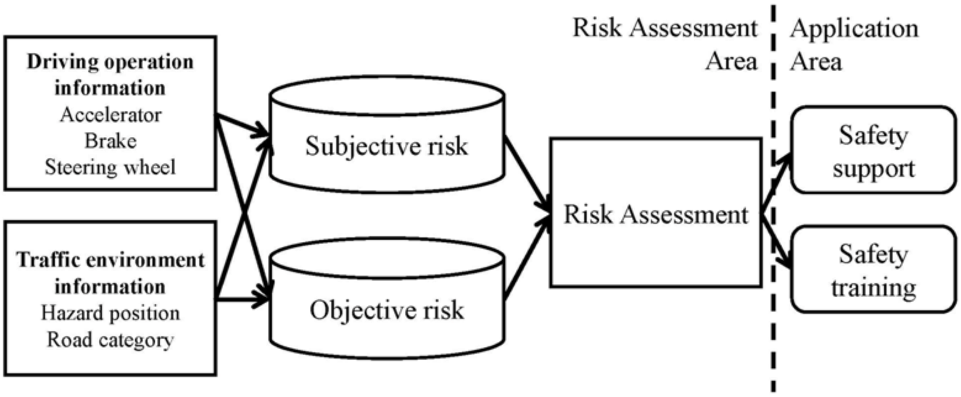


Figure 2. Conceptual diagram of the risk estimation model

relationship between nodes is quantitatively expressed in a Conditional Probability Table (CPT) attached to an arc. The Bayesian network has the characteristic that probability of event occurrence can be probabilistically predicted by expressing the likelihood of complicated and unreliable events by prior probability or CPT and so on. In addition, various algorithms such as the simulated annealing method and the hill climbing method have been proposed as search methods of machine learning, and the optimum method must be selected according to the target application.

3.2. **Creation of an objective risk estimation model.** In constructing an objective risk estimation model, it is necessary to create input/output data sets for learning [7]. First, we selected eleven kinds of variables through interviews with instructors at a driving school on the selection of the input random variables of the model to estimate the risk of hazards. Here, selected eleven input random variables are pedal operation, brake operation, steering wheel, host vehicle speed, vehicle position, vehicle status, other vehicle position, relative distance, road type, legal speed and signal status. Next, we chose the two random variables of the other vehicle risk level and the compliance degree of the law as the output random variable of the model showing the objective risk of the current driving environment. The former is a parameter of model input indicating the degree of influence given to the driver from another vehicle of the traffic participants, and the latter is a parameter of model output indicating how safely the driver himself/herself is performing the driving operation.

Then, we constructed the objective risk estimation model of the Bayesian network by machine learning using the created data set. There are various methods for learning the model structure of the Bayesian network, but in this research we used Weka (Waikato Environment for Knowledge Analysis), machine learning software developed at Waikato University. Figure 3 shows an example of the Bayesian network structure formed by the annealing method in various learning methods. The network constructed by the annealing method has the highest data classification accuracy of 97.12%, compared with other learning methods, and this network was selected as the objective risk estimation model in this research.

3.3. **Creation of a subjective risk estimation model.** Subjective risk estimation first estimates the driving behavior intention in the Bayesian network and then estimates the subjective risk value by the following expression using the probability of the estimated driving behavior intention.

$$R_s = \begin{cases} 1 - P_i, & \arg\max P_i = \text{Acceleration} \\ P_i, & \arg\max P_i = \text{Deceleration} \\ P_i \times 0.5, & \text{other} \end{cases} \tag{1}$$

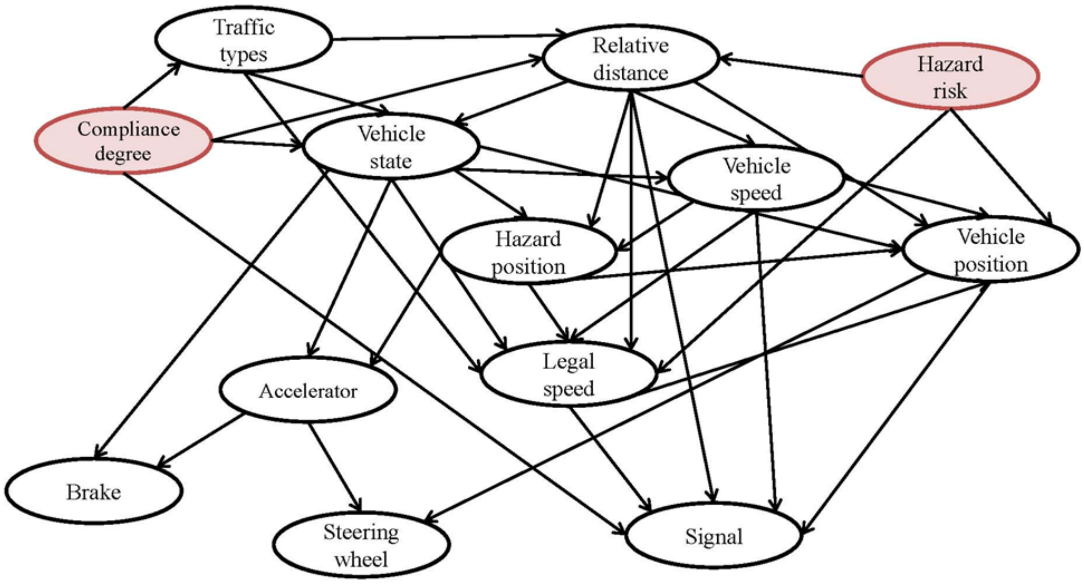


FIGURE 3. Objective risk estimation model by Bayesian network using simulated annealing

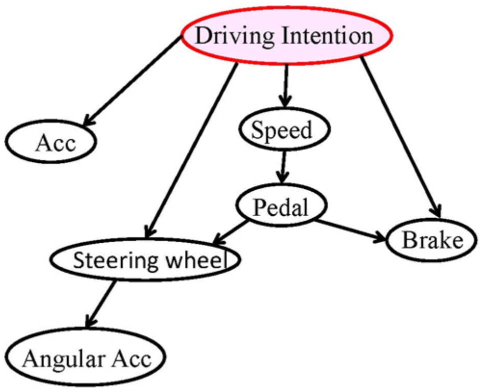


FIGURE 4. Subjective risk estimation model by Bayesian network

Here, as in the objective risk estimation model, the Bayesian network of the driver intention estimation model is constructed using Weka (Waikato Environment for Knowledge Analysis), and is shown in Figure 4. For the data set used, the speed, acceleration, steering wheel, pedal operation, brake operation, and steering angular velocity of the car were used as random variables. The Bayesian network estimates the driver's intention to stop, accelerate, drive, decelerate, turn left and turn right. And then substituting the calculated driver intention probability P_i into Equation (1), the subjective risk value R_s is estimated.

As can be seen in Equation (1), in the case of acceleration/deceleration, as the intent of deceleration increases, the subjective risk value felt by the driver is higher, and as the intention to accelerate by depressing the accelerator is larger, the subjective risk value becomes lower. In addition, the accuracy of behavior estimation model using the Bayesian network showed a relatively high classification accuracy of 92.65% by cross validation.

4. **Driving Situation Estimated by Using Risk Estimation Model.**

4.1. **Cognitive index of collision risk KdB.** In order to prevent a rear-end accident in the following car, a cognitive index of collision risk to the preceding vehicle, KdB, was proposed [8]. KdB represents the change rate of the back area of the front car reflected on the retina of the driver, and is expressed by Formula (2), where $k = 4 \times 10^7 \times R_k/V_k$, R_k represents the distance between the preceding vehicle and the driver's vehicle, and V_k represents the relative speed with the preceding vehicle.

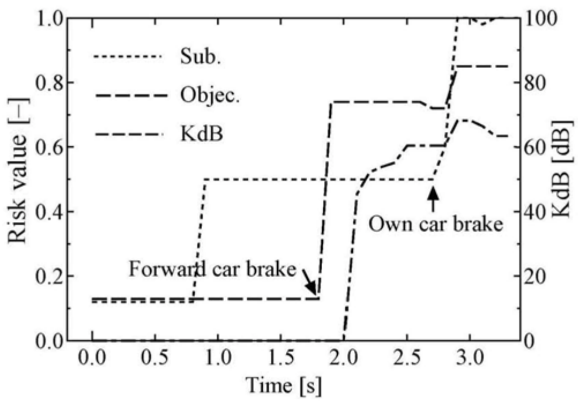
$$\mathrm{KdB} = \begin{cases} 10 \times \log(-k), & k < -1 \\ -10 \times \log(k), & k > 1 \\ 0, & -1 \le k \le 1 \end{cases} \tag{2}$$

It has been reported that the brake start time is evaluated using this index and it is possible to distinguish between a rear-end accident and safe driving with reference to KdB = 50 [dB] [8]. In this study, we estimate the risk of driving situation using the risk estimation model with KdB = 50 [dB] as a reference.

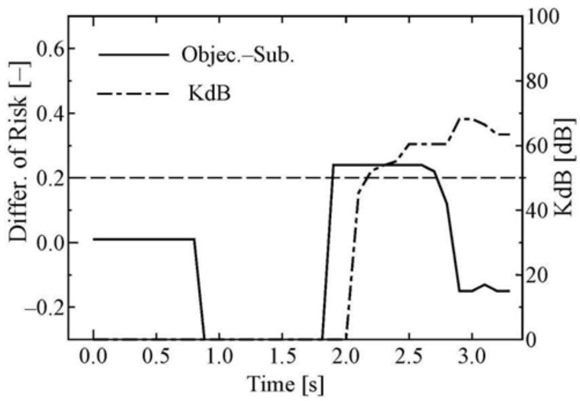
4.2. **Estimation of risk situation by risk estimation model.** Here, we will consider the estimation result of the risk estimation model taking as an example a collision risk situation. Figure 5 shows the estimation result of the risk estimation model and the evaluation result of KdB in the incidents of a collision risk situation. Here, Figure 5(a) shows the comparison between the estimated value of the risk estimation model and KdB, and Figure 5(b) shows the difference between objective risk and subjective risk as the degree of driving risk situation (DRS), and comparison with KdB.

$$\mathrm{DRS} = \text{Objective risk value} - \text{Subjective risk value} \tag{3}$$

In addition, Figure 6 shows the screen of a near miss in a collision risk situation. Here, Figure 6(a) shows the image that corresponds to the time when the objective risk shown



(a) Risk value and KdB



(b) Difference of risk value and KdB

FIGURE 5. Risk values obtained from objective and subjective estimation models in the incidents of collision risk situation

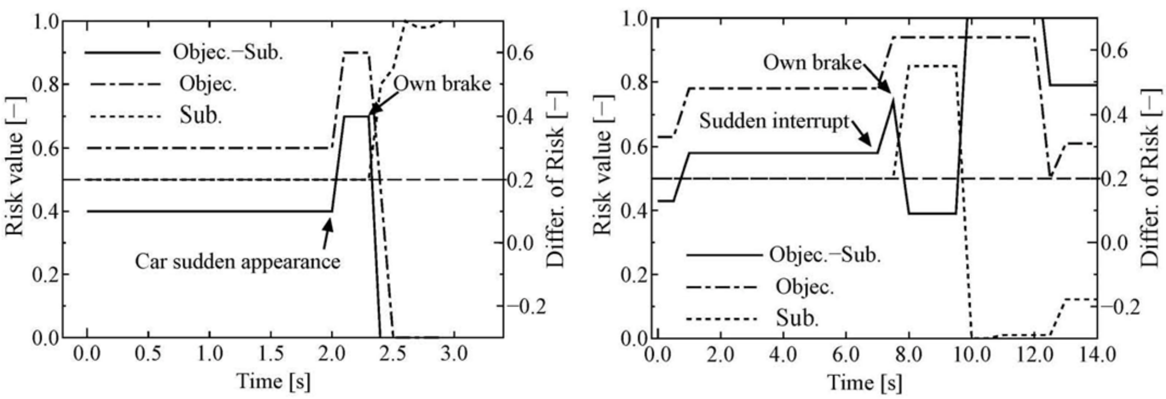
(a) Forward car brake

(b) Own car brake

FIGURE 6. The images of the collision risk situation

in Figure 5(a) suddenly rises when the front vehicle applies the brake, and Figure 6(b) shows the image corresponding to the time when the subjective risk sharply rises in Figure 5(a) when the driver is applying the brake. As can be seen in Figure 5(a), the estimated objective risk increases at a slightly earlier timing than KdB, and thereafter holds a high value with almost the same trend as KdB. Moreover, in Figure 5(b), the risk degree of the driving risk situation defined by this research when KdB exceeds 50 [dB] was about DRS = 0.2. That is, it was found that the driving situation at KdB = 50 [dB] corresponds to the danger degree of about DRS = 0.2, the driving risk situation in this study.

Furthermore, the results of applying the degree of driving risk situation to overtaking and a car heading are shown in Figure 7. Here, Figure 7(a) shows the result in the case of the car heading and Figure 7(b) shows the result in the case of the overtaking. The identifying degree of the driving risk situation is DRS = 0.2, which is indicated by a broken line. In addition, Figure 8 shows an example of the images of the car heading and overtaking. Here, Figure 8(a) shows the image of the emergence of the front vehicle suddenly in the case of the car heading, and Figure 8(b) shows the state of the car which was interrupted suddenly by the lane change in the case of overtaking. In the case of the car heading shown in Figure 7(a), the danger level of the driving risk situation rapidly increased due to the sudden appearance of the front vehicle, exceeding 0.2, but the brake operation of the driver was delayed, and the scene of the near miss period appeared. In the case of overtaking shown in Figure 7(b), although the driver is watching while driving, the danger level of the driving risk situation sharply increases due to the appearance of the interrupted vehicle due to the lane change, and the corresponding braking operation.



(a) Risk of car heading (b) Risk of car overtaking

Figure 7. Risk values obtained from objective and subjective estimation model in the case of the overtaking and car heading

(a) Screen of car heading (b) Screen of car overtaking

Figure 8. The images of the car heading and overtaking

It seemed that it was a little late. In other words, although KdB was the only accident prevention model in following car, the degree of driving risk situation in this research can be considered to be able to the case of overtaking and car heading.

5. **Conclusions and Remarks.** In this research, a method to estimate subjective risk and objective risk existing in the traffic environment and to estimate the degree of Driving Risk Situation (DRS) from the difference of risk values was proposed. In addition, it was found that the driving situation with parameter KdB = 50 [dB] that evaluates the danger of a rear collision corresponded to the danger degree of about DRS = 0.2 driving risk situation in this study. Then, we applied the parameter DRS to evaluating the danger level of the driving risk situation to the scene of the car heading and overtaking, and confirmed its usefulness.

As future work, we believe that hearings will be conducted by the car teacher on many traffic situations and the reliability of the true value of the risk value will be further improved.

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