Modeling of Car Driver Cognitive Process Based on Hazard Perception In Front of Car

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Abstract. Intention estimation is a way to realize an effective driver support. The construction of driving behavior model is an important step for its realization through a model based prediction of driver’s behavior in real driving situation. For the purpose, we constructed a computational model of hazard perception while driving assuming a hazard as a possibility of contact with other objects. We formalized two types of hazard, an explicit hazard and an implicit hazard based on the position probability distribution of object. We compared a reconstructed eye movement by the model and a human eye movement.

Keywords: Driver’s model, Computational model, Hazard perception, Eye movement

1 INTRODUCTION

In the motorized society of today, various types of safety supporting systems are introduced to improve human driving safety. In the near future, driving assistance systems that deeply concern human cognitive process will be introduced. For its realization, a use of driving assist system that compare an observed human driving behavior with that of an ideal driving behavior model might be effective. But the driver’s status observable from outside is limited. So the driving assist system must estimate the cognitive process of the driver and decide its assisting action based on the estimation result. A computational model of driving action production including driver’s cognitive process is necessary for the purpose.

Drivers observe their environment through vision. If we observe a driver’s eye movement, we might be able to estimate what action the driver is planning. It means that if the assist system predicatively calculates driver’s eye movement while driving, compares the prediction with actual human’s eye movement and estimates driver’s internal state that caused current behavior, it will be able to supply an information that the driver is not noticed. For realizing the internal state estimation, we need a computational model of driver’s eye movement while driving a car that reflects the internal state of the driver and the outer world situation of the moment. So, in this study, we try constructing a computational model of driver’s eye movement based on a hazard perception on the environment. Though the eye motion is studied long [1], a computational model of the driver’s eye motion is not established yet.

For the human eye motion, a saliency-based visual attention model [2] is proposed. It predicts allocation of visual bottom-up attention based on saliency computed in a visual system of brain. But this model is focusing on a general image feature processing and not on the understanding of driving process. Huestegge et al. discuss a hazard perception. But they don’t step into the computational theory[3]. To aim a practical driving assist, the model should express the driver’s internal process that explains the driving behavior.

Salvucci et al. succeeded reproduction of human eye movement and steering action using a rule-based system representing a specific driving situation[4]. But the rules tend to task dependent and will not explain a principle of the driving behavior in general. As the variation of driving scenes spreads over very wide range, it is better to find more basic principle of driving behavior generation.

So in this study, we pursuit modeling of the human hazard perception that can explain wide variety of driving scenes. One of the largest purposes of visual perception for driving is detection of hazardous situation. To realize the perception, brain recruits all of visual, decision making and action planning systems. Understanding of these processes will be a foundation for the computational theory of the human driving.

The next section two explains the hazard avoidance model used in this study. In this section, an explicit- and implicit-hazard models are introduced. Section three shows some comparisons between the model behaviors and the real driver’s behaviors. In this section we also present an improvement model of the basic model proposed in Section two according to the experimental results.

2 MODEL OF HAZARD AVOIDANCE

A. Hazard perception that directs driving behaviors

In our previous model, we described a set of rules for the eye movement and fixation to objects[5][6]. But the system did not work well for unassumed situations. To construct a model that can work in various real world driving situations, we need a deeper understanding of the hazard perception mechanism and its computational principle that dominates the driving behavior.
Purpose of the driving behavior in a shorter time span is a moving forward while avoiding hazard. The mental process of driving includes a creating of driving plan, a decision of driving intention of the moment, an environmental observation for the decision, and an execution of the intention at least. All of them relate the avoidance of hazardous situation. For example, if we change a driving plan for a hazardous situation, the hazard may disappear. Thus, the driving is a dynamic behavior relating the hazard perception. If we can understand the mental process of hazard avoidance, we will be able to understand a dynamic aspect of deriving.

B. Factor of hazard in this study

In this study, we assumed the hazard as a possibility that own car contacts with other object. To realize the perception of hazard, we calculate position probability distribution (PPD) for a few seconds future of own car and other objects. If an overlap of PPDs becomes large, we consider the possibility of contact, the hazard perception, is arising. In this study, we assumed two types of hazards.

(1) Explicit Hazard

The explicit hazard is caused by When we see a pedestrian beside a road oncoming car approaching, we care and caused by the explicit hazard perception.

By observing the object that causes information on its position and calculate PPD within a few seconds observed information always includes always has a distribution. The driver observe the object, and will observe because the object may change.

For the calculation of PPD, we used simultaneously: go-straight, right-turn, of the these distributions was used to variance of each distribution accounts for the prediction ambiguity.:For example, the go-straight Kalman Filter is described as follows.

\[
K_{\text{forward}}(t) \leftarrow \sum_{\text{forward}}(t) \left( \sum_{\text{forward}}(t) + \sum_{\text{y}} \right)^{-1} \tag{1}
\]

\[
\hat{x}_{\text{forward}}(t) \leftarrow \hat{x}_{\text{forward}}(t) + K_{\text{forward}}(t) (y(t) - \hat{x}_{\text{forward}}(t)) \tag{2}
\]

\[
\hat{x}_{\text{forward}}(t+1) \leftarrow F_{\text{forward}} \hat{x}_{\text{forward}}(t) + \sum_{\text{forward}}(t) \sum_{\text{forward}}(t) + G \sum_{\text{w}} G^T \tag{4}
\]

where \( \hat{x}_{\text{forward}}(t) \), \( y(t) \), \( K_{\text{forward}}(t) \) denote the estimated object’s velocity and position, observed target information, and the Kalman gain at time \( t \), respectively. \( G \) denotes white noise, and \( F_{\text{forward}} \) and \( \sum_{\text{forward}}(t) \) denote the state transition matrix and error covariance matrix of the go-straight Kalman filter.

The Kalman gain is updated by (1). The internal state and the error covariance matrix of the go-straight Kalman filter are updated using observed information \( y(t) \) by (2) and (3). The inner state of the object’s velocity, position and the error covariance matrix at time \( t+1 \) are predicted by (4) and (5), respectively.

\[
p_{\text{exp}}(x) = w_{\text{forward}} N(\hat{x}_{\text{forward}}(t+n), \sum_{\text{forward}}(t+n)) + w_{\text{left}} N(\hat{x}_{\text{left}}(t+n), \sum_{\text{left}}(t+n)) + w_{\text{right}} N(\hat{x}_{\text{right}}(t+n), \sum_{\text{right}}(t+n)) \tag{6}
\]

where \( N(\mu, \Sigma) \) denotes a normal distribution with average \( \mu \), and covariance \( \Sigma \), coefficients \( w_{\text{forward}}, w_{\text{left}}, w_{\text{right}} \) denote the weights of the Kalman filters for each direction, and \( w_{\text{forward}} + w_{\text{left}} + w_{\text{right}} = 1 \). The weights are determined according to the difference between \( \hat{x}_{\text{forward}}(t) \) and \( y(t) \), where \( \hat{x}_{\text{forward}}(t) \) denotes the inner state of the corresponding Kalman filter. From the results, we can calculate the distribution of the object by (7). We describe the explicit hazard as \( d_{\text{explic}}(x,t) \), that is an overlap of predicted distribution for the visible object and the driver’s own car.

\[
e_{\text{explic}}(x,t) = \max \{ p_{\text{explic}}(x), p_{\text{explic}}(x), \ldots, p_{\text{explic}}(x) \} \tag{7}
\]

\[
d_{\text{explic}}(x) = \min \{ e_{\text{explic}}(x,t), e_{\text{self}}(x,t) \} \tag{8}
\]

where \( e_{\text{self}}(x,t) \) is also calculated with the similar procedure as the above in Eq(20).
Chaer et al. proposed a similar architecture to our model[8]. The difference is that the weight (gain) of each Kalman filter in our model is modified according to the distance between the predicted position of the target-car by each Kalman filter and that of actual one. Therefore, if the two positions are closed to each other, the weight for the Kalman filter is enlarged. On the other hand, Chaer’s model derives the weight (gain) for each Kalman filter only from current input.

(2) Implicit Hazard
The implicit hazard is perceived when the driver directs his/her attention to an object that can’t be seen, but may come out from an occluding corner. The implicit hazard is also calculated by the overlap of PPDs between the self car and the possibly coming out car. The coming out car is located at a place that causes the highest hazard in the driver’s mind, and its PPD doesn’t shrink by the observation because no information is acquired by looking at the corner. Here, we consider a case in which the driver’s car is trying to go through an intersection (Fig. 2).

The most probable scenario is that the invisible car located at a distance \( D_c \) from the intersection with the average speed \( v_0 \) simultaneously arrives at the intersection with the driver’s car ((a) in Fig. 2). We call the distance \( D_c \) critical distance, which is calculated by (9) where the driver’s car speed is denoted as \( v_c \).

\[
D_c / v_c = D_e / v_0 \implies D_e = \frac{v_c}{v_0} D_c \quad (9)
\]

The critical distance changes when the driver’s car approaches the intersection. Assume no car is found when the distance \( D_e \) and the speed of oncoming car is \( v_0 \), the car is most likely located at distance \( D_e \) but with lower probability(Fig.2(b)). The distance \( D_e \) can be calculated by (10) where \( \theta \) is an angle from the front to observe the occluded corner, \( L \) is half of the road width.

\[
D_e = D_e \tan \theta = D_e \left( \frac{L}{D_b} \right) \quad (10)
\]

Based on the estimated position of the oncoming car, we can calculate PPD using (11) and (12).

\[
\hat{x}_{\text{implicit}}(t + 1) \leftarrow F_{im} \hat{x}_{\text{implicit}}(t) \quad (11)
\]

\[
\hat{s}_{\text{implicit}}(t + 1) \leftarrow F_{im} \hat{s}_{\text{implicit}}(t) + G \sum_u G^T \quad (12)
\]

The initial value of \( \hat{x}_{\text{implicit}}(t_0) \) is set to the estimated position of the oncoming car. The matrix \( F_{im} \) originally represents a situation where the oncoming car enters the intersection at a speed to just collide with the driver’s car. But this time, we used \( F_{im} \) with the fixed speed \( v_0 \) for simplicity. Then, the predicted distribution of the non-visible object is calculated by (13) and (14).

\[
p_{\text{visible}}(x) = \mathcal{N}\left( \hat{x}_{\text{implicit}}(t + n), \hat{s}_{\text{implicit}}(t + n) \right) \quad (13)
\]

\[
e_{\text{implicit}}(x, t) = \max \left\{ p_{\text{visible}}(x), p_{\text{visible}}(x), \cdots, p_{\text{visible}}(x) \right\} \quad (14)
\]

Then, we can calculate PPD of the non-visible but might be coming car behind the blind corner.

\[
d_{\text{implicit}}(x, t) = \min \left\{ e_{\text{implicit}}(x, t), e_{\text{Self}}(x, t) \right\} \quad (15)
\]

C. Risk Evaluation and Eye Movement
After calculating PPD for the observable and non-visible objects, we can calculate the risk of each object and detect an object with the highest risk. We assume the driver watch the current position of the highest risk object, but not the risk position.

\[
x^* = \arg \max_x \left\{ d_{\text{explicit}}(x, t), d_{\text{implicit}}(x, t) \right\} \quad (16)
\]

If an object is not visible, the driver sees the corner from which the object comes out.
D. Distribution prediction of the driver’s car:

PPD of driver’s car \( \hat{x}_{\text{Self}}(t) \) is also calculated with the similar procedure as above. In this case, the driver has to get the information of the driver’s own position by observing the front view. We used go-straight Kalman filter to calculate PPD for the driver’s car.

\[
\begin{align*}
\hat{x}_{\text{Self}}^{\text{straight}}(t+1) & \leftarrow F_{\text{straight}} \hat{x}_{\text{Self}}(t) \\
\tilde{\Sigma}_{\text{Self}}^{\text{straight}}(t+1) & \leftarrow F_{\text{straight}} \tilde{\Sigma}_{\text{Self}}^{\text{straight}}(t) F_{\text{straight}}^T + G \Sigma_w G^T
\end{align*}
\]

(17)

\[
p_{t+1}^{\text{Self}}(x) \equiv N(\hat{x}_{\text{Self}}^{\text{straight}}(t+n), \tilde{\Sigma}_{\text{Self}}^{\text{straight}}(t+n))
\]

(18)

\[
e_{\text{Self}}(x,t) = \max \left\{ p_{t}^{\text{Self}}(x), p_{t+1}^{\text{Self}}(x), \ldots, p_{t+n}^{\text{Self}}(x) \right\}
\]

(19)

\[
e_{\text{Self}}(x,t) = \max \left\{ p_{t}^{\text{Self}}(x), p_{t+1}^{\text{Self}}(x), \ldots, p_{t+n}^{\text{Self}}(x) \right\}
\]

(20)

3 Model Simulation and Human Behavior Comparison

A. Driving data acquisition and simulator construction

We reconstructed human eye movement while driving through an actual city traffic scene by the model, and compared it with the actual human driver eye movement while the driver is running through the same traffic scene with the simulator. We asked two instructors of driving school to drive the city and recorded the eye movement, car position, road traffic situation in a rate of 10Hz (Fig.3) and embedded those data into the hazard perception simulator.

Fig.4 shows a scene of the hazard calculation. The left part represents the self car (red box), on coming car from the front and the possibly coming car from the left, and view point of the self car driver (a dot on the road). The right side represents PPDs calculated for each of the self car, the oncoming car from the front and the possibly coming car from the left.

B. Comparison of the model and human eye movement

The eye movement of human and the simulated one is compared in every 10 meter block. In each of the blocks, the target of fixation is encoded for every 0.1 second and the object that is seen longest is compared. Our proposed model successfully reconstructed 74% of the human eye movements. But the model failed to reconstruct the eye movement toward a few narrow intersections.

Fig.5 shows duration of eye fixation to the hazardous object. In the simulated eye movement (Fig.5 upper half), the model gazed object continuously. In the longest case, it continued looking at the possibly coming car from left more than 1.5 second, almost 30 meters in distance. In contrast, human observed the car from left and the car from front alternatively. It is not likely that human driver doesn’t look front of own car for this long time and distance in real world driving.
C. Introduction of front hazard

It is sure that we observe front of own car while driving, and feel large hazard when we don’t look forward so a long time. But we haven’t considered a hazard of front except a case that oncoming car is approaching or turning thus far. But the human behavior suggests a hazard in front. When we don’t see front by other hazard, the front hazard increases and forces us to see front, and reduces the hazard perception by the observed information from front. Then, what hazard are we perceiving in front?

While driving, we always control the steering of car. This is because the car movement is affected by a road surface unevenness or a side wind and shifts away from the road center. It means that the driver is observing the position of self car and calculating the error in position from the driving plan. To represent the process, we introduced a position variance for both sides of road in our model. While the driver is looking at other object, the position of the car become ambiguous, the PPD variance of own car increases toward the left-right direction and PPD overlaps with road border within a few seconds. The variance decreases immediately when the driver observes the front.

According to this insight, we newly introduced front PPD for the driver’s car position. In the case of go-straight,

$$\mathbf{X}_{self}^{\text{stright}}(t) \leftarrow \mathbf{F}_{\text{stright}}^{\text{front}} \mathbf{X}_{self}(t-1)$$

$$\sum_{self}^{\text{stright}}(t) \leftarrow \mathbf{F}_{\text{stright}}^{\text{front}} \sum_{self}^{\text{stright}}(t-1) \mathbf{F}_{\text{stright}}^{\text{front}} + \mathbf{G} \sum_{self} \mathbf{G}^T$$

where \( t = t_0 + n \),

(21)

$$\sum_n$$

(22)

where \( t_0 \) is the last time when the driver confirmed his/her car position by looking forward. Then we obtain the PPD for the straight as

$$p_{Self}^t(x, t_0 + n) = \mathcal{N}(\mathbf{X}_{Self}(t_0 + n), \sum_{self}(t_0 + n))$$

(23)

The final PPD for own car is calculated as a mixture of the three predicted distributions.

$$p_{Self}^t(x, t_0 + n) = w_{\text{left}} \mathcal{N}(\mathbf{X}_{left}(t_0 + n), \sum_{left}(t_0 + n)) + w_{\text{right}} \mathcal{N}(\mathbf{X}_{right}(t_0 + n), \sum_{right}(t_0 + n)) + w_{\text{forward}} \mathcal{N}(\mathbf{X}_{forward}(t_0 + n), \sum_{forward}(t_0 + n))$$

(24)

By calculating the disjunction of the position distributions along time, we get PPD of driver’s car when the driver didn’t see front from time \( t_0 \) by (26).

$$e_{Self}(x, t_0 + n) = \max(p_{Self}^t(x, t_0 + n), p_{\text{left}}^t(x, t_0 + n), \ldots, p_{\text{forward}}^t(x, t_0 + n))$$

(25)

The front hazard can be detected by calculating the overlap between \( e_{Self}(x, t_0) \) and \( e_{\text{RoadBorder}}(x) \). where \( e_{\text{RoadBorder}}(x) \) denotes the PPD for the road border. Therefore, if the following equation is larger than a threshold, the driver recognizes the front hazard.

$$d_{\text{frontHazard}}(x) = \min(e_{Self}(x, t_0), e_{\text{RoadBorder}}(x)),$$

(26)

where \( e_{\text{RoadBorder}}(x) \) was prepared by hand in this experiment. When the driver observes the front, the predicted position and the covariance matrix are set to the observed position \( \mathbf{X}_{self} \) and the unit matrix \( \mathbf{I} \), respectively.

$$t_0 = t, \quad n = 0, \quad \mathbf{X}_{self}(t_0) = \mathbf{X}_{self}, \quad \sum_{self}(t_0) = \sum_{left}(t_0) = \sum_{right}(t_0) = \mathbf{I}.$$  

(27)

Note that in the above equations, the PPD of the driver’s car is different from the PPD calculated in Eq(19). The prediction begins from the last observation timing for the driver’s car position and is continued till the current time or the time when the driver observes front. On the other hand, Eq(19) yields the position prediction in the near future from now. For simplicity, we set the initial position of \( \mathbf{X}_{self}(t) \) in Eq(17) to \( \mathbf{X}_{forward}(t_0 + n) \) of Eq(21) for calculating Eq(19).

Then, by using the new model, we reconstructed driver’s eye movement through an actual city traffic scene (Fig.6). The duration of eye fixation to objects other than front have reduced, and the eye moved alternatively with the front and the objects. The behavior is more likely as human if we compare the eye movement with actual human driver in Fig.5, though some improvement of model description and parameter tuning might be necessary. This result suggests validity of the front hazard model.
4 CONCLUSION

In this study, we constructed the computational model of human hazard perception while driving. Assuming hazard as a possibility of contact with other objects, we formalized two types of hazard. One is the explicit hazard based on the PPD of observable object, and another is the implicit hazard based on the possibility of coming out object’s PPD. By measuring actual human driver behavior and constructing a simulator for real world traffic scene, we compared the model and human behavior. The result suggested us a possibility of hazard in the front that express a position error in left-right direction. By introducing the hazard perception process to our conventional model, the model behavior became more similar to actual human behavior. But we need much more cases of driving scenes including dangerous ones to improve and evaluating validity of the proposed model.

REFERENCES