特集

Driver Turning Behavior Prediction at Intersections -Improving Prediction Performance with Driver Behavior Adaptation- *

内藤貴博 Takahiro NAITO　森本寛 Hiroshi MORIMOTO　伊藤隆文 Takafumi ITO　山本敏雅 Toshimasa YAMAMOTO
福本晴継 Harutsugu FUKUMOTO

In this paper, we propose a new prediction technology for turning behavior at intersections using a driver behavior model to reduce accidents at intersections. The technology adapted the driver behavior model to the individual characteristics of each driver to improve prediction time and accuracy. The driver behavior model consisted of vehicle control signals, such as the accelerator throttle, brake, and velocity. In tests, in order to predict a driver's behavior, the drivers either went straight or turned at intersections in a driving simulator. Consequently, after the adaptation of the proposed technology, the prediction recognition accuracy rate was 95.6% at a position of five seconds driving distance to the intersections, however, before the adaptation, the accuracy rate was only 52.5%.

Additionally, in this paper we propose a new navigation system based on turning behavior prediction at intersections. The navigation system would tell the driver an updated guidance message in case that the driver appears to have misheard the previous guidance.

Key words: Driving behavior prediction, Turning behavior, Driver behavior adaptation, Navigation system

1. INTRODUCTION

The number of traffic accidents continues to increase in the last decade. In response, preventive safety technologies to decrease the dangers or sources of accidents have been researched and developed. We believe that driving behavior prediction technology contributes to decreasing accidents as a preventive safety technology. For example, if a car can predict dangerous driving behavior in advance, the car can warn its driver of the danger early on. In Japan in particular, over 50 % of traffic accidents happen at intersections. Therefore, we focused on predicting turning behavior at intersections[1].

First, we developed a turning behavior model at intersections. The model consists of vehicle control signals, the accelerator throttle, brake, and velocity. We tested it in a driving simulator. The test showed that some drivers had a low recognition rate because the turning behavior model represented the average of plural drivers' behaviors.

In this paper, we propose a prediction technology for turning behavior at intersections with driver behavior adaptation. The technology adapts the weights of the turning behavior model for individual characteristics to improve prediction time and accuracy. Furthermore, we propose a new navigation system using the prediction technology.

2. DRIVER BEHAVIOR MODEL

Studies on driving behavior prediction were started in the late 1990s. Liu modeled driving behavior as a Hidden Markov Model (HMM)[2)8)]. HMM is widely used in driving behavior prediction[9)-11)]. Some researchers also proposed a Bayesian network model[5)6)12)]. These models find it hard to predict driving behaviors at 3 seconds before intersections, because they require a longer observation time.

We utilized both the driver's operation-time and operation-amount to predict the driving behavior earlier. We developed a method for creating a behavior model that represents the preparation for turning at intersections and for comparing it with actual drivers' operations[1)].

The turning behavior model is shown in **Fig. 1**. The horizontal axis represents time, and at time = 0, the car is in the intersection. The vertical axis represents the normalized value of vehicle control signals. Each of the dots with lines indicates a normalized accelerator operation, brake operation, and velocity. We constructed this turning behavior model from 80 samples of the behaviors for preparing to turn at the intersections in the driving simulator. At first, we clustered these samples into five groups using the k-means method[7)]. Next, we defined a typical pattern as the average in each

*（社）自動車技術会の了解を得て，「Review of Automotive Engineering」Vol. 29 No.2 より，一部加筆して転載

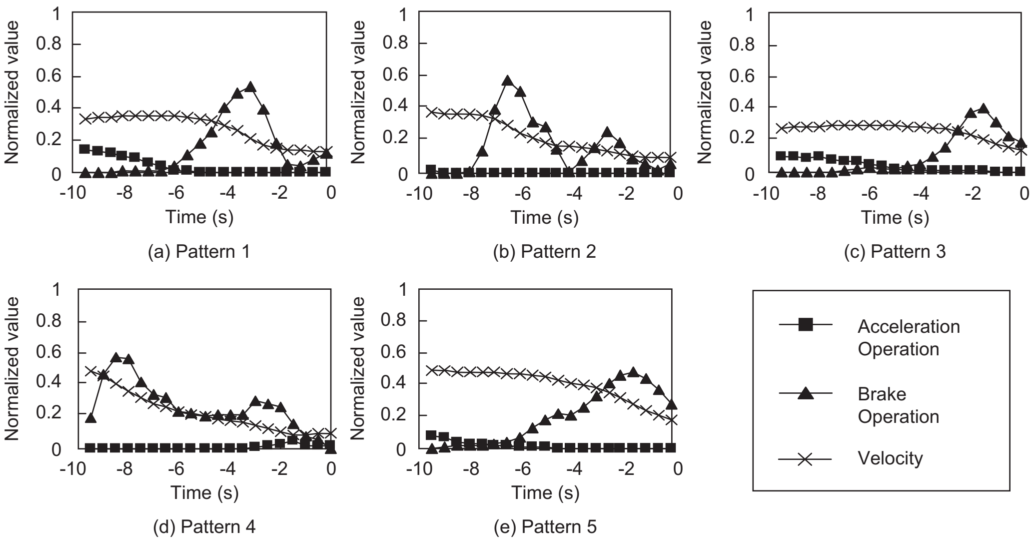


Fig. 1 Turning behavior model

group. Finally, we obtained a behavior model consisting of five typical patterns.

We tested our prediction method in the driving simulator. The driving simulator is shown in Fig. 2. In the experiments, the drivers either went straight or turned at the intersections. The recognition rate of the drivers included in the turning behavior model was better than that of the drivers not included in the turning behavior model. Therefore, we expect to improve prediction performance if we adapt the turning behavior model to the individual characteristics of specific drivers.

In this paper, we propose a prediction technology with driver behavior adaptation. A data flow diagram in our prediction system is shown in Fig. 3. The prediction system consists of two components. One component is the driving behavior prediction, the other is driver behavior adaptation. In the driving behavior prediction, the comparison-(a) block compares vehicle control signals with the turning behavior model and then outputs a similarity. If the similarity is over a threshold, we decide that the driver will turn at the intersection. In the driver behavior adaptation, the driving behavior recognition block outputs a driving behavior the driver has done; this is a recognition result. The comparison-(b) block compares the recognition result with the prediction result and then outputs an evaluation value. The updating weight block re-computes a set of weights in the turning behavior model based on the evaluation value.

In order to achieve the adaptive system, a solution is required to deal with two types of variations causing a similarity error between the turning behavior model and the set of vehicle control signals in actual driving. One is a variation between identities, and the other is a variation within an identity. Therefore, we add the driving behavior adaptation to a compensation mechanism for these variations.

Fig. 2 Driving simulator

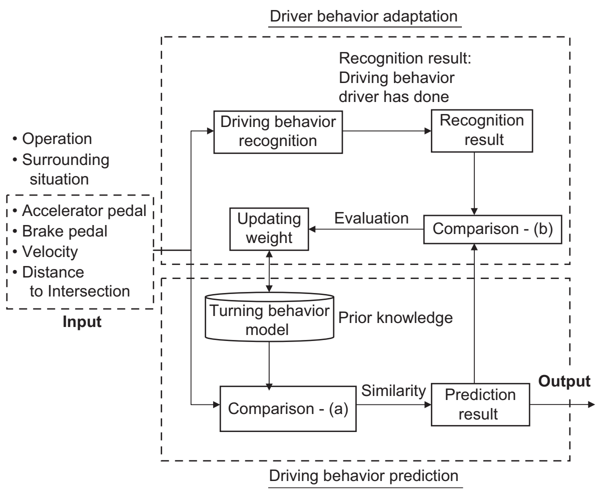


Fig. 3 Data flow in the prediction system

3. VARIATION BETWEEN IDENTITIES AND VARIATION WITHIN IDENTITY

We assume that the variation between identities appears in a frequency rate in the use of typical patterns. Three drivers' pattern frequency rates are shown in **Fig. 4**. The horizontal axis corresponds to the typical patterns of the turning behavior model shown in **Fig. 1**. The vertical axis represents the frequency rate. Driver A has a high frequency rate for patterns 2 and 4. Driver B has a high frequency rate for patterns 1 and 5. Driver C has a high frequency rate for patterns 1 and 4. Therefore, each driver probably has a characteristic combination of the typical patterns.

We assume that the variation within identity appears in time series variations of vehicle control signals[3]. Ten sets of vehicle control signals of specific drivers' preparations for turning at the intersections are shown in **Fig. 5**. Each of the dots indicates a normalized accelerator operation, brake operation, and velocity. The line indicates a summation of the three vehicle-control-signal standard deviations. The horizontal axis represents time, and at time = 0, the car is in the intersection. The left vertical axis represents the normalized value, and the right vertical axis represents the summation of the standard deviations. Each of the vehicle control signals appears dispersive at all time instants. However, the summation of the standard deviations at around 3 seconds before the intersection is smaller than that at any other time instants. Therefore, we estimate that drivers probably have time instants in which the vehicle control signals are relatively constant.

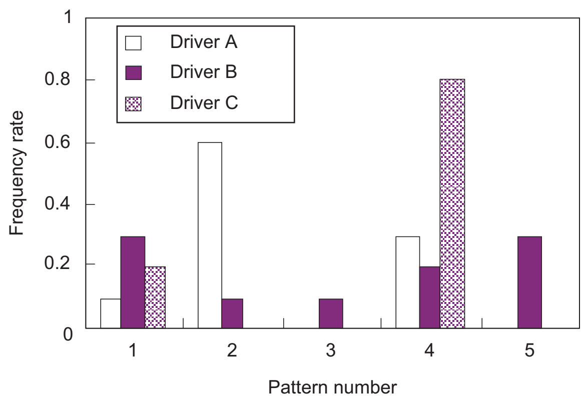


Fig. 4 Pattern frequency

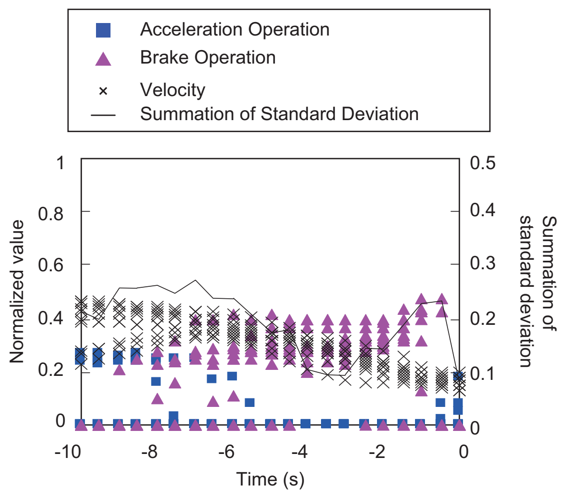


Fig. 5 Vehicle control signals of drivers' preparation for turning at intersections

From the above results and assumptions, we theorize the followings.

(1) Each driver has a distinctive combination of the typical patterns.

(2) Each driver has distinctive time instants in which the vehicle control signals are relatively constant.

Based on these, we develop an adaptive system to optimize the influences of typical patterns of time instants in the turning behavior model.

4. DRIVER BEHAVIOR ADAPTATION

4.1 Prediction: Comparison with turning behavior model

We explain about the comparison-(a) block shown in **Fig. 3**. We divide each pattern in the turning behavior model into sub-patterns by time windows to raise the representative power. The comparison-(a) block compares the sub-patterns with actual vehicle control signals. In this paper, the width of the time windows is 5 seconds and the interval between the time windows is 1 second. The similarity calculation is as follows.

First, we define the actual vehicle control signals at a discrete time t.

$$\mathbf{x}(t) = \left(x_1(t),\, x_2(t),\, x_3(t)\right)^T \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (1)$$

where, $t = 0$ indicates the car is at a start, $x_1(t)$ is an accelerator operation, $x_2(t)$ is a brake operation, and $x_3(t)$ is velocity.

Second, we define the actual vehicle control signals of the last n samplings.

$$\mathbf{X}(t) = \left(\mathbf{x}(t-n+1),\, \mathbf{x}(t-n+2), \cdots, \mathbf{x}(t-1),\, \mathbf{x}(t)\right) \cdots\cdots\cdots (2)$$

where, n is total sampling number equal to the width of the sub-pattern.

Third, we define the vehicle control signals in the sub-pattern.

$$\mathbf{y}(i,s) = \left(y_1(i,s), y_2(i,s), y_3(i,s)\right)^T \quad \cdots\cdots\cdots\cdots\cdots (3)$$

where, i is the sub-pattern number, s is the sampling period of the time window, $y_1(i,s)$ is an accelerator operation, $y_2(i,s)$ is a brake operation, and $y_3(i,s)$ is velocity.

Fourth, we define the sub-pattern.

$$\mathbf{Y}(i,s) = \left(\mathbf{y}(i,s)-n+1), \mathbf{y}(i,s-n+2),\cdots, \mathbf{y}(i,s-1), \mathbf{y}(i,s)\right) \cdots (4)$$

Fifth, we define the Euclidean distance between the data in the sub-pattern and actual vehicle control signals.

$$d\left(\mathbf{x}(t), \mathbf{y}(i,s)\right) = \sqrt{\sum_{k=1}^{3}\left(x_k(t)-y_k(i,s)\right)^2} \quad \cdots\cdots\cdots (5)$$

Sixth, we sum up the distances over the n samples and then multiply the distance summation by a weight.

$$d^*(i,t) = w(i,t)\sum_{k=1}^{n} d\left(\mathbf{x}(t-k+1), \mathbf{y}(i,s-k+1)\right) \quad \cdots\cdots\cdots (6)$$

where, $w(i,t)$ $(0 \le w(i,t) \le 1)$ is the weight of the sub-pattern. The reliability of the sub-pattern i is higher as $w(i,t)$ is closer to 0.

Seventh, we select the minimum $d^*(i,t)$ of all sub-patterns.

$$i_{MD}(t) = \arg\min_{i \in I}\left[d^*(i,t)\right] \quad \cdots\cdots\cdots\cdots\cdots (7)$$

Eighth, we normalize $d^*(i_{MD}(t),t)$ by the maximum $d^*(i_{MD}(t),t)$ until time t and then obtain the similarity.

$$S(t) = 1 - \frac{d^*\left(i_{MD}(t),t\right)}{\max\limits_{0 \le \tau \le t} d^*\left(i_{MD}(\tau),\tau\right)} \quad \cdots\cdots\cdots\cdots\cdots (8)$$

Finally, we predict the driver turning behavior at an intersection if the car is within 150 meters of the intersection and the similarity $S(t)$ is over a threshold θ.

4.2 Driver behavior adaptation: Updating weights

We explain about the updating weight block shown in **Fig. 3**. The updating weight block re-computes the weights $w(i,t)$ of all sub-patterns. The method of updating weight depends on the prediction result and the recognition result.

(1) Correct case: The prediction result is "turning" and is the same as the recognition result.

(2) Incorrect case: The prediction result is different from the recognition result.

For case (1), we attempt to improve the prediction time. For case (2), we attempt to reduce the number of false-positive predictions. No action is taken for any other cases.

(1) Correct case

We assign a reinforcement value to the sub-pattern on correct prediction and then update the weight of the sub-pattern.

First, we determine the reinforcement value $v(t_n)$ when we give a reward at a discrete time t.

$$v(t_n) = \begin{cases} \gamma^{(t-t_n)} r & \text{if } S(t_n) \ge \theta \\ 0 & \text{otherwise} \end{cases} \quad \cdots\cdots\cdots\cdots\cdots (9)$$

where, t_n $(0 < t_n < t)$ is a discrete time, r is the reward, and γ is a common ratio of a geometric progression. The reinforcement value calculation in Eq. (9) is based on profit sharing. Profit sharing is a typical credit assignment method in the classifier system[4]. In this paper, γ is greater than one to improve the prediction time.

Second, we define a function to assign the reinforcement value to the sub-pattern $i_{MD}(t_n)$.

$$f_1(i,t) = \frac{\sum_{t_n=t_l}^{t} \delta_{i i_{MD}(t_n)} v(t_n)}{\sum_{t_n=t_l}^{t} \delta_{i i_{MD}(t_n)}} \quad \cdots\cdots\cdots\cdots\cdots (10)$$

where, δ is the Kronecker delta, and t_l $(0 < t_l < t)$ is a discrete time.

Third, we update an element $u(i,t)$ of the weight using the function $f_1(i,t)$.

$$u(i,t+1) \leftarrow u(i,t) - C_1 f_1(i,t) \quad \cdots\cdots\cdots\cdots\cdots (11)$$

where, C_1 is a constant.

Finally, we normalize $u(i,t)$ to obtain $w(i,t)$.

$$w(i,t) = \frac{\exp\left(Cu(i,t)\right)}{\sum_{j=1}^{K}\exp\left(Cu(j,t)\right)} \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots (12)$$

where, K is the number of total sub-patterns, and C is a constant.

(2) Incorrect case

We assign a penalty value to the sub-pattern based on an incorrect prediction and then update the weight of the sub-pattern.

First, we access the stored data $\mathbf{X}(t_r)$ of the vehicle control signals and then calculate the similarity $S(t_r)$ again. The data is stored from a discrete time t_1 to a discrete time t_2 ($t_1 \leq t_r \leq t_2 \leq t$). At the time t_2, the car is in the intersection.

Second, we determine the penalty value $p(t_r)$.

$$p(t_r) = \begin{cases} S(t_r)-\theta & if\ S(t_r) > \theta \\ 0 & otherwise \end{cases} \quad \cdots\cdots\cdots\cdots\cdots (13)$$

Third, we define a function to assign the penalty value to the sub-pattern $i_{MD}(t_r)$.

$$f_2(i,t_r) = \delta_{i i_{MD}(t_r)} p(t_r) \quad \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots (14)$$

where, δ is the Kronecker delta.

Fourth, we update an element $u(i,t_r)$ of the weight using the function $f_2(i,t_r)$.

$$u(i,t_r+1) \leftarrow u(i,t_r) - C_2 f_2(i,t_r) \quad \cdots\cdots\cdots\cdots\cdots\cdots (15)$$

where, C_2 is a constant.

Fifth, we normalize $u(i,t_r)$ to obtain $w(i,t_r)$ by Eq. (12).

Finally, we update the weight $w(i,t)$ through L iterations.

5. EXPERIMENTS

5.1 Methods

We tested the adaptive system in the driving simulator. Two drivers not included in the turning behavior model drove in the driving simulator courses. Both drivers were male and in their twenties. The data acquisition procedure was as follows.

(1) Each driver drove the estimation course shown in Table 1.
(2) Each driver drove 50 trips around the learning course shown in Table 1.
(3) Then each driver drove the estimation course again.

In the test, instructions for the drivers consisted of "course guidance" or "whether the driver should go straight or turn at an intersection." In the courses, there were no other cars on the road.

The evaluation procedure was as follows. At first, we updated the weights $w(i,t)$ in the learning course trips. The parameters in the prediction system are shown in Table 2. Next, we predicted turning behaviors in the estimation course trips using the updated weights and then output a recognition rate as a test result. In this paper, we define the recognition rate:

Recognition rate
= (the number of TP + the number of TN) / the total number ⋯⋯⋯⋯⋯⋯⋯⋯ (16)

where, TP is true positive and TN is true negative. In this test, TP and TN are followings.

(1) True positive: The prediction result is "turning" before the intersection and the driver has turned at the intersection.
(2) True negative: The prediction result is "non-reaction" before the intersection and the driver has gone straight through the intersection.

5.2 Results

Table 1 Driving courses in the driving simulator

(a) Learning course

Length	About 7 km
Number of intersections for turning	14
Number of intersections for going straight	8

(b) Estimation course

Length	About 5 km
Number of intersections for turning	10
Number of intersections for going straight	7

Table 2 Parameters of the prediction system

Parameter	Value
n	10
$u(i,t)$(initial)	1
θ	0.5
r	0.002
γ	1.2
K	30
C	1
C_1	0.8
C_2	0.2

A part of the similarities using updated weights in the estimation course trip is shown in **Fig. 6**. The horizontal axis represents the time from the start. The vertical axis represents the similarity. The similarity is greater than the threshold θ only before the intersections where the driver has turned.

The averages of the recognition rates are shown in **Fig. 7**. The horizontal axis represents the number of learning course trips. The vertical axis represents the average of the recognition rates. Each of the dots with lines indicates the averages of the recognition rates at 3 seconds before the intersections and at 5 seconds before the intersections. The average of the recognition rates at 3 seconds before the intersections was 98.5% and that at 5 seconds was 95.6% when we used the weights updated with the 50 learning course trips. On the other hand, the average at 3 seconds before the intersections was 92.5% and that at 5 seconds was 52.5% when we used the fixed weights shown in our previous work[1]. In the work, the fixed weights were determined after several attempts. In consequence, the adaptive system improves prediction time and accuracy.

6. NAVIGATION SYSTEM USING DRIVING BEHAVIOR PREDICTION

We propose a new navigation system as one application of our prediction. Today, most systems guide drivers to an intersection they should turn at by informing them of the distance to the intersection. However, drivers often turn at a different intersection or pass through the guided intersection due to misunderstanding the guidance. We believe that our driving behavior prediction can achieve effective guidance that reduces this type of misunderstanding.

If the navigation system understands that the driver will probably turn at a non-target intersection, the navigation system can tell the driver to go straight (**Fig. 8**(a)). If the navigation system understands that the driver will probably not turn at the non-target intersection, the navigation system can stay silent. Moreover, if the navigation system understands that the driver will probably not turn at the target intersection, the navigation system can tell the driver to turn (**Fig. 8**(b)). If the navigation system understands that the driver will probably turn at the target intersection, the navigation system can stay silent.

An example of a guidance scene by our proposed navigation system is shown in **Fig. 9**. The picture is a forward view. The upper graph indicates a similarity and the lower graph indicates actual vehicle control signals. In this scene, the driver shows signs of turning at a block short of the target intersection, therefore the navigation system tell the driver to turn.

7. CONCLUSION

In this paper, we proposed a prediction technology for turning behavior at intersections with driver behavior adaptation. The driver behavior adaptation can optimize the influences of typical patterns and time instants in a turning behavior model. We tested the adaptive system in a driving simulator and then verified that it can improve prediction performance.

The prediction technology described in this paper can predict whether a driver will either go straight or turn at an intersection. In the future, we plan to expand the technology to predict stopping, turning, and going straight behavior.

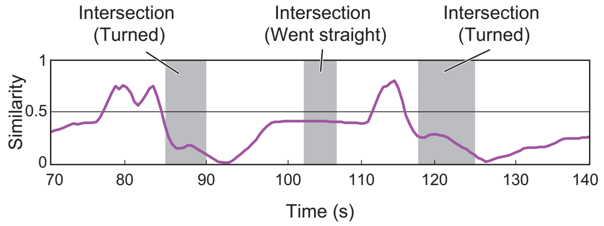


Fig. 6 Part of similarities using updated weights in the estimation course trip

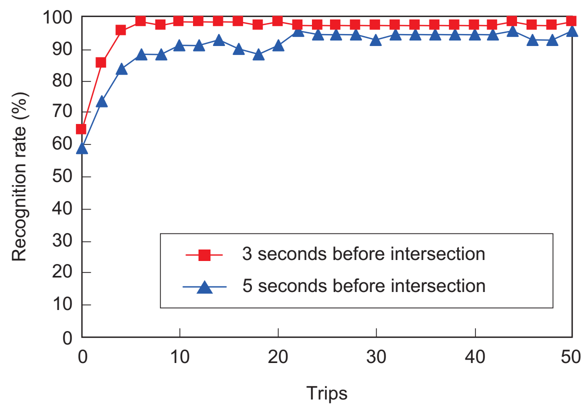
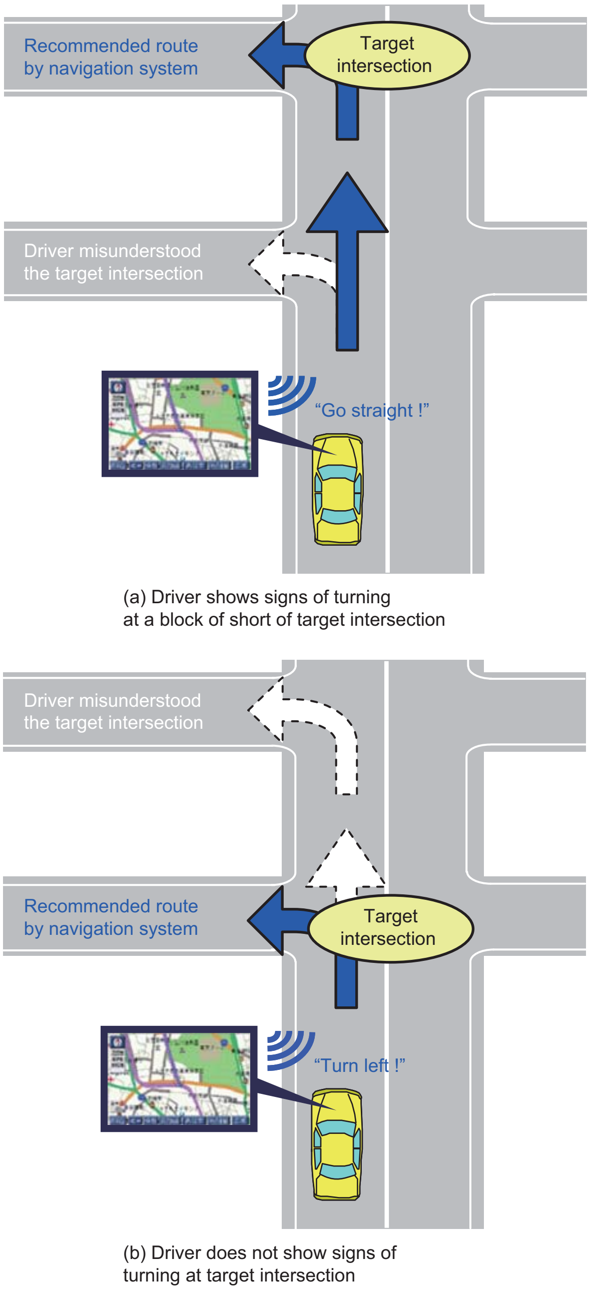


Fig. 7 Averages of recognition rates



(a) Driver shows signs of turning at a block of short of target intersection

(b) Driver does not show signs of turning at target intersection

Fig. 8 Navigation system based on turning behavior prediction at intersection

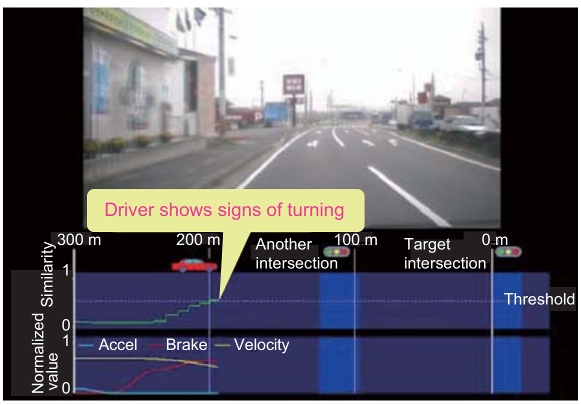


Fig. 9 Example of a guidance scene

REFERENCES

1) Ito, T. Et al.: Prediction of Driver's Turning Intention for Car Navigation System, Proceedings of the 11th World Congress on ITS (2004).
2) Liu, A. Et al.: Recognizing Driver Intentions with Hidden Markov Models, NISSAN TECHNICAL REVIEW, No.41 (1997), pp. 53-56.
3) Reed. E.: The Importance of Information, Encountering the World: Toward an Ecological Psychology, Oxford University Press (1996), Inc. pp. 47-67.
4) Grefenstette, J.: Credit Assignment in Rule Discovery Systems Based on Genetic Algorithm, Machine Learning, Vol. 3 (1988), pp. 225-245.
5) Akamatsu, M.: Establishing Driving Behavior Database and its Application to Active Safety Technologies (in Japanese with English summary, Journal of Society of Automotive Engineers of Japan, Vol. 57, No.12 (2003), pp. 34-39.
6) Tamegai, H. Et al.: Algorithm of Detecting a Start of Right-turn at Intersection for Optimizing Information Timing (in Japanese with English summary), proceedings of JSAE, No.20045044 (2004).
7) Calinski, T. and Harabasz, J.: Dendrite Method for Cluster Analysis, Communications in Statistics, Vol. 3 (1974), pp. 1-27.
8) Pentland, A. and Liu, A.: Modeling and Prediction of Human Behavior, Neural Computation, Vol. 11 (1999), pp. 229-242.
9) Oliver, N. and Pentland, A.: Graphical Models for Driver Behavior Recognition in a Smart Car, Proceedings of the IEEE Intelligent Vehicles Symposium (2000), pp. 7-12.
10) Kuge, N. Et al.: A Driver Behavior Recognition Method Based on a Driver Model Framework, SAE Technical Papers (2000), No.2000-01-0349.
11) Sakabe, M. and Ohno, H.: Development of Collision Warning System Based on Prediction if Driver's Braking Action (in Japanese with English summary), AISIN TECHNICAL REVIEW, Vol. 7 (2003), pp. 20-23.
12) Amano, Y. Et al.: An Approach to Preventing Insufficient Safety Confirmation in Process of Crossing Intersections (in Japanese with English summary), Journal of Society of Automotive Engineers of Japan, Vol. 58, No.12 (2004), pp. 83-88.

＜著　者＞

内藤　貴博
（ないとう　たかひろ）
基礎研究所
ドライバの状態検出技術の研究に
従事

森本　寛
（もりもと　ひろし）
基礎研究所
ドライバの状態検出技術の研究に
従事

伊藤　隆文
（いとう　たかふみ）
基礎研究所
ドライバの状態検出技術の研究に
従事

山本　敏雅
（やまもと　としまさ）
基礎研究所
ドライバの状態検出技術の研究に
従事

福本　晴継
（ふくもと　はるつぐ）
基礎研究所
ドライバの状態検出技術の研究に
従事