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Prediction Model of Driving Behavior Based on Traffic Conditions and Driver Types

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Abstract— **We investigate the driving behavior differences at unsignalized intersections between expert and nonexpert drivers. By analyzing real-world driving data, significant differences were seen in pedal operations but not in steering operations. Easing accelerator behaviors before entering unsignalized intersections were especially seen more often in expert driving. We propose two prediction models for driving behaviors in terms of traffic conditions and driver types: one is based on multiple linear regression analysis, which predicts whether the driver will steer, ease up on the accelerator, or brake. The second predicts driver decelerating intentions using a Bayesian Network. The proposed models could predict the three driving actions with over 70% accuracy, and about 50% of decelerating intentions were predicted before entering unsignalized intersections.**

I. INTRODUCTION

Drive recorders (DRs) are widely used in such transit vehicles as taxis, buses, and delivery trucks [1]. When a triggering event occurs, such as an accident or an abrupt acceleration, braking, or turning, various signals, e.g., acceleration, velocity, and images are automatically recorded. Driving records are used in risk consulting as driver feedback about the results of evaluating driving habits to reduce risky driving behaviors. A risk consulting company argued that about 20 to 80% of traffic accidents could be reduced if drivers were informed about the data analysis results [2]. However, such driver evaluation is time-consuming because it requires manual data analysis by risk consulting experts. Therefore, automatic driver evaluation methods are required.

Driving behaviors are so different in the same traffic conditions that automatically evaluating the driving risks of individual drivers is difficult. However, if we model examples of driving behaviors, the driving risks of each driver could be evaluated by comparing the driving behaviors to the model behaviors in the traffic condition. Therefore, recently several methods for modeling driving behaviors have been proposed. Kumagai et al. predicted the stopping probability of a vehicle by a simple dynamic Bayesian Network, which is a hidden Markov model, or a switching linear dynamic system [3]. Abe et al. predicted the driving maneuver of stopping using a Dynamic Bayesian Network [4][5]. In their studies on driver biosignals, they estimated two mental states, hasty and normal, and switched the applied driving behavior model based on the state. Kishimoto et al. proposed a method of modeling driving behavior concerned with a certain period of past movements using AR-HMM to predict stop probability [6].

In this paper, we focused on the differences in deceleration behaviors between expert and nonexpert drivers at unsignalized intersections, i.e., intersections without traffic lights. We constructed two prediction models for driving behaviors at unsignalized intersections: one predicts whether the driver will take such driving actions as steering, gas pedal off, and brake pedal on based on multiple linear regression analysis; the other, based on a Bayesian Network, predicts decelerating intentions. The predicted decelerating intentions correspond to pedal taps and the switch timing of the gas and brake pedals. In the experiments, participants drove a data collection vehicle [7] on city roads that included many unsignalized intersections. The prediction models were evaluated by comparing the predicted driving behaviors with the actual behaviors of target drivers.

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II. PREDICTION MODELS OF DRIVING BEHAVIOR

Since individual driving behaviors are even different in identical traffic conditions, we assume that such differences might be especially noticeable between expert and nonexpert drivers. Therefore, we constructed two kinds of models that predict driving behaviors based on traffic conditions and driver types.

A. Labels for classifying intersections

To classify unsignalized intersections in terms of traffic conditions, we arranged nine labels for intersections (Table I). See the Appendix for details. In addition, labels for the driving behaviors shown in Table II were also prepared to represent whether the drivers took these driving actions at unsignalized intersections. “Steering,” “Gas OFF,” and “Brake ON” correspond to steering operations, releasing the accelerator, and pressing the brake pedal, respectively. These labels for intersections and driving behaviors take binary values of either 0 or 1.

B. Linear regression model

Assuming the binary labels to be numbers, we investigated the dependences among the variables by multiple linear regression analysis. Let y be a driving operation label (Steering, Gas ON, or Brake OFF) and $\mathbf{X}$ be a nine-dimensional

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TABLE I

LABELS FOR INTERSECTIONS

	Label	0	1
Road types	Halt/Stop line	None	Existed
	Intersection type	T-shape	Cross
	Crosswalk	None	Existed
	Mirror	None	Existed
Obstructions	Pedestrians	None	Existed
	Parked vehicles	None	Existed
	Vehicle in front	None	Existed
	Oncoming vehicles	None	Existed
	Interrupting vehicles	None	Existed

TABLE II

LABELS FOR DRIVING BEHAVIORS

	Label	0	1
Behaviors	Steering	Not done	Done
	Gas OFF	Not done	Done
	Brake ON	Not done	Done

*When a driver released accelerator and braked, both "Gas OFF" and "Brake ON" were labeled.

vector consisting of labels for intersections. We assumed the following regression equation:

$$y_{i,j}(o) = \mathbf{a}_j^{\mathrm{T}}(o)\mathbf{X}_i + b_j(o), \tag{1}$$

where $\mathbf{a}$ is a regression coefficient vector for intersection conditions, b is a constant, i is an intersection index, j is an index of the training data set that corresponds to driver type (expert or nonexpert), and o corresponds to driving operations (steering, gas, or brake). In this regression model, we can predict whether the driver will take driving actions based on the driver type and the traffic conditions at the intersection which the vehicle is approaching.

C. Bayesian Network model

The second model uses a Bayesian Network for predicting the decelerating intentions of drivers. A Bayesian Network is an annotated directed graph that represents the probabilistic relationships among random variables. The qualitative relationships among variables are indicated as arcs in a Bayesian Network, and the quantitative relationships correspond to the conditional probability distributions.

We assumed that driving maneuvers are different even under the same traffic conditions and the vehicle behaviors, and used a Bayesian Network to define the causal relationships between the driving behaviors and the traffic conditions or the vehicle behaviors. The following causal relationships were represented by a Bayesian Network:

1) **traffic conditions → driving behavior**
   Driving behaviors differ depending on the traffic conditions.
2) **driver type → driving behavior**
   Driving behaviors differ between expert and nonexpert drivers even under identical traffic conditions.
3) **driving behavior → vehicle behavior**
   Vehicle behaviors depend on driving behaviors.

Figure 1 shows the basic network structure of these dependencies.

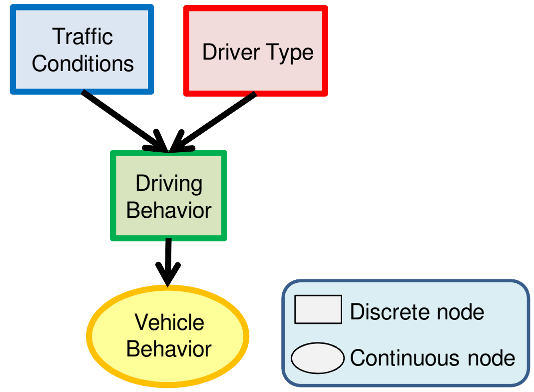

Fig. 1. Structure of a Bayesian Network

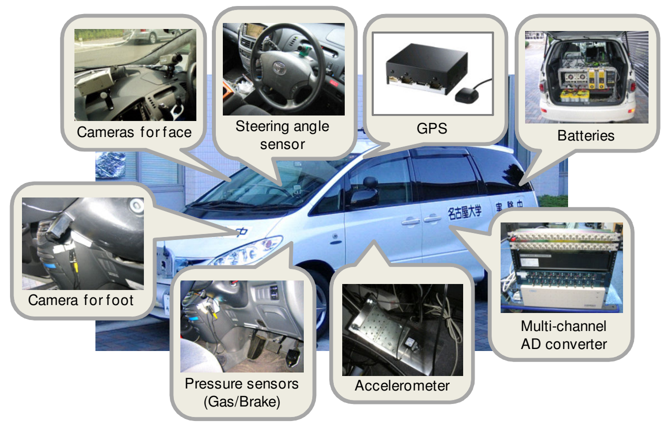

Fig. 2. Instrumented vehicle for recording real-world driving data

III. EXPERIMENT

A. Data collection for our experiments

In our experiments, we used real-world driving data recorded by our own data collection vehicle [7] (Fig. 2). The vehicle is equipped with an accelerometer, velocity sensors, a steering angle sensor, four cameras, 12 microphones, and gas and brake pedal pressure sensors. Six drivers (four experts and two nonexperts) drove the vehicle on city roads near Nagoya University. The four experts are instructors of driving schools and the two nonexperts are a university student and a homemaker. Figure 3 shows the driving route that includes narrow streets and 111 unsignalized intersections, 42 in (A) two-way streets without centerlines, 40 in (B) two-way streets with one lane in each direction, and 29 in (C) two-way streets with two lanes in each direction. The driving data were recorded with a sampling frequency of 16 kHz and downsampled to 10 Hz for our experiments.

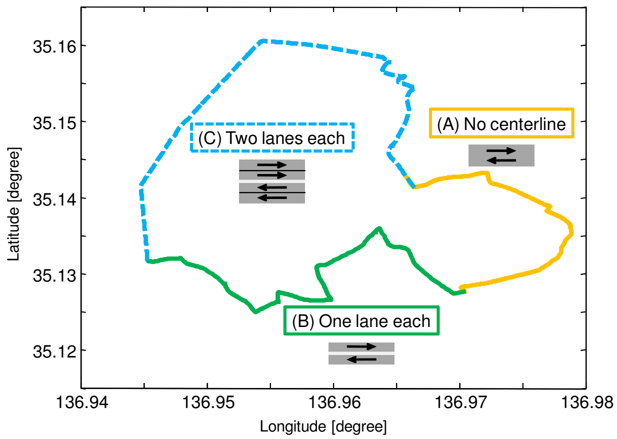

Fig. 3. Route for data recording

TABLE III
FREQUENCIES OF LABELS FOR TRAFFIC CONDITIONS OF OBSTRUCTION [%]

Label	Expert	Nonexpert
Pedestrians	28.7	25.5
Parked vehicles	11.2	10.2
Vehicle in front	19.6	26.0
Oncoming vehicles	13.3	12.2
Interrupting vehicles	10.7	6.6

TABLE IV
FREQUENCIES OF LABELS FOR DRIVING BEHAVIOR [%]

Label	Expert	Nonexpert
Steering	13.1	10.7
Gas OFF	67.9	48.5
Brake ON	44.9	40.8

TABLE V
TRAINING DATA AND CORRESPONDING DRIVER MODELS

Driver model	Driver ID for training
Expert	E1, E2
Nonexpert	N1, N2
Mixed	E1, E2, N1, N2

B. Analysis of labels for intersections and driving behaviors

We labeled all unsignalized intersections in the driving route as well as the driving behaviors. The labels for the intersections and the driving behaviors are shown in Tables I and II.

Analyzing the labels for traffic conditions, each label was almost evenly observed between expert and nonexpert drivers (Table III). However, "Gas OFFs" by expert drivers were seen 1.4 times more often than nonexpert drivers (Table IV). This means that expert drivers tend to ease up on the accelerator more often than nonexpert drivers when they approach unsignalized intersections.

C. Predicting driving behaviors with linear regression model

We calculated three different regression coefficients from three different pieces of training data (Table V). We constructed an expert driver model from the data of two expert drivers, E1 and E2, a nonexpert driver model from the data of two nonexpert drivers, N1 and N2, and a mixed driver model from the data of E1, E2, N1, and N2. Table VI shows the regression coefficients, where a higher coefficient indicates that a driver takes a driving action more sensitively to the traffic condition. Table VI shows the following relationships between the driving behaviors and the traffic conditions.

1) **Steering**
Expert drivers are more aware of interrupting vehicles than nonexpert drivers, but nonexpert drivers are more aware of parked cars and oncoming vehicles.
2) **Gas OFF**
Expert drivers tend to ease off the gas pedal even if the intersection is clear, because the constant term of the expert driver model is large. Experts release the gas pedal more sensitively at intersections with mirrors, i.e., intersections with poor visibility.
3) **Brake ON**
Both expert and nonexpert drivers are aware of pedestrians. Similarly to the behavior of Gas OFF, expert drivers tend to press the brake at intersections with mirrors.

We predicted the behaviors of two other expert drivers using the trained linear regression models. Figures 4 and 5 show how much the predicted operations corresponded to the actual operations of the two expert drivers, E3 and E4. The behaviors of E4 were predicted by the expert model better than by the nonexpert model. However, the driving habits of E3 were so unstable that predicting them by either the expert or the nonexpert model was difficult. Fig. 5 shows a significant difference between the expert and the nonexpert models, especially for "Gas OFF." This corresponds to the difference of the frequencies of easing the accelerator shown in Table IV. As a result, we predicted the expert driver behaviors with more than 70% accuracy.

D. Patterns of pedal operation

As mentioned above, a significant difference was seen in "Gas OFF" between the expert and the nonexpert drivers. Therefore, we focused on pedal operations for five seconds before entering unsignalized intersections. We discretized the gas and brake pedal pressure data into three modes, "Gas pedal ON," "Pedal OFF," and "Brake pedal ON," and generated pedal operation sequences. All pedal operation sequences were clustered into five typical pedal operation patterns by a *k*-means algorithm. Figure 6 shows five centroids made by the *k*-means algorithm. Each centroid corresponds to the following pedal operation:

- **Pattern 1:** Entering intersection with Brake pedal ON
- **Pattern 2:** Easing on Gas pedal and pressing the brake just before entering intersection

TABLE VI
REGRESSION COEFFICIENTS

	Steering			Gas OFF			Brake ON		
	Expert	Nonexpert	Mixed	Expert	Nonexpert	Mixed	Expert	Nonexpert	Mixed
Pedestrians	0.19	0.28	0.26	0.04	0.16	0.13	0.21	0.24	0.24
Parked vehicles	0.06	0.53	0.31	0.11	0.07	0.13	0.17	−0.02	0.11
Vehicle in front	0.02	0.04	0.04	0.05	0.06	0.02	0.04	0.18	0.12
Oncoming vehicles	0.04	0.21	0.15	−0.15	0.15	0.01	−0.08	0.17	0.03
Interrupting vehicles	0.16	−0.19	0.01	0.06	0.13	0.08	0.11	0.24	0.13
Halt/Stop line	0.19	0.12	0.15	0.31	0.21	0.24	0.16	0.22	0.18
Intersection type	0.02	−0.01	0	0	0.08	0.03	0.14	0.05	0.09
Crosswalk	−0.05	−0.11	−0.09	0.01	−0.10	−0.04	−0.06	−0.08	−0.06
Mirror	0.07	−0.02	0	0.15	−0.01	0.09	0.16	−0.10	0.05
Constant term	0.03	−0.03	0	0.59	0.28	0.43	0.18	0.16	0.17

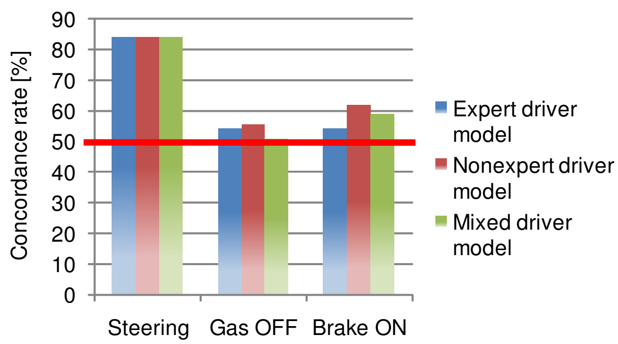

Fig. 4. Concordance rate between predicted and actual driving operations of expert driver E3 [%]. Solid line shows chance rate [%].

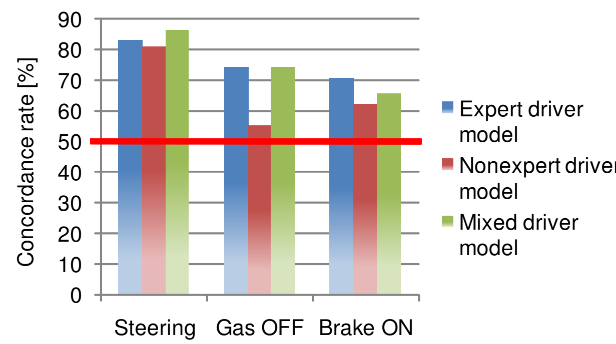

Fig. 5. Concordance rate between predicted and actual driving operations of expert driver E4 [%]. Solid line shows chance rate [%].

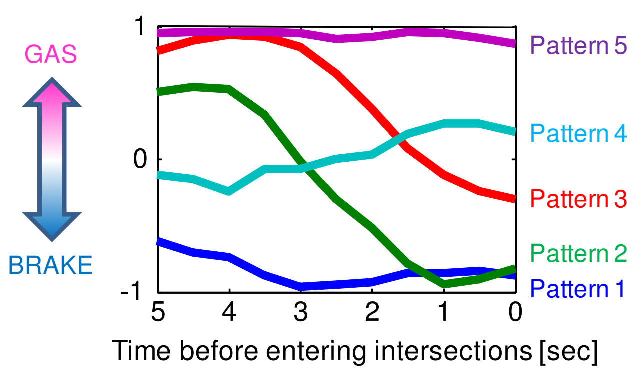

Fig. 6. Five centroids made by k-means denoting five different pedal operation patterns

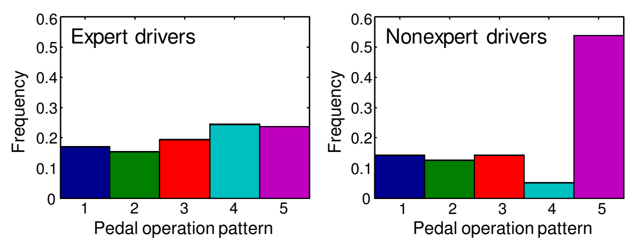

Fig. 7. Histograms of pedal operation patterns. Left side is for experts, and right side is for nonexperts.

- **Pattern 3:** Easing on Gas pedal just before entering intersection
- **Pattern 4:** Entering intersection with both Gas and Brake pedal OFF
- **Pattern 5:** Entering intersection with Gas pedal ON

The histograms of the five typical patterns for expert and nonexpert drivers are shown in Fig. 7. All five patterns are almost uniformly distributed in the expert drivers. This means that the expert drivers properly determine their driving behaviors based on the traffic conditions. On the other hand, pattern 5 is observed very frequently for nonexpert drivers. This means that they tend to enter intersections without deceleration, regardless of the traffic conditions. This corresponds to the difference of the frequencies of driving behavior "Gas OFF" shown in Table IV.

E. Prediction of pedal operation patterns with Bayesian Network

We predicted the pedal operation patterns shown in Fig. 6 using a Bayesian Network and proposed the network structure shown in Fig. 8. Each node corresponds to the parameters in Table VII. We used velocity sequences from

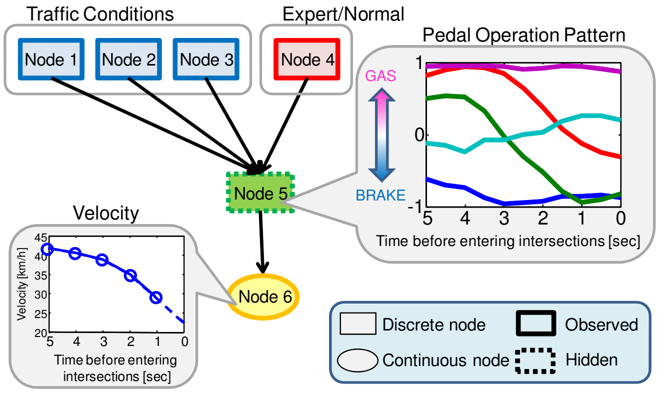

Fig. 8. Proposed structure of Bayesian Network

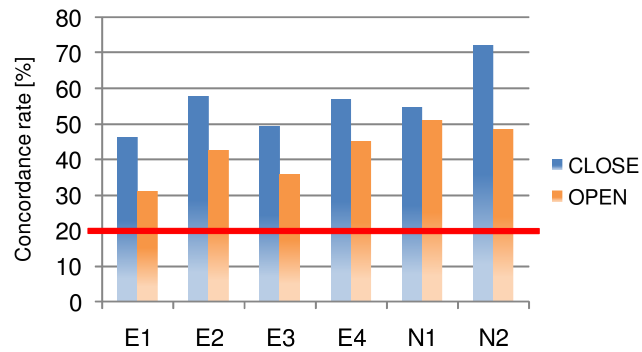

Fig. 9. Concordance rate between estimated and actual driving operation patterns [%]. Solid line means chance rate (20%).

TABLE VII

INPUT NODES OF BAYESIAN NETWORK AND CORRESPONDING PARAMETERS

Node	# of states	Corresponding parameter
Node 1	2	Existence of obstructions (pedestrians or parked/oncoming/interrupting vehicles)
Node 2	2	Existence of stop line or crosswalk
Node 3	2	Existence of following vehicle
Node 4	2	Driver types (Expert/Normal)
Node 5	5	Pedal operation patterns
Node 6	–	Velocity (5-dimensional vector)

one to five seconds before entering the intersections for Node 6, excluding the velocity of the time of entering intersections. Using this model, we predicted the decelerating actions that should be taken just before entering the intersections by getting the traffic conditions in the intersections ahead of time.

We performed an experiment that predicted the deceleration behaviors under two conditions: CLOSE and OPEN.

- CLOSE: Training data set includes test data set.
- OPEN: Training data set excludes test data set.

Figure 9 shows how much the predicted operation patterns corresponded to the actual patterns. About 50% of the pedal operation patterns before entering unsignalized intersections were predicted using our proposed Bayesian Network model.

IV. SUMMARY

We investigated the differences in driving behaviors between expert and nonexpert drivers at unsignalized intersections and found significant differences in pedal operation between such drivers. Expert drivers tend to ease up on the accelerator before entering unsignalized intersections more often than nonexpert drivers.

First, we proposed a prediction model based on linear regression analysis for predicting driving actions and predicted 70% of driving actions of expert drivers. Then we proposed a prediction model based on a Bayesian Network for predicting pedal operation patterns before entering unsignalized intersections and predicted about 50% of pedal operation patterns.

We plan to increase the amount of driving data and investigate better graph structures and variables of Bayesian Networks. Additionally we will evaluate the driving risks by comparing the actual driving behaviors to the model behaviors.

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Appendix

Figures 10-13 show the labels for the intersections.

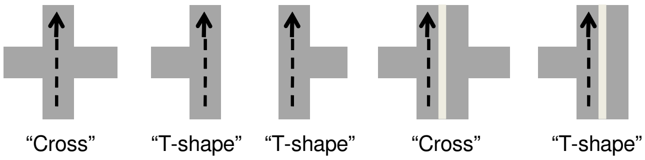

Fig. 10. "Intersection type" is used for intersection shape.

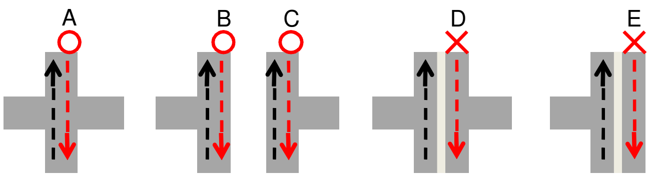

Fig. 11. "Oncoming vehicles" shows existence of vehicles from opposite direction. Vehicles A-C are counted as oncoming vehicles, but not D-E.

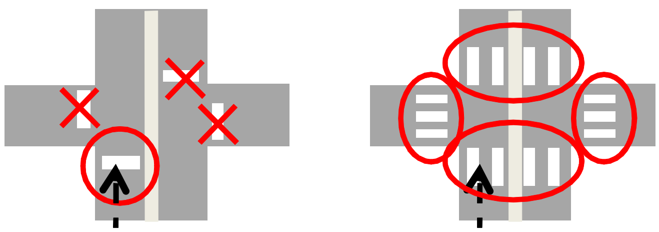

Fig. 12. "Halt/Stop line" and "Crosswalk" show existence of stop lines and crosswalks. Those surrounded by circles are counted as stop lines or crosswalks.

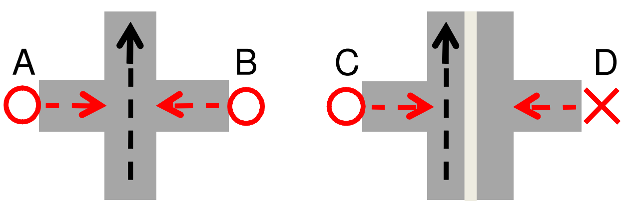

Fig. 13. "Interrupting vehicles" shows existence of vehicles entering driving lane. Vehicles A-C are counted as interrupting vehicles, but not D.