MEASUREING AND MODELING OF DRIVER FOR DETECTING UNUSUAL BEHAVIOR FOR DRIVING ASSISTANCE

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ABSTRACT

It is important to develop the driving assistance system that conforms to the individual driver's characteristics so that the driving assistance technology is widely accepted. Timing and ways of the assistances should fit in individual characteristics of unusual driving behavior.

In order to measure usual driving behavior, we developed test vehicles with an on-board driving recorder and various types of sensors. Several driving parameters (e.g. the driver's operational measures, the vehicle state measures, the traffic condition measures) were recorded with the recorder.

The equipped test vehicles were given to 67 paid volunteer drivers to use for two months in commuting situation. The field operational test was conducted a total of about 1800 driving trips. The measured operation behavior was accumulated to a database.

In order to develop a new driving assist method for the stopping maneuver, we modeled the driving behavior for usual driving by the Bayesian network which was a graphical model obtained from statistical analysis of the measured behavior data. A deviation from the usual operation behavior (i.e. unusual behavior) can be estimated using this model. The unusual behavior can be regarded inappropriate behavior and thus can be applied to a cue for the driving assist such as warning presentation.

INTRODUCTION

Driving assistance systems have been proposed as applications of ITS to avoid traffic accidents, reduce traffic jams or solve environmental problem. In most of these assistant systems such as a warning system, the judgment whether the system assist the driver is mainly based on physical parameters such as vehicle speed and headway distance. Such common assistances are not always accepted with all people. It is important to develop "Driver-Centered System", which conforms to the individual driver's characteristics to avoid unnecessary assist by adapting timing and contents of the assistances to the individual.

Usual driving behavior of an individual driver under a certain traffic situation is an adaptive behavior to the situation. Thus unusual driving behavior can be regarded as the performance that is not adapted to the situation. This means that the unusual behavior increases the risk of driving to the situation. Therefore, detection of the unusual behavior based on the recorded usual behaviors under certain situation is to detect the driver's risky situation. The detection can be the cue for the assistance of driving "Personalized Driving Assist System."

In order to develop such driving assistance system, usual driving behavior data in natural situation are needed to be known. Nevertheless, there were no normalized driving behavior databases that can be referred generally.

We have developed equipped vehicles to measure driver's behavior to obtain basic driving behavior data for the personalized assist system. A Drive recorder system was mounted on the each vehicle. Using these vehicles, we performed driving experiments on the public roads to measure driver's usual behaviors. By the recorded driving data, we established a database which accumulated measured driver's behaviors.

In this paper, we present about the equipped vehicle and the database. And we also describe a modeling method of driving behavior using Bayesian network. The driver model will be used to evaluate deviation from usual behaviors in order to decide whether assistance the driver is necessary or not.

Driving assistant system will be created based on the driving behavior model.

DEVELOPMENT OF EQUIPPED VEHICLES FOR DRIVER BEHAVIOR MESUREMENT

Equipped Vehicles

We have developed the vehicles with a drive recorder was carried on to measure operational behavior data. The system configuration of the drive recorder is shown in the figure 1. The appearance of the experiment vehicle is shown in the figure 2. Because it aimed at the public road experiment by the general drivers, sensors and recorders are arranged to be unseen as possible.

The system consists of the sensors including the D-GPS, wide-angle laser radars, 6 CCD cameras, two microphones, the signal processing device and the laptop computer for the data logging and control. Table 1 shows sensing items with the drive recorder. From the sensing data, we could obtain the following behavior measures.

The measurement of the driving behavior

(1) The operation by the hand Steering wheel angle (by steering sensor), blinker and wiper operation (by lever sensors) and operation of the AT selector (by shift sensor) were measured as the operation of the hand.

(2) The operation by the foot The position of the right foot (over the brake pedal or the accelerator pedal) and the stroke of the brake and accelerator pedal were measured as the operation of the foot.

(3) The movement of the eyes Driver's eyes movement was measured with the view camera which was mounted on the driver's cap and "driver monitor", which was a camera mounted on the instrumental panel.

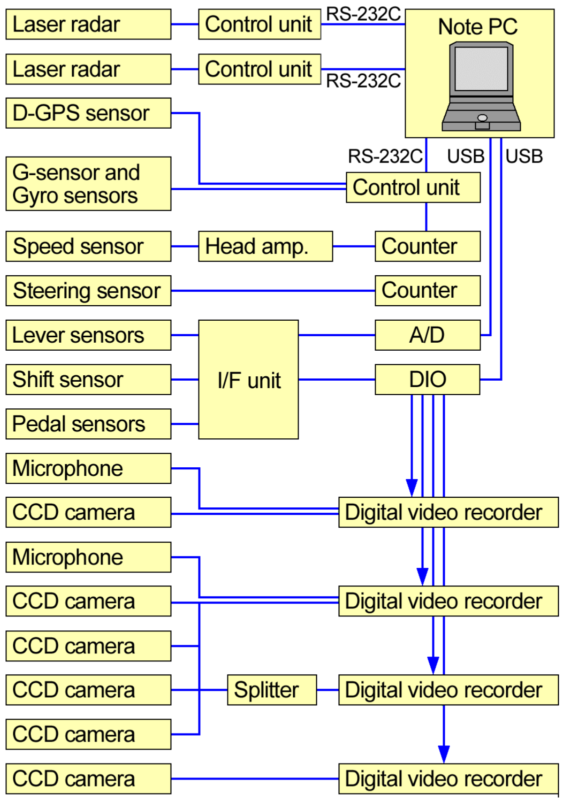

Figure 1. Configuration of the drive recorder system.

Figure 2. An Equipped Vehicle.

(4) Speech Driver's speech was caught with a microphone. Voices were recorded to the video recorder synchronizing with the driver's face image.

The measurement of the vehicles' status

The geometrical position of the vehicle was obtained from D-GPS sensor. Relative position within the lane was identified with the front scene image and the lane-view cameras fixed on the both side of door mirrors. Vehicle condition was measured by the 6-axis G-sensors and the gyro sensors. Velocity of the vehicle was measured by the speed sensor.

Relative distance and relative velocity of the lead vehicle and the behind vehicle were measured with the two (front/rear) wide-angle (20 deg.) laser radar units.

Table 1.
Recording Items of the Drive Recorder

Sensor	Data	Sampling
Laser rader	range, position	10Hz
D-GPS	NMEA	1Hz
G-sensors	Acceleration (X, Y, Z-axis)	30Hz
Gyro sensors	Angular rate (Roll, Pitch, Yaw)	30Hz
Speed	Wheel speed	30Hz
Steering	Steering angle	30Hz
Lever	Turn signal	30Hz
Shift	Shift position	30Hz
Pedal	Foot position Pedal stroke	30Hz
Microphone	Verbal	8kHz
CCD Cameras	Front scene Rear scene Driver monitor Driver's view Lane position	8fps

MESUREMENT OF DRIVING BEHAVIORS

Measurement of driver's behavior was performed by using 4 equipped vehicles described above. Eight driving routes (about 30 minutes from start to goal) with several left and right turns were selected. The subjects were instructed to drive as usual.

The subjects had practic4e drives before the recording trips, so they could drive from the origin to the destination without seeing a map. The subjects were instructed to drive as usual.

During the recording trips, the sensing data were recorded to the drive recorder. At the end of each trip, the subjects were asked to answer to questionnaires about driving workload, and NASA-TLX. Also, they were asked to fill questionnaires about incidents or impatient events. If the subjects felt situation was dangerous and was inpatient, they were requested to describe details about these situations on the rout map. Relationships between dangerous situations and deviated behaviors and the effects of impatience to driving behaviors will be analyzed.

After the end of all trips for each subject, driving style questionnaire (DSQ) and Workload Sensitivity Questionnaire (WSQ) were also conducted.

DEVELOPMENT OF DRIVER BEHAVIOR DATABASE

In order to access to the recorded data easily to analyze the driving behaviors, we established a driving behavior database. All recorded items in table 1 except images and voices were accumulated to the database. Numbers of the stored data were about 1900 trips for 67 subjects. In time of accumulation, driving actions (i.e. left/right turn, changing lane) were labeled to the data, so we can retrieve the driving data using driving action as keys. Oracle (TM) is used for the database management system (DBMS).

MODELING OF STOPPING BEHAVIOR USING BAYESIAN NETWORK

In this section, we describe modeling method of driving behaviors using Bayesian network. The Bayesian network, known as belief network, is a graphical model that encodes probabilistic relationships among variables of interest.

In this paper, we took up the behavior for stopping at the "Stop" sign before an intersection. Driving behaviors on braking and stopping before the stop line in front of the intersection were modeled. The map of the intersection was shown in figure 3. The intersection image was shown in figure 4.

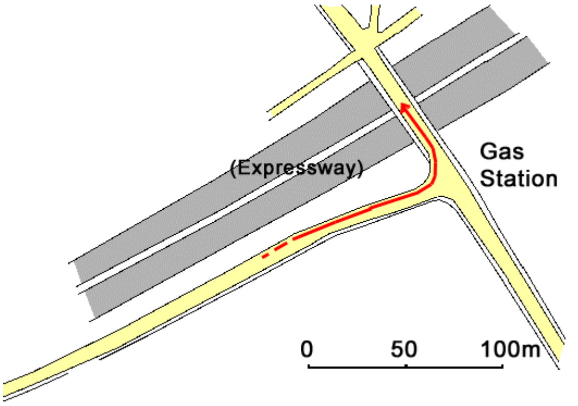

Figure 3. The map of the intersection for driving behavior modeling.

Figure 4. The image of the intersection for driving behavior modeling.

When a driver slowed down and stopped around the stop line in front of the intersection, series of operational events of the behavior occurred as follows:

- Releasing the accelerator pedal
- Put left foot over the brake pedal
- Onset of braking
- Turn on the blinker (if the driver turned to left or right at the intersection)
- Reach maximum deceleration
- Stop (If the vehicle did not stop completely, was is regarded as “stop” when it reached the minimum velocity)

Using the Bayesian network, we modeled relationships of the timing (velocity and TTC: Time To Cross line) of each behavioral events and performance shaping factors. TTC is defined by the following equation.

$$T = \frac{D}{V} \qquad (1)$$

T : TTC [sec]

D : Distance from the stop line [m]

V : Vehicle velocity [m/s]

Table 2.

Performance shaping factors and events which used for nodes of the Bayesian network model

(a) Performance shaping factors (PSF)

PSF	Parameters
Methodical	Score of DSQ*
Weather	Rain or not

(b) Events

Events	Parameters
Release the accelerator pedal (1)	Velocity
	TTC**
Move foot over the brake pedal (2)	Velocity
	TTC
Onset of braking (3)	Velocity
	TTC
Reach maximum deceleration (4)	Velocity
	TTC
Turn on the blinker	Velocity
Stop (or reach the minimum velocity) (5)	Velocity (zero if stopped)
	Distance from stopping line
Time lag between (1) and (2)	Time
Time lag between (1) and (3)	Time
Time lag between (2) and (3)	Time
Time lag between (3) and (4)	Time
Time lag between (4) and (5)	Time

*DSQ : Driving Style Questionnaire

**TTC : Time To Cross line

The events and the performance shaping factors (each parameter became nodes of the Bayesian network) using for modeling are shown in table 2.

Data used for modeling were those recorded for 8 subjects when approaching a specific T-shape intersection from 130 trips which have no lead vehicle. According to the distribution of the recorded data from all the trials, values of the variables except weather parameter were split into 5 ranks based on the percentile of the distribution of the variable; 0-10 percentile (rank 1), 10-30 percentile (rank 2), 30-70 percentile (rank 3), 70-90 percentile (rank 4), and 90-100 percentile (rank 5).

As the result of modeling using BN Power Constructor[2], constructed Bayesian network shown in figure 5 was obtained.

In this figure, the allow between two nodes indicates that valuable of each nodes have correlation. The direction of the arrow represented the causal relationship.

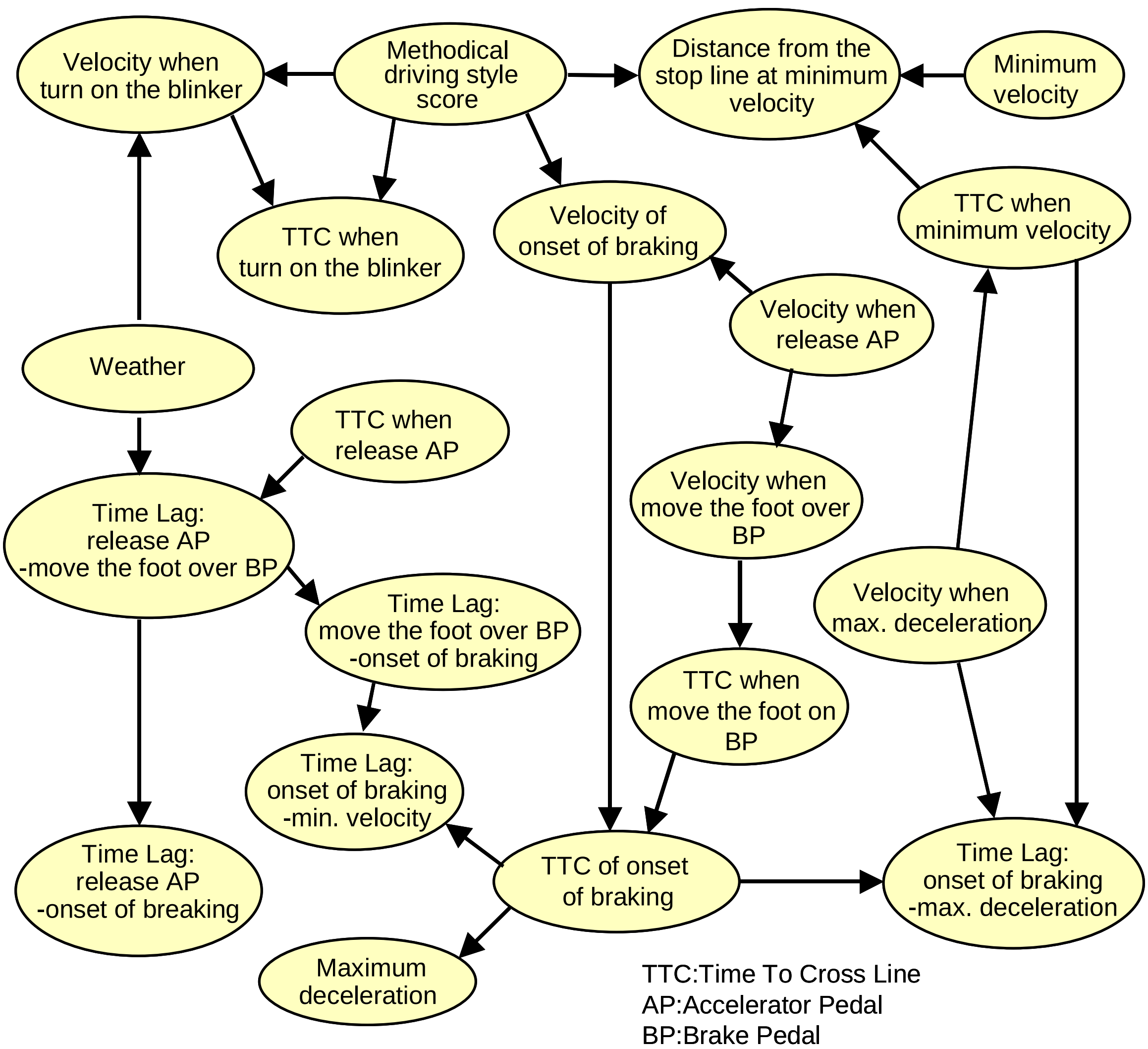

Figure 5 Bayesian network model for deceleration to stop at a certain intersection with the stop line.

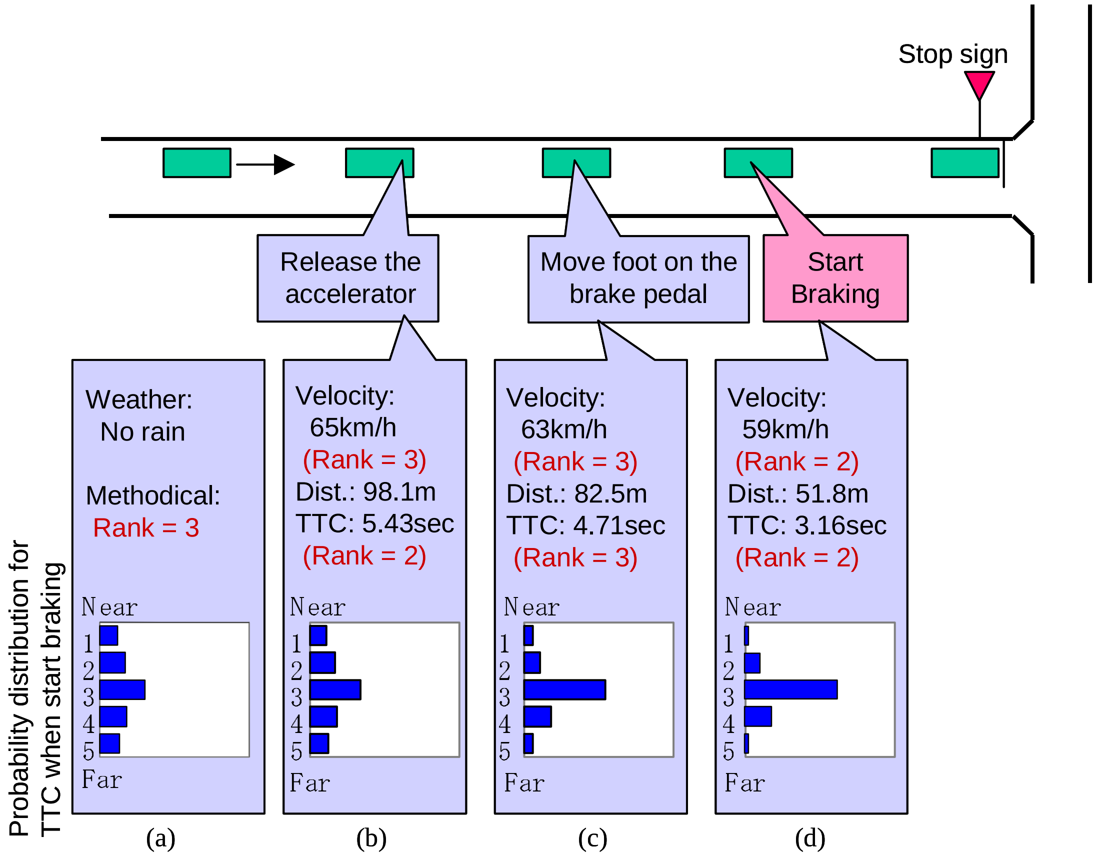

Figure 6 Changes of estimated probability distribution for TTC of onset of braking according to occurrence of operational events while approaching to the intersection.

Detection of the deviated braking behavior

As an example of evaluating of driving behavior using the Bayesian network, we focused on evaluation of the timing of onset of braking while approaching to the T-shape intersection in a certain trip[3]

As the sequence of the stopping behavioral events proceeds, the estimation of the timing of the operational events by the model changes as the followings.

(a) In the stage when the driver was still pressing the accelerator, values of only two nodes were fixed; "Methodical score", which was the driver's characteristics, and "weather" (no rain) (figure .6(a)). Using these values of the two nodes as conditions, the distribution of conditional probability of the other nodes (i.e. "Velocity of onset of braking", "TTC when turn on the blinker") could be calculated. And the distribution of probability of the node of "TTC of onset of braking" which was connected from the nodes "Velocity at the onset of braking" and "TTC when turn on the blinker" could be estimated.

(b) Soon the driver released the accelerator at the point of 98.1m before the intersection. Velocity of the vehicle then was 65km/h (TTC=5.43 sec). Sensing this event by the sensors, value of the nodes "Velocity when release the accelerator pedal" and "TTC when release the accelerator pedal" were fixed. The probability distributions of the other nodes connected to these two nodes were renewed. Then, the estimated probability distribution of the nodes of "TTC of onset of braking" was also renewed (figure .6(b)).

(c) Next, the driver moved his foot to the brake pedal at the point of 82.5m before the intersection when the velocity was 63km/h (TTC=4.71 sec). Sensing this event, value of the nodes "Velocity when move the foot over the brake pedal" and "TTC when move the foot over the brake pedal" were fixed. Then, the estimated probability distributions of the nodes of “TTC of onset of braking” changed again. Probability of rank 3 was in the TTC much larger than other ranks (figure .6(c)).

(d) After that, velocity of the vehicle was decreased. When the value of the velocity was applied to the value of the node “Velocity of onset of braking”, the estimated probability distribution of the node “TTC of onset of braking” changed as the velocity changed according to the model. By sensing the velocity and distance to the intersection of the vehicle, the TTC could be calculated every sampling moment. Probability (i.e. significance level) of onset of the brake pedal at the moment was obtained by to comparing the TTC from the sensors and the probability distribution of the node “TTC of onset of braking”.

If the driver stated brakeing at the point of 51.8m from the intersection and the velocity was 59 km/h then, the calculated probability was less than 10% that the event occurred later than this moment (TTC and velocity), so this cloud be regarded as the deviated behavior (figure .6(d)). In such a situation, the appropriate assistance (e.g.. warning to facilitate the strong braking or increasing the gain of brake servo preparing for the next emergence braking) could be performed.

CONCLUSIONS

In order to develop “Personalized Driving Assistant System”, it is necessary to take consider in individual driving characteristics. Thus, each characteristics of driving behavior is had to be extracted from measured driving data.

We have developed the equipped vehicles for the purpose of measuring the driving behavior. And we measured driving behaviors on the public road. The behaviors were accumulated to the database.

Bye using the database, we modeled the stopping driving behavior data using Bayesian network. We proposed the method for detecting the deviated behavior using the Bayesian network that could be applied to driving assistance system.

In the future, we will add effects of the lead vehicle and the crossing vehicle to the driving behavior model. This model will be base of the “Personalized Driving Assistant System.”

ACKNOWLEGMENTS

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REFERENCES

[1] Finn V. Jansen. 2001. “Bayesian Networks and Decision Graphs”, Springer.

[2] Belief Network (BN) Power Constructor, http://www.cs.ualberta.ca/~jcheng/bnpc.htm

[3] Akamatsu, M. and Sakaguchi, Y. 2002. ”Estimation of Time of Driving Operation Using Stochastic Modeling”, Proc. of SICE Symposium on Systems and Information, pp.163-168 (In Japanese).