Chapter 2

Applying Fuzzy Logic to Understanding Driving Modes in Real Road Environments

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Additional information is available at the end of the chapter

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1. Introduction

Driving a vehicle is a task in which the environment and the situation are changing in real time. The driver controls the vehicle on the road and manages spatial distance to a preceding vehicle, pedestrians, or other stationary or moving obstacles, while travelling from an origin to a destination. The driver must pay attention to objects around the vehicle in addition to the road environment (e.g. road alignment, traffic signals, and traffic signs). The result may be a high workload for the driver.

Advanced driver-assistance systems have been developed over a long period of time in order to enhance road safety and decrease driver workload. Some systems present information that helps the driver recognize a route to the destination and traffic conditions near the driver's vehicle. Other systems provide the driver with warnings regarding possible collision with a lead vehicle or a stationary vehicle, and lane departure warnings. Automatic control systems to avoid collisions (e.g., automatic braking just before a rear-end collision when a lead vehicle suddenly slows down) have been installed in several passenger cars. Recently, autonomous vehicle controls have been developed, and field operational tests using such systems have been planned or have already begun [1].

A key issue for implementation and popularization of advanced driver-assistance systems is human-centered design for information and warning presentations and self-control systems [2,3]. Human-centered design is expected to enhance drivers' acceptance of the information provided and system-paced operations. The presentation and control algorithm, which adapt to a driver's typical driving behavior, might contribute to realizing human-centered design for driver-assistance systems. However, driver acceptance is not ensured when the system presents assistance information at the same timing as the driver's usual maneuver or when the system controls the vehicle in the same manner as the driver's usual time-course stabilization. Most drivers do not objectively understand their own behavior, and they might not understand that the control methods of the assistance systems are similar to their own control. Greater margins for the driver's operational timing and input (e.g., the driver's onset of braking and the driver's maneuvers to avoid collisions) will be necessary when driver-assistance systems are developed based on a driver's usual behavior.

1.1. Task difficulty while driving

The difficulty of a driving task is determined by the interaction between driver capability and task demand. The driver adjusts the task difficulty, which is calculated by subtracting the capability from the task demand. The task-capability interface model suggests the concept of task difficulty controls in driving [4]. When task demand exceeds driver capability, task difficulty is so high that the driver cannot complete the driving task. This condition may lead to a collision or a loss of control. When capability exceeds demand, the task is easy and the driver successfully accomplishes it. Figure 1 presents the concept of task difficulty adjustment. The driver's capability is maintained and the task demand is decreased in order to maintain the driver's capability above the task demand.

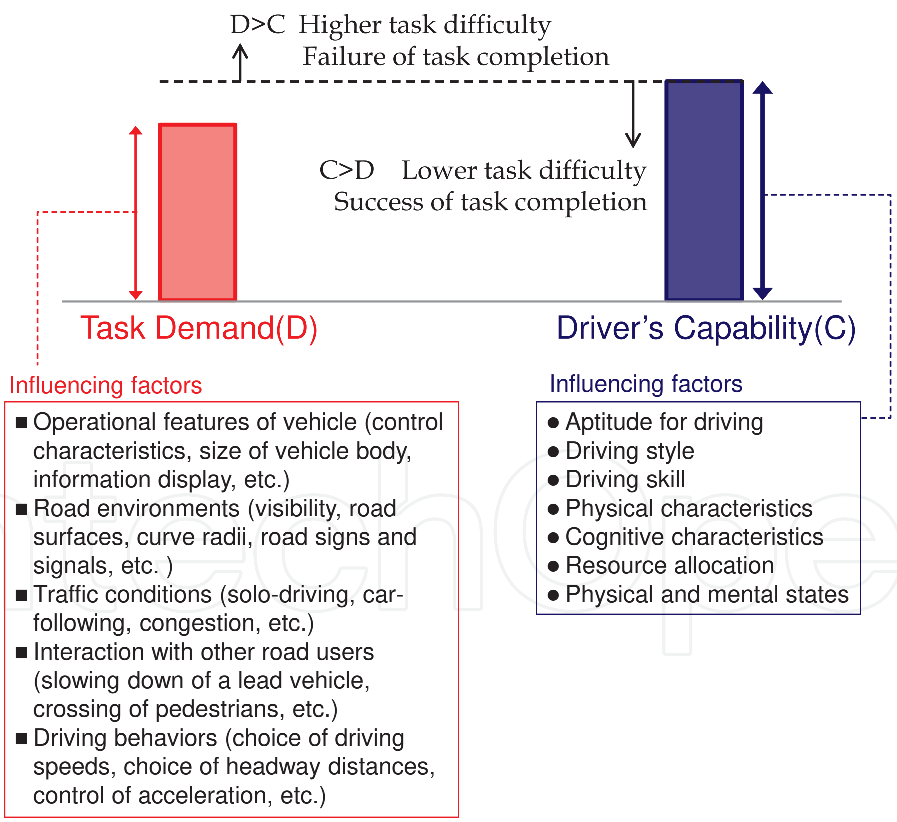

Figure 1. Interaction between task demand and driver capability

The task demand and the driver's capability are influenced by several factors. The task demand is determined by the operational features of the vehicle, environmental factors including the

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road environment and traffic conditions, and interactions with other road users. Different passenger cars have different operational features. The road environment includes visibility and road surfaces changed by the weather, curve radii, and road signs and signals. Traffic conditions differ with the number of vehicles, pedestrians, and bicycles near the driver's vehicle; and the movements of other road users influence task demand. Task demand is also influenced by driving behavior, including control of driving speed, headway distance, and acceleration. For example, shorter headway distance leads to higher task demand and requires higher driver capability of paying attention to the movement of the lead vehicle. In contrast, greater headway distance leads to lower task demand; thus, the possibility of rear-end collision is lower even when the driver does not allocate many resources to the driving task. The important point in the task-capability interface model is that the driving task demand can be controlled by the driver's own driving behavior.

The driver's capability is constrained by aptitude for driving, driving style, driving skill, and physical and cognitive characteristics (e.g., physical reach, reaction time, and information processing capacity). It is also constrained by resource allocation. More concentration on the driving task enhances the driver's capability, and distracted driving decreases the driver's capability. The driver's physical and mental states, including fatigue and drowsiness, also impact the driver's capability and can vary at different times while driving.

1.2. New concept of driver-assistance systems: Reduction of usual task demand

Figure 2(a) presents a typical driving area in the two-dimensional space of task demand and driver capability. The typical driving area has some range because both the task demand and the driver's temporary capability change according to driving conditions. For example, task demand increases when a lead vehicle suddenly decelerates and the headway distance decreases while following the lead vehicle. However, task demand decreases when driving with no other vehicles around the driver's vehicle on a straight road with wide traffic lanes. A driver allocates more resources when changing traffic lanes or overtaking a vehicle, leading to higher driver capability. When a driver glances at objects irrelevant to the driving task, the driver's temporary capability decreases.

Conventional driver-assistance systems that are now installed in passenger cars assist drivers when the task demand suddenly increases and/or the driver's capability decreases. The vertical dashed arrow and the horizontal dashed arrow in Figure 2(b) suggest these situations. The sensors installed in the vehicle detect situations in which task demand suddenly increases due to an immediate change in traffic conditions (e.g., sudden deceleration of a lead vehicle or a traffic jam after a sharp curve) [5]. The vertical dashed arrow shows the change of the task demand in such situations.The camera monitoring the driver's face detects situations in which the driver's capability decreases temporarily due to a glance off the road or a decrease in the driver's awareness level [6]. The horizontal dashed arrow shows the change of the driver's capability in these situation. The assistance systems support safe driving by providing the driver with warnings or by operating the vehicle automatically.

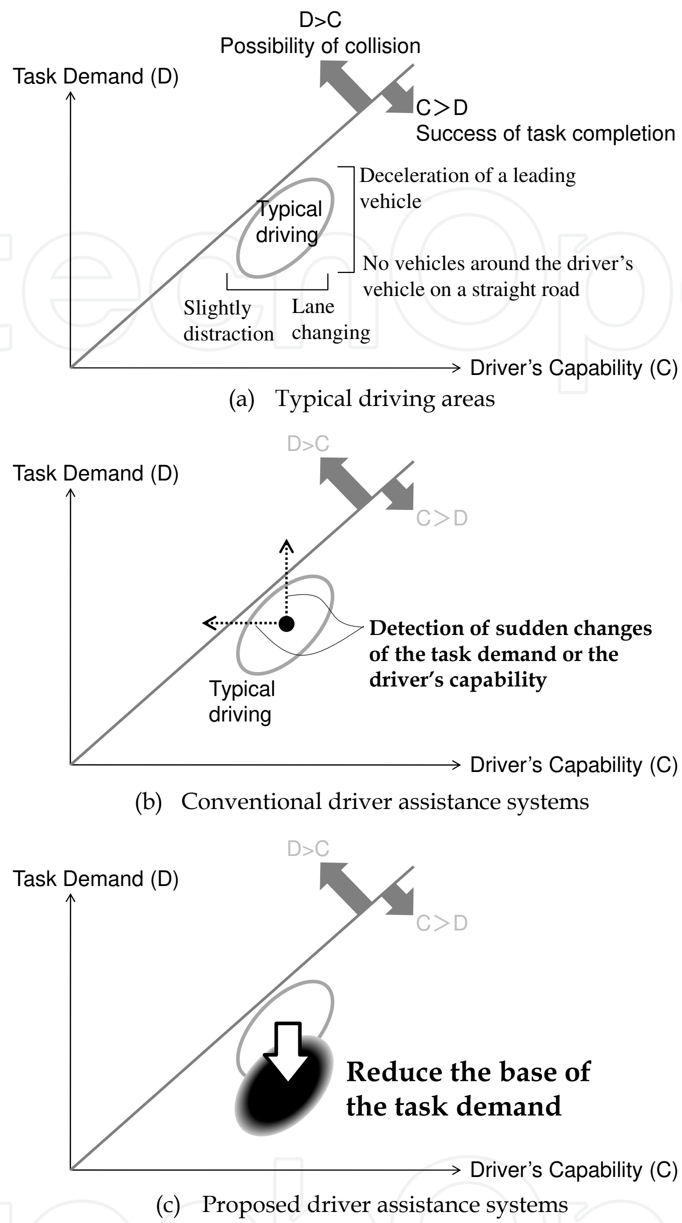

Figure 2. Concept of conventional and proposed driver-assistance systems in the task demand and driver capability space

When the base of the driving task demand is lower during usual driving, sudden changes in traffic conditions may not increase task difficulty because the driver's capability remains higher than the temporal task demand. In addition, the driver can maintain driving safety by reducing the base of the task demand even when the driver is tired or sleepy and the driver's capability decreases temporarily. Figure 2(c) presents the concept of new driver-assistance systems that promote driving with lower task demand. This new system may contribute to reducing driving risk: the possibility of entering the area where task demand is above driver capability, which potentially underlies normal drives. It is essential to clarify how drivers control task demand while driving and to apply the control method of task demand in order to develop the proposed driver-assistance systems. We need mathematical modeling techniques to understand driving behaviors based on the behavioral data.

1.3. Applying fuzzy logic to detecting and understanding of driver behavior

Several research studies have conducted to investigate differences in the driving behavior within and between drivers. Driver states, including a fatigue, a vigilance, and a frustration, are one aspect of the dynamic changes of the individual driver's behavior in a wide sense. These conditions were measured by physiological signals [7-9]. Pattern recognition techniques (e.g., Neural Network Model, Hidden Markov Model, ARX (AutoRegressive with eXogenous) Model) have been applied to driving behavior data, contributing to recognizing and identifying characteristics of the drivers' behaviors [10-12].

In this chapter, we use fuzzy logic to clarify typical driving behavior and behavior with low task demand. A driver recognizes the physical conditions around the vehicle. Human cognition and recognition are subjective and ambiguous. Drivers feel as if they are traveling fast or are late according to road traffic conditions, even at the same speed. For example, drivers feel as if they are driving faster when they accelerate to 40km/h after driving very slowly due to a traffic jam. However, they feel as if they are traveling slowly when they drive on an urban street at 40km/h after driving at 100km/h on a highway. Therefore, traditional controls using a deterministic equation (e.g., PID controller) cannot tell the difference between usual driving and driving with low task demand. Deterministic controls operate pedals or the steering wheel in order to adjust the relationship between the current value and the desired value in a physical space. The driver's perception of driving states in a physical space (e.g., feelings of speed and of relative distance) change according to road conditions and traffic situations. The control algorithm should be changed based on the conditions around the driver's vehicle, in order to adjust the task demand so as to maintain a low level.

The fuzzy logic model constructs if-then rules in divided regional spaces and combines several rules to the representation of input-output relationships [13]. Enabling appropriate control rules according to road traffic conditions contributes to determining the driver's perceived demand while driving. Additionally, fuzzy logic controls correspond to linguistic controls. This model describes driving operations using linguistic terms. Model construction using ordinary language is suitable for estimating the driving mode in real road-traffic environments.

We introduce a case study using fuzzy logic to clarify driving modes, focussing on car-following behavior. Fuzzy logic car-following models were developed by the Transportation Research Group at the University of Southampton [14,15]. These models were applied to behavior data collected on a real bypass in Japan. The input-output relationship estimated by the fuzzy logic model was used to understand differences among car-following behaviors in different driving modes. We compared car-following behavior in a driver's usual manner with the behavior observed in low task-demand conditions.

2. Case study: Applying the fuzzy logic car-following model to clarify car-following behavior with low task demand

Drivers adjust headway distances according to the relative speed of a lead vehicle. Figure 3 presents an example of typical car-following behavior. The data were obtained from field experiments using an instrumented vehicle. The horizontal axis denotes the headway distance between the driver's vehicle and the lead vehicle, and the vertical axis denotes the relative speed of the lead vehicle (the positive relative speed means that the lead vehicle drives faster than the driver's vehicle). Drivers attempt to maintain a preferable following headway. When the speed of the lead vehicle increases and the relative distance to the lead vehicle increases (Figure 3 (1)), the driver accelerates in order to maintain the desired following distance. The speed of the driver's vehicle increases (i.e., the relative speed becomes negative) and the headway distance decreases (Figure 3 (2)); the responses of headway distance occur a few minutes later, due to the driver's response time. When the headway distance decreases to less than the desired distance, the driver decelerates and the relative speed increases. The distance between the two vehicles again opens (Figure 3 (3)). These cycles continue in a car-following situation, and car-following behavior is depicted by several spirals in a plot of headway distance and relative speed.

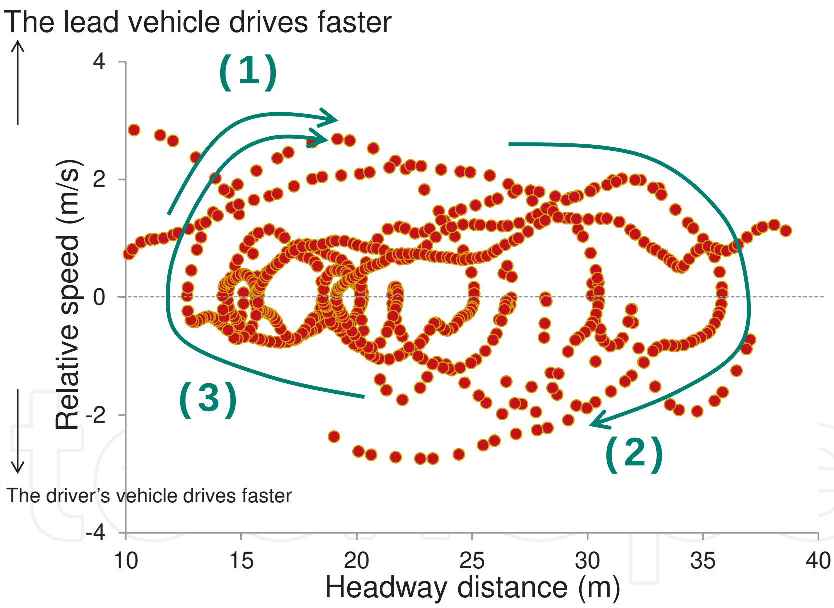

Figure 3. Typical car-following behavior in the plot of headway distance and relative speed

2.1. Fuzzy Logic car-following model

The concept of the fuzzy logic car-following model includes a description of the driver's acceleration in the divided headway distance and relative speed spaces. The relationship among acceleration, headway distance, and relative speed is depicted in a natural manner using verbal terms and associated rules, instead of deterministic mathematical functions. Various car-following models have been proposed for more than sixty years (e.g., General Motors Model [16,17], Stopping-Distance Model [18], and Action-Point Model [19]. See reference [20] for the historical review). The output is driver's acceleration in almost all of the car-following models, and several functions have been proposed to map input spaces to the output space. The fuzzy logic car-following model uses a theory of fuzzy logic to quantify the sensory inputs and the input-output map.

The fuzzy logic car-following model can evaluate car-following behavior that results from incomplete and imprecise sensory data by human modalities. Figure 4 depicts the concept of the fuzzy logic car-following model. If-then rules are developed in each categorized area in the two-dimensional spaces.

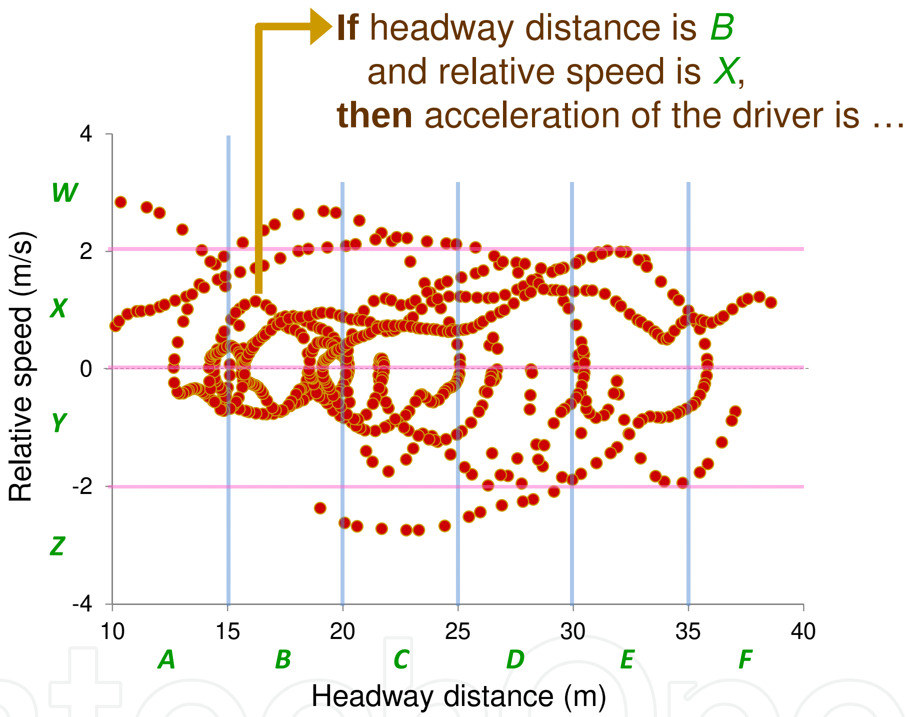

Figure 4. Concept of the fuzzy logic car-following model

Figure 5 presents the structure of the fuzzy logic car-following model. This model uses two inputs: distance divergence and relative speed. Distance divergence is the ratio of headway distance to desired headway distance. The desired headway is calculated using the average of headway distances when relative speeds between vehicles are close to zero. Relative speed is the speed of the lead vehicle minus the speed of the driver's vehicle: a positive value indicates that the lead vehicle drives faster. There are three partitions of "distance divergence" (close, good, and far) and five partitions of "relative speed" (closing+, closing, zero, opening, and opening+).

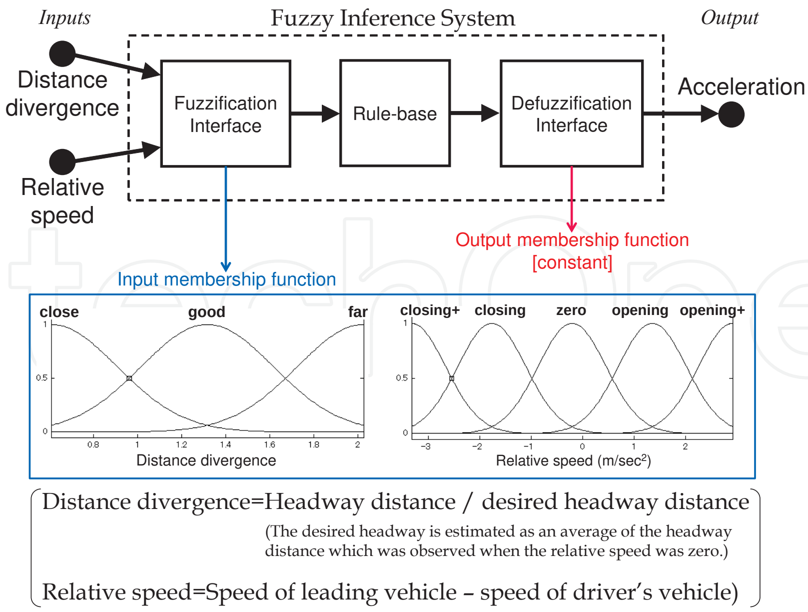

Figure 5. Structure of the fuzzy logic car-following model

The input-output relationship is estimated using fuzzy sets that are described by membership functions. This study uses a Sugeno inference system [21], a Gaussian membership function, and a constant output membership function. The initial fuzzy inference system uses the grid partition method. The membership functions of each input are evenly assigned in the range of the training data. The parameters of the fuzzy-inference system are then estimated using a combination of back-propagation and least-square methods. The parameters of input membership functions are estimated using back propagation in each iteration, in which the differences between training data and model output are propagated backward and the parameters are updated by gradient descent. The parameters of output membership functions are updated in a forward pass using the least-square method. Parameter optimization is repeated until a given number of iterations or an error reduction threshold is reached. The defuzzification method is a weighted average. See reference [22] for details of the fuzzy logic car-following model, including input variable validation and model validation.

2.2. Data collection in real road traffic environments

Two methods are used to collect driving behavior data in a real road environment: using a private car and field experiments using an instrumented vehicle. A simple driving recorder system is installed in the private car that the participant owns and uses in daily living. This recorder system collects the driving behavior data of the owner. This method contributes to recording naturalistic behavior data. A famous research project is the 100-Car Naturalistic Driving Study by the Virginia Tech Transportation Institute (VTTI) [23]. This study suggested the actual conditions of Heinrich's law in the real road traffic environment and the actual occurrence rate of distracted driving of ordinary drivers. One shortcoming is that most drivers do not always drive on the same road, so this research concept is not suitable for investigating

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the influence of road traffic environments on the individual driver's maneuvering and controlling.

An instrumented vehicle is equipped with various sensors to record the vehicle's driving status and the driver's operations of the pedals and steering wheel. Instrumented vehicles were developed in the 1960s and 1970s, mainly in the USA and in Sweden [24-26]. In Japan, a driving behavior database was constructed using four instrumented vehicles, 92 drivers (33 females) of various ages, and measurement drives for 10 to 40 days per driver [27]. The advantage of using an instrumented vehicle is an easy analysis of driving behavior data collected on the same road, contributing to an evaluation of the impact of traffic conditions on the individual driver's behavior under the same road conditions.

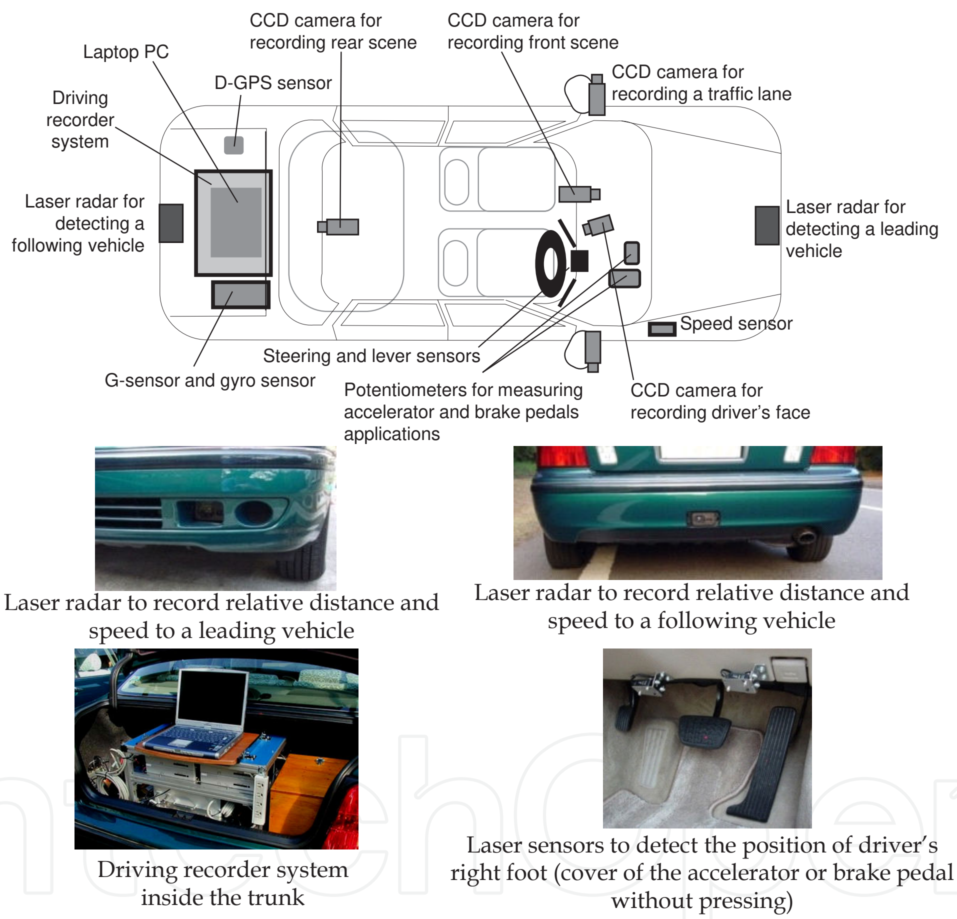

Figure 6. Sensors and driving recorder system of the AIST instrumented vehicle.

Figure 6 presents an overview of the AIST instrumented vehicle used to construct the driving behavior database [28]. Sensors installed in the vehicle include a speed sensor, G-sensor and gyro sensor, a D-GPS sensor, steering and lever sensors and laser radars. Five CCD cameras are used to record visual images outside and inside the instrumented vehicle. The recorder system is fixed in the trunk of the vehicle in order to encourage natural driving behavior in measurement drives. The car-following behavior data introduced in this chapter was also collected using the same vehicle.

2.3. Data collection of driving behavior with low task demand

The experiment drive was made once a day for a total of 15 drives. The participants were instructed to drive in their usual manner (typical driving) for seven trials, and to drive to prevent accumulated fatigue and in a more relaxed manner (driving with low task demand) for the other eight trials. The drives with high task demand would require higher resource allocation to the driving task, and higher concentration on driving would lead to an accumulation of fatigue. Therefore, preventing fatigue while driving corresponds to a condition in which drivers should control task demand by performing driving operations that do not exceed their capability, where their capability is temporarily low due to the instructions.

Eight drivers (four females and four males) participated in the field experiments. The average age was 37.6 years (25 to 51 years), the average driving experience was 15 years (5 to 33 years), and the average annual mileage was 16,000km (8,000 to 30,000km).

Figure 7 depicts a road section used for analysis of car-following behavior with different driving modes. The target road was a one-lane bypass and two different directions. There were several oncoming vehicles, including buses or trucks in the opposite lane. The length was 1.8km (about 2 min drive). We focused on only drives with a lead vehicle, excluding the data during drives without a lead vehicle on the target section.

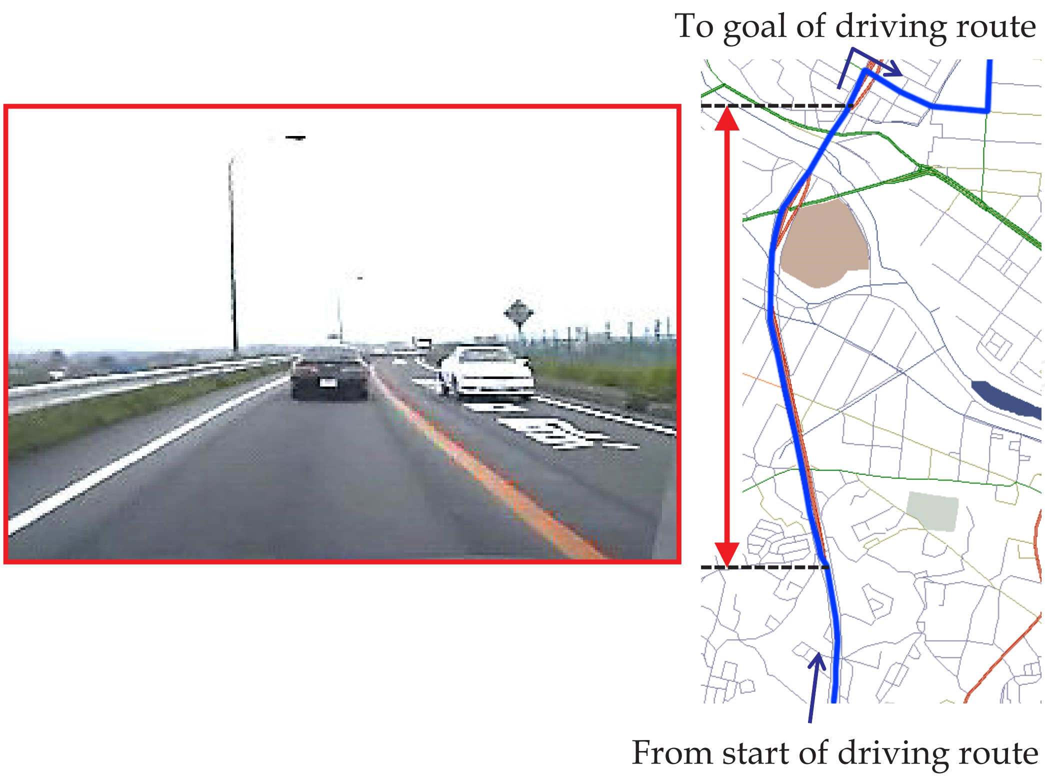

Figure 7. Photo and maps of the road in the analysis of car-following behavior.

2.4. Results

Table 1 presents the number of traces and the data length of the data collection, which were inputted into the fuzzy logic model specification. One trace was defined as a situation in which a driver followed a lead vehicle for more than 20sec. There is a total of 24 traces in the typical driving and 30 traces in the driving with low task demand. The two driving modes have similar data length (typical driving: 20.03min, driving with low task demand: 19.11min).

Performance of fuzzy logic model estimation is usually evaluated using the root mean square error (RMSE) of the model prediction:

$$RMSE=\sqrt{\frac{\sum_{i=1}^{N}(\hat{Y}_i - Y_i)^2}{N}} \tag{1}$$

where $\hat{Y}_i$ is a predicted value using the fuzzy logic model at time increment i, Y_i is raw data at time increment i, and N is the number of data. Table 1 shows the results of the RMSEs calculated in the typical drive and in the drive with low task demand, respectively. The RMSEs between the predicted acceleration and the measured data in the estimated fuzzy logic car-following model were 0.24m/sec^2 in the typical driving and 0.23 m/sec^2 in the driving with low task demand. These indicate a satisfactory model-to-data fit compared to other real-world data [14]. Additionally, the results are similar to the errors calculated in the other car-following data on the same road section [22].

	Results of data collection		**Results of fuzzy logic model estimation**
Driving mode	Traces	Data length (min)	RMSEs (m/sec^2)
Typical driving	24	20.03	0.24
Driving with low task demand	30	19.11	0.23

Table 1. Data volume in the fuzzy logic model specification and the results of the RMSE

Figure 8 presents relative speed-acceleration mapping resulting from the fuzzy logic model estimation. We focus on the relationship between relative speed and acceleration in order to analyze the dynamic aspects of car-following behavior. When the distance between vehicles is increasing, acceleration in drives with low task demand is lower than that in typical drives. When the driver's vehicle approaches the lead vehicle, deceleration of driving with low task demand is less than that of typical driving.

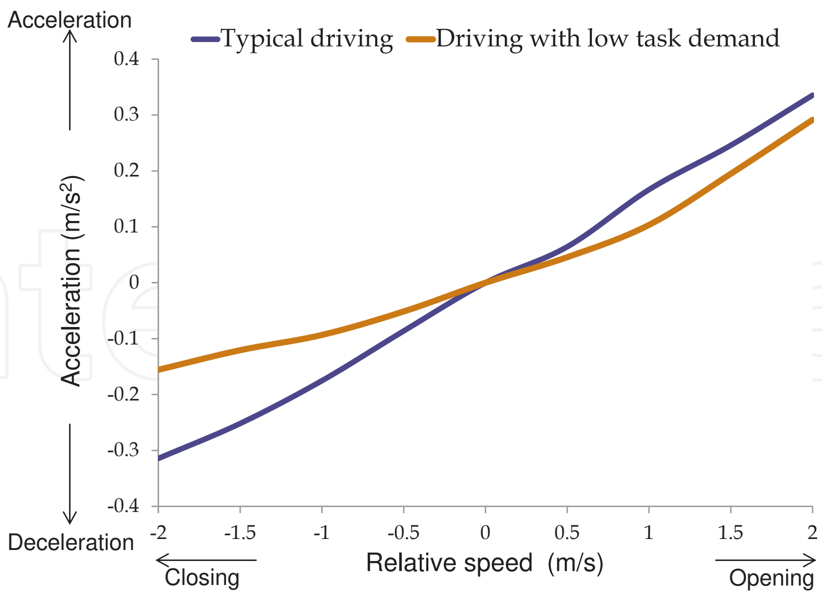

Figure 8. Results of fuzzy logic car-following model specifications in relative speed and acceleration mapping

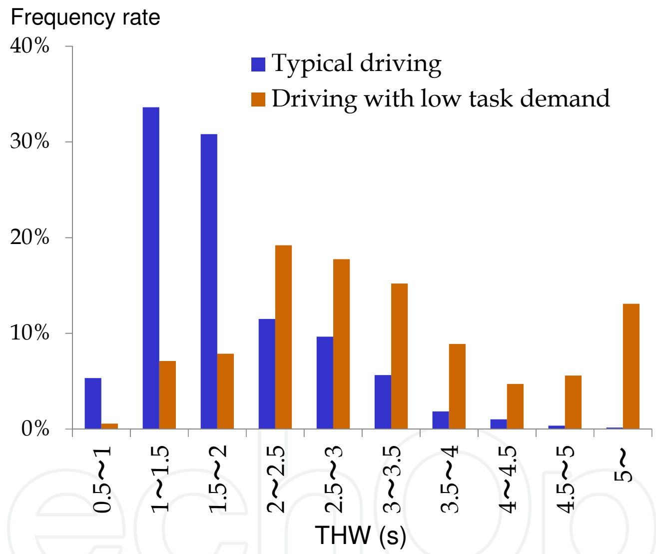

Figure 9. Result of THW distribution between two driving modes

Figure 9 presents the distribution of time headway (THW) (relative distance between the lead vehicle and the driver's vehicle divided by the driving speed of the driver's vehicle). Although the distribution of THW is not a result estimated from the fuzzy logic, this suggests the static aspects of the car-following behavior [29]. Distribution is defined as proportions of the time when drivers take the relevant THW to the total time while driving on the target road section. The graph shows the longer headway distance to the lead vehicle in drives with low task demand. Here, 15% of the data are located in the category of more than 5sec.

2.5. Discussion

2.5.1. Understanding of driving modes

Drivers' acceleration and deceleration were lower when they were conscious of preventing fatigue while driving than when driving in the usual manner. Drivers are not sensitive to movement of the lead vehicle under low task demand conditions, and they do not control the vehicle tightly according to the acceleration or deceleration of the lead vehicle. Comparison of THW distributions suggested that drivers allowed greater headway distances when driving with low task demand. Greater headway distance permits the driver's moderate controls observed in the relative speed and acceleration mapping.

This finding is supported by the control methods of task demands while approaching an intersection with a traffic light [30]. We compared behavioral data when driving in the driver's typical manner and when driving under instructions to prevent fatigue by driving with low task demands. The target situation was approaching and stopping at intersections with red traffic lights. The differences between the two driving modes were found in driving speed, headway distance, accelerator pedal operation, or brake pedal operation. Drivers behaved so as to maintain a margin for the movements of a lead vehicle, in order to reduce the task demands. Our findings in the data analysis of the behaviors approaching the intersections support the results described in this chapter. Our findings suggest that longer spatial distance to a preceding vehicle contributes to reducing the task demands.

THWs of more than 5sec suggest that drivers maintain their desired driving speed and do not follow the driving speed of the lead vehicle. This finding indicates that the driving situation changes from car-following to solo-driving. Drivers often change the driving situation and choose an easy driving task in order to reduce driving task demand.

2.5.2. Advantage of fuzzy logic car-following model

The fuzzy logic can develop smooth relations between the input and output spaces. We calculated averages of the drivers' acceleration in the following categories: when the relative speed between the lead vehicle and the driver's vehicle was from -2 to -1.5 m/sec^2, from -1.5 to -1 m/sec^2, from -1 to -0.5 m/sec^2, from -0.5 to 0 m/sec^2, from 0 to 0.5 m/sec^2, from 0.5 to 1 m/sec^2, from 1 to 1.5 m/sec^2, and from 1,5 to 2 m/sec^2. Figure 10 presents the results of our calculations.

The deceleration of typical driving in the category of "-1.5 ~-1 m/sec^2" exceeded that of driving with low task demand. The acceleration of typical driving in the category of "1.5 ~2 m/sec^2" exceeded that of driving with low task demand. These results were similar to those obtained from the estimation of the fuzzy logic car-following model (Figure 8). However, the deceleration when the relative speeds were "-2 ~-1.5 m/sec^2"and "-1 ~-0.5 m/sec^2"and the acceleration when the relative speeds were "1~1.5 m/sec^2" were almost the same between the two driving modes. We cannot understand the driving behavior when the drivers reduce the task demand based on Figure 10, because the averaged accelerations in some ranges of the relative speeds does not indicate definite differences between when driving in the drivers' typical manner and when driving with low task demand. Linear approximation of the averages suggests the tendencies similar to the fuzzy logic model estimation, while the details of the differences in the relative speed and acceleration mapping between the two driving modes are not described; e.g., the gradient of the acceleration in the range of "1~2 m/sec^2"was almost the same between the two driving modes, although the values of the driving with low task demand were lower than those of the typical driving.

Multivalued logic of the fuzzy membership function, contrast to the concept of two-valued logic, contributes to formulating smooth mapping from inputs to output values. If-then statements in the fuzzy logic are described using natural language, leading to not so large of the partition numbers of the inputs (e.g. "closing+", "closing", "zero", "opening", and "opening+" in the relative speed in this study). The fuzzy operation based on the moderate partition numbers of the Gaussian membership functions could avoid an overfitting to the data collected on a real road.

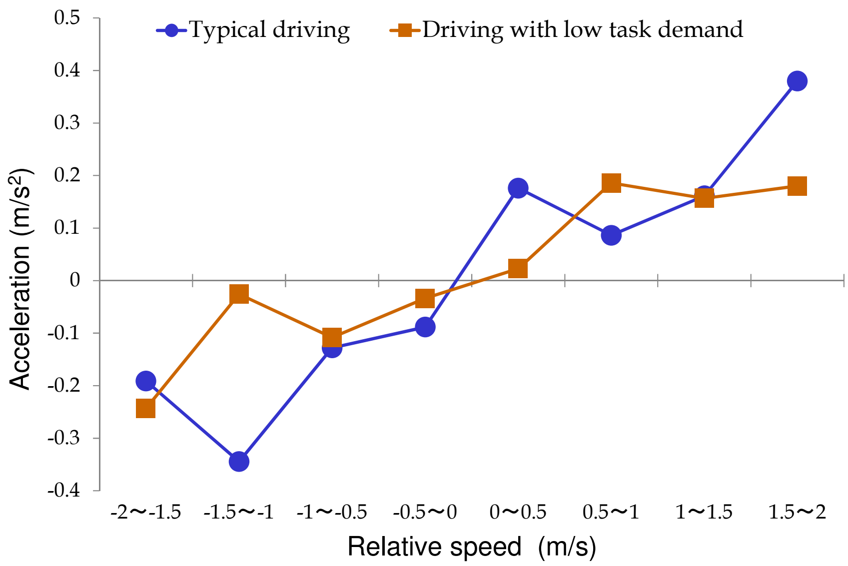

Figure 10. Averages of the acceleration in each categorized relative speed

3. Comparison of factors influencing a driver's acceleration under car-following conditions

In the development of fuzzy logic car-following model, several candidates of behavioral data indices were applied to the fuzzy inference system estimation [15]: headway distance to the leading vehicle, THW, inverse of time to collision (time to collision (TTC) is calculated by the headway distance divided by the relative speed between the lead vehicle and the driver's vehicle), etc. Model estimation tests using a single variable, a combination of two variables, and a combination of three variables were tried. The trials had many numbers because of the large number of all possible combinations. The results confirmed that drivers employed a combination of headway and relative speed for their control strategy in a car-following situation. Distance divergence and relative speed were selected as the inputs of the car-following model. Car-following behavior for typical drives and drives with low task demand were compared assuming that drivers control the vehicle acceleration based on the same information regarding speed matching and headway matching.

The Bayesian network model would be useful in investigating the behavioral index automatically and comprehensively, when we hypothesize that drivers change information for vehicle control in order to manage task demand. The Bayesian network model is a stochastic model that focuses on causal networks between multiple parameters using a set of variables and a set of direct links between variables [31]. The connection in the Bayesian model presents a conditional probability between objective and explanatory variables, indicating a quantitative relationship between variables. The direct link between A and B suggests that the two variables are strongly related: data distribution of variable "A" changes according to variable "B," and vice versa.

We constructed Bayesian network models using the same data sets as when constructing the fuzzy logic car-following model. The Bayesian models were applied to the data for each driving mode (typical drives and drives with low task demand). The following indices were candidates that have influences on driver's acceleration while following a leading vehicle.

- Speed of driver's vehicle
- Speed of the leading vehicle
- Headway distance
- Relative speed
- THW
- Inverse of TTC
- Distance divergence
- Angular velocity: Calculated using the approximate formula of "width*Relative speed/Headway distance^2", where the width of the lead vehicle is assumed to be 2.5m.

Figure 11 and 12 present the results of the Bayesian network model estimation. AIC (Akaike Information Criterion) was applied as the criteria when assessing the relations between variables [32]. The two estimated Bayesian models suggest that drivers use the same behavioral indices for acceleration control between in typical driving and in driving with low task demand. "Distance divergence", "Relative speed", and "Speed of the driver's vehicle" influence the driver's acceleration. "Distance divergence" and "Relative speed" were the same as the input variables of the fuzzy logic car-following model. Thus, Bayesian network model estimation contributes to searching for the behavioral index influencing the driver's operations within all data sets collected in real road traffic environments.

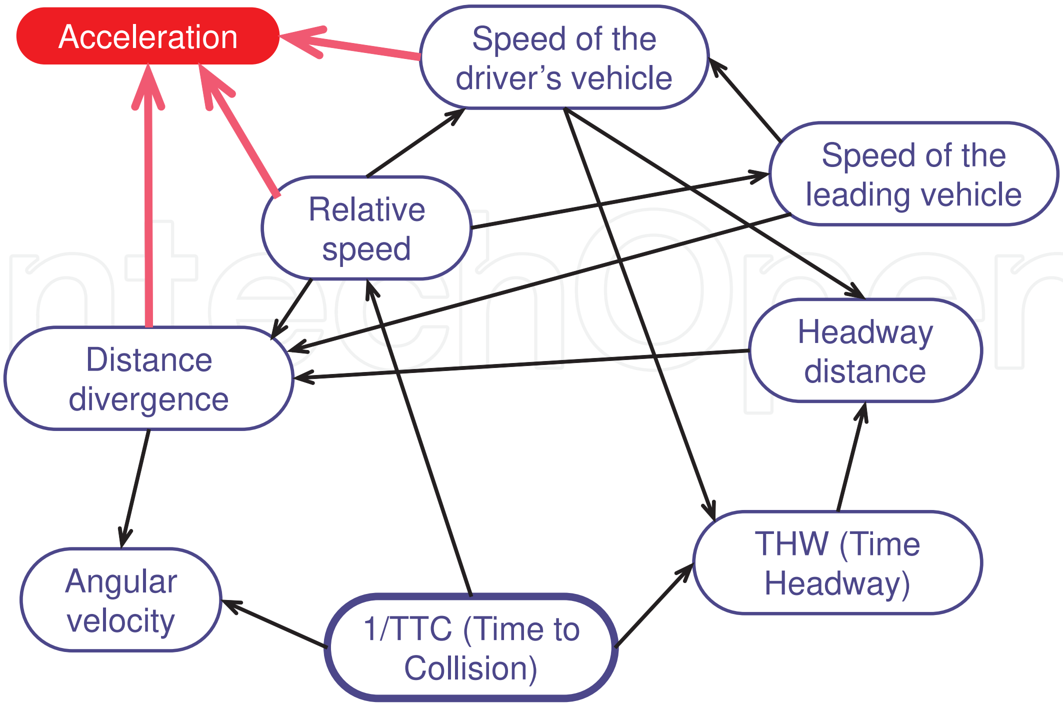

Figure 11. Bayesian network model estimated using the behavior data in typical driving

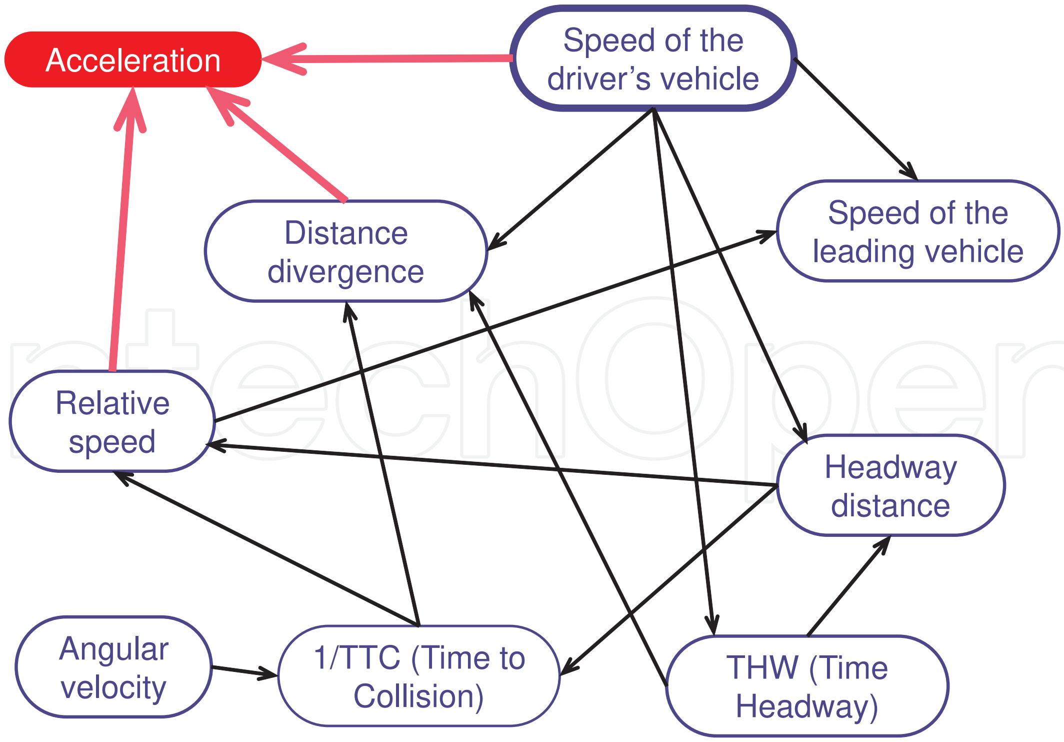

Figure 12. Bayesian network model estimated using the behavior data in driving with low task demand

Differences between in the two driving modes were found in the relationships between the candidates other than the factors influencing the acceleration. “Inverse of TTC“ has no parents in the Bayesian network model of the typical driving. This item influences “Angular velocity“, “Relative Speed“, and “THW“, however, no factors have an influence on “Inverse of TTC“. The drivers might determine the speed and manage the headway distance based on the inverse of TTC which indicates the possibility of collision while following the leading vehicle [33]. On the other hand, “Speed of the driver’s vehicle“ has no parents in the Bayesian network model when driving with low task demand. The speed of the driver’s vehicle influences the most factors: “Acceleration“, “Distance divergence“, “THW“, “Headway distance“, and “Speed of the leading vehicle“. This item might be a determinant when judging how to follow a lead vehicle in order to reduce the task demand. This result supports the change of the driving situation from car-following to solo-driving. Drivers focused on keeping their preferred driving speed when they reduced the task demand, leading to changing the driving situation by themselves.

The Bayesian network model would not be appropriate for clarifying the driver’s dynamic operations such as acceleration response according to the movements of the lead vehicle. The relationship between input and output variables is determined using conditional probability, indicating that data were categorized in the model estimation. The category number and range of one category in the data categorization are key factors in the model development. The data volume in the categorized area directly affects the model‘s estimation performance. Sufficient data volume cannot be necessarily collected in all of the categories when behavior data are recorded in real road traffic environments. In the fuzzy logic model, if-then rules are also developed in the categorized area. The fuzzy relationship in the total spaces combined for each categorization shows a robust estimation ability.

4. Conclusion

This chapter introduces a concept of task demand controlling and describes the application of fuzzy logic to understanding the difference of the driving behaviors between in usual drives and in drives with low task demand. Conventional driver-assistance systems provide a driver with assistance information and warnings or automatically control the vehicle when the systems detect a sudden change of the task demand. We proposed a new concept of driver assistance systems that reduce the base of the usual task demand.

The fuzzy logic, non-linear and linguistic rule-based modelling technique, is suitable to describe the difference of the time-series behavior between in the different driving modes. The fuzzy logic car-following model was applied to clarify the car-following behavior with low task demand. The fuzzy logic model evaluates the degree to which a driver accelerates according to the relation between the preceding vehicle and the driver’s vehicle. The driver controls longitudinal acceleration moderately under low task demand conditions, both when the relations between the two vehicles are opening and closing. Taking long headway distances and moderate controlling of the vehicle, which is not sensitive to movement of the lead vehicle, are essential to develop the assistance systems for keeping lower task demands in usual drives.

Bayesian network model, representing causality between variables using conditional probabilities, was used to select factors influencing a driver's acceleration control while following a lead vehicle. The Bayesian model estimated that the drivers control the vehicle based on a combination of speed matching and headway distance matching strategy, corresponding with the findings obtained from the development of the fuzzy logic car-following model. The detailed insight about the Bayesian model structures implied that the decision-making factors for how to follow a lead vehicle are different between in typical driving and in driving with low task demand. The fuzzy logic model would contribute to evaluating a dynamic aspect of human controls and the Bayesian network model would contribute to understanding the human decision-making process.

We will investigate the driving behaviors on the other driving scenes in further study. Turning at intersections will be a next issue. Behaviors with low task demand should be clarified when drivers prepare for making a turn while approaching an intersection as well as when they make left or right turns at the target intersection.

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