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Understanding Driver Car-Following Behavior Using a Fuzzy Logic Car-Following Model

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1. Introduction

Recently, automatic systems that control driving speeds and headway distances while following a vehicle have been developed worldwide. Some products, such as adaptive cruise control systems, have already been installed in upper segments of passenger vehicles. Car following is an important operation in safe and comfortable driving on straight and/or curved roads. The number of traffic accidents involving rear-end collisions is the highest over the last decade in Japan (Iwashita et al., 2011). A rear-end collision occurs when the distance between two vehicles decreases due to deceleration of the lead vehicle and/or higher speed of the following vehicle. The automatic vehicle control system maintains a safe headway distance while following a vehicle and controls velocity according to the relative speed of the leading vehicle, in order to avoid a rear-end collision.

If the system's automatic controls do not match the driver's manual controls, driver acceptance of the automatic vehicle control systems decreases, and the driver is not likely to use them. For example, when a lead vehicle speeds up and the inter-vehicle distance increases, one driver may accelerate strongly, whereas another driver may accelerate slightly; and other drivers may not accelerate. The system's automatic hard acceleration does not suit drivers whose acceleration is slight and those who do not accelerate, and they may regard such automatic systems as dangerous. Therefore, it is expected that drivers will accept longitudinal control systems that operate in a manner similar to their own usual car-following behavior. Drivers' car-following behavior must be investigated in a real road-traffic environment to develop vehicle control and driver support systems that are compatible with drivers' typical car-following behavior.

Car-following behavior consists of two aspects: how much distance drivers allow for a leading vehicle as an acceptable headway distance, and how they control acceleration according to the movements of the leading vehicle. Figure 1 presents an example of a typical following process. This car-following behavior data was recorded using an instrumented vehicle on a real motorway in Southampton (Sato et al., 2009a). The relative distance and speed were detected by microwave radar. The data length was 5min. Car-following behavior is a goal-seeking process depicted by several spirals as drivers attempt to maintain the desired following headway behind a vehicle in a car-following situation.

In this chapter, the range of headway distances that drivers leave for leading vehicles is the "static" aspect of car-following behavior. A driver's acceleration controls based on the relationship between the driver's own vehicle and the leading vehicle is termed the "dynamic" aspect. Following distances, Time Headway (THW) (defined by the relative distance to a leading vehicle divided by the driving speed of driver's own vehicle), and Time to Collision (TTC) (defined by the relative distance to a leading vehicle divided by the relative speed between the leading and drivers' own vehicles) are indicators for evaluating the static aspect. A number of car-following models deal with the dynamic aspect.
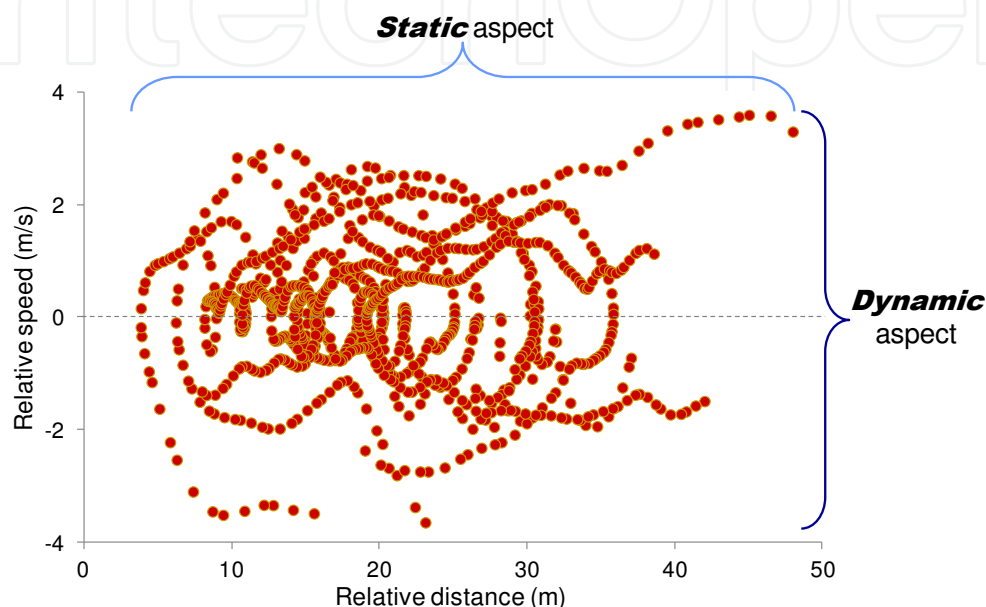

Fig. 1. Example of car-following behavior data collected using an instrumented vehicle on an actual road. (For details of the data collection method, please see section 3.2.)

1.1 Brief review of car-following models

Car-following models have been developed since the 1950s (e.g., Pipes, 1953). Many models describe the accelerative behavior of a driver as a function of inter-vehicle separation and relative speed. The following are representative car-following models (for details, please see Brackstone & McDonald, 1999).

General Motors Model:

The fundamental concept behind the General Motors Model is the stimulus-response theory (Chandler et al., 1958). Equation (1) presents a representative formulation.

$$a_F(t + T) = \alpha \left[\frac{[V_F(t)]^m}{[X_L(t) - X_F(t)]^l} \right] [V_L(t) - V_F(t)] \tag{1}$$

where $a_F(t+T)$ is the acceleration or deceleration rate of the following vehicle at time $t+T$; $V_L(t)$ is the speed of the lead vehicle at time t; $V_F(t)$ is the speed of the following vehicle at time t; $X_L(t)$ is the spacing of the lead vehicle at time t; $X_F(t)$ is the spacing of the following vehicle at time t; T is the perception-reaction time of the driver; and m, l, and α are constants to be determined.

Basically, the response is the acceleration (deceleration) rate of the following vehicle. This is a function of driver sensitivity and the stimulus. The stimulus is assumed to be the difference between the speed of the lead vehicle and that of the following vehicle. Driver sensitivity is a function of the spacing between the lead and following vehicles and the speed of the following vehicle. Several derived equations have been proposed in the last 20 years (see Mehmood et al., 2001).

However, one weakness of the General Motors Model is that the response of the following vehicle is determined by one stimulus, speed relative to the leading vehicle. When the relative speed between the two vehicles is zero, the acceleration or deceleration response is zero. This is not a realistic phenomenon, because a driver decelerates to increase inter-vehicle separation when the relative speed is zero but the spacing is too short. To overcome this problem, Helly developed a linear model that includes the additional stimulus term of the desired headway distance (Helly, 1959):

$$a_F(t + T) = C_1[V_L(t) - V_F(t)] + C_2\{[X_L(t) - X_F(t)] - Dn(t + T)\}$$

$$Dn(t + T) = \alpha + \beta V_F(t) + \gamma a_F(t) \tag{2}$$

where $D_n(t+T)$ is the desired following distance at time t+T; and α, β, γ, C_1, and C_2 are calibration constants.

Another limitation is the assumption of symmetrical behavior under car-following conditions. For example, a lead vehicle has a positive relative speed with a certain magnitude, and another lead vehicle has a negative relative speed with the same magnitude. In these situations, the General Motors Model gives the same deceleration rate in the first case as the acceleration rate in second case. In a real road-traffic environment, deceleration in the second case is greater than acceleration to avoid risk.

Stopping-Distance Model:

The Stopping-Distance Model assumes that a following vehicle always maintains a safe following distance in order to bring the vehicle to a safe stop if the leading vehicle suddenly stops. This model is based on a function of the speeds of the following and leading vehicles and the follower's reaction time. The original formulation (Kometani & Sasaki, 1959) is:

$$\Delta x(t-T) = \alpha v^2_L(t-T) + \beta_l v^2_F(t) + \beta v_F(t) + b_0 \tag{3}$$

where Δx is the relative distance between the lead and following vehicles; v_L is the speed of the lead vehicle; v_F is the speed of the following vehicle; T is the driver's reaction time; and α, β, β_l, and b_0 are calibration constants.

The Stopping-Distance Model is widely used in microscopic traffic simulations (Gipps, 1981), because of its easy calibration based on a realistic driving behavior, requiring only the maximal deceleration of the following vehicle. However, the "safe headway" concept is not a totally valid starting point, and this assumption is not consistent with empirical observations.

Action-Point Model:

The Action-Point Model is the first car-following model to incorporate human perception of motion. The model developed by Michaels suggests that the dominant perceptual factor is changes in the apparent size of the vehicle (i.e., the changing rate of visual angle) (Michaels, 1963):

$$\frac{d\theta}{dt} = \frac{4*W_L}{4*[X_L(t)-X_F(t)]^2+W_L^2}[V_L(t) - V_F(t)] \tag{4}$$

where W_L is the width of the lead vehicle.

This model assumes that a driver appropriately accelerates or -decelerates if the angular velocity exceeds a certain threshold. Once the threshold is exceeded, the driver chooses to decelerate until he/she can no longer perceive any relative velocity. Thresholds include a spacing-based threshold that is particularly relevant in close headway situations, a relative speed threshold for the perception of closing, and thresholds for the perception of opening and closing for low relative speeds (a recent work suggests that the perception of opening and that of closing have different thresholds (Reiter, 1994)). Car-following conditions are further categorized into subgroups: free driving, overtaking, following, and emergency situation. A driver engages in different acceleration behaviors in different situations when the perceived physical perception exceeds the thresholds.

The Action-Point Model takes into account the human threshold of perception, establishing a realistic rationale. However, various efforts have focused on identifying threshold values during the calibration phase, while the adjustment of acceleration above the threshold has not been considered, and the acceleration rate is normally assumed to be a constant. Additionally, the model dynamic (switching between the subgroups) has not been investigated. Finally, the ability to perceive speed differences and estimate distances varies widely among drivers. Therefore, it is difficult to estimate and calibrate the individual thresholds associated with the Action-Point Model.

2. Fuzzy logic car-following model

Drivers perform a car-following task with real-time information processing of several kinds of information sources. The car-following models discussed above have established a unique interpretation of drivers' car-following behaviors. A driver in a car-following situation is described as a stimuli-responder in the General Motors Model, a safe distance-keeper in the Stopping-Distance Model, and a state monitor who wants to keep perceptions below the threshold in the Action-Point Model. However, these models include non-realistic constraints to describe car-following behavior in real road-traffic environments: symmetry between acceleration and deceleration, the "safe headway" concept, and constant acceleration or deceleration above the threshold.

The fuzzy logic car-following model describes driving operations under car-following conditions using linguistic terms and associated rules, instead of deterministic mathematical functions. Car-following behavior can be described in a natural manner that reflects the imprecise and incomplete sensory data presented by human sensory modalities. The fuzzy logic car-following model treats a driver as a decision-maker who decides the controls based on sensory inputs using a fuzzy reasoning. There are two types of fuzzy inference system that uses fuzzy reasoning to map an input space to an output space, Mandani-type and

Sugeno-type. The main difference between the Mamdani and Sugeno types is that the output membership functions are only linear or constant for Sugeno-type fuzzy inference. A typical rule in the Sugeno-type fuzzy inference (Sugeno, 1985) is:

If input x is A and input y is B then output z is $x*p+y*q+r$;

where A and B are fuzzy sets and p, q, and r are constants.

The constant output membership function is obtained from a singleton spike ($p=q=0$).

2.1 Overview

The fuzzy logic car-following model was developed by the Transportation Research Group (TRG) at the University of Southampton (Wu et al., 2000). McDonald et al. collected car-following behavior data on real roads and developed and validated the proposed fuzzy logic car-following model based on the real-world data (briefly mentioned in 2.2 and 2.3; please see Wu, 2003; Zheng, 2003 for further explanation).

The fuzzy logic model uses relative velocity and distance divergence (DSSD) (the ratio of headway distance to a desired headway) as input variables. The output variable is the acceleration-deceleration rate. The DSSD is the average of the headway distance that is observed when the relative speeds between vehicles are close to zero. This model adopts fuzzy functions (fuzzy sets described by membership functions) as the formula for the input-output relationship. Figure 2 depicts the structure of the fuzzy logic car-following model.
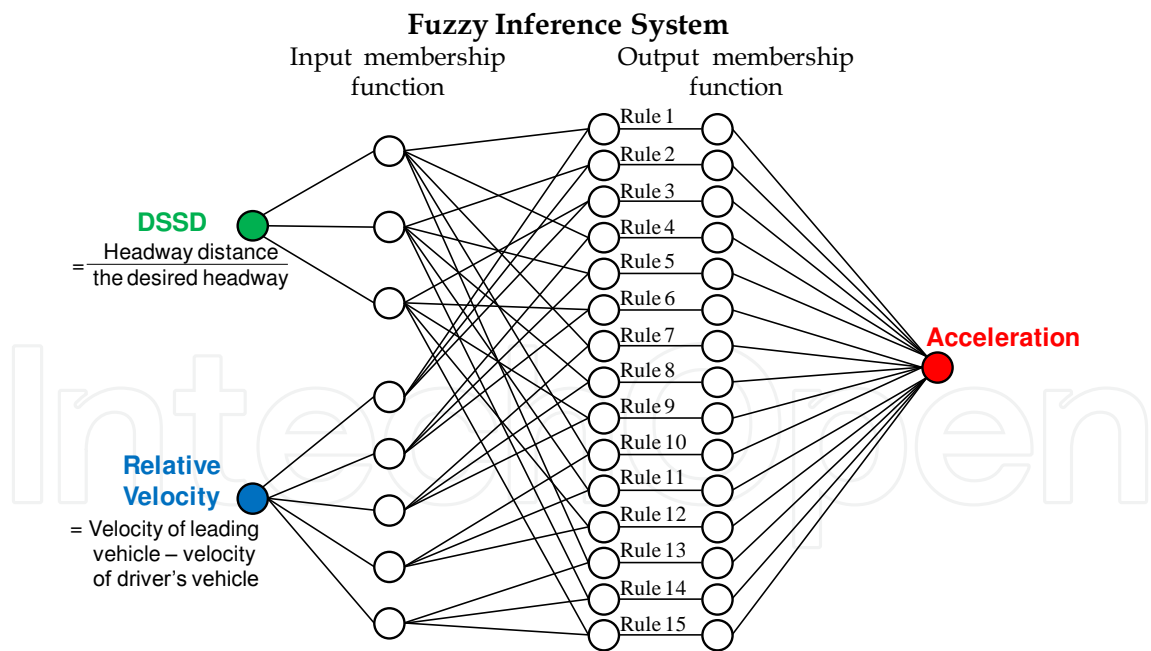

Fig. 2. Structure of the fuzzy inference system in the fuzzy logic car-following model

Specifications of the fuzzy inference system are as follows.

- Type of inference system: Sugeno
- Type of input membership function: Gaussian
- Type of output membership function: Constant

- Number of partitions for input (Relative Velocity): 5 (closing+, closing, about zero, opening, and opening+)
- Number of partitions for input (DSSD): 3 (close, ok, and far)
- Initialization of fuzzy inference system: grid partition method
- Learning algorithm: combination of back-propagation and least square methods
- Defuzzification method: weighted average

The parameter of the fuzzy inference system is estimated using the following combination of back-propagation and least square methods. The initial fuzzy inference system adopts the grid partition method in which the membership functions of each input are evenly assigned in the range of the training data. Next, the membership function parameters are adjusted using the hybrid learning algorithm. The parameters of output membership functions are updated in a forward pass using the least square method. The inputs are first propagated forward. The overall output is then a linear combination of the parameters of output membership functions. The parameters of input membership functions are estimated using back propagation in each iteration, where the differences between model output and training data are propagated backward and the parameters are updated by gradient descent. The parameter optimization routines are applied until a given number of iterations or an error reduction threshold is reached.

The input-output mapping specified by the fuzzy inference system has a three-dimensional structure. We focus on relative velocity-acceleration mapping in order to analyze the dynamic aspect of car-following behavior (i.e., drivers' acceleration controls based on the variation in relative speeds).

2.2 Input variable validation

The following eight candidates were applied to the fuzzy inference system estimation in order to obtain satisfactory performance of the fuzzy logic model.

- Velocity of the driver's own vehicle (V_d)
- Headway distance to the lead vehicle (HD)
- Relative velocity between the lead vehicle and the driver's vehicle (RV = d(HD)/dt)
- Velocity of the lead vehicle ($V_l = V_d + RV$)
- Time headway (THW = HD /V_d)
- Inverse of time to collision (1/TTC, TTC = HD/RV, where the value is infinite when RV = 0.)
- Angular velocity (This value is calculated using the following approximate formula: (width*RV)/HD^2, where the width of the lead vehicle is assumed to be 2.5m.)
- Distance divergence (DSSD, calculated from HD divided by the desired headway. The desired headway was chosen to be the average of the headway observed when the relative speeds between vehicles were close to zero.)

The performance of the fuzzy logic model was evaluated by the Root Mean Square Error (RMSE) of the model prediction:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\widehat{Y_i} - Y_i)^2}{N}} \tag{5}$$

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.

All possible model formulations (a single variable, combination of two variables, and combination of three variables) were tested. The data were collected on real motorways using a TRG instrumented vehicle. Although a three-input model suggested better RMSE performance than a one-input model or a two-input model, the two-input model using relative speed and distance divergence was adopted because of the complexity of the model structure and its applicability to a wide range of car-following situations. For details of the input variable validation, refer to Zheng, 2003.

2.3 Model validation

The developed fuzzy logic car-following model was validated in terms of reproducing a single vehicle's car-following behavior, as well as reproducing traffic flow under car-following conditions (a platoon of vehicles).

The single vehicle's car-following behavior was evaluated from empirical data, and the average RMSE of acceleration was 0.20m/s². The platoon behavior was evaluated using simulation. The response of a platoon of 20 vehicles to step changes of acceleration or deceleration of a lead vehicle was assessed in order to investigate the influence of the movement of the lead vehicle on a line of vehicles. The results validated that the fuzzy logic car-following model could reproduce both stable and unstable traffic behavior. For details of the model validation, refer to Wu et al., 2003 and Zheng, 2003.

3. Case study 1: Car-following behavior comparison between the UK and Japan

3.1 Motivation

This section introduces a case study focusing on a comparison of drivers' car-following behavior in the UK and in Japan (Sato et al., 2009b). The fuzzy logic car-following model was developed using naturalistic data collected in Southampton. We applied this model to behavioral data collected in Japan. One objective is to confirm whether Japanese car-following behavior can be described by the fuzzy logic model with the same structure as the UK model. Another objective is to investigate cross-cultural variations of the car-following behaviors of drivers in the two countries.

With increasing globalization of automotive markets, it is important to understand the differences between driving behavior in different countries. Car-following behavior may differ due to differences in nationality and the road traffic environments of different countries. The findings may contribute to designing human-centered automatic vehicle control systems based on international differences in driving behavior.

3.2 Methods

3.2.1 Instrumented vehicles

An AIST instrumented vehicle and a TRG instrumented vehicle are used for behavioral data collection (Brackstone et al., 1999; Sato & Akamatsu, 2007). Both vehicles are equipped with

various sensors and driving recorder systems in order to detect the vehicle driving status and to measure the driver's operations. Velocity is measured using a speed pulse signal, and acceleration is detected by a G-sensor. The relative distance and relative speed to the leading and following vehicles are recorded with laser radar units (AIST instrumented vehicle) or microwave radar (TRG instrumented vehicle) that are fixed within the front and rear bumpers. Figure 3 presents an overview of the AIST instrumented vehicle. This vehicle collects the following data:

- Driving speed by speed pulse signal,
- Relative distance and speed to the leading and following vehicles by laser radar units,
- Vehicle acceleration by G-sensor,
- Angular velocity by gyro sensor,
- Geographical position by D-GPS sensor,
- Application of gas and brake pedals by potentiometers,
- Position of driver's right foot by laser sensors,
- Steering wheel angle by encoder,
- Turn signal activation by encoder, and
- Visual images (forward and rear scenes, lane positions, and driver's face) by five CCD cameras.

Laser radar for relative distance and velocity to a following vehicle

Laser radar for relative distance and velocity to a leading vehicle

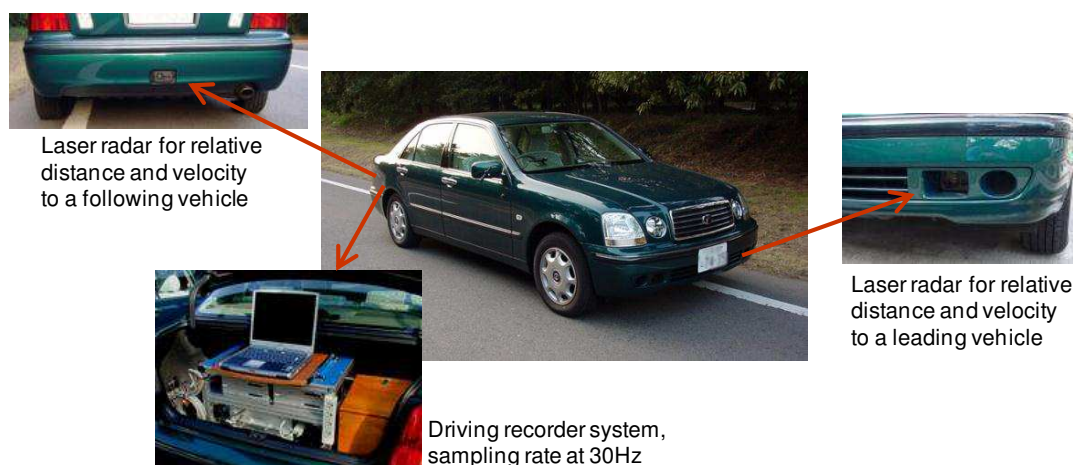Driving recorder system, sampling rate at 30Hz

Fig. 3. AIST instrumented vehicle with sensors and a recorder system for detecting nearby vehicles

The velocity of the following vehicle was calculated based on the velocity of the instrumented vehicles and the relative speed. The visual image of the rear scenes was used for better understanding of the traffic conditions while driving and for clarifying uncertainties identified in the radars.

3.2.2 Road-traffic environment

Figure 4 depicts the road environment in the Southampton (UK) and Tsukuba (Japan) routes. The driving route in Tsukuba was 15km long (travel time 30min). This route included urban roads with several left and right turns at intersections, with a traffic lane that was mostly one lane, and a bypass that had one and two traffic lanes. The driving route in Southampton included trunk roads and motorways with two and three lanes and

roundabout junctions. The driving behavior data in Southampton was collected as part of an EC STARDUST project (Zheng et al., 2006). The field experiments at the two sites were conducted during the morning from 9:00 to 10:45.

3.2.3 Variables

The passive mode was used for the data collected (Fig. 5), reflecting random drivers who followed the instrumented vehicle. The passive mode can collect and evaluate a large population of drivers, rather than just the participating driver in the instrumented vehicle, in a short period and at a lower level of detail (Brackstone et al., 2002). The measured data in the passive mode enable evaluation of car-following behavior trends in each country.

	Urban road	Bypass	Trunk road	Motorway
Tsukuba (Japan)				
Southampton (UK)				
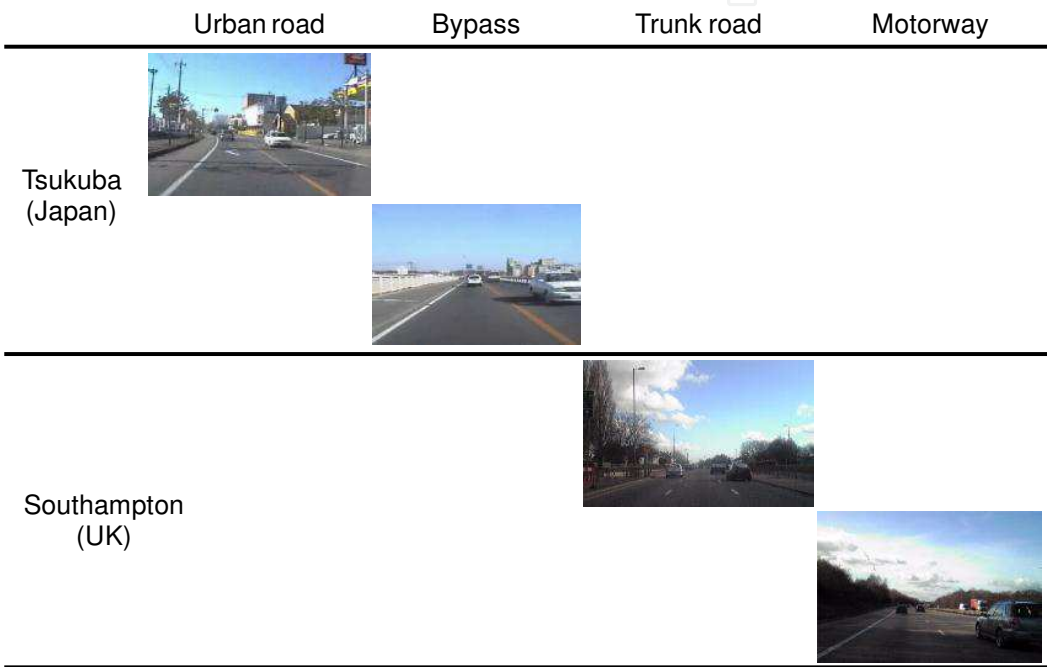
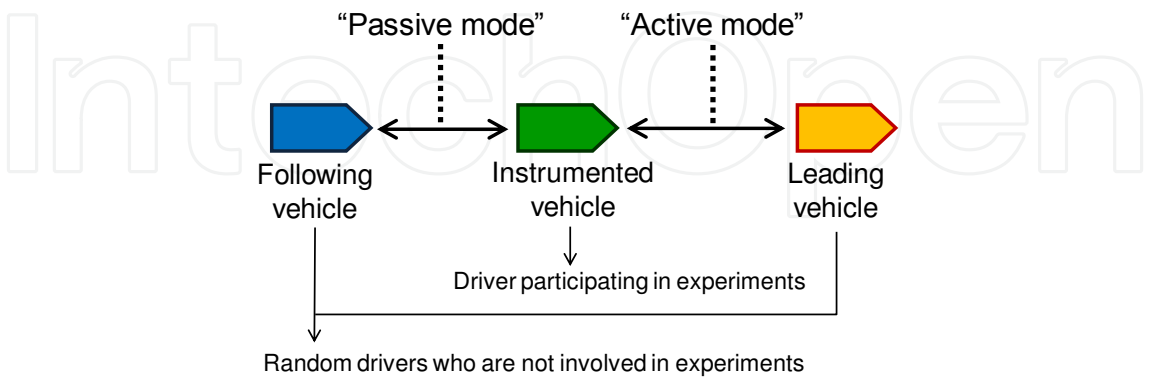Fig. 4. Road environments used for car-following behavior analyses

Fig. 5. Active and passive modes in car-following conditions

In the analysis, the car-following condition was defined as a situation in which a driver followed a leading vehicle with relative speeds between 15km/h and -15km/h. The relative distance to a following vehicle under car-following conditions was obtained from the

measured data. The rear distances collected were divided into two sets in terms of the associated driving speeds: 30 to 49km/h and 50 to 69km/h. The speed range of 30 to 49km/h corresponds to driving on an urban road (Tsukuba) and on a trunk road (Southampton), while the speed of 50 of 69km/h corresponds to driving on a bypass (Tsukuba) and on a motorway (Southampton).

The THW of the passive mode (defined by the relative distance between the following vehicle and the instrumented vehicle divided by the driving speed of the following vehicle) was calculated, and the distributions of the THW at each set were compared for analysis of the static aspect of car-following behavior.

In addition to the rear distances, the relative speeds and acceleration of the following vehicle were used for the fuzzy logic car-following model. Although this model can be used to describe individual drivers' acceleration-deceleration behavior, we applied the model to the passive mode data in order to compare general features of the dynamic aspect of car-following behavior between Tsukuba and Southampton. The continuous data for more than 20sec was input to the model specification within the measured car- following data.

3.3 Results

3.3.1 Static aspect

Figure 6 presents the distributions of the THW for each speed range and proportions of the time when drivers take the relevant THW to the total time while driving at the corresponding velocity.

In the lower speed range (30 to 49km/h), the proportion of Southampton drivers taking very short THW (0.5 to 1s) exceeds that of Tsukuba drivers. The proportion of Tsukuba drivers taking THW longer than 3s exceeds that of Southampton drivers. In the higher speed range (50 to 69km/h), no difference in THW between the two regions is observed. Both Tsukuba drivers and Southampton drivers spend more time with the short THW (0.5s to 1.5s). As mentioned in previous research (Brackstone et al., 2009), THW tends to decrease as velocity increases.
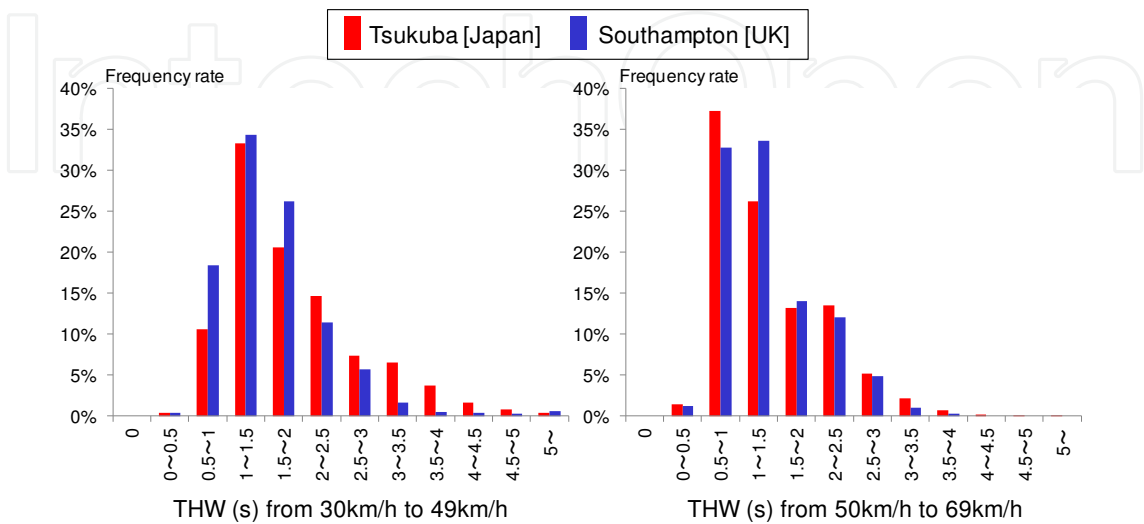

Fig. 6. Comparison of THW between two countries for each speed range

3.3.2 Dynamic aspect

Figure 7 presents the relative velocity–acceleration mapping obtained from the fuzzy inference specification in Tsukuba and Southampton. The two sites have similar traces (Southampton, 15; Tsukuba, 14) and data length (Southampton, 511.5sec; Tsukuba, 522.9sec). The RMSEs of the predicted acceleration and the measured data in the estimated fuzzy logic model were 0.15m/sec^2 in Tsukuba and 0.17m/sec^2 in Southampton. These findings indicate a satisfactory model-to-data fit compared to other published works (Wu et al., 2003).

The deceleration of Tsukuba drivers is greater than that of Southampton drivers when their vehicle approaches the leading vehicle. When the distance between vehicles is opening, the acceleration of Southampton drivers is greater than that of Tsukuba drivers. Thus, the acceleration-deceleration rate of Tsukuba drivers indicates a tendency opposite that of Southampton drivers.
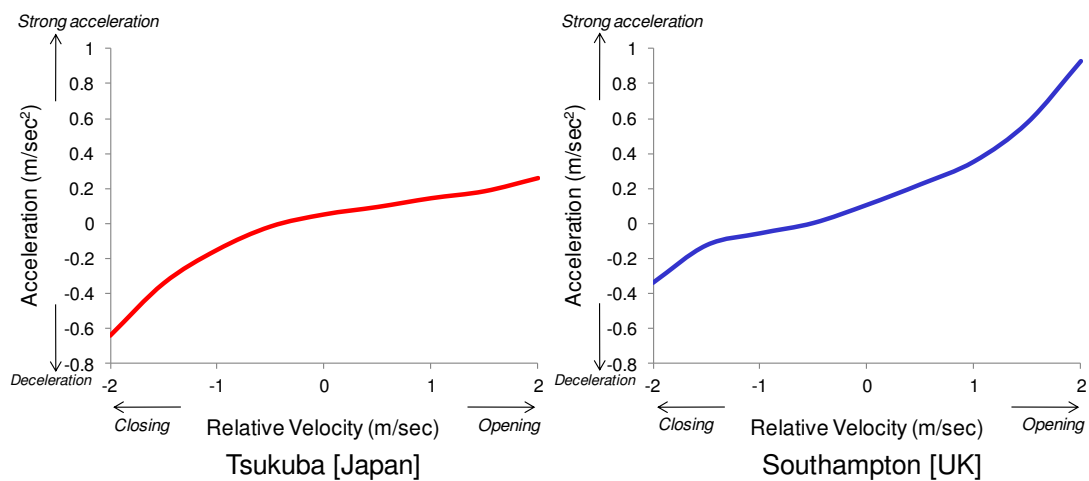

Fig. 7. Results of fuzzy logic model specification: Relative velocity–acceleration mapping between Tsukuba and Southampton

3.4 Discussion

The low RMSE of the Tsukuba acceleration rate suggests that the proposed fuzzy logic model is well-suited to Japanese car-following behavior. The findings imply that Japanese drivers use relative velocity and distance divergence for adjusting acceleration and deceleration while following a vehicle.

The THW of Tsukuba drivers was longer at slow velocity. When Tsukuba drivers approached a preceding vehicle in the same traffic lane, they decelerated more strongly. In addition, Tsukuba drivers accelerated less as the distance to the leading vehicle increased. Strong deceleration while moving toward the leading vehicle and weak acceleration when following a preceding vehicle led to long headway distances.

Southampton drivers tended to adopt shorter THW when in car-following in the low driving speed range. The acceleration rate of Southampton drivers was higher than that of Tsukuba drivers when overtaking a vehicle. It is assumed that such strong acceleration contributes to maintaining a short headway distances in car-following situations.

Tsukuba car-following behavior data were collected on urban roads and a bypass. When driving on urban roads, a leading vehicle often has to decelerate suddenly due to other vehicles at crossroads, a change of traffic signals, and the emergence of pedestrians or bicycles. The leading vehicle might also slow down suddenly on the bypass because a merging car may cut in front of it. Drivers adopted longer headway distances and decelerated more strongly in closing inter-vehicle separations when driving on roads where they should pay more attention to the movements of the leading vehicle.

Southampton car-following behavior data were collected on major roads with two or three lanes. In the speed range of 30 to 69km/h, traffic was quite congested in the morning peak when the field experiments were conducted. The drivers kept short headway distances in order to avoid lane changes of vehicles in front of them, leading to strong acceleration with opening inter-vehicle distances.

The road traffic environment in which the behavior data are collected is an important factor in the differences between car-following behavior in Southampton and that in Tsukuba, indicating that the road-traffic environment influences car-following behavior, regardless of the country of data collection. These findings imply that a single operational algorithm would suffice even when using vehicle control and driver support systems in different counties, although different algorithms would be necessary for different road types (e.g., roads in a city and roads connecting cities).

4. Case study 2: Longitudinal study of elderly drivers' car-following behavior

4.1 Motivation

This section introduces another case study focusing on the assessment of elderly drivers' car-following behavior, using the proposed fuzzy logic car-following model. The number of elderly drivers who drive their own passenger vehicles in their daily lives has increased annually. Driving a vehicle expands everyday activities and enriches the quality of life for the elderly. However, cognitive and physical functional changes of elderly drivers may lead to their increased involvement in traffic accidents. Thus, it is important to develop advanced driver assistance and support systems that promote safe driving for elderly drivers. Automatic vehicle control systems are expected to enhance comfort as well as safety when elderly drivers follow a vehicle. Understanding elderly drivers' car-following behavior is essential for developing automatic control systems that adapt to their usual car-following behavior.

Various studies comparing physical and cognitive functions between young and elderly drivers have been conducted in order to investigate the influence of age-related functional decline on driving (e.g., Owsley, 2004). Driving behavior is influenced by several driver characteristics (e.g., driving skill and driving style); and individual drivers' characteristics differ, especially between young and elderly drivers. Thus, a comparison of the driving behaviors of young and elderly drivers includes the influence of drivers' characteristics as well as the impact of the age-related decline of cognitive functions.

We have been involved in a cohort study on the driving behaviors of elderly drivers on an actual road (Sato & Akamatsu, 2011). A cohort study conducted in real road-traffic environments is expected to focus on changes in elderly drivers' cognitive functions because their cognitive functional changes may be greater than changes in their driving skills or

driving styles within a few years. One aim of this study is to clarify how elderly drivers follow a lead vehicle, based on analysis of how car-following behavior changes with aging. We collected car-following behavior data of elderly drivers determined in one year and compared it with that determined five years later. The distributions of THW in the two field experiments were compared in order to investigate the static aspect of car-following behavior. For analysis of the dynamic aspect, the fuzzy logic car-following model was applied to compare elderly drivers' accelerative behavior while following a vehicle.

4.2 Methods

4.2.1 Procedures

Field experiments were conducted in 2003 (first experiment) and in 2008 (second experiment). The two experiments were conducted using the same instrumented vehicle, the same driving route, and the same participants. The AIST instrumented vehicle was used for the data collection (Fig. 3). Almost all the sensors and the driving recorder system were fixed inside the trunk, so that the participating drivers could not see them, in order to encourage natural driving behaviors during the experiment trials.

The experiments were conducted on rural roads around Tsukuba. The route included several left and right turns, and the travel time was 25min (total distance 14km). The participant rode alone in the instrumented vehicle during the experiment trials. Before the recorded drives, the participants performed practice drives from the starting point to the destination without using a map or an in-vehicle navigation system.

Four elderly drivers (three males and one female) with informed consent participated in the two experiments. Their ages ranged from 65 to 70 years (average 67.3 years) in the first experiment and from 70 to 74 years (average 72.0 years) in the second experiment. Their annual distance driven ranged from 5,000 to 8,000km in the first experiment and from 2,000 to 10,000km in the second experiment (average 6,500km in both experiments).

The participants were instructed to drive in their typical manner. In the first experiment, the recorded trip for each elderly participant was made once a day on weekdays, for a total of 10 trips. In the second experiment, the trial was conducted twice a day on weekdays, for a total of 30 trips. The participants took a break between the experiment trials in the second experiment.

4.2.2 Data analysis

Figure 8 depicts a target section for the analysis of elderly drivers' car-following behavior. We focused on a two-lane bypass, the same road environment as that in section 3.2.2. We included only drives with a leading vehicle, excluding drives without a leading vehicle on the target section.

The active mode (distance between the instrumented vehicle and the leading vehicle) was used in the analysis of the elderly drivers' car-following behavior. We also used the passive mode (distance between the instrumented vehicle and the following vehicle) to investigate traffic characteristics on the analyzed road. The latter is expected to indicate whether changes in elderly drivers' car-following behaviors are influenced by their functional declines or by changes in traffic characteristics on the target road.
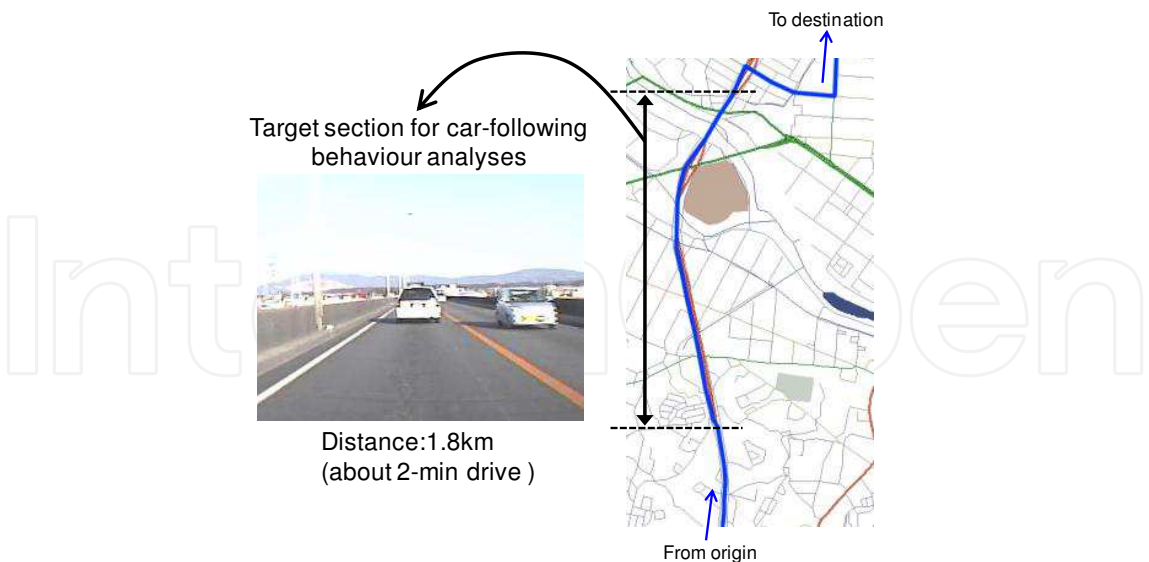
Fig. 8. Road section used for car-following behavior analysis

4.3 Results

4.3.1 Static aspect

Figure 9 presents the distributions of THW for leading and following vehicles. The THW distributions suggest the proportion of time experienced in each category to the total time of the car-following conditions. There were no differences in the distribution of THW to following vehicles between the first and second experiments.

The peak of the distribution of THW to leading vehicles is found in the category from 1 to 1.5s in the first experiment. However, the peak is found in the category from 1.5 to 2s in the second experiment, indicating that the THW in the second experiment exceeds that in the first experiment.
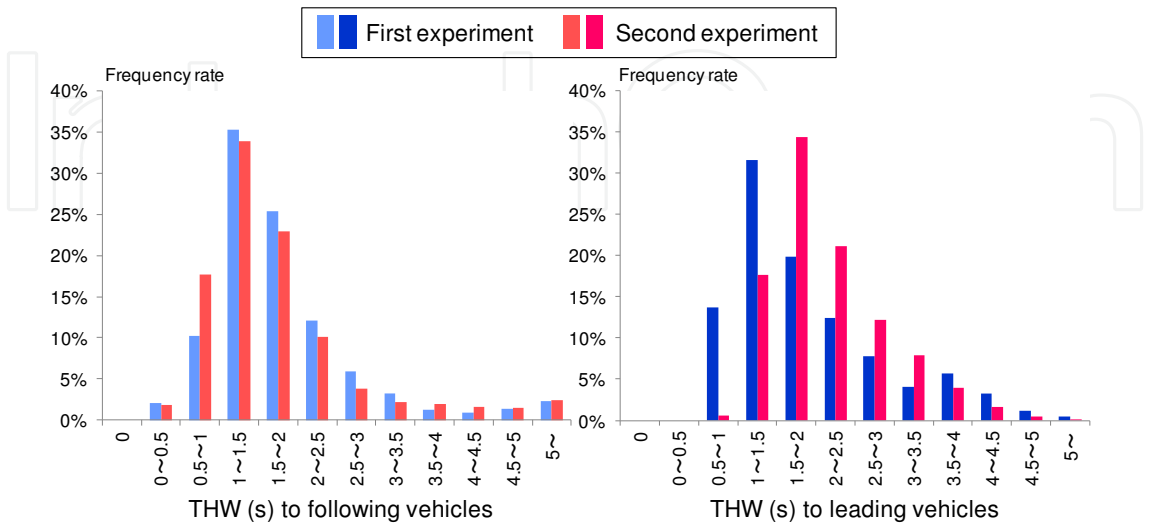
Fig. 9. Comparison of THW to leading and following vehicles between the first and second experiments

4.3.2 Dynamic aspect

Figure 10 compares the relative velocity–acceleration mapping of the first and second experiments. In the fuzzy logic model specification, there is a total of 27 traces (data length 770.5sec) in the first experiment and 29 traces (data length 1481.0sec) in the second experiment.

The RMSEs between the predicted and measured accelerations in the estimated fuzzy logic model were $0.25 m/sec^2$ in the first experiment and $0.14 m/sec^2$ in the second experiment, which are within adequate errors compared to those estimated based on other real-world data (Wu et al., 2003).

The deceleration when the elderly participants approach the lead vehicle was the same in the two experiments. However, the elderly drivers accelerate more strongly in the second experiment than in the first experiment, when the leading vehicle goes faster and the headway distance is opening.
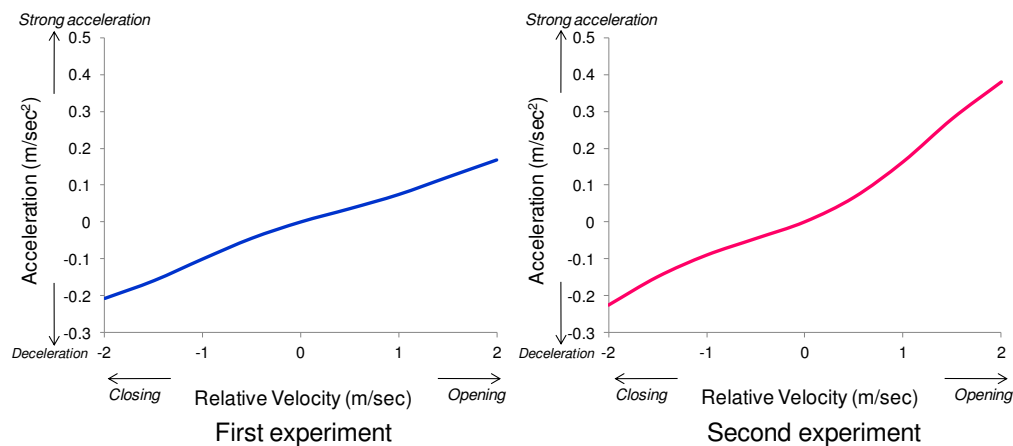

Fig. 10. Results of fuzzy logic model specification of elderly drivers: Relative velocity–acceleration mapping between the first and second experiments

4.4 Discussion

Comparison of THW to following vehicles between the first and second experiments indicates no change in traffic flow on the target section in five years. In contrast, THW to leading vehicles is longer in the second experiment than in the first experiment, suggesting that elderly drivers take longer THW and the static aspect of their car-following behaviors changes over five years.

The task-capability interface model (Fuller, 2005) helps clarify why elderly drivers' car-following behavior changes with aging. In this model, drivers adjust task difficulty while driving in order to avoid road accidents. Task difficulty can be described as an interaction between the driver's capability and task demands. When the driver's capability exceeds the task demands, the task is easy and the driver completes the task successfully. When the task demands exceed the driver's capability, the task is difficult and a collision or loss of control occurs because the driver fails to accomplish the task. Here, the driver's capability is determined by the individual's physical and cognitive characteristics (e.g., vision, reaction time, and information processing capacity), personality, competence, skill, and driving style.

Task demands are determined by the operational features of the vehicle (e.g., its control characteristics), environmental factors (e.g., road surface and curve radii), interactions with other road users (e.g., slowing down of a lead vehicle and crossing of pedestrians or bicycles), and human factors (e.g., choice of driving speeds, headway distances, and acceleration control). The longitudinal assessment in this study is conducted using the same participant, the same instrumented vehicle, and the same route. These experiment settings lead to no differences in driver personality affecting capability or in vehicle operational features and road traffic environments influencing task demands. The decline in physical and cognitive functions may lead to a decrease in the elderly driver's capability. Therefore, elderly drivers reduce task demands by adopting longer THW to a leading vehicle, and they seek to maintain capability higher than the reduced task demands.

The results of the fuzzy logic car-following model estimation suggest that the acceleration rate when the inter-vehicle distance is opening becomes higher after five years, although the deceleration rate while approaching the vehicle in front does not change. The stronger acceleration may be a compensating behavior for maintaining the driver's capability by increasing the task demand temporarily, because the driver's capability interacts with the task demands, and drivers can control the task demands by changing their driving behavior in order to improve their capability (e.g., increasing speed, to wake up when feeling sleepy while driving).

Our findings imply that when a leading vehicle drives faster and the headway distances are opening while driving on multi-traffic lanes or while approaching a merging point, information or warning about the movements of the surrounding vehicles is helpful to elderly drivers because they accelerate more strongly and the temporal task demand is higher in this situation.

5. Limitations

The fuzzy logic car-following model deals mainly with two vehicles: a vehicle in front and the driver's own vehicle. When drivers approach an intersection with a traffic light under car-following conditions, they may pay more attention to the signal in front of the leading vehicle and manage their acceleration based on the traffic light. Drivers allocate their attention to the forward road structure instead of the leading vehicle when they approach a tight curve; thus, they may reduce their driving speed before entering the curve even if the headway distance is opening. The car-following behavior before intersections or tight curves can be influenced by environmental factors other than a lead vehicle. Further car-following models should be developed to reproduce the car-following behavior in these situations.

6. Conclusion

This chapter describes the fuzzy logic car-following model, including a comparison with other car-following models. We introduce two case studies that investigate drivers' car-following behavior using the fuzzy logic car-following model. This model can determine the degree to which a driver controls longitudinal acceleration according to the relationship between the preceding vehicle and his/her vehicle. The fuzzy logic model evaluates the driver's acceleration and deceleration rates using a rule base in natural language. This model contributes to interpretation of the difference in headway distances between Tsukuba and Southampton and changes in elderly drivers' headway distances with aging.

In the cross-cultural study, we compared the car-following behavior gathered on roads where driving is on the left side of the road. Further research will be addressed to compare the car-following behavior between left-hand driving and right-hand driving (e.g., in the United States).

In the longitudinal study, we investigated the car-following behavior of small samples. The next step is to collect and analyze more elderly driver car-following behaviors to validate the findings of this study. Additionally, further study should be conducted to examine individual differences in car-following behaviors to clarify which cognitive function influences changes in car-following behavior with aging. We will assess the relationship between car-following behavior on a real road and elderly drivers' cognitive functions (e.g., attention, working memory, and planning (Kitajima & Toyota, 2012)) measured in a laboratory experiment. Analysis of the relationship between driving behavior and a driver's cognitive functions will help determine how driver support systems may assist driving behavior and detect the driver's cognitive functions based on natural driving behavior.

7. Acknowledgments

8. References

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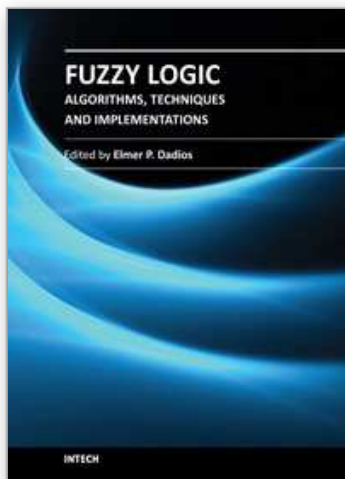
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