Heterogeneity in multi-anticipative car-following behavior by video image data

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Microscopic road traffic flow simulation models are increasingly being used to express the dynamic nature of traffic flow. These microscopic traffic simulations require vehicle movements to be modeled and calibrated. Since individual vehicles exhibit heterogeneity, the parameters within these sub-models must incorporate some disturbances. However, due to limited observational data, the various parameters among individuals have not been well validated. We collected video data from an 800m section of an urban expressway over 1 week using 11 video cameras. By tracking individual vehicles on-screen, we can obtain vehicle trajectories. We applied this manually obtained data to investigate individual heterogeneity of vehicle movement; in particular, we focused on multi-anticipative car following behavior, heterogeneity among individuals and relationship between car-following behavior and road geometry.

Keywords: *Video Image Data, Car-following, Driving heterogeneity*

1. Introduction

In most countries, the road traffic accidents are regarded as one of the serious problems to be mitigated urgently, and are caused mainly by human errors and mistakes. For our sustainable society and avoiding meaningless loss of precious lives, it is necessary to apply an integrated road transportation safety schemes. Among various measures to make road transportation safer, the researchers in the field of transportation engineering have paid much attention to ITS (Intelligent Transportation System). In order to discuss effective measures including ITS implementation for mitigating traffic accidents, it is necessary to understand the detailed vehicle movement in order to understand the mechanism of traffic accident. Especially in merging areas, drivers have much greater workloads than in single stream traffic, and traffic conflicts and accidents are more likely to occur. Also, drivers must be aware of their own position as well as the position of other vehicles, estimate both the longitudinal and lateral distance between vehicles and determine the appropriate action. It is therefore important to develop methods for evaluating safety and improving efficiency in merging section. Within merging areas, the most important kinds of movement are *cross-sectional*, e.g., merging, giving way and cutting in (across the stream of traffic), and *longitudinal*, e.g., car-following behavior (along the stream of traffic). All of these behaviors can cause traffic problems. So, a comprehensive model of these movements requires gathering and analyzing numerous vehicle trajectories in merging areas. Also, microscopic road traffic flow simulation models are generally applied to analyze how traffic changes dynamically in response to various methods of management and control. However, because detailed measurements of vehicle movement are technically limited, most of microscopic simulations are not well calibrated or validated in the level of microscopic vehicle movement. In this study, we use the video image data to model the microscopic vehicle movement. Especially, we focus on a car-following movement as a first step for improving interpretation of vehicle movements.

Among researches for car following behavior, we consider developing a multi-anticipative car following model which may be more realistic. In this model, drivers anticipate traffic conditions further downstream by looking at the movements of several vehicles ahead (Hoogendoorn et al., [1]). It is generally said that the real driving behavior is variable in time and space, and the estimated parameter may not be transferrable to other situation. In addition, Brockfeld et al. [2] and Schultz et al. [3] confirmed the importance of considering drivers heterogeneity. Brockfeld et al. [2] compared the ten different models for each driver following pairs using data obtained from car following experiments. From calibration and validation results, the error difference between the best and worst model for each driver is around 10.11~12.78%, concluding that the diversity among driving behavior is much larger than the diversity of the model structures. They argued that these results can probably not be suppressed no matter what model is used. In contrast, Schultz et al. [3] assumed distributed parameters and their mean and variance are estimated by minimizing the differences between observed and simulated behavior by the genetic algorithm. These researches suggest the importance of considering driver or vehicle heterogeneity. We therefore focus the heterogeneous behavior the impact of road geometry within multi-anticipative car following behavior. We observed the movement of vehicles on an expressway using 11 video cameras. Automatic and manual vehicle identification systems developed by the previous research (Kurauchi et al., [4]) have been used to extract vehicle trajectories from video images. We used manually obtained data when investigating the individual heterogeneity of vehicle movement. By the obtained data, multi-anticipative car following model is constructed.

This paper has 5 sections. In section 1, we explained the objective of this study. In section 2, we will review the existing car following model. The used data are explained in the third section, and the estimation results are evaluated in section 4. Finally, we will summarize the findings of this study in the last section.

2. Review of car-following models

A car following model, which describes the processes how drivers control the vehicle speed in the traffic stream, has been studied for more than half century. Until now, researches for car following models can largely be divided to the single car following model and the multi-anticipative car following model. Basically, the single car following model consider the first leading vehicle only, whereas the follower in the multi-anticipative car following model is assumed to response to the behavior of the multi-leaders.

2.1. Single car-following models

Following the discussions by Brackstone et al. [5], we categorize single car following models into five groups. The first model is so called *Gazis-Herman-Rothery(GHR) model* [6] which is perhaps most well-known. The model has an intuitive hypothesis that a driver's acceleration is proportional to relative speed, and has some relation with headway distance, which could itself be speed dependent. The second model is the *Safety Distance or Collision Avoidance model* (CA) that the original formulation of this approach dates to Kometani and Sasaki [7]. The base relationship does not describe a stimulus-response type function as proposed by the GHR model, but seeks to specify a safety following distance within which a collision would be unavoidable, even if the driver of the vehicle in front were to act 'unpredictable'. The third model is *Linear (Helly) models*. Although the first model suggested by Chandler, Herman and Montroll in the development of GHR equation was linear, this class of models is generally attributed to Helly [8]. He proposed a model that includes additional terms for the adaptation of the acceleration according to whether the vehicle in front is braking. Also, this model expresses relative speed-distance relationship between the follower and leader behavior simply. The fourth model is *Psychophysical or Action Point models* (AP) which is proposed by Michaels [9], who raised the concept that drivers would be able to tell they were approaching a vehicle in-front, primarily due to changes in the apparent size of the vehicle, by perceiving relative velocity through changes on the visual angle subtended by the vehicle ahead. The fifth model is a *Fuzzy logic-based model* that uses the concept of fuzzy logic within car-following models as the latest distinct 'stage' in their development, as it represents the next logical step in attempting to accurately describe driver behavior. Such models typically divided their inputs into a number of overlapping 'fuzzy sets' each one describing how adequately a variable fits the description of a 'term'. The initial use of this method (Kikuchi & Hakroborty, [10]) attempted to 'fuzzify' the traditional GHR model using relative speed, relative distance and acceleration.

In addition to the five groups defined by Brackstone et al. [5] the Optimal Velocity Model proposed by Band o et al. [11] should be reviewed here. In this model, drivers are assumed to respond the deviation their actual travel speed and optimal one, which is defined by a function of the headway to the car in front, and to diminish the deviation by giving the corresponding acceleration to their cars. It is shown that the Optimal Velocity Model describes the transition from free flow to congested flow occurring spontaneously by the collective motion of vehicles, which obey to the same dynamical equation.

2.2. Multi-anticipative car-following models

As an extension of the single car-following models, some multi-anticipative car following models have been proposed to consider the effect of other vehicles or road conditions further downstream (Hoogendoorn et al., [1]).

Lenz et al. [12] developed a multi-leader generalized Bando model. This approach is based on a concept that a driver of following vehicle accelerates or decelerated based on the difference between follower's velocity and the optimum velocity that can have. The acceleration of the following vehicle is expressed as follows.

$$a(t) = \sum_{j=1}^{m} K_j \{V(\frac{\Delta x_j(t)}{j}) - v(t)\} \quad (1)$$

where, $V(s)$ is an optimum speed function describing the speed of the follower in relation to the distances to the vehicles ahead; $\Delta x_j(t)$ is the relative distance between the jth leader, also, $v(t)$ is the speed of follower at time t. And, K_j denotes the sensitivity to the jth leader that quantifies how quickly velocities of each vehicle converge to the optimum velocity when they differ from the optimal one. Note that K_j should be positive.

Generalized Helly model (Hoogendoorn et al., [1])is an extension of the Linear model proposed by Helly. In the Helly model, the following vehicle responses to the vehicle in front only, while in the Generalized Helly model, the follower reacts not only to the directly first leader but also to multi-leaders. A linear relationship is assumed using the relative speed and relative distance. Also, the Bexelius model(Bexelius, [13]) describes simply the multi-anticipative behavior only using the relative speed between the follower and their leaders ahead. Formulation of Generalized Helly model is shown in Eq(2) which originally derived from the single leader car-following model .

$$a_i(t+T) = \sum_{j=1}^{m_{1,i}} \alpha_i^{(j)} \Delta v_i^{(j)}(t) + \sum_{j=1}^{m_{2,i}} \beta_i^{(j)} (\Delta x_i^{(j)}(t) - S_i^{(j)}) \quad (2)$$

where, $a_i(t+T)$: the acceleration of follower i at time t, with response T

$\alpha_i^{(j)}$: the sensitivity parameter of follower i to the relative speed with leader j for j=1,……,m,

$\beta_i^{(j)}$: the sensitivity parameter of follower i to the difference between the actual distance to leader j and the corresponding desired distance of follower i,

$\Delta v_i^{(j)}(t)$:the relative speed between follower i and leader j,

$\Delta x_i^{(j)}(t)$: the relative distance between follower i and leader j,

$S_i^{(j)}$: the distance to leader j desired by follower i

m_1 : the number of considered leaders of which relative speed to the follower i

m_2 : the number of considered leaders of which relative distance to the follower i

T: response time(s).

To keep the linear relationship of parameters, they apply the following formula to determine the desired distance to leader j (Ossen and Hoogendoorn, [14, 15]).

$$S_i^{(j)} = s_{o,i} + j\tau_i v_i \quad (3)$$

where, $S_i^{(j)}$: the desired distance between vehicle i and the its leader vehicle j,

$s_{o,i}$: the minimum desired distance at standstill between vehicle i and its j-th leader,

τ_i : the minimum headway,

v_i : speed of vehicle i at point in time t.

Generalized Helly model also has another parameters, $m_{1,j}$, $m_{2,j}$ representing the number of leaders of which relative distance and speed are considered in the linear relationship to express acceleration / deceleration of follower. Each combination of parameters $m_{1,j}$, $m_{2,j}$ represents the number of leaders which driver i responds with respect to relative speed and deviations from relative distance and the desired following distance. Among researches for the multi-anticipative car following model, the research of Hoogendoorn et al. [1,16] showed that incorporating multi-anticipative behavior substantially improves the model re-productivity.

From these researches, we take notice of the difference for multi-anticipative car following behavior by road geometry, that is, the follower behavior may differ in the response to the behavior for leading vehicles under different road geometry. Also, we assume that the heterogeneity of driver behavior may exist within the multi-anticipative car following behavior. If we consider using Lenz model, the desired speed is required. However, this study analyzes the multi-anticipative car following behavior under different road geometry condition and the desired speed may change by the road geometry. It is relatively difficult to obtain the desired speed in the short section. So, this study applies only Generalized Helly model for analyzing multi-anticipative car following behavior under road geometry and driver characteristics among driver behavior.

3. Video image data and vehicle trajectories

3.1. Study area

The data used in this study were obtained from 11 video cameras installed on tall buildings located near a merging area of the Hanshin Expressway in Osaka, Japan. The video cameras recorded all traffic movement for 1 week beginning on 29 August 2005. The study area is approximately the 800 meters of road section including the merging section mentioned above. Severe traffic congestion and accidents frequently occur in this area and a long queue usually forms upstream of the Moriguchi Line. For analytical convenience, we numbered the lanes from east to west: the first and second lanes come from the Moriguchi Line, and the

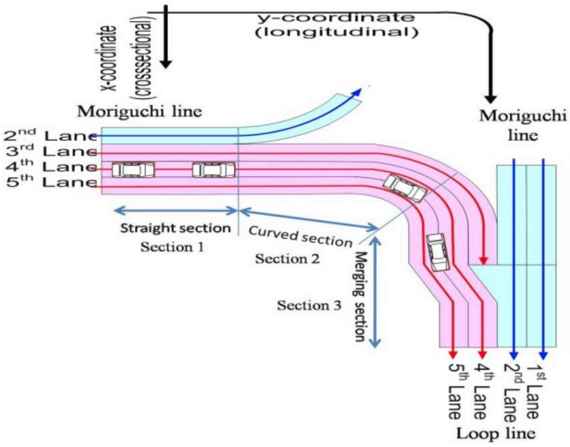


Figure 1. Study area, lane/axis definition and division of section for all sections

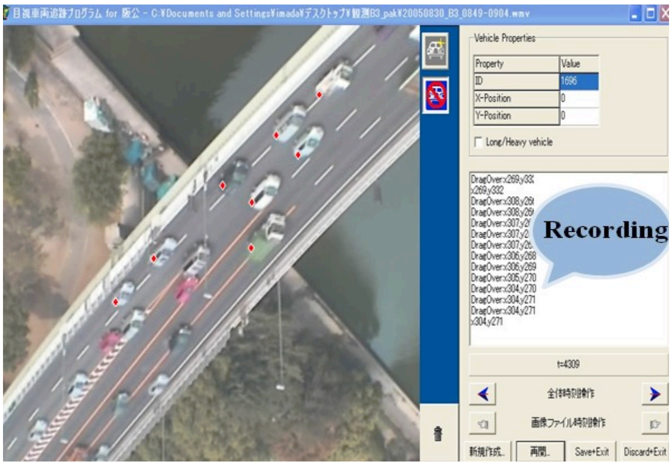
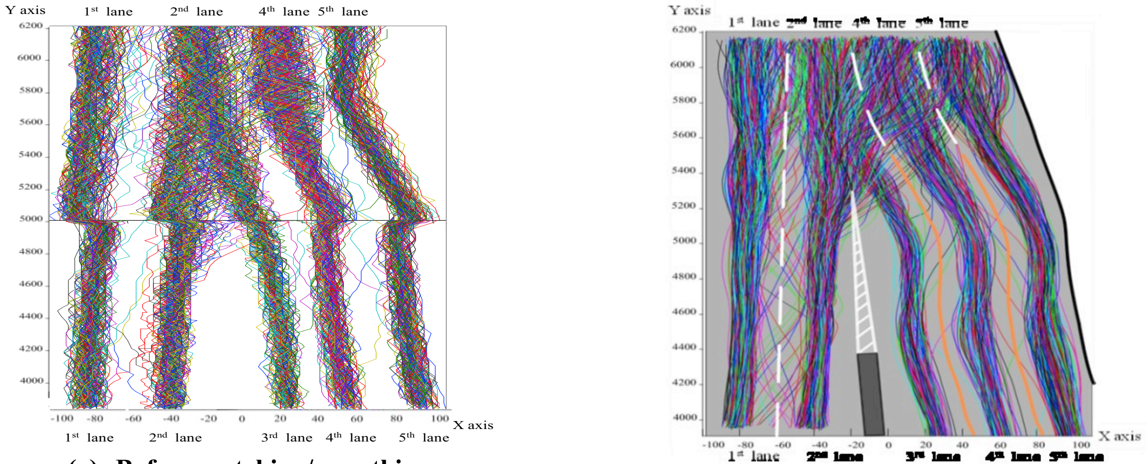


Figure 2. Manual trajectory acquisition system



(a) Before matching/smoothing

(b) After matching/smoothing

Figure 3. Extracted vehicle trajectories

third, fourth, and fifth lanes come from the Loop Line (see Figure 1). In this area, the second lane from the Moriguchi Line and the third lane from the Loop Line merge, and the number of total lanes are reduced to four lanes at the downstream side of merging section. The vehicle trajectory data were extracted from video taken over 15 min (08:49–09:04) on 30 August 2005. Within this period, the traffic conditions changed from uncongested to congested, and hereby the data obtained can be used for analyzing the car-following behavior under different traffic condition.

3.2 Extraction of vehicle trajectory data from video image

We used the manual trajectory acquisition system to collect vehicle trajectory data (Figure 2; Kurauchi et al., [4]). This system can record the position of each vehicle by dragging and dropping a red square on the computer screen. The users firstly click on the centre of the rear-end bumper, and its position on the screen is automatically converted to real-world coordinates. Then, the vehicle's movements are recorded by dragging the square over a 0.2-s observation time. The vehicle trajectory record consists of the camera ID, vehicle ID, date, time, the vehicle location on both screen and real-world coordinates. In the real-world coordinates, the *x*-axis is perpendicular to the traffic stream, and the *y*-axis is parallel to the traffic stream (Figure 1). The system tracks vehicle trajectories independently by each camera, and hereby obtaining the continuous vehicle trajectories for all the study area requires connecting the trajectories extracted from various cameras. Therefore, we developed another system to match the IDs from consecutive two video images. Since real-world coordinates on each video contain errors, obtained vehicle trajectories may sometimes exhibit an unrealistic jump. To correct these errors, we adopted a smoothing spline algorithm using MATLAB®. Figures 3(a) and (b) illustrates the original and smoothened vehicle trajectories around the merging section, respectively.

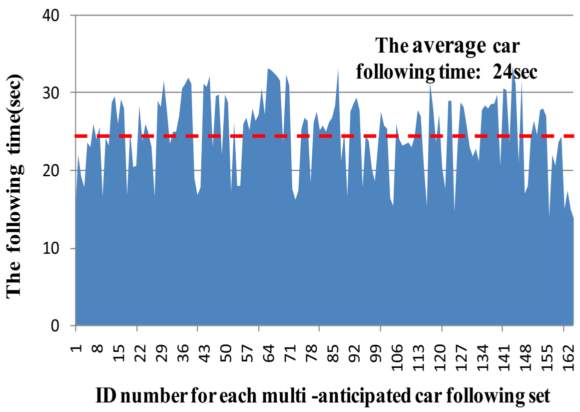


Figure 4. Distribution of following time for each multi- car following set

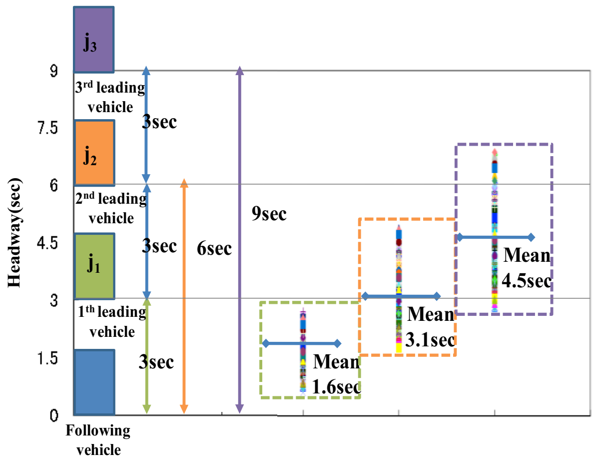


Figure 5. Headway between each the j-th leading vehicle and follower

Finally, about 2400 vehicle trajectories are available for the analysis.

3.3 Definition of multi-anticipative car following behavior and sample size

We assume here that drivers recognize relative speed and relative distance to the multiple leading vehicles on the same lane as stimuli, and accelerate or decelerate as a response. In maximum, three leading vehicles are explicitly considered as one affecting the behavior of the following vehicle. The leading vehicles are numbered from closest(1^{st}) to farthest(3^{rd}). In our previous studies, a following vehicle is defined as a vehicle continues to travel within three seconds of time headway from its leading vehicle (Hong et al., HKSTS, [17]). In this study, the same definition of car-following is applied for the two consecutive vehicles, and hereby the first, second and third leading vehicles are required to have the time-headway from the following vehicle less than or equal to three, six and nine seconds, respectively. For the analysis of the multi-anticipative car-following behavior, we extracted sets of vehicles composed of the three leading vehicles and their following one, which are traveling on the same lane more than eight seconds. Finally, we obtained 164 sets of multi-anticipative car following vehicles. The average number of data included in each set is about 120 plots (estimated by average car following time/ observation time interval) and this means that the car following vehicle of each set follows from the first to third leading vehicle for approximately 24 seconds. Its distribution for the following time is shown in Figure 4 by each multi-anticipative car following set.

We surveyed also the headway between follower and multi-leaders for all 164 sets of car following vehicles in order to confirm the distributions of time-headways. Figure 5 represents the distributions of time-headways between the follower and its multiple leaders. The headway between follower and the first leader(j=1) is distributed less than 3 seconds and its mean is 1.6 seconds. The headways between the follower and the second, the third leaders(j=2,3) are distributed from 1.5 to 4.5 seconds and from 2.8 to 7.0 seconds, respectively.

Also, to discuss the effect of road geometry we divided the whole section into three sections: the straight section at the most upstream side, the curved section and the merging section at the most downstream side in Figure 1. For convenience sake, the straight, curved and merging sections are denoted by Section 1, 2 and 3, respectively. By the comparison of the estimated parameters of Generalized Helly model later, this study confirms the differences in car-following behavior by the road geometry and design.

3.4 Procedure for parameter estimation

The Generalized Helly model can be characterized by the parameters m_1 and m_2 as shown in equation (2). The parameter m_1 represents the number of the leaders of which relative speed to the following vehicle is explicitly considered in the car-following model. The parameter m_2 represents the number of leaders of which distance to the following vehicle is explicitly considered. Accordingly the Generalized Helly model should be estimated assuming 12 combinations of parameters m_1 and m_2 by setting m_1=1~3, m_2=0~3(m_2=0 including Bexelius model). To estimate parameters(α_j, β_j), it is necessary to provide the response time of the vehicle (or driver) as the multiplication of the observation time interval (0.2s) per vehicle locations, and hereby the response time is assumed to range from 0.2 to 3.0 seconds. Then we estimate all the parameters including α_1 to α_3 and β_1 to β_3 using the least-square method. We

Table 1. Average value of parameter and estimation results on all sections using GH model

m_1, m_2	Parameters						Response time(s)	R^2 Value more than 0.5(the N. of data set)	The N.of best model by each pair
	α_1	α_2	α_3	β_1	β_2	β_3			
(1,0)	0.73						1.02	0.62(65)	-
(2,0)	0.47	0.19					1.60	0.67(103)	-
(3,0)	0.42	0.16	0.11				1.30	0.78(126)	40
(1,1)	0.60			0.07			0.92	0.65(90)	-
(2,1)	0.36	0.20		0.05			1.15	0.70(125)	-
(3,1)	0.27	0.10	0.07	0.04			1.34	0.75(135)	6
(1,2)	0.37			0.04	0.01		0.90	0.68(108)	1
(2,2)	0.27	0.13		0.06	0.02		1.20	0.76(132)	8
(3,2)	0.23	0.13	0.09	0.05	0.02		1.26	0.82(139)	38
(1,3)	0.37			0.08	0.04	0.02	0.93	0.74(109)	8
(2,3)	0.28	0.16		0.08	0.04	0.01	1.32	0.79(136)	15
(3,3)	0.26	0.18	0.09	0.06	0.04	0.02	1.39	0.83(142)	48

Table 2. Result of Paired t-test between the single and multi-anticipative following model

m_1, m_2 (Single)-(Multi)	Range of R^2 value (total 164 sets)	t
(1,0)-(3,2)	0.44 – 0.79	-18.216
(1,0)-(3,3)	0.44 – 0.81	-14.982
(1,1)-(3,2)	0.53 – 0.79	-14.800
(1,1)-(3,3)	0.53 – 0.81	-12.932

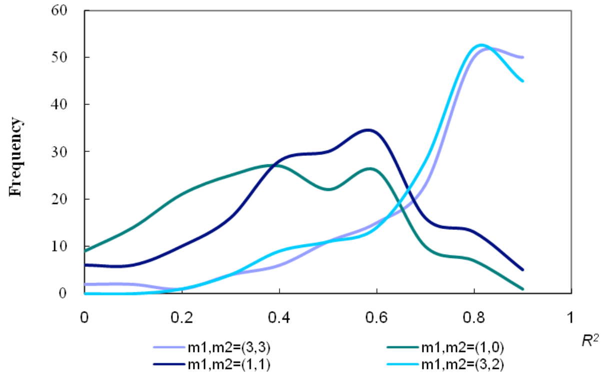


Figure 6. Distribution of determination coefficient R^2

selected the model with the maximum determination coefficient as the best choice among calibrated models.

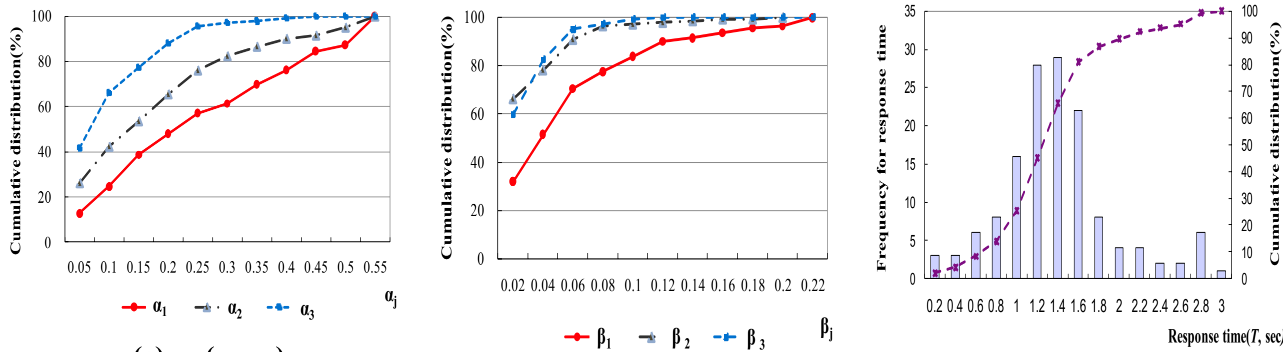
4. Estimation results

4.1 Verification of multi-anticipative car-following behavior

Parameters are calibrated individually for each 164 set of multi-anticipate car-following vehicles. At estimation we first set the values of m_1(from 1 to 3), m_2(from 0 to 3) and response time (T). To ensure the reliability of the results, we only used estimate results whose R^2 values of the best model is greater than 0.5. The mean of the parameters α, β and T with more than 0.5 of R^2 values among 164 estimated parameter sets are calculated. This study estimates the parameters of twelve types of Generalized Helly Models with the different combinations of m_1 and m_2 for each 164 data sets of vehicle trajectories. Here the 'best model' is defined as the model with the highest R^2 value among twelve types of Generalized Helly Models above mentioned.

Table 1 summarizes the result of estimation. This table shows the average of the estimated parameters, response time and determination coefficient. It also represents the number of sets by which the best model is estimated for the corresponding combinations of m_1 and m_2. If this value is larger, then the pair of m_1 and m_2 is likely to describe the majority of the driving behaviors observed. From the Table 1, average R^2 increases consistently when it increases the number of m_1 and m_2. Judging from the average R^2, (3,2) and (3,3) seem to be the best combinations of m_1 and m_2 (0.82 and 0.83). When we only consider one leading vehicle (cases of (1,0) or (1,1)), the values of the average R^2 were 0.62 and 0.65. Also all parameters of α and β are statistically significant and take appropriate signs. Moreover, the estimates consistently decrease from 1st, 2nd to 3rd vehicle. Drivers are more sensitive to the closer vehicle. When we compare the models of (3,2) and (3,3), the model of (3,3) seems to have a better fit since the number of best models is larger.

To prove that the multi-anticipative car following explains the car following relation better than the single one, we test the difference of the R^2 value between the single car following mode and multi-anticipative following model by the paired t-test, because the R^2 value itself is distributed among 164 data sets. The null hypothesis becomes that the mean of the difference of the R^2 value between the single and multi-anticipative



(a) α_j (α_1~α_3) (b) β_j (β_1~β_3) (c) Response time (T)

Figure 7. Distribution of parameter and response time

Table 3. Results of factor analysis for best model within combination of m_1,m_2=(3,3)

Parameters within m_1,m_2=(3,3)	Component	
	1st axis	2nd axis
α_1	0.545	-0.221
α_2	-0.109	0.767
α_3	0.146	0.579
β_1	0.562	-0.031
β_2	0.780	0.443
β_3	0.794	0.365
Initial Eigen values	2.171	1.017
% of Variance	41.788	24.502
Cumulative %	41.788	66.289

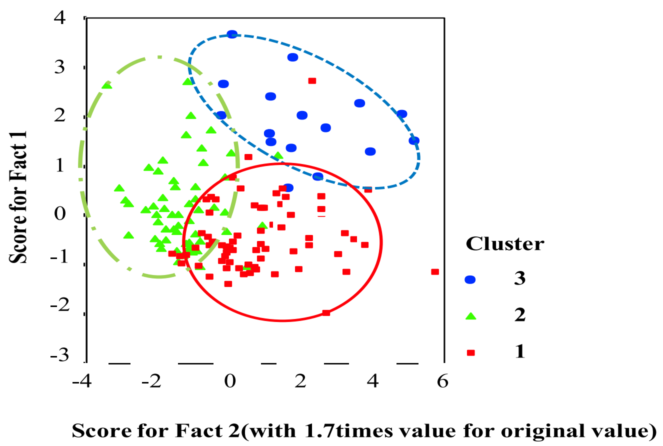


Figure 8. Scatter for fact 1,2 by cluster

Table 4. Average of estimated parameters among each cluster

Cluster		1(■)	2(▲)	3(●)
Num of cases within each cluster		63	58	17
average (CV)	α_1	0.11(0.57)	0.38(0.35)	0.56(0.39)
	α_2	0.29(0.63)	0.11(0.87)	0.59(0.40)
	α_3	0.18(0.82)	0.12(0.93)	0.23(0.68)
	β_1	0.076(0.71)	0.077(1.05)	0.099(0.93)
	β_2	0.060(1.02)	0.071(0.75)	0.165(0.52)
	β_3	0.043(0.96)	0.046(0.93)	0.097(0.67)
Average value of R^2 for each cluster		0.80	0.78	0.85

model is zero. We set the R^2 values of (1,0), (1,1) as the single model, and those of (3,2), (3,3) as the multi-anticipative model. From test results shown in Table 2, each t-statistics between the single and multi-anticipative model suggests the significant difference between single and multi-anticipative car following behavior. Also, the single model takes the R^2 values around 0.4~0.6 while multi-anticipative model leans toward the 0.8~1.0 (see also Figure 6). This suggests that multi-anticipative car following model explains the car following behavior much better than the single model. These results provide empirical evidence that drivers response not only their direct leader, reacting also the behavior of the second and even the third leader.

4.2 Driver heterogeneity

At the previous section, it was found that multi-anticipative car-following behavior can describe the vehicle movement better. Here, we will further discuss the driving heterogeneity. First, analyses are conducted for the distributions of parameter estimates and response time for 142 sets with more than 0.5 of R^2 values among total 164 sets in the case of (m_1, m_2)=(3, 3). Figures 7

Table 5. Comparison for average value of estimated parameters for best model by each section

Section	Parameters	α_1	α_2	α_3	β_1	β_2	β_3	Response time(s)	R^2
Straight	m1,m2=(3,1)	0.33	0.15	0.13	0.05			1.53	0.78
Curved	m1,m2=(3,3)	0.30	0.15	0.13	0.06	0.03	0.01	1.63	0.78
Merging	m1,m2=(3,3)	0.36	0.21	0.14	0.07	0.04	0.02	1.30	0.81

illustrate the cumulative distribution of parameters α_j, β_j and T, and shows the parametersα_1 and β_1 representing the effect of relative relation between the 1st leader and its follower have the biggest values within the same series of parameters $\alpha_j(\alpha_1\sim\alpha_3)$, $b_j(\beta_1\sim\beta_3)$, respectively. In other words, the following vehicle is likely to be strongly affected by the 1st leading vehicle in front compared with the farther leading vehicles ahead. Also, it is clear that all the parameters and the response time estimated are widely distributed, and hereby there is a possibility that the car-following behaviors are diverse among drivers.

Also, in order to analyze the heterogeneity in car-following behavior among drivers in detail and the possibility of classification into some groups based on the estimated parameters, we adopted the cluster analysis and the principal component analysis for the estimated parameters. By the cluster analysis, the drivers are finally categorized into three groups. We also applied the principal component analysis to understand the characteristics of the drivers. We found two principal components shown in Table 3 having larger than 1.0 of Eigen value. The Eigen value and proportion of the first axis is 2.171, 41.79% and 1.017 and 24.50% for the second axis. Looking at the Table 3, the first axis has larger α_1 and βs, and the second axis has larger α_2 and α_3. Therefore, if the score for first axis is larger, the driver tends to put emphasize on the relative speed of the 1st vehicle and the relative distances to all three leading vehicles in front. To see the difference of 3 clusters by the two principal axes, we draw a scattered graph shown in Figure 8. From the Figure 8, the drivers in the 1st cluster have smaller score for the 1st axis but larger on the 2nd axis. They put rather more importance on the 2nd or 3rd leading vehicles. The drivers in the 2nd cluster have larger score for the 1st axis but small score for the 2nd axis. It seems that they put their attention mainly on the relative speed of the vehicle just in front. Finally, the drivers in the third cluster put their attention on all vehicles.

We also compared the average and the coefficient of variance of parameters in order to prove the difference of response to multi-leaders by different clusters. The results are shown in Table 4. Mostly the average of the estimated parameters in the 3rd cluster has not only the largest but also the smallest value in CV. The comparison of the results between cluster 1 and 2 suggests that average value for parameters $\alpha_1, \beta_1, \beta_2$ and β_3 in cluster 2 are larger than those in cluster 1, whereas the values of parameters α_2 and α_3 which explain the relation of the relative speed with the second and third leaders are smaller. In particular, CV for parameters α_2 and α_3 for the cluster 1 are smaller. These results suggest that the followers in the cluster 1 tend to respond to relative speed with the second and third leaders than the first leader in relatively more aggressive manner. Also, the followers in the cluster 2 tend to respond to relative speed with the first leader in relatively more aggressive way. In the case of β_j explaining relationship for relative distance with multi-leaders, the clusters 1 and 2 have all similar value. The drivers in the cluster 3 have generally largest values of parameters and determination coefficient.

We found that each follower can be classified largely into three car-following clusters from the results of cluster analysis. These results show the existence of heterogeneity in car following behaviors among the drivers and the possibility to classify the car following behaviors into three major groups based on the principle component analysis and cluster analysis for the estimated parameters.

4.3 Multi-anticipative car following behavior under different road geometry condition

In this section, we pay our analytical attention to the difference of multi-anticipative car-following behavior for the different road geometry. 118, 144 and 138 data sets of multi-anticipative car following can be extracted, for straight, curved and merging sections, respectively. Also, we selected the best model whose average R^2 is maximum among combinations of m_1 and m_2 for each multi-car following vehicle. Table 5 shows the average value of estimated parameters of the best models for straight, curved and merging sections. While the multi-anticipative car-following model with (m_1, m_2)=(3,3) commonly has the highest capability to describe the actual car-following behaviors without consideration of difference in road geometry based on the analyses at section 4.1, the best model for straight section is likely to be the one with (m_1, m_2)=(3,1).

The multi-anticipative car-following model with (m_1, m_2)=(3,3) is still selected as the best one for both the curved and merging section. From these results, we found that behavior of driver in straight section can sufficiently be described only by the relative speed with respect to the 1~3th leaders and relative distance with first leader only. On the other hand, the model in curved and merging section is explained well by the multi-car following behavior responding to both relative speed and relative distance with respect to the first, second and third leaders. It may be because that the various incidents may often happen at curve and merging sections, and drivers therefore pay more attentions to the 2^{nd} and 3^{rd} vehicles. We further compare the distribution and average value of response time. Comparing results by each section, we found that the straight section has the longest response time. We concluded that the car-following behavior may change by road geometry.

5. Conclusion

In this paper, we analyzed multi-anticipative behavior for an urban expressway using vehicle trajectory of video data from 11 cameras. We also applied the normal least-square method to estimate parameters of the Generalized Helly type of multi-anticipative car following model for each vehicle trajectory data. Accordingly, the estimated parameters of multi-anticipative car-following model are distributed, and it allows us to do some statistical analyses for the estimated parameters in order to realize the actual car-following behaviors. Applying the both principle component and cluster analyses for the estimated parameters can lead to our better understanding of both heterogeneity in car-following behaviors among drivers and possibility of classification of car-following behaviors. In addition, we analyzed the impact affecting by road geometry for multi-anticipative behavior.

Results for these analyses show that, first of all, the multi-anticipative car following model can represent the actual vehicular behaviors much better than a single-leader car-following model. It provides result that driver do not react on their direct leader, but reacting on the behavior of the second and even the third leader. Secondly, the various distributions for parameters and response time show the existence of heterogeneity in car-following behaviors among drivers and classified three major groups as principal and cluster analysis are represented possibility to classify the car following behavior. Thirdly, the characteristics for road geometry affect the car-following behaviors judging from the estimated parameters of the best multi-anticipative car following models, it needs to analyze for multi-car following behavior consider to characteristics of road geometry. In general it can be said that the behavior of the first leader affects largely the following vehicle compared to the second, third leaders, however, their effects upon the follower should not be ignored to make better understanding and description of car-following behavior under very busy traffic environment.

These findings have important implications to the current microscopic simulation practice. Nevertheless its model well describe car following behavior which is the multi-anticipative model consider to multiple leaders and road geometry, the current simulation model not consider not only the multi- leader but characteristics by road geometry. For future research, it is necessary to multi-anticipative car following model including more leaders and higher model complexity from sufficient trajectory data. This paper utilized manually obtained trajectory data. This system has a very high cost per data unit, and we only analyzed vehicle trajectories for 15 min. Improvements to the automatic vehicle trajectory recognition system will be indispensable for more efficient analyses.

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