

Impact of Next-Nearest Leading Vehicles on Followers' Driving Behaviours in Mixed Traffic



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Abstract The number of vehicles on the road is increasing across all vehicle types, especially in developing countries. The rise of heterogeneity in traffic causes greater mixed traffic congestion. This study focuses on the impact of next-nearest leading vehicles on the driving of following drivers in mixed traffic. Although previous studies reported that traffic stability can be improved with the introduction of followers' anticipatory driving that references multiple leaders, these works did not consider whether anticipatory driving occurred in mixed traffic. Using data collected in experiments with groups of two and three vehicles, we found that the operational delay and the maximum acceleration and deceleration of the followers were affected by the presence of next-nearest leaders. In addition, we also found that the height of the next-nearest leading vehicles affected followers' deceleration. These findings imply that model parameters for determining the deceleration of following vehicles should take the height of the next-nearest leading vehicle into account.

1 Introduction

The number of vehicles being driven on roads is increasing across all vehicle sectors and types, and traffic heterogeneity is particularly pronounced in developing countries [6]. This leads to greater traffic congestion, which causes problems such as economic losses and traffic accidents.

This study focuses on the impact of next-nearest leading vehicles on followers' drivings in mixed traffic. Although whether the followers refer the next-nearest leaders' driving is still unclear [4, 5], several studies have reported that in homogeneous

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traffic flow comprising one type of vehicles, stability improves if the followers anticipate driving of the nearest leaders with reference to next-nearest leaders' driving [3]. In heterogeneous traffic, anticipation can also improve stability because visibility of the next-nearest leaders can be improved due to the varying vehicle sizes, e.g. heights and lengths.

In this study, using data collected on a test course, we applied a statistical test to compare the driving characteristics of the followers with and without next-nearest leaders present. These observations clarified which driving characteristics of the followers were affected by the presence of the next-nearest leaders. In addition, we also developed regression models for these affected characteristics and found factors that affect the next-nearest leaders. From these comparisons, we suggest guidelines for how to determine parameters in car-following models under the assumption that followers refer to multiple leaders in heterogeneous traffic.

2 Experiment

To investigate the effects of the next-nearest leaders as well as effective factors of vehicle and driving characteristics, we observed following behaviours in groups comprising two and three vehicles as shown in Fig. 1. A group with two vehicles comprised a follower and a nearest leader. A group with three vehicles included a follower, a nearest leader and a next-nearest leader. We refer to measurements with two vehicles and those with three vehicles as Type A and Type B, respectively. Vehicles were chosen from motorcycles, normal passenger cars and container trucks. The motorcycles were 50-cc scooters. For the normal passenger cars, Toyota Corolla Axios were used. For the trucks, Isuzu Elfs with a container were used.

In the test course, three types of cones instructed the leading vehicles to start, brake or stop. We instructed the leading front end vehicles to commence acceleration from the start cones. After reaching 50 or 60 km/h, the front end vehicles maintained constant velocity. The front end vehicles were instructed to brake starting at the braking cones to stop at the stop cones. In contrast, we did not give any instructions to the followers and next-nearest leaders other than telling them to follow the vehicles in front of them. While these vehicles were driving based on our instructions, the positions of the vehicles were recorded to an accuracy of 60 cm

Fig. 1 Configuration of the test course

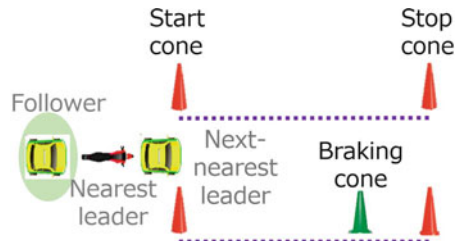


Table 1 Vehicle combinations and measured sample numbers in experiments for Type A and Type B

Test type	Follower	Nearest leader	Next-nearest leader	Trial number
Type A (two vehicles)	MC	MC	–	2
	Car	MC	–	16
	Truck	MC	–	11
Type B (three vehicles)	MC	MC	MC	4
			Car	4
			Truck	4
	Car	MC	MC	3
			Car	18
			Truck	3
	Truck	MC	MC	10
			Car	4
			Truck	10

MC denotes for motorcycle

by GPS antennas (Hemisphere A100) on top of the vehicles. The details of our measurement methods were the same as those in [7].

We conducted our experiments in December 2015 (*Day1*) and September 2016 (*Day2*) to obtain sufficient trial numbers. We utilised test courses of the Japan Automobile Research Institute on both days. On *Day1*, the experiments were held on a straight course. On *Day2*, an oval course was used. The oval course was divided into several sections. Some of these sections were not used due to their sags and curves.

Table 1 shows the numbers of trials that we performed for vehicle combinations. By fixing the nearest leaders as motorcycles, we can ignore the effects from the type of the nearest leaders. All drivers participating in the experiment were males between the ages of 20 and 50 and had at least 3 years of driving experience.

3 Driving and Vehicle Characteristics

To compare differences in driving behaviour, we need to introduce the characteristic features of driving behaviour. Additionally, the physical and performance characteristics of each vehicle need to be considered to explain the changes in the followers' driving. We selected characteristic features from the velocities and accelerations of the leaders and followers as well as the distance gaps between vehicles. V , a

and S denote the velocities, accelerations and distance gaps, respectively. From the velocities, we chose the maximum value, i.e. V_{\max} . From the accelerations, the maximum and the minimum values denoted as a_{\max} and a_{\min} were chosen. From the distance gaps, the initial and maximum values (S_{start} and S_{\max}) were chosen. In addition the ϵ_a was considered as operational delay, and it represents the difference of emerging times of the maximum accelerations between the followers and the nearest leaders, and the nearest leaders and the next-nearest leaders. We refer to these variables as driving characteristics. Note that we use superscripts “f”, “1st l” and “2nd l” to indicate the followers, the nearest leaders and next-nearest leaders, respectively. For example, $a_{\max}^{2\text{nd}l}$ indicates the next-nearest leaders’ maximum acceleration and V_{\max}^f indicates the followers’ maximum velocity. The superscripts of “1st” and “2nd” represent the relationships between the followers and the nearest leaders, and the nearest leaders and the next-nearest leaders, respectively. In following sections, we analyse $\epsilon_a^{1\text{st}}$, V_{\max}^f , a_{\max}^f , a_{\min}^f , $S_{\text{start}}^{1\text{st}}$ and $S_{\max}^{1\text{st}}$ one by one.

For vehicle characteristics, we applied the vehicle longitudinal length, height (including the drivers for motorcycles) and the maximum power divided by the weight, i.e. the power-to-weight ratio (PWR). L , TH and P stand for the length, the height and the PWR, respectively. Note that the same superscripts, i.e. “f”, “1st l” and “2nd l”, are used to indicate the relations between vehicles.

In addition to these characteristics, we initially considered whether the vehicle weight, width, height or torque-to-weight ratio should be included to the vehicle characteristics. However, we finally removed these parameters because they were strongly correlated with other characteristics, at least in our datasets. Such strong correlations could cause problems of multi-collinearity in the analysis that we present in Sect. 5. In Sect. 5, we develop regression models of the driving characteristics of followers using these vehicle characteristics along with other driving characteristics.

4 Impact of Next-Nearest Leaders’ Presence

In this section we consider whether or not $\epsilon_a^{1\text{st}}$, V_{\max}^f , a_{\max}^f , a_{\min}^f , $S_{\text{start}}^{1\text{st}}$ and $S_{\max}^{1\text{st}}$ are affected by the presence of next-nearest leaders. If we statistically conclude that these characteristics are different with and without next-nearest leaders present, we will find that follower driving is affected by the presence of next-nearest leaders. Therefore, we applied a statistical test for whether driving characteristics are different with two (Type A) or three vehicles (Type B) in a group. To evaluate only the effect of next-nearest leaders’ presence, we compared only the data when the follower is the car for Type A and the data when the follower is a car and the next-nearest leader is the car for Type B.

We applied the Wilcoxon–Mann–Whitney test because the parameters we measured could not be necessarily assumed to follow a Gauss distribution. The p -values of $S_{\text{start}}^{1\text{st}}$ and $S_{\max}^{1\text{st}}$ were over 20%. We could not conclude that the distance gaps were

affected by the presence of a next-nearest leader. As the p -value of ϵ_a^{1st} was less than 0.1%, ϵ_a^{1st} was affected by the next-nearest leaders. The maximum acceleration and deceleration of the followers returned p -values of 16% and 13%, respectively. These values leave possibility that these characteristics are driven by the leaders' behaviour open. Therefore, we focus more closely on effects of next-nearest leaders in the next section

5 Effective Factors of Next-Nearest Leaders

In this section, we compare differences between linear regression models for Type A and Type B to clarify which characteristics of the next-nearest leaders affect the followers' behaviour. We assume that explanatory variables included in the regression model for Type A are also included in the model for Type B for the same follower driving behaviours.

Figure 2 shows how we developed our models. We refer to the procedures to develop models for Type A and Type B as Step A and Step B, respectively. To obtain the models for Type A datasets, we first calculated the relative importance of

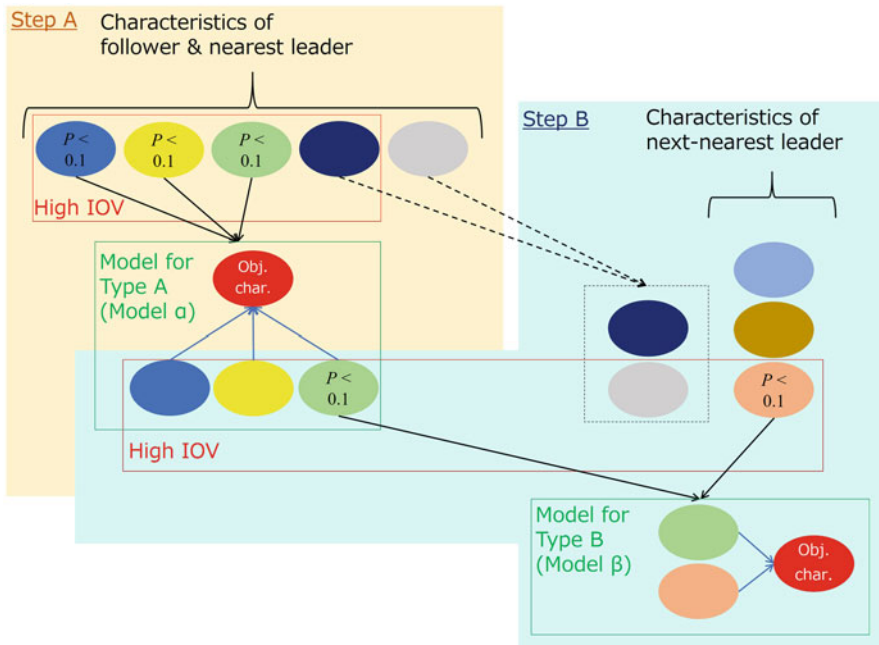


Fig. 2 Selection procedure for models for Type A and Type B (two- and three-driver groups). Respective coloured ellipses represent driving and vehicle characteristics, i.e. explanatory and objective variables

variable candidates, i.e. IOV. Variable candidates included all vehicle characteristics, dummy variables for *Day* and test drivers and related driving characteristics from the perspective of the timing of emergence. The IOV is a value from 0 to 1 and is often used to practically check which explanatory variables play important roles in candidate models. IOV can be obtained by summing up the Akaike weights [2, 8] for possible models using every combination of explanatory variables. Since the Akaike weight of a certain model grows large when the model is close to the best model from the perspective of the Akaike information criterion (AIC) [1], large IOVs for each variable mean that the explanatory variable is frequently included in better models from the AIC perspective. Here we summed up the Akaike weights of models within 2.0 of AIC difference from the best model.

Using all the variables with high IOVs, a regression model to explain the objective variable can be constructed. Although it is common in practice to apply a threshold IOV of 0.8 as the standard for variable importance, we eliminated variables for which the IOV became small suddenly. As each variable has a p -value whether its regression coefficient is significant or not, we finally developed a regression model for Type A, i.e. Model α with variables with p -values less than 0.1.

Next, we explain Step B. Using the explanatory variables in Model α , excluding the characteristics in Step A and characteristics of next-nearest leaders, we calculated IOVs again. Note that we only summed up the Akaike weights of models including all variables in Model α . Once we obtained a set of variables with high IOVs, we made a model that included all of these variables. Based on the p -values in the model, we collected variables with p -values less than 0.1 and developed a model for Type B, i.e. Model β . Although we assumed that the variables in Model α would also be included in Model β , some variables in Model α were eliminated in Step B due to their p -values.

Models β of respective driving characteristics are shown in Fig. 3. Characteristics with red font indicate that they were added in Model β and not present in Model α . The characteristics marked with chequered pattern indicate that they were eliminated in Step B due to their statistical significance. The numbers shown next to the explanatory variables are their regression coefficients in standardised regression models. In other words, we can evaluate degree of effectiveness of variables based on their regression coefficients. In Fig. 3, we do not display the effects of the dummy variables that represent the *Day* and which test drivers operated the variable.

Regarding operational delay, i.e. ϵ_a^{1st} , no effects were detected except for *TD3* in model β . The follower length, i.e. L^f , included in Model α was removed due to its significance in Model β . In Fig. 3b, the maximum velocity of the next-nearest leaders, i.e. V_{max}^{2nd1} , was added to Model β . From the regression coefficients, we recognised that effectiveness of V_{max}^{2nd1} was more strong than that of V_{max}^{1st1} . In contrast, regarding the acceleration in Fig. 3c, the effect of nearest leaders' behaviour seemed to be larger than that of the next-nearest leaders. In Fig. 3d, the vehicle characteristics of the next-nearest leaders are included. The model implies that the followers' deceleration decreases as the height of the next-nearest leader

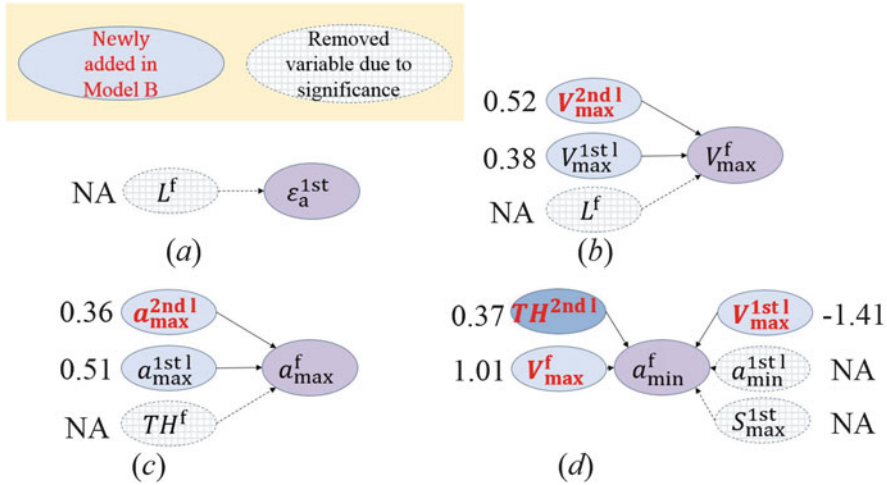


Fig. 3 Obtained Model β for each driving characteristic of the followers. Characteristics printed in red indicate that they were newly added in Model β and not included in Model α . The characteristics marked with a chequered pattern indicate that they were eliminated in Step B due to statistical significance. (a) Delay. (b) Velocity. (c) Acceleration. (d) Deceleration

increases. This seems to be a natural effect from the perspective of driver safety and anticipatory behaviours.

6 Conclusion

In this study, we investigated the factors of next-nearest leaders that affect followers' driving as well as what driving behaviours of the followers are affected by the presence of next-nearest leaders.

We conducted experiments with groups comprising of two and three vehicles on a test course. While varying the collection of vehicle types in the groups, we observed the following behaviours of each driver. Our experimental context enabled us to measure differences in car-following behaviour without any interference such as lane changes.

From the statistical tests, we conclude that the initial and maximum distance gaps were not affected by the presence of next-nearest leaders. In contrast, we suggest that the maximum velocity, acceleration, deceleration and operational delay of the followers were affected by the presence of next-nearest leaders.

In addition, we developed regression models to explain follower behaviours in terms of other drivers' behaviour and vehicle characteristics. By comparing the statistical models of experimental data from groups of two and three vehicles, we conclude that the maximum velocity and acceleration of the followers are both

affected by those of the nearest leaders and the next-nearest leaders. These effects naturally appear from car-following models that consider multiple leading vehicles. We also conclude that the maximum deceleration of the followers was affected by the height of the next-nearest leading vehicles. This implies that the height of the next-nearest leading vehicles should be considered when we fit parameters dedicated to reproducing following drivers' deceleration.

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References

1. Akaike, H.: Information theory and an extension of the maximum likelihood principle. In: Selected Papers of Hirotugu Akaike, pp. 199–213. Springer, New York (1998)
2. Burnham, K.P., Anderson, D.R.: Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach. Springer, New York (2003)
3. Ge, H., Dai, S., Dong, L., Xue, Y.: Stabilization effect of traffic flow in an extended car-following model based on an intelligent transportation system application. *Phys. Rev. E* **70**(6), 066134 (2004)
4. Helbing, D., Hennecke, A., Shvetsov, V., Treiber, M.: Master: macroscopic traffic simulation based on a gas-kinetic, non-local traffic model. *Transp. Res. B Methodol.* **35**(2), 183–211 (2001)
5. Herman, R., Rothery, R.W.: Car following and steady state flow. In: Proceedings of the Second International Symposium on the Theory of Road Traffic Flow London 1963, pp. 1–11. Organisation for Economic Co-operation and Development, Paris (1965)
6. Hsu, T.P., Sadullah, A.F.M., Dao, N.X.: A comparison study on motorcycle traffic development in some Asian countries—case of Taiwan, Malaysia and Vietnam. In: The Eastern Asia Society for Transportation Studies (EASTS), International Cooperative Research Activity, Washington (2003)
7. Nagahama, A., Yanagisawa, D., Nishinari, K.: Dependence of driving characteristics upon follower–leader combination. *Physica A* **483**, 503–516 (2017)
8. Wagenmakers, E.J., Farrell, S.: AIC model selection using Akaike weights. *Psychon. Bull. Rev.* **11**(1), 192–196 (2004)