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Using Asymmetric Theory to Identify Heterogeneous Drivers' Behavior Characteristics Through Traffic Oscillation

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ABSTRACT This paper applies the asymmetric driving theory to capture driving characteristics of car-following behavior throughout traffic oscillation. Unmanned aerial vehicle (UAV) was employed to record videos near a bottleneck on an expressway in Nanjing, China, from which authors used advanced image processing technology to track and extract the high-fidelity vehicles trajectory data for a microscopic analysis in this study. First, with analyzing the individual vehicle trajectory throughout oscillation, authors find that the driving characteristics of drivers are heterogeneous but show several consistent features: before and after experiencing oscillation, relatively more drivers tend to maintain aggressive driving, i.e., 49.7% are originally aggressive (OA) and 37.2% are later aggressive (LA). Second, the statistical analysis indicates some representative characteristics of Chinese drivers: the polarization (aggressive or timid) is more significant before oscillation (OA 49.7%, originally Newell ON 18.9% and originally timid OT 31.4%) but changing to relative equilibrium after oscillation (LA 37.2%, later Newell LN 33.8% and later timid LT 29%). Finally, the authors also find that the type and intensity of each driver's reaction in oscillation are related to the characteristics he or she have before encountering oscillation. These findings of asymmetric driving behavior evolution in this paper may help to explain the causes of hysteresis and unstable traffic flow phenomena.

INDEX TERMS Car-following, driver behavior, reaction to oscillations, transition, asymmetric theory.

I. INTRODUCTION

In congested traffic condition, drivers are largely affected by movements of nearby vehicles. Therefore, many scholars have noticed that the growth, propagation and dissipation of traffic oscillation are closely related to driver behavior characteristics. Early theoretical studies [1], [2] analyzed the linearity of car-following models and attributed the propagation of oscillation to the over-reaction of car-following behaviors.

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Gipps developed a car-following model based directly on driver behavior and expectancy as regards downstream traffic [3]. Recently, many researches on driving behavior are based on simplified car-following theory that proposed by Newell [4], which considers reaction time and congested spacing. However, numerous driver behavior models fail to adequately describe the complex driving behaviors in congested traffic, as they are pervasively based on the assumption of symmetry during acceleration and deceleration processes. In fact, asymmetric driving behavior is related to hysteresis phenomenon which indicates the retardation in speed

recovery, i.e., when a platoon of vehicles goes through a traffic disturbance, prevailing conditions prior to the disturbance are not restored immediately [5]. The separation between the deceleration-acceleration forms hysteresis loops when vehicles meet oscillation as observed first by Edie [6]. In short, the hysteresis shows that the driving behavior is asymmetric when the speed changes.

In contrast to previous approaches, the asymmetric features of traffic behavior have been studied to explain the instability of microscopic traffic flow with increased interest lately. Li and Ouyang proposed a mathematical framework to accurately quantify oscillation characteristics for a general class of nonlinear car-following laws [7], [8]. Although this approach provides a perspective to understand traffic oscillations based on mathematical asymmetric method, it is still not clear how the asymmetry occurs. In addition, Yeo *et al.* analyzed individual vehicle trajectories in congestion and confirmed the heterogeneous features of driving behavior [9], [10]. Other studies have analyzed traffic safety based on individual vehicle trajectories [11], [12]. However, the relationship between human maneuvering errors and the changing process of driving behavior has not been studied, and the intrinsic mechanism between asymmetry and driving category is not clear. Laval *et al.* attributed the formation and propagation of traffic oscillations to the aggressive or timid behavior of drivers in their model, referred to as the L-L model hereafter [5]. However, the behavioral methodology assumed in this model has not been verified empirically. Zheng *et al.* used wavelet transform method to analyze vehicle trajectories and investigate driver behavior during oscillations based on asymmetric lane-changing model [13]–[15]. Nevertheless, their concentration was on comparing the driver's behavior on lane-changing, while the overall dynamic description of the car-following behavior throughout oscillation was still not given. Thus, authors argue that aforementioned studies are deficient in providing insights to better understand driver behavior in traffic oscillations.

An asymmetric behavior model was proposed by Chen *et al.* [16] to capture the driver's behavior in congested traffic by analyzing vehicles trajectories data. This model provides a dynamic and concise method to study asymmetric driving behavior. However, they only revealed the distribution of driver characteristics before oscillation, while did not show the distribution after oscillation as well as the changes of driver characteristics through oscillation.

With the rapid development of computer image processing technology in recent years, tracking and extracting the object movement data in video has become a hot emerging technology. For instance, many notable researches on driving behavior and other subjects in traffic flow were using the vehicles trajectories data extracted from video streams provided by the NGSIM (Next Generation Simulation) program [17], such as [13]–[15]. Vehicle trajectory data can contain a complete movement process, from which researchers can obtain the information of speed, acceleration, lane change time, detailed location of the vehicle and its adjacent vehicles at any

time, and can easily reconstruct their space-time movement. Prevalently but flawed is that the movement data acquired by GPS or road sensors are discontinuous, larger time interval (often more than a few seconds, but video data can be accurate to one frame) and that real spatiotemporal traffic dynamics between the detectors is not known. Using detector data, it is not possible to resolve microscopic spatiotemporal features of traffic patterns. GPS data are often discontinuous or error-prone. Thus, better than GPS and sensors, the trajectory extracted from the video is more reliable as well as easy to reconstruct the data for microscopic traffic flow analysis.

This paper aims to fill this void: authors comprehensively study the driving behaviors when experiencing traffic oscillations using vehicles trajectories data obtained in Nanjing. In particular, authors aim to observe the driving behaviors from an asymmetric perspective, and study the heterogeneity of drivers' behavior. Authors explore how the driver's original characteristics affect his/her reactions in oscillations. In addition, authors further compare the behavioral characteristics of Chinese drivers with those [16] in United State.

The rest of paper is organized as follows. Section II introduces the trajectory data, acquisition methods and site used in this study. Section III introduces the basic research theory refer to driving behavior. Section IV presents the measurement methodology. Section V conducts statistical analysis of asymmetry in driving behavior. Finally, conclusions and discussions are provided in Section VI.

II. STUDY SITE AND DATA

FIGURE 1 shows a bottleneck area on Yingtian Viaduct (Yingtian Street Elevated Bridge), which is a segment of expressway with speed limit of 80 km/h and the one of the important interchange hubs in Nanjing city, the capital of Jiangsu province, China. In this paper authors only study the segment of which the direction from east to west (i.e. the flow direction in red line rectangle). This segment is an independent on-ramp bottlenecks with heavier traffic congestion daily, the length of which is approximate 350 m, shown in FIGURE 1(b). The lanes number of this on-ramp bottleneck decreases from five lanes to four lanes at location 128m and finally to three lanes at location 116m. A large number of lane-changing activities occur in this area, causing frequent traffic congestion during rush hours. Note that lane 1 and lane 2 are the main lanes and lane 3–lane 5 are on-ramps.

In this study, authors use UAV (Unmanned Aerial Vehicle) to record aerial videos with a broader view and an unobstructed bird's-eye view, from which authors can obtain the videos that are not blocked by obstacles, and facilitate the subsequent extraction of high-precision data information from the videos. Notice that the programming software MATLAB was used to implement all the process after the video recording such as: detect the vehicles, extract the trajectories, process, analyze organize the data, etc. Further, authors provide a concise presentation about the data extraction methodological framework of this paper in FIGURE 2. In fact, based on our previous research methods [18]–[21],

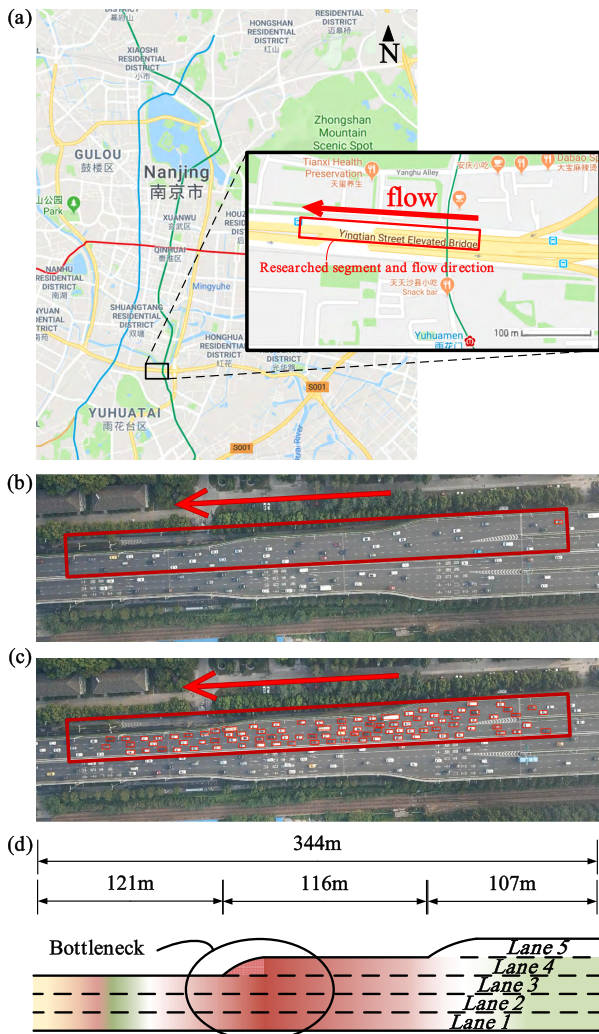


FIGURE 1. The location where this paper investigates – the Yingtian Viaduct in Nanjing, China; (b) At the beginning of the study period, the first vehicle begins to be identified with a red tracking box. (c) At the end of the study period, the last vehicle is identified with a red tracking box. (d) a diagrammatic sketch of the local segment between upstream and downstream of the on-ramp where we study.

the videos were processed by the Image Recognition and Tracking Technology with 24 frames per second (fps), as well as the original trajectory data have been completed data processing: The complete database contains 621 vehicles, in each lane, it was detected 133, 111, 128, 144 and 105 vehicles, respectively and it was found a total of 26 trajectories considered unreliable. Due to the low percentage of noise found, authors may assume that the final database contains reliable information. The final database contains that vehicle ID, lane log, tracking rectangles dimensions (x, y), accumulated and partial traveled distances, time gaps, two columns of velocity (in m/s and km/h) and row numbers, etc. In addition, authors have published the trajectory data in regards to this study, more detailed information and descriptions are available on: <https://github.com/andychen166/trajectory-data-and-video>.

The reliable trajectories of 621 vehicles in this study are fitted and shown in FIGURE 3. However, the complexity of evolution of traffic condition lead to that many vehicles

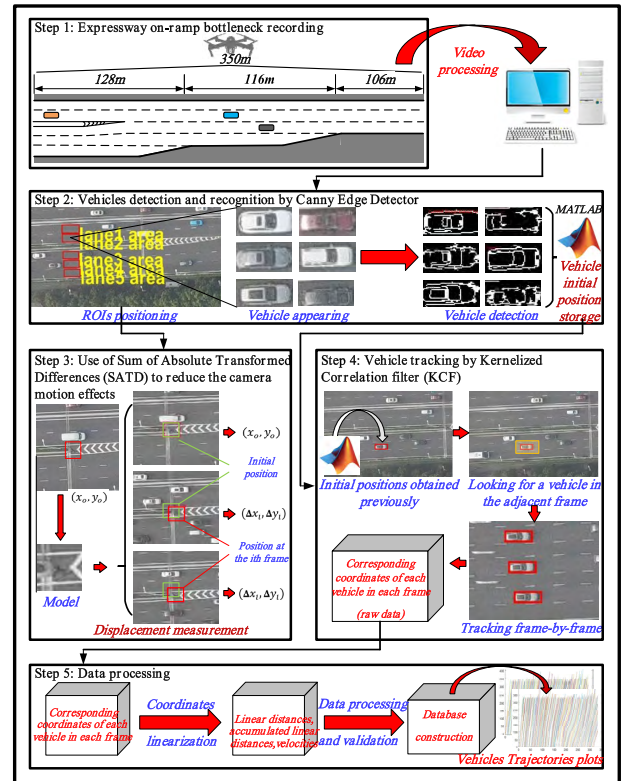


FIGURE 2. Methodological framework: Video capture, vehicle tracking and data processing. For habitual observation, authors rotated the studied segment 180 degrees in Step 1.

trajectories are not complete enough to be studied with frequently interlaced lane-changing behavior. Thus, authors selected 90 pairs trajectories with lane-changing excluded to analyze the car-following behavior from 621. Note that authors will introduce the selecting criteria for the 90 pairs trajectories in section V.

As can be seen from FIGURE 3, the cause of the traffic state transition investigated in this paper is lane-changing (LC) behavior. With the purpose of spatiotemporal reconstruction of traffic state transition on main-lines, in FIGURE 4 authors shows the formation process of congestion (i.e. the density and speed change process) near the on-ramp bottleneck, obviously, the changes in magnitude and trend of speed and density on the three lanes are similar. With the increase of density, the mutual restriction between vehicles becomes more obvious. At this time, the change of traffic flow state is likely to cause the change of driving behavior; if so, the change of driving behavior may affect the change of traffic flow state (or the evolution of oscillation) because that drivers always want to find ways to move faster through crowded areas or emotional changes.

III. DRIVING BEHAVIOR MODEL

A. NEWELL'S CAR-FOLLOWING MODEL

Authors first summarize the aforementioned Newell's simplified car-following theory [4] because it forms the basis of our methodology, which illustrates the relationship

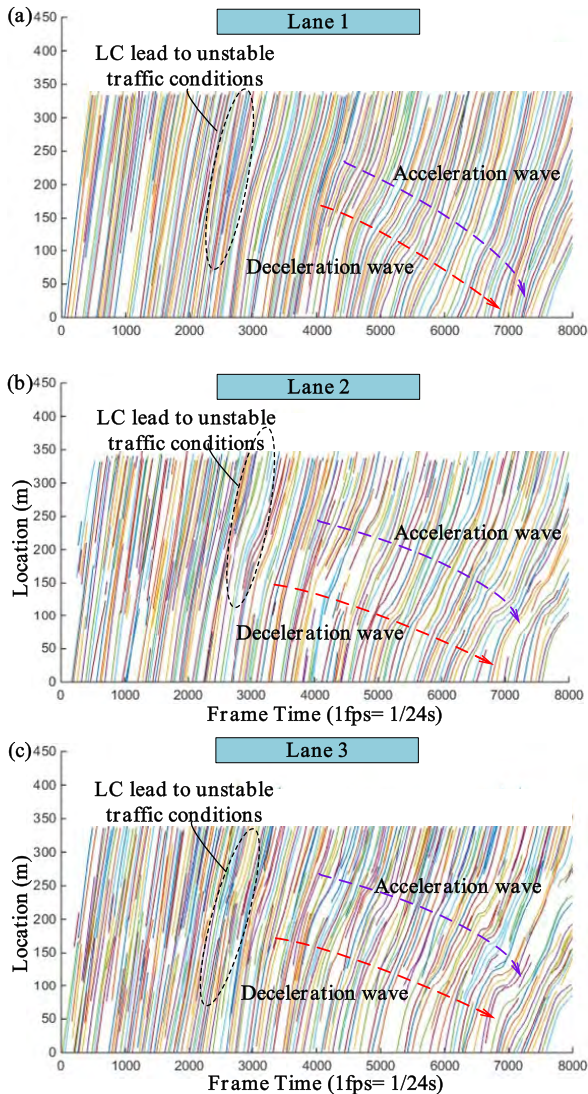


FIGURE 3. Microscopic spatiotemporal measurement: Complete vehicle trajectories data on lane1-lane3, i.e.(a)-(c), 7:05-7:11, August 2, 2018 in Nanjing, China.

between speed and spacing with only two parameters and gives the exact solution of the kinematic wave model with a triangular fundamental diagram (KWT model), shown in FIGURE 5.

The variable τ is the wave trip time between two consecutive drivers and d is the jam spacing. In theory, vehicle n 's trajectory is identical to vehicle $(n-1)$'s with a time displacement τ_i and a space displacement d_i . u is the free-flow speed. Thus, τ_i represents the duration that vehicle n waits until it accelerates (which refer to this as response time). Newell further proposed that (τ_i, d_i) may vary from vehicle to vehicle as if they were sampled independently from some joint probability distribution, but they were constant and independent of speed for a given driver. Notably, these two parameters can be written using two parameters in the KWT model, i.e.:

$$\tau = \frac{1}{wk} \quad \text{and} \quad d = \frac{1}{k} \quad (1)$$

where $-w$ is wave speed and k is jam density.

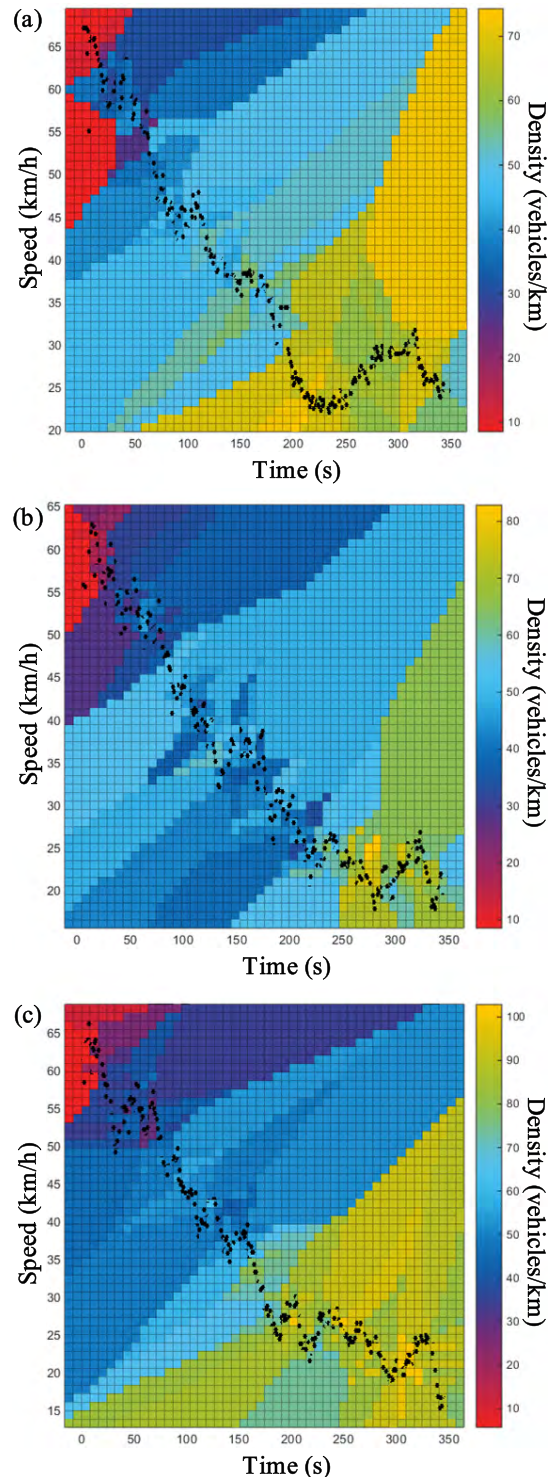


FIGURE 4. Means of velocity and density per second for each lane (lane1-lane3, a-c) in the study area.

B. ASYMMETRIC BEHAVIORAL THEORY

Laval and Leclercq [5] observed that vehicle trajectories accord well with Newell' car-following model before experiencing traffic oscillations, however, deviations were significant during the oscillation, i.e., driver n may have

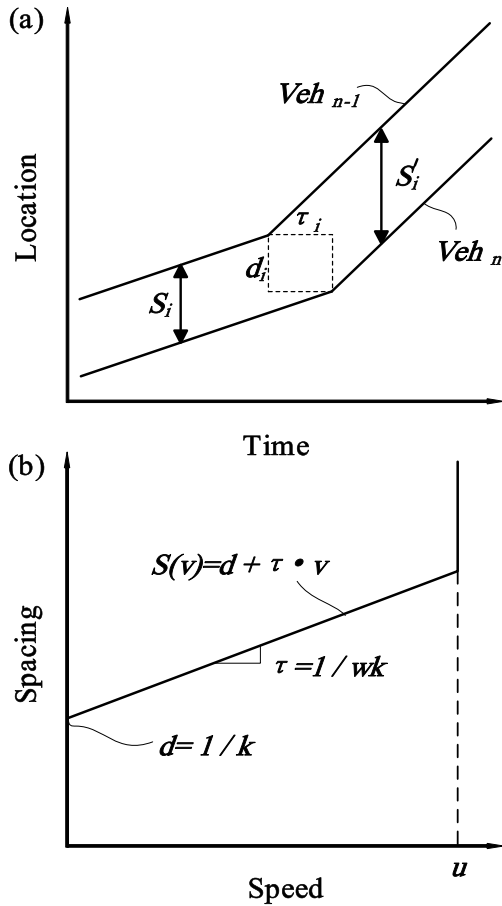


FIGURE 5. (a) Newell's car-following theory using vehicle trajectories; (b) speed-spacing relationship based on Newell's car following theory.

(τ_i, d_i) deviate from constant value. In this paper, two sample of our data for car-following and lane-changing respectively is used to illustrate their observations. FIGURE 6 shows that if a follower's driving behavior does not change in car-following mode, he/she should almost always follow the trajectory shifted by leader's (i.e. Newell trajectory, blue dashed line); To capture the deviation, they proposed a variable $\eta_i(t)$, defined as

$$\eta_i(t) = \tau_i(t) / \bar{\tau} \quad (2)$$

where, $\tau_i(t)$ is the actual wave travel time of driver n at time t and $\bar{\tau}$ is the equilibrium value given by Eq. (1). The wave speed w is assumed to be constant. Actually, the measurement of $\eta_i(t)$ boils down to measuring $\tau_i(t)$, which is much more convenient than measuring the steady-state spacing. Thus, the term $\eta_i(t)$ is sufficient to capture the dynamics of the two parameters (τ_i, d_i) because of $d = \tau w$. Note that $\eta_i(t)$ is equivalent to the ratio of the actual steady spacing to the equilibrium spacing [22].

Therefore, based on empirical observations, Zheng et al. [14] proposed an asymmetric behavioral model to illustrate driver's car-following behavior throughout traffic oscillation, which was extended from the aforementioned

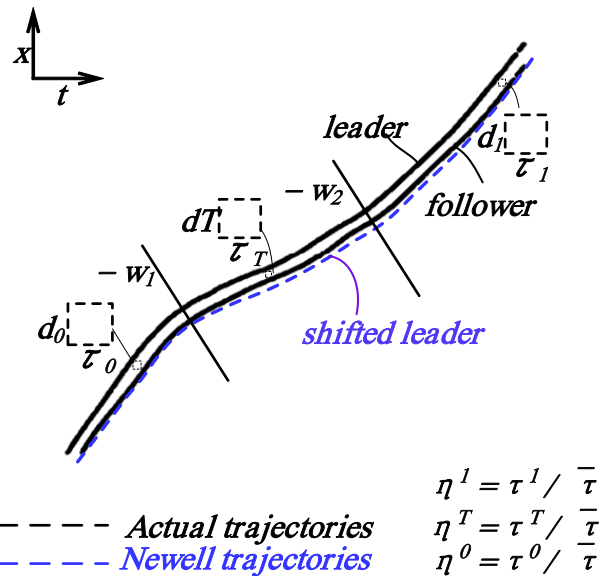


FIGURE 6. An empirical example of car-following from our data, solid lines represent actual trajectories, and dashed lines represent theoretical trajectories which shifted leader trajectory by ($\tau, -\tau w$) in blue.

model of Laval et al. [5]. The asymmetric behavioral model can well capture drivers' driving behavior changes before and after oscillation and their reaction patterns to oscillation. In addition, this model explains that in equilibrium drivers tend to maintain constant $\eta_i(t)$ -value; in non-equilibrium, which is triggered whenever the deceleration wave of an oscillation starts, drivers deviate from the average value $\bar{\tau}$ that before oscillation.

FIGURE 7 is a profile which shows the parameters involved in this model: $\eta_i^0(\eta_i^1)$ refers to the stable value of $\eta_i(t)$ before (after) the nonequilibrium (i.e. oscillation), and η_i^T is the value when the vehicle has the maximum deviation in car-following mode. Therefore, $\eta_i^0(\eta_i^1)$ can capture the characteristics of driver in equilibrium branch before (after) meeting traffic oscillations.

When η_i^0 is equal to 1, the behavior of driver n accords well with the theoretical fundamental diagram of the KWT model. Thus, η_i^0 is used to define driver categories: (i) originally aggressive (originally timid) when $\eta_i^0 \ll 1$ ($\eta_i^0 \gg 1$), abbreviated as OA (OT); (ii) the driver behavior at the average level when η_i^0 is close to 1 (i.e. $0.9 \leq \eta_i^0 \leq 1.1$), named as "originally Newell" driver and abbreviated as ON. In TABLE 1, authors explain the parameters of the asymmetric model.

According to the asymmetric theory of Chen et al. [16], shown in FIGURE 7, the ensuing evolution of $\eta_i(t)$ in non-equilibrium exhibit three reaction patterns to capture driver behavior: concave triangle pattern ($\eta_i^T > \eta_i^0$, and $\eta_i^T > \eta_i^1$); convex triangle pattern ($\eta_i^T < \eta_i^0$, and $\eta_i^T < \eta_i^1$); and constant ($\eta_i^0 \sim \eta_i^T \sim \eta_i^1$). The measurement of $\eta_i(t)$ for the different state can be written as:

- Before nonequilibrium:

$$\eta_i(t) = \eta_i^0 \quad (3)$$

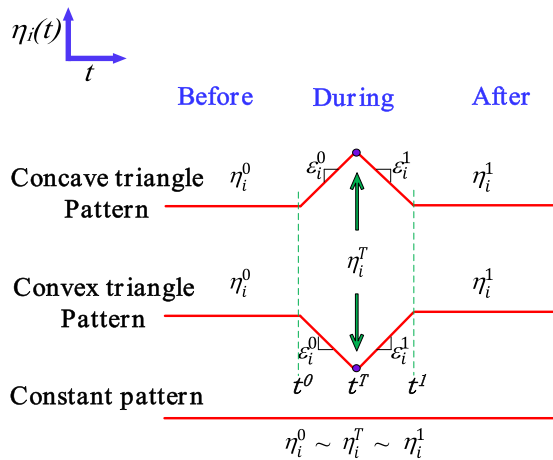


FIGURE 7. Behavior reaction patterns and the evolution of $\eta_i(t)$ in asymmetric behavioral model proposed by Chen *et al.* [16].

TABLE 1. Parametric description of asymmetric behavior model.

Parameters	Description
η_i^0	the stable value of $\eta_i(t)$ before the nonequilibrium
η_i^T	the value when vehicle has the max/min deviation from η_i^0
η_i^1	the stable value of $\eta_i(t)$ after the nonequilibrium
ε_i^0	the average slope of $\eta_i(t)$ between η_i^0 and η_i^T .
ε_i^1	the average slope of $\eta_i(t)$ between η_i^T and η_i^1 .
t^0	the start time point of non-equilibrium
t^T	the time point of $\eta_i(t)$ to the max/min η_i^T
t^1	the end time point of non-equilibrium
δ^0	the difference $\eta_i^T - \eta_i^0$, i.e. the relationship between the original equilibrium state and the max/min deviation value.
δ^1	the difference $\eta_i^T - \eta_i^1$, i.e. the relationship between the later equilibrium state and the max/min deviation value.

- During nonequilibrium:

$$\eta_i(t) = \begin{cases} \eta_i^0 + \varepsilon_i^0 * (t - t^0), & t \in (t^0, t^T) \\ \eta_i^T + \varepsilon_i^1 * (t - t^T), & t \in (t^T, t^1) \end{cases} \quad (4)$$

- After nonequilibrium:

$$\eta_i(t) = \eta_i^1 \quad (5)$$

where $\varepsilon_i^0(\varepsilon_i^1)$ is the average slope of $\eta_i(t)$ between $\eta_i^0(\eta_i^T)$ and $\eta_i^T(\eta_i^1)$. The triangles are not necessarily isosceles or symmetric, i.e. $\eta_i^0 \neq \eta_i^1$, $\varepsilon_i^0 \neq \varepsilon_i^1$. $t^0(t^1)$ denotes the start (end) point of non-equilibrium, and t^T is the time of $\eta_i(t)$ to the maximum or minimum η_i^T .

IV. BEHAVIOR MEASUREMENTS

Authors use the model proposed by Chen *et al.* [16] to study driver behavior throughout oscillations, and to compare with their results. Thus, the measurement of $\eta_i(t)$ is given from Eq. (3) to (5). Fortunately, authors have observed our data that

within a narrow range of values of w and k , as well as found that general shape of $\tau_i(t)$ was constant across different measurements. Thus, in our analysis authors observed and used mean $w = 6$ km/h, similar with the common value in many studies using NGSIM data such as the literatures [16], [23]. The wave speed used in the measurement is fixed for a given driver but it varies across drivers. With this given wave speed, authors measure the trip time $\tau_i(t)$ along the follower's trajectory and obtain a time series of $\tau_i(t)$ as illustrated in FIGURE 6(a). The $\bar{\tau}$ value is set to be the mean of $\tau_i(t)$ before oscillation from all trajectories sampled, i.e. the mean value of all τ^0 .

According to Chen *et al.* [16], authors also use the threshold to be $\eta_i^0 < 0.9$ for OA drivers, $\eta_i^0 > 1.1$ for OT drivers and $0.9 \leq \eta_i^0 \leq 1.1$ for ON drivers. In a similar way, for comparing the driver's changing characteristics, authors further propose that $\eta_i^1 < 0.9$ ($\eta_i^1 > 1.1$) is referred to as "later aggressive" ("later timid") driver, abbreviated as LA (LT), to define the categories of drivers returning to equilibrium throughout oscillation. Moreover, authors also define $0.9 \leq (\eta_i^1) \leq 1.1$ named as "later Newell" driver and abbreviated as LN.

To indicate the amount of deviation, in this paper authors define a coefficient: $\delta^0 = \eta_i^T - \eta_i^0$ and $\delta^1 = \eta_i^T - \eta_i^1$, which clearly illustrates the relationship between the equilibrium state and the maximum/minimum deviation value. Based on our data observations and the research results from Chen *et al.* [16], authors reasonably set thresholds to classify reaction patterns by Eq. (6) as follows,

reaction patterns

$$\begin{cases} \text{concave, } (\delta^0 > 0, \delta^0 > 0.1 \text{ and/or } \delta^1 > 0.1, \\ \hspace{15em} \delta^1 > 0) \\ \text{convex, } (\delta^0 < 0, \delta^0 < -0.1 \text{ and / or } \delta^1 < 0.1, \\ \hspace{15em} \delta^1 < 0) \\ \text{constant, } (\delta^0, \delta^1 \in [-0.1, 0.1]) \end{cases} \quad (6)$$

V. RESULTS OF ANALYSIS

The trajectory screening criteria for the pair samples to study car-following behavior analysis as follow:

any pair of vehicles (a leader and a follower) which have complete trajectories within the time and space of this study, i.e., they travel on the same lane all the way when through the measured segment without any lane changer insertion.

Therefore, authors have selected 90 pairs complete vehicles' trajectories. An empirical car-following sample authors analysis shown in FIGURE 6.

FIGURE 8 shows the evolution of $\eta_i(t)$ of 90 pairs trajectories, where the horizontal and vertical axes are the $\eta_i(t)$ value for the leaders and followers at different stages, respectively. The distribution of η_i^0 and η_i^1 seem to be balanced, shown in FIGURE 8(a) and (c), which indicates that there is no obvious correlation for two successive drivers. This indicates that driver's behavior is "personalized characteristic" (i.e. heterogeneous) before and after an oscillation, in other words,

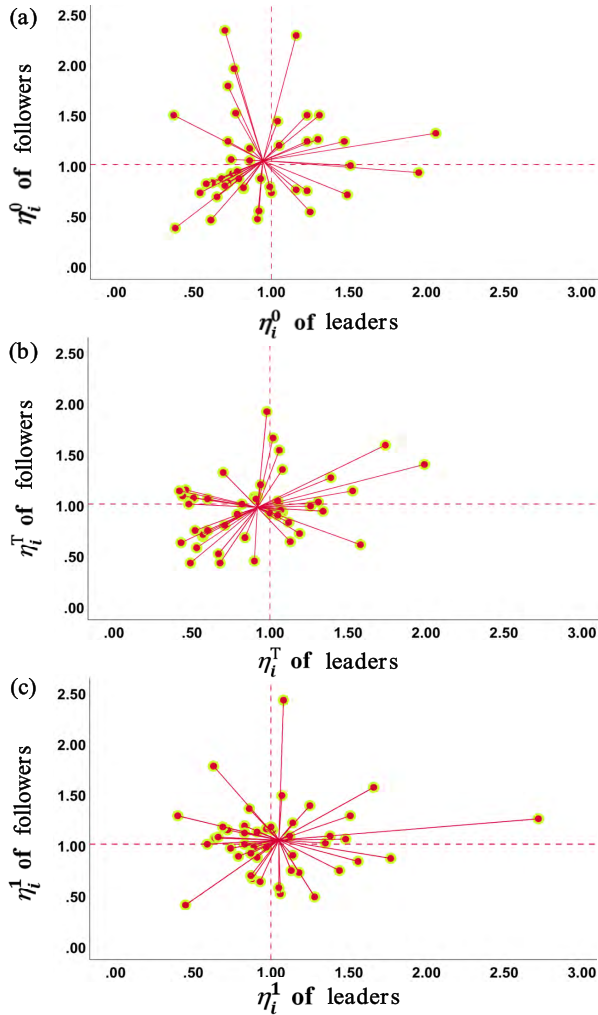


FIGURE 8. Correlation in successive drivers in car-following behavior.

independent from other drivers. However, there are some differences during oscillation in FIGURE 8(b): If a leader tends to take action $\eta_i^T > 1$, its follower can travel freely ($\eta_i^T < 1$); however, when leader takes $\eta_i^T < 1$, its follower may be slightly affected and takes $\eta_i^T \leq 1$, though not obvious, which indicating that when leader is aggressive, follower also seems to be inclined to keep a little aggressive as the leader does. Therefore, it indicates that there is a slight correlation for them during oscillation.

Moreover, note that the convergence of distribution of η_i^1 is higher than that of η_i^0 , which shows that the driving characteristics of adjacent drivers become more convergent to the average level after oscillation.

TABLE 2 introduces the changes of parameters before and after oscillation for OA and OT drivers (note that authors omitted the ON drivers because there most of ON drivers have not obvious change during the whole process). The “convergent to the average” effect can be clearly seen from the mean value: some OA drivers are less aggressive ($\eta_i^1 > \eta_i^0$) after oscillations and some OT drivers are less timid ($\eta_i^1 < \eta_i^0$), which is consistent with the results in Chen et al. [16].

TABLE 2. Characteristic evolution statistics of oa and ot.

Category		η_i^0	η_i^T	η_i^1	ε_i^0	ε_i^1
OA (46)	Mean	0.73	0.71	0.89	0.02	0.14
	σ	0.13	0.24	0.29	0.14	0.29
	c.v	0.19	0.31	0.35	9.10	2.16
OT (29)	Mean	1.53	1.31	1.41	-0.13	0.01
	σ	0.35	0.31	0.43	0.24	0.69
	c.v	0.23	0.24	0.31	-2.13	1.67

σ : Standard Deviation. cv: coefficient of variation.

Differently, authors find that the standard deviation (σ) and coefficient of variation (c.v) of η_i^1 more than that of η_i^0 , which indicates the dispersion increase, although only slightly.

FIGURE 9 shows the distribution histograms of η_i^0 and η_i^1 for all 90 trajectory pairs. Due to the threshold of ON drivers is set to be $0.9 \leq \eta_i^0 \leq 1.1$, the lower (upper) level corresponds to OA (OT) drivers. An analogous analysis can be applied to η_i^1 . Certainly, the proportions may change if the threshold varies, but the magnitude should almost constant. FIGURE 9(a) shows that there are more aggressive drivers in China before oscillation, and the polarization of driving characteristics is evident. However, statistics of Chen et al. [16] using NGSIM data show that ON drivers is higher (about 58%) in 111 trajectories pairs, and the distribution of η_i^0 converges to 1, which indicates that the polarization of driving characteristics is not as significant as China. It can be seen from FIGURE 9(b) that the convergence and distribution of η_i^1 are more balanced than η_i^0 , indicating that the polarization is alleviated after oscillation.

FIGURE 10 exhibits some typical examples of the evolution of $\eta_i(t)$ in three reaction patterns for different behavior categories. Firstly, it demonstrates the universality of asymmetry ($\eta_i^0 <> \eta_i^1$ and $\varepsilon_i^0 <> \varepsilon_i^1$) of driver’s behavior. Then, before and after oscillation, it demonstrates that driver categories may change or remain consistent in different reaction patterns. In detail, authors will show the categories variety of 90 drivers in FIGURE 11.

Statistics in FIGURE 11(a), authors find a correlation between the different original driver categories and three reaction patterns: (i) OA drivers are more inclined to the convex pattern, although a small portion of who slightly tend to concave and constant patterns; (ii) OT drivers are obviously more inclined to convex pattern than concave pattern; (iii) Clearly, ON drivers tend to keep constant pattern.

The results of Chen et al. [16] show that OA (OT) drivers tend to have the concave pattern (convex pattern), and ON drivers are equally likely to have any of the three patterns. Obviously, it shows that there are significant differences between Chinese and American drivers from NGSIM in terms of driver categories corresponding reaction patterns: firstly, our result (i) show that more OA drivers are still adventurous enough to take an convex pattern to further reducing spacing

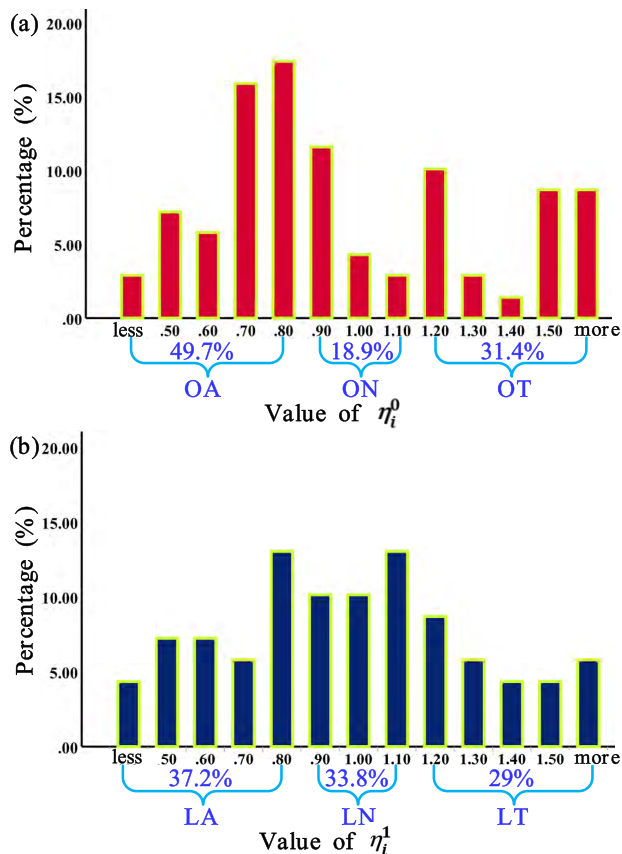


FIGURE 9. Driver categories distribution histogram of (a) η_i^0 and (b) η_i^1 in car-following behavior.

and maintain aggressive characteristics, although a few take the concave pattern; (ii) indicates that OT drivers preserve more than enough spacing and may feel less pressure to react, thus, they can have a try to reduce space and close to leader. In other words, some OT drivers are less timid. Result (iii) show that ON drivers tend to maintain the “average level”, i.e. the constant pattern. In FIGURE 11(b), the statistics in change of driver categories show that about 20% of OA drivers change to LT or LN drivers (i.e. less drivers are aggressive) after oscillation, but ON and OT drivers did not change significantly, which is consistent with the distribution of FIGURE 9(b).

Refer to above different phenomena in our data, authors speculate that the most likely inducement is different traffic status data: (i) in our data, traffic status is the evolution process from free to congestion, which shows that drivers who experience traffic state transition process (not directly in congestion state) may exhibit the above-mentioned characteristics different from statistics in Chen *et al.* [16] based on congested state from NGSIM. Therefore, in a sense, authors can be regarded as a supplementary of them; (ii) for the convex pattern of OA drivers, there is an unexpected result. At first, authors speculated whether it was due to the different lanes of data sources, because our data distribute in three lanes, while Chen *et al.* [16] only have lane 1 data. However, most of the OA drivers with convex pattern in our data are also

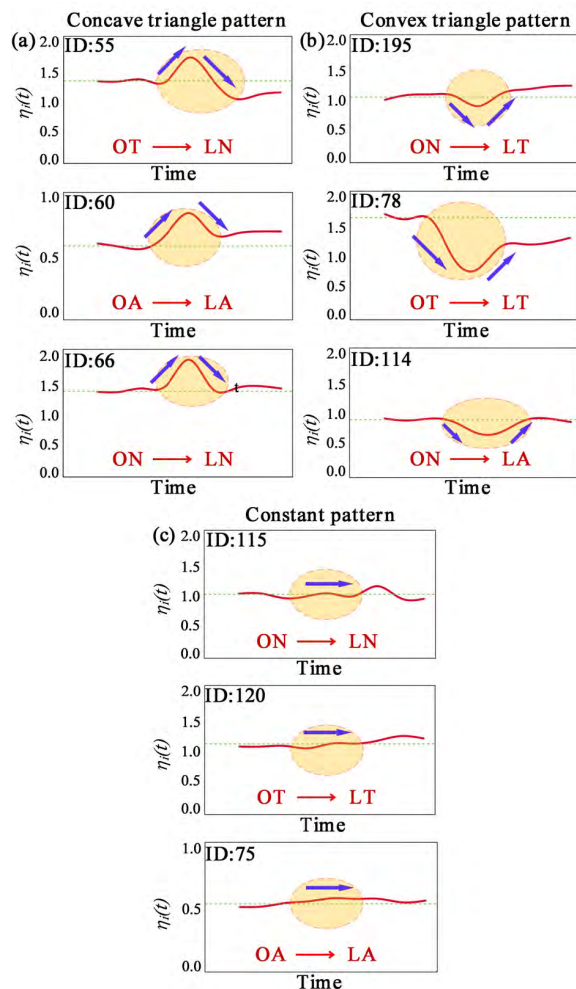


FIGURE 10. Representative examples of the change of driver categories with different patterns before and after oscillation (circled in yellow circle).

from lane1 (more trajectories on lane 1 that meet our sampling criteria due to less lane-changing). Therefore, authors still attribute the reason to the Chinese drivers' driving habits and his/her personality, and this is not a few cases. Of course, in the future authors will collect more similar field data to further verify.

TABLE 3 shows the mean value, standard deviation and coefficient of variation (c.v) for three reaction patterns. In convex and concave patterns, the c.v of $\eta_i(t)$ is about 35-50%, slightly more than 20-35% in Chen *et al.* [16], which indicates that Chinese drivers are more discrete than the average level in any one reaction pattern. A high variability is observed in case of the ε_i^0 and ε_i^1 , which shows that the driver's reaction intensity has obvious heterogeneity to oscillation.

In order to further study the correlation of each driver's own characteristics in different stages, Pearson correlation coefficients (PCCs) among five parameters were evaluated. Note that due to the parameters in constant pattern have not changed significantly, authors do not need to evaluate the aforementioned PCCs for this pattern. The PCCs can

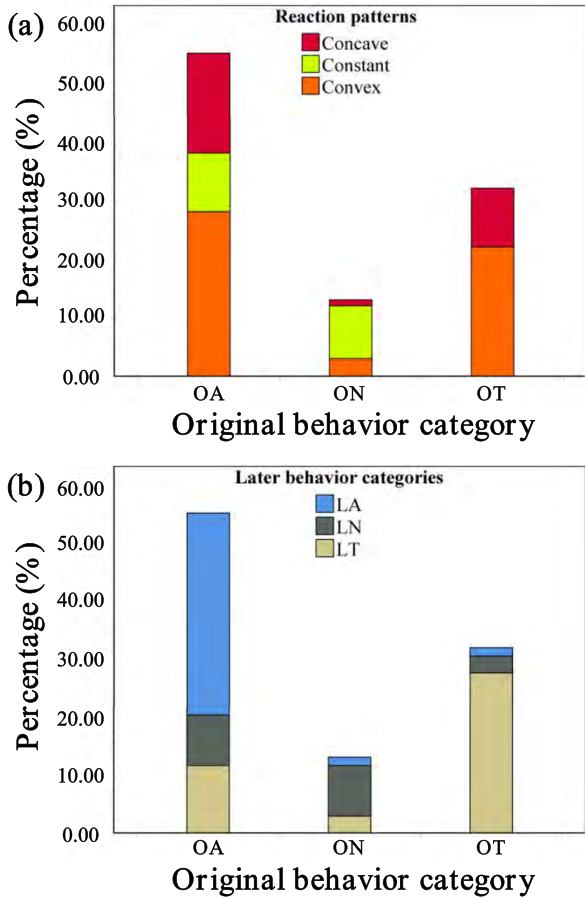


FIGURE 11. (a) correlation between the driver categories and reaction patterns; (b) the changes of drivers categories after oscillation.

TABLE 3. Characteristic statistics of evolution process of three reaction patterns.

		η_i^0	η_i^T	η_i^1	ε_i^0	ε_i^1
Convex (44)	Mean	1.11	0.86	1.14	-0.16	0.27
	σ	0.50	0.38	0.44	0.19	0.33
	c.v	0.45	0.44	0.39	-1.15	1.24
Concave (27)	Mean	0.94	1.17	1.08	0.18	-0.21
	σ	0.34	0.32	0.35	0.15	0.56
	c.v	0.36	0.28	0.34	0.85	-2.64
Constant (19)	Mean	0.78	0.91	0.81	0.13	0.00
	σ	0.05	0.08	0.06	0.03	0.02
	c.v	0.07	0.09	0.08	1.02	2.87
All (90)	Mean	1.00	0.94	1.06	-0.03	0.08
	σ	0.44	0.57	0.42	0.22	0.44
	c.v	0.44	0.39	0.38	-8.27	5.70

σ : Standard Deviation. cv: coefficient of variation.

provide the analysis whether there is a significantly positive or negative correlation between any two parameters.

TABLE 4. Pearson correlation statistics of five parameters.

Patterns		η_i^0	η_i^T	η_i^1	$ \varepsilon_i^0 $	$ \varepsilon_i^1 $
Convex (44)	η_i^0		0.863	0.695	0.654	0.175
	η_i^T	0.873		0.957	0.346	0.407
	η_i^1	0.695	0.917		0.250	0.623
	$ \varepsilon_i^0 $	0.576	0.376	0.250		0.026
	$ \varepsilon_i^1 $	0.167	0.427	0.669	0.037	
Concave (27)	η_i^0		0.886	0.820	0.092	0.273
	η_i^T	0.856		0.899	0.129	0.334
	η_i^1	0.860	0.899		0.232	0.053
	$ \varepsilon_i^0 $	0.097	0.319	0.332		-0.06
	$ \varepsilon_i^1 $	0.156	0.332	0.153	-0.06	
Combined (71)	η_i^0		0.761	0.734	0.379	0.204
	η_i^T	0.751		0.772	0.350	0.222
	η_i^1	0.771	0.772		0.236	0.387
	$ \varepsilon_i^0 $	0.329	0.290	0.242		0.040
	$ \varepsilon_i^1 $	0.214	0.242	0.334	0.143	

Sig. (2-tailed): green box: $p < 0.01$; blue box: $p < 0.05$

TABLE 4 indicates the main conclusions at the 95% confidence: (i) η_i^0 , η_i^1 and η_i^T are all significantly and strongly positive correlation with each other for three reaction patterns (Shown in the green box, $p < 0.01$); (ii) $|\varepsilon_i^0|$ is not obviously related to $|\varepsilon_i^1|$; (iii) Notably, in convex pattern $|\varepsilon_i^0|$ and η_i^0 (η_i^T) show a moderate (slight) positive correlation, as well as $|\varepsilon_i^1|$ and η_i^1 (η_i^T) show a moderate (slight) positive correlation but there was a slight decline in the overall sample. However, authors do not have a negative correlation between any pair of parameters.

Above conclusion (i) illustrates that there is a strong positive correlation between each driver's own driving characteristics before and after oscillation, that is to say, if an original driver is more aggressive (timid), there is a great possibility that he/she may still maintain the aggressive (timid) behavior during and after oscillation. (ii) shows that there is no correlation between the movement towards η_i^T and the movement from η_i^T returning to equilibrium, which indicates that the reaction intensity of the former and the latter stages are asymmetric. Clearly, (iii) indicates that the more aggressive (or timid) the driver is, the stronger intensity of reaction when he/she moves toward η_i^T ; meanwhile, the stronger intensity of reaction when he/she leaves from η_i^T returning to new equilibrium, the more aggressive (or timid) he/she would show in new equilibrium branch.

VI. CONCLUSION AND DISCUSSION

This paper explores the longitudinal (car-following) movements characteristics of drivers when they experience

an oscillation, based on the empirical trajectory data collected in Nanjing, China. To some degree, the characteristics of drivers in equilibrium state will affect their reaction patterns to traffic oscillation. Authors find a significant difference between Chinese and American drivers [16] (which based on NGSIM): there are more aggressive drivers (OA) in China before meeting oscillation, and the polarization of driving characteristics (OA and OT) is more significant.

In brief, authors find that the distribution of η_i^1 is more balanced than that of η_i^0 , indicating that the polarization of driver characteristics converges after oscillation. Moreover, the correlation between the original driver category and subsequent reaction pattern are found that OA drivers are still adventurous enough to take a convex pattern to further reducing spacing and maintain aggressive characteristics; OT drivers are obviously more inclined to convex pattern rather than concave pattern; ON drivers tend to keep constant pattern. Moreover, the driver's reaction intensity to oscillation is positive correlated with his/her own polarized degree (aggressive or timid).

Driving behavior still needs further investigation. For example, it is still not known how their driving behavior characteristics change when some drivers participate in multiple oscillations; and the effect of driver characteristics change on oscillation is still unknown either. Authors are currently investigating these unsolved problems. Note that though current model is applied to the human driving cars, the methodology can also be applied to the connected and autonomous vehicle which driving behavior is different [23], [24]. This is because the heterogeneity in vehicle moving behavior is the main reason for traffic phenomenon such as capacity drop and stop-and-go. Thus, it would be interesting to compare the asymmetric model parameters between different vehicle types [25].

New technologies in emerging vehicle engineering can also improve the traffic flow during traffic oscillations. With the rise of computers and networks, the development of autonomous driving and networking vehicles is in full swing, which is very expected. This paper demonstrates the heterogeneity and variability of human driving behavior, which may be caused by the changes in environment and traffic conditions. However, in future, even if some expected automatic vehicles can be used on the actual road, it is still difficult to achieve a wide range or full popularization in a short time. Reasonably, authors speculate that there are still a considerable number of human-driven vehicles on the road, so it is necessary to consider the characteristics of human driving behavior. It would be very interesting to compare the asymmetric techniques with machine learning techniques [26]–[28]. It requires large samples to train the machine learning models and the work is our future plan.

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REFERENCES

- [1] R. Chandler, R. Herman, and E. Montroll, "Traffic dynamics: Studies in car following," *Oper. Res.*, vol. 6, no. 2, pp. 165–184, 1958.
- [2] R. Herman, E. Montroll, R. Potts, and R. Rothery, "Traffic dynamics: Analysis of stability in car following," *Oper. Res.*, vol. 7, no. 1, pp. 86–106, 1959.
- [3] P. G. Gipps, "A behavioural car-following model for computer simulation," *Transp. Res. B, Methodol.*, vol. 15, no. 2, pp. 105–111, 1981.
- [4] G. F. Newell, "A simplified car-following theory: A lower order model," *Transp. Res. B*, vol. 36, no. 3, pp. 195–205, 2002.
- [5] J. A. Laval and L. Leclercq, "A mechanism to describe the formation and propagation of stop-and-go waves in congested freeway traffic," *Philos. Trans. Roy. Soc. A*, vol. 368, pp. 4519–4541, Aug. 1928.
- [6] L. C. Edie, "Discussion of traffic stream measurements and definitions," in *Proc. 2nd Int. Symp. Theory Road Traffic Flow*, London, U.K., 1965, pp. 139–154.
- [7] X. Li and Y. Ouyang, "Characterization of traffic oscillation propagation under nonlinear car-following laws," in *Proc. 19th Int. Symp. Transp. Traffic Theory*, 2011, pp. 678–697.
- [8] X. Li, F. Peng, and Y. Ouyang, "Measurement and estimation of traffic oscillation properties," *Transp. Res. B*, vol. 44, no. 1, pp. 1–14, 2009.
- [9] H. Yeo and A. Skabardonis, "Understanding stop-and-go traffic in view of asymmetric traffic theory," in *Proc. 18th Int. Symp. Traffic Transp. Theory*, W. Lam, S. C. Wong, and H. K. Lo, Eds. New York, NY, USA: Springer, 2009, pp. 99–116.
- [10] H. Yeo, A. Skabardonis, J. Halkias, J. Colyar, and V. Alexiadis, "Over-saturated freeway flow algorithm for use in next generation simulation," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1, pp. 68–79, Jan. 2008. doi: 10.3141/2088-08.
- [11] X. Gu, M. Abdel-Aty, Q. Xiang, Q. Cai, and J. Yuan, "Utilizing UAV video data for in-depth analysis of drivers' crash risk at interchange merging areas," *Accident Anal. Prevention*, vol. 123, pp. 159–169, Feb. 2019.
- [12] C. Xu, Y. Wang, and P. Liu, "Quantitative risk assessment of freeway crash casualty using high-resolution traffic data," *Rel. Eng. Syst. Saf.*, vol. 169, pp. 299–311, Jan. 2018.
- [13] Z. Zheng, S. Ahn, D. Chen, and J. Laval, "Applications of wavelet transform for analysis of freeway traffic: Bottlenecks, transient traffic, and traffic oscillations," *Transp. Res. B*, vol. 45, no. 2, pp. 372–384, 2011.
- [14] Z. Zheng, S. Ahn, D. Chen, and J. A. Laval, "Freeway traffic oscillations: Microscopic analysis of formations and propagations using wavelet transform," *Transp. Res. B*, vol. 45, no. 9, pp. 1378–1388, 2011.
- [15] Z. Zheng, S. Ahn, D. Chen, and J. Laval, "The effects of lane-changing on the immediate follower: Anticipation, relaxation, and change in driver characteristics," *Transp. Res. C*, vol. 26, pp. 367–379, Jan. 2013.
- [16] D. Chen, J. Laval, Z. Zheng, and S. Ahn, "A behavioral car-following model that captures traffic oscillations," *Transp. Res. B*, vol. 46, no. 6, pp. 744–761, 2012.
- [17] NGSIM. (2006). *Next Generation Simulation*. [Online]. Available: <http://ops.fhwa.dot.gov/trafficanalysis/tools/ngsim.htm>
- [18] X. Chen, Z. Li, Y. Yang, H. Wu, R. Ke, and W. Zhou, "Extracting and denoising vehicle trajectory automatically from aerial roadway surveillance videos," in *Proc. 98th Annu. Meeting Transp. Res. Board*, Washington, DC, USA, 2019, Art. no. 19-03147.
- [19] Z. Li, X. Chen, L. Ling, H. Wu, W. Zhou, and C. Qi, "Accurate traffic parameter extraction from aerial videos with multi-dimensional camera movements," in *Proc. 98th Annu. Meeting Transp. Res. Board*, Washington, DC, USA, 2019, Art. no. 19-02817.
- [20] X. Chen, S. Wang, C. Shi, H. Wu, J. Zhao, and J. Fu, "Robust ship tracking via multi-view learning and sparse representation," *J. Navigat.*, vol. 72, no. 1, pp. 176–192, 2019.
- [21] P. Liu, Z. Li, C. Xu, Z. Pu, and Y. Guo, "Reinforcement learning-based variable speed limit control strategy to reduce traffic congestion at freeway recurrent bottlenecks," *IEEE Intell. Transp. Syst. Mag.*, vol. 18, no. 11, pp. 3204–3217, Nov. 2017.
- [22] S. Ahn, S. Vadlamani, and J. Laval, "A method to account for non-steady state conditions in measuring traffic hysteresis," *Transp. Res. C*, vol. 34, pp. 138–147, Sep. 2013.
- [23] Y. Li, Z. Li, and H. Wang, "Evaluating the safety impact of adaptive cruise control in traffic oscillations on freeways," *Accident Anal. Prevention*, vol. 104, pp. 137–145, Jul. 2017.

- [24] Y. Li, H. Wang, and W. Wang, "Evaluation of the impacts of cooperative adaptive cruise control on reducing rear-end collision risks on freeways," *Accident Anal. Prevention*, vol. 98, pp. 87–95, Jan. 2017.
- [25] A. A. Alkheir, M. Aloqaily, and H. T. Mouftah, "Connected and Autonomous Electric Vehicles (CAEVs)," *IT Prof.*, vol. 20, no. 6, pp. 54–61, 2018.
- [26] D. Chen, "Research on traffic flow prediction in the big data environment based on the improved RBF neural network," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 2000–2008, Aug. 2017.
- [27] S. Otoum, B. Kantarci, and H. T. Mouftah, "On the feasibility of deep learning in sensor network intrusion detection," *IEEE Netw. Lett.*, vol. 1, no. 2, pp. 68–71, Jun. 2019.
- [28] M. Aloqaily, "An intrusion detection system for connected vehicles in smart cities," *Ad Hoc Networks*, vol. 90, Jul. 2019, Art. no. 101842.
- [29] D. Chen, J. Laval, S. Ahn, and Z. Zheng, "Microscopic traffic hysteresis in traffic oscillations: A behavioral perspective," *Transp. Res. B*, vol. 46, pp. 1440–1453, Dec. 2012.
- [30] P. Hidas, "Modelling vehicle interactions in microscopic simulation of merging and weaving," *Transp. Res. C, Emerg. Technol.*, vol. 13, no. 1, pp. 37–62, Feb. 2005.
- [31] A. Durent, S. Ahn, and C. Buisson, "Passing rates to measure relaxation and impact of lane-changing in queue," *Comput. Aided Eng. Infrastruct. Eng.*, vol. 26, no. 4, pp. 285–297, 2011.
- [32] Z. Zheng, S. Ahn, and C. M. Monsere, "Impact of traffic oscillations on freeway crash occurrences," *Accident Anal. Prevention*, vol. 42, no. 2, pp. 626–636, 2010.
- [33] C. Xu, S. Xu, C. Wang, and J. Li, "Investigating the factors affecting secondary crash frequency caused by one primary crash using zero-inflated ordered probit regression," *Phys. A, Stat. Mech. Appl.*, vol. 524, pp. 121–129, Jul. 2019.
- [34] S. Ahn and M. J. Cassidy, "Freeway traffic oscillations and vehicle lane-change maneuvers," in *Proc. 17th Int. Symp. Transp. Traffic Theory*. Amsterdam, The Netherlands: Elsevier, 2007, pp. 691–710.
- [35] S. Ahn, M. J. Cassidy, and J. A. Laval, "Verification of a simplified car-following theory," *Transp. Res. B*, vol. 38, no. 5, pp. 431–440, 2004.
- [36] C. F. Daganzo, "A variational formulation of kinematic waves: Basic theory and complex boundary conditions," *Transp. Res. B*, vol. 39, no. 2, pp. 187–196, 2005.
- [37] L. C. Edie and R. S. Foote, "Experiments on single-lane flow in tunnels," in *Proc. 1st Int. Symp. Transp. Traffic Theory*, 1961, pp. 175–192.
- [38] T. W. Forbes, "Human factor consideration in traffic flow theory," *Highway Res. Rec.*, vol. 15, pp. 60–66, May 1963.
- [39] J. A. Laval and L. Leclercq, "Microscopic modeling of the relaxation phenomenon using a macroscopic lane-changing model," *Transp. Res. B*, vol. 42, no. 6, pp. 511–522, 2008.
- [40] G. F. Newell, "Instability in dense highway traffic, a review," in *Proc. 2nd Int. Symp. Transp. Traffic Theory*, 1965, pp. 73–83.
- [41] H. M. Zhang, "A mathematical theory of traffic hysteresis," *Transp. Res. B, Methodol.*, vol. 33, no. 1, pp. 1–23, 1999.
- [42] B. A. Zielke, R. L. Bertini, and M. Treiber, "Empirical measurement of freeway oscillation characteristics: An international comparison," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1, pp. 57–67, Jul. 2008.



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