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Trajectory data-based traffic flow studies: A revisit

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ABSTRACT

In this paper, we review trajectory data-based traffic flow studies that have been conducted over the last 15 years. Our purpose is to provide a roadmap for readers who have an interest in the latest developments of traffic flow theory that have been stimulated by the availability of trajectory data. We first highlight the critical role of trajectory data (especially the next generation simulation (NGSIM) trajectory dataset) in the recent history of traffic flow studies. Then, we summarize new traffic phenomena/models at the microscopic/mesoscopic/macroscopic levels and provide a unified view of these achievements perceived from different directions of traffic flow studies. Finally, we discuss some future research directions.

1. Introduction

Traffic flow studies have focused on the interactions among various traffic participators (e.g., vehicles, drivers, pedestrians, and bicyclists) and infrastructure (e.g., highways, signal control devices), aiming to reveal the relationship between individual traffic participants and the resulting traffic flow phenomena. As a result, traffic flow studies are empirical studies that heavily rely on high-quality measurements of real data.

Since the 1920s, researchers have worked to improve traffic flow measurements by collecting more useful data for a comprehensive understanding of traffic flow (Greenshields, 1935; Transportation Research Board, 2011). Unfortunately, it is not easy to obtain accurate and rich empirical data to support traffic flow studies due to the limitation of data collection technology and devices. The initial attempts were carried out by hand and with the aid of stopwatches. For example, the number of vehicles that had passed certain cross lines on roads and the time headways between two consecutive vehicles were recorded. This type of measurement only outputs low-accuracy data at a certain cross line of the road to estimate traffic flow rates. Additionally, noting that traffic flow in those early years was not heavy, researchers often made additional assumptions (for instance, the arrival of vehicles followed Poisson distributions) to further characterize traffic flow. However, these assumptions may not always fit with real situations, particularly because traffic has become increasingly congested.

In the 1960s, two new traffic measures were introduced. First, radar-based devices, such as hand-held or vehicle-mounted radar meters, were used to directly measure vehicle speed by calculating the difference in the frequency between the emitted radar wave and the wave reflected by the oncoming vehicle. This approach may be the most straightforward methodology to observe vehicle

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speed (Roess and Prassas, 2004). Second, loop detectors gradually became the dominant sensor in transportation management (Federal Highway Administration, 2006). (Double) loop detectors can measure traffic flow rates, time occupancy, and vehicle speed, making it possible to reconstruct the key macroscopic-level tuples of traffic flow. Thus, loop detectors are a vital element for many traffic engineering applications, particularly in traffic control systems (Roess and Prassas, 2004). However, loop detectors can only measure the traffic flow passing by an individual cross line on a road. We still lack a full sketch of the overall spatial–temporal dynamics of traffic flow along a specific road segment.

Moreover, researchers have shown increasing interest in microscopic driving behavior modeling. Chandler et al. (1958) tested the car-following behavior of eight drivers. The distance and relative speed between two consecutive cars were measured by recording the dynamics of the coil wire that linked the two cars. In the test, the front vehicle speed varied from 15 km/h to 120 km/h, and the test lasted for 30 min. However, this method was inaccurate because of the influence of the steel coil on vehicle dynamics. In recent years, more onboard radar detectors, cameras, or laser sensors have been deployed to record the change in the spacing/speed between two consecutive vehicles (Abbas et al., 2010; Sangster et al., 2013; Zhu et al., 2018a; Wu et al., 2019a). Although these approaches could provide more accurate information on the car-following or lane-changing behavior between neighboring vehicles, the obtained data are limited in terms of the spatial scope and the number of monitored traffic participators.

More recently, vehicles mounted with dedicated global positioning system (GPS) devices were used to monitor daily traffic (Wolshon and Hatipkarasulu, 2000). Such vehicles, called probe vehicles or floating cars, travel in a road network as regular vehicles but consistently upload their status information (e.g., latitude, longitude, instantaneous speed, and moving direction) to data centers at short time intervals via wireless communications (Kerner et al., 2005; Wang et al., 2011; Shen and Stopher, 2014; Massaro et al., 2016; Feng and Timmermans, 2016; He et al., 2017a, 2019c; Liu et al., 2019). We can further estimate traffic flow properties along the roads that were just traveled by the studied probe vehicles. The intermittent trajectory data obtained from probe vehicles are useful for travel behavior studies but conventionally inadequate to reconstruct the details of traffic flow dynamics in both temporal-spatial scopes. The shortcoming of the probe vehicle data comes from two aspects. First, since the states of probe vehicles were not cautiously updated, the detailed driving behavior of the studied vehicles cannot be retrieved. Second, the low penetration rate (only a limited number of probe vehicles usually appear along a road segment at the same time) of probe vehicles makes it impossible to reflect 100% of traffic flow dynamics (He et al., 2017a; Guo et al., 2019).

Seminal work by Treiterer and Myers in 1974 opened the door of vehicle trajectory collection and analysis in traffic flow theory (Treiterer and Myers, 1974; Coifman et al., 2018). These investigators used high-speed aerial photography and manual data reduction to retrieve trajectory data from hundreds of vehicles. However, the high cost and low accuracy of aerial photography in the early days prevented us from obtaining more useful trajectory data. Almost 40 years later, until the very recent emergence of drones, researchers have turned to other methods to collect vehicle trajectories (see discussions in *Section 4.1*).

Along with the rapid evolution of information techniques, roadside video cameras and the corresponding video-based traffic flow monitoring systems emerged as new tools for traffic flow measurements. Initially, video cameras were used to count the arrival of vehicles and serve as virtual loop detectors (Michalopoulos, 1991; Masaki, 1998; Kastrinaki et al., 2003; Buch et al., 2011). When the image quality of video cameras and computation capability became more powerful, researchers realized that they could simultaneously monitor and track detailed movements of multiple vehicles (Smith, 1985; Smith et al., 1996; Maurin et al., 2005). In some recent studies, high-resolution cameras that were either installed on high buildings, helicopters, or drones were used to capture the high-resolution 2D motions of individual vehicles from a bird's eye view (Ossen, 2008; Knoop et al., 2008; Hickman and Mirchandani, 2008; Zhang et al., 2016; Krajewski et al., 2018). The time series of vehicle positions were recorded as continuous vehicle trajectories, representing almost 100% traffic conditions and vehicle motion information; see Fig. 1 for an illustration. Such trajectory data significantly boost related traffic flow studies since it is the first time that we have obtained complete and high-accuracy information regarding the microscopic-level behavior of individual traffic participants.

Among existing open-source vehicle trajectory datasets, the next generation simulation (NGSIM) trajectory dataset (NGSIM, 2006) is undoubtedly the most widely used dataset. Its release has ignited the passion of researchers over the last decade. Some visualization results of the NGSIM dataset could be found at (NGISM-I-80-Trajectory-Animation, 2017; NEXTA, 2018). Based on the NGSIM dataset, various related studies ranging from the microscopic level to the macroscopic level of traffic flow studies have been conducted worldwide, and many significant new findings have been obtained.

In this paper, we aim to provide a roadmap for readers who have trouble obtaining a useful landscape regarding related research topics from different directions but latently linked by the trajectory data analysis. We aim to provide a bird's eye view of the problems as well as the models that are currently addressed by researchers in the traffic flow study field, explain the latent links between these studies, and highlight the common stimulus of these studies as the introduction of vehicle trajectory data. There are some well-written surveys of traffic flow studies that have been published recently. However, some of these surveys, e.g., Ahn et al. (2019), covered even boarder topics and were less detailed in trajectory related studies; some of these surveys, e.g., Zheng (2014), Li and Chen (2017), and (Wang et al. (2019a,b), focused on a very specific area and did not show the significantly changing landscape of traffic flow studies urged by vehicle trajectory data.

The trajectory data based research issues covered are quite extensive. Since we intend to review the research line from a widely used type of data source, to save space, we neglect some issues and promote the following issues: In *Section 2* and *Section 3*, we highlight the new findings of traffic phenomena and the resulting changes in traffic flow models stimulated by video-based trajectory data, respectively. We show that video-based trajectory data significantly influence not only the types of models but also the calibration/training of the models. In *Section 4*, we discuss the current shortcomings and future research directions of traffic flow data collection. Finally, *Section 5* concludes the whole paper.

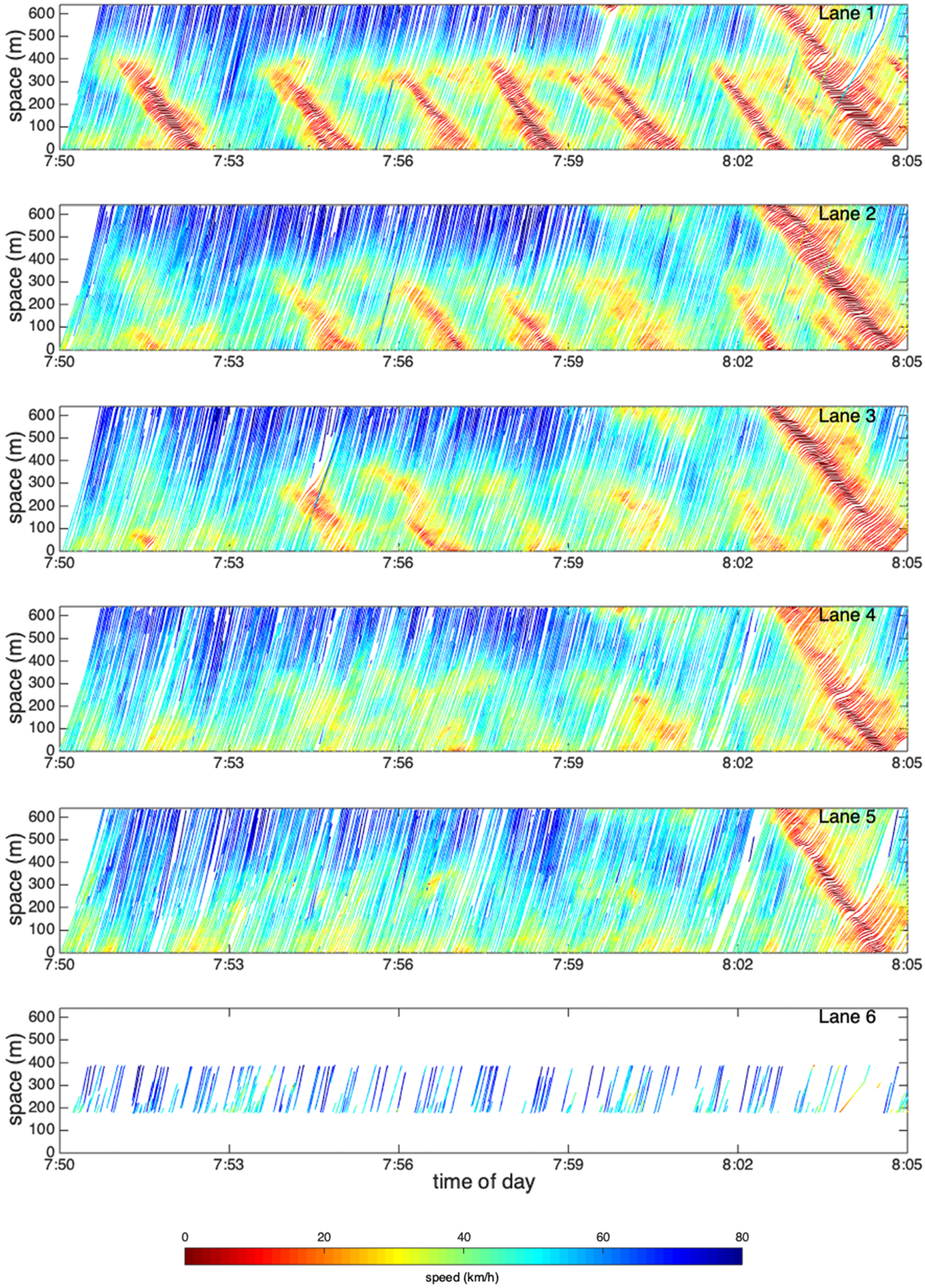

Fig. 1. Vehicular trajectories with instantaneous speeds observed in the NGSIM U.S. Highway 101 dataset (June 15, 2005).

2. New traffic phenomena verified/explained by trajectory data

According to the level of detail, we can roughly categorize traffic flow studies into three kinds: microscopic-level studies (e.g., car-following models and lane-changing models), mesoscopic-level studies (e.g., headway/spacing distributions), and macroscopic-level studies (e.g., fundamental diagram, and traffic wave models). In the remainder of this paper, we will sequentially revisit the new traffic phenomena recovered by the trajectory data in the literature.

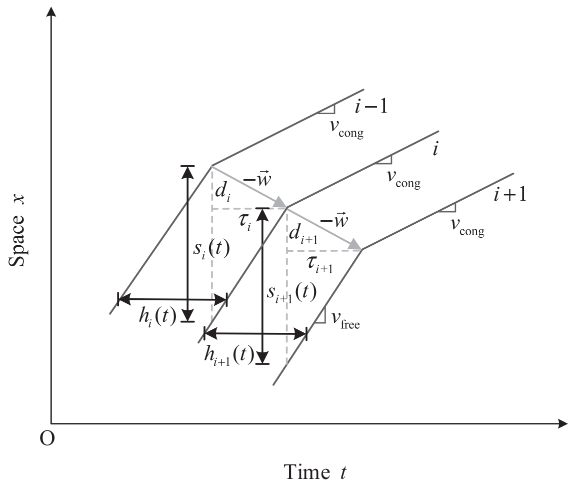

Fig. 2. An illustration of Newell's car-following model. The spacing $s_i(t)$ refers to the distance between the leading vehicle $(i-1)$ and its following vehicle i at time t. The parameter v_{free} is the traffic velocity under free-flow conditions, and v_{cong} is the traffic velocity under congested conditions. The following vehicle i will adjust its velocity in the same way after a space displacement of d_i and an adjustment time of τ_i to reach the preferred spacing for a new velocity.

2.1. New microscopic traffic phenomena

The first issue is the verification of the simple Newell's car-following model (Newell, 2002). Newell's model hypothesizes that if a vehicle is following another vehicle on a homogeneous highway, then the time–space trajectory of the following vehicle is essentially the same as the leading vehicle with a translation in both space and time. If stochastic disturbances are omitted, then the trajectories of a few consecutive vehicles can be roughly modeled as piecewise segment lines whose kinks have translations in space and time (Kim and Zhang, 2008; Chen et al., 2014c); see Fig. 2 for an illustration. Newell's model can be viewed as a microscopic formulation of the kinetic wave model (Newell, 1993; Daganzo, 2001). Thus, the verification of Newell's model (Ahn et al., 2004) soon promoted many related studies.

The second issue is the exposure of asymmetric driving behavior. Asymmetric driving behavior indicates that drivers are usually more attentive during deceleration than during acceleration. It is a critical characteristic of human drivers and has a significant impact on traffic flow. Yeo and Skabardonis (2008, 2009) are among the first to emphasize asymmetric behavior using the NGSIM trajectory dataset. As shown in Fig. 3, the speed-spacing plot for a vehicle was shown to contain two separate groups of data forming two separated virtual lines denoted as 'A-curve' and 'D-curve'. The acceleration curve (A-curve) is lower than the D-curve in the speed-spacing plane. The A-curve is the boundary curve on the acceleration side, and the D-curve is the one on the deceleration side. The related studies have shown that asymmetric behavior may be the origin of several traffic phenomena (e.g., Li et al., 2013a,b), including traffic hysteresis (Laval, 2011; Chen et al., 2012a; Ahn et al., 2013), capacity drop (Chen et al., 2014a), and relaxation after lane changes (Smith, 1985; Laval and Leclercq, 2008; Yeo and Skabardonis, 2009). In contrast, Treiber and Kesting (2013b) focused on the observed hysteresis of the follower's dynamics in the speed-spacing space and argued that finite accelerations combined with the reaction times of drivers could explain this phenomenon without introducing the attention level of drivers. However, such assumptions need to be validated via future experiments (see discussions in *Section 4.2*).

The third issue is the verification of the memory of drivers (Sipahi and Niculescu, 2010; Treiber and Helbing, 2013; Pei et al., 2016). In the early days, researchers assumed that drivers purely exhibited an instant response (acceleration/deceleration) to a stimulus (e.g., the change of speeds, speed differences, and gaps that were observed in the current time). The availability of long-term trajectory data revealed the possible memory effect of drivers. The acceleration/deceleration of a vehicle has been shown to be affected by the vehicles' speeds, speed differences, and gaps that are observed during a certain range of historical times (Wang et al., 2019a,b).

The fourth issue is complex lane-changing behavior (Zheng, 2014; Sharma et al., 2018). Initial studies have often neglected the detailed driving behavior and assumed a lane change as an instantaneous event with zero time or an event with a constant duration. The introduction of trajectory data had considerably changed this research field (Melo et al., 2006). For example, the spatial shape of lane-changing curves was studied in Wang et al. (2014). It was shown that the kernel part of every normal discretionary lane-changing trajectory could be approximately depicted by a certain fifth-order polynomial. The temporal duration time of a lane change was investigated in Toledo and Zohar (2007); Hamdar and Mahmassani (2009); Wang et al. (2014). Moreover, it was demonstrated that car-following behavior before and after lane changes could also be well described by Newell's model (Wang and Coifman, 2008; Ma and Ahn, 2008). The anticipation, relaxation, and change in driver characteristics during a lane-changing process were further studied in Zheng et al. (2013a) by measuring the induced transient behavior and change in driver characteristics (e.g., changes in the driver response time and minimum spacing). Additionally, we could further calibrate the lane-changing decision model (Rahman et al., 2013) and analyze the driving behavior of neighboring vehicles (Yang et al., 2015) based on trajectory data. All the new

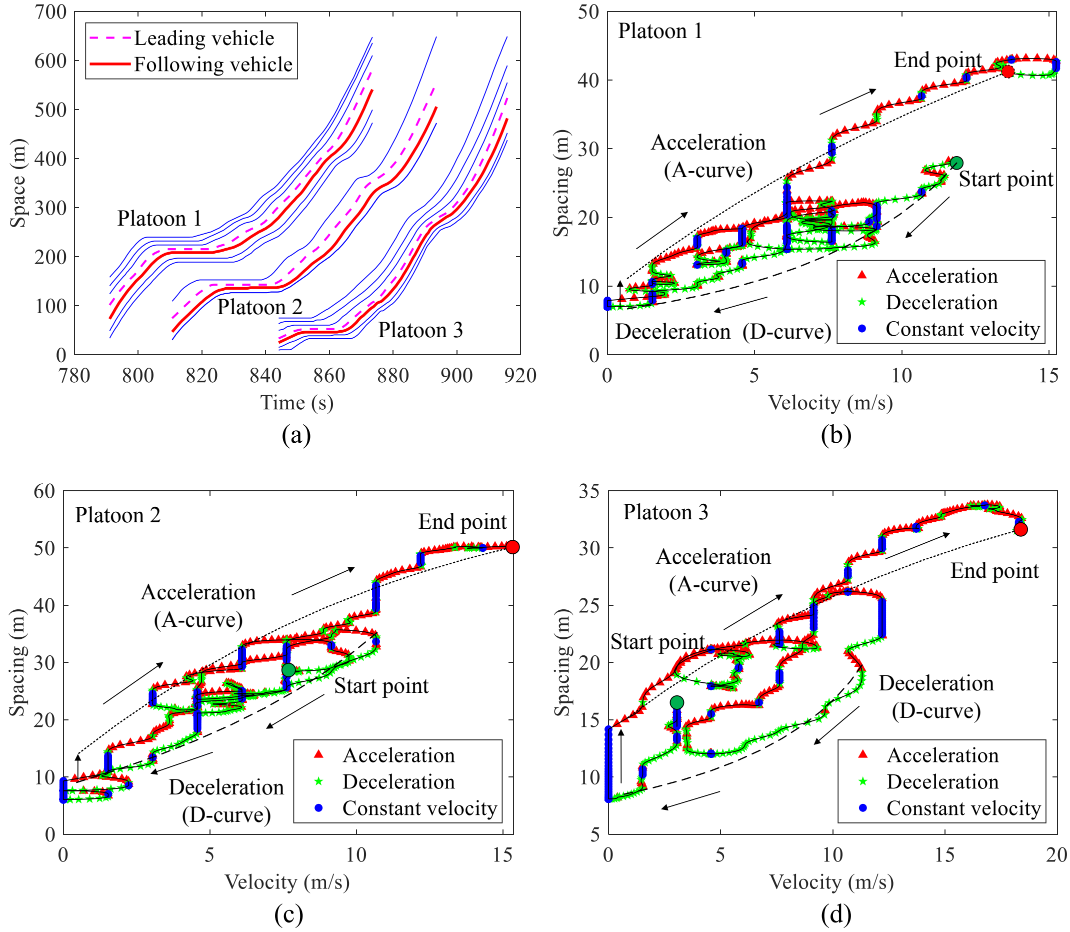

Fig. 3. Asymmetric car-following behavior of the following vehicles in typical platoons (NGSIM US Highway 101 dataset, Los Angeles, CA, on June 15, 2005). (a) Trajectories of vehicular platoons; (b) Acceleration/deceleration curves of Platoon 1; (c) Acceleration/deceleration curves of Platoon 2; and (d) Acceleration/deceleration curves of Platoon 3.

findings can help promote the temporal and spatial accuracy of lane-changing models. Readers who have an interest in related studies may refer to Zheng (2014) for a more detailed discussion.

The fifth issue is the identified heterogeneous car-following behavior with respect to drivers (Ossen and Hoogendoorn, 2011) and vehicle types (Moridpour et al., 2010, 2012, 2015; Chen et al., 2016; Cao et al., 2016). For example, analyses of trajectory data indicated that car-following and lane-changing behavior of heavy vehicles significantly differed from that of passenger cars. Tests have shown that only trajectory data contain enough information to calibrate the behavioral parameters of driving styles (Wang et al., 2010; Ravishankar and Mathew, 2011; Kim et al., 2013; Taylor et al., 2015; Zheng et al., 2019).

2.2. New mesoscopic traffic phenomena

Mesoscopic traffic flow studies, especially vehicle headway studies, have also been boosted with the aid of trajectory data (Li and Chen, 2017). Headway is usually defined as the quotient between the spacing and the corresponding speed of the following vehicle. Conventionally, headway data have been collected via loop detectors. However, we cannot distinguish between the variations in the headway caused by the inaccuracy of human perceptions and memory effects (intradriver variability) and the variations in the headway caused by the different preferred time gaps of each driver (interdriver variation).

If we view the headway data as the resulting stationary distribution of the stochastic driving processes, then we can obtain an equivalent definition of the headway, i.e., the time between two successive vehicles as they pass the same location on the roadway, measured from the same common features of both vehicles (Chen et al., 2010a; Li and Chen, 2017). Based on the trajectory data, we can achieve a zoomed-in look at headway distributions to distinguish intradriver variability and interdriver variation. The new findings of headway data include but are not limited to the following.

First, headway distributions are speed-dependent in congested traffic. In other words, headway distributions within a road segment are not equivalent to the distribution of the vehicle arriving rates in this segment (Chen et al., 2010a, 2014b; Zahiri and Chen, 2018). This fact is noticeably different from the hypothesis made for free-flow traffic in earlier times (Adams, 1936).

Furthermore, this finding is useful in many other interdisciplines. One of these interdisciplines is the communication performance of vehicular ad hoc networks (VANETs), which highly depend on an appropriate model of vehicle density variations (Abboud and Zhuang, 2014; Jia et al., 2016; Wang et al., 2018a).

Second, drivers tend to maintain a generally consistent headway within a specific speed range. However, it is impossible for a driver to maintain a fixed headway because of the unpredictability of leading vehicle movements and the inaccuracy of human perceptions. Therefore, drivers continuously adjust their behavior in an attempt to maintain their preferred headways. This process, which depends on the psychophysical-physiological response of drivers, yields the observed headway distribution.

Third, vehicle headway distribution models are asymmetric, or more precisely, right-skewed. Such a skewness feature characterizes the preference of drivers to maintain a short headway rather than a large headway (Chen et al., 2010a, 2014b). This phenomenon is tightly related to microscopic asymmetric driving behaviors.

Fourth, departure headways measured in interrupted flows on urban streets and headways measured in uninterrupted flows on highways were shown to have common features, enabling us to describe headways in both interrupted and uninterrupted flows by using the same family of log-normal type distribution models (Jin et al., 2009; Krbálek and Šleis, 2015; Hao and Ma, 2017; Li and Chen, 2017).

Fifth, the tight relationship between the stochastic origin in microscopic driver maneuvers and the macroscopic stochastic features of traffic flows is further proven by using the trajectory data and loop detector data collected at the same road segments and sampling time period (Chen et al., 2010b, 2014b; Li et al., 2013a,b). The test results show that appropriate headway distribution models provide a concise way to describe uncertainty in traffic flow dynamics and serve a bridge to link microscopic and macroscopic traffic flow studies.

2.3. New macroscopic traffic phenomena

The first macroscopic traffic phenomenon clarified by trajectory data is the formation, evolution, and dissipation of different congested traffic flow patterns (Kerner, 2009, 2017; Treiber et al., 2010; Kessels, 2019). Researchers have realized that, without the aid of trajectory data, it is impossible to fully characterize the properties of a jam cluster using only loop detector data (Wilson, 2008; Treiber et al., 2011). For example, we began to accurately know the propagation speed of the upstream front of a jam cluster after the trajectory data became available (Yeo and Skabardonis, 2009; Chiabaut et al., 2010; Chiabaut and Leclercq, 2011; Deng et al., 2013; Suh and Yeo, 2016; Sun et al., 2017; Chen et al., 2019a; He et al., 2019a).

The second macroscopic traffic flow issue that had been re-emphasized is the relationship between the traffic speed, flow rate, and density. Loop detector data only allow us to set up the fundamental diagram (Greenshields, 1935; Transportation Research Board, 2011), while trajectory data enable us to examine these measures of traffic flow within any arbitrarily chosen regions (Wang et al., 2007; Duret et al., 2008, Chiabaut et al., 2009; Laval and Leclercq, 2010; Yeo and Skabardonis, 2011), according to Edie's generalized definitions (Edie, 1963; Daganzo, 1997).

The third macroscopic traffic phenomenon reshaped is traffic oscillations. Traffic oscillations refer to stop-and-go driving on freeways and are characterized by recursions of decelerations followed by accelerations (Ahn, 2005); see Fig. 1 for an illustration. Occasionally, oscillations develop into stop-and-go waves, which not only make drivers and passengers uncomfortable and unsafe but also lead to more fuel consumption and emissions (He et al., 2017b). Based on trajectory data, researchers recovered the periodicity/magnitude pattern of traffic oscillations (Li and Ouyang, 2011; Li et al., 2010, 2012a, 2014; Chen et al., 2014a; Jiang et al., 2018), concave growth pattern of traffic oscillations (Tian et al., 2015, 2016a, 2016b), and formation/propagation pattern of traffic oscillations (Laval and Leclercq, 2010; Zheng et al., 2011a, 2011b). All these patterns cannot be accurately analyzed using only loop detector data.

The fourth macroscopic traffic phenomenon is traffic hysteresis (Newell, 1962; Zhang, 1999). Traffic hysteresis can be viewed as a macroscopic reflection of the asymmetry between deceleration and acceleration patterns (Yeo and Skabardonis, 2009, 2011) and is usually associated with retardation in the vehicles' acceleration as they escape from a kinematic disturbance (Ahn et al., 2013). Trajectory data provide us with a chance to take a close look at the hysteresis phenomenon; see Fig. 4 for an illustration. For example, recent research has shown that the memory effect of drivers might be an important cause of hysteresis (Laval, 2011; (Wang et al., 2019a,b).

The fifth macroscopic traffic phenomenon is the so-called relaxation phenomenon; that is, a short spacing headway is first accepted by a lane-changing vehicle and its following vehicle at the target lane and then is relaxed to a normal spacing at an equilibrium state. At a macroscopic level, relaxation usually refers to the phenomenon that the traffic state temporarily falls outside the fundamental diagram (Leclercq et al., 2007; Laval and Leclercq, 2008). By using an aerial photography digitizing system, Smith (1985) first revealed the relaxation phenomenon and primarily found that the short spacing existed for 20 s or 30 s and then gradually recovered to a more comfortable spacing. Subsequently, Wei et al. (1999) developed a video-capture-based method to extract multiple vehicle trajectories, and those trajectory data made it easy to obtain values of the headways between the lane-changing vehicle and its surrounding vehicle involved. Therefore, the probability models for lane-changing conditions can be obtained by fitting those observed data (Wei et al., 2000).

With the release of NGSIM trajectories, it is more intuitive to understand and model the relaxation phenomenon, particularly by plotting those lane-changing trajectories in a time–space plane. For example, Leclercq et al. (2007) and Laval and Leclercq (2008) investigated the empirical characteristics of the relaxation phenomenon and proposed a microscopic model imbedded in a macroscopic lane-changing model. The model was then reformulated by using the passing rate measurement of backward-moving kinematic waves in congestion (Duret et al., 2011). Observing that the impact of a lane change may occur immediately after the lateral

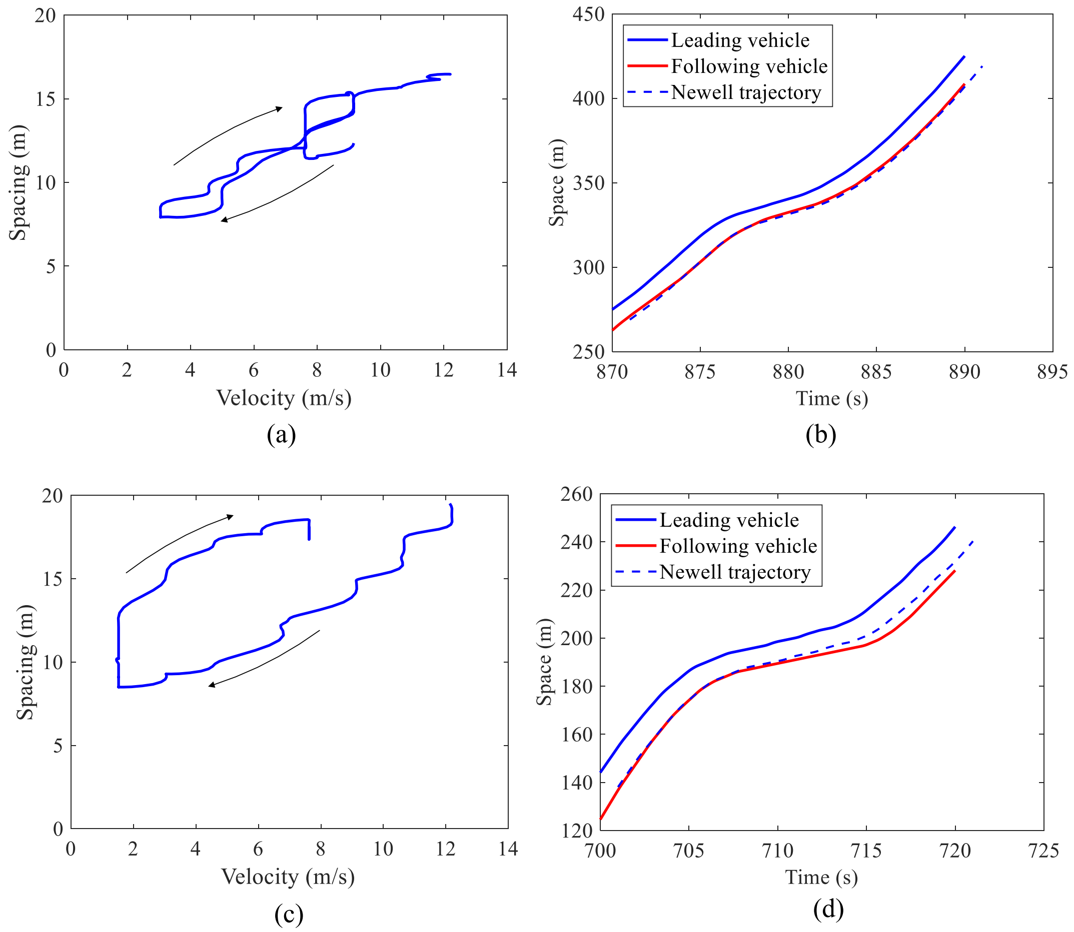

Fig. 4. Examples of traffic hysteresis in the velocity-spacing plane and trajectories: (a) and (b) nominal hysteresis and (c) and (d) ordinary hysteresis.

movement of the lane-changing vehicle, Zheng et al. (2013a) defined an anticipation period to describe the vehicle's behavior during lane-changing execution and completion. It is safe to say that the availability of high-fidelity trajectory data makes it possible to conduct careful studies on the details of vehicle motions (Zheng, 2014).

3. New traffic flow models built upon trajectory data

3.1. Data processing for trajectory data

Raw trajectory data are complex and often contain noise and errors (Kesting and Treiber, 2008; Thiemann et al., 2008; Punzo et al., 2011; Li et al., 2013a,b; Montanino and Punzo, 2013; Treiber and Kesting, 2013a, 2013b; Wang et al., 2014; Wang et al., 2015; Li et al., 2016a,b; Jiang et al., 2017; Li et al., 2018a). Before building new traffic flow models, we need to filter out abnormal/error data and categorize data for further analysis.

For example, if we focus on car-following studies, then the trajectory data that contain lane-changing motions should not be considered. If we study lane-changing, then the trajectories in which vehicles run around the lane boundary (it keeps touching the lane boundary before or after lane change) for a relatively long time should be carefully handled since such trajectories indicate that the vehicles are trying to reach the target lane but being blocked by surrounding vehicles.

Another vital aspect for data preprocessing is to distinguish vehicle types (such as cars and heavy trucks) because the driving behaviors of heavy trucks may be noticeably different from cars (Sarvi, 2013; Moridpour et al., 2012; Aghabayk et al., 2014; Moridpour et al., 2015; Cao et al., 2016; Chen et al., 2016). A straightforward way to reach this goal is to group trajectory data according to the associated vehicle length (for instance, data smaller than 3 m indicates error data, and data larger than 7 m indicates heavy trucks). However, vehicles with lengths less than 3 m can be motorcycles instead of errors; vehicles exceeding 7 m can be either heavy trucks or light-duty trailers. Additionally, one has to distinguish between trailers and a pair of vehicles that move closely. Researchers must consider these pitfalls in practice.

When applying Newell's model based on trajectory data, we often need to pay attention to the change points of speed. To reach this goal, we can either smooth the trajectory (Ma and Jansson, 2013; Mamouei et al., 2016; Zhu and Ukkusuri, 2017) to suppress the small fluctuation points introduced by noise or directly match the most corresponding changing points of two consecutive trajectories (Taylor et al., 2015; Przybyla et al., 2015).

3.2. New microscopic models built upon trajectory data

The rich information brought by trajectory data has germinated many new models for traffic flow studies. According to their design philosophy, we can roughly categorize these new approaches into three kinds.

The first kind of new approach aims to keep models as simple as possible to highlight one or a few features of driving behavior and to reproduce one or a few patterns of traffic flow. For example, several extensions of Newell's model (Li et al., 2012a; Chen et al., 2012a, 2012b) have been proposed to account for hysteresis phenomena that cannot be straightforwardly explained by Newell's original model. Another example is the extended Tau theory model proposed in (Jin et al., 2009; Li et al., 2013a,b; Li and Chen, 2017). This model provides a psychophysically and/or physiologically explainable model that can yield log-normal type speed-dependent headway distributions observed from trajectory data. Some researchers also slightly modified classic models to account for the newly identified traffic phenomena, e.g., asymmetric driving behavior (Gong et al., 2008; Xu et al., 2015).

The second kind of new approach aims to calibrate the existing microscopic car-following models based on trajectory data. If only loop detector data were available, then researchers mainly checked whether the macroscopic features (e.g., fundamental diagrams) of simulated traffic flows fit with those of observed traffic flows (Brockfeld et al., 2004, 2005; Rakha et al., 2007, Rakha and Wang, 2009) to calibrate the parameters of microscopic car-following models. In contrast, more new approaches compared the simulated trajectory data with real trajectory data to calibrate model parameters. Generally, these approaches can be further divided into four types (Panwai and Dia, 2005; Punzo et al., 2012, 2014; Li and Chen, 2017).

Type I calibration explicitly assumes the relationship between the disturbance and the stimulus–response mapping of drivers, as well as the distribution properties of the disturbance (Ossen and Hoogendoorn, 2005). The calibration problem can then be transformed into likelihood estimation problems that are well addressed in statistics and machine learning. According to the detailed model settings and the resulting estimation problems, existing approaches included the standard maximum likelihood estimation (MLE) (Hoogendoorn and Hoogendoorn, 2010a, 2010b; Rhoades et al., 2016), expectation–maximization (EM) method (Kim et al., 2013), maximum a posteriori estimation (MAP) (Miyajima et al., 2007; van Hinsbergen et al., 2009, 2015; Rahman et al., 2015), cross-entropy method (Zhong et al., 2016), and copula-based estimation of distribution algorithm (Fard and Mohaymany, 2019). Since most of those approaches assume that the disturbance at different time points is independent, we can sample many inputs (states of the leading vehicle and following vehicle) and outputs (actions of the following vehicle) discontinuously at different time points to fit model parameters (which is called *local-fit*) in Type I calibration approaches (Li and Chen, 2016). In other words, the empirical state information of both vehicles is used as the input at each simulation time step, and the outputs of the car-following model at the next time steps can be calculated and compared for calibration.

Type II calibration does not explicitly assume a disturbance (Wu et al., 2003; Wagner, 2005; Hollander and Liu, 2008; Li and Chen, 2016). Instead, this approach directly simulates a complete trajectory to compare with an observed trajectory (which is called *global fit*) (Panwai and Dia, 2005; Li and Chen, 2016). Only the empirical state information of the leading vehicle is used as input at each time step. The state of the following vehicle is only given at the initial step. The movements of the following vehicle at the remainder of the time steps are calculated sequentially. The best parameters are assumed to be the ones that minimize the deviation between the simulated and observed trajectories. Various optimization algorithms have been proposed to reach the optimal parameter values (Ma and Abdulhai, 2002; Schultz and Rilett, 2004; Ma et al., 2007; Lee and Ozbay, 2009; Wang et al., 2010; Ciuffo and Punzo, 2013; Paz et al., 2015; Papathanasopoulou and Antoniou, 2015; Papathanasopoulou et al., 2016). A recent study indicated that the DIRECT + SQP (sequential quadratic programming) algorithm seemed to be a good solution for Type II calibration problems due to the limited number of model parameters and the Lipschitz smooth property of the objective function (Li et al., 2016a,b).

Type III calibration highlights the long-range interactions among some vehicles within a vehicle platoon (Laval et al, 2014; Kurtc and Treiber, 2016; He et al., 2015). In such approaches, only the platoon leader's trajectory and the initial conditions are prescribed, while all the followers of the platoon are simulated. The complete trajectories of all the vehicles are compared with the corresponding observed vehicle trajectories (which is called a platoon fit) to check the fitness of the proposed car-following model.

Type IV calibration aims to validate car-following models based on mesoscopic or macroscopic simulated traffic flow patterns. For example, the headway distributions of car-following models were studied in (Jin et al., 2009; Li and Chen, 2017) and phase diagrams were studied in (Treiber and Kesting, 2012; Chen et al., 2012c). In these approaches, the trajectory data were used as ground truth to calculate the mesoscopic or macroscopic simulated traffic flow patterns, e.g., headway distributions or phase diagrams. However, these approaches usually address the semiquantitative alikeness between the simulated and empirical observations and cannot provide accurate parameter calibration for car-following models.

The third kind of new approach aims to directly learn a car-following model from the trajectory data by using machine learning techniques (Ma, 2006; Panwai and Dia, 2007; Aghabayk et al., 2014; He et al., 2015; Wang et al., 2018b; Zhu et al., 2018b). Usually, these models take velocities, velocity differences, and position differences that were observed in the last few time intervals as the input and directly output the estimated velocity or acceleration in the next interval (Khodayari et al., 2013; Chong et al., 2013; Yang et al., 2019b). The benefits of such models include the following. First, the whole model is self-trained from the empirical data. This data-driven method reduces artificial human interference to the minimum amount. Second, the entire model may have enough parameters to fit any complex driving behavior observed in practice.

Among various approaches, neural networks/deep learning-based approaches have received noticeably increasing interest (Wei and Liu, 2013; Zheng et al., 2013b, Colombaroni and Fusco, 2014; Zhou et al., 2017; Wang et al., 2018b, 2019; Wu et al., 2019c) due to the convenience and power of (deep) neural networks. The only aspect that we need to consider is the structure and implementation details of the deep neural networks. We can either select the data or add prior knowledge into the learning model to address some special features of the driving behavior or patterns of traffic flows, e.g., heterogeneity of drivers (Aghabayk et al., 2013, 2014), asymmetric car-following behavior (Huang et al., 2018a,b), and long-memory effect of drivers ((Wang et al., 2019a,b; Wu et al., 2019c). Such methods can also help build lane-changing models (Hou et al., 2015; Zhang et al., 2019; Nishi et al., 2019; Xie et al., 2019). However, how to avoid overtraining in these approaches remains to be further analyzed.

3.3. Mesoscopic and macroscopic models built upon trajectory data

The introduction of vehicle trajectory data has also led to new mesoscopic and macroscopic models. For example, several bivariate distribution models of the headway, spacing, and speed were proposed to describe the complicated interactions among these basic mesoscopic measures (Jabari et al., 2014; Zou et al., 2014; Zou and Zhang, 2016; Das and Maurya, 2018). Moreover, we could further establish the mapping relationship between the mesoscopic measures of traffic flow (vehicle velocity, headway, and spacing) and macroscopic measures of traffic flow (traffic speed, flow rate, and density), and explain uncertainty of traffic flows existing on both the mesoscopic and macroscopic levels (Chen et al., 2010b, 2014b).

The trajectory data also help propose new models to explain macroscopic phenomena that cannot be explained by using loop detector data. For example, loop detector data cannot clearly explain why queue discharge flows consist of sequences of nearly uniform flow that gradually change over time (Cassidy and Bertini, 1999; Bertini and Cassidy, 2002). Recently, researchers have proposed some behavior models to answer this question. In related studies, the relationship between fundamental diagram and capacity drop observed around bottlenecks on freeways (Coifman and Kim, 2011; Chen et al., 2012c; Chen et al., 2014c; Chen and Ahn, 2018), relationship between hysteresis and capacity drop (Ahn et al., 2010; Saberi and Mahmassani, 2013), reproduction of oscillations and hysteresis (Ahn et al., 2010; Li and Ouyang, 2011; Li et al., 2010, 2012a, 2014; Zheng et al., 2011a, 2011b; Chen et al., 2012a, 2012b; Ahn et al., 2013; Tian et al., 2015, 2016a, 2016b; (Wang et al., 2019a,b), etc., were investigated. It was shown that many macroscopic phenomena were intrinsically interlaced with each other. For example, Chen et al. (2012b) indicated that hysteresis was closely related to asymmetric driving behavior; moreover, the different development stages of oscillations were associated with different traffic hysteresis orientations and thus driver characteristics. The microscopic causes of traffic hysteresis and capacity drop have been unveiled from the driver's behavioral perspective. For example, the transition from the precursor to growth stages occurs when aggressive drivers exhibit a large hysteresis by adopting longer response time and minimum spacing.

The last but not the least, integrating the traffic flow at different levels of detail based on trajectory data remains an attractive yet challenging problem (Daganzo, 2006; Zheng, 2014; Li and Chen, 2017). We expect more attention to be paid to this interesting problem.

4. Discussions

4.1. More trajectory data are needed

Although the release of some trajectory datasets, e.g., the NGSIM dataset (NGSIM, 2006), had achieved great success in traffic flow studies, we are still facing a shortage of high-quality trajectory data (Krajewski et al., 2018).

First, the currently available trajectory data are usually limited in both spatial scope and temporal scope. For example, the NGSIM dataset only covers several small segments of highways or arterials whose lengths are all less than 1 km. We are eager to precisely track vehicles and accurately know the corresponding traffic flow dynamics in even broader spatiotemporal scopes.

Second, sampling traffic scenarios are limited. For example, the NGSIM data contain very little free-flow trajectory data, resulting in the availability of only low vehicle speeds (less than 60 km/h). The geometries of the road segments monitored in the NGSIM data are also limited. In contrast, almost all traffic scenes recorded in the highD dataset are in free-flow states. The lack of trajectory data in special traffic scenarios prevents us from identifying or explaining some traffic phenomena that may be important. We cannot satisfactorily calibrate or train our traffic flow models with limited data (Li et al., 2016a,b; Wang et al., 2017b; Wang et al., 2018a,b,c, 2019).

Third, the inaccuracy of some video-based trajectory collection methods needs to be dealt with. Although image processing techniques have been significantly improved, the errors in vehicle recognition and localization are still unavoidable for several reasons (Coifman and Li, 2017). The optical constraints of cameras cannot be easily relaxed. The cameras cannot "see" every part of the road as clearly as possible. Usually, one part of the road in the focus of cameras is clearer than the other part. The fusion of multiple cameras may alleviate this problem, but this leads to higher financial costs.

Fourth, the high equipment costs and data preprocessing time hinder us from collecting more high-quality trajectory data. Most conventional video-based trajectory collection methods can only monitor fixed road segments since the equipment is installed at a fixed location. Thus, we have to install several cameras to retrieve trajectory data. This process usually leads to considerable financial and time costs and thus prevents pervasive usage of the video-based trajectory collection method.

Generally, there are two potential ways to address the above four problems. The first method is the aerial-based trajectory collection method (Ossen, 2008; Park et al., 2015). Early attempts carried out by renting helicopters or aircraft showed that a much larger spatial area could be monitored compared with roadside camera-based approaches, but the cost was too expensive. Recently, unmanned aerial vehicles (UAV) have been employed as a new alternative to reduce costs (Coifman, 2006; Ke et al., 2017, 2019;

Kaufmann et al., 2018; Barmpounakis and Geroliminis, 2020). In recently released pNEUMA project, a swarm of 10 UAV was sent to hover over the central business district (a 1.3 km^2 congested area) of Athens (Barmpounakis and Geroliminis, 2020). Half a million vehicle trajectories were recorded on multiple days and detailed traffic conditions in a large number of lanes, intersections and bus stops were thus known. Image sensors and image processing algorithms associated with UAV have become increasingly powerful in preprocessing video data returned by unmanned aerial vehicles to retrieve high-accuracy trajectory data (Angel et al., 2003). For example, in the highD dataset (Krajewski et al., 2018), videos were recorded by the consumer quadcopter DJI Phantom 4 Pro Plus in 4 K resolution (4096 × 2160 pixels, 25 fps). This new device enabled much better videos than that of the NGSIM dataset that was recorded at 480p resolution (640 × 480 pixels, 10 fps) (Coifman and Li, 2017). Therefore, we expect more useful trajectory data to be obtained via UAV.

The second way is to collect trajectory data via the growing number of vehicles that have been equipped with high-accuracy GPS sensors (Jiang et al., 2014; Coifman et al., 2016; Shrestha et al., 2017; Jiang et al., 2018; Huang et al., 2018a,b) and even vehicle-to-everything (V2X) communication equipment. Unlike conventional probe vehicles or floating cars, vehicles currently collect their position data with significantly higher spatial and temporal resolution levels to obtain high-quality trajectory data for vehicles (Guo et al., 2019). When these vehicles send back their positions, we can collect their trajectory data in various traffic scenarios and within almost unlimited spatiotemporal scopes. If the penetration of these vehicles is large enough, then we can collect ambient vehicle trajectory data for traffic flow studies. If these vehicles can share their geolocations and other information in a real-time manner, e.g., connected vehicles (CV), then we can monitor real-time traffic flow dynamics (Zhu and Ukkusuri, 2017; Guo et al., 2019).

The trajectory data can be collected via GPS sensors and V2X communication in both controlled experiments (Jiang et al., 2014; Jin et al., 2015; Jiang et al., 2018; Huang et al., 2018a,b) and ordinary driving situations (Coifman et al., 2016). Generally, special traffic dynamic patterns can be zoomed in and carefully examined with other factors diminished to the maximum degree. This setting could help to reproduce special traffic phenomena and recover its origins. However, the complexity of practical traffic flows cannot be fully reflected in controlled experiments, and the costs of such experiments are still too high.

It should be noted that we do not deny the benefits of the trajectory data collected by video methods. Instead, trajectory data collected by video methods still are a cornerstone for traffic flow studies. These data may help us calibrate and validate the trajectory data collected by newly developed GPS sensors.

Recent studies have suggested that the trajectory data collected from driving simulation systems are also useful and may serve as alternatives (Papadimitriou and Choudhury, 2017; Li et al., 2019). However, the equivalence between the trajectories collected by driving simulation systems and empirical observations need to be further examined.

4.2. Other data sources for traffic flow studies are needed

Trajectory data are the cornerstone of traffic flow studies. However, we still need many other types of data to better measure and understand the behavior of traffic participators and the characteristics of traffic flow (Wu and Coifman, 2019).

First, researchers studied how human drivers control their vehicles and how the observed vehicle trajectories are affected (Li et al., 2012b). Conversely, researchers have been exploring how to retrieve the common driving features of humans from the observed trajectory data. For example, Li et al. (2018b) showed that human drivers roughly adopt a similar preview control mode in discretionary lane changes (DLC) and may share some common steering characteristics. Moreover, researchers have also combined road scene data with the drivers' behavior data (e.g., drivers' gaze direction, and hand gesture) to study the influence of traffic flow dynamics on driving behaviors (Abbas et al., 2010; Li et al., 2012b; Chong et al., 2013; Sangster et al., 2013; Shrestha et al., 2017; Yang et al., 2018; Zhu et al., 2018a; Xing et al., 2019; Yang et al., 2019a; (Wang et al., 2019a,b).

Second, the physiological and psychological measurement data of human drivers should be better integrated with trajectory data to uncover the origins of some traffic phenomena. For example, most existing studies regarding the reaction time delay and memory effect of human drivers were carried out in an indirect way. Typically, researchers first assumed a special model with certain parameters that correspond with the reaction time delay and memory effect. Then, simulations or estimations were executed to show that these parameters truly affect the circumstantial evidence of our hypothesis. In the future, we hope that related techniques could be advanced to allow direct and accurate measures for such factors in traffic flow studies.

All these studies belong to the submicroscopic level of detail and require appropriate fusion of trajectory and other related data. Some research topics have received attention from both the transportation side and vehicle side. This fact reflects the accelerating merger of transportation and vehicle studies.

4.3. Trajectory data can be used for other related studies

Trajectory data are also valuable for many other traffic flow-related studies. First, researchers have discussed how to use incomplete trajectories to reconstruct the whole trajectories of individual vehicles (Coifman, 2002; Toledo et al., 2007; Sun et al., 2008; Ni and Wang, 2008; Ou et al., 2008; van Lint, 2010; Li et al., 2013a,b; Venthuruthiyil and Chunchu, 2018). A direct application of such studies is to estimate or predict travel times of individual vehicles. Another important application is to establish the detailed relationship between driver behavior and fuel costs/emissions when trajectory data, fuel consumption data, and emission data are available (Chen et al., 2014; Sun et al., 2015; Zhou et al., 2015; Wang et al., 2017a; Wu et al., 2019b, He et al., 2019b). For example, Zhou et al. (2015) showed that the speed-acceleration distributions (Frey et al., 2013; Liu and Frey, 2015) obtained from the trajectory could help adjust the simplified Newell's model and more accurately estimate the emissions of vehicles.

Second, researchers have also examined how to estimate trajectories of all vehicles and reconstruct traffic states based on the incomplete or sparse trajectories of a few vehicles (Treiber and Helbing, 2002; Treiber et al., 2011; Guo et al., 2012). A related yet different problem that had been studied is how to reconstruct traffic states based on loop detector data. In such studies, trajectory data were usually used as ground truth for model calibration or validation. It must be noted that trajectory data-based traffic state reconstruction has also been heavily used for performance evaluation and signal timing design of traffic control systems. However, in this paper, we intentionally omit the applications of trajectory data for traffic control studies since we have recently provided a dedicated survey (Guo et al., 2019) for these applications. Related studies usually combine both traffic flow studies and traffic control studies. We believe these two research fields will become more tightly integrated in the future.

Third, real-time trajectory data can also be used to analyze the movement characteristics of road users (Zaki and Sayed, 2013) to detect dangerous driving behavior (Chen et al., 2017; Wang et al., 2018c; Li et al., 2018b), identify errorable driving behavior (Dingus et al., 2006; Williamson et al., 2011; Li et al., 2012a; Przybyla et al., 2015), and prevent collisions (Hu et al., 2004; Atev et al., 2005; Machiania and Abbas, 2016; Chen et al., 2019b). The first two problems are relatively easier since dangerous or errorable driving behavior make the resulting trajectories noticeably different from normal trajectories. The third problem is more difficult. Usually, we have to build simulation systems based on the collected trajectories to reproduce driving scenarios in simulation and test whether the observed trajectories indicate a potential collision (Saunier et al., 2010; Li et al., 2019). One of the major 10-year study efforts of the Federal Highway Administration (FHWA), United States, involves surrogate-safety methods using simulated or real-world trajectories. We expect more achievements to be obtained in this direction in the near future.

Fourth, the detailed trajectory data were also valuable to train or validate machine learning models of autonomous vehicles (Wang et al., 2017c; Li et al., 2018c; Li et al., 2019; Han et al., 2019; Feng et al., 2020) so that they can mimic human drivers to implement complex driving tasks or share roads with human-driven vehicles.

Since these studies did not belong to the main theme of this paper, we neglect them here. However, all these issues are important and should not be neglected in practice.

5. Conclusions

To discover fundamental laws governing traffic flow, researchers have been collecting high-resolution trajectory data for investigation since the early 2000s. This process soon led to a tremendous number of traffic flow studies. Several critical traffic phenomena were identified and explained. Many new traffic flow models were proposed. We believe that the publicly accessible trajectory dataset, e.g., the NGSIM dataset (NGSIM, 2006), significantly contributed to this period of prosperity of traffic flow studies.

Looking back on the last 20 years, we witnessed that traffic flow studies have gone through a period of significant change with the newly introduced data. However, all current achievements indicate an end of the beginning rather than a beginning of the end. The arrival of a large data deluge introduces both promises and perils into traffic flow studies. We need to build the new ark and ride on it toward the new world.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trc.2020.02.016.

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