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A Survey on Visual Traffic Simulation: Models, Evaluations, and Applications in Autonomous Driving

Qianwen Chao[1,2,*], Huikun Bi[3,4,5,*], Weizi Li[6], Tianlu Mao[3], Zhaoqi Wang[3], Ming C. Lin[7] and Zhigang Deng[5]

[1]Department of Computer Science, Xidian University, Xi'an, China
chaoqianwen15@gmail.com
[2]Multiscale Robotics Laboratory, ETH Zurich, Zurich, Switzerland
[3]Beijing Key Laboratory of Mobile Computing and Pervasive Device, Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China
xiaobi361@gmail.com, {ltm, zqwang}@ict.ac.cn
[4]University of Chinese Academy of Sciences, Beijing, China
[5]Department of Computer Science, University of Houston, Houston, TX, USA
zdeng4@uh.edu
[6]Department of Computer Science, University of North Carolina at Chapel Hill, Chapel Hill, NC, USA
weizili@cs.unc.edu
[7]Department of Computer Science, University of Maryland, College Park, MD, USA
lin@cs.umd.edu

Abstract

Virtualized traffic via various simulation models and real-world traffic data are promising approaches to reconstruct detailed traffic flows. A variety of applications can benefit from the virtual traffic, including, but not limited to, video games, virtual reality, traffic engineering and autonomous driving. In this survey, we provide a comprehensive review on the state-of-the-art techniques for traffic simulation and animation. We start with a discussion on three classes of traffic simulation models applied at different levels of detail. Then, we introduce various data-driven animation techniques, including existing data collection methods, and the validation and evaluation of simulated traffic flows. Next, we discuss how traffic simulations can benefit the training and testing of autonomous vehicles. Finally, we discuss the current states of traffic simulation and animation and suggest future research directions.

Keywords: traffic simulation, data-driven traffic animation, model validation and evaluation, autonomous driving

ACM CCS: • Computing methodologies → Agent/discrete models, Procedural animation

1. Introduction

Visual traffic has attracted increasing attention from a variety of research communities in recent years, including, but not limited to computer games, urban visualization, urban planning and autonomous driving. Urban scenes are indispensable in virtual reality, games and animation, which inevitably involve a large number of vehicles moving around. In order to control the motion of a single vehicle, a simple solution is to use keyframe methods. However, simulating traffic congestion, frequent lane-changing and pedestrian-vehicle interactions in large-scale traffic scenarios using keyframe methods not only requires complex design and repetitive adjustments from an animator, but also the resulting vehicle movements are rarely in accordance with physical laws.Therefore, effectively simulating large-scale traffic flows has become an increasingly necessary topic in Computer Graphics. Additionally, incorporating real-time traffic flow into virtual road networks has become critical due to the popularity of road network visualization tools, such as OpenStreetMap, ESRI, and Google Maps. Nevertheless, accessing actual trajectories of vehicles and incorporate them to virtual applications in real time is difficult. These trends have motivated research efforts on data-driven traffic simulation [WSLL15].

In addition to the above-mentioned applications in animation and visualization, traffic simulation has a wide range of applications in

*The first and the second authors contributed equally.

Figure 1: *The generated traffic flows via various traffic simulation and animation approaches: (a) synthesized traffic flows on a highway network from Chao et al. [CDR*18], (b) a dense traffic scenario with signalized crossing from Shen and Jin [SJ12], (c) the reconstruction of virtual traffic flows using in-road sensor data from Wilkie et al. [WSL13], (d) the reconstructed city-scale traffic using GPS data from Li et al. [LWL17], and (e) a heterogeneous traffic simulation used for autonomous driving testing [CJH*19].*

transportation research. Traffic simulation software packages, such as VISSIM [PTV11], TSIS [TSI18] and PARAMICS [PAR18], serve as effective tools for researchers to study the performance of a traffic network. Virtual reality-based driving training programs have helped new drivers to improve driving skills by producing realistic traffic environments [VRd18, LWX*18]. Traffic simulation can also be used as an effective tool for generating various traffic conditions for training and testing autonomous vehicles [SAMR18].

Furthermore, the increasing volume of vehicular traffic and complex road networks have led to many traffic-related problems, such as traffic jams, incident management, signal control and network design optimization. These problems are difficult to solve using traditional tools that are based on analytical models [SHVDWVW16]. Thus, many research efforts have been attempted on the modelling, simulation and visualization of traffic using advanced computing technologies—either to analyse traffic conditions for traffic management [PBH12, WLY*13, WYL*14] or to assist traffic reconstruction in urban development [GDGAVU14].

One major focus of traffic simulation is to answer the following question: Given a road network, a behaviour model and initial vehicle states, how would the traffic evolve? There are massive mathematical descriptions on the modelling and simulation of traffic flows, which can be roughly classified into macroscopic models [SWML10], microscopic models [SJ12] and mesoscopic models [SWL11]. Although macroscopic methods treat the collection of vehicles as a continuous flow, microscopic methods model the dynamics of each vehicle under the influence of its surrounding vehicles. Mesoscopic models, in contrast, combine the strengths of both microscopic and macroscopic models to simulate traffic at different levels of detail. In addition, the generation and representation of road networks is also a fundamental problem in traffic simulation.

Although the aforementioned traffic models are effective in capturing high-level flow appearance, the resulting simulations, however, usually do not resemble real-world traffic at the street level. With the development of advanced sensing hardware and computer vision techniques, empirical traffic flow data sets in the forms of video, LiDAR and GPS sensors are becoming increasingly available. This phenomenon gives rise to data-driven traffic animation techniques. Example works include the reconstruction of traffic flows from spatio-temporal data acquired by existing in-road sensors [SVDBLM11, WSL13, LWL17], the synthesis of new traffic flows from limited trajectory samples [CDR*18] and the generation of traffic flows through learning behaviour patterns and individual characteristics from traffic monitoring data sets [CSJ13, BMWD16].

In spite of significant advances achieved in traffic simulation and animation, how to measure the realism of simulated traffic has been largely under-explored to date. Moreover, In model-based traffic simulation and data-driven animation approaches, model validation in terms of the similarity between simulated and real-world traffic is always a concern. In order to address these issues, current approaches include using subjective user evaluations and incorporating objective evaluation metrics into the measurement [CDX*18].

Virtual traffic via various traffic simulation and animation techniques has also been applied to the training of autonomous driving. Autonomous driving has the potential to revolutionize our transportation systems. However, recent failures in testing have emphasized the training of these automated machines in simulated environments before deploying them to the real world [BNP*18, LWL19, LPZ*19].

Currently, the performance of autonomous vehicles is typically tested using a single interfering road user (e.g. vehicle, pedestrian or bicycle) with predefined behaviours in a virtual

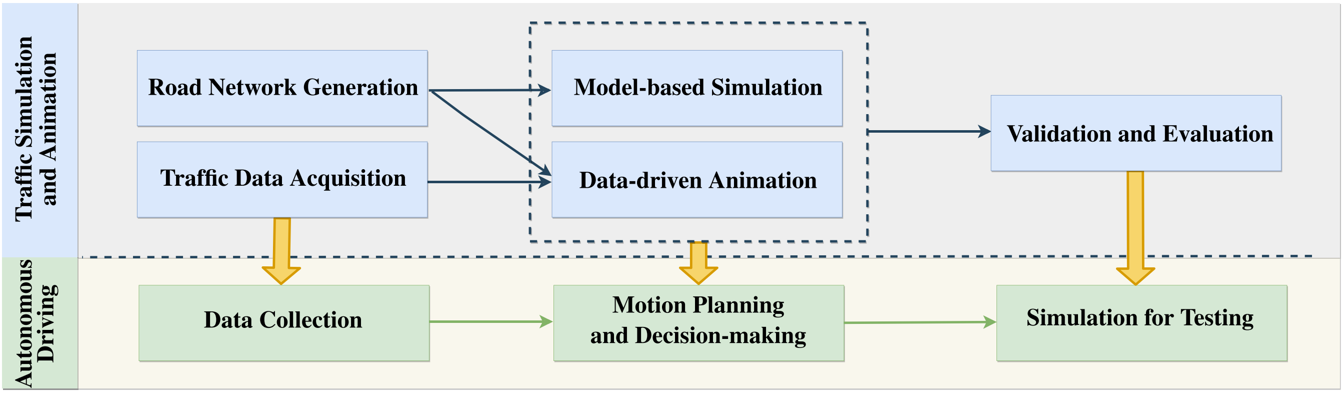

Figure 2: *Schema of traffic simulation and animation components introduced in this survey. First, the components of traditional traffic simulation and animation: road network generation (Section 2.4); traffic data acquisition (Section 3.1); model-based simulation (Section 2); data-driven animation (Section 3.2); and validation & evaluation (Section 4). Second, the components of autonomous driving research: autonomous driving training data sets (Section 5.1); motion planning and decision-making methods.*

environment [WEG*00, DRC*17, apo18]. Trained in simulated traffic flows with rich interactions among various road users, an autonomous vehicle can potentially gain the ability to handle intricate traffic conditions in complex urban environments. In addition, traffic simulation and animation can also benefit from learning-based motion planning and decision-making algorithms developed for autonomous vehicles. Specifically, with an increasing number of driving data sets collected, the resulting accurate traffic simulation can enrich the motion planning and decision-making of autonomous vehicles in terms of more accurate traffic semantics.

For safe autonomous driving, a high-fidelity driving simulator, which incorporates realistic traffic flows and complex traffic conditions, is necessary. Such a simulator can produce critical training environments in an efficient and reproducible manner. Because traffic simulations are becoming essential in autonomous driving research, in this survey, we will particularly describe the latest developments in autonomous driving from three aspects: data acquisition, motion planning and simulations for testing.

Organization. The remainder of this survey is organized as follows. Section 2 presents three classes of model-based traffic simulation methods, and provides different representative approaches for the procedural modelling and geometric representation of road networks. Section 3 surveys various data-driven animation techniques based on different data acquisition methods. Section 4 investigates the validation of animation methods and evaluation of generated virtual traffic. Section 5 presents recent efforts on data acquisition, motion planning and the use of virtual traffic for autonomous driving research. Finally, Section 6 and Section 7 conclude this survey with a discussion of the current states of existing studies and our perspectives on future research directions.

2. Model-Based Traffic Simulation

An essential component in traffic simulation is portraying the motions of vehicles at various levels of detail. Early research on the modelling and simulation of traffic flows can be traced back to

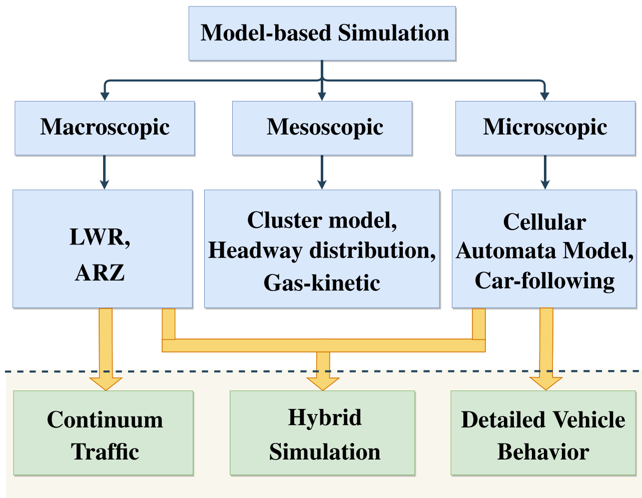

Figure 3: *Classification of model-based traffic simulation methods based on the levels of detail which these models simulate. Here, LWR and ARZ refer to two popular macroscopic traffic models proposed by Lighthill.Whitham.Richards [LW55, Ric56] and Aw.Rascle.Zhang [AR00, Zha02], respectively.*

1950s, when the prototypes of macroscopic and microscopic traffic models were proposed, respectively [Pip53, LW55]. After years of development, there are three general types [VWKVLVH15, FSS18] of traffic simulation techniques (illustrated in Figure 2), namely, macroscopic (Section 2.1), microscopic (Section 2.2) and mesoscopic (Section 2.3).

Traffic flows can be treated as a type of crowd flows: vehicles in a flow share similar goals and behavioural rules, interacting with neighbours while maintaining individual driving characteristics. In Computer Graphics, crowd simulation has been an important research area, supporting the study of collective behaviours and dynamics [PAB08, ZCC*10]. Crowd simulation can be achieved in

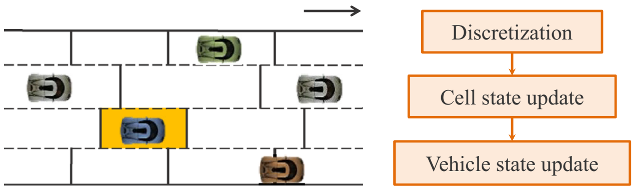

Figure 4: *Illustration of the macroscopic traffic simulation approach [SWML10]. Each lane is divided into discrete cells. At a given time step, the states of each cell are updated by solving the ARZ equations, which solutions are then used to update the states of each vehicle in each lane.*

either a macroscopic manner (modelling a crowd as a whole at the expense of realistic motions of individual agents) [NGCL09] or a microscopic manner (modelling a crowd as a collection of movements from individual agents) [WLP16].

2.1. Macroscopic methods

Macroscopic methods, also called continuum methods, describe vehicles' behaviours and interactions at a low level of detail: a traffic stream is represented by a continuum in terms of speed, flow, density, etc. Macroscopic methods are mainly designed for efficient traffic simulation on a large-scale road network, focusing on reproducing aggregated behaviours measured with collective quantities such as flow density and traffic flux.

One of the early first-order macroscopic models was developed by Lighthill and Whitham [LW55] and Richards [Ric56], referred to as the LWR model. Their model assumes that the traffic flow rate depends only on traffic density that describes the flow-density relationship.

The model builds a non-linear scalar conservation law for modelling traffic flows, based on the similarities between one-dimensional compressible gas dynamics and the evolving of traffic flows on a single lane. Essentially, the LWR model describes the motion of large-scale traffic flows with low-resolution details. One of its limitations is that it cannot model the movements of a vehicle under non-equilibrium conditions, such as stop-and-go waves.

Later, a continuous second-order traffic flow model was proposed by Payne [Pay71] and Whitham [Whi74], which is known as the Payne–Whitham (PW) model. Although the first-order model assumes the existence of a fixed equilibrium state, the second-order model introduces a second differential equation to describe traffic velocity dynamics. As an limitation, the PW model can introduce negative velocities and the information generated from vehicle dynamics can travel faster than vehicle velocity, meaning drivers can be affected by their following vehicles. Aw and Rascle [AR00] and Zhang [Zha02] proposed a modification to the PW model in order to eliminate its non-physical behaviours. To be specific, Aw and Rascle [AR00] introduced a pressure term to guarantee that no information travels faster than the speed of a car. Zhang [Zha02], similarly, proposed a modification to the momentum equation of the PW model to handle backward-propagating traffic. The resulting model is referred to as the Aw–Rascle–Zhang (ARZ) model, which has been thoroughly studied since [Ras02, GP06, LMHS07, MR07]. Mammar *et al.* [MLS09] showed that the ARZ model fits real-world data better than the LWR model numerically.

In order to produce detailed 3D animation and visualization of traffic flows, Sewall *et al.* [SWML10] presented a continuum traffic simulation model to generate realistic traffic flows on large-scale road networks. They adapt the single-lane ARZ model to handle multi-lane traffic by introducing a novel model of lane-changing and using a discrete representation for each vehicle. As illustrated in Figure 4, the flow of traffic is simulated by discretizing each lane into multiple cells. In order to update the states of each cell, the Finite Volume Method for spatial discretization [LeV02], combined with a Riemann solver, is used to solve the ARZ equations. In order to model lane-merging and lane-changing behaviours, Sewall *et al.* combine continuum dynamics with discrete vehicle information by representing vehicles as "carticles". These "carticles" are driven by the underlying continuum flow.

In summary, macroscopic traffic models are efficient tools to simulate large-scale traffic. However, such techniques are limited to networks of highways, thus not suitable for simulating street-level traffic which consists of rich interactions among individual cars. Moreover, because these models do not model lane-merging behaviours of a vehicle, they cannot handle density transfer during the lane-changing process.

2.2. Microscopic methods

Microscopic models produce vehicle motions at a high level of detail: each vehicle is treated as a discrete agent satisfying certain governing rules. A number of microscopic models have been developed for specific urban traffic simulations, attributing to their flexibility in modelling heterogeneous behaviours of agents, diverse road topologies and interactions among surrounding vehicles.

Early examples of microscopic models include the cellular automata model [NS92] and car-following models [Pip53, HG63]. The motions of the vehicles in the cellular automata model are described by evolution rules in pre-specified time, space and state variables. To be specific, a road is discretized into cells, and the model determines when a vehicle will move from the current cell to the next cell. Owing to its simplicity, the cellular automata model is computationally efficient and can simulate a large group of vehicles on a large road network [KSSS04]. However, due to its discrete nature, the generated virtual traffic can only reproduce a limited number of real-world traffic behaviours.

In contrast, car-following models, first introduced by Pipes [Pip53] and Reuschel [Reu50], can generate realistic driving behaviours and detailed vehicle characteristics at the cost of computation. They assume that the traffic flow consists of scattered particles [SZ14] and model detailed interactions among cars. These models represent the position and speed of each car through continuous-time differential equations based on the stimulus-response framework: $Response = Sensitivity \times Stimulus$, in which the stimulus is associated with the position and velocity of the leading vehicle.

Over the past decades, numerous variations and extensions of the car-following model have been developed by modelling the

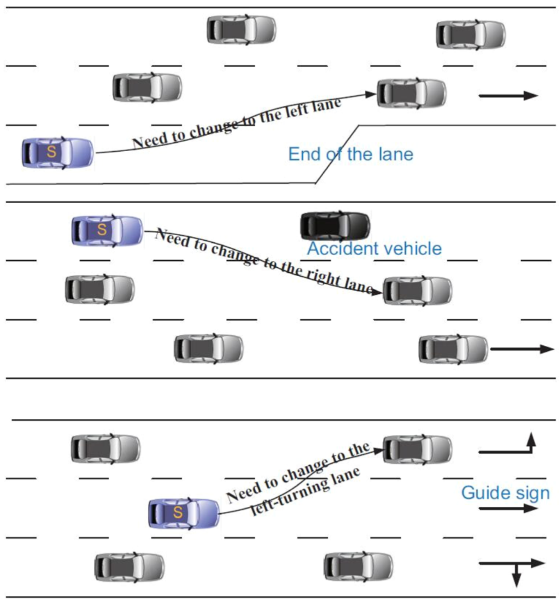

Figure 5: *Situations where a vehicle must change its lane [SJ12]: (a) reaching the end of the current lane, (b) an accident vehicle appears in front in the current lane, and (c) a guidance sign appears at the road crossing.*

responses of a subject vehicle to its front vehicle. Two well-known examples are the optimal velocity model (OVM) [BHN*95] and the intelligent driving model (IDM) [TH02]. In the OVM model, the subject vehicle is assumed to maintain its optimal velocity. Its acceleration is determined by the difference between its velocity and the optimal velocity of the front vehicle. In the IDM model, the vehicle's acceleration or deceleration is computed according to its current speed and relative speed and position to its front vehicle. The vehicle-specific parameters enable the IDM model to simulate various vehicle types and driving styles.

Besides simulating traffic flows on a single lane, multi-lane simulations have also been studied [SN03, Dav04, THG05, HNT07]. One example is the modified optimal velocity model [Dav04], which is used to simulate traffic on a dual-lane highway and a single-lane highway with an on-ramp; another example is the two-lane traffic model [THG05], which is used to simulate traffic lateral effects.

In order to generate detailed traffic simulations, Shen and Jin [SJ12] proposed an enhanced IDM together with a continuous lane-changing technique. Their technique can produce traffic flows with smooth acceleration/deceleration strategies and flexible lane-changing behaviours. The model modifies the original IDM model to make it more suitable for signalized urban road networks. Specifically, the acceleration process is separated into a free-road acceleration term describing the driver's intention to reach its desired velocity, and a deceleration term describing the driver's intention to keep safe distances to its nearby vehicles. The deceleration term is modified by adding an activation governing control part for generating smoother reactions to stopped vehicles. Also, the model divides the lane-changing behaviours on urban roads into two situations:

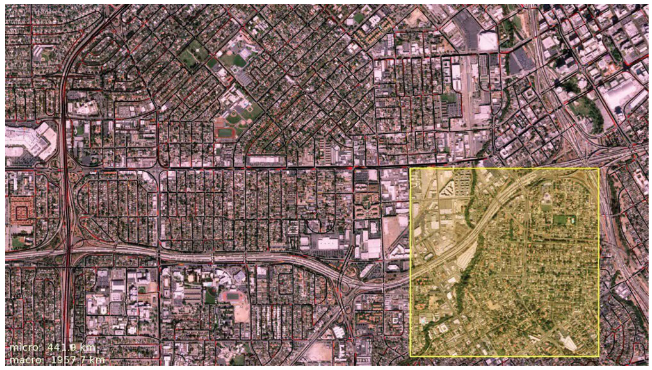

Figure 6: *Illustration of a hybrid traffic simulation method [SWL11]. The traffic within the yellow bounding box is simulated using an agent-based technique, whereas the rest traffic is simulated using a continuum technique.*

free lane changing and *imperative lane changing*, and provides a flexible continuous model for both situations.

Free lane changing frequently occurs in a comparatively free road condition. This behaviour is modelled by the double-lane MOBIL model from Kesting *et al.* [KTH07]. Imperative lane changing is applied when the subject vehicle demands a lane-changing action because of some imperative factors, such as reaching the end of lane or turning at the crossing, while the gap between the subject vehicle and its leading vehicle may be insufficient for free lane changing (Figure 5). Lu *et al.* [LCX*14] extended the full velocity difference model [JWZ01] to handle close-car-braking circumstances in rural traffic simulations. Later, Lu *et al.* also introduced a personality model into traffic simulation [LWX*14].

Compared to simulating traffic on lanes (either signle or multiple), simulating traffic at intersections is more difficult. Doniec *et al.* [DMPE08] proposed a multi-agent behavioural model for traffic simulation by treating intersectional traffic as a multi-agent coordination task. To be specific, first, each vehicle perceives the surrounding traffic and makes a decision; second, an anticipation algorithm is introduced to generate the anticipation abilities for the simulated vehicles. Wang *et al.* [WXZ*18] introduced the concept of shadow traffic for modelling traffic anomalies in a unified way in traffic simulations. Chao *et al.* [CDJ15] designed a rule-based process to model vehicle-pedestrian interactions in mixed traffic simulations.

In summary, as microscopic traffic models aim to describe specific vehicle behaviours, they can be used to simulate traffic in both continues lanes and intersections. The bottleneck is usually the computational cost, especially when a large-scale simulation is needed.

2.2.1. *A hybrid method*

Although continuum methods (i.e. macroscopic models) excel the large-scale traffic simulation and agent-based techniques (i.e. microscopic models) excel the modeling of individual vehicles, Sewall *et al.* [SWL11] combined these two types of approaches and proposed a hybrid method. Their approach simulates traffic in the areas of interest using an agent-based model, while the rest areas using a continuum model (see Figure 6). By dynamically and automatically switching between the two modelling methods, their approach can simulate traffic under different levels of detail based on user preference.

2.3. Mesoscopic methods

Mesoscopic models are an intermediate approach between macroscopic and microscopic approaches. The core idea of the mesoscopic models is to describe traffic flow dynamics in an aggregate manner while representing the behaviours of individual drivers using probability distribution functions [HB01c]. Mesoscopic models can be divided into three classes: cluster models, headway distribution models and gas-kinetic models [FSS18]. The cluster models represent the dynamics of traffic flows by describing groups of vehicles with the same properties [KMLK02, MKL05]. The headway distribution models focus on the statistical properties of time headways. Among mesoscopic approaches, the most known models are gas-kinetic models, in which an analogy between the gas dynamics and the traffic dynamics is drawn. [PA60, THH99, HHST01, HB01a].

In transportation engineering, gas-kinetic models are usually not applied in simulations but maintain their roles in deriving other continuum models [Hel01]. For example, Hoogendoorn and Bovy [HB00, HB01b] derived a multi-class multi-lane continuum traffic flow model based on gas-kinetic models. Gas-kinetic models are also basis for many macroscopic models, for example adaptive cruise control policies [DNP15]. The kinetic theory is also used to derive a mathematical model of vehicular traffic [FT13], in which the assumption on the continuously distributed spatial positions and speed of the vehicles is relaxed. In Computer Graphics, mesoscopic models are rarely utilized in traffic simulations due to a large number of unknown parameters and complex differential or integral terms, which restrict the simulation and animation efficiency.

2.4. Road network generation

Traffic simulation is a form of interplay between the vehicles and the road network. The acquisition and modelling of the underlying road network is an important yet challenging aspect. Digital representations of real-world road networks have been increasingly available, but these data are often not directly usable for simulating traffic. Traffic simulations, based on macroscopic and microscopic modelling methods, take place on a road network formed with lanes. A road network contains many features such as lanes, intersections, merging zones and ramps. Many methods have been proposed for the procedural modelling and geometric representation of a road network.

Parish *et al.* [PM06] proposed a system called *CityEngine* [cit18], using a procedural approach based on L-system to generate a road network (Figure 7a). Taking map images as the input, the system can generate a set of highways and streets, divide a land into lots and build appropriate geometry for buildings on the respective allotments. Later, many researchers improved road network generation models based on *CityEngine* [CEW*08, BN08, GPMG10].

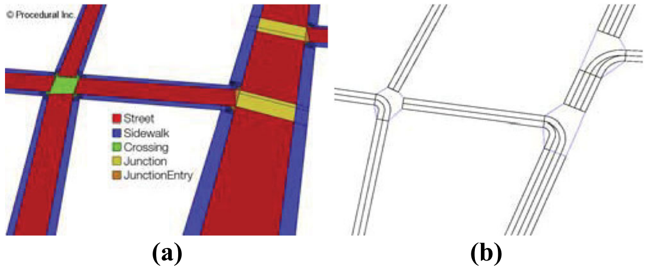

Figure 7: *A road network created using (a) CityEngine [cit18] and (b) the technique from Wilkie et al. [WSL12].*

For example, Sun *et al.* [SYBG02] presented a template-based road network generation model. Endowed with more flexibility, users can edit a road network directly using the automatic road network generation model from Chen *et al.* [CEW*08]. Recently, Nishida *et al.* [NGDA16] presented an interactive road design system using the patches and statistical information extracted from example road networks. Hartmann *et al.* [HWWK17] proposed an example-based approach for synthesizing a road network using Generative Adversarial Networks (GAN). They use a binary image to represent a road network patch. Because these approaches are designed for building virtual scenes, they often fail to provide the necessary information for traffic simulation, such as lane-to-lane connections and adjacencies.

Several road modelling techniques were proposed for traffic simulation. Yang and Koutsopoulos [YK96] use *node*, *link*, *segment* and *lane* to describe the semantics of a road network. Their model has been incorporated into the traffic simulation software MITSIM [BAKY02]. In this model, a *segment* denotes a set of lanes with the same geometric polylines, and a *link* denotes a collection of segments. Vector data are stored in the segment's data structure. The stored information includes the starting/ending points and the curvature of a segment arc. A *node* is used to describe an intersection. Here, the *node* must be supplied to the model as input data and only used to describe whether the links are connected. The conflict relationship between links in each direction at an intersection is not considered. In VISSIM [PTV11], traffic simulation software, *link* and *connector,* are adopted to describe the topology of a road network, which helps the presentation of roads with more complex geometries. However, the road network in VISSIM only consists of consecutive *segments*, so it is difficult to handle the conflicts among different directions at an intersection. Similarly, other road network representation models [Par03, BC05, SWL11, SJ12] have been made available. Recently, Cura *et al.* [CPP18] use real Geographic Information System (GIS) data to produce a coherent street-network model, containing topological traffic information, road surface and street objects. The system can provide lanes and lane inter-connections as basic geometric information needed for traffic simulation. However, they use *lane* as an atomic unit to define and organize a road network, while ignoring the vector data of a road network. Worth mentioning, in order to facilitate the data exchange among different driving simulators, an open data format named OpenDRIVE [DG06] was proposed to standardize the logical road description.

Aiming at improving the visualization of vehicle motions, Wilkie *et al.* [WSL12] proposed a novel road network model (Figure 7b) to automatically transform low-detailed GIS data into high-detailed functional road networks for simulation. The lane-centric topological structure and the arc road representation can be generated using this model. This model defines an *intersection* on the basis of a *lane*. An intersection is managed in a simulation via traffic signals and pre-determined moving priorities. The resulting Road Network Library [WSLL15] can be found at http://gamma.cs.unc.edu/RoadLib/. The model has motivated more lane-based simulation techniques, for example Mao *et al.* [MWDW15] model lanes based on the road axis under the Frenet frame to facilitate complex traffic simulations.

Worth meaning, depends on applications, traffic simulation at different levels of detail require different information regarding the underlying road network. In general, macroscopic traffic simulation requires less details of a road network—mainly the geometrical information is needed so that the propagation of density and speed of a traffic flow can be modelled. Microscopic traffic simulation, in contrast, as it outputs detailed motion of individual vehicles, usually requires more information regarding a road network. Such information include lane (instead of road) separation and joining, traffic signal logic, moving priorities at intersections and ramps, etc.

3. Data-Driven Traffic Simulation

In this section, we explore the acquisition of real-world traffic data (Section 3.1) and various data-driven approaches for traffic reconstruction and synthesis (Section 3.2).

3.1. Traffic data acquisition

Traffic sensors come in several forms [LBH*10, Led08]. To list few examples, one fixed sensor is inductive-loop detector, which is usually placed on highways and major roads to record the attributes of every vehicle that passes. Another fixed sensor is video camera, which is also used for monitoring traffic. In addition to fixed sensors, mobile sensors are also ubiquitous: cell phones and GPS devices are used to record the speed of a vehicle along with its position.

The inductive-loop detector has become the most utilized sensor since its introduction in the early 1960s [AKH*12, KMGK06]. It can detect vehicles' passing or arriving at a certain point, for instance, approaching a traffic light or in motorway traffic. An insulated, electrically conducting loop is installed in the pavement. Vehicles passing over or stopped within the detection area decreases the inductance of the loop. Then, the electronic unit senses this event as a decrease in frequency and sends a pulse to the controller to signify the passage or presence of a vehicle. This in-road sensor can usually track the passing time, the lane id and the velocity of a vehicle.

Video camera, as an over-roadway sensor, has also been widely deployed. An example is the Next Generation Simulation (NGSIM) program [NGS18], in which the cameras are installed along the road capturing traffic data at 10 frames per second. The resulting dataset encloses detailed vehicle trajectories. Table 1 lists four popular NGSIM data sets in terms of road length, road types, record time and the number of vehicles. Figure 8 shows an example of data collection on U.S. 101 Highway: eight synchronized video cameras, mounted from the top of a 36-story building adjacent to the freeway, recording vehicles passing through the study area. In order to process the large amount of data being captured, NGSIM-VIDEO [NGS18] is developed to automatically extract vehicle trajectories from images.

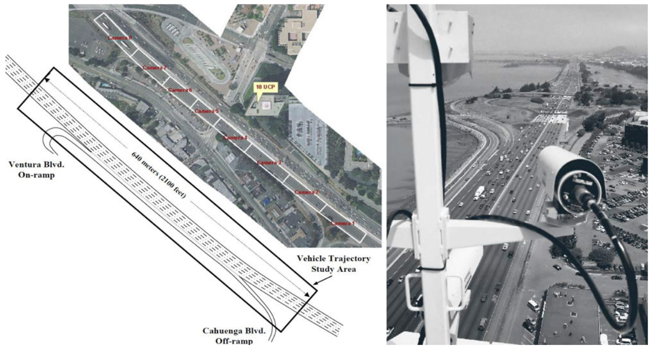

Figure 8: *Eight cameras installed over U.S. Highway 101. The photo on the right shows a video camera mounted on the top of a building overlooking the highway.*

Table 1: *Four selected NGSIM data sets [NGS18].*

Location	Road length (feet)	Road type	Record time	# of vehicles
I-80, Emeryville, California	1650	Freeway, one on-ramp	4:00 pm–5:30 pm	3200+
US 101, Los Angeles, California	2100	Freeway, one on-ramp & off-ramp	7:50 am–8:35 am	3000+
Lankershim Blvd, Universal City, California	1600	Arterial, four intersections	8:30 am–9:00 am	1500+
Peachtree Street, Atlanta, Georgia	2100	Arterial, five intersections	12:45 pm–1:00 pm 4:00 pm–4:15 pm	1500+

Although traditional traffic data collection methods through in-road sensors are costly in general, mobile data such as GPS reports have becoming increasingly available and have been used in estimating citywide traffic conditions [AA06, LNWL17]. Taxicabs and shared ride services (e.g. Uber and Lyft) systematically equip their car fleets with these devices. Attributes such as locations, speed and directions of a car are sent to a central processing centre. After processing, useful information (e.g. status of traffic, and alternative routes) will be broadcast to drivers on the road [TEBH98]. The current public available GPS data sets include Mobile Century [HWH*10], T-Drive [tdr19], GeoLife [geo19] and Uber Movement [ube17]. Although promising, besides the inherent noise, GPS data usually contain a low sampling rate, meaning the time

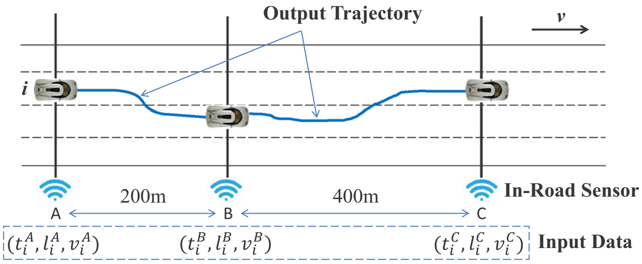

Figure 9: *Illustration of traffic reconstruction from temporal-spatial data acquired from in-road sensors. For the vehicle* i*, the sensors provide a vector* $(t_i^A, l_i^A, v_i^A, t_i^B, l_i^B, v_i^B, t_i^C, l_i^C, v_i^C)$ *as data input, where* t_i^A, l_i^A, v_i^A *are, respectively, the passing time, the lane id and the velocity of vehicle* i *when passing point* A *(similarly for point* B *and point* C*).*

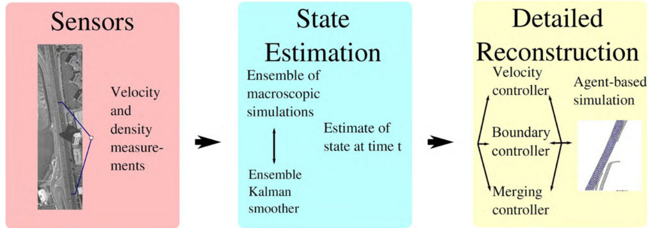

Figure 10: *Pipeline of a traffic flow reconstruction algorithm [WSL13]. The algorithm integrates an efficient state estimation method using Ensemble Kalman Filter and continuum traffic simulation to efficiently reconstruct traffic. The results are visualized using agent-based traffic simulation to produce realistic motion for individual vehicles.*

difference between two consecutive points can be large (e.g. greater than 60 s), and exhibit spatial-temporal sparsity, meaning the data can be scarce in certain time periods and areas. So, in order to use GPS data in reconstructing traffic dynamics, several processing steps are required [LNWL17, LJCL18].

Besides single-vehicle data, many efforts have been invested in collecting traffic data from connected vehicles [HL08, RMR14]. As an example, the Safety Pilot Model Deployment (SPMD) program was launched at Ann Arbor, Michigan, United States in 2012. Approximately 3000 vehicles were equipped with GPS antennas and DSRC (Dedicated ShortRange Communications) devices. Each vehicle was broadcasting Basic Safety Messages including its position and velocity to nearby vehicles and roadside units. These connected-vehicle data provide opportunities to improve intelligent transportation system applications as well as detailed multi-lane traffic simulation and animation. Because this type of data can be sampled at a high frequency (e.g. 10 Hz [BS15]), which can result in considerable cost of storage and communication systems, they are usually processed via a down-sampling but information-preserving technique [MOH*14, LLP19].

3.2. Traffic reconstruction and synthesis

Creating a digital representation of traffic that corresponds to real world conditions is referred to as “virtualized traffic” and was first introduced by Van Den Berg *et al.* [SVDBLM11]. In their work, a continuous traffic flow is reconstructed and visualized from the spatio-temporal data provided by traffic sensors. As shown in Figure 9, the sensors (points A, B and C) are placed on the road at intervals of 200–400 m. For a specific vehicle i, the sensor A provides a tuple $(t_i^A, l_i^A, v_i^A, t_i^B, l_i^B, v_i^B, t_i^C, l_i^C, v_i^C)$ as data input, where t_i^A, l_i^A, v_i^A are, respectively, the passing time, the lane id and the velocity of the vehicle i (similarly for the points B and C). The task is to compute trajectories (the blue curve in Figure 9) for the vehicle i on the road starting and arriving in the given lanes, at the given times, and with the given velocities. The approach first discretizes possible state-time space and constrains the motion of a vehicle to a pre-computed roadmap. Then, it searches for an optimal trajectory for each vehicle in the roadmap that minimizes the number of lane-changing and the amount of acceleration/deceleration, and maximizes the distance to other vehicles to obtain smooth and realistic motions. For multiple vehicles, a priority based multi-robot path planning algorithm [VDBO07] is utilized to compute the trajectories of vehicles. However, the priority-based, multi-agent route planning algorithm is time consuming, which makes this approach quickly become intractable as the resolution of discretization in the search space increases.

With the same goal of reconstructing traffic flow from in-road sensor measurements, Wilkie *et al.* [WSL13] introduced a real-time technique by integrating macroscopic state estimation from sparse sensor measurements with an agent-based traffic simulation system to reconstruct realistic motions of individual vehicles. As illustrated in Figure 10, this method features a traffic state estimation phase, in which an ensemble of Kalman smoothers (EnKS) [Eve03] and a continuum traffic simulator are used to create an estimate of velocity and density fields over the entire road network. The state estimate is then used to drive an agent-based traffic simulation model to produce the detailed motions of individual vehicles. Finally, the output is a 2D traffic flow consistent with the original traffic signals measured by the sensors. Compared to the traffic reconstruction work by Sewall *et al.* [SVDBLM11], this method shows a higher flexibility and a lower computational cost. However, this estimation method is fundamentally macroscopic except the matching of individual vehicles.

Recently, Li *et al.* [LWL17] proposed a method to reconstruct city-scale traffic from GPS data. To address the issue of insufficient data coverage, this method takes a GIS map and GPS data as input, and reconstructs city-scale traffic using a two-phase process. At the first phase of initial traffic reconstruction, the flow conditions on individual road segments are reconstructed and progressively refined from the sparse GPS data using statistical learning combined with optimization, map-matching and travel-time estimation techniques. At the second phase of dynamic data completion, a metamodel-based simulation optimization is introduced to efficiently refine the reconstructed results from the first phase, along with a microscopic simulator to dynamically interpolate missing data in the areas of insufficient data coverage. To ensure that the reconstructed traffic is correct, the method further fine-tunes the simulation with respect to

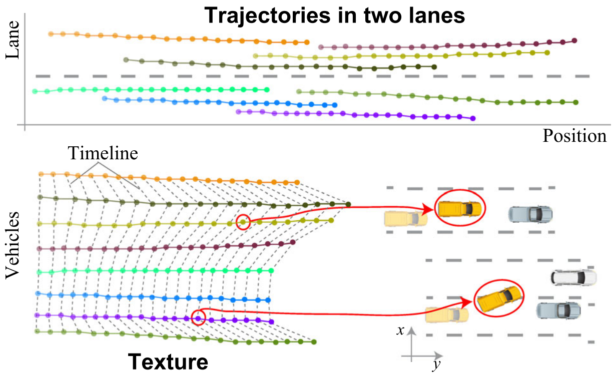

Figure 11: *Texture analogy of a set of two-lanes vehicle trajectories [CDR*18]. The spatial-temporal information of the trajectory set can be conceptually viewed as a 2D texture, and each traffic texel encodes a vehicle's states at a certain frame, including its movement information and position relationship with its neighbouring vehicles.*

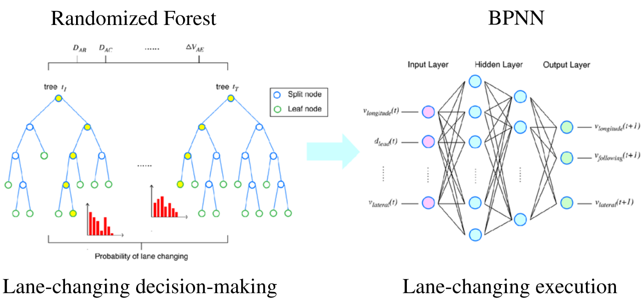

Figure 12: *Illustration of the pipeline of the data-driven lane-changing model [BMWD16]. The pre-processing step extracts the most relevant features from the pre-collected traffic data set. Then, the decision-making module infers whether the subject vehicle should perform lane-changing as well as which target lane/gap it should change to. Finally, the execution module computes the detailed trajectories of involved vehicles to accomplish a lane-changing task.*

citywide boundary (traffic) constraints and the reconstructed traffic flow from the first phase. This is achieved through the error approximation of the traffic flow computed by the metamodel-based formulation.

Although the above-mentioned traffic reconstruction techniques are dedicated to predict complete traffic flows with sparse input data in the same scenario, there are other data-driven traffic synthesis methods aiming to generate new traffic flows from limited traffic trajectory samples. Chao *et al.* [CDR*18] synthesize new vehicle trajectories through a fusion of texture synthesis and traffic behaviour rules, using a limited set of vehicle trajectories as input samples. The example (input) vehicle trajectory set contains a variety of traffic flow segments in terms of the number of lanes and flow density. As illustrated in Figure 11, by taking the spatial-temporal information of traffic flows as a 2D texture, the generation of new traffic flow can be formulated as a texture synthesis

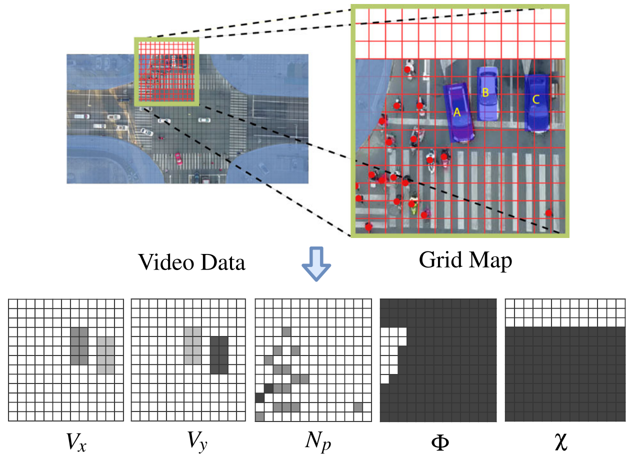

Figure 13: *Illustration of the environment matrices in intersectional traffic simulation [BMWD19]. For vehicle* A*, a window with size 31 × 31 is use to describe the surrounding area. An environment matrix including five channels (V_x, V_y, N_p, Φ, χ). V_x (or V_y) visualizes the velocities of vehicle* B *and* C*. N_p denotes the number of pedestrians and cyclists. Φ and χ represent the area into which vehicle* A *can drive and the visible area from the drone's perspective, respectively.*

process, which is effectively solved by minimizing a newly developed traffic texture energy metric. To be specific, each texel in traffic texture encodes a vehicle's state at a certain frame, including its velocity, position and dynamic relationships with its neighbouring vehicles. The traffic texture energy metric measures the similarity between the synthesized traffic flows and given traffic flow samples. Each vehicle's velocity in the synthesized traffic flow is determined by finding the best matched texel in the input traffic flow samples. The synthesized output not only captures the spatial-temporal dynamics of the input traffic flows, but also ensures traffic features such as the safe distance between vehicles and lane-changing rules.

Instead of reconstructing virtual traffic based on data acquired from in-road sensors or synthesizing new traffic flows from existing trajectory data, researchers have also employed machine learning algorithms to learn the detailed motion characteristics of vehicles, including acceleration/deceleration in longitudinal direction, and lane-changing process. Chao *et al.* [CSJ13] presented a video-based approach to learn the specific driving characteristics of drivers from videos for traffic animation. This approach formulates the estimation of each vehicle's unique driving habit as a problem of finding the optimal parameter set of a microscopic driving model, which can be solved using an adaptive genetic algorithm. The learned characteristics can be used to reproduce the traffic flow in a given video with a high accuracy and can also be applied for any agent-based traffic simulation systems. Bi *et al.* [BMWD16] learn the lane-changing characteristics from vehicle trajectory data. As illustrated in Figure 12, this approach first extracts the features that are most relevant to a lane-changing task from a pre-collected vehicle trajectory data set. The extracted features are then utilized to model the lane-changing decision-making process and estimate the lane-changing execution process.

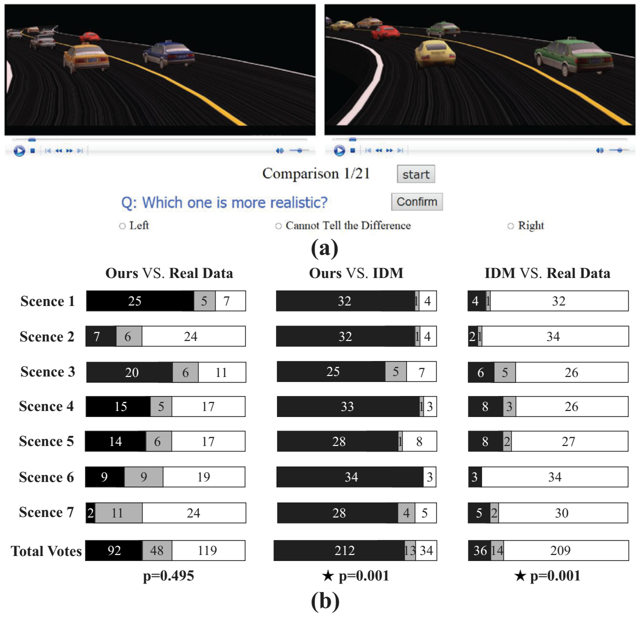

Figure 14: *Snapshots of the driver's view study (a) and the experiment outcomes (b) [CDR*18]. Black boxes at the left side and white boxes at the right side indicate the total number of times when the participants voted the results using the corresponding method. Gray boxes in the middle indicate "undecided choices" (i.e. perceptually equivalent). The symbol ∗ indicates the computed statistical significance according to a two-tailed independent one-sample* t*-test with* $p < 0.05$.

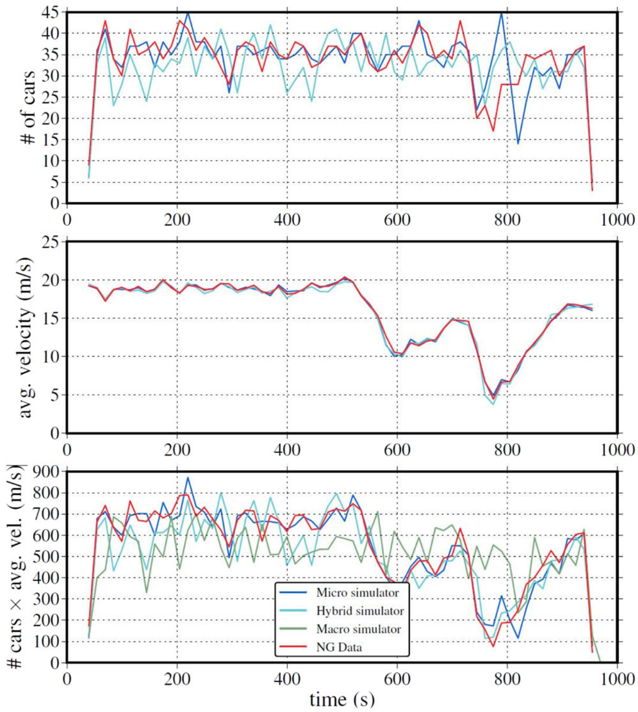

Figure 15: *Comparison between agent-based (micro) simulation, continuum (macro) simulation, our hybrid simulation technique and real-world NGSIM data on highway 101. These graphs show density, velocity and flux recorded over 15-s intervals centred around the times shown at a sensor near the end of the highway (620 m from the start) [SWL11].*

The above-mentioned works were focused on simulating vehicles on freeways or large urban networks. Recently, Bi *et al.* [BMWD19] proposed a deep learning-based framework for traffic simulation at intersections. In order to describe the visual perception of vehicle-environment interactions, a grid coordinate system called *grid map* is built to encode interactions among heterogeneous vehicles mixed with pedestrians. As shown in Figure 13, a window with five channels sliding on the grid map can generate an environment matrix for each vehicle. The environment matrices capture the velocities and positions of vehicles and pedestrians around a vehicle. Besides environment matrices, vehicle identities based on a collected intersectional traffic data set are adopted to describe the current vehicle states. Then, convolution neural networks and recurrent neural networks are employed to learn the patterns of vehicle trajectories at intersections. Besides simulating intersectional traffic, it can also be used to alter existing intersectional traffic animation by providing vehicles new destinations and driving environments.

4. Validation and Evaluation

Broadly speaking, two types of virtual traffic evaluations could be performed: visual and statistical [TK04]. In the visual validation, graphical representations of the real-world traffic and the simulated traffic are displayed side by side to determine whether they can be differentiated [SVDBLM11, CSJ13]. In the work of Chao *et al.* [CDR*18], researchers conducted user studies [KS40] using pairwise comparison on the generated traffic flows with three different methods: (1) the ground-truth (i.e. the NGSIM traffic flow data), (2) the proposed texture-based traffic synthesis method [CDR*18] and (3) one of the latest developments of the IDM model [SJ12]. For each test scene, three different traffic flow animations are generated using the above three different approaches, respectively. As shown in Figure 14(a), participants are asked to select the more realistic one in a pair of two animation clips. In addition, the participants are allowed to select the "Undecided" option, if they cannot determine which clip is more visually appealing. To counter-balance the order of the visual stimuli, the pairs are displayed according to the Williams design latin square [Wil49]. The experiment outcomes of this user study are shown in Figure 14(b). In addition to the counted votes, the researchers also performed the one-sample *t*-test and the paired-sample *t*-test, and computed the corresponding *p*-value to quantify the statistical significance of the voting outcomes.

As subjective user studies are unavoidably time consuming and error-prone, statistical validation through quantitative and objective measures can be used not only for measuring the realism of various simulated traffic flows but also for objectively comparing the performance of different traffic simulation models in a consistent manner. For traffic simulation and animation techniques, direct trajectory comparisons are usually not performed due to the stochastic nature of traffic. Instead, comparisons of the averaged velocities

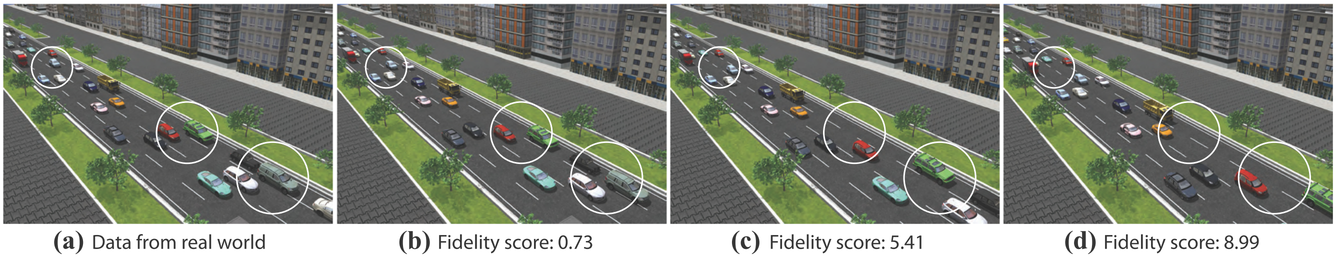

Figure 16: *Fidelity measure comparisons among three virtual traffic flows generated by the IDM model [SJ12] using three different parameter sets ((b)–(d)). The initial traffic states of the simulator were set to the same values as the real-world traffic flow (a). Differences between the simulated traffic and real-world ground truth are highlighted using white circles. For the dictionary-based fidelity evaluation, a smaller value of the metric indicates a higher fidelity of virtual traffic [CDX*18].*

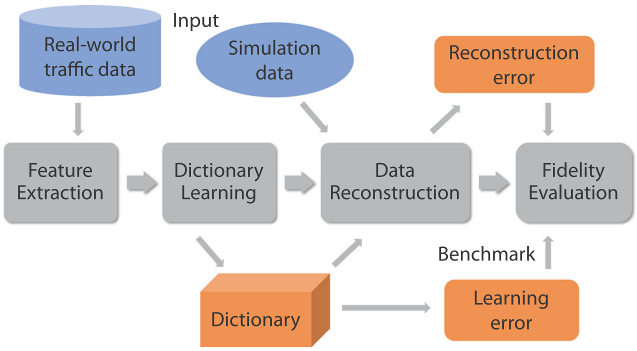

Figure 17: *The pipeline of the dictionary-based fidelity measure for virtual traffic [CDX*18]. The blue boxes show the to-be-evaluated input of the system, which contains real world traffic dataset and simulation data.*

and traffic volumes over time are common (e.g. Figure 15 from Sewall *et al.* [SWL11]). At a more detailed level, specific motion parameters, including velocity, acceleration and vehicle gap, have also been used to validate the effectiveness of traffic simulation techniques [CSJ13, BMWD16].

Recently, Chao *et al.* [CDX*18] introduced a general, dictionary-based learning method to quantitatively and objectively measure the fidelity of traffic trajectory data. First, a traffic-pattern dictionary that characterizes common patterns of real-world traffic behaviour is built offline from pre-collected ground-truth traffic data. The intermediate learning error is set to the benchmark of the dictionary-based traffic representation. With the aid of the constructed dictionary, the realism of input (simulated) traffic flows can be evaluated by comparing its dictionary-based reconstruction error with the benchmark dictionary error. As shown in Figure 17, this method consists of four stages: (1) the extraction of spatial-temporal traffic flow features, (2) dictionary learning (i.e. construction of the traffic pattern dictionary) from real-world traffic data, (3) dictionary-based reconstruction of any input traffic flow data and (4) the computation of a quantitative measure based on the reconstruction error. This evaluation metric can be robustly applied to any simulated traffic flows. Figure 16 shows the evaluation results of several different traffic data. The range of fidelity scores is set to [0..10]. If the simulated traffic is closer to the real-world (training) traffic data set, the fidelity score will have a smaller value, and vice versa.

5. Applications in Autonomous Driving

Autonomous vehicles have the potential to release people from driving a vehicle thus improving their productivity during a trip, increase the safety and efficiency of current transportation systems and transform transportation into a utility available to anyone, anytime. In this section, we will describe the recent developments in autonomous driving, including training data collection for autonomous driving (Section 5.1), deep-learning based motion planning methods(Section 5.2) and simulations for autonomous driving (Section 5.3).

5.1. Autonomous driving data sets

The traffic data sets mentioned in Section 3.1 are collected for traffic flow reconstruction and virtual traffic animation. Those data sets may not be useful for building an autonomous driving system. Knowing that training data are essential for autonomous driving, we survey existing driving data sets (described below), in the forms of first-view video, LiDAR data and GPS information under different traffic conditions. These data sets have facilitated the development of autonomous driving systems and the learning of various driving behaviours.

Jain *et al.* [JKR*15] collected a diverse data set with 1180 miles natural freeway and city driving behaviours from 10 drivers. Video clips from both inside and outside the car, GPS reports and speed measurements were recorded.

The *comma.ai* [SH16] data set is a public data set, which contains around 7.25 hours' highway driving data. The data set has been divided into 11 video clips. The released video has a resolution at 160×320. The speed, steering angles, GPS reports, gyroscope and IMU from several sensors were also recorded.

The Berkeley DeepDrive Video data set (BDDV) [GKB*16] consists of real driving video and GPS/IMU data. A variety of driving scenarios, such as cities, highways, towns and rural areas in several US major cities, were recorded. The BDDV contains over 10k hours dashboard-camera video streams.

The LiDAR-Video data set (LiVi-Set) [CWL*18] includes large-scale high quality point clouds from a Velodyne laser scanner and images from a dashboard camera. The Velodyne laser scanner collects point clouds in 360 degrees horizontal view and from -30.67 to $+10.67$ degrees vertical view. The total amount of point clouds data is around 1TB. The density is about 700 000 points per second. About 15G video clips were recorded via a dashboard camera. A recording software toolkit was remotely connected to the vehicle controller in order to obtain the velocity from on-board sensors. This data set covers various traffic conditions including arterial roads, primary roads, mountain roads, school zones and special tourist routes.

The Honda Research Institute Driving Dataset (HDD) [RCMS18] includes 104 hours of driving data in San Francisco Bay Area. A diverse set of traffic scenes is included. The total size of the post-processed data set is around 150GB and 104 video hours.

Drive360 [HDVG18] includes 60 h of driving video from eight surround-view cameras. Low-level driving maneuvers (e.g. steering angles and speed control) were recorded via the vehicle's CAN bus. The data have a high temporal resolution, 360 degrees view coverage, frame-wise synchronization and diverse road conditions.

Some other data sets without driving behaviours can also contribute to visual semantic understanding and vision-based control in autonomous driving. The KITTI data set [GLSU13, GLU12] is recorded using Foru high resolution video cameras, a Velodyne laser scanner and a localization system. This data set consists of 289 stereo and optical flow image pairs, stereo visual odometry sequences of 39.2 km length, and more than 200k 3D object annotations captured in cluttered environments. This data set is intended for the tasks of stereo, optical flow, visual odometry/SLAM (Simultaneous Localization And Mapping) and 3D object detection.

The Cityscape data set [COR*16] consists of a large, diverse set of stereo video sequences recorded on the streets of 50 cities. A total of 5000 of these images have high quality pixel-level annotations; 20,000 additional images have coarse annotations. The data set captures diverse street scenes in different seasons.

The Oxford RobotCar dataset [MPLN17] includes over 1000 km driving data with almost 20 million images collected from six cameras, along with LIDAR and GPS data, from a variety of weather conditions, including heavy rain, nigh, direct sunlight and snow. Because the recording time of this data set spans a year, some roads and buildings are subject to change. Another data set from Udacity [Uda] includes low-level driving maneuvers via the CAN bus.

Vision-based semantic segmentation of an urban environment is essential for autonomous driving. Various data sets have been proposed [RSM*16, TKWU17, WU18] including a wide variety of synthetic driving or street scenes of semantic segmentation, contributing to semantic understanding and vision-based control. A detailed comparison of different autonomous driving data sets is shown in Table 2.

It is worth noting that an autonomous driving data set can also contribute to traffic simulation and animation. To be specific, first, vehicle trajectories can be used to calibrate traffic simulation models; second, large-scale traffic data sets can enrich data-driven traffic synthesis methods; third, the evaluation of virtual traffic can benefit from various real-world traffic data sets.

5.2. Motion planning and decision-making

Motion planning and decision-making are critical for autonomous agents to navigate in their environments. In this section, we review several learning-based motion planning methods and decision-making algorithms for autonomous vehicles and other intelligent agents. We refer interested readers to additional review articles include [KQCD15, PČY*16, SAMR18] for further reading.

Pomerleau [Pom89] introduced ALVINN (Autonomous Land vehicle In a Neural Network), which has pioneered end-to-end approach for autonomous navigation. The ALVINN takes the images from cameras and laser range finders as the input to navigate a vehicle. Instead of taking the mediated perception for driving decision-making and the behaviour reflex with regressors approaches, Chen *et al.* [CSKX15] map several affordance measures in driving with images-based direct perception. A deep convolutional neural network (CNN) is trained based on the screenshots from a car racing video game TORCS with labels. This method was tested on car-mounted smartphone videos and the KITTI dataset [GLSU13].

With a variety of acquired traffic data sets and the development of advanced computing devices, more end-to-end deep learning frameworks for autonomous driving have been developed over the years. Bojarski *et al.* [BDTD*16] use CNN (called PilotNet [BYC*17]) to take the raw pixels from front-facing cameras as the input to produce steering behaviour. This framework is powerful for road following without manual decomposition and semantic abstraction. Gurghian *et al.* [GKB*16] presented an end-to-end deep CNN to estimate lane positions directly for the vehicles. The input images are from laterally mounted down-facing cameras, which provides a more optimized view than those from front-facing cameras for lane-marking.

Later, Xu *et al.* [XGYD17] use a FCN-LSTM framework based on a large-scale crowd-sourced vehicle action data to learn generic vehicle motion. This approach adopts a new paradigm to learn models from uncalibrated sources. After training, it can produce either discrete actions (e.g. straight, stop, left turn, and right turn) or a continuous action (e.g. lane following and steering control) for navigating an autonomous vehicle. Instead of learning autonomous driving model based on traffic videos data, the work by Chen *et al.* [CWL*18] demonstrates that extra information, such as LiDAR point clouds and videos recordings, can be useful for autonomous driving.

Lenz *et al.* [LDLK17] focus on vehicle motions at a highway entrance. They trained a deep neural network to predict vehicle motions using Partially Observable Markov Decision Processes. Kuefler *et al.* [KMWK17] adopt the Generative Adversarial Imitation Learning to learn driving behaviours. This approach overcomes the problem of cascading errors and can produce realistic driving behaviours. Hecker *et al.* [HDVG18] learn a novel end-to-end driving model by integrating the information from surrounding 360-degrees view cameras into the route planner. The network used in this approach directly maps the sensor outputs to low-level driving maneuvers including steering angles and speed. Kim *et al.* [KRD*18] introduced an end-to-end, explainable

Table 2: *Comparison of various autonomous driving datasets. .*

Data set	Intention	Driving behaviours	Driving time (h)	Areas	Camera view	Sensors & videos			Conditions
						Video image	LiDAR	GPS IMU	
KITTI [GLSU13] [GLU12]	Semantic & geometric understanding	–	1.4	City, Highway	Front-view	√	√	√	one weather condition, daytime
Cityscape [COR*16]	Visual semantic & geometric understanding	–	< 100	City	Front-view	√	–	√	multiple weather conditions, daytime
Comma.ai [SH16]	Driving behaviour learning	√	7.25	Highway	Front-view	√	–	√	night, daytime
BDDV [GKB*16]	Semantic & geometric understanding, driving behaviour learning	√	10k	City, Highway	Front-view	√	–	√	multiple weather conditions, daytime
Oxford [MPLN17]	Long-term localization & mapping	–	214	City	360-degree view	√	–	√	multiple weather conditions, daytime
Udacity [Uda]	Semantic & geometric understanding, driving behaviour learning	–	8	City, Highway	Front-view Left-view Right-view	√	√	√	multiple weather conditions
HDD [RCMS18]	Driving behaviour learning, causal reasoning	√	104	City, Highway	Front-view Left-view Right-view	√	√	√	multiple weather conditions, daytime
LiVi-Set [CWL*18]	Driving behaviour learning	√	20	City, Highway	Front-view	√	√	√	multiple weather conditions, daytime
Drive360 [HDVG18]	Driving behaviour learning	√	60	City, Highway	360-degree view	√	–	√	multiple weather conditions, daytime

driving approach for autonomous driving by incorporating a grounded introspective explanation model. This model consists of two parts: the first is a CNN-based visual attention mechanism that maps images to driving behaviours, and the second is an attention-based, video-to-text model for textual explanations of model actions. Yang *et al.* [YLWX18] exploit the virtual traffic data collected in CARLA and TORCS to predict vehicle behaviours, called DU-drive (Figure 18). Maqueda *et al.* [MLG*18] propose a deep neural network approach to predict the steering angles of vehicles.

Reinforcement learning has also been adapted for autonomous driving in recent years. Abbeel *et al.* [ADNT08] presented an efficient algorithm to mediate the trade-off between global navigation and the local planning for generating vehicle trajectories. Silver *et al.* [SBS13] presented a proper coupled cost functions for autonomous navigation systems to balance different preferences including where and how a vehicle should be driven. Lillicrap *et al.* [LHP*15] adopt a deep Q-Learning algorithm to implement an actor-critic, model-free system that learns a policy to lead a vehicle to stay on the track in a simulated driving environment. Kuderer *et al.* [KGB15] proposed a feature-based inverse reinforcement learning method to learn individual driving styles for autonomous driving. Wolf *et al.* [WHW*17] presented a Deep Q-Networks to steer a vehicle in 3D physics simulations. In this approach, the goal of a vehicle is to follow the lane to complete laps on arbitrary courses, and an action-based reward function is motivated by a potential in real word reinforcement learning scenarios. Pan *et al.* [PYWL17] use a novel realistic translation network to train an

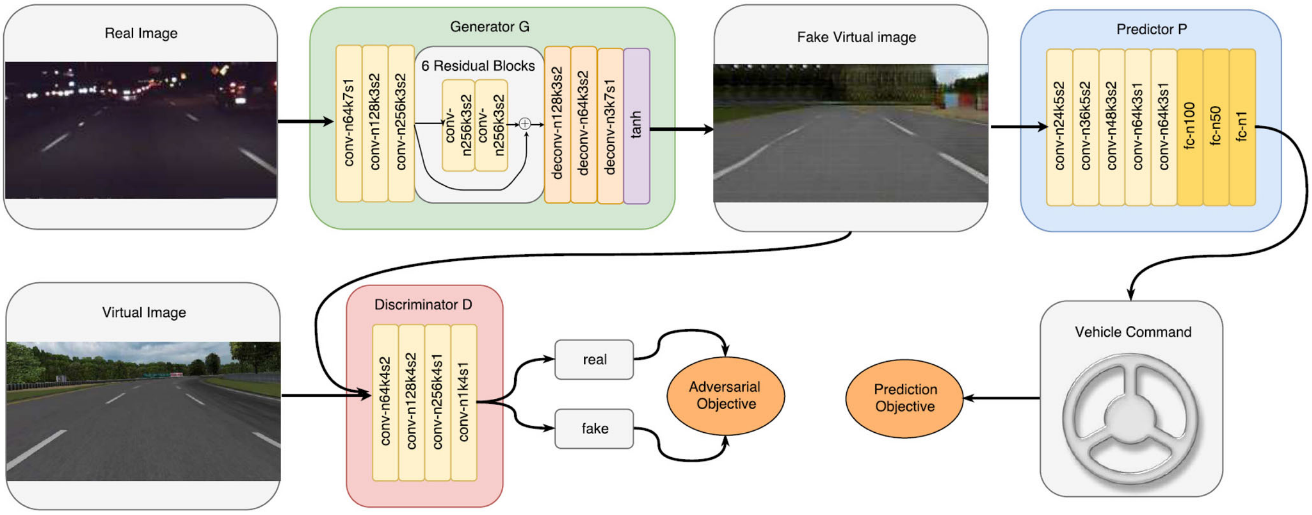

Figure 18: *The architecture of DU-Drive [YLWX18]. The model is closely related to conditional GAN. The generator network* G *transforms a real image to a virtual image, from which the vehicle command is predicted by the predictor network* P*. The discriminator network* D *distinguishes fake virtual images from true virtual images. Both the adversarial objective and the prediction objective drive the generator* G *to produce the virtual representation that yields the best prediction result.*

autonomous driving model in a virtual environment and then use it in the real-world environment. In this virtual-to-real reinforcement learning framework, the images from virtual environment are segmented to scene-parsing representations first and then are translated to synthetic images. Liang *et al.* [LWYX18] presented a general Controllable Imitative Reinforcement Learning approach to alleviate the low exploration efficiency for a large continuous action space. Based on the vision inputs directly from the CARLA simulator, autonomous driving can be achieved with a high success rate.

In order to efficiently and safely navigate vehicles in complex traffic environments, autonomous vehicles need to forecast the motions of surrounding vehicles. The interaction among vehicles and pedestrians should be accurately represented [LVL14]. The task of trajectory prediction can be divided to several categories: physics-based, maneuver-based and interaction-aware models. Also, a significant amount of deep learning based works have been done for human trajectory prediction [AGR*16, VMO18, GJFF*18, MA18, SKS*19, XPG18, HST*18]. Here we limit our focus to vehicle trajectory prediction using deep neural networks.

Lee *et al.* [LCV*17] proposed a Deep Stochastic IOC RNN Encoder-decoder framework to predict future distances for interacting agents in dynamic scenes, which can produce accurate vehicle trajectories in driving scenarios. Kim *et al.* [KKK*17] proposed an LSTM-based probabilistic vehicle trajectory prediction approach which uses an occupancy grid map to characterize the driving environment. Deo and Trivedi [DT18] adopt a convolutional social pooling network to predict vehicle trajectories on highways. The whole network includes an LSTM encoder, convolutional social pooling layers, and a maneuver-based decoder. Specifically, it first uses an LSTM encoder to learn vehicle dynamics based on track history. Then, it uses convolutional social pooling layers to capture the inter-dependencies of the trajectories of all vehicles, and finally it trains a maneuver-based LSTM decoder to predict a distribution of future vehicle trajectories.

5.3. Simulation for autonomous driving

Although the development of machine learning approaches largely facilitates the motion planning and decision-making in autonomous driving, the amount of real-world data is still insufficient to cover many complex traffic scenarios, thus constraining autonomous driving systems from learning diverse driving strategies and, more importantly, recovery actions in dangerous situations. This makes unmanned vehicles always adopt the most conservative and inefficient decisions for safety reasons. It has been reported that autonomous vehicles have caused some fatal accidents. These observations have stimulated the development of a high-fidelity driving simulator as an alternative and effective tool to provide various types of traffic conditions for training autonomous vehicles. In addition, a simulator can enable comprehensive and thorough safety tests of an autonomous vehicle before its deployment in the real world [ARB*15, APPI11, LF09].

In fact, simulation has been used for training driving models since the early days of autonomous driving research [Pom89]. Later, racing simulators have been used to evaluate various driving approaches. For example, Chen *et al.* [CSKX15] use TORCS [WEG*00] to evaluate the proposed direct perception model for autonomous driving. Recently, researchers [RVRK16, JRBM*17, RHK17] leverage Grand Theft Auto V (GTA V) to derive autonomous driving policies, which result in comparable performance to control policies that derived from manually annotated real-world images.

CARLA [DRC*17], as an open-source simulator, has been developed to support development, training and validation of autonomous

Figure 19: *A street traffic in the CARLA Simulator [DRC*17], shown from a third-person view in four weather conditions. Clockwise from top left: clear day, daytime rain, daytime shortly after rain and clear sunset.*

urban driving models. This simulation platform supports flexible setup of sensor suites and provides signals that can be used to train driving strategies. The signals include GPS coordinates, speed, acceleration/deceleration and detailed data on collisions. A wide range of environmental factors can be specified, including weather and time of day (Figure 19). With these settings, CARLA has been used to study the performance of many autonomous driving approaches, including classic modular approaches, end-to-end trained models via imitation learning and end-to-end trained models via reinforcement learning.

Best *et al.* [BNP*18] presented AutonoVi-Sim, a high-fidelity simulation platform for autonomous driving data generation and driving strategy testing. AutonoVi-Sim is a collection of high-level extensible modules. Similar to CARLA, it also supports specification of vehicle sensor systems and the changing of time of day and weather conditions, and movements of non-vehicle participants in traffic such as cyclists and pedestrians.

In addition, several recent projects seek to build simulation platforms to train end-to-end driving systems and provide rich virtual traffic scenarios for the testing of autonomous driving. An example project is Apollo [apo18], which incorporates a large amount of driving data from actual traffic and virtual traffic. The goal of Apollo is to create a powerful virtual close-loop for the development of autonomous driving systems: from algorithms to evaluation, and back to updating algorithms. One limitation of Apollo is that the virtual traffic data are created manually with specific and well-defined obstacles and traffic signals, which are less realistic and complex than real-world traffic conditions.

Recently, Li *et al.* [LPZ*19] have developed a simulation framework, AADS, which can augment real images with simulated traffic flows for generating realistic-looking images. Using data from LiDAR and cameras, the framework can compose simulated traffic flows, based on actual vehicle trajectories, into the background. The composite images could be altered to different viewpoints and are fully annotated, which are ready to be used for development and testing of autonomous driving systems. This framework aims to overcome the burden of manually developing virtual environments and the degraded performance of training autonomous vehicles using virtual images.

Another framework developed by Li *et al.* [LWL19], ADAPS, takes a different perspective—enabling learning autonomous driving from accidents. The framework consists of two simulation platforms. The first simulation platform runs in 3D and is used to test a learned policy and simulate accidents; the second simulation platform runs in 2D and is used to analyse an occurred accident in the first simulation platform and resolve the accident by providing alternative safe trajectories. A large quantity of annotated data is then generated based on the safe trajectories for training and updating a control policy. ADAPS also represents a more efficient online learning mechanism compared to previous techniques such as DAGGER [RGB11], which can greatly reduce the number of iterations required to derive a robust control policy.

6. Discussion

In this section, we discuss potential future research directions.

First, a traffic simulation model should be able to model as many complex traffic behaviours as possible, while maintaining the computational efficiency. However, for existing microscopic traffic models, each behaviour of the vehicle, such as acceleration/deceleration and lane-changing, is individually modelled and controlled. In addition, microscopic traffic models focus more on the vehicle movement in forward direction, which is limited in a way that lane-changing behaviours, and vehicle lateral motions in general, are ignored. In addition, as the motion of a vehicle is mainly affected by its leading vehicle according to the car-following rule, the resulting simulation rarely involves other vehicles in the field of view for computing the acceleration/deceleration. In order to simulate more realistic traffic flows, it is necessary to develop a unified, scalable simulation framework for rich vehicle behaviours, including acceleration/deceleration, staying in lane, lane changing and interactions with non-vehicle traffic participants (e.g. pedestrians and bicyclists).

Second, despite of many successful demonstrations, current data-driven traffic animation approaches cannot handle non-trivial interactions between vehicles and other moving objects (e.g. pedestrians). One of the main reasons is that it is a daunting task to acquire large-scale, spatial-temporal data of vehicles, pedestrians and the environment factors at the same time. For traffic reconstruction, in-road sensors and GPS data, as two types of traffic data, are usually utilized separately in computation. Meanwhile, the accuracy of traffic reconstruction is limited by the available data. Thus, combining various data sources, such as in-road sensors, video streams and GPS traces, has the potential to improve the reconstruction accuracy.

Third, regarding the evaluation of fidelity of virtual traffic, the dictionary-based metric [CDX*18] provides a feasible solution. However, as a common problem with data-driven methods, the quality and composition of traffic data have a direct and substantial impact on the generated dictionary, therefore affecting the evaluation outcome. In addition, this framework extracts each vehicle's acceleration, velocity, relative speed and gap distance to its front vehicle to describe the vehicle's instantaneous states. To better capture traffic patterns for dictionary learning, more features on traffic flow, including vehicle kinematic constraints, road restrictions and driver characteristics should also be considered and extracted. For macroscopic traffic simulation, it is necessary to develop fidelity metrics that can measure traffic flows in an aggregate fashion, including flow density and velocity.

Finally, for autonomous driving, addressing the interactions between autonomous vehicles and other road users remains a challenge. Existing simulators consider less mutual influences between the two parties. To give some examples, in the Apollo simulation platform [apo18] and the work of [BNP*18], both simulations implement two types of non-vehicle traffic participants: pedestrians and cyclists. However, the behaviours of these non-vehicle agents are pre-defined, so they cannot react to vehicles in real time. In addition, although dynamic pedestrians are introduced in CARLA [DRC*17], the interactions between vehicles and pedestrians are handled in a simple, pre-specified way: Pedestrians will check if there are any vehicles nearby before their movements, then continuing the movements without further checking.

7. Conclusion

Methods for modelling and simulating traffic flows have seen considerable progress since their introduction nearly 60 years ago. In Computer Graphics, various traffic simulation techniques based on traffic flow models have been proposed in the last decade. In addition, with advancements in sensing technology, many data-driven approaches have been proposed for developing traffic animation and simulation. The increasing amount of traffic data from various sensors can also contribute to the development and testing of autonomous driving algorithms.

In this report, we survey the key traffic simulation and animation techniques, emphasizing, but not limited to, the discussion from the computer graphics perspective. A subset of these methods focuses on simulating traffic flow based on macroscopic, microscopic and mesoscopic flow models. Other methods utilize the collected traffic data to reconstruct traffic, synthesize new traffic flows or learn characteristics of various traffic patterns. Various evaluation and validation techniques of virtual traffic are also discussed.

As an important application, recent developments in autonomous driving using traffic simulations are also presented. Especially, we have focused on data-driven methods, motion planning techniques, decision-making algorithms and simulators created for autonomous driving development. We have also explored some research challenges and future directions.

In conclusion, traffic simulation and animation will continue to evolve and advance. Many exciting applications and novel approaches remain to be explored and developed. In terms of autonomous driving research, we believe that the various models and applications discussed in this survey would stimulate interesting research topics for years to come.

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