A SURVEY ON VISUAL TRAFFIC SIMULATION: MODELS, EVALUATIONS, AND APPLICATIONS IN AUTONOMOUS DRIVING

SEMINAR REPORT

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DECLARATION

I undersigned hereby declare that the seminar report, **"A Survey on Visual Traffic Simulation: Models, Evaluations, and Applications in Autonomous Driving"** submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of **Prof. Vipin Vasu A V**. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

Place: Trivandrum **Adithya D Rajagopal**

Date: August 22, 2020

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
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CERTIFICATE

This is to certify that the Seminar entitled **"A Survey on Visual Traffic Simulation: Models, Evaluations, and Applications in Autonomous Driving",** is a bonafide record of the Seminar work done by **Aditya D Rajagopal**, in the partial fulfilment of the requirement for the award of Degree of Bachelor of Technology in Computer Science and Engineering from **APJ ABDUL KALAM TECHNOLOGICAL UNIVERSITY, KERALA.** This work is done during the academic year 2020-2021.

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ABSTRACT

Virtual traffic via various simulation models and animation techniques using real-world traffic data are promising approaches for reconstructing detailed traffic flows. Many applications such as video games, virtual reality, autonomous driving etc. can profit from virtual traffic simulation. In this survey, a comprehensive review on the state-of-the-art techniques for virtual traffic simulation and animation are given.

Initially, a discussion on three classes of traffic simulation models are discussed. Then, various data-driven animation techniques and the validation and evaluation methods of simulated traffic flows are introduced. Next, the application of virtual traffic simulation models for the training and testing of autonomous vehicles is discussed. Finally, the current states of traffic simulation and animation is discussed and future research directions are suggested.

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Chapter 1

Introduction

Visual traffic is a trending topic among a wide variety of research communities such as autonomous driving, computer games, urban planning and visualization etc. Urban scenes are a necessity in virtual reality, computer games and animation, which consists of many vehicles moving around. Keyframe methods can be used to control the motion of a single vehicle. However, keyframe methods are not feasible for simulating traffic congestion, pedestrian-vehicle interactions and lane-changing in large-scale traffic scenarios as it requires complex design and repetitive adjustments from the animator. Another limitation of using keyframe methods is that the vehicle movements obtained hardly follow any physical laws. Thus, effective simulation of large-scale traffic flow has become a vital topic in the field of computer graphics. Moreover, including real-time traffic flow into virtual road networks has become critical due to the popularity of road network visualization tools like Google Maps, Open-StreetMap etc. Also, incorporating actual trajectories into virtual application is a very difficult task. These trends have motivated research efforts on data-driven traffic simulation.

Additionally, virtual traffic simulation is also applied in transportation research. Nowadays, virtual reality based driving programs are being used to help new drivers to learn and improve their driving skills in realistic traffic environments. Traffic simulation can also be used to generate various conditions for training and testing autonomous vehicles.

The increasing amount of vehicular traffic and complex road networks is causing several traffic related problems like traffic jams, signal control, incident management and network design optimization. Such problems are tough to solve using conventional tools based on analytical models. Hence, advanced computing technologies are used, at present, for the modelling, simulation and visualization of traffic. Such technologies can be used for various purposes such as analysing traffic conditions for signal control, assisting traffic reconstruction in urban development etc.

One major focus of virtual traffic simulation is to understand how the traffic would evolve, given a road network, vehicle states and a behavioural model. Traffic models are roughly classified into three types, macroscopic models (10), microscopic models (2) and mesoscopic models (11). Macroscopic models treat the collection of vehicles as a continuous flow, whereas microscopic models consider the dynamics of each individual vehicle under the influence of its surrounding vehicles. Mesoscopic models combine the merits of both both macroscopic and microscopic models for the simulation of traffic. The generation and representation of road networks is also one of the major problems in virtual traffic simulation.

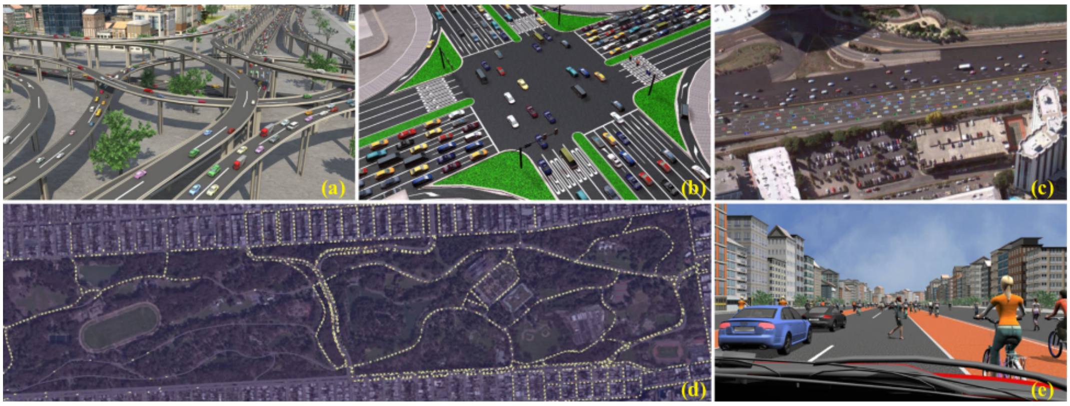


Figure 1.1: The generated traffic flows via various traffic simulation and animation approaches: (a) synthesized traffic flows on a highway network (1), (b) a dense traffic scenario with signalized crossing (2), (c)the reconstruction of virtual traffic flows using in-road sensor data (3), (d) the reconstructed city-scale traffic using GPS data (4), (e) a heterogeneous traffic simulation used for autonomous driving testing (5).

Although the above mentioned traffic models are effective in catching high-level flow appearance, the resulting simulations usually do not resemble real-world traffic. With the evolution of advanced sensors and computer vision techniques, experimental traffic flow data sets in the forms of video, LiDAR and GPS sensors are becoming increasingly available.

This gives rise to data-driven virtual traffic simulation techniques. Examples include the synthesis of new traffic flows from trajectory samples (Figure 1.1 (a)) (1), reconstruction of traffic flows from spatio-temporal data obtained by in-road sensors (Figure 1.1 (d))(4) and generation of traffic flows by learning behaviour patterns and individual characteristics from data sets (15).

Even though noteworthy advancements have been achieved in virtual traffic simulation and animation, the originality of the simulated traffic is under-explored. Also, in model-based traffic simulation and data-driven methods, the validation of the model in terms of resemblance between simulated and real traffic is always a concern. The current approaches address these problems by using subjective user evaluations and including objective evaluation metrics into the calculation (17).

Virtual traffic simulation techniques is also used for training autonomous vehicles. Autonomous vehicles have the potential to transform our transportation systems. But, continuous failures in testing have made it mandatory for these autonomous vehicles to be trained in virtual environments before deploying them into the real world.

The working of autonomous vehicles is usually tested using a single interfering vehicle or pedestrian with predefined behaviours in virtual environment (29). An autonomous vehicle will gradually gain the ability to handle complicated traffic scenarios in complex urban environments when trained in simulated traffic flows with rich interactions among various road users. Traffic simulation and animation can also benefit from learning based motion planning and decision-making algorithms developed for autonomous vehicles. With an increase in the number of driving data sets, more accurate traffic simulation models can be developed. This would in turn benefit the motion planning and decision-making of autonomous vehicles.

A high-fidelity driving simulator, which includes realistic traffic flows in complex traffic conditions is necessary for safe autonomous driving. Such a simulator can produce more accurate training environments in a reproducible manner. This report will describe the advancements in autonomous driving from three aspects: data acquisition, motion planning and simulations for testing.

1.1 Overview

The remainder of the report is organized as follows. In Chapter 2, the different types of model-based traffic simulation methods and road network generation techniques are discussed. Data-driven traffic simulation techniques based on various data acquisition methods are discussed in Chapter 3. The validation and evaluation of the generated virtual traffic is surveyed in Chapter 4. Chapter 5 focuses on the application of virtual traffic simulation for the development of autonomous driving models. Finally, Chapter 6 conclude the survey by discussing the current states of existing studies and the future research directions on this field.

Chapter 2

Model Based Traffic Simulation

A vital component in virtual traffic simulation is portraying the motions of vehicles at various levels of detail. The research on modelling and simulation of traffic flows dates back to 1950s, when the prototypes of macroscopic and microscopic traffic models were proposed (6). After several years of development, traffic simulation techniques (Figure 2.1) is roughly classified into three: macroscopic, microscopic and mesoscopic (Figure 2.2).

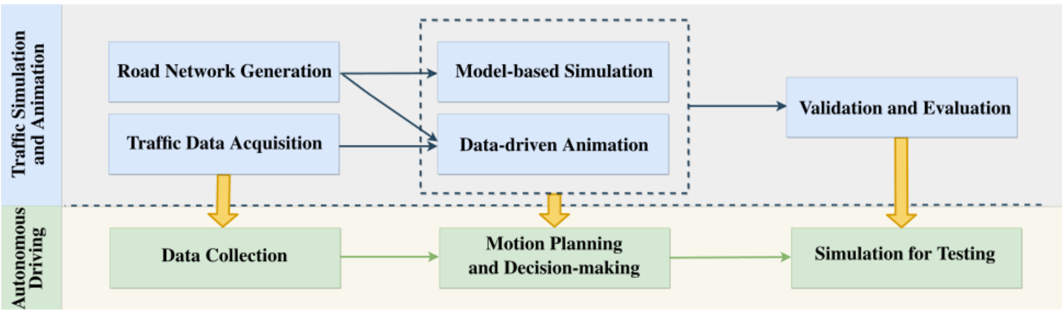


Figure 2.1: Schema of traffic simulation and animation components introduced in this survey.

Traffic flows can be considered as a type of crowd flow. The vehicles in traffic flow share similar goals and behavioural rules, interacting with neighbours while preserving individual driving characteristics. Simulation of crowd flows has been an important research are in computer graphics. Crowd simulation can be achieved either in a macroscopic manner (Modelling the crowd as a whole by ignoring the realistic motions of individual agents) or a microscopic manner (Modelling the crowd as a collection of movements from individual agents).

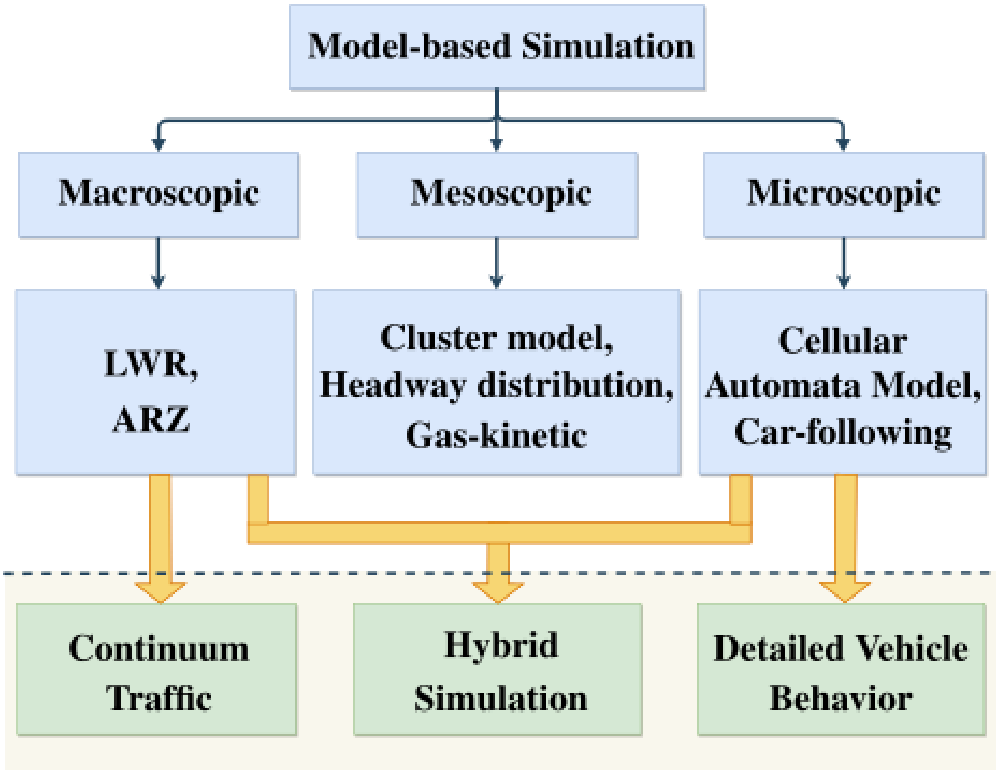


Figure 2.2: Classification of model-based traffic simulation methods based on the levels of detail which these models simulate. Here, LWR and ARZ refer to two popular macroscopic traffic models proposed by Lighthill.Whitham.Richards (6; 7) and Aw.Rascle.Zhang (8; 9), respectively.

2.1 Macroscopic Methods

Macroscopic methods, also known as continuum methods, are used to describe the vehicles' behaviours and interactions at a low level of detail. In this method, a traffic stream is represented by a continuum in terms of speed, density, flow, etc. They are designed for effective traffic simulation on a large-scale road network. Macroscopic methods focuses on replicating aggregated behaviours measured with collective quantities such as flow, density, traffic flux, etc.

One of the earliest first-order continuum models called the LWR model was developed by Lighthill and Whitham (6) and Richards (7). The LWR model assumes that the rate of flow of traffic depends only on the traffic density. Based on the similarities between one-dimensional gas dynamics and the evolving of traffic flows on a single lane, this model shapes a non-linear scalar conservation law for modelling traffic flows. Essentially, the LWR model describes the motion of large-scale traffic flows with low-resolution details. One of the limitations of the LWR model is that it cannot construct the motion of vehicles under non-equilibrium conditions, such as stop-and-go waves.

Later, a continuous second-order model, the PW model, was proposed by Payne and Whitham. The second-order model describes the traffic velocity dynamics rather than the fixed equilibrium state described by the first-order model. The limitation of PW model is that it can introduce negative velocities and speeds grater than the vehicle velocity. Aw and Rascle (8) and Zhang (9) modified the PW model in order to remove its non-physical behaviours. Aw and Rascle (8) introduced a pressure term to make sure that no information travels faster than the velocity of the vehicle. Zhang (9) modified the momentum equation of the Payne-Whitham model to handle the problem of negative velocities. The resulting model is referred to as the ARZ model. The ARZ model has proven to be better than the LWR model in terms of resemblance with real-world scenario.

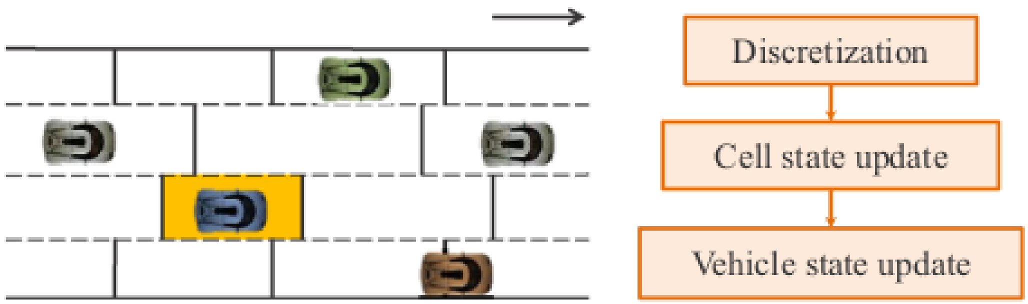


Figure 2.3: Illustration of the macroscopic traffic simulation approach (10). Each lane is divided into discrete cells. At a given time step, the states of each cell are updated by solving the ARZ equations, which solutions are then used to update the states of each vehicle in each lane.

For producing detailed three dimensional animation and visualization of traffic flows, Sewall et al. (10) presented a macroscopic traffic simulation model to generate realistic traffic flows on large-scale road networks. They modified the single-lane ARZ model so as to handle multi-lane traffic by developing a lane-changing model and using a unique representation for each vehicle. The flow of traffic in this model was simulated by discretizing each lane into multiple cells (Figure 2.3). In order to simulate lane-changing and lane-merging behaviours, Sewall et al. combine macroscopic dynamics with unique vehicle representations.

To sum up, macroscopic traffic models are efficient tools to simulate large-scale traffic flows. However, such models are not apt for simulating street-level traffic which involves rich interaction among individual vehicles. Also, since these models do not simulate lane-changing behaviours of a vehicle, these models cannot handle density transfer during the lane-changing process.

2.2 Microscopic Methods

Microscopic methods are used to produce vehicle motion at a high level of detail. In such models, each vehicle is considered a discrete agent satisfying certain rules. A number of microscopic models have been developed for urban traffic simulations, owing to their flexibility in modelling heterogeneous behaviours of discrete agents, diverse road topologies and interactions with pedestrians and surrounding vehicles.

Early examples of microscopic models include the cellular automata model and car-following models. In the cellular automata model, the motions of vehicles are described by evolution rules in pre-determined time, space and state variables. In other words, the model discretizes the road into cells and determines when a vehicle will move from current cell to the next cell. Due to its simplicity, this model is computationally efficient and can be used for simulating a large number of vehicles in a large-scale road network. But, thanks to its discrete nature, the simulated virtual traffic can only replicate a limited amount of real-world traffic behaviours.

On the other hand, car-following models, first launched by Pipes and Reuschel, can simulate realistic traffic behaviours and detailed vehicle characteristics at the expense of computation efficiency. These models assume that the traffic flow consists of scattered particles and model detailed interactions among the vehicle. They represent the position and velocity of each vehicle through continuous-time differential equations.

Over the decades, several variations and extensions of the car-following model have been developed. Two popular examples are the optimal velocity model (OVM) and the intelligent driving model (IDM). In the optimal velocity model, the vehicle under consideration is assumed to maintain its optimal velocity. The acceleration of the subject vehicle is determined by the difference between its velocity and the optimal velocity of the vehicle in front. In the intelligent driving model, the acceleration of the subject vehicle is determined by its current speed and relative position and speed to the vehicle in front. The vehicle-specific variables enable the intelligent driving model to simulate various vehicle types and driving techniques.

Other than simulation of traffic flows on a single lane, multi-lane simulation of traffic have also been explored. Some notable examples for multi-lane traffic models are modified optimal velocity model and two-lane traffic model. The former is used to simulate traffic on a dual-lane highway and a single-lane highway with an on-ramp, while the latter is used to simulate traffic lateral effects.

Shen and Jin (2) proposed an enhanced intelligent driving model with a continuous lane-changing technique to generate detailed traffic simulations. Their model can generate traffic flows with smooth acceleration/deceleration and flexible lane-changing behaviours. The model modifies the intelligent driving model so as to make it more suitable for urban road networks. Precisely, the acceleration process was separated into a free-road acceleration term to describe the driver's intention to reach desired velocity, and the deceleration term to describe the driver's intention to keep safe distance from nearby vehicles. The deceleration term is altered by adding an activation governing control part for generating smoother response to stopped vehicles. Moreover, the model divides the lane-changing behaviour into two scenarios: free and imperative lane-changing, and provides a flexible and continuous model in both scenarios.

Free lane changing usually occurs in a free road condition. This behaviour is modelled by the double-lane MOBIL model from Kesting et al. Imperative lane-changing is applied when the vehicle under consideration demands a lane-change due to some imperative factors such as reaching the end of the current lane, an accident vehicle appears in front in the current lane or a guidance sign appears at the road crossing (Figure 2.4).

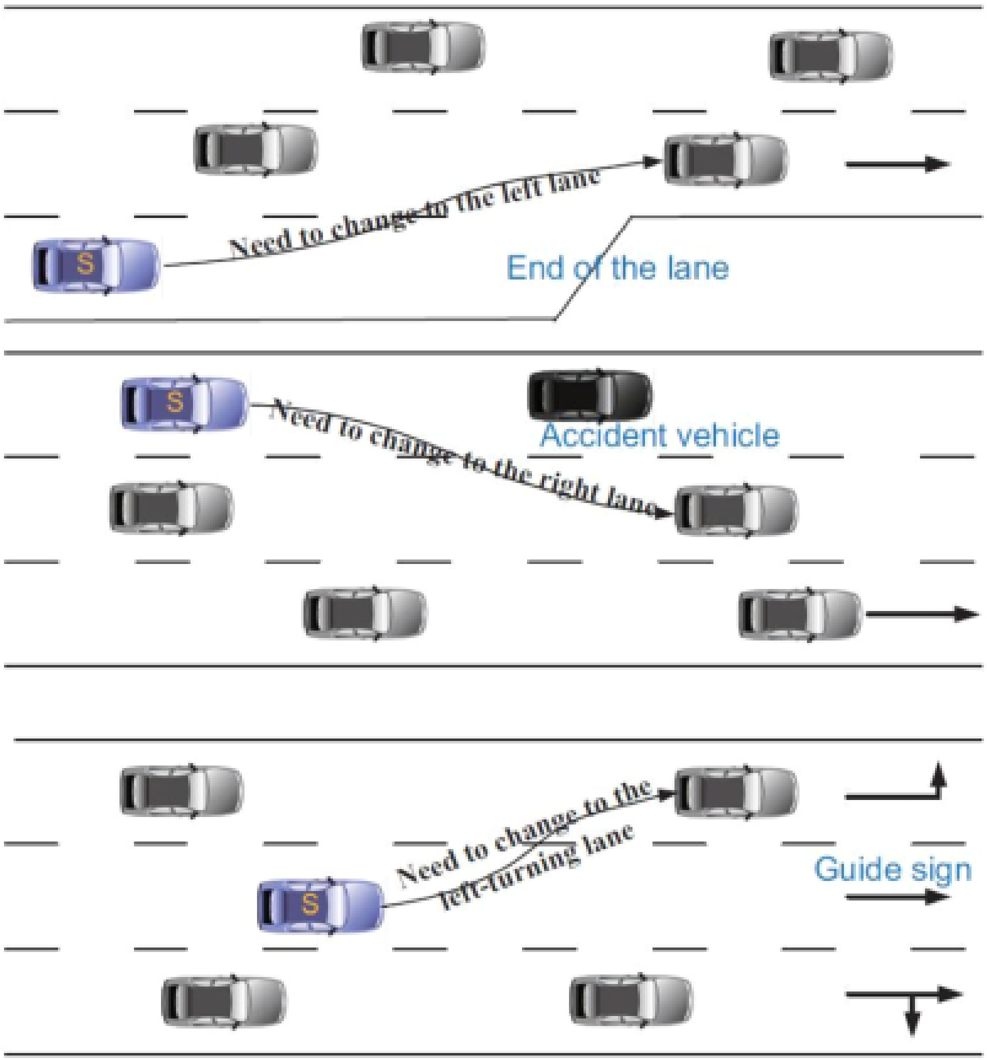


Figure 2.4: Situations where a vehicle must change its lane (2): (a) reaching the end of the current lane, (b) an accident vehicle appears in front in the current lane, and (c) a guidance sign appears at the road crossing.

Simulating traffic at intersections is more difficult compared to simulating traffic on lanes. A multi-agent behavioural model for traffic simulation was proposed by Doniec et al. This model treats intersectional traffic as a multi-agent coordination task. In other words, each vehicle perceives the surrounding traffic and makes their own decisions. An anticipation algorithm is used to generate anticipation abilities for the simulated vehicles. Wang et al. launched the concept of shadow traffic to model traffic anomalies in a unified manner.

Chao et al. designed a rule-based process for modelling interactions between vehicles and pedestrians in mixed traffic simulations.

On the whole, microscopic models can be used to simulate traffic in both lanes and intersections. The disadvantage is that the computational cost will be higher, particuarly when a large-scale simulation is needed.

A Hybrid Method

Sewall et al. (11) combined the macroscopic an microscopic approaches and proposed a hybrid method for traffic simulation. Their model simulates large-scale traffics using macroscopic models, while the modelling of individual vehicles is done using microscopic models (Figure 2.5). By switching between the two models, their approach can simulate traffic under different levels of detail.

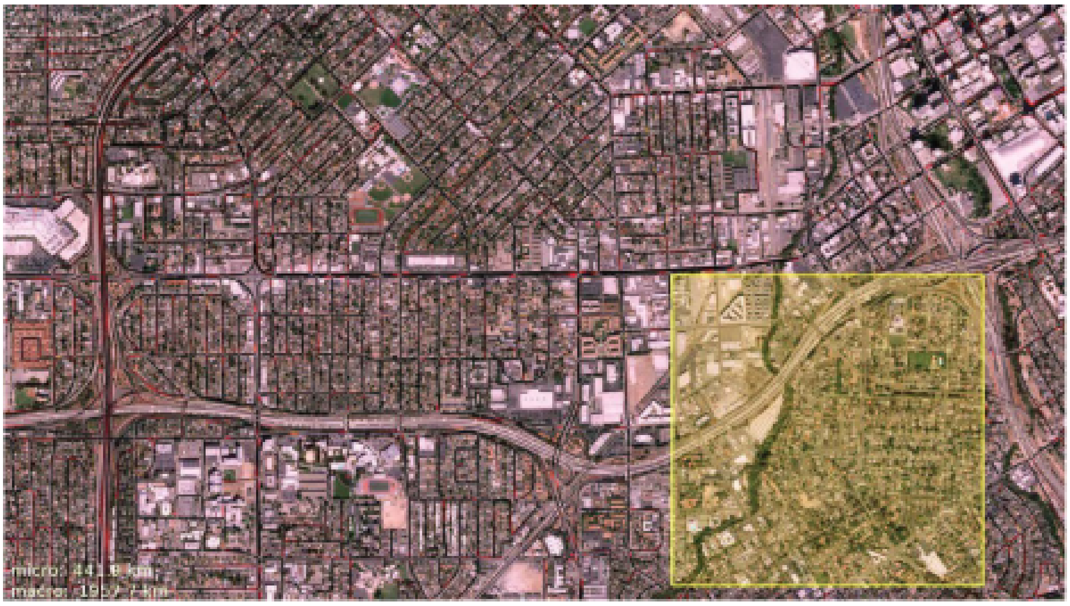


Figure 2.5: Illustration of a hybrid traffic simulation method (11). The traffic within the yellow bounding box is simulated using a microscopic model, while the rest traffic is simulated using a macroscopic model.

2.3 Mesoscopic Methods

Mesoscopic methods lie in between macroscopic and microscopic models. The idea of mesoscopic models is to describe traffic flow dynamics in a complete manner while representing the behaviours of individual vehicles using probability distribution functions. Mesoscopic models are further categorised into three classes: cluster models, headway distribution models and gas-kinetic models. The cluster models describe groups of vehicles with same characteristics and, in turn represent traffic flow dynamics. The headway distribution models emphasize on the statistical properties of time head-ways.

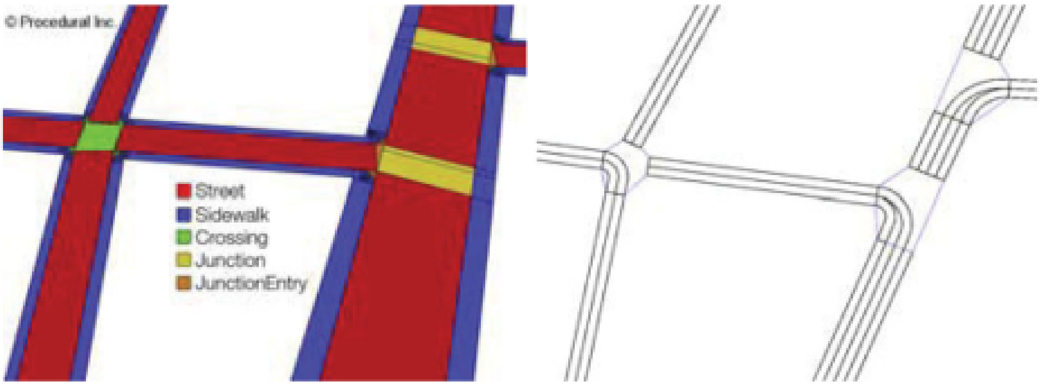
The most popular class of mesoscopic models is the gas-kinetics model. The gas-kinetics model draws an analogy between gas dynamics and traffic dynamics. They are usually not applied in traffic simulations but are used to derive other macroscopic models for transportation engineering.

Mesoscopic models are rarely used in traffic simulations due to many uncertainties like unknown parameters and complex integral or differential terms. This limits the simulation and animation efficiency of virtual traffic simulation using mesoscopic methods.

2.4 Road Network Generation

Traffic simulation may be defined as the interaction between the vehicles and the road network. The modelling of the underlying road network is an important and challenging task. Digital representations of real-world road networks are available in abundance but cannot be directly used for simulating traffic. Traffic simulations using macroscopic and microscopic models take place on a road network formed with lanes. A road network consists of many features like lanes, intersections ramps, etc. A number of methods have been proposed for modelling and representing a road network.

Parish et al. proposed a system called CityEngine (12), which uses a procedural approach based on L-system to simulate a road network (Figure 2.6(a)). The system generates a set of highways and streets by taking map images as inputs. Several road network generation models have been developed by improving the CityEngine model. For example, Chen et al. developed a road network generation model where the users can edit the road network directly. Recently, an interacive road design system using statistical information was developed by Nishida et al.



(a) (b)

Figure 2.6: A road network created using (a) CityEngine (12), (b) the technique from Wilkie et al. (13)

Wilkie et al. (13) proposed a road network generation model (Figure 2.6(b)) to automatically transform low-detailed GIS (Geographic Information System) data into high-detailed functional road networks. The sole objective of this model is to improve the visualization of vehicle motions. The lane-centric structure and the arc road representation can be simulated using this model. The model manages an intersection using traffic signals and prearranged moving priorities. This model has inspired many more lane-based simulation models. For example, Mao et al. facilitates complex traffic simulations by modelling lanes based on the road axis.

In summary, traffic simulation at different levels require different information concerning the underlying road network. In general, macroscopic traffic simulation models require geometrical information of a road network to model the speed and the propagation of density of the traffic flow. On the other hand, microscopic traffic simulation models require more information concerning the underlying road network like lane separation and joining, signal logic, moving priorities at intersections, etc.

Chapter 3

Data-driven Traffic Simulation

In this section, the acquisition of real-world traffic data and different data-driven approaches for traffic reconstruction and synthesis are explored.

3.1 Traffic Data Acquisition

Traffic sensors are used to acquire traffic data. They are generally of two types: fixed sensors and mobile sensors. Examples for fixed sensors are video cameras which are used for monitoring traffic and inductive-loop sensors which are placed on highways to record the attributes of each vehicle. Apart from fixed sensors, mobile sensors are also omnipresent. Examples for mobile sensors are cell phones and GPS devices that are used to record the speed and position of the vehicle.

The inductive-loop sensor has become the most widely used sensor since its introduction in the early 1960s. It can sense the vehicles passing or arriving at a certain point. An insulated, electrically conducting loop is installed a the base of the sensor. When a vehicle passes over of stops within the detection area, the inductance of the loop decreases. The electronic unit detects the decrease in inductance as a decrease in frequency and sends a signal to the controller to denote the passage or presence of a vehicle. This sensor usually senses the passing time, lane id and velocity of the vehicle.

Video camera has also been widely used as an over-roadway sensor. An example for the usage of video cameras is the Next Generation Simulation (NGSIM) (14), in which cameras are deployed along the road that captures traffic data at 10 frames per second. The obtained data set encloses detailed vehicle trajectories. Table 3.1 lists four NGSIM data sets in terms of road length, road type, record time and number of vehicles, respectively. Figure 3.1 illustrates the data collection in US 101 Highway, where eight synchronized video cameras are installed on the top of a 36-storey building adjacent to the Highway, recording vehicle details passing through the area. NGSIM video (14) automatically extract the vehicle trajectories from images so as to process the large amount of data captured. Nowadays, mobile sensors such as GPS are becoming increasingly available and are used to estimate traffic conditions. Attributes such as locations, speed directions of a vehicle can be obtained using the mobile sensors. After, processing, the useful information can be broadcasted to the drivers on road. The major limitation of GPS data is that the difference between two consecutive points can be large. Therefore, several processing steps are required to reconstruct traffic dynamics.

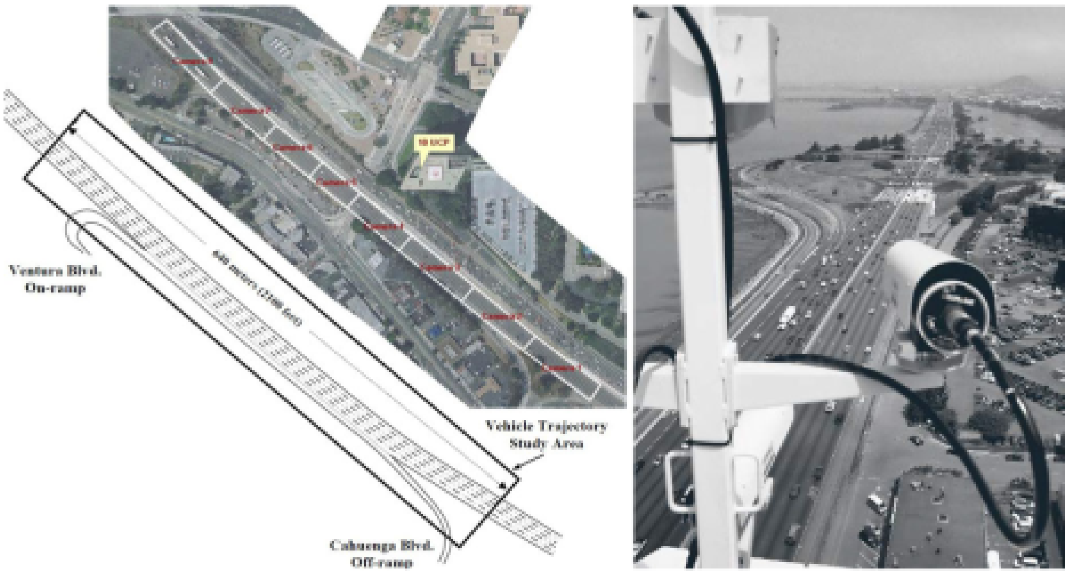


Figure 3.1: Eight cameras installed over U.S. Highway 101. The photo on the right shows a video camera mounted on the top of a building overlooking the highway.

Location	Road Length (ft)	Road Type	Record Time	Number 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+

Table 3.1: Four selected NGSIM data sets (14).

Traffic data acquisition from connected vehicles have also been explored by many researchers. For example, the Safety Pilot Model Deployment (SPMD) was launched in 2012. Around 3000 vehicles were equipped with GPS and dedicated short range communication devices. Each vehicle broadcasted basic safety messages including its position and velocity to nearby vehicles. These connected-vehicle data allows to improve detailed multi-lane virtual traffic simulation as well as intelligent transportation systems. Since connected-vehicle data can be sampled at a high frequency, they are usually processed via a down-sampling but information preserving technique.

3.2 TRAFFIC RECONSTRUCTION AND SYNTHESIS

Virtualized traffic refers to the creation of a digital representation of traffic that corresponds to the real-world traffic scenario. The term was first introduced by van der Berg et al. In their model, a continuous traffic flow is reconstructed and synthesized using the spatio-temporal data provided by the traffic sensors. As illustrated in Figure 3.2, three sensors are placed on the road at intervals of 200-400m each. For a given vehicle, the sensors return 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 and v_i^A are the passing time, lane id and velocity of the vehicle i recorded by sensor A. The same goes for sensors B and C. The model computes the trajectories for vehicle i on the road starting and arriving at the given lanes, in given times and with given velocities. This approach discretizes state-time space and restricts the motion of a vehicle to a pre-computed road map. Then, the model generates an optimal trajectory for each vehicle in the road map that has minimum number of lane-changing, minimum acceleration/deceleration and maximum distance from other vehicles. This ensure the smooth and realistic motion of the vehicles on the road map. A priority based multi-agent path planning algorithm is used to compute the trajectories for multiple vehicles. But, the algorithm is time consuming, which makes this approach quickly become ungovernable.

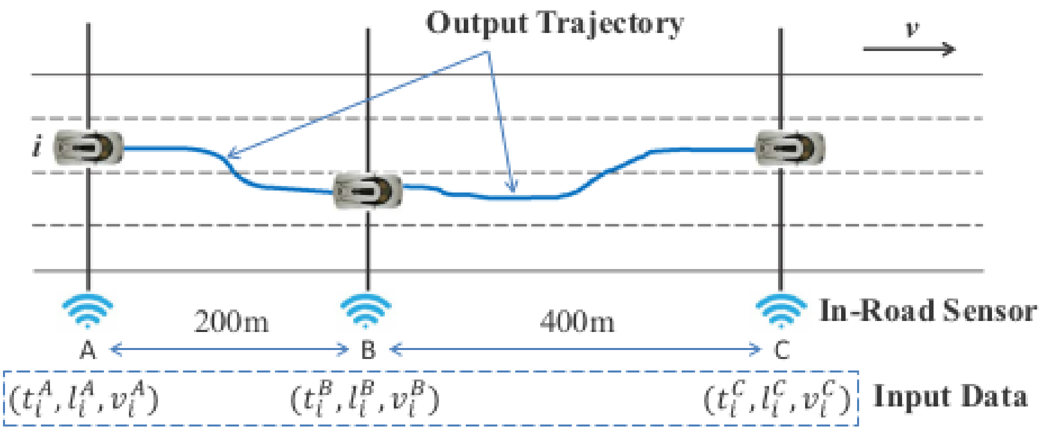


Figure 3.2: Illustration of traffic reconstruction from spatio-temporal data acquired from in-road sensors.

Wilkie et al. (3) introduced a real-time technique to reconstruct traffic flow from in-road sensors by integrating a macroscopic state estimation from sensor measurements with a microscopic traffic simulation system to reconstruct realistic motion of individual vehicles. As shown in Figure 3.3, the algorithm integrates an efficient estimation method using continuum traffic simulation and ensemble of Kalman smoothers to create an estimate of the velocity and density fields over the road network. The results obtained are visualized using microscopic traffic simulation to produce realistic motion for individual vehicles. The output obtained is a two dimensional traffic flow that is consistent with original traffic signals measured by the sensors. This method has higher flexibility and lower computational cost compared to virtualized traffic by van der Berg et al. However, this method is basically macroscopic except for the matching of individual vehicles.

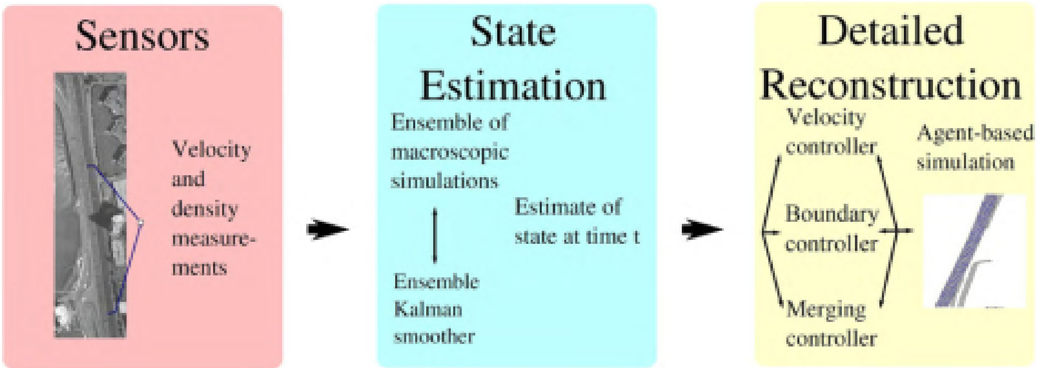


Figure 3.3: Pipeline of a traffic flow reconstruction algorithm (3).

Quite recently, Li et al. (4) proposed a method for the reconstruction of city-scale traffic using GPS data. This method takes GPS data and a GIS map as input and reconstructs city scale traffic using a two-phase process. At the first phase of traffic reconstruction, the flow conditions of traffic on individual road segments are reconstructed and progressively polished from the sparse GPS data using statistical learning methods combined with optimization, travel-time estimation and map-matching techniques. At the second phase of dynamic data completion, the reconstructed results obtained from the first phase are fed to a metamodel-based simulation optimization model and a microscopic simulator to efficiently refine and dynamically insert missing data in the areas of inadequate data coverage. The method further adjusts the simulation with respect to citywide boundary traffic constraints and the reconstructed traffic flows from the first phase to ensure the correctness of the reconstructed traffic.

Chao et al. (1) proposed a data-driven traffic simulation method to generate new traffic flows from limited traffic trajectory samples using a fusion of texture synthesis and behaviour rules. The sample input vehicle trajectory consists of a variety of traffic flow segments. As shown in Figure 3.4, the generation of traffic flows can be considered as a texture synthesis process by acquiring the spatio-temporal information of traffic flows as a two dimensional texture. It can be effectively solved by reducing a newly developed traffic texture energy metric. To be precise, each texel in traffic texture is used to encode a vehicle's state at a certain frame. This includes its velocity, position and dynamic relationship with nearby vehicles. The traffic texture energy metric computes the similarity between the simulated traffic flows and the given traffic flows. The velocity of each vehicle can be determined by finding the best matched texel in the input traffic flows. The simulated output captures the spatio-temporal dynamics of the input traffic flow samples and ensures other traffic features like lane-changing and safe distance between vehicles.

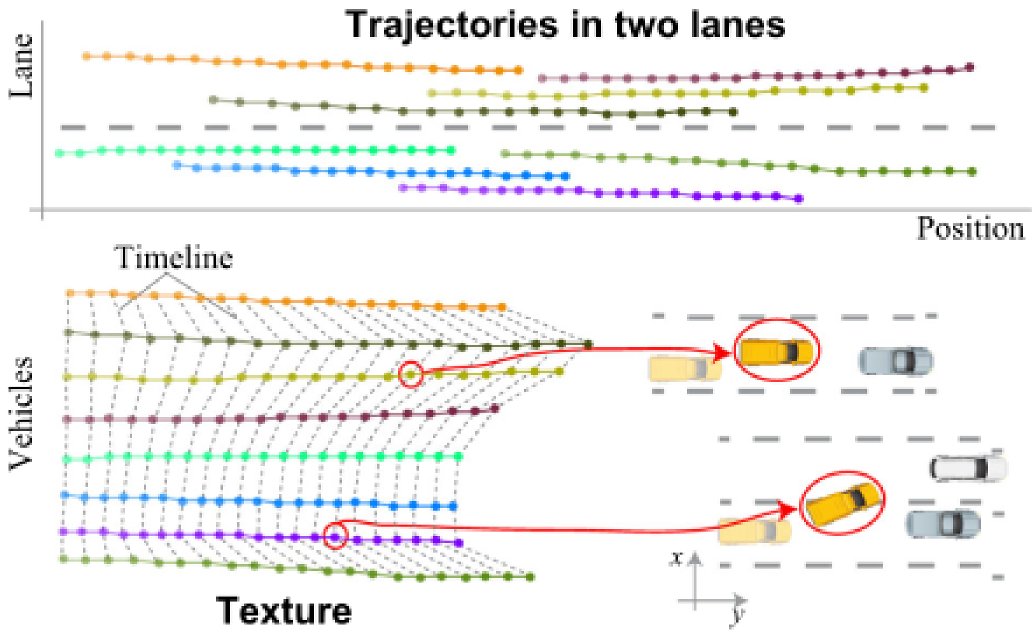


Figure 3.4: Texture analogy of a set of two-lanes vehicle trajectories (1).

Machine learning algorithms have also been used by researchers to learn the detailed motion characteristics of vehicles. The characteristics include acceleration/deceleration in longitudinal section and lane-changing process. A video based model, for learning the specific driving characteristics of drivers from videos, have been presented by Chao et al. The model formulates the approximation of each driver's unique driving characteristics into a problem of finding the optimal parameter set of an agent-based driving model. The optimal parameter problem can be solved using adaptive genetic algorithm. The learned characteristics can be used to reproduce the traffic flow obtained from a given video with high accuracy. Bi et al. (15) use vehicle trajectory data to learn the lane-changing characteristics. As shown in Figure 3.5, this model extracts the features that are most relevant to the lane-changing task from a pre-collected traffic data set. These features are the used to model the lane-changing decision-making process and also to estimate the lane-changing execution process.

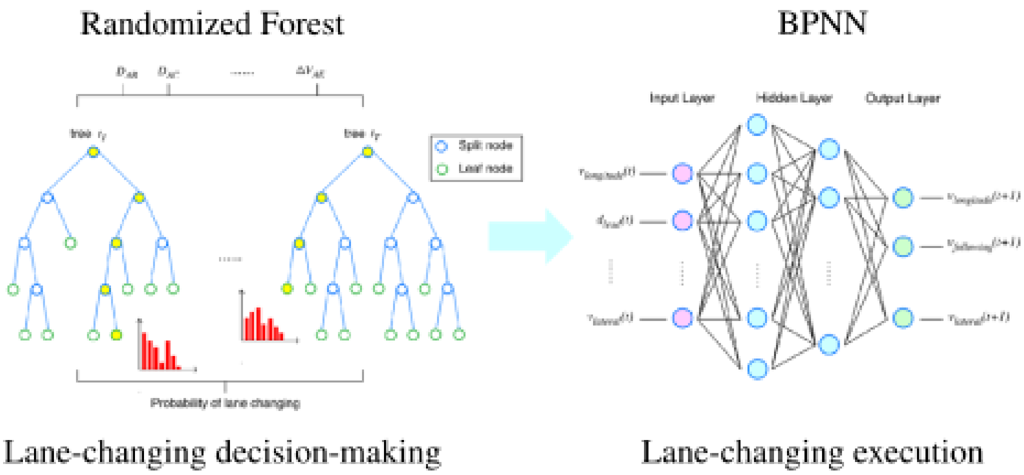


Figure 3.5: Illustration of the pipeline of the data-driven lane-changing model (15). The pre-processing step extracts the most relevant features from the pre-collected traffic data set. Then, the decision-making module infers whether the subject vehicle should perform lane-changing as well as which target lane/gap it should change to. Finally, the execution module computes the detailed trajectories of involved vehicles to accomplish a lane-changing task.

Recently, a deep learning model for traffic simulation at intersections was presented by Bi et al. (16). A grid coordinate system known as grid map was built to describe the visual perception of vehicle-environment reactions and to encode vehicle-pedestrian interaction. As illustrated in Figure 3.6, a window with five channels sliding on the grid map generates an environment matrix for each vehicle which captures its velocity and position. The environment matrices also capture the pedestrians around the vehicle. The current vehicles are also described by vehicle identities based on a collected intersection data set. Convolutional and recurral neural networks are used to learn the patterns of vehicle trajectories at intersections. The model can also alter the existing intersectional traffic simulation by providing the vehicles with new driving environments and new destinations.

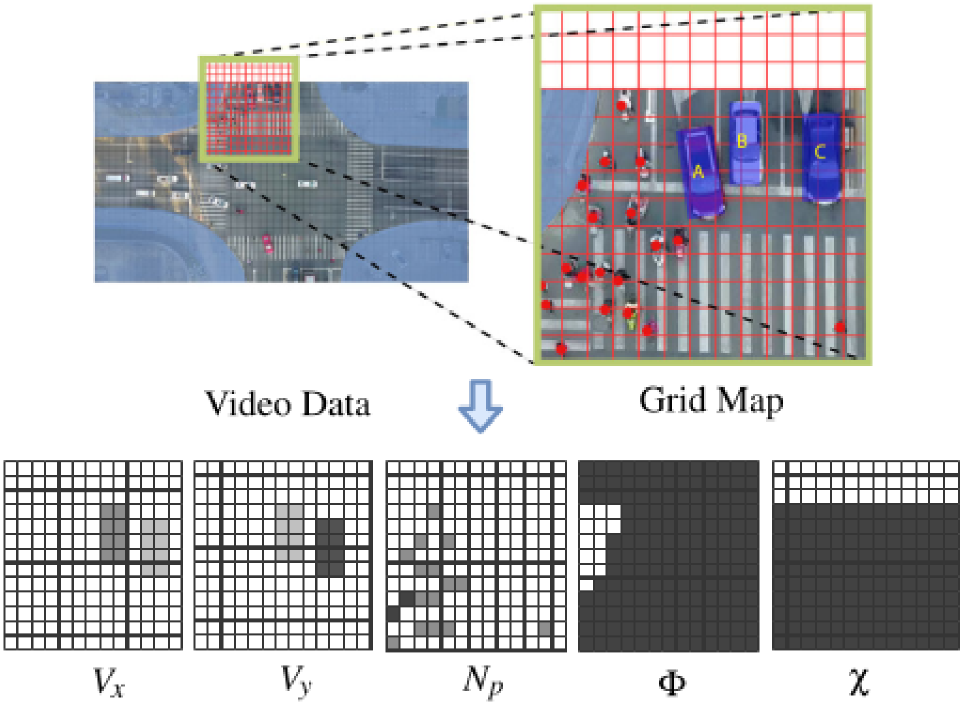


Figure 3.6: Illustration of the environment matrices in intersectional traffic simulation (16). For vehicle A, a window with size 31×31 is used to describe the surrounding area. An environment matrix including five channels (V_x,V_y,N_p,Φ,χ). V_x (or V_y) visualizes the velocities of vehicle B and C. 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.

Chapter 4

Validation and Evaluation

Virtual traffic evaluation can be performed in two ways: visual and statistical. In visual validation, simulated and real-world traffic are compared by displaying them side by side. Many researchers have conducted user studies using the work of Chao et al. (1) using pairwise comparison of the simulated traffic flows with three methods: (1) the NGSIM (14) traffic flow data, (2) the texture-based traffic synthesis methods (1) and (3) one of the latest development of intelligent driving model (IDM) (2). For each test case, three different traffic flow animations are generated using the above mentioned three different models. As illustrated in Figure 4.1(a), the participants were asked to select the more realistic clip from a pair of two different animation clips. In addition, if the participants were not able to decide which clip is more visually appealing, they were allowed to take the "undecided" option. The results from this user study are given in Figure 4.1(b). Besides the voting, the researches also performed one-sample t-test and the paired sample t-test. Using these test they computed the p-value which quantifies the significance of the voting results.

Since subjective use studies are time-consuming and error-prone, statistical validation using objective measures are used for measuring the realism and comparing the performance of different traffic simulation models. Direct trajectory comparisons are usually not performed for traffic simulation due to its random nature. Alternatively, average velocities and traffic volumes over time are compared (Figure 4.2).The effectiveness of traffic simulation techniques at a more detailed level is validated using specific motion parameters such as vehicle gap, velocity, acceleration/deceleration etc. (15).

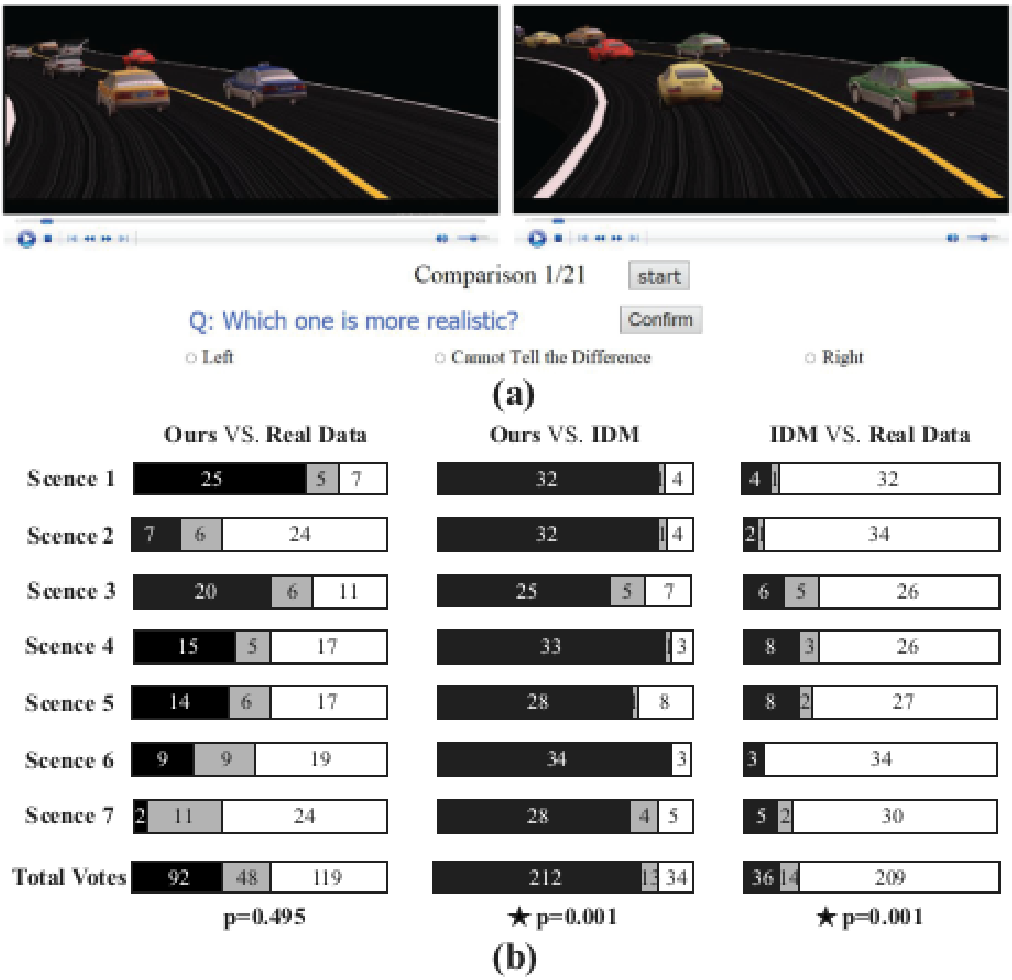


Figure 4.1: Snapshots of the driver's view study (a) and the experiment outcomes (b) Chao et al. (1). Black boxes at the left side and white boxes at the right side indicate the total number of times when the participants voted the results using the corresponding method. Gray boxes in the middle indicate "undecided choices". The symbol $*$ indicates the computed statistical significance according to a two-tailed independent one-sample t-test with p<0.05.

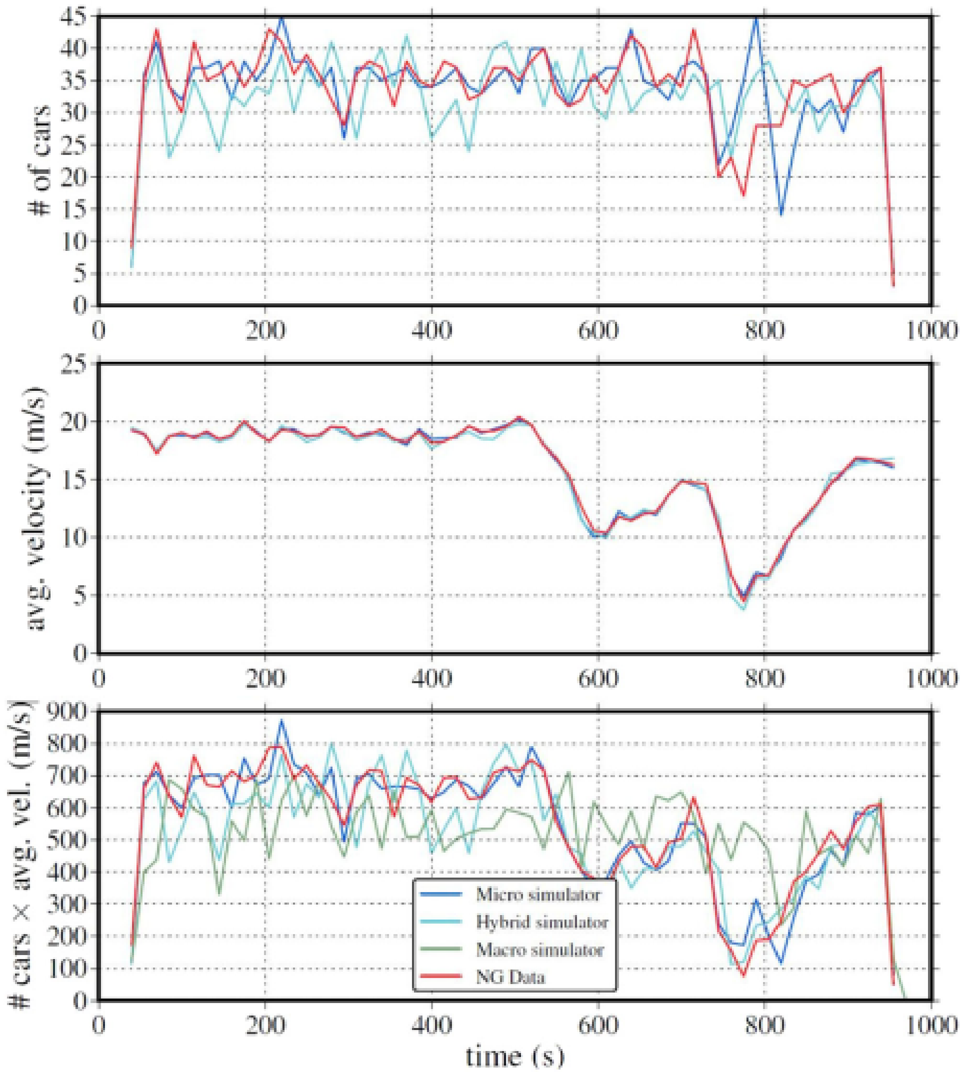


Figure 4.2: Comparison between microscopic simulation, macroscopic simulation, hybrid simulation technique and real-world NGSIM (14) data on highway 101. These graphs show density, velocity and flux recorded over 15s intervals centred around the times shown at a sensor near the end of the highway (11).

Recently, Chao et al. (17) found a dictionary-based learning method to quantitatively and objectively measure the fidelity of traffic data. A traffic-pattern dictionary for characterizing common patterns of real-world traffic behaviour was built offline from NGSIM data (14). This dictionary is used to evaluate the realism of the simulated traffic flows by comparing its dictionary based reconstruction error with the benchmark dictionary error. As shown in Figure 4.4, this method is done in four stages: (1) extraction of spatio-temporal traffic flow features,

(2) dictionary learning from real-world traffic data, (3) dictionary-based reconstruction of any simulated traffic flow data and (4) finding a quantitative measure based on reconstruction error. This evaluation method can be applied to any simulated traffic flow. The fidelity scores are set in the range [0,10]. The closer the simulated traffic is to the real-world traffic, the lower will be its fidelity score.

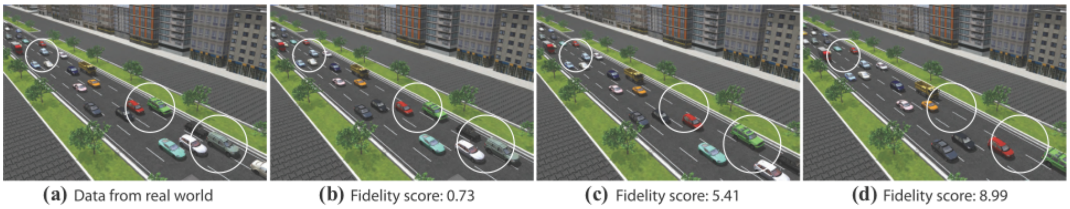


Figure 4.3: Fidelity measure comparisons among three virtual traffic flows generated by the IDM model (2) using three different parameter sets ((b)–(d)). The initial traffic states of the simulator were set to the same values as the real-world traffic flow (a). Differences between the simulated traffic 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 (17).

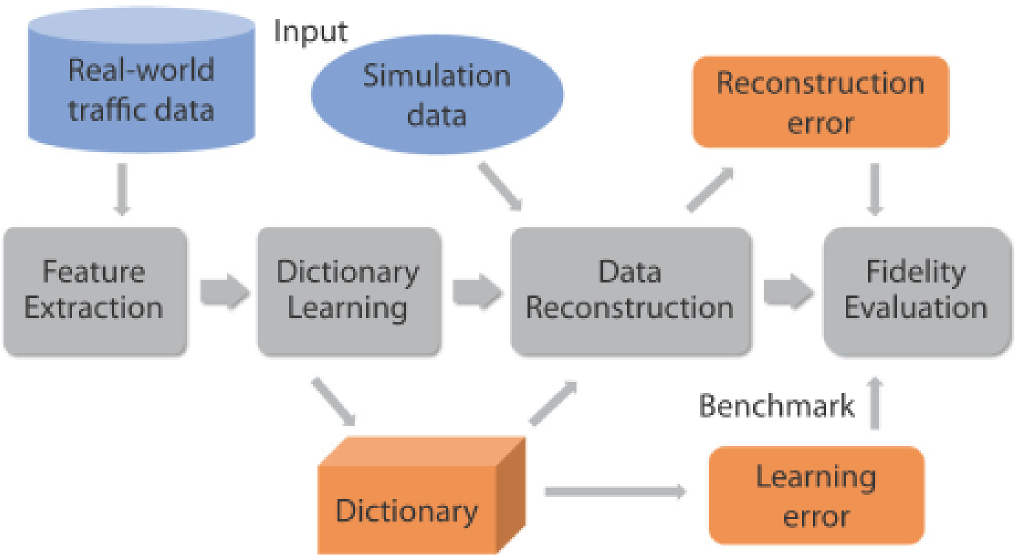


Figure 4.4: The pipeline of the dictionary-based fidelity measure for virtual traffic (17). The blue boxes show the to-be-evaluated input of the system, which contains real world traffic data set and simulation data.

Chapter 5

Applications in Autonomous Driving

One major application of virtual traffic simulation is the development of autonomous vehicles. They have the potential to increase the safety and efficiency of current transportation systems. Autonomous vehicles can transform the current transportation system into a utility available to anyone at any time. In this section, the recent developments in autonomous vehicles, motion planning methods for autonomous driving and simulation of autonomous vehicles, are discussed.

5.1 AUTONOMOUS DRIVING DATA SETS

The traffic data sets are collected for traffic reconstruction and virtual traffic simulation and cannot be used for building an autonomous driving system. The existing autonomous driving data sets are surveyed in this report in the forms of first-view video, LiDAR data and GPS information under various traffic scenarios. These autonomous driving data sets have facilitated the expansion of autonomous vehicles and learning different driving behaviours.

Jain et al. collected a diverse data set that has 1180 miles natural freeway and city driving behaviours of 10 drivers. They recorded video clips from inside and outside the vehicle, speed measurements of the vehicle and GPS report of the vehicle.

The Comma.ai (21) data set contains 7.25 hours' highway driving data. The data set has been split into 11 videos each having a resolution of 160 x 320. It also recorded the speed, steering angles, GPS reports, gyroscope and IMU from several sensors.

The BDDV (Berkeley Deep Drive Video) data set (22) contains real driving videos and

GPS/IMU data. It recorded a wide variety of driving scenarios from several major US cities. It contains over 10,000 hours of dashboard-camera video streams of driving in various driving scenarios, like cities, towns, highways, rural areas, etc.

The LiDAR-Video data set (26) consists of large-scale high quality point clouds from a Velodyne Laser scanner, which collects point clouds in 360° horizontal view and from -30.67° to 10.67° vertical view, and the images from a dashboard camera, which recorded around 15G videos. The vehicle controller used a recording software toolkit to obtain the velocity from on-board sensors. Various traffic scenarios like primary roads, mountain roads, arterial roads, school zones, tourist routes, etc. have been covered by the LiDAR-Video data set.

Another autonomous driving data set is the Honda Research Institute Driving Data Set (HDD) (25) which consists of 104 hours of driving data in the San Francisco Bay Area. The post-processed data obtained from HDD is around 104 video hours and has a size of 150GB. It includes a diverse set of traffic scenes.

Drive360 (27) data set contains 60 hours of driving video from eight 360° cameras. The vehicle's CAN bus recorded low-level driving information such as steering angles and speed control. The data in Drive360 includes diverse road conditions, 360° view coverage, high temporal resolution and frame-wise synchronization.

The KITTI data set (18; 19) used four high resolution video cameras, a localization system and a Velodyne laser scanner. This data set stereo and optical flow image pairs and stereo visual odometry sequences of 39.2 km. It also captures more than 2,00,000 3D object annotations in clustered environments. This data can be used for a variety of tasks such as stereo, optical flow, 3D object detection, visual odometry etc.

Another autonomous driving data set is the Cityscape data set (20) which contains a large, diverse set of stereo video sequences recorded in the roads of 50 cities. This data set collects various street scenes in different seasons.

The Oxford RobotCar data set (23) consists of over 1000 km driving data with around 2 crore images obtained from six cameras. This data set also include LiDAR and GPS data, from several weather conditions like direct sunlight, heavy rain, night and snow. Another data set from Udacity (24) contains low-level data collected from the vehicles' CAN bus.

Data set	Intention	Driving behaviours	Driving time (h)	Areas	Camera view	Sensors & videos: Video image	LiDAR	GPS IMU	Conditions
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

Table 5.1: Comparison of various autonomous driving data sets.

Several other data sets have been proposed for autonomous driving including synthetic driving, street scenes, etc. The different data sets are compared in Table 5.1.

Autonomous driving data sets can also be used for the simulation of traffic flows. Vehicle trajectories from autonomous driving data sets can be used to develop traffic simulation models and enrich data-driven traffic synthesis methods. Virtual traffic evaluation can also benefit from various real-world traffic data sets developed for autonomous driving.

5.2 MOTION PLANNING AND DECISION MAKING

A critical step for autonomous vehicles to navigate in the environment is motion planning and decision making. In this section, different motion planning and decision-making methods are explored.

Autonomous Land Vehicle in a Neural Network (ALVINN) was introduced by Pomerleau in 1989. ALVINN pioneered end-to-end approach for autonomous navigation. The input for ALVINN is taken from cameras and laser range finders. Based on screenshots taken from a video game called TORCS, a deep convolutional neural network was trained. This method was tested on the KITTI data set (18).

More and more end-to-end deep learning frameworks for autonomous driving were developed over the years. The raw pixels from the front-facing cameras were taken as input for a CNN by Bojarski et al. This input was used to produce steering behaviour of the vehicle. An end-to-end deep CNN to estimate lane positions directly was proposed by Gurghian et al. (22). This model took input images from laterally mounted down-facing cameras which provides a better view for lane-making than the front-facing cameras.

Recently, Xu et al. proposed a model that learns generic vehicle motion from a large-scale crowd source vehicle action data. After training the model, it can produce both discrete action and continuous action for navigating an autonomous vehicle. Chen et al. (26) used LiDAR point clouds and video recordings for developing autonomous driving rather than traffic videos data.

Lenz et al. developed and trained a deep neural network to predict vehicle motions at a highway entrance. The model proposed by Kuefral et al. overcomes the problem of cascading error and produce realistic driving behaviours. Hecker et al. (27) integrated the information from neighbouring 360° cameras into the route planner for learning an end-to-end driving model. The sensor outputs are directly mapped to low-level driving maneuvers by the network used in this approach. Kim et al. proposed an end-to-end driving approach for autonomous driving. Du-drive is another autonomous driving technique proposed by Yang et al. (28). Du-drive predicted vehicle behaviours for autonomous driving by utilizing the traffic data collected in CARLA and TORCS (Figure 5.1).

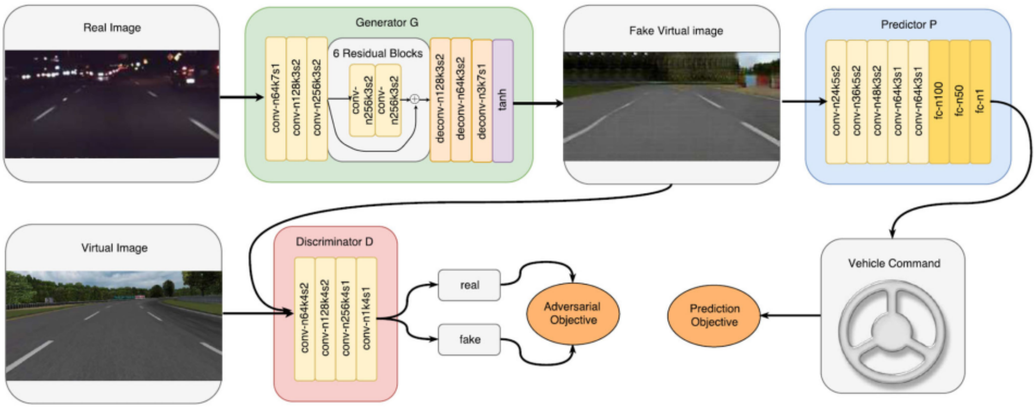


Figure 5.1: The architecture of DU-Drive (28). The generator network G transforms a real image to a virtual image, from which the vehicle command is predicted by the predictor network P. The discriminator network D distinguishes fake virtual images from true virtual images. Both the adversarial objective and the prediction objective drive the generator G to produce the virtual representation that yields the best prediction result.

Reinforcement learning has also been used for developing autonomous driving. Abeel et al. presented an algorithm to moderate the local planning for generating vehicle motion and global navigation. Silver et al. proposed a cost function for autonomous driving and navigation systems to balance different priorities. Lillicrap et al. adopted a deep learning method that lead a vehicle to stay on the track in a virtual traffic environment. A method for learning individual driving styles was presented by Kuderer et al. Wolf et al. proposed a Deep Q-Networks for the navigation of a vehicle in a three dimensional simulated environment. Pan et al. developed a virtual-to-real reinforcement learning framework which trains an autonomous driving model in a virtual environment to make it competent enough for usage in the real-world environment. Autonomous driving can be developed with a high success rate by taking vision inputs directly from CARLA simulator.

Autonomous vehicles must also predict the motion of other vehicles to safely and effectively navigate in complex traffic environments. The vehicle-pedestrian interactions should be accurately represented. Vehicle motion forecasting can classified into several types: physics-based, maneuver-based, interaction-aware, etc.

Lee et al. presented a Recurrent Neural Network framework for forecasting future distances for interacting objects in dynamic scenes. This approach can produce accurate vehicle trajectories in complex driving conditions. Deo and Trivedi proposed a convolutional social pooling network for predicting vehicle motion o highways. To be specific, this approach uses an LSTM encoder in order to learn vehicle dynamics based on track history. Then, it captures the interrelation of the trajectories of all vehicles using a convolutional social pooling network. Finally, a maneuver-based LSTM decoder is trained to forecast future vehicle trajectories.

5.3 Simulation for Autonomous Driving

Motion planning and decision-making processes in autonomous driving are largely facilitated by machine learning methods. But, real-world data is insufficient to train these machine learning based models to cover all complex traffic scenarios. This restricts the autonomous vehicles from learning different driving strategies and recovery actions in risky situations. This makes autonomous vehicles take inefficient decisions for safety reasons. These restrictions have stimulated the development of high-fidelity driving simulator as an alternative tool to provide different types of complex traffic scenarios for training autonomous vehicles. Moreover, a simulator can ensure the safety of an autonomous vehicle before deploying it into the real world.

Since the early days of autonomous driving, simulation has been used for training the driving models. They have also been used for the evaluation of various driving approaches. For example, TORCS has been used by many researchers to evaluate the proposed model for autonomous driving. Recently, Grand Theft Auto V was used by researchers to derive various autonomous driving policies. These models produced comparable results to models derived from real-world data.

Another commonly used simulator for training and evaluating autonomous driving models is the CARLA simulator (29). The CARLA simulator sets up sensor suites and provides signals that can be utilized to train driving strategies. These signals consists of GPS data, speed, acceleration, data on collisions etc. It can also specify a wide variety of environmental factors (Figure 5.2). The CARLA simulator has been used to evaluate the performance of various autonomous driving models including end-to-end trained models via imitation and reinforcement learning.

Figure 5.2: A street traffic in the CARLA Simulator (29), shown from a third-person view in four weather conditions. Clock-wise from top left: clear day, daytime rain, daytime shortly after rain and clear sunset.

Autonovi-Sim is another high-fidelity platform for autonomous driving data generation and strategy checking. It was presented by Best et al. Like CARLA, it also supports motion of non-vehicle participants, sensor systems in vehicles and time of day and weather conditions.

Many recent projects are trying to build simulation platforms for training end-to-end driving systems and providing diverse traffic conditions for testing autonomous driving. For example, Apollo is creating a powerful and efficient virtual close-loop for developing autonomous driving systems. Apollo utilizes a large amount of real and virtual driving data. One major limitation of Apollo is that the virtual traffic data are manually created. This makes it less realistic and more complex than the actual traffic scenario.

Recently, a simulation framework called AADS was developed by Li et al. which augments real images with simulated traffic scenarios to generate realistic images. This framework can be used to overcome the limitation of the Apollo framework, that is manual creation of virtual traffic environments for training autonomous vehicles.

Li et al. also developed another framework called ADAPS which learns autonomous driving from accidents. It consists of two simulation platforms. The first simulation platform a three dimensional platform and is used to simulate accidents and the second one is two dimensional and is used to analyse the accident simulated by the first platform. The second platform also provides alternative trajectories to avoid the generated accident by the first platform.

Chapter 6

Conclusion and Future Scope

This chapter discusses the current states of existing studies and future research directions on virtual traffic simulation.

6.1 Future Scope

The future scope of virtual traffic simulation and autonomous driving are discussed below.

1. An ideal traffic simulation model should be able to model as many complex traffic behaviours as possible. But, each behaviour of the vehicle, like lane-changing and acceleration, in the existing microscopic models is individually modelled. Also, the focus of agent-based traffic models is more on the forward motion of the vehicle. The lateral and lane-changing motion of the vehicles are generally ignored by the microscopic traffic models. Moreover, the resulting simulation from microscopic models rarely involves other neighbouring vehicles for computing the acceleration/deceleration. To simulate more realistic traffic flows, a unified simulation framework for rich traffic behaviours, such as lane-changing and vehicle-pedestrian interaction, has to be developed.

2. Despite many successful demonstrations of virtual traffic simulation, the interactions between vehicles and other moving objects are still not handled properly. One of the major reasons for the same is that it is a very difficult task to obtain the large-scale spatio-temporal data of vehicles, pedestrians and environment factors at the same time. Two types of data obtained by GPS and in-road sensors are separately used for

traffic reconstruction. The accuracy of traffic reconstruction depends on the available data. Thus, the accuracy of traffic reconstruction can be improved by combing the different data sources such as GPS, in-road sensors, video streams etc.

3. The dictionary-based metric provides a practical solution for the evaluation of fidelity of virtual traffic (17). However, the generated dictionary depends on the quality and composition of traffic data. This would significantly affect the evaluation outcome. Additionally, the extracted features from each vehicle such as its velocity, acceleration, relative speed and gap distance to its nearby vehicles, are used to describe the vehicle's instantaneous state. Traffic patterns for dictionary learning can be captured better by considering the extraction of other features like vehicle motion restrictions, driver characteristics and road constraints. Developing fidelity metrics are a necessity for continuum traffic flow models.

4. The major challenge fo autonomous driving is the interaction between autonomous vehicles and other road users. For example, both Apollo simulation platform and Best et al. implemented two types of non-vehicle participants, pedestrians and cyclists. However the behaviour of these non-vehicle participants are pre-defined and hence they cannot react to vehicles in real-time. Dynamic pedestrians are introduced in the CARLA (29) simulator. In this model, the pedestrians will check if there are any vehicles before their movements and then continue their course of action.

6.2 Conclusions

Traffic simulation and modelling have made considerable progress since their introduction almost 60 years ago. In computer graphics, several traffic simulation techniques based on traffic flow models have been suggested in the last 10 years. Additionally, with progression in sensing technologies, many data-driven methods have also been proposed for developing virtual traffic simulation. The increasing amount of traffic data from across the globe using various sensors can also contribute to the development and testing of autonomous vehicles.

In this report, the key traffic simulation and animation techniques have been surveyed from a computer graphics perspective. A subgroup of these methods looks upon the simulation of traffic flow based on macroscopic, microscopic and mesoscopic flow models. Other methods use the obtained traffic data to reconstruct traffic, develop new traffic scenarios or learn the characteristics of different traffic patterns. Various validation and evaluation techniques of virtual traffic were also discussed.

As an application of virtual traffic simulation, latest developments in autonomous driving technologies using traffic simulation and animation were also given. Data-driven methods, motion planning techniques, decision-making algorithms and simulators created for autonomous driving development were some of the ares explored in this report. We have also inspected some of the future research challenges.

In conclusion, virtual traffic simulation and animation will continue to be researched. Many exciting angles for traffic modelling remain to be explored. In terms of autonomous driving research, the various models and applications summarised in this report would encourage fascinating research topics to come forward in the coming years.

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