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

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INTRODUCTION

- 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.

MODEL-BASED TRAFFIC SIMULATION

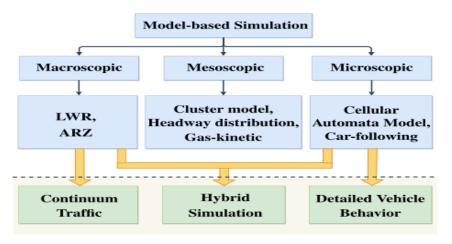


Figure: Classification of model based traffic simulation [1].

MACROSCOPIC METHODS

- Describe vehicle's behaviours and interactions at a low level of detail.
- A traffic stream is represented as a continuum in terms of speed, flow, density etc.
- Focuses on reproducing aggregated behaviours measured with collective quantities.
- ✓ Efficient tools to simulate large-scale traffic.
- × Not suitable for simulating street-level traffic.
- × They cannot model lane-changing behaviour of vehicles.



LWR Model

- Developed by Lighthill and Whitham [2] and Richards [3].
- Model builds a non-linear scalar conservation law for modelling traffic flows, based on similarities between one dimensional compressible gas dynamics and the evolving of traffic flows in a single lane.
- Model describes the motion of large-scale traffic flows with low resolution details.
- × It cannot model the movements of a vehicle under non-equilibrium conditions.

PW Model

- Continuous second-order traffic model proposed by Payne [4] and Whitham [5].
- Introduces second order differential equation to describe traffic velocity dynamics.
- × The model can introduce negative velocities.
- Information generated from vehicle dynamics can travel faster than vehicle velocity.

ARZ Model

- Aw and Rascle [6] and Zhang [7] modified PW model to eliminate its non-physical characteristics.
- Aw and Rascle [6] introduced a pressure term to guarantee that no information travels faster than the speed of the car.
- Zhang [7] modified the momentum equation of the PW model to handle backward-propagating traffic.

SEWALL et al.

- Macroscopic traffic simulation model to generate realistic traffic flows on large-scale road networks.
- Adapted single-lane ARZ model to handle multi-lane traffic by :
 - introducing a novel model for lane-changing.
 - using a discrete representation for each vehicle.

SEWALL et al.

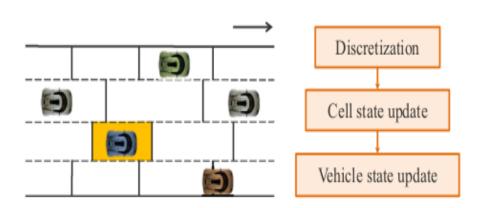


Figure: Illustration of macroscopic traffic simulation approach [8].

MICROSCOPIC METHODS

- Produce vehicle motion at a high level of detail.
- Each vehicle is treated as a discrete agent satisfying certain governing rules.
- Flexible in modelling:
 - 4 Heterogeneous behaviours of agents.
 - ② Diverse road topologies.
 - Interactions among surrounding vehicles.
- ✓ Used to simulate traffic in both continuous lanes and intersections.
- × Computational cost is very large.



CELLULAR AUTOMATA MODEL

- Motions of vehicles are described by evolution rules in pre-specified time, space and state variables.
- The road is discretized into cells.
- Model determines when a vehicle moves from current cell to next cell.
- ✓ Can simulate a large group of vehicles on a large road network.
- Generated virtual traffic can only a limited number of real-world traffic behaviours.

CAR-FOLLOWING MODELS

- Introduced by Pipes and Reuschel.
- Assumed traffic flow consisted of scattered particles.
- Modelled detailed interactions among cars.
- Represented the position and speed of each car through continuous-time differential equations based on stimulus-response framework.

INTELLIGENT DRIVING 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.
- Shen and Jin [14] enhanced the IDM to incorporate lane-changing behaviours of vehicles.

SHEN AND JIN

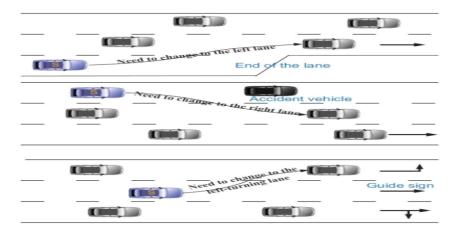


Figure: Situations where a vehicle must change its lane [14].

HYBRID METHOD

microscopic models excel in modelling of individual vehicles.

Macroscopic models excel in large-scale traffic simulation and

- Sewall et al. combined these two models and proposed a hybrid method.
- Their approach simulates traffic in the areas of interest using a microscopic model, while the rest areas using a macroscopic model.
- Their approach can simulate traffic by dynamically switching between the two models.

HYBRID METHOD



Figure: Illustration of a hybrid traffic simulation method [10].

MESOSCOPIC METHODS

- Intermediate approach between macroscopic and microscopic methods.
- Describe traffic flow dynamics in an aggregate manner while representing the behaviours of individual drivers using probability distribution functions.
- Can be divided into three classes:
 - Cluster models
 - 2 Headway-distribution models
 - Gas-kinetic Models



MESOSCOPIC METHODS

- The cluster models represent the dynamics of traffic flows by describing groups of vehicles with the same properties.
- The headway distribution models focus on the statistical properties of time headways.
- The gas-kinetic models draws analogy between the gas-dynamics and the traffic dynamics.

ROAD NETWORK GENERATION

- Traffic simulation is a form of interplay between the vehicles and the road-network.
- Digital representations of road networks are increasingly available, but cannot be directly used for traffic simulation.
- A road network contains many features such as lanes, intersections, ramps etc.
- Road network generation is an important yet challenging aspect.

ROAD NETWORK GENERATION

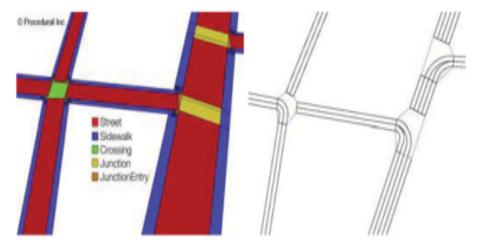


Figure: A road network created using (a) CityEngine [18] (b) Wilkie et al. [9] [19].

DATA-DRIVEN TRAFFIC SIMULATION

- The resulting animations from the above mentioned traffic models usually do not resemble real-world traffic at street level.
- This problem is solved using data-driven traffic animation techniques.
- Nowadays, empirical traffic flow data sets in the forms of video, LiDAR and GPS sensors are increasingly available.

TRAFFIC DATA ACQUISITION

- Traffic data is acquired using traffic sensors.
- Sensors can be categorised as:
 - Fixed Sensors → Inductive-loop detector, video camera
 - Mobile Sensors → Cellphones, GPS devices
- Video camera as an over-roadway sensor has been employed in Next Generation Simulation (NGSIM).

NGSIM DATASET

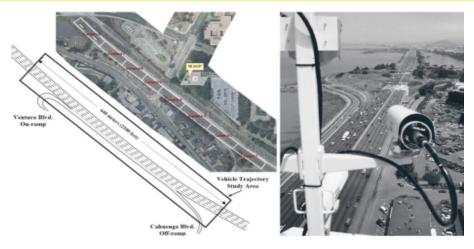


Figure: Next Generation Simulation [17]

NGSIM DATASET

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

Table: Four selected NGSIM data sets [17].

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 virtualized traffic was first introduced by van den Berg et al. [11].
- In van den Berg et al., a continuous traffic flow is reconstructed and visualized from spatio-temporal data provided by traffic sensors.

VAN DER BERG et al.

- For a given vehicle i, the sensors provide 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.
- The task is to compute trajectories for the vehicle i on the road.
- 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.

VAN DEN BERG et al.

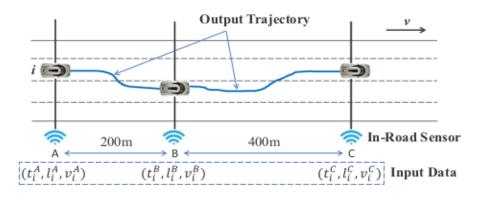


Figure: Illustration of traffic reconstruction from temporal-spatial data acquired from in-road sensors [11].

VALIDATION AND EVALUATION

- Virtual traffic evaluation is categorised into two:
 - 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.
 - Statistical Validation
 - → Different traffic simulation methods are compared on the basis of other features such as average velocities and traffic volumes over time.

SEWALL et al.

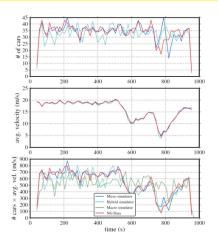


Figure: Comparison between micro, macro, hybrid simulation and real-world data [10].

- In the work of Chao et al. [13], researchers conducted user studies using pairwise comparison on the generated traffic flows with three different methods:
 - NGSIM traffic flow data
 - 2 Texture based traffic synthesis method by Chao et al. [13].
 - 3 One of the latest developments of IDM model [14].

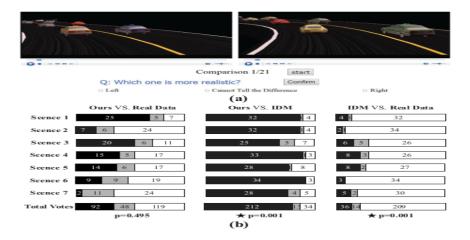


Figure: Visual validation [13] [14].

 Recently, Chao et al. [15] introduced a general, dictionary-based learning method to quantitatively and objectively measure the fidelity of traffic trajectory data.

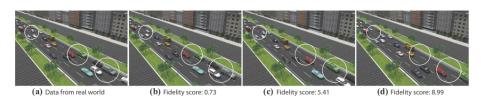


Figure: Fidelity measure comparisons among three virtual traffic flows [15].

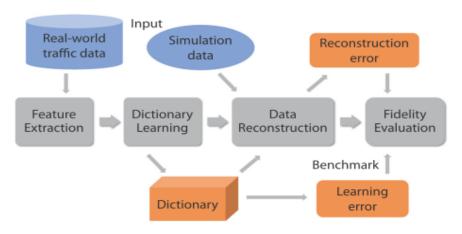


Figure: The pipeline of the dictionary-based fidelity measure for virtual traffic [15].

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.

AUTONOMOUS DRIVING DATASETS

Dataset	Intention	Driving	Driving	Areas	Camera View	Sensors and Videos		Conditions	
		Behaviours	Time			Video	LiDAR	GPS	
			(hours)			Image		IMU	
KITTI [20]	Semantic & geomet-	-	1.4	City, highway	Front-View	✓	✓	✓	One weather con-
	ric understanding								dition, daytime
Cityscape [21]	Visual Semantic &	-	<100	City	Front-view	✓	-	✓	Multiple weather
	geometric under-								conditions, day-
	standing								time
Comma.ai [22]	Driving behaviour	✓	7.25	Highway	Front-view	✓	-	✓	Night, daytime
	learning								
BDDV [23]	Semantic & geomet-	✓	10k	City, highway	Front-view	✓	-	✓	Multiple weather
	ric understanding,								conditions, day-
	driving behaviour								time
	learning								
Oxford [24]	Long-term localiza-	-	214	City	360-degree view	✓	-	✓	Multiple weather
	tion & Mapping								conditions, day-
									time

 $\textbf{Table:} \ \, \mathsf{Comparison} \ \, \mathsf{of} \ \, \mathsf{various} \ \, \mathsf{autonomous} \ \, \mathsf{driving} \ \, \mathsf{datasets} \ \, [1]$



AUTONOMOUS DRIVING DATASETS

Dataset	Intention	Driving	Driving	Areas	Camera View	Sensors and Videos		Conditions	
		Behaviours	Time			Video	LiDAR	GPS	
			(hours)			Image		IMU	
Udacity [25]	Semantic & geomet-	-	8	City, highway	Front-View,	✓	✓	✓	Multiple
	ric understanding,				left-view,				weather condi-
	driving behaviour				right-view				tions
	learning								
HDD [26]	Driving behavioural	✓	104	City, highway	Front-View,	✓	✓	✓	Multiple
	learning, casual rea-				left-view,				weather condi-
	soning				right-view				tions, daytime
LiVi-Set [27]	Driving behaviour	✓	20	City, highway	Front-View	✓	✓	✓	Multiple
	learning								weather condi-
									tions, daytime
Drive360 [28]	Driving behaviour	✓	60	City, highway	360-degree	✓	-	✓	Multiple
	learning				view				weather condi-
									tions, daytime

 $\textbf{Table:} \ \, \mathsf{Comparison} \ \, \mathsf{of} \ \, \mathsf{various} \ \, \mathsf{autonomous} \ \, \mathsf{driving} \ \, \mathsf{datasets} \ \, [1]$



MOTION PLANNING AND DECISION-MAKING

- Motion planning and decision-making are critical for autonomous agents to navigate in their environments.
- 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.
- Some examples for autonomous driving systems using motion planning and decision-making are ALVINN, Du-Drive, etc.

SIMULATION FOR AUTONOMOUS DRIVING

- 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.

CARLA SIMULATOR

training and validation of autonomous urban driving models.

• Supports flexible setup of sensor suites and provides signals that can be

• It is an open-source simulator developed to support development,

- Supports flexible setup of sensor suites and provides signals that can be used to train driving strategies.
- A wide range of environmental factors can be specified, including weather and time of day.

CARLA SIMULATOR



Figure: A street traffic in CARLA simulator [16].

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, would encourage fascinating research topics to come forward in the coming years.

FUTURE SCOPE

- A traffic simulation model must be able to model as many complex situations as possible, while maintaining computational efficiency.
- Current data-driven traffic animation approaches cannot handle non-trivial interactions between vehicles and other moving objects.
- Fidelity metrics have to be developed that can measure traffic flows in an aggregate fashion.
- For autonomous driving addressing the interactions between autonomous vehicles and other road users remain a challenge.



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- [15] Chao Q., Deng Z., Xiao Y., He D., Miao Q., Jin X.: Dictionary-based fidelity measure for virtual traffic. IEEE Transactions on Visualization Computer Graphics (2018).
- [16] Dosovitskiy A., Ros G., Coevilla F., Lopez A., Koltun V.: CARLA: An open urban driving simulator. In Proceedings of the 1st Annual Conference on Robot Learning (2017).

LINKS TO DATASETS

- [17] Next generation simulation fact sheet (2018).
- [18] Cityengine manual (2018).
- [19] Road network library (Wilkie et al.) (2015)
- [20] KITTI Dataset
- [21] Cityscape Dataset
- [22] Comma.ai Dataset



LINKS TO DATASETS

- [23] Berkeley DeepDrive dataset
- [24] Oxford robotcar dataset
- [25] Udacity self driving car
- [26] Honda research institute Driving Dataset
- [27] LiDAR Video Driving dataset
- [28] Drive360 dataset

