A dynamic-data-driven driving variability modeling and simulation for emergency evacuation

Shengcheng Yuan
Institute of Public Safety Research,
Tsinghua University, Beijing, China
yuancc12@mails.tsinghua.edu.cn

Yi Liu
Institute of Public Safety Research,
Tsinghua University, Beijing, China
liuyi@tsinghua.edu.cn

Gangqiao Wang
Institute of Public Safety Research,
Tsinghua University, Beijing, China
wanggq13@mails.tsinghua.edu.cn

Hongshen Sun
Department of Engineering Physics,
Tsinghua University, Beijing, China
shs10@mails.tsinghua.edu.cn

Hui Zhang
Institute of Public Safety Research,
Tsinghua University, Beijing, China
zhhui@tsinghua.edu.cn

ABSTRACT

This paper presents a dynamic data driven approach of describing driving variability in microscopic traffic simulations for both normal and emergency situations. A four-layer DGIT (Decision, Games, Individual and Transform) framework provides the capability of describing the driving variability among different scenarios, vehicles, time and models. A four-step CCAR (Capture, Calibration, Analysis and Refactor) procedure captures the driving behaviors from mass real-time data to calibrate and analyze the driving variability. Combining the DGIT framework and the CCAR procedure, the system can carry out adaptive simulation in both normal and emergency situations, so that be able to provide more accurate prediction of traffic scenarios and help for decision-making support. A preliminary experiment is performed on a major urban road, and the results verified the feasibility and capability of providing prediction and decision-making support.

Keywords

Microscopic traffic simulation, Driving variability, Emergency evacuation.

INTRODUCTION

Large-scale traffic evacuation is one of the most important issues in emergency management. There exist some challenge in decision-making for evacuation: 1) Uncertainty. Due to the complexity under disaster condition as well as human behavior, evacuation processes always show significant uncertainty. 2) Less of experiences and unrepeatable. Evacuation process can hardly be exactly found in historical cases nor repeated. 3) Decision-making pressure. Failure to make decisions may lead to serious consequences. Therefore, decision makers will expect to get forecasts of possible future scenarios in order to make decisions better and more comprehensively. Microscopic traffic simulation, which means that each vehicles of reality that is to be simulated is simulated individually, is an effective tool to solve the problem, which is expected to make more accurate simulation results considering driving variability.

Modeling and calibration on microscopic traffic simulation has gotten more attention in non-disaster situations. One of the most widely used model is the car-following model, which describes the dynamic processes of how drivers follow each other in the traffic stream, such as Gipps' model (Gipps, 1981), Newell's model (Newell, 2002), etc. However, driver behaviors are not identical. Ossen and Hoogendoorn pointed out the heterogeneity of the driver population, i.e. the inter-driving variability (Ossen and Hoogendoom, 2011). Treiber and Helbing discussed the diversity and uncertainty of the behavior of a single driver, i.e. the intra-driving variability (Treiber and Helbing, 2003). Based on the existing modeling and calibration studies, how to describe driving variability under disaster condition is widely interested.

This paper presents an approach of improving the modeling and simulation of driving variability, based on the urban traffic evacuation decision-making model (Yuan, Ma, Zhang, and Liu, 2013). It consists two parts. First, a four-layer simulation framework called DGIT is adopted in the simulation system, enabling the system to describe the driving variability in different levels. Secondly, run a data-mining process based on dynamic real traffic data synchronously with the simulation system. With collecting real-time data of vehicles behavior, driving behavior patterns are analyzed and probability distribution of driving variability is reconstructed. Combining above two parts makes simulation system able to describe driving variability and provide more accurate predictions. A computational experiment is performed in this paper and the results prove feasibility and capability of providing decision-making support.

SYSTEM DESIGN

This section focuses on the implementation of microscopic traffic simulation considering driving variability. There are two key points: 1) how a simulation gains the capability to describe the driving variability, and 2) how the system captures the variability in a self-adaptive way.

In order to enhance the capability of simulating the driving variability within one simulation system, a modular framework is proposed, which is called DGIT framework. The DGIT framework consists four modules that are named as Decision, Game, Individual and Transform. The four modules carry following jobs respectively. 1) Decision: Where should a vehicle go in the current state? 2) Game: Which pattern of behaviors should it select in order to get this destination? 3) Individual: What could it do in this pattern of behaviors? 4) Transform: How could it move during this operation?

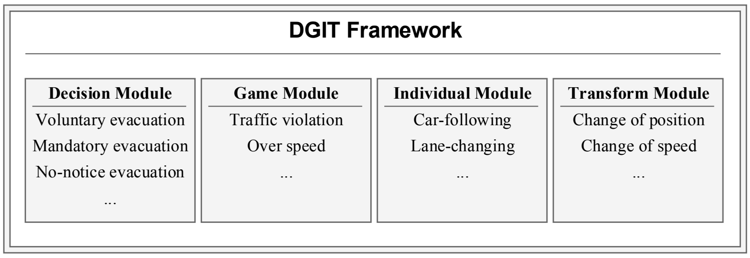


Figure 1. Variability in DGIT Framework

The framework combines heterogeneous models from various aspects and granularities, as shown in Figure 1. In Decision Module, simulated vehicles choose their own destination (rather than a global decision) independently, so that different evacuation scenarios (e.g. voluntary evacuation, mandatory evacuation, no-notice evacuation) could be represented. Game Module is designed to describe different patterns of driving behaviors with the approach of the Game Theory. Here a pattern of driving behaviors is the repeated way in which vehicles may be driven, including normal driving and traffic violence. Individual Module contains the set of the specific individual behaviors (e.g. following, overtaking, and waiting). Transform Module describes the effect of individual behaviors on vehicles in the sense of simulation parameters, that is, how a behavior finally changes the position and speed of a vehicle in the virtual world. Most of the existing models, including evacuation planning models (Lämmel, Grether and Nagel, 2010), driver route choice models (Dia, 2002), car-following models, etc. are capable of performing coupling calculations in the same workflow when embed into DGIT framework.

DGIT framework provides the possibility of integrating different models in one simulation system for describing more driving behavior patterns. It will be more convenience for changing models as needed without simulation breaking. However, in many situations during emergency evacuation, only changing model is not enough for describing driving variability. As most models are parameter-fixed but emergency situation and driving behavior are dynamic. A parameter-free way is highly requested for simulation of emergency condition, especially for high accurate simulation.

A simulation procedure is developed in this paper to solve the problem, which is named as CCAR procedure. It consists of four steps: Capture, Calibration, Analysis, and Refactor. In the Capture step, the information of every two following vehicles is extracted from real-time video images, and summarized into micro dataset, which is equal to $\{(v_n, v_{n-1}, g_n, v_n^*)_i\}$, where vehicle n-1 is the closest one in front of vehicle n, v_k is the speed of vehicle k, g_n is the gap between vehicle n and n-1, and v_n^* is the speed of vehicle n in the next unit of time. In the Calibration step, the micro dataset are fit for probability density distribution which figures out the statistical characteristics of the driving variability. In the Analysis step, the system analyzes the patterns and the proportion of different behaviors according to the existing car-following models. The observed patterns and the corresponding operations will be integrated into Game Module and Individual Module of the DGIT framework so that they can be selected and applied for specific simulated vehicles. At last, in the Refactor step, the simulation system adjusts the proportion of the various patterns to fit the real system, and thus the simulation of driving variability is achieved for both normal and emergency situations.

The overall system with DGIT framework and CCAR procedure is shown in Figure 2.

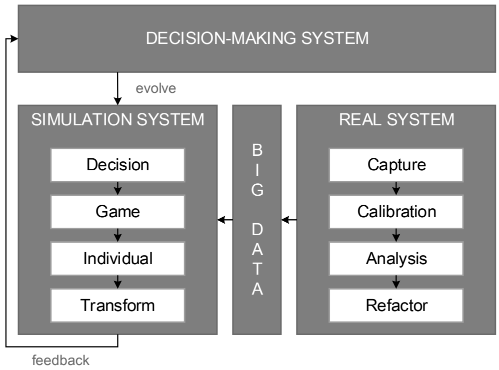


Figure 2. Simulation System with DGIT framework and CCAR procedure

EXPERIMENTAL DATA

Experiment is carried out in a major urban road, and the observation parameters are listed in Table 1. There are no traffic lights within 3km around the experimental area on the road in order to reduce traffic lights influence to the vehicle speed. Real-time traffic scenarios are recorded by HD camera, which is located in a very tall building near the road. Figure 3 shows one of the video frames.

	Length	Lane Number	Lane Width	Speed Limit	Height Limit
Value	84.2 m	3	3.6 m	60 km•h^{-1}	4 m

Table 1. Observation Parameters of the Experimental Road

Figure 3. A Video Frame of the Experimental Road

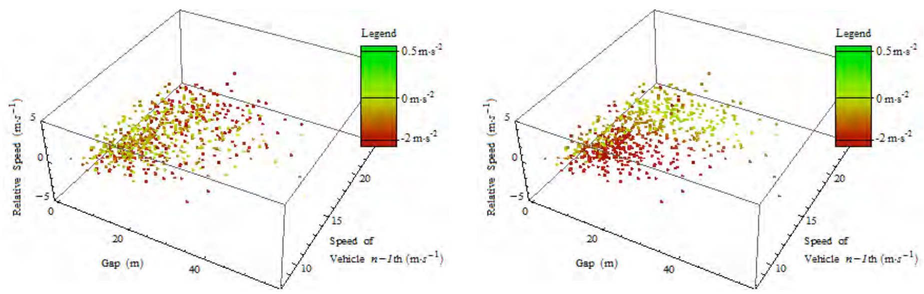
Using the video, 717 sets of micro data are recorded daily. Since each point is a four-dimensional vector, the figure is drawn as a 3D graph whose colors represent the fourth dimension, as shown in Fig.4. In Fig.4(a) and 4(b), the points refer to gap and the speed difference respectively, where speed difference refers to speed of vehicle n-1th, and the relative speed between vehicle n and n-1, identifying the position of the points, stand for the micro state of vehicles. The color between red and green shows the next action of each vehicle, i.e. acceleration or deceleration after 0.67s -- the average reaction time of drivers. Meanwhile, a simulation with the same dataset is carried out using the Gipps' car-following model (Gipps, 1981) whose formula is,

$$v_n^* = \min[v_n + 2.5A_n\tau(1-\frac{v_n}{V_n^M})(0.025+\frac{v_n}{V_n^M})^{1/2}, -B_n(\frac{\tau}{2}+\theta) + (B_n^2(\frac{\tau}{2}+\theta)^2 + B_n(2g_n - \tau v_n + \frac{v_{n-1}}{\hat{B}_{n-1}}))^{1/2}] \quad (1)$$

where τ is the reaction time, θ is the safety margin time, V_n^M is the speed limit of vehicle n, A_n is the largest acceleration of vehicle n, B_n is the actual braking, and B_{n-1} is the perceived braking. The calibrated parameters are listed in Table 2, and the simulation results are shown in Figure 4(b). Statistically, the calculating results with eq.(1) fit the experiment data quite well. The mean and standard deviation of the difference between calculating results and experimental data are -0.07 m•s^{-2} and 1.05 m•s^{-2} respectively. However, for each specific vehicle, most data show great difference between Figure 4(a) and Figure 4(b). 37.0% of the acceleration values between the model results and the experimental data have opposite signs. Compared with model results, the experimental data shows much more fluctuation. It shows that the Gipps' model is good at simulating driver behaviors statistically, but short for simulating variability.

	θ	τ	A_n	B_n	B_{n-1}
Value	0.33s	0.67s	2 m•s^{-2}	2 m•s^{-2}	1.8 m•s^{-2}

Table 2. Calibration Parameters of the Gipps' Model

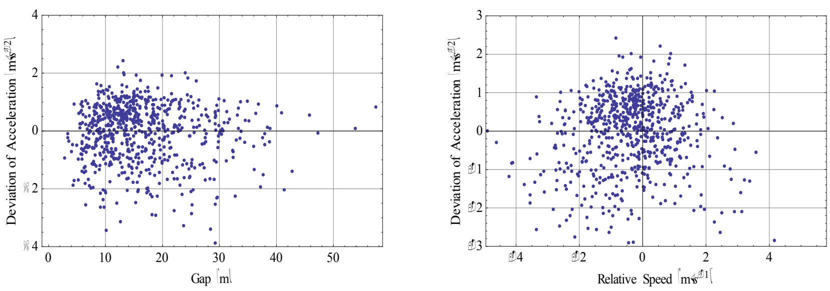


(a) Experimental Data (b) Simulation Data

Figure 4. Micro Dataset from experiment and simulation

PRELIMINARY RESULTS

The acceleration difference, which is calculated by subtracting experimental data from the model result of each specific vehicle, is shown in Figure 5. No clear patterns can be found for the experiment-model results difference.



(a) Experiment-model difference-Gap (b) Experiment-model difference-Speed

Figure 5. Experiment-model difference

However, some patterns emerge when the difference is counted as the probability distribution graph shown in Figure 6. If the driving variability is random, the distribution should be a Gaussian distribution. However, five peaks, instead of one peak in general, appear in the distribution. These fine structures in the distribution indicate that there may be several patterns of behaviors among the driver group. In addition, in the negative direction of the horizontal axis (i.e. the vehicles that move faster than anticipated), the distribution is more dispersed and has more peaks. It infers that drivers may obey different rules when they are stepping on the accelerator and the brake.

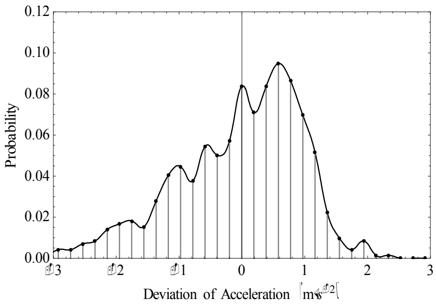


Figure 6. Probability Distribution Graph of the Acceleration Difference

CONCLUSION

This paper presents a dynamic data driven approach of describing driving variability in microscopic traffic simulations for both normal and emergency situations. A four-layer DGIT framework provides the capability of describing the driving variability among different scenarios, vehicles, time and models. A four-step CCAR procedure captures the driving behaviors from mass real-time data to calibrate and analyze the driving variability. Combining the DGIT framework and the CCAR procedure, the system can carry out adaptive simulation in both normal and emergency situations, so that be able to provide more accurate prediction of traffic scenarios and help for decision-making support. A preliminary experiment is performed on a major urban road, and the results verified the feasibility and capability of providing prediction and decision-making support.

Future work will focus on the analysis of different driving patterns. For example, perform various predictions with random combination of driving patterns starting from a certain initial scenario. This study will also pay attention to the method of emergency decision-making support with the simulation approach proposed in this paper.

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