A Cross-Simulation Method for Large-Scale Traffic Evacuation with Big Data

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Abstract. Microscopic traffic simulation is one of the effective tools for transportation forecast and decision support. It is a challenge task to make reasonable prediction of traffic scenarios during emergency. Big data technology provides a new solution for this issue. This paper proposes a cross-simulation method to apply the mass data collected in normal situations into large-scale traffic evacuations to provide better supporting information for emergency decision. The method consists of three processes: Acquisition, Analysis and Adaptation. It captures the dynamic distance-speed relation of every vehicles on the real roads and build a database of driving behaviors according to the existing car-following models. After calibration and analysis, various driving behaviors can be identified. During emergency, the distribution of driving behaviors will be refactored to adapt the fast-changing situation automatically so that the simulation system gains the adaptive ability in emergency situations. An experimental result on a real road preliminarily validates the practicability of the method and shows the supporting information which it can provide. The new method will make contributions on enhancing the predictive ability of traffic simulation systems in emergency situations.

Keywords: Transportation system · Large-scale evacuation · Cross simulation · Big data

1 Introduction

Large-scale evacuation is a significant topic in emergency management. A thorough contingency plan which neglects to consider transportation management might eventually collapse. In situations concerning emergency management, making quick decisions on traffic evacuation is usually required. Therefore it is essential for people who take part in emergency management to make quick judgments and reasonable estimations concerning transportation events.

Microscopic traffic simulations are one of the effective tools for the estimation and decisions of traffic situations. By simulating each vehicle individually, this tool is able to express the diversity of driving behavior. However, it is still challenging to reasonably estimate transportation during emergency due to the following reasons:

1. Large amount of data is required. Simulation systems require information drawn from real transportation systems for correction. Yet during emergency such information is often lacking.

Y. Chen et al. (Eds.): WAIM 2014, LNCS 8597, pp. 14–21, 2014.
DOI: 10.1007/978-3-319-11538-2_2

2. High uncertainty. During emergency the driving behavior is often various, rendering the traffic evacuation system highly unstable. The available models cannot cope with the estimation of the changing transportation system.
3. Wide range. Due to high density of population and over-crowdedness, simulation models are required to cover a range of a couple million of vehicles.

Existing research on diverse driving behavior was often achieved through traditional experimentation. For example, a typical research was aimed at the choice of route that a driver makes in order to get to a certain location. Dia et al. presented the belief-desire-intention agent architecture, describing whether or not the driver would give up behavioral choices of route when receiving real-time information [1]. Tawfik et al. researched the diversity in a driver's ability to perceive different route data and their decisions [2]. The interaction between transportation environment and the psychological influences of drivers is an important factor in causing intra-variability [3] in drivers. Parker et al. surveyed the drivers from Finland, UK, and the Netherlands, studying the extend to which drivers react to unreasonable driving behaviors, enabling them to react radically [4]. Kaysi et al. used a U-turn intersection to study the impact of radical behaviors on the transportation environment.

The big data technology has provided an excellent opportunity to solve this issue. It can provide better supporting information for the decision-making process. For example, Yuan et al. used trajectory data of taxies to provide route recommendations, and the results of which are notable [5]. However, in times of emergency the driver's psychological state is unstable, the behavior therefore differs highly from the usual state, which has an impact on transportation systems. How to use normal transportation data gaining useful information in times of emergency has become a challenging issue.

This paper provides a solution to converging the big data technology in a standard situation and adapting it to be used in a large-scale evacuation. This solution is separated into three processes: Acquisition, Analysis, and Adaptation. It uses video cameras in transportation systems and other sensory equipment to collect data, generating the probability distribution of driving behaviors, and analyzing similar behavior patterns. This paper adapted a road into a calculation experiment, proving primarily the practicality of this method and its ability to provide supporting information for the decision-making process.

This method is helpful in improving the estimation capability in a simulation transportation system during an emergency. The decision-making system could distribute a certain evacuation decision to a validation system for multiple meticulous simulation, evaluating the robustness of the decision. Because the driving behavior data comes from a standard scenario, the use of this method could achieve to form a self-adapting simulation evacuation system using big data.

2 System Design

In general, traffic simulation system needs to obtain real information on driving behavior in order to achieve accuracy. In a standard situation, this process would be simple and efficient. However, these methods can hardly be applied to emergencies, because there is limited time for collecting mass data from the emergency system.

Therefore, it is necessary for an emergency system to conditionally use the data collected in a normal state. Using traffic flow data (i.e. the flow rate, quantity and density on motorways) might risk the loss of accuracy, because the relationship between flow-rate and velocity differs greatly in emergencies [6]. Relatively speaking, using micro transportation data (i.e. the acceleration, moderation, and driving route) attains more effective information, because the function of the vehicle does not alter with psychological changes of the driver. Through attaining micro information in normal states, a large range of diverse driving behavior is covered, obtaining driving behavior information in emergencies.

This research captures diverse driving behaviors through real-time video data, providing models for simulation systems. This method consists of three processes: Acquisition, Analysis and Adaption. This method captures diverse driving behaviors through the mass data of normal traffic environment, and adapts them reasonably in situations of emergencies, providing effective data support for emergency evacuation models.

2.1 Acquisition

In the process of Acquisition, the time t of the video data is used to analyze the relationship between the distance between two vehicles and the state of speed:

$$s_{n,t} = \left\{ (v_n, v_{n-1}, g_n)_t \right\}, \tag{1}$$

where n and $n-1$ represent the identity number of two vehicles traveling in succession while occupying the same lane, $n-1$ is the former, and n is the latter, v_n is the velocity of the latter vehicle, v_{n-1} is the velocity of the latter, g_n is the distance between two vehicles, and t is the time that the data is obtained.

For a single vehicle, the camera needs to obtain a set of data concerning the relationship between distance and velocity:

$$\mathbf{S_{n,t}} = \left\{ s_{n,t_i} \right\}, \tag{2}$$

$$t_i = t_0 + i\tau, i = 0, 1, 2, \ldots, k. \tag{3}$$

where τ represents the reflective time of the driver (usually 0.33 s [7]), and t_0 is the starting observation time.

In the car-following model, $\mathbf{S_n}$ describes the vehicle's motion in a micro state. This paper is based on the Gipps' model [8], whose form is as follows:

$$\begin{aligned} v_n^* = \min \Bigg[& v_n + 2.5A_n\tau \left(1 - \frac{v_n}{V_n^M}\right)^{1/2}, -B_n\left(\frac{\tau}{2} + \theta\right), \\ & + \left(B_n^2 \left(\frac{\tau}{2} + \theta\right)^2 + B_n \left(2g_n - \tau v_n + \frac{v_{n-1}}{\hat{B}_{n-1}} \right) \right)^{1/2} \Bigg] \end{aligned} \tag{4}$$

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 $\widehat{B}_{n-1}$ is the perceived braking.

Through the data in $s_{n,t}$, the Gipps' model would be able to calculate the new velocity of the car v_n^* in the next time step $s_{n,t+\tau}$. Therefore the system could tag the state of these vehicles. Because τ and θ have a small range of changes, and V_n^M is usually only affected by the road, the only parameters that needs to be calibrated are A_n, B_n and $\widehat{B}_{n-1}$. These are the three parameters that form a vector and is used to describe driving behavior:

$$d_{n,t} = \left\{A_n, B_n, \hat{B}_{n-1}\right\}, \tag{5}$$

Because the driving behavior could be very diverse, in normal states the data set $d_{n,t}$ is not exclusive. The set of driving behaviors that could arise in the standard state is defined as $\mathbf{D_N} = \{d_{n,t}\}$. The set needs to input all of the data sets of driving behaviors which appeared in the normal situation, forming a spatiotemporal database for normal driving behaviors, as Table 1 has shown. This mass database will become the foundation for calculation in the process to come.

Table 1. Table structure of the spatiotemporal database for normal driving behaviors

Name	ID	Time	Road ID	A_n	B_n	$\widehat{B}_{n-1}$
Type	int	datetime	int	float	float	float

2.2 Analysis

In the process of Analysis, the system needs to analyze the spatiotemporal data for normal driving behavior, in order to calculate the distribution of these data, and whether they would form in an emergency scenario.

Apart from the normal driving behavior set $\mathbf{D_N}$, the set of behavior that may occur to all of the vehicles on a route is defined as $\mathbf{D_V}$, and the set which occurs during an emergency is defined as $\mathbf{D_E}$. The probability distribution functions of normal and emergency driving behaviors are set as p_N and p_E.

If the following hypothesis are correct, it can be assumed that the behaviors in standard situations could also appear in situations of emergency:

1. The performance of vehicles and road characteristics in an emergency does not differ from the normal scenario.
2. The amount of data is large enough. In this condition, all of the driving behaviors that could be expressed in all vehicles could be observed in a standard situation:

$$\mathbf{D_E} \subseteq \mathbf{D_V} = \mathbf{D_N} \tag{6}$$

3. In emergencies the distribution of driving behaviors are different from those in normal situations.

If the above stands correct, the outcome of the process of Acquisition $\mathbf{D_N}$ could be adapted into the Analysis process, which is divided into three steps:

Step 1: Categorize the spatiotemporal data of driving behaviors using time. For example, using thirty minutes as an interval to categorize the data.

Step 2: Set tolerance rate $\Delta d = \{\Delta A_n, \Delta B_n, \Delta \hat{B}_{n-1}\}$, divide the space of driving behavior by Δd into multiple blocks $\Delta_{\mathbf{m},\mathbf{t}}$. For each time interval, calculate the probability of normal driving behavior (i.e. p_N) landing in each block.

Step 3: Using month as a unit, gather individually the information of workdays and weekends, getting the patterns of driving behavior in normal situations, as Table 2 states below.

Table 2. Table structure of database of the patterns for normal driving behaviors

Name	ID	Time	Road ID	Weekend	A_n	B_n	$\widehat{B}_{n-1}$	p_N
Type	int	datetime	int	boolean	float	float	float	float

2.3 Adaptation

Finally, in the process of Adaptation, the system adjusts the ratios of each behavioral pattern in the simulation system based on the present scenario, developing a cross-simulation system which surpasses the normal and emergency driving behaviors. The system follows the process of Analysis, calculating the driving behaviors probability of the last time period p^*, using the following formula to determine the outcome of p_E:

$$p_E = kp_N + (1 - k)p^*, \tag{7}$$

where $k \in [0, 1]$ is called the adjustment ratio. It is defined as the probability of normal driving behaviors in the present emergency circumstances. Especially, if k = 1, the system remains normal, not considering the impact of recent driving behavior probability. If k = 0, the system ignores all of the data in normal situations, only consider the driving behavior information of the last time period. This way, the system could then continuously alternate between normal and emergency situations.

Because all of the processes have been claimed through experimental data, the self-adapting method would not create new driving behaviors, which would ensure the actual meaning in each of the individual driving behaviors generated from the simulation system.

3 Experimental Data

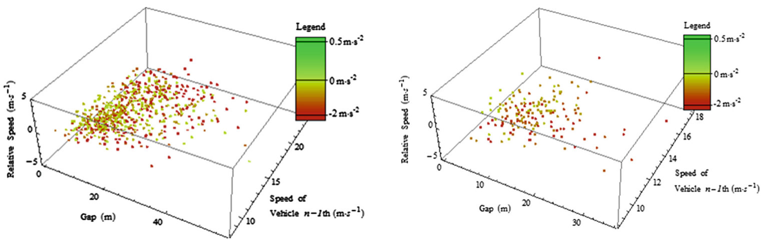
This research uses a main road in a city as an experiment subject. The object road captured by cameras is as Fig. 1 has shown. The road parameters is shown in Table 3. There are no traffic lights for 3 km in front or behind the road so that the impact of driving behavior due to traffic lights could be overlooked.

Fig. 1. Video image of the experimental section

Table 3. Key parameters of the experimental section

Length	Lanes	Lane width	Speed limit	Height limit
84.2 m	3	3.6 m	60 km/h	4 m

During the gathering process, 700 sets of normal data and 175 sets of "emergency data" are recorded. The "emergency data" here uses a different set of data than the normal data, which has been sampled at different times. In this paper it is only used to prove the effectiveness of the procedure. In real operation, it would just be required to transfer man-made data into real data. Since each $s_{n,t}$ is a three-dimensional vector, the figure is drawn as a 3D graph whose colors represent the next action of each vehicle, as shown in Fig. 2. The points in Fig. 2 refer to gap and the speed difference respectively, where speed difference refers to speed of vehicle n−1, 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 (shown as green) or deceleration (shown as red). Through the process of Acquisition, all of the data is collected into the database in the spatio-temporal database for normal driving behaviors as shown in Table 1.



(a) Normal Data (b) Emergency Data

Fig. 2. Micro traffic state of the normal and emergency data (Color figure online)

Based on traditional statistic method, the data could be fit with the Gipps' model (Eq. 3). The calibrated parameters are listed in Table 4. Statistically, 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.

Table 4. Calibration parameters of the Gipps' model

θ	τ	A_n	B_n	$\widehat{B}_{n-1}$
0.33 s	0.67 s	2 m•s^{-2}	2 m•s^{-2}	1.8 m•s^{-2}

In the process of Analysis, normal and emergency data has been summarized individually into the probability density graph, as shown in Fig. 3. The horizontal axis is the deviation between the actual vehicle acceleration and the acceleration calculated by the Gipps' model based on the calibration parameters in Table 4. The positive value represents the vehicle has a slower acceleration rate than the model estimation, and negative value represents that the acceleration rate is higher than the estimation. As seen, in the two situations, driving behavior does not fit the Gauss distribution. Multiple peaks suggest the existence of multiple models of driving behavior in research subjects.

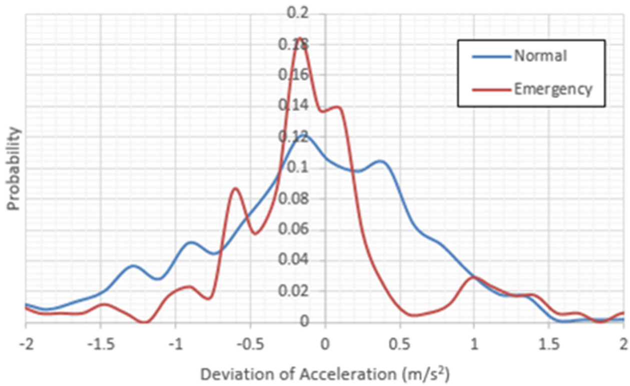


Fig. 3. Probability distribution graph in the process of Analysis

Lastly, in the process of Adaptation, using Eq. 6, the system could estimate recent states of driving behavior distribution patterns. It would be used as supporting data in simulation systems to implement microscopic evacuation.

4 Conclusion

This paper proposes a cross-simulation method to apply the mass data collected in normal situations into large-scale traffic evacuations to provide better supporting information for emergency decision. This method captures micro driving behaviors data from normal traffic environment, generates a series of probability distribution, and adapt the distribution for emergency situations. The paper uses a road as an example for experiments, primarily proving the practicality of this method and its ability to provide supporting decision-making information. Using this method, it is able to achieve the self-adapting simulation in different situations based on big data technologies.

In the further work, the system will continue to collect mass data, implementing the complete process, and providing effective evacuation decision-making support.

Acknowledgement. This work was partially supported by the National Natural Science Foundation of China (No. 91324022, No.91224008, No.91024032, No.70601015, No.70833003).

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http://www.springer.com/978-3-319-11537-5

Web-Age Information Management
WAIM 2014 International Workshops: BigEM, HardBD, DaNoS, HRSUNE, BIDASYS, Macau, China, June 16-18, 2014, Revised Selected Papers
Chen, Y.; Balke, W.-T.; Xu, J.; Xu, W.; Jin, P.; Lin, X.; Tang, T.; Hwang, E. (Eds.)
2014, XXII, 428 p. 182 illus., Softcover
ISBN: 978-3-319-11537-5