International Journal of Modern Physics C

MODELING DRIVER BEHAVIOR ON URBAN STREETS

Ruili Wang*, Mingzhe Liu, Ray Kemp
Institute of Information Sciences and Technology, Massey University
Palmerston North, New Zealand
{*r.wang, m.z.liu, r.kemp*}*@massey.ac.nz*

Min Zhou
Department of Electrical and Computer Engineering, Manukau Institute of Technology
Manukau, Auckland, New Zealand
Helen.Zhou@manukau.ac.nz

Received Day Month Year
Revised Day Month Year

Traffic flow on straight roads is the most common traffic phenomenon in urban road traffic networks. In this paper, a realistic cellular automaton (CA) model is proposed to investigate driver behavior on urban straight roads based on our field observations. Two types of driver behavior, free and car-following, are simulated. Free driving behavior is modeled by a novel five-stage speeding model (two acceleration stages, one steady stage and two deceleration stages). Car-following processes are simulated by using 1.5 seconds as the average headway (1.5-second rule), which is observed in local urban networks. Vehicular mechanical restrictions (acceleration and deceleration capabilities) are appropriately reflected by a five-stage speeding model, which has the dual-regimes of acceleration and deceleration. A fine grid (the length of each cell corresponds to 1 m) is used. Our simulation results demonstrate that the introduction of the dual-regimes of acceleration and deceleration, 1.5-second rule and fine grid matches actual driver behavior well on urban straight roads.

Keywords: Cellular automata; Driver behavior; Traffic flow; Urban traffic.

PACS Nos.: 89.40.-a, 45.70.Vn, 05.45.-a, 02.60.Cb

1. Introduction

Vehicular traffic flow has been studied from the point of view of statistical physics for several decades. The main issues of modeling traffic flow in urban networks include (i) how to properly describe driver behavior and the interactions between drivers at microscopic level; and (ii) how to obtain macroscopic properties of traffic flow. Recently, cellular automata (CA) have been widely used in traffic flow modeling (details can be found in the reviews presented in Refs. 1 and 2). The reason for this is

*Corresponding author.

that cellular automata are capable of modeling the behavior of an individual vehicle and the interactions between vehicles. Also, they can recapture the macroscopic properties of traffic flow by aggregating the values of the parameters obtained from the simulation.

Traffic flow in urban networks is more complex than that on highways due to factors such as more sophisticated topology and geometry of urban roads, more diverse vehicles, different directional crossing flow, various travel demands, and the scale of the system needed to be considered. Also, the interactions at unsignalized junctions (not controlled by traffic lights) are believed to be more complicated than those at signalized junctions (intersections and roundabouts).[3]

Modeling traffic flow in urban networks needs to simulate both cross traffic at a junction and straight traffic (the traffic flow on a road). A number of CA models[3,4,5,6,7,8] have been developed to simulate cross traffic flow at unsignalized junctions. These efforts have deepened the understanding of interactions between drivers and exhibition of collective behavior. However, as these models mainly focus on interactions between vehicles in cross traffic, they normally simplify the traffic on urban straight roads by assuming that vehicular arrivals follow a special distribution (e.g., Poisson distribution), without directly modeling traffic flow on those roads in detail. This assumption cannot accurately reflect real-world situations. In particular, in urban networks, traffic lights may block traffic and generate *platoons*. A *platoon* is a number of vehicles traveling together as a group, either voluntarily or involuntarily, because of signal control, geometrics, or other factors.[9] Therefore, it is necessary to investigate driver behavior on straight roads and dynamics on such roads.

Research in straight road traffic can provide a foundation for the study of traffic flow in urban networks. Traffic dynamics (e.g., queue lengths, congestions and crashes) on straight roads can directly influence local or even the whole city traffic network. Therefore, modeling traffic flow on straight roads is worthwhile to investigate at both theoretical and practical levels. However, modeling traffic flow on straight roads has not attracted much attention so far, due to the following incorrect perceptions: (i) Road segments are much shorter than highways and vehicles can pass segments quickly, so modeling on straight roads is believed to be trivial; (ii) Highway traffic models can be directly applied on straight roads just by adjusting some parameters (e.g., the maximum velocity). In practice, complexity of driving behavior on straight roads should not be underestimated due to frequent starting and stopping, random pedestrian interactions and the heterogeneous nature of human behavior. Moreover, traffic flow on highways is normally uninterrupted, which has totally different dynamic features. Recently, a primary objective of research in highway traffic has been focused on reproducing synchronized flow which is characterized by a remarkably high flux without any clear density-flux relation.[10] However, traffic flow in urban networks is frequently interrupted by red traffic lights, stop or give-way signs. Thus, synchronized flow is transient or almost nonexistent in urban traffic. The description of vehicular acceleration and deceleration behaviors in urban networks is becoming a focus.

In this paper, we have developed a realistic CA model to simulate driver behavior and interactions between vehicles on urban straight roads. Free driving behavior is simulated by five-stage speed changes (two acceleration stages, one steady stage and two deceleration stages) and car-following behavior is described based on the observed average headway (headway = distance/velocity) of 1.5 seconds.

This paper is organized as follows. In Sec. 2, related work is briefly introduced. In Sec. 3, the single-lane CA models for urban straight roads are proposed. In Sec. 4, simulation results of the proposed models are presented. The conclusion is given in Sec. 5.

2. Related Work

CA have been used to model traffic flow in urban networks in recent years. The first CA model (known as the BML model) for city traffic was proposed by Biham *et al.*[11] Initially, vehicles are randomly distributed among the streets. The states of east-bound vehicles are updated in parallel at odd time steps, whereas those of the north-bound vehicles are updated in parallel at even time steps. The update rule is the same as that of the NaSch model[12] with the maximum velocity (v_{max}) = 1 and the probability of random fluctuations (p) = 0, i.e., a vehicle moves forward one cell if and only if the cell in front is empty; otherwise, the vehicle does not move at the next time step.

As Chowdhury *et al.*[1] note, the dynamics of the BML model are fully deterministic and randomness arises only from the initial random conditions. Therefore, stochasticity of traffic flow cannot be reproduced in the BML model. Later, the BML model is generalized and extended in order to more realistically simulate urban traffic situations. Ref. 13 extended one-way traffic to two-way traffic on all streets. Each east-west (north-south) street is assumed to consist of two lanes, one of which allows east-bound (north-bound) traffic while the other has west-bound (south-bound) traffic. However, the update rules in their model are also deterministic as in the BML model. The phenomenon of green-wave synchronization has been considered,[14] which involves the synchronization of traffic lights in order to allow continuous traffic flow and which is often found along major roads. In this situation, vehicles move in platoons and the traffic volumes on major roads are greatly improved.

The ChSch model[15] incorporates the BML and NaSch models, and assumes that vehicles may stop at entrances of junctions. Thus, the conditions of vehicles slowing down include: collision avoidance with the preceding vehicle, and being still at the entrances of a junction. In general, the BML model and its extensions are incapable of realistically simulating the dynamics of traffic flow for the following reasons: (i) These models adopt constant acceleration and deceleration rates. In reality, drivers with manual gears will never use the same gear for different speeds. Different gears have different acceleration capacities. Obviously, automatic gears have similar effects; (ii) The coarse-grained grids are adopted in those models which cannot precisely describe speed changes and lead to drastic speed change in some cases. In these models, the length of each cell is assumed to be 7.5 m, the maximum speed can be up to 5 cells in a time step and a time step corresponds to 2 seconds in real time. Clearly, those models are not able to describe detailed vehicular dynamics. Furthermore, a time step in micro-simulation is recommended to be between 0.1 and 1 second.[16]

Acceleration Rates (m/s^2)	References
1.1 for speeds < 12.19 km/h; 0.37 for speeds > 12.19km/h	20
2.0 (maximum)	21
varies with street conditions	22
normal distribution (μ = 2.0, σ = 0.3) for cars normal distribution (μ = 1.5, σ = 0.2) for trucks	17
1.6 for cars; 1.2 for city buses; 1.3 for trams; 1.0-1.2 for trucks	23
2.5 for cars; 1.2 for bus/coaches; 1.8 for light goods vehicles 1.4 for straight trucks; 1.1 for truck with trailers	24
1.5 (normal) for cars; 2.0 (maximum) for cars 1.2 (normal) for trucks; 1.6 (maximum) for trucks	25

Deceleration Rates (m/s^2)	References
3.0 for avoidance collision	21
varies with street conditions	22
normal distribution (μ = 2.0, σ = 0.3) for cars normal distribution (μ = 1.5, σ = 0.2) for trucks	17
3.05 (normal) deceleration; 6.4 for emergent conditions	26
1.9 for cars; 1.3 for city buses; 1.3 for trams; 1.2 for trucks	23
4.5 for cars; 3.7 for bus/coaches; 3.9 for light goods vehicles 3.7 for straight trucks; 3.2 for truck with trailers	24
2.0 (normal) for cars; 5.0 (maximum) for cars 1.5 (normal) for trucks; 2.5 (maximum) for trucks	25

Fig. 1. Empirically observed acceleration and deceleration rates in the literature.

Different acceleration and deceleration rates, used in the models other than CA models (e.g., car-following models) for highway traffic and urban networks, are summarized in Fig. 1. The normal acceleration rates in Fig. 1 range from 1 m/s^2 to 2 m/s^2. The maximum acceleration rate is approximately 2.9 m/s^2 $(= \mu + 3 * \sigma)$.[17] The deceleration rates normally range from 1 m/s^2 to 3 m/s^2. The maximum deceleration rate for collision avoidance in Fig. 1 is 6.4 m/s^2. By contrast, in most previous CA models (e.g., ChSch model), the maximum deceleration rate is 18.75

m/s^2 (from the maximum speed unit 5 to 0) and the normal acceleration and deceleration rates are 3.75 m/s^2 (= 7.5/2 m/s^2). It can be seen that the acceleration and deceleration rates in Fig. 1 are more close to real road situations than that in most CA models. Furthermore, these CA models normally oversimplified vehicular mechanical capabilities. On one hand, vehicular acceleration is normally assumed to be a constant. On the other hand, vehicular braking capabilities are often assumed to be infinite; that is, a vehicle can be assigned arbitrary values to prevent collision. In this paper, vehicular mechanical capabilities are realistically reflected. That is, we describe the acceleration capabilities of vehicles in different gears and limit deceleration capabilities to a given value. The realistic acceleration and deceleration rates are simulated through fine grid CA. The length of each cell corresponds to 1 m on a road, which allows us to simulate speed changes more realistically (see details in Sec. 4).

It should be noted that one shortcoming of previous car-following models is that the behavior of free driving (a large distance between leading car and following one) has not been described realistically.[18,19]

3. Methodology

Generally speaking, traffic in urban networks consists of free flow and car-following flow. In free flow, a vehicle can be driven at its desired speed. In this case, speed changes of the vehicle depend on the driver's preference as the driver normally has enough time to safely stop the vehicle. We refer to this kind of driving behavior as free driving. With regard to the latter, a car can loosely or closely follow its predecessor; that is, speed changes of the following vehicle depend on the distance to the vehicle ahead and the speed of its predecessor.

We note that there can be a smooth transition between these two types of driving behaviors (i.e., free and car-following) in the real world and in our model. We denote H_c as the critical headway to distinguish free and car-following driving behavior. If the headway between the leading vehicle and the following one is larger than H_c, it is assumed that the driver behavior of the following vehicle is free driving. Otherwise, it would be car-following.

3.1. *Free-driving behavior*

As mentioned, constant acceleration and deceleration rates used in most CA models cannot accurately model real traffic conditions. Here, a five-stage model for speed changes is developed to describe free driving behavior on a straight road. The five stages are: (i) high acceleration, (ii) low acceleration, (iii) steady state, (iv) low deceleration, and (v) high deceleration stages. These five stages are illustrated in Fig. 2 and can be applied to a vehicle driving between junctions.

In the high acceleration stage (stage A), speed increases quickly due to a high acceleration rate. This normally happens when a vehicle just starts to move and, in practice, drivers normally use the lowest gear. During this stage, the speed of

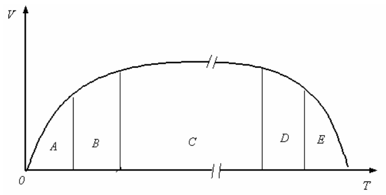

Fig. 2. Five-stage model of speed changes with traveling time between junctions. V and T denote current speed and traveling time, respectively. A, B, C, D and E are the five stages.

a vehicle increases up to a certain level v_a (about 40 km/h based on field observations). In stage B, speed increases with a relatively moderate acceleration rate, which gradually leads to a desired speed in stage C (about $50km/h$). Clearly, the acceleration rate in stage B is much lower than that in stage A, but vehicles drive at higher speeds.

In the steady stage (stage C), speed is assumed either to be unchanged or to randomly fluctuate within a certain range, i.e., $\pm 1\ m/s^2$. Speed in this stage may be maintained in a certain range within and close to the legal limit. The duration of this stage depends on the length of the road.

Based on field observations, a vehicle slows down with two different deceleration stages (depending on how close to the downstream junction it is): a low and a high deceleration stage. At the low deceleration stage (stage D), a vehicle will decelerate gradually with a moderate deceleration rate, followed by a high deceleration stage (stage E), in which speed decreases rapidly until the vehicle is stationary.

The update rules of the nth vehicle depend on its speed $v_n(t)$ and the distance to the next junction or the distance to the tail of the queue ahead, $D_n(t)$, at time step t:

1. Acceleration

If $v_n(t) < v_a$,

$$v_n(t+1) = v_n(t) + a_1. \tag{1}$$

If $v_a \leq v_n(t) \leq v_{max}$,

$$v_n(t+1) = v_n(t) + a_2. \tag{2}$$

2. Randomization

If $v_n(t) > 0$,

$$v_n(t+1) = v_n(t) + a_3. \tag{3}$$

3. Deceleration

If $D_n(t) \leq D_1$,

$$v_n(t+1) = v_n(t) + d_1. \quad (4)$$

If $D_n(t) \leq D_2$,

$$v_n(t+1) = v_n(t) + d_2. \quad (5)$$

4. Movement

$$x_n(t+1) = x_n(t) + v_n(t+1). \quad (6)$$

where:
a_1 and a_2 are the acceleration rates of the high and low acceleration stages
d_1 and d_2 are the deceleration rates of the low and high deceleration stages
v_a and v_{max} are the gear-shifting and maximal velocities of a vehicle
D_1 and D_2 are two different distances which indicate that a vehicle starts to use the deceleration rates d_1 and d_2
a_3 is the change of velocity in the steady stage

$$a_3 = \begin{cases} 1 & : \text{with probability } p_1 \\ -1 & : \text{with probability } p_2 \\ 0 & : \text{with probability } p_3 \end{cases} \quad (7)$$

with $p_1 + p_2 + p_3 = 1$.

The first three rules describe how a vehicle adjusts its velocity in free driving, and the fourth rule indicates that a vehicle moves to a new position according to its current position and updated velocity which is obtained from the above steps. Rule 1 postulates that there is a gear-shifting velocity v_a at which the acceleration rate changes. If the velocity of a vehicle is less than v_a, the vehicle acceleration is a_1. Otherwise, the acceleration changes to a_2 until the vehicle reaches the maximal velocity v_{max}. Rule 2 indicates that the velocity fluctuates randomly. Randomicity in most CA traffic models (e.g., in Refs 1 and 2) has been represented as a random deceleration. In practice, a random fluctuation should also include both random accelerations and decelerations. In stage C, three probabilities are used to reflect the fluctuation process. For simplicity, all three probabilities are assumed to be equal, namely, $p_1 = p_2 = p_3 = 1/3$. Rule 3 describes deceleration driver behavior in stages D and E. A vehicle starts to decelerate with rate d_1 if the distance is less than D_1. When the distance is less than D_2, the deceleration rate is switched to d_2. The parameters a_1, a_2, d_1, d_2, v_a, D_1, and D_2 are calibrated in Sec. 4.1.

3.2. *Car-following driving behavior*

Free-driving behavior reflects no interactions (i.e., $headway > H_c$) between the following and the preceding vehicles, while car-following behavior[27,28,29] has emphasized the interaction between the following and preceding vehicles. In other words, the speed of the following vehicle changes in relation to its gap, the gap of its predecessor, and the speed of its predecessor. In this case, $headway \leq H_c$. That is, the update rules of the nth vehicle at time step t+1 depend on its position $x_n(t)$, the speed of its predecessor $v_{n+1}(t)$, the gap between the nth and the (n+1)th vehicles $g_n(t)$, and the gap between the (n+1)th and the (n+2)th vehicles $g_{n+1}(t)$:

1. Speed adjustment

$$v_n(t+1) = \min\{v_{max}, \frac{2}{3}E_n(t+1)\}. \tag{8}$$

$$E_n(t+1) = g_n(t) + \min\{v_{n+1}(t), g_{n+1}(t)\}. \tag{9}$$

$E_n(t+1)$ denotes the anticipated traveling distance in the next time step. This rule is based on the so-called 1.5-second rule. The average headway in car-following processes was observed to be 1.5 seconds in local urban networks. We refer to this phenomenon as the 1.5-second rule. This averaged 1.5-second headway means that some headways are less than 1.5 seconds due to close car-following behavior and others are larger than 1.5 seconds due to loose car-following behavior. On average, the vehicle can only drive up to 2/3 of the total anticipated distance between it and the preceding vehicle in one time step.

2. Movement

$$x_n(t+1) = x_n(t) + v_n(t+1). \tag{10}$$

Each vehicle moves to a new position according to its current position and updated speed obtained from the above steps.

4. Simulation and Discussion

4.1. *Model formulation*

In this paper, the length of each cell corresponds to 1 *m* on a real road, which provides better resolution in modeling actual traffic flow than most CA traffic models. Each time step corresponds to 1 second and therefore one unit of speed is equal to 3.6 *km/h*. One unit of acceleration is equal to 1 m/s^2 and this corresponds to a 'comfortable acceleration' rate.[30]

In urban networks, a lower speed is required than on open roads due to speed constraints. The legal speed limit in urban networks is usually 50 *km/h* in New Zealand; however, some people drive at around 58 *km/h*, which is just below the apprehension limit (61 km/h in New Zealand). Therefore it is assumed that the maximum speed of each vehicle ranges from 46.8 *km/h* to 57.6 *km/h*. This means that a vehicle can move through 13 -16 cells in 1 *s* when driving at the maximum speed.

Normally, previous models have implicitly assumed that the headway is 1 *s*, for example in Refs. 12, 31 and 32. However, a safe headway of 2 *s* and a minimum headway of 1.44 *s* are recommended for all drivers.[33] In practice, the headways that drivers use are normally shorter than 2 seconds[34] and longer than 1 second. In this research, over 10 hours of traffic data was recorded between 16 August 2004 and 27 August 2004. An average car-following headway of approximately 1.5 *s* was observed in local urban networks and this 1.5-second rule has been built into the proposed model. Fig. 3 shows a comparison between the parameters of the proposed model and those in other CA models.

Parameters(unit)	Proposed models	Previous CA models
Length of each cell (m)	1	7.5
Time step (s)	1	1
Speed unit (km/h)	3.6	27
Basic A or D (m/s^2)#	1	7.5
Ave headways (s)*	1.5	1

Fig. 3. Comparison of parameters in the proposed models versus those of earlier models. A (D) - Acceleration (Deceleration).

The critical headway H_c is set to 3 seconds. This assumption is consistent with that suggested in Ref. 35 where a headway value of approximately 2.6 seconds is used to define free flow versus car-following flow. And we set $v_a = 11$, $D_1 = 40$ and $D_2 = 22$, based on observations. Other parameters in Eqs. (1), (2), (4) and (5) have been calibrated and are shown below:

$$a_1 = \begin{cases} 1 & p \leq 0.36 \\ 2 & \text{otherwise} \end{cases} \quad (11)$$

$$a_2 = \begin{cases} 0 & p \leq 0.5 \\ 1 & \text{otherwise} \end{cases} \quad (12)$$

$$d_1 = \begin{cases} 0 & p \leq 0.5 \\ -1 & \text{otherwise} \end{cases} \quad (13)$$

$$d_2 = \begin{cases} -1 & p \leq 0.22 \\ -2 & \text{otherwise} \end{cases} \quad (14)$$

Here, p is a random number within [0, 1] generated at each time step for each vehicle.

4.2. *Simulation results*

The proposed model has been calibrated using real data recorded during off-peak hours, when there was less interaction between vehicles. These field observations were all made in good weather in order to avoid driver behavior fluctuations due to different weather conditions. The data was collected on five roads in Palmerston North City, New Zealand.

Over 50 data sets are used in this research. Five speeding stages were observed. At the steady stage (stage C), driver behavior is basically uniform. Therefore, the main concern in this paper is driver behavior relating to acceleration and deceleration between junctions. In order to compare driver behavior, relating to acceleration and deceleration on different roads, the different speed-time relationships were collected into one graph. Figs. 4 (a) and (b) show the speed changes of vehicles on urban roads in high and low acceleration stages. Figs. 4 (c) and (d) show the speed changes of vehicles on the same roads in low and high deceleration stages. It can be seen that our simulation results are in good agreement with the average values. This indicates that our model is able to simulate driver behavior in different road sections. Therefore, our model can be considered as a basic model for simulating traffic flow in a large-scale urban network.

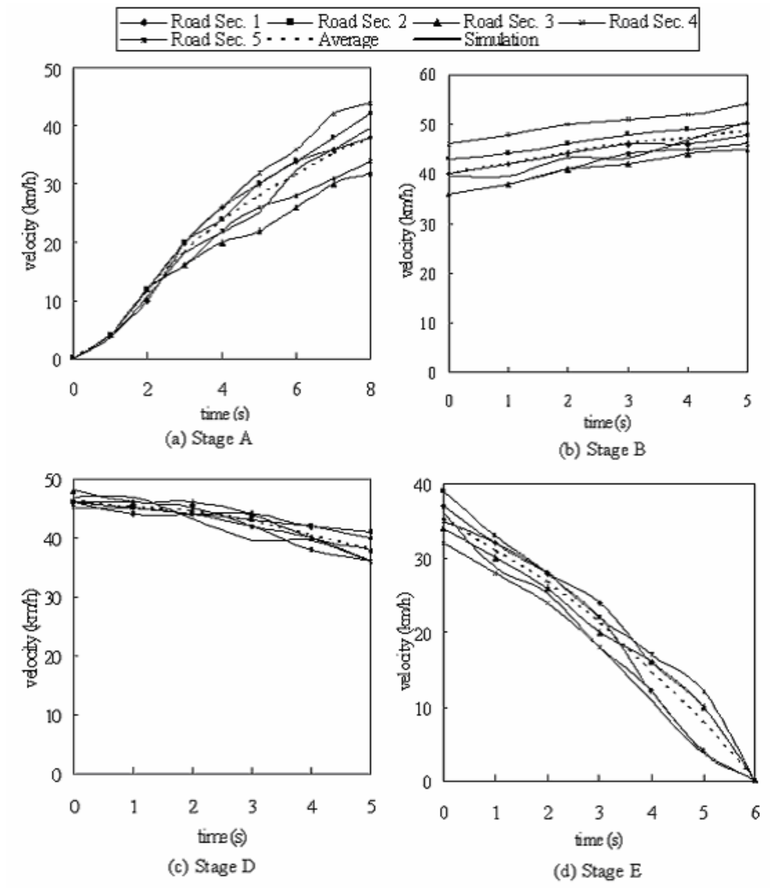

Fig. 4. Acceleration and deceleration in actual traffic and the proposed model under different stages.

Error tests are used to quantitatively measure the ability of fitness from simulation, compared to the field data. The mean relative error (MRE) test is one such test, which is expressed as:

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - x_s|}{x_i}. \tag{15}$$

where x_i is the actual observation value and x_s is the simulated value.

Both the simulation results and the MRE results (see Fig. 5) show that the proposed models can closely reproduce the field data with regards to the speeds of individual vehicles in different acceleration and deceleration stages.

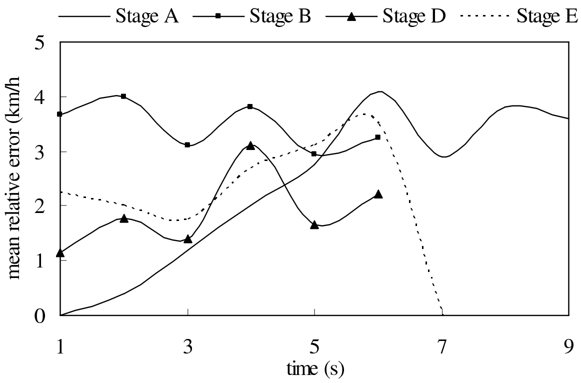

Fig. 5. Mean relative errors in the different acceleration/deceleration stages.

Benekohal[36] indicates that validation of models should be performed at both the microscopic and macroscopic levels. For microscopic validation, the speed or position of individual vehicles should be compared to the field data. For macroscopic validation, average speed, traveling time, average density and flow should be compared to corresponding values from the field data. In this paper, due to the scope of the research, average speed and traveling time have been validated. We plan to apply our proposed model and the models developed in Refs. 3 and 6 to simulate the traffic flow in an entire city road network. So that we can further validate the proposed model.

Fig. 6 shows observed single-vehicle speeds from three different drivers (driver 1, driver 2 and driver 3) and simulation results using the proposed method with calibrated values for acceleration and deceleration rates. The field data in this study was recorded using a digital video camera on Park Road between Cook Street and Fitzherbert Avenue in Palmerston North City, New Zealand. The dual-regimes of acceleration and deceleration means that the model maintains a good correspondence with the real data, especially in the initial acceleration and final deceleration stages. Also, it can be seen that the simulation curve in our model is not smoother than that in actual driving. This is because that space, time, and system variables are discrete in CA. A finer discretization (e.g., the length of a cell corresponds to 0.1

m) may map to a smoother output, but it increases the computational complexity of the model as well.

Fig. 6. Observed single-vehicle speeds and simulation results.

5. Conclusion

This paper proposed a new cellular automaton (CA) model to simulate driver behavior on urban straight roads based on field observations. Two types of driving behaviors are presented, i.e., free and car-following. A novel five-stage speed changes model (two acceleration stages, one steady stage and two deceleration stages) is used to describe free driving behavior. The average observed headway of 1.5 seconds in urban networks is employed to simulate a car-following process, which replaces 1-second headway used in previous CA models.

Our model is a realistic CA model, which is based on the mechanical restriction and fine grid CA. On one hand, we use dual-regime acceleration rates to reflect the actual vehicular acceleration capabilities, while vehicular acceleration in most previous traffic CA models is assumed to be a constant. On the other hand, the deceleration limitation has been enforced in our model. That is, the deceleration process including collision avoidance is moderate rather than drastic. Most previous CA traffic models assume that braking capability is too large and vehicles can be assigned arbitrary values to prevent collision.

Our simulation results have shown that the introduction of dual-regime acceleration and deceleration, 1.5-second rule and fine grid simulates the real driver behavior well on urban straight roads, especially in the initial acceleration and final deceleration stages. This means that our model can better reflect the details of vehicle movement and interactions among drivers.

Acknowledgments

We are grateful for supports from the Massey University Research Fund (MURF) and the ASIA 2000 Foundation High Education Exchange Programme (HEEP).

References

1. D. Chowdhury, L. Santen and A. Schadschneider, *Phys. Rep.* **329**, 199 (2000).
2. A. Schadschneider, *Physica A* (2006) in press.
3. R. Wang and H.J. Ruskin, *Int. J. Mod. Phys. C* **17**, 693 (2006).
4. B. Chopard, A. Dupuis and P. Luthi, *Traffic and Granular Flow'97*, (World Scientific, Singapore, 1998), p. 153.
5. R. Wang and H.J. Ruskin, *Comp. Phys. Comm.* **147**, 570 (2002).
6. A. Dupuis and B. Chopard, *Networks and Economics* **3**, 9 (2003).
7. E.G. Campari, G. Levi and V. Maniezzo, *Proc. Int. Conf. Cellular Automata for Research and Industry*, (Springer-Verlag, German, 2004), 25-27, October, Amsterdam, Netherlands.
8. M.E. Fouladvand, Z. Sadjadi and M.R. Shaebani, *Phys. Rev. E* **70**, 046132 (2004).
9. Transportation Research Board, *Highway Capacity Manual*, National Research Council, Washington, D.C., USA (2000).
10. H.K. Lee, R. Barlovic, M. Schreckenberg and D. Kim, *Phys. Rev. Lett.* **92**, 23 (2004).
11. O. Biham, A. Middleton and D. Levine, *Phys. Rev. A* **46**, R6124 (1992).
12. K. Nagel and M. Schreckenberg, *J. Phys.* **2**, 2221 (1992).
13. J. Freund and T.P. Poschel, *Physica A* **219**, 95 (1995).
14. J. Torok and J. Kertesz, *Physica A* **231**, 515 (1996).
15. D. Chowdhury and A. Schadschneider, *Phys. Rev. E* **59**, R1311 (1999).
16. M. Brackstone and M. McDonald, *Proc. IEEE Int. Veh. Symp.* (IEEE Society), 9-11 June, 2003.
17. H. Suzuki and T. Nakatsuji, *JSAE Rev.* **24**, 403 (2003).
18. A. Schadschneider, *Physica A* **313**, 153 (2002).
19. A. Schadschneider, W. Knospe, L. Santen and M. Schreckenberg, *Physica A* **346**, 165 (2005).
20. J. Treiterer, *Final Report EES278*, Department of Civil Engineering, Ohio State University (1975).
21. P.G. Gipps, *Tran. Res. B* **15**, 105 (1981).
22. H.M Barbosa, M.R. Tight and A.D. May, *Tran. Res. A* **34**, 103 (2000).
23. R.T. Luttinen, *Finnish Road Administration* ISSN 1457-9871, 2004.
24. T. Oketch, M. Delsey and D. Robertson, *Transportation Association of Canada Annual Conference*, Quebec City, 19-22 September, 2004.
25. P. Bonsall, R. Liu and W. Young, *Tran. Res. A* **39**, 425 (2005).
26. G.H. Bham and R.F. Benekohal, *Tran. Res. C* **12**, 1 (2004).
27. M. Brackstone and M. McDonald, *Tran. Res. F* **2**, 181 (1999).
28. S. Ahn, M.J. Cassidy and J. Laval, *Tran. Res. B* **38**, 431 (2004).
29. H.M. Zhang and T. Kim, *Tran. Res. B* **39**, 385 (2005).
30. Institute of Transportation engineers, *Traffic Engineering handbook* (1992).
31. W. Knospe, L. Santen, A. Schadschneider and M. Schreckenberg, *J. Phys. A* **35**, 3369 (2002).
32. M.E. Larraga, R.A. Rio and L. Alvarez-lcaza, *Tran. Res. C* **13**, 63 (2005).
33. Land Transport Safety Authority, *New Zealand Road Code* New Zealand, (2003).
34. L. Neubert, L. Santen, A. Schadschneider and M. Schreckenberg, *Phys. Rev. E* **60**, 6480 (1999).

35. M.F. Aycin and R.F. Benekohal, *Tran. Res. Rec.* **1320**, 190 (1998).
36. R.F. Benekohal, *Tran. Res. Rec.* **1320**, 190 (1989).