Exploring Traffic Patterns and Phase Transitions with Cellular Automaton

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Abstract: Traffic patterns and the associated phase transitions for pure and mixed traffic are explored in this study. Local traffic parameters are defined in a spatiotemporal (3-D) domain so that the cellular automaton (CA) modeling can precisely capture the traffic features. Refined CA simulations are performed under pure and mixed traffic scenarios on a multilane stretch of road where virtual detectors are placed to measure the 3-D traffic parameters. It is found that the proposed measuring techniques with refined CA modeling can copiously explore the local traffic patterns with associated phase transitions in both upstream and downstream of a bottleneck. Finally, a comparison of the local traffic parameters with the global counterparts is also presented.

Key Words: Cellular automaton (CA), Mixed traffic, Traffic Patterns, Phase transitions.

1. INTRODUCTION

Cellular automaton (CA) has become an effective tool for reproducing the basic features and for exploring the phase transitions of real traffic since Nagel and Schreckenberg (1992) first proposed a simple CA model—the renowned NaSch model. To date, a considerable number of modified CA models have been proposed, for instance, Nagel (1996, 1998), Rickert et al. (1996, 2002), Chowdhury et al. (1997), Barlovici et al. (1998), Knospe et al. (2000), Jiang and Wu (2003), Bham and Benekohal (2004), and Larraga et al. (2005). Most of these CA models were for pure traffic on rather coarse cell systems wherein all vehicles are treated as identical size (same length and width). Recently, some CA studies have devoted to mixed traffic scenarios in which vehicles come in various sizes (e.g., Nagel et al., 1998; Ez-Zahraouya et al., 2004; Kerner, 2004; Wang et al., 2007; Meng et al., 2007). However, these studies merely considered different vehicle lengths without factoring in the different vehicle widths into the models, except for Meng et al. (2007). In reality, a multilane roadway space used by mixed traffic (e.g., bus, car, motorcycle) should take into account the lengths and widths of different vehicles so as to more precisely elucidate their interactive movements, especially the overtaking or lane change behaviors. Besides, using coarse cell systems may oftentimes fail to capture the essential traffic features emerging in a spatiotemporal domain for real traffic.

To address the mentioned weaknesses, Hsu et al. (2007) first proposed a refined CA modelling by introducing a generalized spatiotemporal definition for traffic parameters (occupancy, flow and speed) which can precisely capture the collective behaviors of mixed
traffic with different vehicular sizes. One important advantage of the refined CA modeling is that the “resolution” of simulation results is greatly enhanced; therefore, more detailed traffic features can be observed. Lan et al. (2007, 2010) have successfully applied the refined CA modeling to mixed traffic simulations in the contexts of freeway (comprising cars and buses/trucks) and surface roadway (comprising cars and motorcycles).

Because observation of traffic over a long spatial stretch is difficult and expensive, traffic parameters are generally measured in a local (temporal) manner with stationary detectors, rather than in a global (spatiotemporal) manner. Despite this, methodologies for deriving the local traffic parameters, especially on a fine cell system, remain seldom addressed (Mallikarjuna and Ramachandra, 2006, 2008). To fill in this gap, this paper attempts to measure the local traffic parameters and to further explore the local spatiotemporal features of mixed traffic with the refined CA modeling.

The rest of this paper is organized as follows. A short description of the refined CA modeling is given in Section 2, followed by the definition of local traffic parameters in Section 3. The simulations, the derived local traffic parameters, and comparisons between pure and mixed traffic are presented in Section 4. Section 5 compares the derived local traffic and their global counterparts for both pure and mixed traffic. Conclusions and suggestions for future studies then follow. In addition, to enhance readability, a notation table summarizing all variables and parameters utilized are given in the Appendix.

2. PROPOSED CA MODEL

2.1 Common Unit for Cells and Sites

The concept of “common unit” (CU) was first introduced by Hsu et al. (2007) to gauge different vehicle dimensions (length and width) and their required clearances for safe longitudinal and lateral movements. Following the same concept, this study defines 1×1.25 meters as the CU for cells (representing the vehicles) and sites (representing the roadway spaces).

![Image of cell/site system utilized and allocations of vehicles of various sizes in the proposed CA model. For demonstration, the virtual local detector is also defined.](image)

For instance, for a two-lane road with 3.75-meter width in each lane, as shown in Figure 1, the road width can be represented by 6 CUs (i.e., each lane is represented by 3 CUs in width, which can be equally divided into 3 sub-lanes). According to Figure 1, for safe movement with acceptable clearances, a heavy vehicle (bus, truck) can be set as 12×3 CUs, taking 36 CUs of the roadway space; a light vehicle (car) is represented by 6×2 CUs, occupying 12 CUs of the roadway space; a two-wheel vehicle (motorcycle, bicycle) can be represented by 2×1 CUs, taking up 2 CUs of the roadway space. Other vehicle types can also be defined in...
accordance with their lengths and widths. For demonstration, in Figure 1 a local detector which occupies 1×6 CUs is also depicted.

2.2 Spatiotemporal Traffic Parameters

In conventional traffic flow theory, there are three important traffic parameters—flow \(q\), density \(k\) and speed \(v\). For a single-lane roadway with length \(L\), the 1-D local traffic parameters can be defined as:

\[
k(t) = \frac{\text{number of vehicles observed over a road of given length } L \text{ at time } t}{\text{length of observed roadway } L}
\]

\[
q(x) = \frac{\text{number of vehicles observed during given time period } T \text{ at loc. } x}{\text{length of observed time period } T}
\]

The speed \(v\) can be calculated by the following equation:

\[
q = kv
\]

It is understood that Eq. (3) was originally developed by scholars in the field of fluid mechanics upon the assumption that fluid flow is continuous. This formula later was introduced by Wardrop (1952) for analyzing traffic features and, since then, commonly utilized for estimating vehicular average speed. However, one may be confused regarding the validity of such applicability since traffic flow is not continuous but in essence discrete by nature. Besides, by definition, the 1-D local traffic flow-\(q(x)\) is a time-based parameter measured over a period of time at a specific fixed point, whereas the local traffic density-\(k(t)\) is a space-based parameter measured over a distance of space at a specific time instant. So, although Eq. (3) seems reasonable from dimensional perspective, it has been constantly criticized in the past. For example, Highway Research Center (2005) argued that this formula is strictly correct only under some very restricted conditions, i.e., homogeneous state in which each vehicle are equipped with identical features (e.g., same headway, identical speed, etc.), or as the limits of both the space and time measurement intervals approach zero. If neither of those situations hold, then the use of Eq. (3) to calculate speed can give misleading results, which would not agree with empirical measurements.

To overcome this restriction, Daganzo (1997) extended the 1-D local traffic parameters to 2-D to cover both time and distance and hence defined the 2-D traffic parameters. However, the 2-D definition failed to capture the lateral movements of vehicles in multilane contexts. Therefore, Hsu et al. (2007) further expanded this concept by introducing the generalized 3-D traffic parameters, including occupancy \(\rho(S)\), flow \(q(S)\), and space-mean-speed \(v(S)\) over a spatiotemporal domain \(S\) as follows:

\[
\rho(S) = \frac{\sum N(x) \Delta t}{\sum N \Delta t} = \frac{t(S)}{|S|}
\]

\[
q(S) = \frac{\sum N(y) \Delta x}{\sum T \Delta x} = \frac{d(S)}{|S|}
\]

\[
v(S) = \frac{q(S)}{\rho(S)} = \frac{d(S)}{t(S)}
\]

The above generalized 3-D traffic parameters defined by Hsu et al. (2007) will be used in this
2.3 Longitudinal Movements

The forward rules utilized in this study follow those proposed by Lan et al. (2009) who took limited deceleration capability into consideration. The proposed forward update rules apply to both light and heavy vehicles. However, vehicle attributes (e.g., maximum speed, allowable acceleration and deceleration) will be different in accordance with the vehicle category simulated. The forward update rules include the following seven steps.

Step 1: Determination of the randomization probability.

\[
p(v_n(t), t, S_{n+1}(t)) = \begin{cases} 
  p_b & \text{if } S_{n+1} = 1 \text{ and } t_s < t_s \\
  p_0 & \text{if } v_n = 0 \text{ and } t_s \geq t_{s,c} \\
  p_d & \text{in all other cases}
\end{cases}
\]  

(7)

In this study, \( k=1 \) denotes light vehicles and \( k=2 \) denotes heavy vehicles.

Step 2: Acceleration. Determine the speed of vehicles in the next time step.

\[
\text{if } (S_{n+1}(t) = 0) \text{ or } (t_s \geq t_s) \text{ then } v_n(t+1) = \min(v_n(t) + a_k, v_{k,\text{max}})
\]

else \( v_n(t+1) = v_n(t) \)  

(8)

Step 3: Deceleration. If \( v_{n+1}(t+1) < v_n(t+1) \), check the following safety criteria to determine speed at the next time step.

\[
x_n(t+1) + \Delta + \sum_{i=1}^{\tau_x(v_n(t+1))} (c_n(t+1) - \frac{D}{2} i) \leq x_{n+1}(t+1) + \sum_{i=1}^{\tau_x(v_n(t+1))} v_{n+1}(t+1)
\]

(9)

Step 4: Randomization.

\[
\text{if } (\text{rand}() < p) \text{ then } v_n(t+1) = \max(v_n(t+1) - 1,0)
\]

(10)

Step 5: Determination of vehicle status identifier \( S_n(t) \) in the next time-step.

\[
S_n(t+1) = \begin{cases} 
  0 & \text{if } v_n(t+1) > v_n(t) \\
  S_n(t) & \text{if } v_n(t+1) = v_n(t) \\
  1 & \text{if } v_n(t+1) < v_n(t)
\end{cases}
\]

(11)

Step 6: Determination of time (\( t_s \)) stuck inside the jam.

\[
t_s = \begin{cases} 
  t_s + 1 & \text{if } v_n(t+1) = 0 \\
  t_s & \text{if } v_n(t+1) > 0
\end{cases}
\]

(12)

Step 7: Update position.

\[
x_n(t+1) = x_n(t) + \text{roundoff} \left( \frac{v_n(t) + v_n(t+1)}{2} \right)
\]

(13)

2.4 Lateral Movements

In real world, most road systems comprise at least two lanes, thus allowing vehicles to change
lane or make lateral displacement to overtake a slow vehicle or fixed object in front. Over a two-lane (6 sites in width) roadway, for instance, a heavy vehicle (3 CUs in width) will have only one kind of lateral movement—lane change (either from left lane to right lane or from right lane to left lane). A light vehicle (2 CUs in width) may have one additional lateral movement option: lateral drift, beside lane change. The lateral drift of a light vehicle will be triggered if the situation allows it to overtake a smaller size vehicle (e.g., motorcycle) in front of the same lane and with comparatively slower speed, which refers to moving forward within the same lane but drifting from rightmost two sub-lanes to leftmost two sub-lanes or from leftmost two sub-lanes to rightmost two sub-lanes; provided that each sub-lane is 1-site in width. However, the present paper does not deal with the motorcycle traffic—only pure traffic and mixed traffic that comprised by heavy vehicles (buses or trucks) and light vehicles (cars) are simulated, the lateral positions of light vehicles within each lane will not significantly affect the simulated traffic flow rate. Therefore in this study lane change behavior is only considered for both light and heavy vehicles. The lane change rule for a vehicle located in the left lane of one two-lane roadway that intends to lane change toward the right lane can be described as:

$$LC^{LR}: \text{If } v_{l,n}(t) > v_{l,n}(t) \text{ and } v_n(t) > v_{l,n}(t)$$

and

$$g_{l,n}(t) > \min(d_{l,n}^{\text{eff}}, v_n(t+1))$$

and

$$g_{b,n}(t) > \min(d_{b,n}^{\text{eff}}, v_{b,n}(t+1)) \quad (14)$$

where $g$ means the gap and the suffix $b$ means the vehicle in nearby upstream.

3. LOCAL TRAFFIC PARAMETERS DETECTION

3.1 Local Traffic Parameters

In this section, the method for deriving local traffic flow and occupancy (a proxy of density) is defined. The fundamental diagrams are established to illustrate the traffic features and the coupled phase transitions.

The measurement of local traffic flow rate is conceptually simple and straightforward. According to the definition in Eq. (2), traffic flow rate is collected directly through point measurements and then takes the average over the measured time span. This feature coincides with the nature of local traffic conditions on the stationary location. In contrast, it would be complicated when one intends to obtain the local density at a fixed spot. As mentioned before, density is defined as the number of vehicles occupying a certain length of roadway at a given instant by Eq. (1). Basically density is a measure over space; however, it would not be practical (due to being too expensive) to continuously take aerial snapshots on a fixed length of road for density measurement, thus occupancy is measured instead. Occupancy is defined as the percent of time a point of roadway is occupied. It can be measured only over a short section (shorter than the minimum vehicle length) with the preset detectors, and therefore is not necessarily applicable if we intend to cover a long stretch of roadway.

There are three major reasons for putting forward the adoption of occupancy as the surrogate of density for local traffic measurement. The first is that there should be improved consistency between theoretical and practical approaches. The second reason is that density, as vehicles per length of road, ignores the effects of vehicle length and traffic composition. Therefore it
would be difficult to implement into mixed traffic analysis. Occupancy, on the other hand, is
directly affected by both of these variables and therefore gives a more reliable indicator of the
amount of a road space being used by the vehicles. The last merit for using occupancy instead
of density is the ease of measurement. For the pure traffic context, in the case that the
averaged vehicular length is known, local density can still be estimated from the derived
occupancy by the formula (May, 1990):

\[
k = \frac{52.8}{l(A) + L_d} O(t)
\]  

where \(L_d\) is the detection zone length, \(l(A)\) is the averaged vehicular length. \(O(t)\) represents the
local occupancy at instant \(t\).

Normally occupancy considers a single lane only and can vary from 1 to 100 percent.
Compared with the traditional definition of occupancy that only takes vehicular length into
consideration, the proposed measurement takes both vehicular length and width into
consideration, yet basically retains the merit of simplicity. The proposed occupancy \(O(t)\) and
the local traffic flow rate \(q(t)\) are derived via virtual detectors arranged into the simulated road
section. In the following discussion, both local traffic flow rate and local occupancy are
counted by “occupied cells.” However, they can be converted into “occupied vehicles”
through simple manipulations.

It is worth noting that since one car occupies only two sites laterally in the refined CA
modeling, for a two-lane roadway with 6 sites in width, the maximum occupancy available for
pure car traffic would be two-thirds (0.667) only if counted on the CU (cell/site) basis. Only
in pure bus (3 CUs in width) traffic can a theoretical maximum occupancy (1.000) be reached,
which implies that the lateral 6 sub-lanes (sites) are fully occupied.

### 3.2 Traffic Detection and Measurement

For a local virtual detector with length 1 site located at position \(m_s\) on the roadway of width
\(W\), four possibilities can be identified for one vehicle with width \(VW\) and length \(VL\) to pass
through it within each time-step. All the possibilities are shown in Figure 2. The first
possibility is that at time \(t\) a vehicle did not arrive the detector but the vehicle “passed
through” it at time \(t+1\) (Figure 2(a)). The second possibility is that at time \(t\) a vehicle did not
arrive the detector, but the vehicle “stand” on the detector at time \(t+1\) (Figure 2(b)). In the
third case, a vehicle remains standing on the detector for consecutive two time-steps (Figure
2(c)), this happens in congested traffic. The final case is that a vehicle touches the detector at
time-step \(t\) and “passed it through” at time \(t+1\) (Figure 2(d)).

![Figure 2. Four possibilities for a vehicle detected by a virtual detector](image)

Based on the above, for a virtual detector arranged at the simulated road section, the local
flow rate and occupancy can be extracted respectively by Eqs. (16) and (17). Note that both
flow rate and occupancy are counted by number of cells instead of number of vehicles.

\[
O(t) = O(t-1) + \begin{cases} 
\frac{VL \times VW}{W \times v(t)} & \text{if } T_i(t) > ms \text{ and } H_i(t-1) < ms \\
\frac{H_i(t) - ms}{v(t)} \times \frac{VW}{W} & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) < ms \\
\frac{(ms - T_i(t) + 1) \times VW}{v(t)} & \text{if } (T_i(t) > ms) \text{ and } H_i(t-1) \geq ms \text{ and } T_i(t-1) \leq ms \\
0 & \text{otherwise}
\end{cases} 
\]  
(16)

\[
q(t) = q(t-1) + \begin{cases} 
\frac{VL \times VW}{W} & \text{if } T_i(t) > ms \text{ and } H_i(t-1) < ms \\
\frac{(H_i(t) - ms) \times VW}{v_i(t)} & \text{if } H_i(t) \geq ms \text{ and } T_i(t) \leq ms \text{ and } H_i(t-1) < ms \\
\frac{(ms - T_i(t) + 1) \times VW}{v_i(t)} & \text{if } (T_i(t) > ms) \text{ and } H_i(t-1) \geq ms \text{ and } T_i(t-1) \leq ms \\
0 & \text{otherwise}
\end{cases} 
\]  
(17)

where \(O(t)\) denotes the cumulated occupancy at time-step \(t\). \(q(t)\) denotes the cumulated flow (in terms of cells) at time-step \(t\). \(ms\) indicates the location of a virtual detector. \(VL\) denotes the vehicle length counted in cells. \(VW\) denotes the vehicle width also counted in cells. \(H_i(t)\) is the head of vehicle \(i\) at time-step \(t\). \(T_i(t)\) is the tail of vehicle \(i\) at time-step \(t\). \(W\) stands for road width counted in sites.

Traditionally, the derived traffic parameters are expressed in arithmetic average (AA) over a fixed time interval to alleviate the drastic fluctuations raised by local noise. For comparison, an unweighted moving average (UMA) of traffic data is also introduced. The moving average technique is commonly used with time series data to smooth out short-term fluctuations and highlight longer-term trends or cycles. For example, given a series of traffic data and a fixed time interval (say, 30 seconds), the moving average data can be obtained in the following way. At the beginning, the average value of the first time interval is calculated. Then the fixed time interval is rolling forward to form a new time interval with the same duration and the second average value is also calculated. The process is repeated over the entire traffic data. Thus, a moving average traffic is not a single value but a group of numbers, each of which is the average of the corresponding time interval of a larger set of traffic data points.

The simplest UMA may be the mean of previous \(n\) data points, which can be calculated via the following formula:

\[
V_{ma}(t) = \frac{1}{n} \sum_{i=1}^{n} V_{i-1+i}
\]  
(18)

\[
V_{ma}(t+1) = V_{ma}(t) - \frac{V_{t-n+1}}{n} + \frac{V_{t+1}}{n}
\]  
(19)

where \(V_i\) is the local parameters (\(O(t)\) and \(q(t)\)) detected by Eqs. (16) and (17) at time-step \(t\), whereas \(V_{ma(t)}\) is their UMA.
4. SIMULATIONS

4.1 Scenarios
The simulations are performed on a closed track containing 1,800×6 sites (CUs), which represents a two-lane freeway mainline stretch with width 7.5 meters and length 1,800 meters. Pure light vehicle (car) traffic and mixed light/heavy vehicle (car/bus or truck) traffic are simulated. Based on field observations on Taiwan’s Freeway, the prevailing mixed ratio—80% light vehicles, 20% heavy vehicles—is selected. At time-step 0, all vehicles are set in the front end of the circular track with velocity 0 as the initial condition and simulated for 600 time-steps. The maximum speeds are defined in accordance with the speed limits on Taiwan’s Freeway, that is, 31 cells/sec for light vehicle (around 110 kph) and 25 cells/sec for heavy vehicle (90 kph) respectively. For global (macroscopic) traffic analysis, a warm-up period—the first 60 time-steps, data is discarded, in order to get rid of the impact of preset initial parameters setting. However, for local traffic data collection, all the derived data is retained, since we intend to evaluate whether the local traffic data derived through the proposed schemes can effectively reflect their global counterparts.

4.2 Results of AA Traffic Data
To explore the diversified traffic patterns, we place a bottleneck in the middle of the right lane of the simulated track. Two local virtual detectors are introduced—one located at 100 sites (meters) upstream and the other at 100 sites downstream of this bottleneck, as shown in Figure 3. Both pure light vehicle and mixed light/heavy vehicle traffic are simulated. It can be clearly identified that the shapes of both x-t plots (Figure 3(a) and 3(b)) are similar, there are sequential traffic patterns transiting around the downstream of the virtual detector from F, F→J, J→S, S→F (denoted by through respectively); while in the upstream, traffic patterns transit from F, F→S, S→J, J→S (denoted by through respectively). F denotes free flow, J represents jammed flow, and S stands for synchronized flow.

Using the 30-second AA traffic data, the above complex traffic patterns and transitions can be further elucidated with a q-O diagram (Figure 4). It can be found from Figure 4 that due to the reduced capacity at the bottleneck and thus the reduced flow rate, vehicles passing the virtual detectors have enjoyed longer headways, except for the first 200 seconds. Therefore, in the fundamental diagram (left panels of Figure 4(a) and 4(b)), the q-O pairs mainly spread in the free flow region. On the other hand, the middle panels of Figure 4(a) and 4(b) provide the q-O information around the upstream detector. Owing to the bottleneck, complicated traffic patterns and transitions in the upstream can be observed (F, F→S, S→J, J→S). As a consequence, q-O pairs are spread in the congested area. It is worth mentioning that for the last 300 seconds, synchronized flow prevails, so the q-O pairs reflect this phenomenon in a consistent manner, i.e., it randomly spread in the congested region. Furthermore, once we combine the upstream and downstream data, an aggregated q-O profile (right panels of Figure 4(a) and 4(b)) that supports Kerner’s three-phase traffic theory (2004) can be clearly identified.
4.3 Results of UMA Traffic Data

For comparison, the unweighted moving average (UMA) traffic data, as derived by Eqs. (18) and (19), are also calculated to clarify the same scenarios. For pure light vehicle traffic (Figure 3(a)), we first focus on the area downstream of the bottleneck. According to Figure 3(a), traffic patterns around the downstream detector will be free flow at the beginning (region
I, F phase, also refer to Figure 5(a)) and then pass through the bottleneck to reach upstream of the jam. Vehicles joining the jam will keep stationary (region II, J phase, also refer to Figure 5(b)) until all vehicles in front have left and then start to move (region III, J→S phase transition, also refer to Figure 5(c)). Later on, as the flow rate reduces due to the impact of bottleneck, the traffic transits into free flow (region IV, S→F phase transition, also refer to Figure 5(d)). A clearer picture of these flow patterns and the associated phase transitions can be obtained by aggregating all UMA traffic data into one plot, shown in Figure 5(f).

Similarly, we can describe the upstream flow patterns through the same algorithm, as shown in Figure 6. Also per x-t diagram (Figure 3(a)), traffic patterns around upstream detector will be free flow at the beginning (region V, F phase). When approaching the bottleneck, the flow patterns will transfer to synchronized flow (region VI, F→S phase, also refer to Figure 6(a)) until reaching the upstream front of jam (region VII, S→J phase, also refer to Figure 6(b)). Vehicles stand still to wait for the front condition for movement (region VIII, J→S phase transition, also refer to Figure 6(c)). For the rest of time, because the bottleneck shrinks the road capacity which in turn influences the upstream traffic significantly, the patterns will keep as synchronized flow (region VIII, S phase, also refer to Figure 6(d)). Aggregating all data into one plot, as shown in Figure 6(f), the whole picture of flow patterns and associated phase transitions can be grasped. For further comparison, in addition to the above 30 second AA and UMA traffic data, the precise 1second (1s) local data are also gathered and shown in Figures 5(e) and 6(e), respectively. One can easily find that the 1s data widely scatters in both plots, wherein no significant traffic patterns or transitions can be found. It is clear that time average traffic parameter is more powerful than that of the original 1s data created by each time-step (1s) to gain insights into the traffic phenomena.

Per the similar measurement, the q-O relationships for the mixed light/heavy vehicle traffic are shown in Figure 3(b). The derived q-O plots are shown in Figures 7 and 8. Compared with the pure vehicle traffic scenario, it is surprising to find that although 20% light vehicles are replaced by heavy vehicles, similar results have been obtained, including the traffic patterns and the associated phase transitions. This outcome is the evidence of the validity of the proposed measurement for local traffic parameters.
5. LOCAL VERSUS GLOBAL TRAFFIC FEATURES

As discussed above, it is costly and difficult to observe the global traffic features ($\rho(S)$ and $q(S)$) over a long distance within a long period of time, thus temporal local traffic features ($O(t)$ and $q(t)$) are usually measured via stationary detectors. One criticism that arises is as to whether the local traffic data $O(t)$ and $q(t)$ could serve as the appropriate proxies for their global counterparts, $\rho(S)$ and $q(S)$. Because the trajectories of all vehicles during the simulated period can be precisely gauged, CA simulations have the excellent capability to monitor the
vehicular behaviors both in space and time frames. In addition, the global traffic features are in essence the aggregation of all local traffic features; thus, global traffic features can also be deemed as a paradigm for evaluating the effectiveness of locally derived traffic information. As such, this study selects $q(S)$ rather than $q(t)$ as the reference index for evaluating the traffic performance.

Considering the above, it is interesting to discover the relationship or linkage between global and local traffic parameters, including: (1) Can locally derived traffic data reflect the trends shown in global perspective? If yes, what level of precision might be achieved? (2) What is the difference between the outcomes of AA and UMA local traffic data? Which one would be a better proxy for global traffic data? (3) What are the proper time intervals for taking AA or UMA while measuring the local traffic data? To answer these questions, this study further simulates pure light vehicle traffic scenarios and compares the local traffic features ($q-O$ plots) with their global counterparts as follows.

Four generalized occupancies ($\rho(S)=0.06, 0.12, 0.25$ and $0.50$), corresponding to traffic densities ($15, 30, 62.5$ and $125$ veh/km/lane), from free flow to jam are simulated respectively. Simulations are initiated with all the vehicles equally spaced on the circular track wherein a virtual detector is placed in the middle. The derived local traffic data ($O(t)$ and $q(t)$) are taken by AA and UMA with different time intervals (1s, 30s and 60s). Finally, the outcomes for these four simulations are collected and compared with their global counterparts ($\rho(S)$ and $q(S)$). The fundamental diagrams are displayed in Figures 9 to 11.

As shown in Figure 9 and as expected, the 1s local flow rate $q(t)$ significantly deviates from its global counterpart $q(S)$, especially around the region $\rho(S)=0.1-0.4$. The maximum flow rate is overestimated. This is deemed reasonable since the 1s data only focuses on the local traffic information for a very short instant; thus, the effect of some extreme situations that occurred locally may be greatly exaggerated. In conclusion, although the aggregated local 1s data transforms into some traffic patterns that can perfectly match the three-phase traffic theory, it is never sufficient to reflect the traffic conditions from the global perspective.

Figure 10 provides the comparison of 30s and 60s AA local data with the global curves. One may find that there is no considerable difference between them. Basically, both 30s and 60s AA data groups spread in the neighborhood of global $\rho(S)-q(S)$ curves. However, one may find that the 60s AA data performs a bit better than the 30s data in gauging the global features. In general, the 60s data points scatter within a relatively smaller region along the global $\rho(S)-q(S)$ curve compared to that of the 30s data points.
Similarly, Figure 11 provides the comparison of 30s and 60s UMA local data with the global curves. Again, the 60s UMA data performs a bit better than the 30s data in reflecting the global features because the 60s data tends to be closer to the global $\rho(S)-q(S)$ curve. However, when compared with the outcomes of AA data in Figure 10, UMA data in general provides relatively poorer simulation quality than the AA data, regardless of 30s or 60s being chosen. This is because a local fluctuation (noise) of traffic data can influence a series of data points if UMA is used; however, the same fluctuation will affect only one data point if AA is used. In conclusion, the AA local traffic data is excellent for smoothing out the oscillations and thus can better cope with the global traffic features as shown in Figure 10.

Nonetheless, one must agree that, as mentioned in Section 4.3, the UMA traffic parameters are more effective than the AA traffic parameters in reflecting the complicated traffic phase transitions. Also, for each individual simulation, implementation of the UMA technique provides notably more valuable data than that via the AA technique.

Overall, the UMA measurement is effective in reflecting the local traffic phase transitions. However, this merit will reversely turn into a weakness if one is interested in the global traffic features either for pure or mixed traffic simulation. If one is interested in scrutinizing the local traffic data, the AA data would provide better simulation quality than the UMA data since the AA data points scatter within a smaller region in the neighborhood of the global curve. It
makes sense because the impact of some local noises of AA data with short lifetime will be few when independent time intervals are considered. In contrast, by the rolling nature of UMA data, some local noises will have greater influence and henceforth force more UMA local traffic data to deviate from the global curve.

6. CONCLUSIONS

The proposed Arithmetic Average (AA) and Unweighted Moving Average (UMA) measurements for extracting local traffic parameters from the refined cellular automaton modeling has been successfully validated using complex scenarios under pure and mixed traffic contexts. The UMA measurement is more effective in reflecting the complicated phase transitions while the AA measurement can better reflect the global traffic features and is also consistent with the Kerner’s three-phase traffic theory. This evidence supports the speculation that three-phase traffic theory is developed through the AA field data. Finally, based on the findings, it is recommended that the time interval for measuring either AA or UMA traffic data would be at least 30 seconds.

For the mixed traffic simulation, this study only considered a mixed ratio of 80% light vehicles with 20% heavy vehicles. The traffic patterns and associated phase transitions under other mixed ratios require further exploration. In many Asian cities, motorcycles are ubiquitously sharing the roadway space with cars and/or buses on the surface roads. Therefore, it would be interesting to conduct more sophisticated CA simulations to capture the traffic features for mixed motorcycle/car or mixed motorcycle/car/bus traffic situations.

ACKNOWLEDGEMENTS

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REFERENCES


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### APPENDIX NOTATION TABLE

<table>
<thead>
<tr>
<th>Variable/Parameter</th>
<th>Definition</th>
<th>Variable/Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a )</td>
<td>Acceleration</td>
<td>( q )</td>
<td>Traffic flow rate</td>
</tr>
<tr>
<td>( a_k )</td>
<td>Maximum acceleration capacity of ( k )-type vehicle</td>
<td>( q(S) )</td>
<td>Generalized traffic flow over domain ( S )</td>
</tr>
<tr>
<td>( D )</td>
<td>Maximum deceleration capacity of ( k )-type vehicle</td>
<td>( q(t) )</td>
<td>Accumulated local traffic flow at instant ( t )</td>
</tr>
<tr>
<td>( AA )</td>
<td>Arithmetic average</td>
<td>( S )</td>
<td>Spatiotemporal domain under consideration with size ( L \times W \times T )</td>
</tr>
<tr>
<td>( d )</td>
<td>Space headway</td>
<td>(</td>
<td>S</td>
</tr>
<tr>
<td>( d(S) )</td>
<td>The total distance traveled by all cells in domain ( S )</td>
<td>( S_n )</td>
<td>Status identifier of ( n )^th vehicle, representing its brake light status</td>
</tr>
<tr>
<td>( d_m )</td>
<td>Preset deceleration capacity</td>
<td>( t )</td>
<td>Time:</td>
</tr>
<tr>
<td>( d_{sp} )</td>
<td>Effective distance of ( n )^th vehicle</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( g )</td>
<td>Distance (Gap)</td>
<td>( t(S) )</td>
<td>Accumulated time of ( N_0(t) ) spent in ( S ) for all times simulated</td>
</tr>
<tr>
<td>( H_i(t) )</td>
<td>Head location of vehicle ( i ) at instant ( t )</td>
<td>( t_h )</td>
<td>( t_s = d_{sp}/v(t), ) time headway of ( n )^th vehicle to front</td>
</tr>
<tr>
<td>( l(A) )</td>
<td>Averaged vehicular length</td>
<td>( t_{s\text{st}} )</td>
<td>Accumulated time of ( n )^th vehicle that stuck in traffic jam</td>
</tr>
<tr>
<td>( L )</td>
<td>Longitudinal length of area ( A ) and/or domain ( S )</td>
<td>( t_{k,c} )</td>
<td>Time threshold of vehicle of type ( k ) for initiating delay-to-start behavior</td>
</tr>
<tr>
<td>( L_d )</td>
<td>Detection zone length</td>
<td>( \tau )</td>
<td>Safe time gap for collision prevention</td>
</tr>
<tr>
<td>( ms )</td>
<td>Location of virtual detector</td>
<td>( T )</td>
<td>Observed time period</td>
</tr>
<tr>
<td>( T_i(t) )</td>
<td>Tail location of vehicle ( i ) at instant ( t )</td>
<td>( V )</td>
<td>Speed</td>
</tr>
<tr>
<td>( W )</td>
<td>Transverse width of roadway, counted in sites</td>
<td>( v(S) )</td>
<td>Generalized space-mean speed over domain ( S )</td>
</tr>
<tr>
<td>( VL )</td>
<td>Vehicular length, counted in cells</td>
<td>( V_i )</td>
<td>Local parameters (( O(t) ) &amp; ( q(t) ))</td>
</tr>
<tr>
<td>( VW )</td>
<td>Vehicular width, counted in cells</td>
<td>( \rho )</td>
<td>Density</td>
</tr>
<tr>
<td>( x )</td>
<td>Position of ( n )^th vehicle</td>
<td>( \rho(S) )</td>
<td>Generalized density over domain ( S )</td>
</tr>
<tr>
<td>( h )</td>
<td>Time headway</td>
<td>( \Delta )</td>
<td>Minimum clearance for the follower</td>
</tr>
<tr>
<td>( k, k(t) )</td>
<td>Traffic density</td>
<td>( P_0 )</td>
<td>Probability reflecting delay-to-start behaviors of vehicles that stuck in traffic jam</td>
</tr>
<tr>
<td>( N )</td>
<td>Total number of sites arranged in domain ( S )</td>
<td>( S_n )</td>
<td>Safe speed of ( n )^th vehicle</td>
</tr>
<tr>
<td>( N_0(t) )</td>
<td>Total number of sites occupied by cells (vehicles) at the instant ( t )</td>
<td>( c_n )</td>
<td>Safe speed of ( n )^th vehicle</td>
</tr>
<tr>
<td>( NC )</td>
<td>Number of cars in mixed traffic of given ( S )</td>
<td>( v )</td>
<td>Speed</td>
</tr>
<tr>
<td>( NM )</td>
<td>Number of motorcycles in mixed traffic of given ( S )</td>
<td>( \rho(S) )</td>
<td>Generalized density over domain ( S )</td>
</tr>
<tr>
<td>( O(t) )</td>
<td>Accumulated local occupancy at instant ( t )</td>
<td>( \Delta )</td>
<td>Minimum clearance for the follower</td>
</tr>
<tr>
<td>( P )</td>
<td>Probability:</td>
<td>( P_0 )</td>
<td>Probability reflecting delay-to-start behaviors of vehicles that stuck in traffic jam</td>
</tr>
<tr>
<td>( P_b )</td>
<td>Probability accounting for impact of decelerating vehicle in near front</td>
<td>( P_0 )</td>
<td>Probability reflecting delay-to-start behaviors of vehicles that stuck in traffic jam</td>
</tr>
<tr>
<td>( P_a )</td>
<td>Probability for other situations</td>
<td>( r(l) )</td>
<td>The right (left) lane or site considered for lane change or lateral drift</td>
</tr>
<tr>
<td><strong>Suffix</strong></td>
<td></td>
<td>( b )</td>
<td>Downstream</td>
</tr>
<tr>
<td>( i )</td>
<td>The ( i )^{\text{th}} vehicle</td>
<td>( f )</td>
<td>The nearby upstream in the next or next second site</td>
</tr>
<tr>
<td>( k )</td>
<td>Type of vehicles: ( k=1 ), light vehicle (car); ( k=2 ), heavy vehicle (bus/truck)</td>
<td>( \text{eff} )</td>
<td>Effective</td>
</tr>
<tr>
<td>( ma )</td>
<td>Un-weighted moving average</td>
<td>( \text{sup} )</td>
<td>Superposed</td>
</tr>
<tr>
<td>( \max )</td>
<td>The maximum value</td>
<td>( \text{shift} )</td>
<td>Shifted</td>
</tr>
<tr>
<td>( n )</td>
<td>The ( n )^{\text{th}} vehicle</td>
<td>( \text{up} )</td>
<td>Upstream</td>
</tr>
<tr>
<td>( n+1 )</td>
<td>Vehicle in front</td>
<td>( \text{down} )</td>
<td>Downstream</td>
</tr>
<tr>
<td>( t )</td>
<td>Instant ( t )</td>
<td>( r(l) )</td>
<td>The right (left) lane or site considered for lane change or lateral drift</td>
</tr>
</tbody>
</table>