Estimating Fundamental Diagram for Signalized Intersections Using
Connected Vehicle Data*

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INTRODUCTION

The fundamental diagram (FD) is to describe the macroscopic relationships between traffic flow and density. It is widely used in the traffic analysis for freeways and urban streets [1]–[3]. In the previous studies [4], [5], the aggregated empirical measurements from detectors are commonly used to fit the diagram. However, this detector-based method has data quality issues related to detector installation or the deterioration of the pavement, and a methodology issue because the detectors at fixed locations cannot fully capture vehicle dynamics [6]. In this study, a set of connected vehicles (CV) trajectory data is considered to construct a FD (i.e., flow-density relation) at a signalized intersection based on the traffic states.

With development of Intelligent Transportation System (ITS), higher resolution data (e.g., probe data) become available [7]–[9]. Probe data are usually used in research to find critical points in a FD for capturing the traffic states. With the emergence of CV technology, this line of research can be moved one step forward [10], [11]. On one hand, the data collected in CV trajectories provide more information. Beyond fixed-point data collector systems (e.g., loop) or roadside collector system (e.g., radar), CV trajectory is continuously available in time and space. On the other hand, the CV trajectory is defined as higher-resolution event-based data which include information, such as vehicle interaction status and network communicated driving status, along with those traditional vehicle trajectory variables (e.g., location, speed, and acceleration) [12], [13]. What is more, compared to probe vehicle information, which focuses on the mobility of the detection for ITS traffic management purposes, CV not only provides this information but also obtains network-wide data via communications with other CVs or the infrastructure. In this study, it is assumed that Signal Phase and Timing (SpaT) message are incorporated into the trajectory of CVs.

Given that collected data are from microscopic detections and the FD is a macroscopic level demonstration, shock waves usually act as a connection between two representations [14]–[16]. Shock waves are the transition zones between traffic states that move through a traffic region.

By 2025, more than 400 million vehicles on our roadways will with the basic connected technology onboard (e.g., adaptive cruise control) [17]. It is meaningful to take advantage of their massive trajectory data and explore a method to build a macroscopic FD from microscopic data (i.e., CV trajectory data). Hence, the primary objective of this study is to estimate a FD using CV trajectory at a signalized intersection. This study is with a motivation on revealing traffic flow dynamics for signalized intersections through the vehicular interactions. A CV trajectory method constructs a FD with three step, data filtering and categorization, critical point extraction and state identification, shock wave formation. The method is then validated through an experimental design with VISSIM trajectory data to prove the concept. The potential applications of this study with emerging connected vehicle technologies will benefit traffic flow modeling and the development of traffic management strategies.
METHOD DEVELOPMENT

This proposed trajectory-based method is to reveal traffic flow dynamics for signalized intersections by constructing a FD using CV data. With the development of CV technologies and the increasing market penetrations of CV on road, CV trajectory data is collectible by either roadside units or traffic operation center, or both. This study explores eight dynamic properties/states of traffic at a signalized intersection:

1. Approaching State,
2. Queue Formation State,
3. Stopped Queue State,
4. No Vehicle State,
5. Queue Dissipation State,
6. Capacity State,
7. Following State, and

These macroscopic states of traffic are continuous and bounded by shock waves. The Queue Formation State and the Queue Dissipation State, are essential to describe traffic flow in an intersection area, but have been simplified or neglected in the previous research [18], [19]. In this study, the authors aim to observe only a portion of the trajectory data (i.e., CV trajectory data at a certain penetration rate), estimate a shock wave through those observed CV interactions, and constructs a FD.

At a single intersection, the authors first assumed that a set of connected vehicles approaches the intersection where traffic flow is under-saturated. Each connected vehicle is assumed to provide GPS coordinates, time step, speed, acceleration, and driving status from its trajectories. The variables - GPS position, timing and speed - have been used widely in previous research [20], [21]. Driving status is a relatively novel variable in the study of vehicle trajectory set. In this study, the authors took the recommendation in HCM 2010 [22] and set the driving status as a binary variable. That is, the driving status is “in queue”, when the speed of a vehicle is lower than 5 mph; the driving status is not “in queue”, otherwise. In this CV trajectory method development section, the method includes the following steps, (1) data filtering and categorization, (2) critical point extraction and state identification, (3) shock wave formation and structure formation of FD.

Step 1 - Filtering and Categorization

A prior filtering process is needed on CV trajectory dataset, and the process applies the following assumptions within the analysis zone:

- Single vehicle type, that is passenger car only,
- No turning vehicles,
- No lane changing, and
- No flow interruptions turning from minor streets before, after and at the intersection.

After trajectory filtering, then the method categories vehicle trajectory data into queued and non-
queued vehicle sets based on the driving state (i.e., “in queue” or not). It is important to category as queued and non-queued vehicle sets, rather than other factors (e.g., green duration, red duration and etc.) This is because vehicle trajectory is not bounded in time and space. It is a continuous record of an individual vehicle in the analysis zone. Once one vehicle’s trajectory identified itself as queued or non-queued, it is then assigned into its belonged cycle by its starting time as entering the analysis zone (i.e., about 750 ft upstream from the stop bar). Since the intersection approach is assumed to be under-saturated, the vehicle approaching the intersection is passing through it within the same cycle.

**Step 2 - Critical Points Extraction and State Identification**

As introduced earlier, eight traffic states are considered in this study. They are plotted in the space time diagram in Figure 1 below. A shock wave (e.g., dash lines in Figure 1) separates one state from its next state in traffic flow; and a critical point indicates the changing point between states for each vehicle’s trajectory. In the previous research [20] on vehicle trajectory, the critical point extraction is based on speed and acceleration. However, speed and acceleration are sensitive to change in driving. For instance, when a driver slightly accelerates during a deceleration process, such change in acceleration may cause a false critical point extraction. To overcome such difficulty in critical point extraction from vehicle trajectory data, previous literature added thresholds or ranges around identified critical point for verification. For instance, Cheng et al. [20] introduced a method to identify the data points representing the changes in vehicle dynamics by establishing thresholds on speed, and acceleration to extract critical points. The authors adopted a similar approach in this study.

![Figure 1. Eight traffic states at a signalized intersection identified by CV trajectory data](image)

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Step 3 - Shock Wave Formation and Structure Formation of FD

After extracting critical points and identifying traffic states, backward forming shock wave ($\omega_{BE}$), frontal stationary shock wave ($\omega_{B}$), backward recovery shock wave ($\omega_{GB}$), and forward forming shock waves ($\omega_{F}$, $\omega_{A}$, $\omega_{H}$, $\omega_{C}$, $\omega_{G}$, $\omega_{E}$) are illustrated by different colors in Figure 2 below.

Figure 2. A schematic diagram of the Fundamental Diagram formed by shock waves at a signalized intersection

SIMULATION DESIGN

The proposed method was evaluated using connected vehicle trajectory data generated with VISSIM. This allows the authors to have the knowledge of (assumed) ground truth for macroscopic flow and density. Macroscopic measurement (i.e., link performance evaluation) from VISSIM is used as the ground truth values of flow and density.

In order to obtain the individual vehicle’s trajectory, a signalized intersection located between Kensington Ave and Bailey Ave, in Buffalo, NY, is coded in VISSIM as shown in Figure 3.
Figure 3. Kensington Ave & Bailey Ave intersection layout in VISSIM

The traffic counts for this signalized intersection are in Table 1 and were based on PM peak (5:00 PM to 6:00 PM) provided by the Modern Traffic Analytics and Greater Buffalo Niagara Regional Transportation Council through the open-source Traffic Count Database System. The intersection was with a $v/c$ ratio of 0.76 for the northbound approach of the intersection. The intersection implemented a two-phase pre-timed signal timing plan with permitted left turns. The cycle length was set as 80 seconds. The green time for Kensington Ave (minor street) was 28 seconds, and 42 seconds for Bailey Ave (major street). The yellow and all-red intervals were 3 seconds and 2 seconds. The timing plan was recorded from a field study.

Table 1. Volume Inputs of Kensington Ave & Bailey Ave

<table>
<thead>
<tr>
<th>Duration</th>
<th>Number of Vehicle (veh)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Northbound</td>
</tr>
<tr>
<td>5:00-5:15 PM</td>
<td>139</td>
</tr>
<tr>
<td>5:15-5:30 PM</td>
<td>164</td>
</tr>
<tr>
<td>5:30-5:45 PM</td>
<td>146</td>
</tr>
<tr>
<td>5:45-6:00 PM</td>
<td>137</td>
</tr>
</tbody>
</table>
With this established VISSIM simulation network, a composition of regular vehicles and CV in different MPRs (i.e., 10% and 100%) is coded into along with the vehicle input of the northbound. Then, a set of CV trajectory is collected in 5 runs of a 3600-second simulation (excluding 300-second “warm up” period) at 10 Hz with different seeds. With a fixed cycle length, a total of 45 cycles were studied. A variety of variables are available in a VISSIM trajectory. However, the collected CV trajectory in this study only includes GPS positions, time step, speed, acceleration, and driving status, which are required variables to construct a FD. Lastly, the SPaT Message (i.e., signal head status report in VISSIM) is also collected at every time step. It helps the method assign trajectories into their corresponding signal cycles.

RESULTS

The following Results Section are presented in two parts. In part 1, the proposed CV trajectory method is validated using CV trajectory data to construct a FD under 100% CV MPR. In part 2, the method is evaluated with 10% and 100% CV MPRs to show its effectiveness in a low MPR.

Fundamental Diagrams with 100% CV MPR

At each cycle, a shock wave is generated by those critical points extracted in CV trajectory. Seven traffic states (except No Vehicle State) then are represented by intercept points (i.e., dots in Figure 4) between a forward shock wave/speed and a backward shock wave at a signal cycle. In Figure 4, out of 45 cycles (if there were at least two CVs per cycle), the shock wave with a maximum slope value was generated.

![Figure 4. Example of a formed Fundamental Diagram (100% MPR)](image)

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![Figure 4. Example of a formed Fundamental Diagram (100% MPR)](image)
The FD formed with CV trajectory in Figure 4 is found similar to those triangular shaped FD at an intersection in previous research [23], [24]. Moreover, this FD is able to capture and present the Queue Formation State (i.e., cyan dots) and Queue Dissipation State (i.e., magenta dots). In this study, the speed range of the queue status is from 0 mph to 5 mph according to HCM 2010. In each cycle, the number of vehicles (i.e., flow) in the queue is different and the corresponding queue backward forming speed is different. Then, per cycle, an intercept point between the brown Backward Forming Shock Wave and the cyan Entering Queue Speed is then plotted as a cyan dot (i.e., Queue Formation State) in Figure 4. Similarly, in each cycle, an intercept point between the navy Backward Recovering Shock Wave and the magenta Dissipating Speed is then plotted as a magenta dot (i.e., Queue Dissipation State) in Figure 4. Although the Entering Queue Speed and the Dissipating Speed are set within the same speed range following the HCM guideline, the Queue Formation State spread out within its state (i.e., flow ranges from 100 veh/hr to 800 veh/hr, density ranges from 20 veh/mile/lane to 270 veh/mile/lane) while the Queue Dissipation State centered around a density of 220 veh/mile/lane and a flow of 750 veh/hr. This is because the variety of speeds is wider when a queue is forming than when it is dissipating.

Although the slopes of shock waves depend on the simulation settings of the intersection, it is clear that the shape of the constructed FD is obvious, and one can easily define different traffic states from the FD. This indicates that the CV trajectory method is applicable to construct a FD.

Comparison in Different CV MPRs

After testing the applicability of the CV trajectory method with 100% CV MPR, the next step is to check the effectiveness of the CV trajectory method by evaluating it at 10% CV MPR. The results are shown in Figure 5.

The constructed FDs are overall in a consistent shape between a low CV MPR and a large CV MPR as shown in Figure 5. The slopes of backward recovering shock waves are about -12.9 mph in 10% CV MPR, and about -10.3 mph in 100% CV MPR. That is, the slope of the backward recovering shock wave becomes larger when the CV MPR becomes larger. With more CVs in the queue, a more complete observation of queue dissipation process is obtained. Further, the center of each state formed by the colored dots are consistent regardless the CV MPR in Figure 5, while there are fewer dots in each state under a lower MPR. This indicates that a FD constructed with a lower CV MPR is still able to demonstrate traffic states, but with a smaller coverage of each state. This is because, under a lower MPR, there are fewer cycles with enough CVs (i.e., at least two in the same queue) to interact and generate shock waves.
Lastly, as the flow and density values collected by the link performance in VISSIM are assumed as ground truth, a comparison of the FDs at 10% and 100% CV MPRs in terms of their capacity and jam density values is studied. The averaged “true” capacity and jam density over 5 runs are 3,083 veh/hr and 322 veh/mile/lane, respectively. At 10% CV MPR, the capacity is captured as a value of 2,663 veh/hr (i.e., (2,663 – 3,083)/3,083 = -13.6%), where the jam density is about 290 veh/mile/lane (i.e., (290 – 322)/322 = -9.9%). The capacity and jam density at 100% CV MPR are 3,517.84 veh/hr (i.e., +14.1%) and 341.75 veh/mile/lane (i.e., +6.2%). Firstly, this shows that estimated values in flow is more sensitive than those values in density. Secondly, the estimates from CV trajectory method with 100% CV MPR are likely to overestimate the capacity and jam density at an intersection, whereas the estimates with 10% CV MPR are probably underestimate those values. Nevertheless, it is remarkable to observe that with only 10% CV MPR, the CV trajectory method can keep the performance of its estimation on the triangular shape up to 86.4% in height and 90.1% in width.

Figure 5. Evaluations of the CV trajectory method under different MPRs

This figure shows the evaluations of the CV trajectory method under different MPRs. The evaluations are conducted by comparing the estimated values with the ground truth values collected by the link performance in VISSIM. The figure illustrates the flow versus density for different MPRs, with different colors representing different states of vehicles. The comparison shows that the estimated values from CV trajectory method are more sensitive to changes in flow than those in density. Moreover, the estimates with 100% CV MPR are likely to overestimate the capacity and jam density at an intersection, whereas the estimates with 10% CV MPR are likely to underestimate those values. Nevertheless, it is remarkable to observe that with only 10% CV MPR, the CV trajectory method can keep the performance of its estimation on the triangular shape up to 86.4% in height and 90.1% in width.
CONCLUSIONS

This study proposed a novel method to construct a flow-density FD using CV trajectory by interpreting driving status and shock waves. The method is validated using VISSIM generated trajectory by assigning different CV MPRs. The method shows its efficiency to provide consistency in the estimations of density and flow from 100% CV MPR till as low as 10%. By comparing with the “true” capacity and jam density recorded by VISSIM, the CV trajectory method with a 10% CV MPR highlights its good accuracy. The method demonstrates its potential to benefit the traffic management society by generating an accurate fundamental diagram at relatively low CV MPRs.

The generated FDs in this paper reflect the vehicle movement logic in VISSIM. The shape of a FD will change in response to different vehicle movement logic. Nevertheless, the main purpose of this paper is to demonstrate the effectiveness of constructing FDs with CV trajectory data even at a low MPR. The proposed FD using the field CV trajectory data will be investigated in the future.

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REFERENCES


