An Exploratory Shockwave Approach for Signalized Intersection Performance Measurements Using Probe Trajectories

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ABSTRACT

An innovative approach for arterial intersection performance measurement using vehicle trajectory data is proposed in this paper. The vehicle trajectories are first processed to extract the points representing the changing vehicle dynamics, which are named the "critical points" on the trajectory. The extraction technology can also be used as a data reduction method in on-vehicle devices to reduce the communication cost. A shockwave based method then uses the critical points to detect the signal timing, providing a basis for real time performance measurement. A cycle-by-cycle queue length estimation method is also proposed as a case study of signalized intersection performance measurement. The performance of this approach is tested both by simulation and NGSIM trajectory data. The results indicate that this trajectory based approach is promising.

INTRODUCTION

Arterial performance measurements are essential for advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). Although nearly 40% of the nation's vehicle miles traveled (VMT) occur on arterials, real-time arterial performance measurement systems are not as mature as their freeway counterparts. Two of the biggest challenges are: 1) arterial traffic conditions are more complicated than the ones on freeways because of the periodic interruptions from traffic signals, random friction from crossing traffic on minor streets, driveway related activities, etc; 2) the current traffic collection technologies deployed on arterials are not sufficient for measuring real-time operational performance(*1*).

Given these challenges, recent research development is focused on two areas: 1) modeling the relationship performance measures (such as travel time, delay, queue length) and traffic flow as well as signal timing; and 2) developing new data collection technologies or using new data sources (*1-3*) . For example, in the first area, arterial travel time or delay is modeled as the function of occupancy, flow, speed and/or signal timing parameters. Usually, regression methods are used to calibrate these parameters to obtain the best goodness of fit (*4-6*). These models are usually site-specific, which limits the transferability for different prevailing traffic conditions, signal control and intersection geometries. One of the improved solutions proposed by Xie et al (*7*) used calibration-free parameters, which decomposed the travel time into cruise time and signal delay. Cruise time was the running time calculated using detected speed via inductive loop detectors and signal delay was calculated by a simplified Webster formula. Skabardonis and Geroliminis (*8*) proposed an analytical model using inductive loop detector data (aggregated in 20 or 30 seconds) and signal timing, which carefully calculates the delay as the sum of signal delay, queuing delay and oversaturation delay. An important improvement is that their model addressed the cases when the queue is longer than the distance from the loop detector to the stop bar. By the same token but with different methodologies, other works uses stochastic theories (*9, 10*), or artificial intelligence (AI) methods (*11, 12*). Growing interests in the second area develop along with the emerging and advancement of traffic signal and probe technologies with which new data sources or high resolution data such as the timestamps for individual vehicle arrival (*1, 3, 13*), vehicle re-identification technologies (*14-17*), and probe data (*18-23*) become readily available.

In most current studies, vehicle re-identification and probe data are only used to generate sample travel times between points which are subsequently modeled in a statistical sampling domain (*18-21*). The sample rate requirement was discussed (*24*). Some of the reasons for this type of application are: 1) general automatic vehicle identification (AVI) technologies, such as toll tag, automation license plate match, vehicle re-identification, can only provide travel times between two pre-defined points; 2) some automatic vehicle location (AVL) devices have relatively long sampling intervals, such as 1 minute, which makes it impossible to obtain vehicle trajectories from the scattered points.

The development of traffic detection technologies makes the utilization of probe vehicle trajectory data possible. There are some studies about using trajectories of the total vehicle population for shockwave identification and analysis. The work of Lu and Skabardonis (*25*) studied the "local minima" in the speed domain of the trajectory and

used the "local minima" to analyze the back propagating shockwaves caused by congestion. Izadpanah et al (*26*) modeled the actual trajectories in the distance domain as a piece-linear line and defined "joint point" (major shockwave intersection points) at the trajectory. An iterative two-phase piecewise regression was employed to extract joint points from a trajectory. "Joint points" were used to detect the major shockwaves and their speed. There are also a few attempts of using vehicle trajectories for performance measurements (*2, 27*). The detailed trajectory data can provide more abundant and detailed traffic information than simple travel times between two ends of a pre-defined route, especially for the interrupted and discontinuous traffic flow on arterials. More importantly, congestion can be easily detected using trajectory data because unusually low speeds and frequent stops can be detected directly. Conversely, the number of available sampled travel times would drastically decrease due to a low flow rate and the responding time (assuming real time) will dramatically increase because the sampled travel will only be available after the probe vehicle finishes the pre-specified route. However, the main challenge of developing a trajectory-based model is how to convert the microscopic detections into macroscopic performance measurements, which is not as straightforward as sampling travel time. One trajectory only represents the individual behavior of one vehicle, which is often subject to actual situations encountered by the driver. Therefore the data are more volatile. On the contrary, arterial performance measures should be macroscopic and easily understood such as average travel time and maximum queue length. Recent attempts of performance measurements using probe trajectory include the research conducted by Claudel et al (*27*). In their study, the probe trajectory measurement was converted to density estimation using the Moskowitz function (*28, 29*) for freeway travel time estimation. The trajectories of probes on signalized arterials are more complicated than freeways because of the periodic turbulence due to signals and local friction. Comer and Cetin (*18*) studies the conditional probability distribution of the queue length at an isolated intersection given the locations of probe vehicles in the queue. They found that only the location of the last probe in the queue is necessary for queue length estimation, however, the assumption that the actual percentage of probe vehicles among the traffic stream is known limits the applications of this method.

The existing work related to arterial trajectory data has not really led to practical applications of providing useful information such as queue length and travel time. This paper explores the feasibility of using the vehicle trajectory data for intersection performance measurement. The proposed approach first defined the critical points (CPs) on a trajectory which are able to capture the dynamics of the vehicular movement in a space-time diagram. A method was developed to extract the CPs and then shockwave based methods were used to detect signal timing and to estimate the cycle-by-cycle queue length. The theories were tested by numeric experiment using both simulation data and real trajectory data from NGSIM. The paper is concluded with an overview of the study and a discussion of future studies.

METHODOLOGY

Given the intersection and link geometric characteristics, the intent is to develop a real-time intersection performance estimation model using vehicle trajectory data as the only model input. Figure 1 shows the overall building blocks for the methodology as well as

the relationship between them. The workflow can be described as follows: "Critical Point Extraction" module first processes the real-time trajectories to generate a series of CPs; the "Critical Points Filter" module selects part of the generated CPs for different purposes; using shockwave speed, the signal timing can be detected and determined; and finally the maximum queue length in a cycle can be estimated based on the detected end of queue.

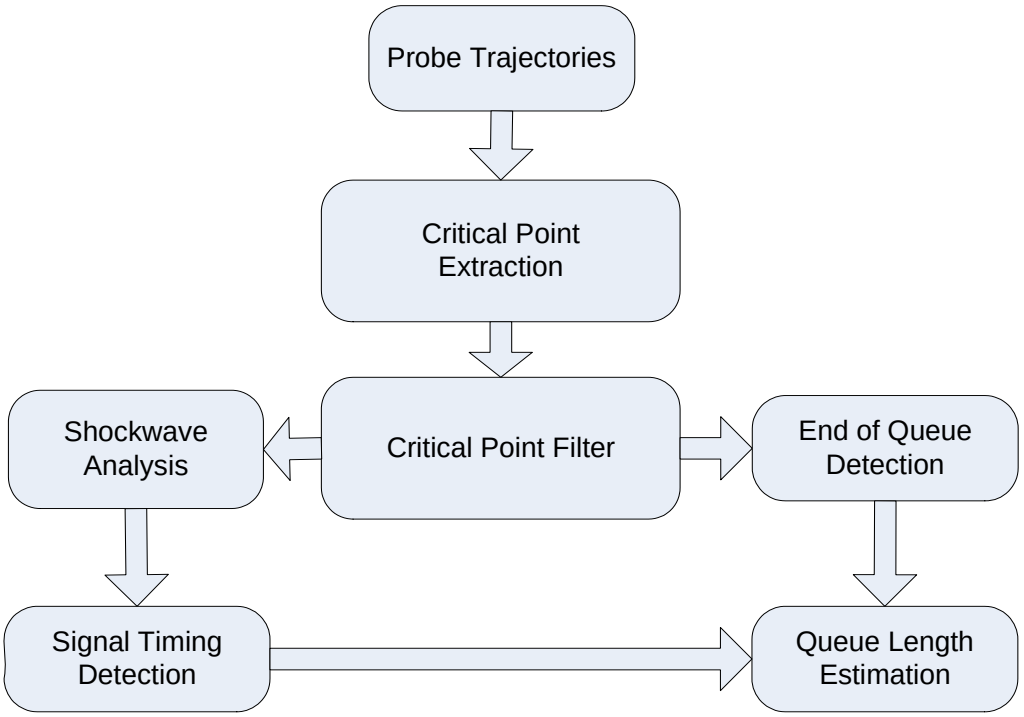


FIGURE 1 Methodology Flow Chart

Modeling Trajectories

The trajectory of a vehicle can be described as a series of points, $\{x_t\}$, where x_t is a record of the vehicle at time t. x_t is a vector and describes the dynamics of vehicle at time t; $x_t = [l, v, a]$, where l is the location, v is the speed and a is the acceleration rate. l, v and a represent the three dynamic features.

The movements of vehicle are not totally random; drivers can be assumed rational and they fulfill three major tasks: 1) maintain a desired speed; 2) keep a safe distance from the lead vehicle; 3) follow the signal indication. For instance, when a vehicle travels in a platoon on a well coordinated corridor, it travels at a near constant speed and its trajectory is already known given the start point x_{t0} and the speed v_0, where t_0 is the start of time. For a general case, the trajectory of a vehicle can be divided into several regimes which are either uniform motion or uniformly accelerated motion. Therefore, critical points (CPs), $\{x^c{}_t\}$, which are a subset of $\{x_t\}$ can be defined. These CPs correspond to changing points on the borders of the movement regimes. Therefore, "non-critical" points become redundant and the trajectory $\{x_t\}$ can be reduced to a set of CPs $\{x^c{}_t\}$, as shown in Figure 2.

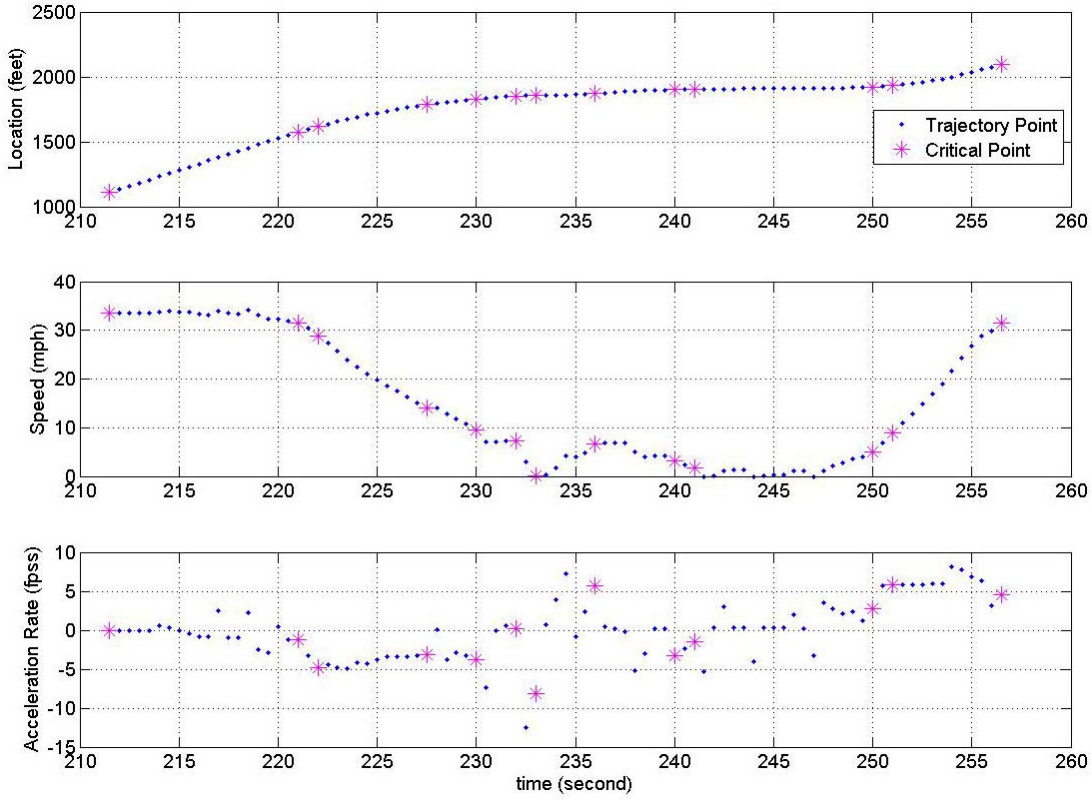


FIGURE 2 CPs at a Trajectory (Paramics Simulation Data)
($c_v = 3mph,\ c_a = 3\ fpss,\ c_{v,stop} = 3mph$ See next section)

For the purpose of traffic detection, CPs result from the changes in traffic conditions, significant and trivial. For example, the CP from slowing down to speeding up indicates the distance headway is increased, resulting from a queue clearance. Some CPs correspond to local traffic turbulence and . Hence, the features of the critical points can be used for signalized intersection performance estimation, which will be presented in detail in the following sections.

In the above analysis, lane changing is not explicitly discussed. In fact, for simplicity, the vehicles are assumed to travel on a one-dimensional road. Note that the trajectory modeling approach can be easily extended to two-dimension by defining the current traveling lane as the fourth dynamic feature besides location, speed and acceleration rate.

It is also interesting to treat the trajectories from the view of information science as a signal serial. A new CP extraction algorithm could be developed by borrowing data compression ideas. Converting $\{x_t\}$ to $\{x^c{}_t\}$ is analogous to "data reduction", which has another benefit for the real-time floating car data (FCD) collection by reducing data to be transmitted. If the onboard device has a CP extraction program running, the real-time data uploaded would be CPs. Therefore the communication cost is reduced. Obviously, this approach has advantages over the current probe measurement technologies which record at a fixed time interval.

Critical Points Extraction

As analyzed above, the main idea of CP extraction is that the movement of a vehicle between two CPs is definitive and belongs to one of the two basic movements: 1) uniform motion; 2) uniformly accelerated motion (the acceleration rate is negative for deceleration motion). Therefore, a trajectory can be divided into several regimes with CPs as the boundaries. The extraction of a CP can be formulated as:

Find $\max(n)$, when Equation (1) or (2) is satisfied for all the:

if $|a_i| < c_a$,

$$\left|\tilde{v} - v_i\right| < c_v \tag{1}$$

or, if $|a_i| >= c_a$,

$$\left|\tilde{a} - a_i\right| < c_a \tag{2}$$

Where $\tilde{v}$ is the median speed of $\{x_i\}$, c_v is a threshold, $\tilde{a}$ is the median acceleration rate of $\{x_i\}, i = 1, 2...n$, c_a is a threshold, x_1 the previous CP or the first point on the trajectory. Eq. (1) represents the uniform motion and Eq. (2) represents uniformly accelerated motion.

In addition, considering the end of queue detection, it is necessary to treat stopping or very low speed as a special case; otherwise, the actual point when and where the vehicle joins the standing queue might be missed:

$$\left|v_i\right| < c_{v,stop} \tag{3}$$

The CP extraction algorithm can be summarized as: given the consecutive feeding of trajectory points, one of Eq. (1) and (2) will be applied according to whose condition is satisfied; however, if Eq. (3) satisfies, it overrides, continuing to search the following "stopping" segment and put down the first and last as CPs and then Eq. (1) and (2) apply again.

The selection of thresholds would not be affected by traffic or geometric conditions since CPs are intended to be the "change" points on a vehicle trajectory; that is, CPs are the associated directly with vehicle dynamics. As long as how detailed the dynamics needed to be known is determined, the thresholds are determined. The *Travel Time Data Collection Handbook* (*30*)mentions that "typically" less than 5 mph can be considered as stopping; it was found that lower threshold, could locate the point when the vehicle join the standing queue more accurately, which shall benefit the selection of Type II CP in the next section, As for the thresholds of speed and acceleration rate, c_v and c_a, it is found that smaller values of thresholds would produce more CPs; however, the selected Type I, II and III CPs afterwards (in the next section) usually have very small shifts in the location and time. In the *Numeric Experiment* section, $c_v = 3mph$, $c_a = 3\,fpss$ and $c_{v,stop} = 3mph$.

An example is shown by Figure 2, where an entire trajectory is processed and the generated CPs are marked. As mentioned in the Introduction, there are a few studies in identifying and analyzing shockwaves using vehicle trajectories, such as the work by Lu and Skabardonis (*25*) and by Izadpanah et al. (*26*). The CP defined in this paper share similarities with and "joint points" in but also have significant differences:

1. Assumptions are different
   The CP in this paper is used to extract the movement changing at the trajectory while "joint point" and "local minima" are for detecting "major shockwaves". It can almost be certain that for arterials, the "joint points" are a subset of the CPs for the same trajectory. In a word, CP is for a sampled probe approach while "local minima" and "joint points" are not.
2. Extraction algorithms are different
   Given the different assumptions, the CP extraction algorithm proposed in this paper is simple for real-time implementation with lower computational cost. "Local minima" method searches the local minimal speed points within a time window and "joint point" method uses an iterative two-phase piecewise regression model for the location domain. Although generated CPs tend to be noisier, setting proper thresholds and a well designed "Selection of Critical Points" module can reduce the harmful noise to a minimum.
3. Potential applications are different
   Our algorithm can also be used as a data reduction method in the onboard GPS device to reduce the communication cost without cost of traffic detection. In addition, although CPs tend be noisier, they may also include useful details about how speed changes which could be valuable for other researches such as emission and safety studies.

Critical Points Filter for Various Purposes

For different applications, different parts of the extracted CPs should be used. In other words, a filter should be applied to choose the appropriate CPs. For example, when critical points are used for signal detection, only the critical points which result from signal changes should be used.

Figure 3 demonstrates the three types of CPs which will be referred in the following discussion. Type I is defined as the CP which is the beginning point of a deceleration regime caused by signal light turning to red; Type II is defined as the CP which is the point when the vehicle slows down and joins the queue; Type III is defined as the CP which is the beginning point of an acceleration regime caused by signal light turning to green.

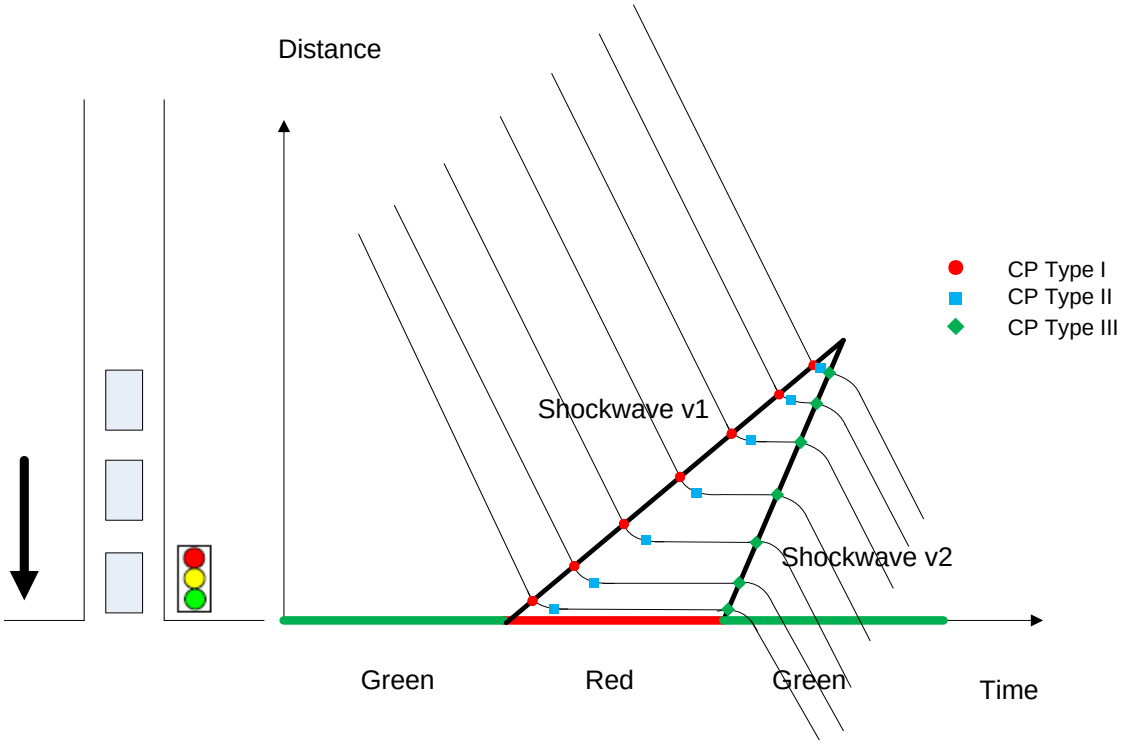


FIGURE 3 Shockwaves and Critical Points (CP)

The three types of CPs are selected from the whole extracted CPs by the features of CPs. These features are: 1) the time difference; and 2) the speed difference. The algorithm can be described as:

(a) Order all the CPs from this vehicle chronologically and find the min speed CPs (index $j_1, j_2 \ldots j_m$) with speeds less than $c_{v,stop}$; if no such CP exist, this vehicle is not stopped by a standing queue, and Type II and Type III CPs do not exist in the current trajectory.

(b) Let $p = j_1$, find the first CP whose speed is less than its immediate previous CP with index of i; if the speed of CP i is higher than all the CPs from i to j, i is the Type I CP and go to (c); if not, throw away the CP from first to i, do this step again;

(c) CP j_m is the Type II CP; CP $j_m + 1$ is the Type III CP.

For simplicity, the above algorithm does not consider the case that the probe could not pass the intersection within a cycle. In that case, the trajectory has one than one stable stopping segments and the time differences (can be defined as center to center time difference) between them are comparable to the cycle length. One needs to divide the trajectory into segments using the max speed points between two consecutive stopping segments and apply the CP extract and filtering algorithms for each segment.

Figure 4 shows the selected Type I, II and II CPs from the generated CPs.

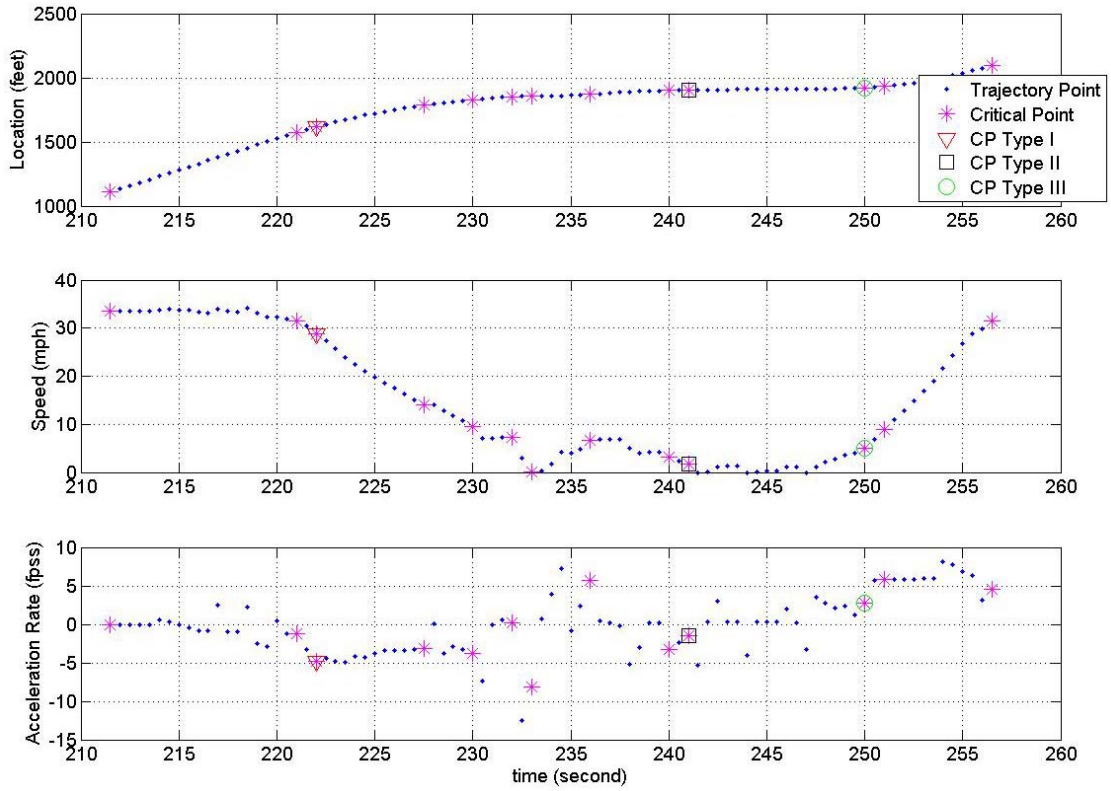


FIGURE 4 CPs and the Selected CPs for Further Applications at a Trajectory (Paramics Simulation Data)

Signal Timing Detection

Signal timing is the major factor which affects the travel time on signalized arterials. Most studies related to arterial travel times use signal timing as input for their models (*6, 7, 31, 32*). However, real-time signal timing is not always available for online or even offline operations. According to the *2007 National Traffic Signal Report Card* (*33*), "Traffic Monitoring and Data Collection" received a score of F and "almost half of agencies (43 percent) reported having little to no regular, ongoing program for collecting and analyzing traffic data for signal timing." Ban el al. explored the methods to derive signal timing using the delay measurements by Virtual Trip Line (VTL) technology based on GPS-equipped cell phones(*34*). Using sampled travel times, they found that a 40% penetration rate of probe was needed in order to obtain reliable signal timing detection. Below, we are going to demonstrate that the use of trajectory data can help detect signal timing data with a lower sample rate than only using sampled travel times.

The formation and dissipation of the queue before a stop-bar at signal changes cause vehicle movement changes which are then extracted as CPs. The time of the shockwaves caused by signal changes traveling to a vehicle is essentially the corresponding CP's timestamp after the traffic light change. That being said, the signal timing parameters such as cycle length and green time can be obtained.

The fundamental and most widely used traffic flow model is the Lighthill-Whitham-Richards (LWR) model (*35-37*). The solution of LWR model is based on the

conservation equation of the traffic flow and a function of speed, flow (or density). The propagation speed of a shockwave is calculated as:

$$v = \frac{q_u - q_d}{k_u - k_d} \quad (4)$$

Where,

q_u, q_d are the flow rate for upstream and downstream, respectively, and

k_u, k_d are the density for upstream and downstream, respectively.

As demonstrated in Figure 3 and 4, since the location and time of CPs are known from the trajectories, the start times of green time and red time can be detected as long as the shockwaves speeds can be estimated.

After the start of green, the queue accumulated before the stop bar starts to discharge. Therefore, the start time of the green light can be calculated as:

$$T_g = T^*_{CP3} - \frac{L^*_{CP3}}{v_{dis}} \quad (5)$$

Where,

T^*_{CP3} is the adjusted time stamp of the Type III CP, ($T^*_{CP3} = T_{CP3} - v_{CP3} / a_{CP3}$, T_{CP3} is the time stamp of the Type III CP, v_{CP3}, a_{CP3} are the speed and acceleration rate of this Type III CP),

L^*_{CP3} is the adjusted distance of a Type III CP to the stop-bar ($L^*_{CP3} = L_{CP3} + v^2_{CP3} / 2a_{CP3}$, L_{CP3} is the time stamp of the Type III CP), and

v_{dis} is the queue discharge shock wave speed.

At the beginning of a green light, assume there is no queue spillback at the downstream intersection, the queue discharges at the saturation flow rate. The queue discharge shock wave speed can be estimated as:

$$v_{dis} = \frac{q_s - 0}{k_m - k_j} \quad (6)$$

Where

q_s is the saturation flow rate,

k_m is the saturation flow density, and

k_j is the jam density

In the *Numeric Experiment*, $v_{dis} = 15 mph$ was used.

After the start of red, traffic is stopped before the stop bar and the queue is formed. Therefore, the start time of the red light can be obtained by:

$$T_r = T^*_{CP1} - \frac{L^*_{CP1}}{v_{form}} \quad (7)$$

Where
T^*_{CP1} is the adjusted time stamp of the Type I CP, ($T^*_{CP1} = T_{CP1} - c_v / |a_{CP1}|$, T_{CP1} is the time stamp of the Type I CP, a_{CP1} are the speed and acceleration rate of this Type I CP),
L^*_{CP1} is adjusted distance of Type I CP to stop-bar, $L^*_{CP1} = L_{CP1} + (2v_{CP1} + c_v)c_v / 2|a_{CP1}|$,
v_{CP1} is the speed of the Type I CP, L_{CP1} is the time stamp of the Type I CP), and
v_{form} is the queue formation shock wave speed.

The queue formation shockwave can be estimated as:

$$v_{form} = \frac{0 - q_u}{k_j - k_u} \quad (8)$$

Where
q_u is the upstream arrival flow rate,
k_u is the upstream arrival density, and
k_j is the jam density.

The problem now becomes how to get q_u and k_u. Using the basic flow-speed-density relationship $q = kv$, either q_u or k_u can be determined by the other because the inflow speed can be estimated by the vehicle speed before deceleration. There is no direct way to estimate k_u or q_u, but the average density $\overline{k_{CP1}}$ from the stop bar to the Type I CP can be estimated: assuming lane changing is limited when vehicles begin to slow and join the queue, the number of vehicles before the probe vehicle can be accurately estimated from dividing the distance from the Type II CP to the stop-bar by:

$$\overline{k_{CP1}} = \frac{L_{CP2}}{L_{CP1}} k_j \quad (9)$$

Where
L_{CP2} is the distance of the Type II CP from the stop-bar.

Therefore, Equation (8) is re-written and approximated as:

$$v_{form} = \frac{0 - q_u}{k_j - \overline{k_{CP1}}} = -\frac{q_u / \overline{k_{CP1}}}{k_j / \overline{k_{CP1}} - 1} \approx -\frac{v_{CP1}}{L_{CP1} / L_{CP2} - 1} \quad (10)$$

Where
v_{CP1} is the speed of the Type I CP.

Dynamic Queue Length Estimation

End of the Queue Detection

The detection of the end of the queue means the detection of an instantaneous queue length. Some CPs correspond to the time and location when the vehicle joins the queue. As discussed, Type II CPs are used.

Maximum Queue Length Estimation during a Cycle

The progress of queue formation and dissipation is greatly affected by the arrival pattern. For an isolated intersection, the arrival flow rate within a cycle can be assumed to be constant. Therefore, the queue length increasing rate can be calculated using the detected end of queue and its timestamp. Given the already detected signal timing, the maximum queue length can be calculated as:

$$L_q = \frac{q_s q_u (T_g - T_r)}{k_j (q_s - q_u)} \tag{11}$$

The upstream arrival rate q_u can be estimated as:

$$q_u = \frac{L_{CP2}}{k_j (T_{CP2} - T_r)} \tag{12}$$

Where,

L_{CP2} is the distance from the Type II CP to the stop-bar, and

T_{CP2} is the timestamp of the Type II CP.

Equation (11) is used for cases without an initial queue. Considering there are stopped vehicles from the previous cycle, initial queue should be detected first and then the total queue length can be estimated. The following formula can help to detect initial queues:

$$q_s (T_{CP2} - T_r) > L_{CP2} k_j \tag{13}$$

If Equation (13) does not satisfy, the initial queue is detected and the length of the initial queue can be estimated by:

$$L_{q0} = L_{CP2} - (T_{CP2} - T_r) q_s / k_j \tag{14}$$

For an intersection affected by an upstream signal, such as coordination, the arrival pattern varies within a cycle because of the “gating effect”. The flow pattern from upstream crossing streets may be significantly different from the main direction. The resulting queue formation process is a complex process. As an approximation, the queue increase process is modeled as a piecewise linear line. More than one Type II CPs are needed for this case. Assume there are $n-1$ available Type II CPs, and use the point of start of red as additional point (with the distance to stopbar is zero), order them chronologically as a list of points on the queue length and time plane.

The average queue increase rate between each two consecutive points can be calculated as:

$$q_i = \frac{L_{CP2,i+1} - L_{CP2,i}}{T_{CP2,i+1} - T_{CP2,i}} \quad (15)$$

Where

i is the index, $i \in \{1, 2, ..., n\}$,

$L_{CP2,i}$ is the distance from the ith Type II CP to the stop-bar, and

$T_{CP2,i}$ is the timestamp of the ith Type II CP.

Then several queue length estimates can be obtained:

$$\begin{aligned} L_{\max} &= L_{CP2,n} + q_{\max} t_{inflow} \\ L_{last} &= L_{CP2,n} + q_{n-1} t_{inflow} \\ L_{\min} &= L_{CP2,n} \end{aligned} \quad (16)$$

Where

$L_{\max}, L_{\min}, L_{last}$ are the three queue length estimates which use the max queue increase rate, the last available queue increase rate, and no queue increase, respectively,

$q_{\max} = \max(q_i)$, and

$t_{g,n}$ is the time duration from the nth Type II CP to the green light shockwave, and is calculated by: $t_{g,n} = \frac{L_{CP2,n}}{v_{dis}} + t_g - T_{CP2,n}$ (see Figure (5), and note that the line of the queue dissipation shockwave is: $y = v_{dis}(x - t_g)$).

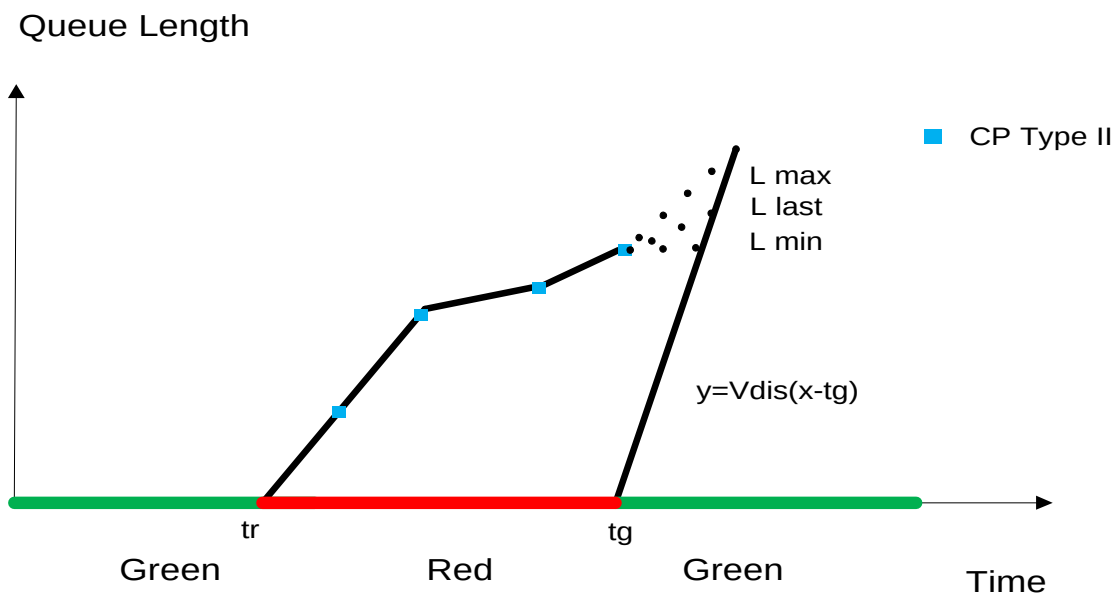


FIGURE 5 Queue Formation in Various Arrival Rates

The queue length of the cycle can be estimated as a weighted average:

$$L_q = w_1 L_{\max} + w_2 L_{last} + w_3 L_{\min} \quad (17)$$

Where w_1, w_2, w_3 are the weights and $w_1 + w_2 + w_3 = 1; w_1, w_2, w_3 \in [0,1]$. In the *Numeric Experiment*, $w_2 = w_3$ and $w_1 = t_{g,n} / (t_{g,\max} + 2t_{g,n})$ ($t_{g,\max}$ is the time duration from the end Type II CP on the segment where the max queue increase rate is achieved.)

Note that the proposed models above are based on the critical points on a single trajectory excepted queue length estimation under various arrival rates, which implies low sample rate requirement. Model improvement for various sample rates and sensitivity analysis of the sample rate impact to models are beyond the scope of this paper, and are part of further work.

NUMERICAL EXPERIMENT

Data Source

There are two types of data used in this paper. One is a simulation network by Paramics (Figure 6) and the other is a trajectory data set from NGSIM((*38*)). The Paramics network is built as follows:

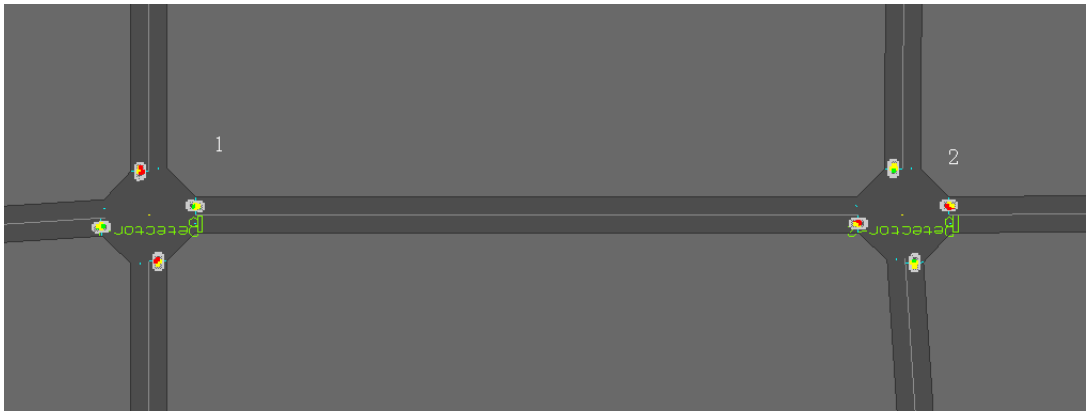


FIGURE 6 Paramics Simulation Network

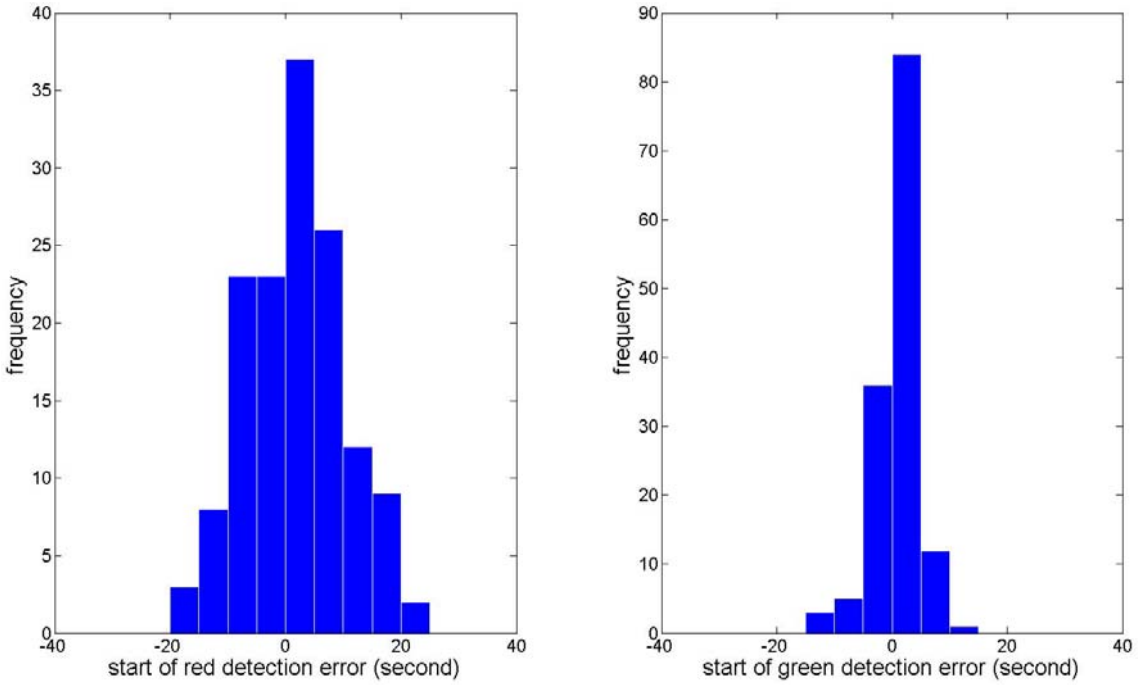
The traffic on the link from Intersection 1 to Intersection 2 are studied. Intersection 1 is the upstream intersection in the case of coordination. There are one exclusive through lane on the study direction and speed limit is 40 mph. The cycle length of two intersections is 80 seconds and the green time for the EB traffic is 45 seconds. For the isolated intersection case, EB traffic do not stop at Intersection 1; for coordinated mode, the offset of the two signals is 17 seconds which is the free flow travel time. The demand flow rates have two levels, one is 800 veh/hr/ln for non-peak and the other is 1800 veh/hr/ln for peak hour.

The NGSIM (*39*) data set used in this study are trajectory data on the southbound link from 11th St to 10th St on Peachtree St. from 4 PM to 4:15 PM. The signal is coordinated with upstream intersections with a cycle length of 100 seconds. NGSIM has two sets of arterial data, Peachtree and Lankershim. The Lankershim set has more measurement errors than the Peachtree set (*40*) , therefore the Peachtree set is chosen.

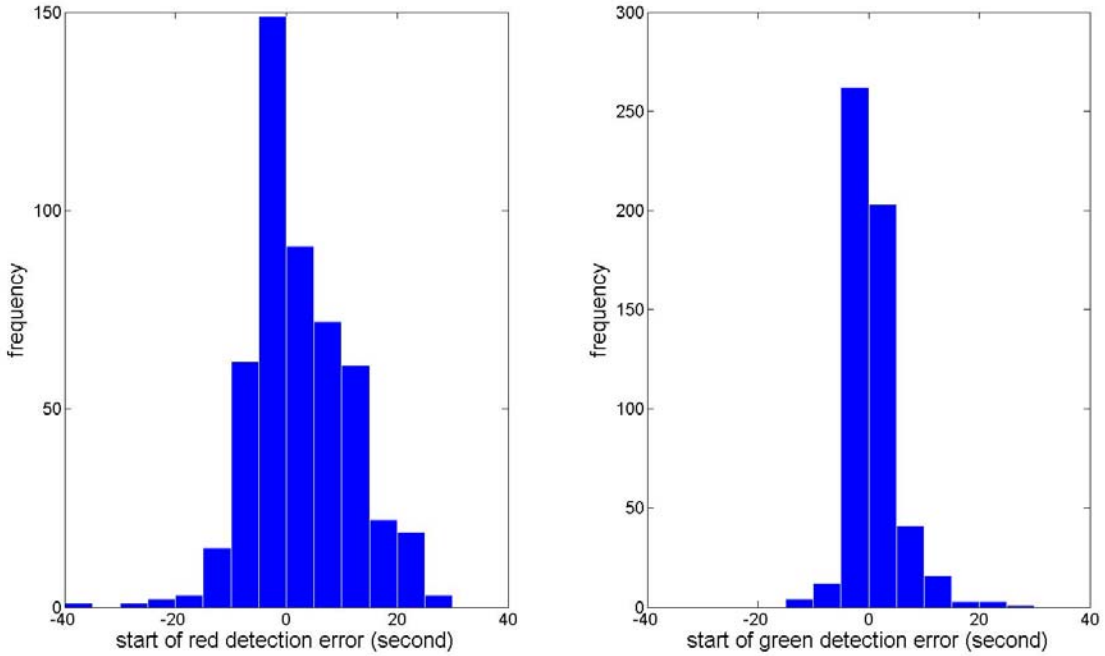
Experiment Results

Signal Timing Detection

The signal detection results are displayed in Figure 7 and 8. Figure 7 shows the results for the case of the isolated intersection. Figure 8 shows the results for the case of coordinated intersections.



(a) Signal Detection for an Isolated Intersection at Non-Peak Hour



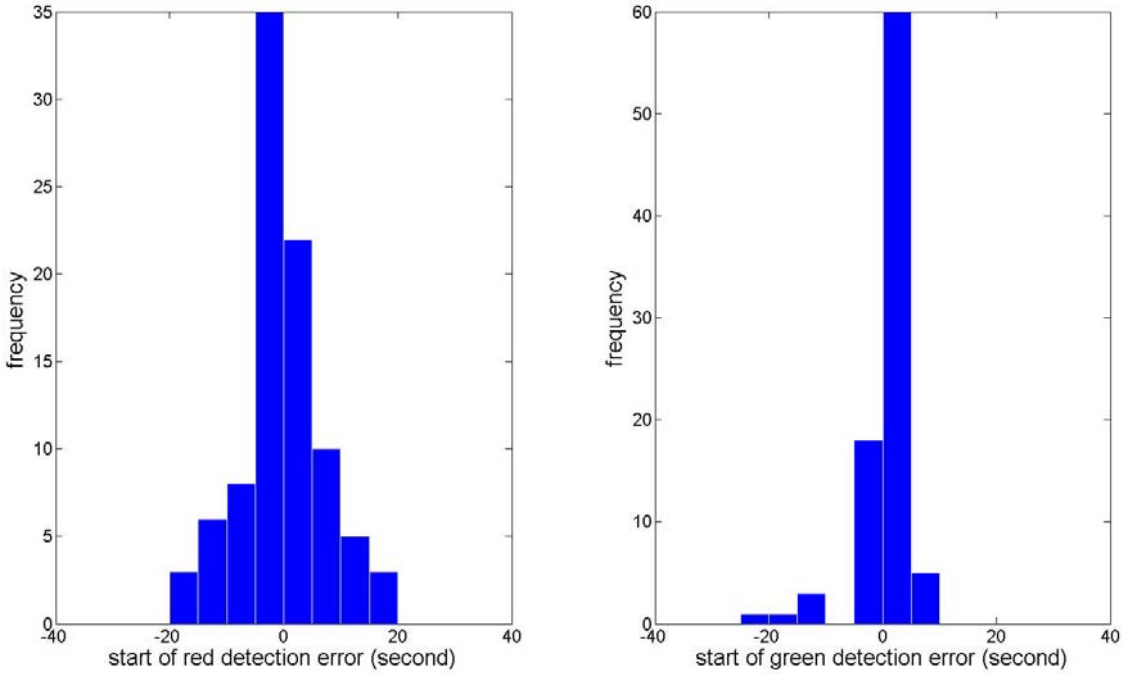
(b) Signal Detection for Isolated Intersection at Peak Hour

FIGURE 7 Signal Detection for an Isolated Intersection

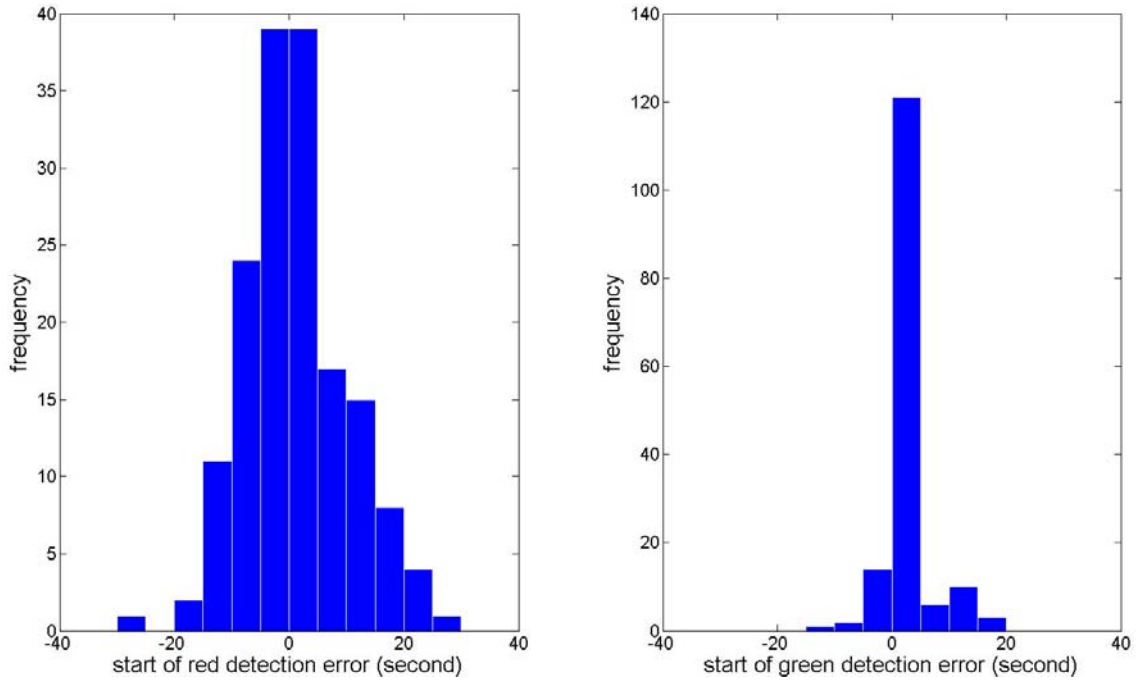
Figure 7 shows the results using 15 consecutive cycles' data for each traffic demand case. The results for the isolated-intersection case are promising. The detected start times of red and green are quite accurate. The detection of the start of green has lower errors because the shockwave speed of queue discharging is nearly constant and traffic in queue discharging usually has fewer disturbances, while the queue formation shockwave varies more and traffic is "unstable far away"(*41*). For the peak hour case, errors distributes similarly to non-peak hour except some "outliers". Further investigation shows that these "outliers" were from the end of long queues (close to the upstream intersection) which the traffic is unstable and has more disturbances. By observation, sometime the shockwaves caused by signal were concealed by the local disturbances and even human eye has a big difficulty in distinguishing them.

Figure 8 shows the results for the case of a coordinated intersection. Figure 8 (a) and (b) shows the results using 15 consecutive cycle's data for each traffic demand case and Figure 8 (c) using 10 consecutive cycle's data by NGSIM Figure 8 (a) shows the results for a non-peak hour case when the coordination is working well. One thing worth noticing is that there were two cycles when all the vehicles went through the intersection without significantly slowing down. Hence no available CPs for signal detection were extracted and therefore the actual timing for the two cycle could not be detected.

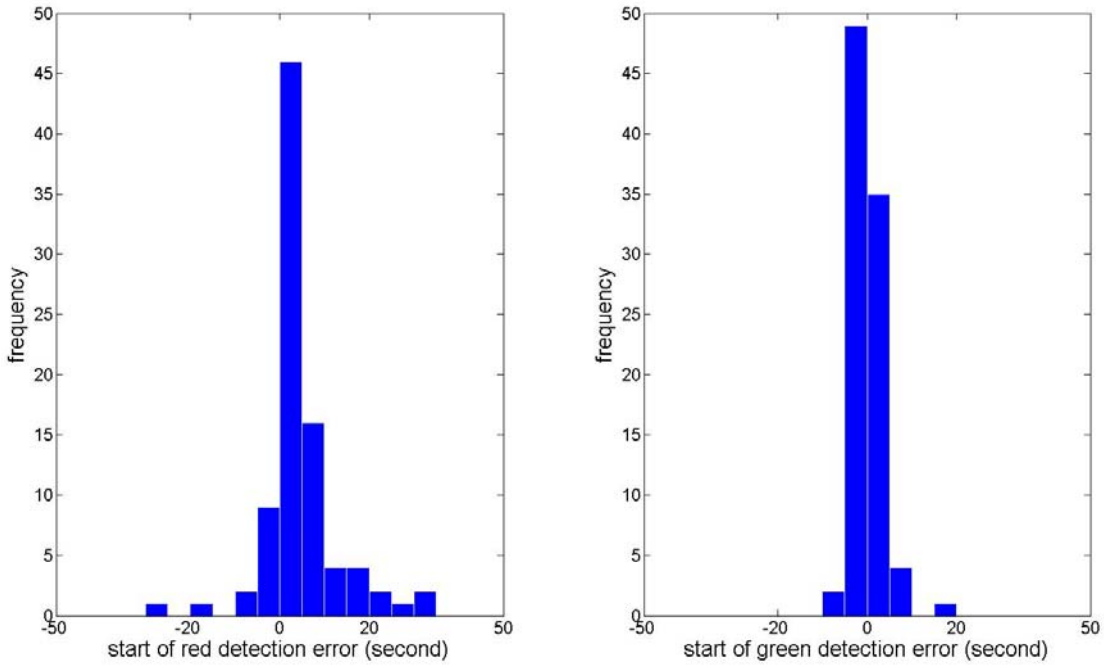
The overall results indicate that this method gives relatively consistent output for signal detection.



(a) Signal Detection for Coordinated Intersection at Non-Peak Hour



(b) Signal Detection for Coordinated Intersection at Peak Hour



(c) Signal detection using NGSIM data

FIGURE 8 Detection of Signal Timing for a Coordinated Intersection

Maximum Queue Length Estimation

The performance of the maximum queue length estimation is measured by Mean Absolute Percentage Error (MAPE) which is calculated as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{GroundTrue - Estimation}{GroundTrue}\right| \times 100\% \quad (18)$$

Where,
n is the total sample size.

The ground truth queue lengths were collected by observing the overall vehicle trajectories. For the isolated intersection cases, one trajectory was randomly picked for estimation in each cycle. For the coordinated intersection cases as well as NGSIM, three trajectories were randomly picked in each cycle. For each case, experiments were run for 20 times. Table 1 gives the results.

TABLE 1 MAPE of Queue Length Estimation

		# of Cycles	MAPE
SIMU	Isolated (non-peak)	12	18.41%
	Isolated (peak)	12	19.56%
	coordinated (non-peak)	12	22.43%
	coordinated (peak)	12	21.07%
NGSIM	Lane 1*	7	23.35%
	Lane 2**	7	24.16%

* Lane 1 is the lane next to median except left turn lane.
** Lane2 is the lane on the right.

Liu et al. (*13*) proposed a real-time queue length estimation for congested signalized intersection using the event-based data by SMART-SIGNAL system and the reported MAPE is 14.93%. The results here are comparable to theirs, considering the differences of data resolution. , Since the queue estimation model here is straightforward and serves as a prototype, we expect improved results in future work.

CONCLUSION AND FUTURE STUDY

An innovative approach for arterial intersection performance measurement using vehicle trajectory data is proposed in this paper. To address the challenge of converting the microscopic detections into macroscopic performance measurements, a “critical point” (CP) extraction method is presented. CPs can capture the dynamics of the vehicle and the extraction algorithm has the potential ability for reducing communication cost for onboard GPS devices. Since the extracted CPs represent all the major and minor turbulence and frictions of the vehicle, a CP feature based selection method chooses different types of CPs for difference applications. Using the detected instantaneous end of

queue, cycle-by-cycle queue length estimation methods are proposed for both isolated intersections and intersections with upstream signal impacts. The models are evaluated by simulated data and the NGSIM trajectory data. The signal timing detection is relatively accurate except that there are a few start-of-red detection outliers resulting from stop-and-go flow under oversaturation conditions. The performance of queue length estimation is also acceptable.

Future study will include: 1) the improvement of the CP extraction algorithm and CP selection design to address the stop-and-go flow; 2) the sensitivity analysis of the probe data error and sample rate for estimation performance; 3) the adoption of nonlinear shockwave models which are suitable for arterial traffic flow and are able to support CP extraction and selection.

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REFERENCE

1. Balke, K.N., H. Charara, and R. Parker, *Development of a Traffic Signal Performance Measurement System (Tspms)*. 2005, Texas Transportation Institute. p. 83.
2. Berkow, M., C.M. Monsere, P.J.V. Koonce, R.L. Bertini, and M. Wolfe. *Prototype for Data Fusion Using Stationary and Mobile Data Sources for Improved Arterial Performance Measurement.* in *Transportation Research Board 88th Annual Meeting*. 2009: Transportation Research Board p.14p.
3. Liu, H.X., W. Ma, X. Wu, and H. Hu, *Development of a Real-Time Arterial Performance Monitoring System Using Traffic Data Available from Existing Signal Systems*. 2008, University of Minnesota, Twin Cities, Minnesota Department of Transportation. p. 117.
4. Sisiopiku, V.P. and N.M. Rouphail, *Toward the Use of Detector Output for Arterial Link Travel Time Estimation: A Literature Review*. Transportation Research Record, Vol. 1457,1994 pp. 158-165.
5. Zhang, H.M., *Link-Journey-Speed Model for Arterial Traffic.* TRANSPORTATION RESEARCH RECORD, Vol. 1676,1999 pp. p. 109-115.
6. Zhang, H.M., *Link-Journey-Speed Model for Arterial Traffic.* Transportation Research Record, Vol. 1676,1999 pp. 109-115.
7. Xie, C., R.L. Cheu, and D.-H. Lee, *Calibration-Free Arterial Link Speed Estimation Model Using Loop Data*. Journal of Transportation Engineering, Vol. 127(6),2001 pp. 507-514.
8. Skabardonis, A. and N. Geroliminis, *Real-Time Monitoring and Control on Signalized Arterials.* Journal of Intelligent Transportation Systems, Vol. 12(2),2008 pp. 64 - 74.
9. Geroliminis, N. and A. Skabardonis, *Prediction of Arrival Profiles and Queue Lengths Along Signalized Arterials by Using a Markov Decision Process.*

Transportation Research Record: Journal of the Transportation Research Board, Vol. 1934,2005 pp. 116-124.
10. Viti, F. and H.J. Van Zuylen, *The Dynamics and the Uncertainty of Queues at Fixed and Actuated Controls: A Probabilistic Approach*. Journal of Intelligent Transportation Systems, Vol. 13(1),2009 pp. 39-51.
11. Robinson, S. and J.W. Polak, *Modeling Urban Link Travel Time with Inductive Loop Detector Data by Using the K-Nn Method.* Transportation Research Record: Journal of the Transportation Research Board, Vol. 1935,2005 pp. 47-56.
12. Cheu, R.L., D.-H. Lee, and C. Xie. *An Arterial Speed Estimation Model Fusing Data from Stationary and Mobile Sensors*. in *Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE*. 2001p.573-578.
13. Liu, H.X., X. Wu, W. Ma, and H. Hu, *Real-Time Queue Length Estimation for Congested Signalized Intersections.* Transportation Research Part C: Emerging Technologies, Vol. 17(4),2009 pp. 412-427.
14. Liu, H.X., J.S. Oh, S. Oh, L. Chu, and W.W. Recker, *On-Line Traffic Signal Control Scheme with Real-Time Delay Estimation Technology*. 2001, Partners for Advanced Transit and Highways (PATH) University of California, Berkeley California Department of Transportation California PATH. p. 15.
15. Ritchie, S.G., S.-T. Jeng, Y.C. Tok, and S. Park, *Corridor Deployment and Investigation of Anonymous Vehicle Tracking for Real-Time Traffic Performance Measurement*. 2008, California Partners for Advanced Transit and Highways (PATH), University of California Berkeley, California Department of Transportation. p. 152.
16. Wilson, R.E. *From Inductance Loops to Vehicle Trajectories*. in *Symposium on the Fundamental Diagram: 75 Years (Greenshields 75 Symposium)*. 2008: Transportation Research Board p.11p.
17. Coifman, B., *Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors.* Transportation Research. Part A: Policy and Practice, Vol. 36(4),2002 pp. 351-364.
18. Comert, G. and M. Cetin. *Queue Length Estimation from Probe Vehicle Location: Undersaturated Conditions*. in *Transportation Research Board 86th Annual Meeting*. 2007: Transportation Research Board p.16p.
19. Hellinga, B.R. and L. Fu, *Reducing Bias in Probe-Based Arterial Link Travel Time Estimates.* Transportation Research Part C: Emerging Technologies, Vol. 10(4),2002 pp. p. 257-273.
20. Kothuri, S.M., K.A. Tufte, E. Fayed, and R.L. Bertini, *Toward Understanding and Reducing Errors in Real-Time Estimation of Travel Times.* Transportation Research Record: Journal of the Transportation Research Board, Vol. 2049,2008 pp. 21-28.
21. Li, Q., T. Miwa, T. Yamamoto, and T. Morikawa. *Some Statistical Properties of Arterial Link Travel Time Derived from Historical Probe-Vehicle Data*. in *11th World Conference on Transport Research*. 2007: World Conference on Transport Research Society p.34p.
22. Pan, C., J. Lu, D. Wang, and B. Ran, *Data Collection Based on Global Positioning System for Travel Time and Delay for Arterial Roadway Network.*

Transportation Research Record: Journal of the Transportation Research Board No 2024, Vol.,2007 pp. 35-43.

23. Liu, H.X., A. Danczyk, R. Brewer, and R. Starr, *Evaluation of Cell Phone Traffic Data in Minnesota*. Transportation Research Record: Journal of the Transportation Research Board No 2086, Vol.,2008 pp. 1-7.
24. Green, M.W., M.D. Fontaine, and B.L. Smith, *Investigation of Dynamic Probe Sample Requirements for Traffic Condition Monitoring.* Transportation Research Record, Vol. 1870,2004 pp. 55-61.
25. Lu, X.-Y. and A. Skabardonis. *Freeway Traffic Shockwave Analysis: Exploring Ngsim Trajectory Data*. in *Transportation Research Board 86th Annual Meeting*. 2007: Transportation Research Board p.19.
26. Izadpanah, P., B. Hellinga, and L. Fu. *Automatic Traffic Shockwave Identification Using Vehicles' Trajectories*. in *Transportation Research Board 88th Annual Meeting*. 2009: Transportation Research Board p.14.
27. Claudel, C.G., A. Hofleitner, N. Mignerey, and A.M. Bayen. *Guaranteed Bounds on Highway Travel Times Using Probe and Fixed Data*. in *Transportation Research Board 88th Annual Meeting*. 2009: Transportation Research Boardp.18p.
28. Daganzo, C.F., *A Variational Formulation of Kinematic Waves: Basic Theory and Complex Boundary Conditions.* Transportation Research Part B: Methodological, Vol. 39(2),2005 pp. 187-196.
29. Newell, G.F., *A Simplified Theory of Kinematic Waves in Highway Traffic, Part I: General Theory*. Transportation Research. Part B: Methodological, Vol. 27(4),1993 pp. 281-287.
30. Turner, S.M., W.L. Eisele, R.J. Benz, and D.J. Holdener, *Travel Time Data Collection Handbook*. Travel Time Data Collection Handbook. 1998: Texas Transportation Institute, Federal Highway Administration. 348 p.
31. Levinson, D.M., *Speed and Delay on Signalized Arterials.* Journal of Transportation Engineering, Vol. 124(3),1998 pp. 258-263.
32. Chen, M. and S. Chien, *Determining the Number of Probe Vehicles for Freeway Travel Time Estimation by Microscopic Simulation.* Transportation Research Record, Vol. 1719,2000 pp. 61-68.
33. *National Traffic Signal Report Card Technical Report 2007*. 2007, Federal Highway Administration, Institute of Transportation Engineers, American Public Works Association, American Association of State Highway and Transportation Officials, ITS America. p. 61.
34. Ban, X.J., R. Herring, P. Hao, and A. Bayen. *Delay Pattern Estimation for Signalized Intersections Using Sampled Travel Times*. in *Transportation Research Board 88th Annual Meeting*. 2009. Washington DC21.
35. Lighthill, M.J. and G.B. Whitham, *On Kinematic Waves. I. Flood Movement in Long Rivers.* Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences, Vol. 229(1178),1955 pp. 281-316.
36. Lighthill, M.J. and G.B. Whitham, *On Kinematic Waves. Ii. A Theory of Traffic Flow on Long Crowded Roads.* Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences, Vol. 229(1178),1955 pp. 317-345.

37. Richards, P.I., *Shock Waves on the Highway*. operations research, Vol. 4(1),1956 pp. 42-51.
38. Fhwa. *Next Generation Simulation Website*. 2009 http://www.ngsim.fhwa.dot.gov/ Accessed 2009 May 6.
39. Alexiadis, V., J. Colyar, and J. Halkias, *The Next Generation Simulation Program*. ITE Journal, Vol. 74(8),2004 pp. 22-6.
40. Punzo, V., M.T. Borzacchiello, and B.F. Ciuffo. *Estimation of Vehicle Trajectories from Observed Discrete Positions and Next-Generation Simulation Program (Ngsim) Data*. in *Transportation Research Board 88th Annual Meeting*. 2009: Transportation Research Board p.17.
41. Smilowitz, K.R., C.F. Daganzo, M.J. Cassidy, and R.L. Bertini, *Some Observations of Highway Traffic in Long Queues.* Transportation Research Record, Vol. 1678,1999 pp. 225-233.