An Analysis Model of Queue Length Fluctuation at Signals Using Vehicle Trajectories

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***Abstract*—Floating car systems have attracted much attention. In particular, trajectory information of vehicles, which cannot be obtained in legacy traffic monitoring systems, would be significant for more detailed and precise traffic prediction. In this paper, we focus on vehicle queues formed in front of intersections and present a model that analyzes the dynamics of their length using vehicle trajectory information. In general, a queue grows in a red phase of the traffic signal cycle and shrinks in a green phase. We assume that vehicles arrive at a signal with a Poisson process, and estimate the queue length for each signal cycle. Our method was evaluated using a traffic simulator where the real field data were injected. Evaluation results have shown that the queue length could be estimated and the mean error was about 5 vehicles, which is acceptable compared with the whole queue sizes.**

Keywords—floating car, queue length, traffic signal

I. Introduction

The comfort and safety of drivers and pedestrians in road environments have been recently improved by the development of Intelligent Transportation Systems (ITS). A typical example of ITS in Japan is Vehicle Information and Communication System (VICS) [1]. In the system, infrastructure sensors such as infrared beacons and loop detectors monitor the number of passing vehicles and provide real-time traffic information. Such a system contributes traffic smoothness and safety, but it can monitor only traffic conditions in the regions covered by the infrastructure. Meanwhile, floating car systems have attracted much attention. A floating car is equipped with various sensors and cellular communication devices, and its positions as well as motion information like acceleration and velocity are periodically reported to a server. As those vehicles drive through various roads including those without infrastructure sensors, coverage of monitoring has been significantly extended compared with legacy infrastructure-based systems.

A lot of efforts have been dedicated to realizing smooth traffic using the data aggregated from floating cars (called *floating car data*) [2], [3]. For example, "Internavi" developed by Honda Motor Co., Ltd. [4] provides traffic prediction and related services based on utilizing both floating car data and the VICS information. The optimal routes to a destination can be precisely estimated along with travel time based on such information. Similar services have also been provided by different companies like Toyota and Nissan.

Although there are a number of studies on vehicular traffic estimation using floating car data, most of them and most of the services that are currently in use rely strongly on statistical data (the past trend of congestion). Due to the very low penetration rate of floating cars (less than a few percent), it is hard to cover the whole region tempo-spatially, and therefore, it is hard to estimate detailed behavior of congestion. However, focusing on stop-and-go behavior of each vehicle in its trajectory, it would be possible to identify queues through which it passes, and more precise estimation is possible, which is more robust to dynamic situation changes (*e.g.* congestion by accidents).

In this paper, we propose a method to estimate the length of queues formed near traffic signals. The length of queues is estimated based on our estimation model from given trajectory data with speed information, where the model captures the dynamic nature of queues' growth and reduction. Based on stop-and-go information, the number of vehicles which have not passed through the signal in a green phase is estimated, we assume that vehicles arrive at the tails of queues with a Poisson process in the model. Then we calculate the parameters of the Poisson process based on the time and location where each floating car stops. Then we estimate traffic conditions in each signal cycle recursively in real time.

To evaluate the proposed method, we have estimated the queue length and examined the estimation accuracy using a traffic simulator, Vissim [5]. In addition, we have observed vehicles' behavior in a real intersection. In these experiments, we have chosen the trajectories of some cars as floating car data from all vehicle trajectories at random, and applied the proposing estimation process based on the data. Evaluation results have shown that the queue length could be estimated with small errors. The mean error is around 5 vehicles when sufficient vehicles exist on the road.

II. Related work

To grasp traffic conditions, a number of methods have been proposed and used. At first, infrastructure based methods installing sensors such as loop sensors, radio wave and light beacons are widely used. For example, a kind of methods using road side sensors at two different points is popular. Each sensor identifies the vehicles pass by it and records the passing times. The data are shared with the other sensor and the travel times of vehicles can be estimated by comparing them [6]–[8].

In the method of Kwon et.al. [6], the travel times of vehicles are estimated using linear regression from the sensor data and the data about travel times collected before. Through the evaluation using actual data, they have shown that the travel times at the time at most 20 minutes after observing time can be estimated accurately by their method. Rice et.al. [7] have proposed a method to estimate travel times on each segment of the highway using the characteristics that the travel times in the future linearly depend on those at the current time. They have also shown that the travel times after one hour from the current time can be estimated only with 10 percent of error, by considering the effects between neighboring multiple segments instead of calculating the travel time for each single segment independently. Wang et.al. [8] have proposed an adaptive method that estimates travel times in various conditions accurately using Kalman filter considering changes of environmental factors such as weather conditions or speed limits. In order to estimate traffic volumes in an urban area, a state space model based estimation method for dynamics of traffic volumes, where the model is constructed considering the neighboring relationships among sensors installed in urban roads with high density, has been proposed [9]. In the evaluation, the authors have shown that their method reduced the estimation error with 8 percent from a simple method based on autoregressive moving average(ARMA) model. Like described above, a lot of methods based on sensor infrastructure have been proposed and the traffic condition can be grasped and estimated well by such methods. However, such methods require that the sensors are installed onto the target roads. So, to adapt such method for wide area, too large installation cost is needed.

On the other hand, floating car data based systems have attracted much attentions recently. Differ from infrastructure based methods, we can collect a lot of data from a wide area in real time without much cost. For a typical example of floating car data systems, we can find a number of traffic survey systems for wide area in an urban area [2], [3]. Fabritiis et.al. [2] have proposed a method for estimation and prediction of traffic conditions. They have collected data from more than 600,000 vehicles driving on a loop highway in Rome with 3 minutes of intervals. Their method is based on pattern matching using a neural network technique. They have shown that they can predict the average speed after 30 minutes from the observing time with errors between 3.5 to 9.5 km/h using previously collected data. Yokota et.al. [3] have collected floating car data from about 300 trucks around Osaka and classified the road segments into two groups by the frequency of passing of floating cars. They have shown that they can estimate the density of floating car data, the average travel time and the average speed accurately by using the modes. Lee et.al. [10] have proposed a data mining technique for collected floating car data. By their method, changing patterns of the traffic volumes can be found in real time.

For more detailed traffic survey, a number of studies about methods for estimation of traffic condition in link-level have been carried out. For example, there have been propositions for estimation of weight of traffic congestions from estimated queue lengths at intersections [11]–[13]. In Comert et.al. [11], they estimate the queue lengths using probability models constructed from information about stopped positions of floating cars on each link. Cheng et.al. [12] have used the *shockwave theory* [14] to represent the growth and reduction of queues using a mathematical model in order to estimate the queue lengths. Unal et.al. [15] also used the shockwave theory to estimate the queue lengths, where they can estimate them accurately when the ratio of floating cars to all the cars is more than 30 percent. Combination of floating car data systems and infrastructural sensors has been also studied. For example Cai et.al. [13] have proposed a method by which they can estimate queue lengths with about 10 percent of errors. Nakata et.al. [16] have proposed a method for estimation of travel times. In their method, they have collected and analyzed a large amount of data and found periodically changing pattern of traffic volumes depends on hours, days of weeks and seasons. The method proposed by Uno et.al. [17] is also based on previously collected data. They have shown that they can construct a database that covers the geometrical and time spaces widely from floating car data collected by buses, which are served under a fixed schedule. Then they can predict travel times accurately by using the database.

As shown above, there are many methods proposed to estimate and predict traffic conditions. Many of them are based on comparison between the data previously collected by sensors and floating cars and current information collected in real time. So we cannot grasp the changes of sudden traffic conditions caused by unexpected events such as traffic accidents. On the other hand, our method does not depend on previously collected data. In our method, we have realized accurate estimation of queue lengths at traffic signals depends on detailed analysis of trajectory information of each floating car.

III. Queue Length Estimation at a Signalized Intersection

In this section, we explain how to model the fluctuation of the queue length in the proposed method to know traffic conditions in a target intersection precisely. In order to detect the queue length variation, we propose an estimation method for the queue length based on floating cars and signal control timings.

At first, we show our idea in Fig. 1. This figure shows the number of vehicles and the position of a floating car in a traffic queue. The x and y axes show the time and the number of vehicles, respectively. The red and green lines over the x axis show the duration of red signals and green signals, respectively. The blue line shows the position of a floating car in the queue. As shown in the figure, during a red signal, the number of vehicles increases before the signal changes to green. Then, the number of vehicles in the queue decreases and reaches to zero since the vehicles in the queue depart from the intersection during the green signal. As shown in the blue line in the figure, after the floating car arrived at the end of the traffic queue, the floating car stopped until the green signal. At that time, from the position of the floating car, we can know how many vehicles are in the front of the floating car, which are the vehicles waiting for the next green signal at the intersection. In addition, if the signal control timing for the target intersection is given, we can also know the passed time from the last green signal and the remaining time of the red signal. Thus, we can estimate vehicles' arriving ratio within the passed red period. Also we can estimate how many vehicles will arrive at the intersection within the remaining time based on the arrival ratio obtained by the floating car arrival. In this paper, according to this idea, we proposed a method to estimate the queue length

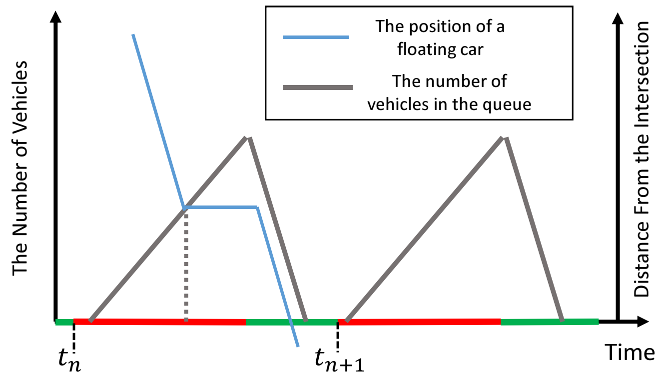


Fig. 1. The number of Vehicles in a Target Intersection

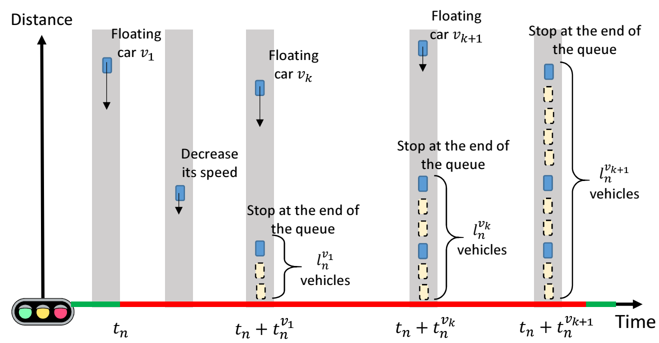


Fig. 2. Floating Cars' Behavior in a Target Intersection

in an intersection for each signal cycle to know the fluctuation of the queue length.

A. Queue Length Estimation for a Single Signal Cycle

We explain how to model the fluctuation of the queue length in the proposed method. In order to estimate the number of vehicles in the queue from the information obtained by several floating cars for each signal cycle correctly, we assume that the signal schedule for the target intersection is given. A signal cycle is composed of a red signal and a green signal, and a signal cycle begins with a red signal. We denote the beginning of the time in cycle n as t_n, the duration of the red signal as R and the duration of the green signal as G, respectively. Fig. 2 shows how floating cars join the traffic queue during a red signal. Since the positions of floating cars can be obtained with high accuracy nowadays, we assume that we can calculate the number of vehicles based on the position of the floating car when the floating car stops in the queue as shown in Fig. 2. We also denote the number of vehicles that could not pass and still stayed in the intersection in cycle n as r_n. Using the above variables, we show how to model the queue length in detail.

At first, we model how the queue increases during a cycle. We assume that floating car v_1 stops as $l_n^{v_1}$ th vehicles at time $t_n^{v_1}$ after from t_n in signal cycle n. As shown in Fig. 2, $l_n^{v_1}$ vehicles have already waited at the intersection at $t_n^{v_1}$. Since not all the vehicles arrived at the intersection within cycle n and r_{n-1} vehicles waited before, the number of vehicles arrived at $t_n^{v_1}$ in cycle n is $l_n^{v_1} - r_{n-1}$. According to a Poisson process, we can see that the average arrival ratio in cycle n at $t_n^{v_1}$ can be represented as the following equation.

$$\lambda_n^{v_1} = \frac{l_n^{v_1} - r_{n-1}}{t_n^{v_1}} \tag{1}$$

If two or more floating cars arrive at the queue in the same cycle, our method can estimate the average arrival ratio more accurately. We calculate an average arrival ratio for each floating car, and estimate the average arrival ratio in the cycle according to maximum likelihood estimation. For example, we assume that floating car v_k stops as $l_n^{v_k}$ th vehicle at $t_n^{v_k}$, and the next floating car v_{k+1} stops as $l_n^{v_{k+1}}$ th vehicle at $t_n^{v_{k+1}}$ in the queue. In this case, the average arrival ratio between t_n^k and t_n^{k+1} can be calculated by the following equation.

$$\lambda_n^{v_k} = \frac{l_n^{v_{k+1}} - l_n^{v_k}}{t_n^{v_{k+1}} - t_n^{v_k}} \tag{2}$$

From this equation, we can calculate the average arrival ratio for each arrival of the floating car. Then, we also calculate the arrival ratio in the cycle by the following equation where there are m floating cars in a cycle according to maximum likelihood estimation for a Poisson process.

$$\lambda_n = \frac{1}{m} \sum_{k=1}^{m} \lambda_{v_k} \tag{3}$$

Hereafter, a latest floating car, its arrival time and its position are denoted as v_m, $t_n^{v_m}$ and $l_n^{v_m}$, respectively. Since we assume that the vehicles arrive at the intersection according to a Poisson process, the percentage where x vehicles arrive after $t_n^{v_m}$ is shown in the following equation based on the average arrival ratio in the cycle denoted as λ_n.

$$P_n(x) = \frac{\lambda_n e^{-\lambda_n}}{x!} \tag{4}$$

Thus, the probability distribution of the queue length at the end of the red signal is represented as the following equations.

$$\lambda_n^{red} = \lambda_n \cdot (R - t_n^{v_m})$$
$$P_n^{red}(x) = \frac{\lambda_n^{red} e^{-\lambda_n^{red}}}{(x - l_n^{v_m})!} \quad (x - l_n^{v_m} \geq 0) \tag{5}$$

The queue length in cycle n is obtained as the expected value of the distribution.

$$P_n^{red} = E(P_n^{red}(x))$$

Also, the number of vehicles that have stayed in the queue in the cycle can be represented by the following equations since such cars have arrived at the intersection until the end of the cycle.

$$\lambda_n^{green} = \lambda_n \cdot (R + G - t_n^{v_m})$$
$$P_n^{green}(x) = \frac{\lambda_n^{green} e^{-\lambda_n^{green}}}{(x - l_n^{v_m})!} \quad (x - l_n^{v_m} \geq 0) \tag{6}$$
$$P_n^{green} = E(P_n^{green}(x))$$

We also calculate the capacity of the intersection. The capacity is estimated in saturated and unsaturated conditions differently. In a saturated condition, when a floating car stops in the queue twice for red signals of different cycles, we can know how many vehicles pass through the intersection within one cycle directly. The capacity can be estimated from the distance that the floating car moves within the cycle because this distance is proportional to the number of the transmitted vehicles in the green signal. Thus, the capacity is obtained by $l_k - l_{k+1}$ in this case. In an unsaturated condition, we can estimate the capacity using the trajectory from a floating car that stops in front of the intersection once. When a floating car v stopped at the intersection as l_n^v th vehicle, and passed the intersection after t_n^v from t_n, the capacity can be represented in the following equation.

$$c_n = \frac{l_n^v}{R - t_n^v} \cdot G \tag{7}$$

Since at least l_n^v vehicles could pass the intersection within $R - t_n^v$, the average departure ratio can be obtained by $\frac{l}{R - t_n^v}$. Usually, the capacity of the intersection does not change over time. We use the latest estimated capacity for several cycles in the proposed method if we can not observe floating cars in the cycles.

From above variables, we can calculate r_n, which is the number of vehicles that could not pass and still stayed in the intersection in cycle n. Such vehicles can be calculated by subtracting the capacity from the vehicles that have stayed in the queue in cycle n. This can be represented by the following equation.

$$r_{n+1} = P_n^{green} - c_n \tag{8}$$

Using above equations, our method can calculate the queue length for each signal cycle sequentially if at least one floating cars arrive at the intersection in every cycle.

B. Queue Length Estimation for Multitple Signal Cycles

However, floating cars do not always arrive at the intersection in every cycle even though the number of floating cars increases recently. In a cycle without any floating car, we estimate the queue length based on the latest observing results, since the arrival and departure volumes from the intersection do not change in a short term. In such cases, the average arrival ratio and capacity, which are obtained in the latest cycle with floating cars are used, as the current inputs for the proposed method.

In addition, we fix the previous estimation results from the current situations in the cases where we can know that the derived result in the previous cycle does not match the observation in the current cycle. We assume that floating car v_n stops in the queue at $t_n^{v_n}$ as $l_n^{v_k}$ th car in cycle n, and the next floating car v_{n+d} stops at time $t_{n+d}^{v_{n+d}}$ as $l_{n+d}^{v_{n+d}}$ th car in cycle $n+d$. If a certain amount of cars arrived in the previous cycle n, we can expect that many cars might remain in the queue in a next cycle $n+d$, and r_{n-1} should be less than l_n^{v+d}. Thus, in the case where $r_{n-1} > l_n^v$, we can see that the results in the previous cycles are wrong, and re-calculate the average arrival ratio between cycle n and cycle $n+d$. The interval between two floating cars is represented as the following equation.

$$(R + G - t_n^{v_n}) + (R + G) \cdot (d - 1) + t_{n+d}^{v_{n+d}}$$

The first term is remaind time in cycle n, and the second term is the duration between cycle $n+1$ and cycle $n+d-1$. The third term is time when v_{n+d} is observed in cycle $n+d$. Then, the number of incoming cars within the cycles is

$$((R + G - t_n^{v_n}) + (R + G) \cdot (d - 1) + t_{n+d}^{v_{n+d}}) \cdot \lambda$$

where λ is the new average arrival ratio in the cycles. Therefore, we obtain the following equation since the number of outgoing cars is $c_n \cdot d$.

$$l_n^{v_n} + ((R + G) \cdot d - t_n^{v_n} + t_{n+d}^{v_{n+d}}) \cdot \lambda - c_n \cdot d = l_{n+d}^{v_{n+d}}$$

From this equation, we can also calculate the average arrival ratio, and estimate the queue length based on it.

$$\lambda = \frac{c_n \cdot d - l_n^{v_n} + l_{n+d}^{v_{n+d}}}{(R + G) \cdot d - t_n^{v_n} + t_{n+d}^{v_{n+d}}} \tag{9}$$

IV. Detection of Change of Traffic Volume

In this section, we will explain how we can detect the change of incoming traffic volumes by comparing the conditions among multiple signal cycles. The detection can be done as follows. First, we calculate the vehicles' arriving ratio λ of each cycle using the method explained in Sec. III. Then, we check if the λs of the cycles are changed or not, by using two-sample t-test.

Here, since we can assume that the incoming traffic volume does not change so rapidly, we have introduced a window size k, which represents the number of cycles considered as a single stable group. Then, we check the λs are changed between k cycles to the next k cycles. That is, if we start the detecting process at cycle x, we calculate the set of average arriving ratios in cycles x to $x + k - 1$ as λ_1 and that in cycles $x + k$ to $k + 2k - 1$ as λ_2. Then we use two-sample t-test to check if $\lambda_1 = \lambda_2$ is satisfied. If the formula is satisfied, the traffic volume is not changed and stable during the cycles in the two groups. If it is not satisfied, we also check the averages of two groups of λs; $\bar{\lambda}$ and $\bar{\lambda_2}$. In the cases when $\bar{\lambda_1} > \bar{\lambda_2}$, the traffic volume is considered to decrease. Otherwise, it is considered to increase.

V. Evaluation

To evaluate the proposed method, we have conducted some experiments using a traffic simulator, Vissim [5]. We have estimated the queue lengths using the proposed method based on vehicle trajectory data under several conditions. In addition, we have observed vehicles' behavior in a real intersection, and estimated queue lengths against the data.

A. Experiment in Simulations

1) Simulation Environment: Table I shows the simulation environment, and Table II shows the scenarios in the experiment. In the simulation, we have built a straight link where a signal is installed at the center of it. We randomly selected vehicles in the simulation as floating cars, and estimated the queue lengths. Here, the results become different depending on the choice of floating cars, we have carried out multiple simulations for each scenario with different sets of floating cars, and evaluated the mean value resulting from the estimation.

TABLE I. SIMULATION ENVIRONMENT

Link shape	Straight one-lane link
Link length	400-meter-long road
Signal cycle	Red 80 seconds, Green 40 seconds
Simulation time	4800 seconds (40 cycles)
The Quantity of floating cars	7 grades: 0.2 to 2.0 vehicles per cycle
Average length of vehicles	6.6 meters

TABLE II. EXPERIMENT SCENARIOS

Scenario	Traffic volume
Fixed (not congested)	360 [veh/h]
Fixed (slightly congested)	620 [veh/h]
Fixed (congested)	700 [veh/h]
Dynamic (congested → not)	360 → 800 → 360 [veh/h]
Dynamic (not → congested)	800 → 360 → 800 [veh/h]

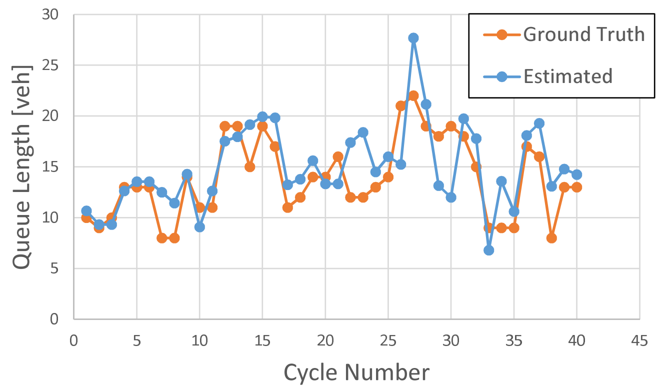


Fig. 3. Estimated Queue Lengths With Ideal Car Arrivals

TABLE III. MAEs OF QUEUE LENGTHS

Scenario	MAE of queue lengths [veh]
Fixed (not congested)	3.03
Fixed (slightly congested)	2.42
Fixed (congested)	2.85
Dynamic (congested → not)	2.21
Dynamic (not → congested)	2.12

2) Estimation Accuracy with Ideal Car Arrivals: Before evaluating our method through realistic scenarios, we have checked a kind of ideal performance of it. We have checked the performance when a floating car approaches to the intersection in every cycle. Here, we have selected just one vehicle randomly for each cycle as a floating car instead of selecting floating cars from all the vehicle randomly. Fig. 3 shows the queue lengths estimated in the slightly congested scenario. The vertical axis indicates the queue length and the horizontal axis indicates the cycle number. The mean absolute errors (MAE) are about 2.4 vehicles. From the result, we can say the rough trend of queue length fluctuation can be grasped when floating cars arrive at each cycle.

We have calculated the MAEs for each scenario with different sets of floating cars, and calculated the averages of them as shown in Table III. This table shows that the queue lengths can be estimated with sufficient accuracy when a floating car arrives at each cycle, and the MAEs are less than about 3 vehicles in any scenario.

3) Estimation Accuracy of Queue Lengths: Fig. 4 presents the MAEs of the queue lengths for various quantities of floating cars. In any scenario, the queue lengths can be estimated

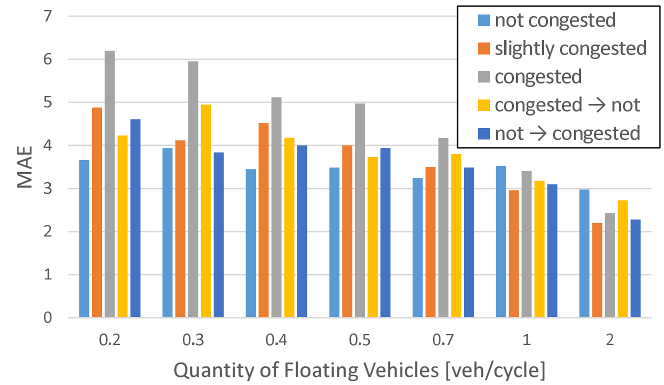


Fig. 4. MAEs of Queue Lengths in Five Different Quantities of Floating Cars

TABLE IV. LARGEST MAEs OF QUEUE LENGTHS IN 70% CYCLES

Scenaio	the quantity of floating cars [veh/cycle]						
	0.2	0.3	0.4	0.5	0.7	1.0	2.0
Fixed (not congested)	6	6	5	5	5	5	4
Fixed (slightly congested)	6	5	5	5	5	4	3
Fixed (congested)	9	9	7	7	5	4	3
Dynamic (congested → not)	6	6	6	5	5	4	4
Dynamic (not → congested)	7	6	6	6	5	4	3

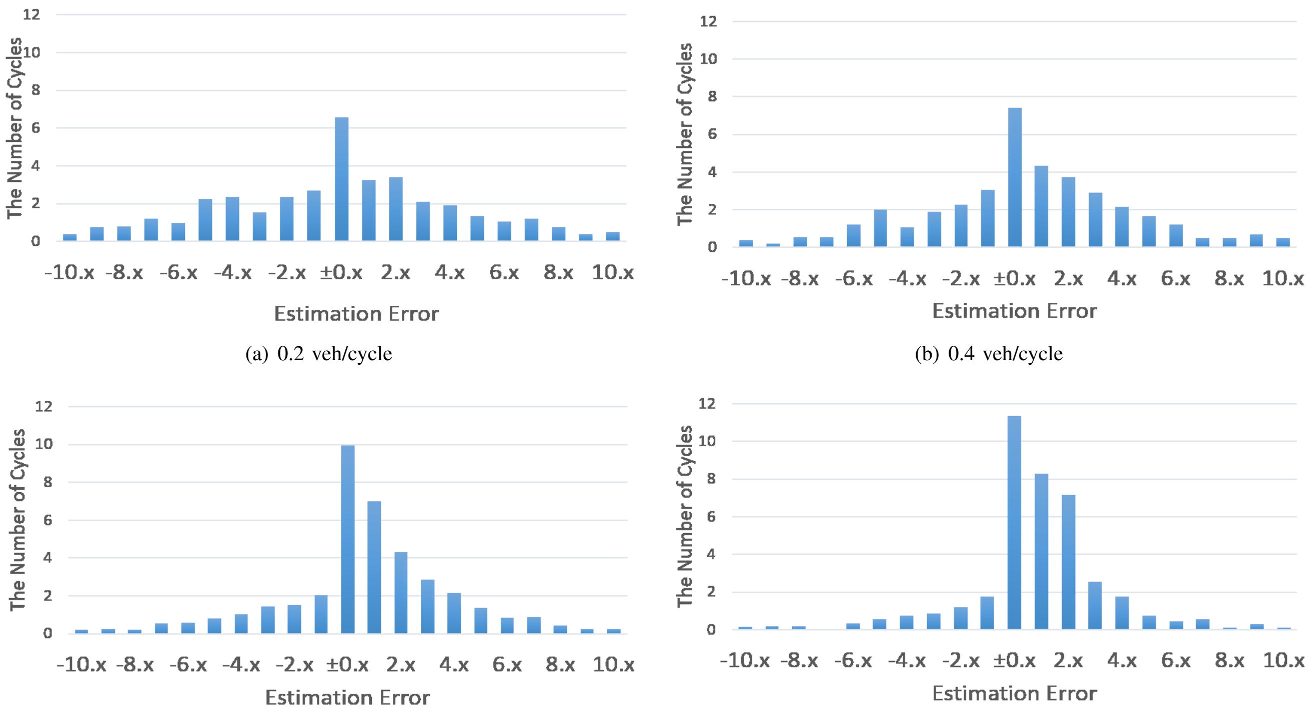
when the quantity of floating cars is more than 1 [veh/cycle], and the MAEs are less than about 3 vehicles. Also, the histogram shows the numbers of the cycle in each estimation error category in the slightly congested scenario in Fig. 5. The bin width is two vehicles. In the cases with one or more floating cars in a cycle, the estimation errors are sufficiently small. In these four cases, the MAEs of the queue lengths in 70 % cycles are at most 6, 5, 4 and 3 vehicles respectively. We can obtain similar distribution in other scenarios, and summarized them as shown in Table IV.

There are several cycles which have very short queue lengths when the traffic volume is small. In such cases, floating cars rarely pass through the signal. In our method, for such cases that no floating car passed, we use the estimation result in the previous cycle, in which more vehicles may have passed. Therefore, for such cases, the traffic volume is overestimated because there are some floating cars in the cycle with many vehicles, and the proposed method uses the queue length in such a case.

B. Experiment in the Real World

We have also conducted an experiment in a real intersection. We have observed the time and location of vehicles stopped and passed the stop line. The intersection is located in Suita City, Osaka Prefecture, Japan. The data was recorded in the evening (from 17:30 to 18:20; 30 cycles). The vehicles on the link can go straight or turn left. The vehicles pass along the link are not affected by oncoming cars because Japan is one of left-side driving countries. We have chosen a part of the data collected as floating car data, and estimated the queue lengths by our proposed method.

Table V shows the MAEs of the queue lengths for every quantity of floating cars. The MAEs become little larger than the results of simulation shown above. The histograms show



(a) 0.2 veh/cycle

(b) 0.4 veh/cycle

(c) 1.0 veh/cycle

(d) 2.0 veh/cycle

Fig. 5. The Number of Cycles for Each Estimation Error Category in the Simulation

TABLE V. MAEs OF QUEUE LENGTHS

the quantity of floating cars [veh/cycle]	0.2	0.3	0.4	0.5	0.7	1.0	2.0
MAE	5.28	4.86	4.76	4.98	4.67	4.84	4.00

the number of cycles in each estimation error category in this experiment in Fig. 6. The bin width is two vehicles. The estimation errors become larger than the results of the simulations. On the other hand, the queue lengths are often overestimated. An example of overestimation results is shown in Fig. 7. The vertical axis indicates the queue length and the horizontal axis indicates the cycle number. We can see that our proposed method overestimated the queue length in the first 4 cycles. A big factor of this overestimation is that vehicle groups intensively arrive at the intersection in the first half of a cycle. Such unstable arrivals of vehicles are caused by signals installed on the upstream link. So, we think we can solve this problem by combining estimation results with other intersections.

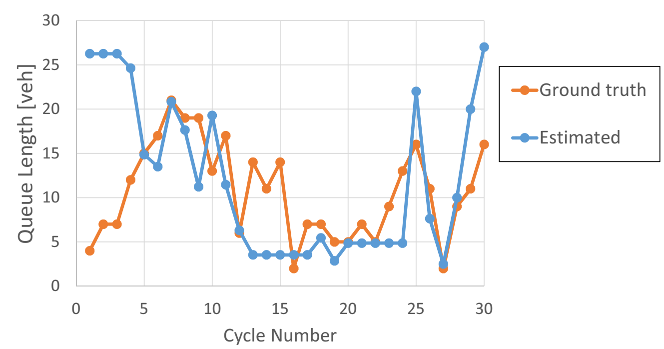


Fig. 7. Observation Result of a Real Intersection

VI. CONCLUSION

In this study, we have proposed an approach to estimate the queue length fluctuation and detect change in traffic volume based on vehicle trajectories. We have conducted an experiment using VISSIM. The simulation result has shown that our method can estimate the queue lengths with small errors by using several floating cars and a signal schedule of the target intersection. Furthermore, we have observed the vehicles' behavior in a real intersection and estimated the queue lengths. The mean absolute error is around 5 vehicles.

As future work, we are planning to improve the proposed model to estimate with more accuracy, and extend the queue estimation model based on a relationship between links.

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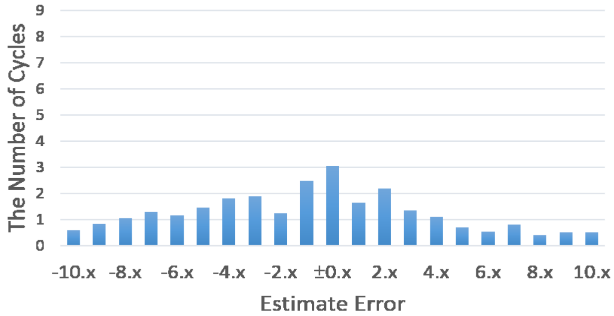
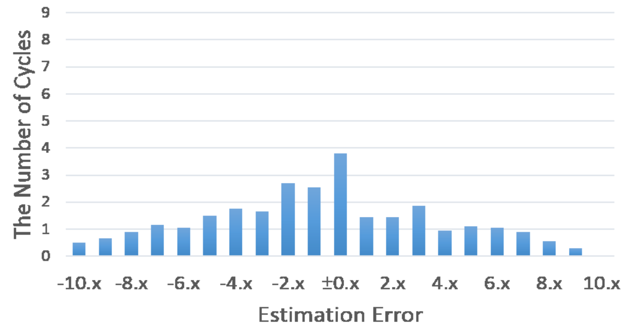
REFERENCES

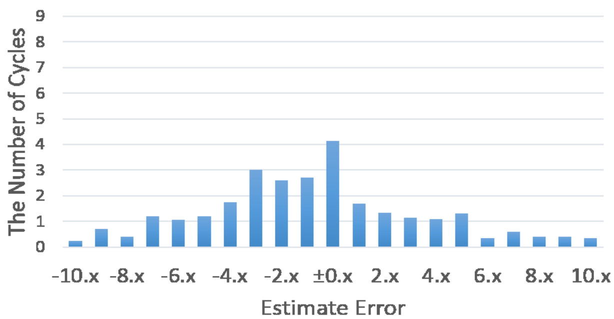
[1] Vehicle Information and Communication System Center. VICS. http://www.vics.or.jp/english/vics/index.html.



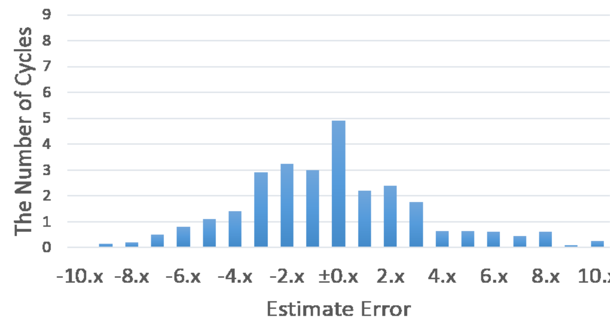
(a) 0.2 veh/cycle



(b) 0.4 veh/cycle



(c) 1.0 veh/cycle



(d) 2.0 veh/cycle

Fig. 6. The Number of Cycles for Each Estimation Error Category in a Real Intersection

[2] Corrado de Fabritiis, Roberto Ragona, and Gaetano Valenti. Traffic estimation and prediction based on real time floating car data. In *Proceedings of the 11th International IEEE Conference on Intelligent Transportation Systems (ITSC 2008)*, pp. 197–203, Beijing, China, 2008. IEEE.

[3] Takayoshi Yokota and Dai Tamagawa. Constructing Two-Layered Freight Traffic Network Model from Truck Probe Data. *International Journal of Intelligent Transportation Systems Research*, Vol. 9, No. 1, pp. 1–11, 2011.

[4] Honda Motor Co., Ltd. Internavi. http://www.honda.co.jp/internavi/.

[5] Vissim. Traffic Simulation with PTV Vissim for Efficent Junction Design.

[6] Jaimyoung Kwon, Benjamin Coifman, and Peter Bickel. Day-to-day travel-time trends and travel-time prediction from loop-detector data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1717, No. 1, pp. 120–129, 2000.

[7] John Rice and Erik van Zwet. A simple and effective method for predicting travel times on freeways. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 5, No. 3, pp. 200–207, 2004.

[8] Yibing Wang, Markos Papageorgiou, Albert Messmer, Pierluigi Coppola, Athina Tzimitsi, and Agostino Nuzzolo. An adaptive freeway traffic state estimator. *Automatica*, Vol. 45, No. 1, pp. 10–24, 2009.

[9] Anthony Stathopoulos and Matthew G. Karlaftis. A multivariate state space approach for urban traffic flow modeling and prediction. *Transportation Research Part C: Emerging Technologies*, Vol. 11, No. 2, pp. 121–135, 2003.

[10] Wei-Hsum Lee, Shian-Shyong Tseng, and Sheng-Han Tsai. A knowledge based real-time travel time prediction system for urban network. *Expert Systems with Applications*, Vol. 36, No. 3, pp. 4239–4247, 2009.

[11] Gurcan Comert and Mecit Cetin. Analytical Evaluation of the Error in Queue Length Estimation at Traffic Signals From Probe Vehicle Data. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 12, No. 2, pp. 563–573, 2011.

[12] Yang Cheng, Xiao Qin, Jing Jin, Bin Ran, and Jason Anderson. Cycle-by-Cycle Queue Length Estimation for Signalized Intersections Using Sampled Trajectory Data. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 2257, pp. 87–94, 2012.

[13] Qing Cai, Zhongyu Wang, Lingyu Zheng, Bing Wu, and Yinhai Wang. A Shockwave Approach to Estimating Queue Length at Signalized Intersections by Fusing Data of Point and Mobile Sensors. In *Proceedings of the 93rd Annual Meeting of Transportation Research Board*, Washington D.C., USA, 2014.

[14] M. J. Lighthill and G. B. Whitham. On Kinematic Waves, I. Flood Movement in Long Rivers. In *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, pp. 281–316, 1955.

[15] Ozhan Unal and Mecit Cetin. Estimating Queue Dynamics and Delays at Signalized Intersections from Probe Vehicle Data. In *Proceedings of the 93rd Annual Meeting of Transportation Research Board*, Washington D.C., USA, 2014.

[16] Takayuki Nakata and Jun-ichi Takeuchi. Mining Traffic Data from Probe-Car System for Travel Time Prediction. In *Proceedings of the 10th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'04)*, pp. 817–822, Seattle, USA, 2004.

[17] Nobuhiro Uno, Fumitaka Kurauchi, Hiroshi Tamura, and Yasunori Iida. Using Bus Probe Data for Analysis of Travel Time Variability. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, Vol. 13, No. 1, pp. 2–15, 2009.