SCIENCE CHINA
Information Sciences

• LETTER •

April 2021, Vol. 64 149203:1–149203:3
https://doi.org/10.1007/s11432-018-9629-2

Queue estimation for isolated signalized intersections in intelligent vehicle-infrastructure cooperation systems

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Received 9 July 2018/Revised 16 September 2018/Accepted 23 October 2018/Published online 14 May 2020

Citation Wang Y P, Guo G, Yue W. Queue estimation for isolated signalized intersections in intelligent vehicle-infrastructure cooperation systems. Sci China Inf Sci, 2021, 64(4): 149203, https://doi.org/10.1007/s11432-018-9629-2

Dear editor,

Traffic jams have become an important issue in urban networks, particularly for arterial roads [1]. The need for more efficient traffic control techniques has become critical. One good solution is the so-called intelligent vehicle-infrastructure cooperation systems (i-VICS), which assumes autonomous vehicles in the traffic flow (i.e., a mixed traffic flow). The aim of i-VICS is to achieve cooperative vehicle intersection control, i.e., to enable cooperation between vehicles and traffic signals, for safe and efficient intersection operations.

The cooperative control of vehicles and traffic lights relies on the accurate estimation of queue length using real-time traffic data such as vehicle location, velocity, and acceleration. Queue length is one of the most crucial indexes in intersection performance evaluation and also serves as the feedback for traffic signal control.

Although traffic data are easily available in i-VICS, the queue length estimation is rather difficult. To date, significant research attention has been contributed to this field from different aspects and viewpoints. For example, Ref. [2] presented a probability model and a method of calculating the queue length based on the location of the last probe vehicle in the queue. In [3], a queue length estimation method was derived using real-time vehicle trajectory data and a travel time model. The method in [4] estimates the queue length based on the locations of the vehicles in the queue, which is realized by reconstructing the discharging process using a kinematic model. The queue length estimation was transformed into the problem of deriving the number of queued vehicles [5], using the operational data of all vehicles that approach the intersection. An interpolation algorithm was used to reconstruct the incomplete traffic data.

Most of the existing results on queue estimation assume a uniform traffic flow environment, which makes them inapplicable to mixed traffic flow scenarios in which autonomous cars may behave unlike those with human drivers. Unlike the human driver's narrow vision and non-cooperation, autonomous control system can use the upcoming traffic signal information to avoid idling at red lights [6]. The trajectory of vehicle is optimized in passing through the intersection, which also has an impact on the trajectory of the following vehicles in the traffic flow. In [7], autonomous vehicle trajectories and traffic signals at signalized intersection can be collaboratively optimized in a unified framework to avoid stopping at the intersection. Autonomous vehicles have a different car-following behavior to human-driven vehicles, changing the traffic flow characteristics accordingly, e.g., preventing shockwave formation and propagation at the intersection. The stop-and-go motions of vehicles are avoided, and thus the queue length at the intersection is reduced. In this study, we present a novel method for real-time queue estimation in an i-VICS environment. First, a discrete traffic flow model is designed under mixed traffic conditions. We model traffic signal, autonomous vehicles and human-driven vehicles in a common framework by extending the general car-following concepts. In this traffic flow model, the autonomous vehicles' maneuvers and the traffic signal control strategy are integrated. Then, we present an analysis method of the queue forming and discharging dynamics. The relationship between the dynamics of the queue length and the control inputs of traffic signal and vehicle maneuvers using the vehicle operational data is predicted based on the traffic flow model. Based on these models and schemes, we present a novel queue length estimation model for i-VICS.

The main contributions of this study lie in the following aspects.

(1) The quantitative relationship between the traffic signal control strategy, the autonomous vehicles' maneuvers, and the queue dynamics is derived, by which one can evaluate the i-VICS performance directly.

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(2) Based on vehicle operational data prediction, the queue dynamics can be estimated with a small amount of sampling data in real time, instead of offline estimation using a large amount of data in the entire passing process as in [5].

Traffic flow model formulation. Considering the effects of the control inputs (i.e., traffic signal control strategy and autonomous vehicles' maneuvers) on traffic flow, a novel discrete traffic flow model on a single-lane road is developed by extending the car-following concepts.

Consider a mixed traffic flow environment consisting of human-driven and autonomous vehicles. Assume M vehicles are approaching the intersection in a traffic signal cycle, in which there are N autonomous vehicles (randomly distributed). Overtaking is not allowed. The model is described by the following equation:

$$\begin{cases} a_i(k|\theta)=f(v_i(k),\Delta l_i(k),h_i^{itd}(k),v_i^{itd}(k)|\theta), \\ v_i(k+1|\theta)=v_i(k)+a_i(k|\theta)\cdot T, \\ l_i(k+1|\theta)=l_i(k)+v_i(k)\cdot T+a_i(k|\theta)\cdot\dfrac{T^2}{2}, \end{cases} \tag{1}$$

where $l_i(k)$, $v_i(k)$, and λ_i are the i-th vehicle's location, speed, and body length, respectively; $\Delta l_i(k) = l_{i-1}(k) - \lambda_{i-1} - l_i(k)$ represents the current space headway; $f(\cdot)$ is a special function that describes the car-following behavior and θ is a set of parameters that characterizes $f(\cdot)$; T is the sampling interval; $h_i^{itd}(k|\theta)$ and $v_i^{itd}(k|\theta)$ are the desired safe space headway and desired travel speed, respectively, that reflect the different driving characteristics of the human driver and autonomous control system; and $a_i(k|\theta)$ is the acceleration rate in the time interval $[k, k+1)$, which can be generated by given the car-following parameter set θ, where θ is obtained using a supervised learning approach. The details are described in Appendix B.

The desired safe space headway is used to reflect the sensitivity of an individual driver to the safety in the car-following behavior.

$$h_i^{itd}(k|\theta) = \alpha_i \cdot v_i(k) + \beta_i \cdot v_i(k)^2 + \delta_i, \tag{2}$$

where α_i, β_i, and δ_i are three car-following parameters, which represent the driver's reaction time, deceleration rate, and minimum safe space headway, respectively.

The desired travel speed is used to reflect the intent of the individual driver and the impact of traffic signal when a vehicle approaches a signalized intersection, as follows.

(1) When $i > 0$, for a human-driven vehicle, the desired travel speed is the driving intent of the human driver, which is a specific sequence obtained from historical vehicle speed data. For a autonomous vehicle, the desired travel speed is the optimal advisory speed sequence, which is determined by the planning layer of the autonomous control system based on intelligent maneuvers (further detail is provided in Appendix A).

(2) When $i = 0$, the desired travel speed is used to describe the impact of the traffic signal on the flow. In this case, the traffic signal is seen as a virtual autonomous vehicle (λ_0=0). The desired travel speed of the virtual autonomous vehicle, v_0^{itd}, is calculated based on the real-time signal phase and timings. In this way, the traffic signal strategy and the autonomous vehicles' maneuvers can be integrated in (1). When the signal turns red, the virtual autonomous vehicle appears in the intersection and v_0^{itd} is set to zero, which causes the subsequent vehicles to decrease in speed and automatically form a queue as their headway decreases. When the signal turns from red to green, v_0^{itd} is set as the maximum road speed. The virtual vehicle begins to accelerate to its new desired travel speed, causing the subsequent vehicles to increase in speed and the queue is automatically dissipated.

Based on model (1), we can predict the complete operational data of all vehicles passing through the intersection, using the data collected upstream of the intersection. Then, the queue length can be estimated.

Analysis of queue forming and discharging. By analyzing the dynamics of the queue length based on the traffic model, we predict the number of vehicles arriving and leaving the queue in the sampling interval $[k, k+1]$.

Assume that, at time k, the head and tail vehicles of the queue are vehicle m and vehicle n, respectively. Vehicles $m-1,\dots,1$ have left the queue from the front and vehicles $n+1,\dots,M$ are approaching the tail of the queue.

We introduce the decision point (DP) to assist in determining whether an approaching vehicle will arrive at the tail of the queue in $[k, k+1]$. The DP is located upstream of the queue tail where the driver decides to decelerate at a normal deceleration rate and stop at the tail of the queue. The DP location of vehicle $n+h$ ($h = 1,\dots,M-n$) can be obtained as follows:

$$\begin{aligned} l_{n+h}^{\rm DP}(k) = l_n(k) - \sum_{p=0}^{h-1}(\lambda_{n+p} + \delta_{n+p+1}) \\ - \alpha_{n+h}v_{n+h}(k) - \beta_{n+h}\cdot v_{n+h}^2(k). \end{aligned} \tag{3}$$

Note that the location of decision point ${\rm DP}_{n+h}$ is determined under the assumption that vehicles $n+1,\dots,n+h-1$ approach the queue in $[k, k+1]$. The location of vehicles $m+h$ ($h = 0,\dots,M-m$) at time $k+1$, $l_{m+h}(k+1)$, can be predicted by traffic model (1).

For queue forming, we regard the arrival of a vehicle at the DP as entering the queue. Search the last value of h from $n-m+1$ to $M-m$ for which $l_{m+h}(k+1) \geqslant l_{m+h}^{\rm DP}(k)$ is satisfied; then, the value of $h+m-n$ is the predicted number of vehicles to arrive at the queue in $[k, k+1]$. In contrast, for queue discharging, we regard passing of the location of the stop-line $l_{\rm stop}$ as leaving the queue. Search the last value of h from 0 to $n-m$ for which $l_{m+h}(k+1) \geqslant l_{\rm stop}$ is satisfied; then, the value of $h+1$ is the predicted number of vehicles to depart from the queue in $[k, k+1]$.

From this analysis, if the vehicles and traffic signal information are considered as the known information, the number of vehicles arriving and leaving the queue in $[k, k+1]$, $N_{\rm in}(k+1|k)$ and $N_{\rm out}(k+1|k)$, are functions of the control inputs of the traffic signal and the autonomous vehicles (further detail is provided in Appendix C).

Queue estimation model. We can estimate the queue length at time $k+1$ using the collected information of vehicles and the traffic signal at time k. The queue length estimation model can be given as follows:

$$\begin{aligned} Q(k+1|k) = Q(k) + N_{\rm in}(k+1|k) \\ - N_{\rm out}(k+1|k),\ k \in [k_0, k_c], \end{aligned} \tag{4}$$

where $Q(k)$ is the real-time number of vehicles in the queue at time k; k_0 and k_c are the beginning and end times of the signal cycle, respectively; and $Q(k_0)$ is the residual queue from the previous signal cycle.

This estimation model is demonstrated via simulations, as shown in Appendix D. In practical applications, the estimation model can be used for multistep prediction. Because the number of vehicles on the road is limited, the amount of calculation in the prediction is not too large. Thus, the presented method can be implemented online, e.g., as part of a model predictive controller for cooperative vehicle intersection control.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant Nos. 61273107, 61573077) and in part by National Key R&D Program of China (Grant No. 2017YFA0700300).

Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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