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Cycle-by-cycle intersection queue length distribution estimation using sample travel times

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ABSTRACT

We propose Bayesian Network based methods for estimating the cycle by cycle queue length distribution of a signalized intersection. Queue length here is defined as the number of vehicles in a cycle which have experienced significant delays. The data input to the methods are sample travel times from mobile traffic sensors collected between an upstream location and a downstream location of the intersection. The proposed methods first classify traffic conditions and sample scenarios to seven cases. BN models are then developed for each case. The methods are tested using data from NGSIM, a field experiment, and microscopic traffic simulation. The results are satisfactory compared with two specific queue length estimation methods previously developed in the literature.

1. Introduction and motivation

Arterial performance measurement, such as the delay and queue length at a signalized intersection, has been extensively studied in the past. For example, Highway Capacity Manual (Transportation Research Board, 2010) documents the standard methodologies on how this can be done for "static" performance measures calculated and averaged over a period of time, say one hour. The recent focus is to estimate "dynamic" arterial performances, such as cycle-by-cycle signal queue length profile, using aggregated detector data and detailed signal timing parameters (Skabardonis and Geroliminis, 2008), or from event-based signal and vehicle detection data (Balke et al. 2005; Smaglik et al. 2007; Liu and Ma, 2009; Liu et al. 2009). More recently, the wide deployment of mobile traffic sensors – those that move with the flow they are monitoring including Global Position Systems (GPS), cellular phones, and other tracking devices – have provided great opportunities and unique challenges to conduct dynamic arterial performance measurement (Ban and Gruteser, 2012).

In this paper, we focus on estimating cycle-by-cycle signalized intersection queue length distribution. Queue length here is defined as the number of vehicles in a cycle which have experienced significant delays (Ban et al., 2011). Signalized intersection queue length is a crucial measure for traffic signal operations and optimization. Using mobile data, in various forms, to estimate the static or dynamic signalized intersection queue length profile is a relatively new topic, which has been

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recently receiving increasing attention from the research community. Ban et al. (2011) presented a cycle-by-cycle queue length profile estimation method using mobile sensor data based on the delay pattern model in Ban et al. (2009). A unique feature of the method is that only sample intersection travel times collected from mobile sensors were used in the modeling process, which can better address/protect privacy (Hoh et al., 2008; Sun et al., 2011, 2013). Cheng et al. (2012) constructed cycle-by-cycle queue length information by analyzing the detailed vehicle trajectories from mobile sensors. Hao and Ban (2013) developed a long queue estimation method based on short vehicle trajectories, which can estimate the queue length when the queue exceeds the region of detection by mobile sensors for certain cases. Argote et al. (2011) analyzed the sampling issue of mobile data by estimating measures of effectiveness and minimum penetration using Next Generation Simulation (NGSIM) data. Both methods in Ban et al. (2011) and Hao and Ban (2013) applied the uniform arrival assumption; so is the method in Cheng et al. (2012). As a result, the methods work well if the arrivals spread out evenly in a cycle, but not so well if vehicles arrives in obvious platoons (e.g., for closely spaced intersections in urban areas).To relax the uniform arrival assumption, Hao et al. (in press) proposed a kinematic-based approach that only focuses on the queue departure process. In particular, it was assumed that the location where a vehicle joins the queue can be solely indicated by its acceleration and departure processes, without imposing any arrival pattern assumptions. However, the queue locations of sample vehicles only provide a lower bound to the queue length in a cycle. The method thus works well under relatively high penetration, but not so well if the penetration rate is very low.

All the above cycle-by-cycle queue length estimation methods using mobile data share one common feature: they are deterministic, while arterial traffic is widely understood as a stochastic process. In this paper, we propose a stochastic modeling approach, based on stochastic learning, for dynamic queue length estimation. The approach can produce cycle-by-cycle queue length distribution, as well as the cycle-by-cycle average queue length and profile. We believe that such a stochastic modeling framework should be more robust than its deterministic counterpart. As we will show later in this paper, the stochastic method presented here also turn out to be more accurate. We note that some mobile-data-based stochastic queue length studies have also been conducted in the past. Comert and Cetin (2009) proposed a sampling based statistical model to estimate the average queue length based on probe vehicle data under a given penetration rate. Comert (2013) further developed an analytical model for queue length estimation, which is applicable to both normal and over-saturated conditions. The model requires queue locations and queue joining time as the input, which might not be available directly from mobile sensors especially sample travel times.

The stochastic learning approach we propose here is based on the Bayesian Network (BN). The BN is a probabilistic graphical model which systematically integrates stochastic relationships among variables (Jordan and Weiss, 2002; Neapolitan, 2003). The BN has already been introduced in the transportation area mainly for freeway modeling; see Fei et al. (2001), Zhang and Taylor (2006) and Sun et al. (2006). While the above references applied fixed-location sensor data to BN, Herring et al. (2012) proposed a Hidden Markov Model, similar to the BN framework, for the spatial congestion correlation between neighboring roads from a sparse GPS probe dataset. Hofleitner et al. (2012) further applied a BN-based model to predict the arterial travel time distribution for a short period of time, e.g. 15 min. Hao et al. (2013) proposed a BN model to describe the relationship between the arrival and departure processes of a signalized intersection. Vehicle index, defined as the position of a vehicle in the departure process of the queue, is then estimated to connect these two processes in the BN. As the vehicle index of a queued vehicle also indicates the queue information, it is possible to estimate queue length based on vehicle indices.

In this paper, BN-based methods are proposed to estimate the cycle-by-cycle queue distribution of a signalized intersection. The methods are based on the vehicle index estimation approach in Hao et al. (2013). Similar to vehicle index estimation, the proposed methods consider the relationships among the arrival, departure, and vehicle index. They however localize the problem around the end of the queue. It first classifies the traffic and sampling conditions to seven cases based on the sample travel times of vehicles from mobile sensors. For the normal case (Case 1A as defined later in Section 4), we focus on the hidden vehicles between the last queued sample vehicle and the first free flow sample vehicle. Using Bayes' theorem, we can relate the queue length of a cycle to the hidden variables that can be considered as the attributes of the un-sampled vehicles. Then we show the construction and quantification of the BN to infer the hidden variables given sample vehicle travel times and estimated vehicle indices. The queue length distribution can then be derived. For the other six cases, similar BN models can be applied, which are not presented in detail due to space limitation. They are briefly discussed in Appendix of the paper.

The proposed BN-based queue length distribution methods are based on, but significantly extend those in Hao et al. (2013). First, the BN-based methods introduce a new case identification method to classify cases under different traffic conditions and sampling scenarios. This is a critical step in constructing the BN-based queue estimation methods. Second, as the index estimation method aims to infer the indices of sample vehicles, the corresponding BN model is relatively easier to construct. For the queue length distribution estimation in this paper, we need to estimate the index of a hidden vehicle based on a given queuing state, which is much more challenging. Thus in Section 5 more rules are formulated mathematically to ensure that the constructed BN models do not conflict with common traffic knowledge. Constructing the BN models while considering all the rules turns out to be a quite challenging task as presented in detail in Sections 5 and 6.

We test the BN-based queue length distribution models using data from NGSIM, a field experiment, and micro-simulation. The results show that the proposed BN-based models have 100% success rate (defined as the percentage of cycles that the method can be applied) under any penetration, and is more accurate and robust than the linear fitting method (Ban et al., 2011) and queue location method (Hao et al., in press) proposed previously in the literature.