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Second-order models and traffic data from mobile sensors

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A B S T R A C T

Mobile sensing enabled by GPS or smart phones has become an increasingly important source of traffic data. For sufficient coverage of the traffic stream, it is important to maintain a reasonable penetration rate of probe vehicles. From the standpoint of capturing higher-order traffic quantities such as acceleration/deceleration, emission and fuel consumption rates, it is desirable to examine the impact on the estimation accuracy of sampling frequency on vehicle position. Of the two issues raised above, the latter is rarely studied in the literature. This paper addresses the impact of both sampling frequency and penetration rate on mobile sensing of highway traffic. To capture inhomogeneous driving conditions and deviation of traffic from the equilibrium state, we employ the second-order *phase transition model* (PTM). Several data fusion schemes that incorporate vehicle trajectory data into the PTM are proposed. And, a case study of the NGSIM dataset is presented which shows the estimation results of various Eulerian and Lagrangian traffic quantities. The findings show that while first-order traffic quantities can be accurately estimated even with a low sampling frequency, higher-order traffic quantities, such as acceleration, deviation, and emission rate, tend to be misinterpreted due to insufficiently sampled vehicle locations. We also show that a correction factor approach has the potential to reduce the sensing error arising from low sampling frequency and penetration rate, making the estimation of higher-order quantities more robust against insufficient data coverage of the highway traffic.

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1. Introduction

With the increased availability of mobile traffic data and the advancement of sensing technology, data collected through GPS, smart phones or other mobile devices have become a major source of traffic information for various applications. Advantages of mobile sensing, in comparison with fixed-location sensing (e.g. using loop detectors and cameras), include potentially complete spatial and temporal coverage of traffic network and high positioning accuracy (Herrera et al., 2010).

Traffic data related to speed, density, queue size and travel time, which are categorized as *lower-order* quantities, can often be estimated in conjunction with first-order traffic flow models such as the Lighthill–Whitham–Richards (LWR) model (Lighthill and Whitham, 1955; Richards, 1956) and the cell transmission model (CTM) (Daganzo, 1994). Strub and Bayen (2006) employ a weak formulation of boundary conditions for the LWR model based on the Godunov scheme, which is then

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applied to the I-80 highway dataset. In Christiani et al. (2010), the LWR model is discretized in connection with initial and boundary conditions, which is applied to traffic estimation on a circular urban motorway using mobile data. Claudel and Bayen (2011) propose convex formulations for data assimilation using both Eulerian (fixed) and Lagrangian (mobile) traffic data based on the Hamilton–Jacobi representation of highway traffic and the generalized Lax–Hopf formula. Work et al. (2010) employ a velocity-based LWR model with transformed fundamental diagram to perform data fusion using ensemble Kalman filter. Independently, Yuan et al. (2011) consider the LWR model with a transformed coordinate system, namely the Lagrangian coordinates, and perform traffic estimation using extended Kalman filter. These studies mainly focus on freeway traffic.

In another line of research, mobile data have been used extensively for estimating queue size and delay at signalized intersections in arterial networks. Ban et al. (2009) use sampled vehicle travel times to estimate delay patterns near a signalized junction, where the authors use the LWR theory with a triangular fundamental diagram to express the relationship among flow, shock speed, queue size and queuing time. Following this work, Ban et al. (2011) devise a reverse modeling process that construct the dynamic queue length in real time. Cheng et al. (2012) further explore probe vehicle trajectories in estimating queue size in real time with the benefit of less communication cost in data collection. Comert and Cetin (2009) propose a statistical approach for estimating queue length using an analytical formulation based on conditional probabilities. The authors also address the estimation accuracy with a wide range of probe penetration rates. Argote et al. (2011) consider several *measures of effectiveness* and estimation methods to identify proper penetration rates.

Although the LWR model and the CTM have been used effectively in estimating lower-order quantities, they have been used less frequently in estimating higher-order traffic quantities such as acceleration/deceleration, deviation (perturbation), emission and fuel consumption rates. There exist a number of attempts to estimate acceleration/deceleration or emission rates through differentiating macroscopic traffic quantities analytically or numerically (e.g. Luspay et al., 2010). However, in this process higher-order variations inherent in these quantities, typically on a microscopic scale, are insufficiently captured due to the low temporal-spatial resolution of the traffic data and the discrete models. To fill this gap, this paper proposes a second-order traffic flow model supported by high-resolution mobile data to address the issue of estimating high-order traffic quantities. Unlike most existing studies on mobile sensing which primarily focus on probe penetration rate (Demers et al., 2006; Kwon et al., 2007; Yim and Cayford, 2001), we consider the additional effect of under sampling on the estimation accuracy. This is a concern because most mobile data provide location or speed of a moving vehicle every 3-4 s (such as GPS data), but higher-order variations in speed, acceleration and emission may take place on a smaller time scale; this is true especially for congested and unstable traffic. Such an observation has urged the need to examine the efficacy of existing sensing technologies and estimation methods in reconstructing the profiles for these higher-order quantities.

The second-order traffic flow model employed by this paper is the hyperbolic *phase transition model* (PTM), first introduced by Colombo (2002) and studied subsequently by Colombo and Corli (2002), Colombo et al. (2007) and Blandin et al. (2012). Second- and higher-order traffic models were proposed by many researchers to overcome some limitations of the LWR model in describing complex waves observed in vehicular traffic. Most second-order models tend to pose, in addition to the LWR-type equation for the conservation of vehicles, a second equation for the conservation or balance of momentum. One of the first such models is by Payne and Whitham in the 1970s (Payne, 1971; Whitham, 1974). In a celebrated paper (Daganzo, 1995) Daganzo criticized second-order models by showing various drawbacks including the possibility of cars going backward. Most of such drawbacks were later addressed by the Aw–Rascle–Zhang model, independently proposed by Aw and Rascle (2000) and Zhang (2002). More recently, the phase transition models drew increased attention from researchers for their capability of representing complex waves while keeping the LWR structure for light traffic, see Blandin et al. (2011) for more detailed discussion.

Let us further comment on the possible use of second-order model for urban arterial traffic. The aforementioned complex wave phenomenon, well captured by second-order models, are mainly observed in highway traffic. Indeed, phantom waves, stop-and-go waves and others need a long stretch of road with no interruption to manifest themselves. The situation of arterial traffic is quite different because of the presence of many junctions with traffic signs or signals. Since the LWR model captures well backward wave propagation from junctions or signals, and vehicle movements on arterials are relatively uniform, it is typically sufficient to describe arterial traffic, while very limited to model more complex waves in highway traffic.

In order to address issues related to higher-order traffic quantities, we focus on the *Next Generation SIMulation* (NGSIM) dataset.[1] The NGSIM program collected high-quality traffic and vehicle trajectory data on a stretch of I-80 highway in California. A total of 45 min of traffic data were collected, segmented into three 15 min periods. The dataset contains vehicle trajectory recorded at a high resolution of every 0.1 s. Derived information on instantaneous velocity and acceleration is also available. A detailed description of the NGSIM field experiment and data will be provided in Section 5.

1.1. Contribution and findings

This paper addresses the effectiveness of mobile sensing and traffic estimation taking into account two main factors: sampling frequency and probe penetration rate. The subject of estimation will include both lower- and higher-order traffic quantities. To support this study, we employ the second-order phase transition model (PTM) as well as its modifications. The

[1] http://ngsim-community.org/.

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