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A generic data assimilation framework for vehicle trajectory reconstruction on signalized urban arterials using particle filters

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ABSTRACT

With trajectory data, a complete microscopic and macroscopic picture of traffic flow operations can be obtained. However, trajectory data are difficult to observe over large spatiotemporal regions—particularly in urban contexts—due to practical, technical and financial constraints. The next best thing is to estimate plausible trajectories from whatever data *are* available. This paper presents a generic data assimilation framework to reconstruct such plausible trajectories on signalized urban arterials using microscopic traffic flow models and data from loops (individual vehicle passages and thus vehicle counts); traffic control data; and (sparse) travel time measurements from whatever source available. The key problem we address is that loops suffer from miss- and over-counts, which result in unbounded errors in vehicle accumulations, rendering trajectory reconstruction highly problematic. Our framework solves this problem in two ways. First, we correct the systematic error in vehicle accumulation by fusing the counts with sparsely available travel times. Second, the proposed framework uses particle filtering and an innovative hierarchical resampling scheme, which effectively integrates over the remaining error distribution, resulting in plausible trajectories. The proposed data assimilation framework is tested and validated using simulated data. Experiments and an extensive sensitivity analysis show that the proposed method is robust to errors both in the model and in the measurements, and provides good estimations for vehicle accumulation and vehicle trajectories with moderate sensor quality. The framework does not impose restrictions on the type of microscopic models used and can be naturally extended to include and estimate additional trajectory attributes such as destination and path, given data are available for assimilation.

1. Introduction

Vehicle trajectory data provide critically important information for many application areas, ranging from calibration and validation of microscopic traffic flow models (Kesting and Treiber, 2008; Punzo and Montanino, 2016), traffic state reconstruction (van Lint and Hoogendoorn, 2010; Wang et al., 2006), travel time estimation (van Lint, 2010; Coifman, 2002), vehicle energy/emissions estimation (Sun et al., 2015; da Rocha et al., 2015), to name just a few. With trajectory data, a complete picture of traffic flow operations can be obtained, both microscopically and macroscopically. Trajectory data can be collected using a wide range of sensing

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technologies, such as aerial photography, video, and mobile traffic sensors based on GPS and/or GSM (Montanino and Punzo, 2015; Sun and Ban, 2013). Whereas reconstructing trajectories from microscopic information (e.g., aerial images, GSM traces) requires considerable methodological effort in itself (Montanino and Punzo, 2015), there are only a few cases for which comprehensive data that cover 100% of all vehicle trajectories are available. Collecting such comprehensive trajectory data over large distances (routes, networks) and long time periods is expensive. With infrastructure based sensors or aerial imaging, the collected data can only cover a limited spatiotemporal region due to the high installation and maintenance costs, and it will take a few years (if not longer) before 100% of all vehicles/drivers are equipped with location tracking systems or apps that continuously communicate these data for use in modeling, control or other applications. The next best alternative is to *estimate* vehicle trajectories from whatever data *are* available.

1.1. Estimating vehicle trajectories

Many methods for estimating vehicle trajectories from data have been proposed, which in general terms (should) combine three ingredients: data (from various types of sensors); assumptions (models, equations) that describe the relation between the data and the underlying vehicle trajectories; and data assimilation techniques that combine these ingredients and in the process address measurement and modeling errors. For example, Coifman (2002) reconstructs vehicle trajectories in order to estimate travel times on freeways using traffic data from a single dual loop detector. The proposed method exploits basic traffic flow theory to extrapolate local traffic conditions to an extended freeway link. However, this method will fail when a queue covers the link, which is very common in signalized arterials. An obvious remedy is to reconstruct vehicle trajectories along a route using multiple loop detectors (van Lint, 2010), so that the trajectory reconstruction process is based on information from both up- and downstream locations. The resulting vehicle trajectories are essentially idealized average vehicle trajectories, similar to Lagrangian solutions of kinematic wave theory. However, the adaptive smoothing method used in van Lint (2010) is not suitable for urban trajectory reconstruction in the original form (Treiber and Helbing, 2002; van Lint and Hoogendoorn, 2010), because it would smooth speeds over intersections. Adjusting the method for use in urban settings seems doable in principle, but has not been reported yet. Mehran et al. (2012) propose a data fusion framework to reconstruct vehicle trajectories on urban arterials by incorporating probe and fixed sensor data and the signal timing parameters. The proposed method is also based on kinematic wave theory and employs the variational formulation (VF) (Daganzo, 2005a; Daganzo, 2005b) to solve a dense solution network which is constructed by discretizing the time–space plane. The key principle of the VF method is that the cumulative number of vehicles at each node in this solution network can be computed by a shortest path search from nodes where the cumulative numbers are known (boundary conditions). As a result, any curve which connects nodes with the same cumulative number in the solution network represents an individual vehicle trajectory. Sun and Ban (2013) also apply the VF method to estimate trajectories by fusing probe vehicle trajectories and the signal timing data. However, in both papers using the VF method, sensor errors such as miss-counting and over-counting are not considered; whereas these pose common and difficult problems when using loop detector data (Lu et al., 2008). With these errors, the cumulative numbers at boundaries will be inaccurate. Worse still, the error resulting from using such erroneous counts in the estimation of the number of vehicles between these cumulative count stations becomes unbounded (van Lint and Hoogendoorn, 2015). Another problem is that, due to the use of first order traffic flow theory, the speeds (trajectory slopes) between nodes are piece-wise constant (no acceleration) yielding piecewise linear vehicle trajectories. As shown by Sun et al. (2015) and da Rocha et al. (2015), in case such piece-wise linear trajectories are used to estimate energy consumption or emissions, large errors result, since energy consumption and emissions are influenced largely by the acceleration/deceleration process. This point holds for any traffic state estimation method based on first order traffic flow theory (e.g., Nantes et al., 2016; Yuan et al., 2012; van Hinsbergen et al., 2012), with which (indirect) also vehicle trajectories can be estimated.

In general, when the (behavioral) assumptions of these trajectory estimation methods are insufficient for the application at hand, more elaborate assumptions are required. This could involve estimation methods using higher order macroscopic models (that include speed dynamics as in Wang et al. (2006)), or methods using microscopic models for driving behavior. Goodall et al. (2016) present such a microscopic estimation method for vehicle trajectories on freeways. The objective here is to use trajectory estimation to artificially increase the penetration rate (in sample size as well as frequency) of connected vehicles. The method proposes a strategy about when and where to add or remove simulated vehicles (called *estimated vehicles*) in the microscopic simulation in order to make the actual behavior of the probe vehicles align with their expected behavior predicted by their car-following models. The results show that the effective penetration rate can be increased by around 20–30% using this method, which turned out beneficial for a ramp metering application. However, in this approach no principled method to deal with data or modeling errors is discussed.

1.2. Contribution and outline of this paper

The contribution of our paper is a generic data assimilation framework based on particle filters to reconstruct (plausible) vehicle trajectories on signalized urban arterials, that *does systematically address errors both in the measurements and in the model*. Like Goodall et al. (2016), our framework uses microscopic models of driving behavior and it assimilates *noisy* data from different sensors using particle filters (Arulampalam et al., 2002; Djurić et al., 2003). The framework does not impose restrictions on the type of microscopic models used; however, to illustrate the working, in this paper we consider the longitudinal movements of vehicles only. In terms of data, the method takes in noisy vehicle passages of individual vehicles (and as a result noisy vehicle counts) from loop detectors; signal timing parameters, and coarsely available travel time observations. By 'noisy', we mean that the passage data contains miss- and over-counts, resulting in counting errors. In this paper, an extensive simulation study is conducted to test the proposed data assimilation framework for trajectory reconstruction. The results show that the proposed method produces reasonable results for the