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Dynamic data-driven local traffic state estimation and prediction

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ABSTRACT

Traffic state prediction is a key problem with considerable implications in modern traffic management. Traffic flow theory has provided significant resources, including models based on traffic flow fundamentals that reflect the underlying phenomena, as well as promote their understanding. They also provide the basis for many traffic simulation models. Speed–density relationships, for example, are routinely used in mesoscopic models. In this paper, an approach for local traffic state estimation and prediction is presented, which exploits available (traffic and other) information and uses data-driven computational approaches. An advantage of the method is its flexibility in incorporating additional explanatory variables. It is also believed that the method is more appropriate for use in the context of mesoscopic traffic simulation models, in place of the traditional speed–density relationships. While these general methods and tools are pre-existing, their application into the specific problem and their integration into the proposed framework for the prediction of traffic state is new. The methodology is illustrated using two freeway data sets from Irvine, CA, and Tel Aviv, Israel. As the proposed models are shown to outperform current state-of-the-art models, they could be valuable when integrated into existing traffic estimation and prediction models.

1. Introduction

Traffic state prediction is a key problem with considerable implications in modern traffic management. Several modeling approaches have been used, including Kalman Filter (e.g. Wang et al., 2006a,b; Liu et al., 2006), neural networks (e.g. Vlahogianni et al., 2005; van Lint, 2005, 2008; Vlahogianni et al., 2008; Dunne and Ghosh, 2012) and others (e.g. Stathopoulos and Karlaftis, 2003; El Faouzi et al., 2009). Karlaftis and Vlahogianni (2011) compare statistical methods and neural networks in transportation research, highlighting some of the differences similarities of the two types of data analysis tools. With the emergence of a number of data collection technologies (e.g. c.f. Antoniou et al., 2011, for a review) data-driven approaches offer the potential for the development of approaches that are more appropriate for capturing the dynamic characteristics of traffic. In this paper, an alternative approach is presented, which exploits available (traffic and other) information and data-driven computational approaches to predict local traffic state and speed.

The fundamental traffic flow diagram has been often criticized as restrictive, but has proved useful over the past decades. Hall (1997) and May (1990) provide thorough discussions of traffic stream models, including a number of extensions, such as multi-regime models. Examples include two- and three-regime linear models, and combinations of single regime models (see e.g. Edie, 1961; May and Keller, 1967; Drake et al., 1967).

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Three somewhat related terms are used in the remainder of this paper; in order to avoid any ambiguity or confusion between them, they are clearly defined here:

- (Traffic) state: the state in which traffic is at any given time can be described by a number of parameters such as flow, density, speed; as these are continuous variables, there can be an infinite number of traffic states.
- Regime: traffic states can be grouped in regimes that reflect a somewhat homogeneous group with similar characteristics; the number of regimes may be determined purely on the basis of mathematical properties of the variables, and the regimes may not have direct interpretations.
- Phase: simple traffic flow theory models assume a small (usually 2 or 3) number of traffic phases, which have direct physical interpretations (e.g. congested or uncongested).

Several papers in the literature have discussed empirical situations in which the fundamental diagram seems to break down. Kerner (2004) has attempted to interpret such empirical observations in terms of a three-phase traffic theory (the three-phase traffic theory includes (i) a free traffic phase, (ii) wide moving jams and (iii) synchronized flow), while new microscopic traffic models that fit the interpretations of three-phase traffic theory (e.g. Kerner and Klenov, 2002) have been developed. It should be noted, however, that there is also vocal criticism to the three-phase traffic theory (e.g. Schoenhof and Helbing, 2009), as it also sometimes fails to fit and explain empirical data.

Various techniques have been used to estimate multi-regime traffic models. For example, Einbeck and Tutz (2004) present an application of multimodal regression to speed-flow data, while Sun and Zhou (2005) use cluster analysis to segment speed–density data and determine the regime boundaries for typical (two-regime and three-regime) speed–density models. Sun et al. (2003, 2004) applied local regression for short term traffic forecasting and report that local regression was superior when compared to nearest neighborhood and kernel smoothing. Toledo et al. (2007) present a local regression approach for processing vehicle position data in order to develop continuous vehicle trajectories and consequently obtain speed and acceleration profiles. The proposed methodology was successfully applied to a set of position data to develop profiles that were subsequently used for the calibration of car-following models. Antoniou and Koutsopoulos (2006b) provide a review of several flexible regression approaches [loess (Cleveland, 1978; Cleveland et al., 1988), support vector regression (SVR) based on support vector machines (Vapnik, 1995, 1998), neural networks (Haykin, 1999)] applied to the task of speed estimation and find that loess behaves better (in terms of accuracy and computational performance) in this context. One particular advantage of the presented approaches (loess, neural networks, and support vector regression) is that, unlike the typical speed–density relationship, they are flexible in incorporating additional explanatory variables, such as time of day, day of week and weather.

Clustering and classification are popular techniques with many applications. El Faouzi (2004) presents a data-driven approach that aggregates multiple estimators, attempting to aggregate all the information which each estimation model embodies (some of which might be lost if only the "best" model was chosen and applied), while El-Faouzi and Lefevre (2006) use two different approaches from evidence theory (classifier fusion and distance-based classification) for clustering and classification for road travel time estimation. Wang et al. (2005) use fuzzy clustering for the classification of car-following behavior into multiple regimes. Azimi and Zhang (2010) apply three different unsupervised learning methods (K-Means, Fuzzy C-Means, and CLARA) to classify freeway traffic flow conditions based on the characteristics of the flow.

The objective of this research is to develop and validate a dynamic data-driven framework that allows for traffic state estimation and prediction. Antoniou and Koutsopoulos (2006a) present a framework for the estimation of speeds using machine-learning approaches. While that work focused on estimation, in the current research the emphasis shifts to traffic state prediction using similar approaches, augmented by additional suitable models, required for the prediction part. Therefore, the main contributions of this paper include the development of a methodology for traffic state prediction. This methodology is based on a set of flexible models, both in terms of functional specification and data to which they can be applied. As the proposed models are shown to outperform current state-of-the-art models, they could be valuable when integrated into existing traffic estimation and prediction models (such as DynaMIT, Ben-Akiva et al., 2002, 2010, DYNASMART, Mahmassani, 2001, or RENAISSANCE, Wang et al., 2006a,b), resulting in more accurate traffic predictions. These predictions could then better support downstream applications, such as traffic guidance generation.

In this paper, the methodology will be presented and results will be provided illustrating how the presented approach performs compared to the existing state-of-the-art. The main components of the methodology and the application setup are presented next, followed by application results and related discussion. Two freeway data sets from Irvine, CA, and Ayalon, Israel, have been used for this research. A discussion section provides further insight and directions for future research.

2. Methodology

2.1. Overall framework

The overall framework is outlined in Fig. 1: the left figure outlines the main methodological components and shows the information flows, while the right figure provides simple examples of the main tasks achieved by each methodological component. In general, each observation may include multiple attributes [e.g. (lagged) speed, density, flow, number of lanes, grade, meteorological information, vehicle mix, driver mix].