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On the short-term prediction of traffic state: an application on urban freeways in Rome

L. Mannini [a] *, S. Carrese [a], E. Cipriani [a], U. Crisalli [b]

[a]*Department of Engineering, Roma Tre University, Via Vito Volterra 62, 00146 Rome, Italy*
[b]*Department of Enterprise Engineering, University of Rome Tor Vergata, 00133 Rome, Italy*

Abstract

This paper explores the traffic state estimation on freeways in urban areas combining point-based and route-based data in order to properly feed a second order traffic flow model, recursively corrected by an Extended Kalman Filter. In order to overcome the possible lack of real-time information, authors propose to use simulation-based data in order to improve the accuracy of the traffic state estimation. This model was tested on a urban freeway stretch in Rome, for which a set of real-time data during the morning of a typical workday was available. Results of the application point out the benefits of the proposed approach in predicting the traffic state, as shown by GEH, RMSE and RME values similar to those presented in the literature.

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Keywords: freeway; traffic state estimation; extended kalman filter; traffic flow model

1. Introduction

Today, large urban areas are affected by high road traffic congestion also in off-peak periods. Therefore, the capability to forecast such traffic conditions, particularly travel times, is of utmost importance in management applications aiming at relieving negative social, environmental and economic impacts for people. Nowadays different advanced monitoring systems providing new different types of information are available, and several

* Corresponding author. Tel.: +39-06-5733-3402; fax: +39-06-5733-3441 .
E-mail address: livia.mannini@uniroma3.it

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models and methods have been studied and implemented in order to improve both traffic state estimation in off-line applications and travel time prediction in on-line ones. Vlahogianni et al. (2014) provide a comprehensive and updated literature review for short term traffic forecasting and underline that the combination of recent huge availability of data is moving the ITS research area from macroscopic and microscopic models based on traffic flow theories towards data driven procedures such as, for instance, methods for the travel time estimation that highly depends on available data sources, as in Schrader et al. (2004) where authors use historical data with respect to the time horizon. Differently, the spatial dimension is analyzed along links in Xie et al. (2004) and in Yang et al. (2004), or along routes in Chakroborty and Kikuchi (2004) and in Ni and Wang (2008) where trajectories are obtained.

As for data fusion techniques, many authors study and propose methods in order to use the different current data provided by the several types of detectors (Zhu and Chen, 2012; Hwang and Wu, 2012; Chu et al., 2005) or by combining real-time observations with historical ones (Wu and Shen, 2009). In Lee et al. (2009) authors observe that the combined model that assimilates historical and current data has better accuracy than the two single models. A combined use of probe and point data is also reported in Liu et al. (2010).

As for estimation issues, the most applied models are simulation models, learning models (e.g. neural networks and support vector regression based models) and statistical models (e.g. linear regression and time series, Bayesian models and Kalman Filter algorithms (KF). The Kalman Filter (KF) has been studied by many authors considering a first order traffic model, as in Yuan et al (2011), and in Zuurbier and Knoop (2006). Work and Bayen (2008) applied the Ensemble Kalman Filter (EnKF). Differently, Wang et al. (2008) and Nanthanwichit et al. (2007) apply the Extended Kalman Filter (EKF) to a second order traffic model: the former reports a data testing of a real-time freeway traffic state estimator; the latter integrates probe data into the observation equation of the EKF.

In Chen and Chien (2001), authors observe that direct measurements of route based travel time rather than link based one could generate a more accurate prediction. They applied the KF both for path-based and for link-based methods. KF is also applied in Kuchipudi and Chien (2003) and the experimental results reveal that in peak hours the travel times predicted with the path-based model are more accurate than those predicted with the link-based model. Differently, Van Lint and Hoogendoorn (2010) propose a data fusion algorithm based on the Extended Generalized Treiber-Helbing filter.

Many authors combine two or more methods in order to improve the estimation of travel time. Yang et al. (2004) present a comparison between KF and adaptive recursive least-square methods, while a state-space neural network and the EKF algorithm is combined in Liu et al. (2006). In Van Lint (2008) a delayed EKF algorithm is applied and the weights of the state-space neural network model are trained with the realized travel times replying to the changes in traffic flow conditions. In Kwon and Petty (2005) the section travel times are forecasted through current probe data in order to predict the long route travel time made of the sections sequence. Zhang and Rice (2003) propose a model that updates its coefficients through historical data at each time interval, while a Bayesian dynamic linear model based on loop detector data is formulated in Fei et al. (2011), where the freeway travel time is the sum of the median values of historical travel times, taking into account the travel time random variations and a model evolution error.

Bayesian forecasting is a learning process that sequentially reviews the state of the travel time a priori knowledge based on new available data. A Bayesian estimator and an expanded neural network model are merged in Park and Lee (2004) using roadside and in-vehicle sensors; in the Bayesian procedure the forecasted travel time is an a posteriori distribution estimated on the basis of an a priori travel time distribution and current traffic measurements. Van Hinsbergen et al. (2008) combine a linear regression model and a locally weighted linear regression model in a Bayesian framework.

Rahmani et a. (2014) proposes a non parametric method for travel time estimation based on Floating Car Data (FCD) and camera data overlapping, even partially, on specific routes. A multiple linear regression model and an artificial neural network are merged in Ramakrishna et al. (2006).

This paper aims at improving the accuracy of travel time prediction when real-time point-based measurements, provided by loop detectors, are combined with route-based data, produced by an automatic number plate recognition system (ANPR), and link-based data represented by historical FCD data. The prediction model is based on a second order macroscopic traffic flow model (Wang and Papageorgiou, 2005) recursively corrected by an Extended Kalman Filter (EKF) properly fed by a measurement data fusion technique (Cipriani et al., 2012). Moreover, aiming at