Transportation Research Part C 43 (2014) 20–32

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Flow rate and time mean speed predictions for the urban freeway network using state space models

Chunjiao Dong [a,*], Chunfu Shao [b], Stephen H. Richards [a], Lee D. Han [c]

[a] *Center for Transportation Research, The University of Tennessee, 600 Henley Street, Knoxville, TN 37996, USA*
[b] *MOE Key Laboratory for Urban Transportation Complex Systems Theory and Technology, School of Traffic & Transportation, Beijing Jiaotong University, Beijing 100044, China*
[c] *Department of Civil & Environmental Engineering, The University of Tennessee, 319 John D. Tickle Building, Knoxville, TN 37996-2321, USA*

ARTICLE INFO

Article history:
Received 23 February 2013
Received in revised form 8 February 2014
Accepted 13 February 2014

Keywords:
Traffic flow
Short-term prediction
Congested and non-congested traffic
State-space model
Spatial-temporal pattern

ABSTRACT

Short-term predictions of traffic parameters such as flow rate and time mean speed is a crucial element of current ITS structures, yet complicated to formulate mathematically. Classifying states of traffic condition as congestion and non-congestion, the present paper is focused on developing flexible and explicitly multivariate state space models for network flow rate and time mean speed predictions. Based on the spatial–temporal patterns of the congested and non-congested traffic, the NSS model and CSS model are developed by solving the macroscopic traffic flow models, conservation equation and Payne–Whitham model for flow rate and time mean speed prediction, respectively. The feeding data of the proposed models are from historical time series and neighboring detector measurements to improve the prediction accuracy and robustness. Using 2-min measurements from urban freeway network in Beijing, we provide some practical guidance on selecting the most appropriate models for congested and non-congested conditions. The result demonstrates that the proposed models are superior to ARIMA models, which ignores the spatial component of the spatial–temporal patterns. Compared to the ARIMA models, the benefit from spatial contribution is much more evident in the proposed models for all cases, and the accuracy can be improved by 5.62% on average. Apart from accuracy improvement, the proposed models are more robust and the predictions can retain a smoother pattern. Our findings suggest that the NSS model is a better alternative for flow rate prediction under non-congestion conditions, and the CSS model is a better alternative for time mean speed prediction under congestion conditions.

1. Introduction

One of the most critical aspects of ITS success is the provision of accurate real-time information and short-term predictions of traffic parameters such as flow rates, speeds, and occupancies. Although many different methodologies have been used for short-term predictions, most of them fail to formulate mathematically. The difficulty lies in the nature of traffic flow, which is a dynamically evolving phenomenon through both time and space (Vlahogianni et al., 2005). Traffic flow predictions for a freeway network refers to estimating all traffic variables of the network in the future (less than 15 min) based on

---

* Corresponding author. Tel.: +1 8659741826.
E-mail address: cdong5@utk.edu (C. Dong).

http://dx.doi.org/10.1016/j.trc.2014.02.014
0968-090X/© 2014 Elsevier Ltd. All rights reserved.

available real-time traffic measurements. More precisely, based on a limited amount of available measurement data from traffic detectors, the prediction algorithms should deliver a complete image of the network's traffic states at the future time.

According to the definition of the problem, one would note that single point traffic flow prediction can be described as a time series problem. During the past few years, many researchers have focused on predicting traffic flow with various time series methodologies such as time series methods (Ahmed and Cook, 1979; Hamed et al., 1995; Williams et al., 1998; Yeon et al., 2008), artificial neural network models (Smith and Demetsky, 1994; Zhang et al., 1997; Dougherty and Kirby, 1998; Park et al., 1998; Vlahogianni et al., 2005), regression models (Zhang and Rice, 2003), Kalman filter (Okutani and Stephanedes, 1984; Wang and Papageorgiou, 2005), and nonparametric regression models (Davis and Nihan, 1991; Smith et al., 2002). The use of Bayesian statistics is quite recent in the field of traffic low prediction. Some studies have been done using Bayesian networks (using the concept of neural networks) in short-term traffic flow prediction (Petridis et al., 2001; Tebaldi et al., 2002; Zheng et al., 2006). The Bayesian combination approach is a type of method that tries to combine several predictors based on the conditional probability and Bayes' rule. Current research in traffic flow prediction based on data-driven approaches indicates that applied stochastic linear modeling such as the Autoregressive Integrated Moving Average (ARIMA) fails at predicting shifts to extreme volume values (Hamed et al., 1995; Williams et al., 1998; Williams, 2001; Stathopoulos and Karlaftis, 2003), which could suggest that the process underlying traffic is more complicated than can be captured by a single linear statistical algorithm. On the other hand, with the nonlinear models, such as artificial neural networks (ANNs), researchers must rely on time consuming and questionably efficient rules-of-thumb when developing them, because of limited knowledge regarding a network's optimal structure given a specific dataset (van Lint et al., 2002; Smith and Oswald, 2003; Ishak and Alecsandru, 2004; Vlahogianni et al., 2005).

Furthermore, the dynamics of spatial–temporal patterns (as shown in Fig. 1) in traffic flow are of fundamentally importance for the prediction, but they remain poorly understood as they have not received adequate attention in previous research. Two papers (Abdulhai et al., 2002; Zeng and Zhang, 2013) have described recent attention to analytical method development. Works undertaken by Abdulhai et al. (2002) are most directly related to this issue. They presented a new short-term traffic flow prediction system based on an advanced Time Delay Neural Network (TDNN) model, the structure of which is optimized using a Genetic Algorithm (GA). The model predicted flow and occupancy values at a given freeway site based on spatial–temporal contributions. Both temporal and spatial effects were found essential for proper prediction in this research. However, this study does not explore the interaction impacts between temporal pattern and spatial pattern under the network condition.

Zeng and Zhang (2013) discussed the effects of temporal–spatial input on the ANN travel time prediction process. The results show that including inputs from both upstream and downstream sites is statistically better than using only the inputs from current site. They also investigated the evolution of spatial–temporal input interactions. The results reveal that historical information on downstream and current sites is useful in improving prediction accuracy, whereas historical inputs from the upstream site do not provide as much constructive information. These efforts demonstrate that including temporal and spatial contributes as input becomes necessary in short-term prediction modeling when, instead of a time-delayed representation of the fluctuation pattern, one wishes to provide more rapid and synchronized response prediction behavior. However, taking the ANN model as the predictor ignores the disadvantages of its "black box" nature, greater computational burden, proneness to overfitting, and the empirical nature of model development, which has been raised by an increasing number of researchers (Benediktsson et al., 1990; Tu, 1996).

Overall, we can conclude that an ideal approach for short-term traffic flow prediction is a network-based model that combines recent temporal profile at a given freeway network during the past few minutes and the spatial contribution from neighboring sites. The current paper develops two flexible and explicitly multivariate state space models for network flow

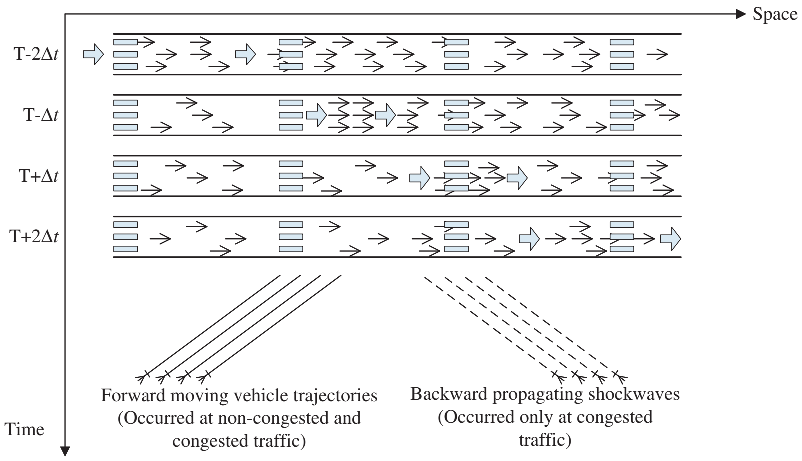

Fig. 1. Illustration of the dynamics of spatial–temporal patterns.