Transportation Research Part C 43 (2014) 50–64

Contents lists available at ScienceDirect

Transportation Research Part C

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

Adaptive Kalman filter approach for stochastic short-term traffic flow rate prediction and uncertainty quantification

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ARTICLE INFO

Article history:
Received 17 June 2013
Received in revised form 26 January 2014
Accepted 13 February 2014

Keywords:
Congestion
Intelligent transportation system
Short term traffic flow forecasting
SARIMA
GARCH
Adaptive Kalman filter

ABSTRACT

Short term traffic flow forecasting has received sustained attention for its ability to provide the anticipatory traffic condition required for proactive traffic control and management. Recently, a stochastic seasonal autoregressive integrated moving average plus generalized autoregressive conditional heteroscedasticity (SARIMA + GARCH) process has gained increasing notice for its ability to jointly generate traffic flow level prediction and associated prediction interval. Considering the need for real time processing, Kalman filters have been utilized to implement this SARIMA + GARCH structure. Since conventional Kalman filters assume constant process variances, adaptive Kalman filters that can update the process variances are investigated in this paper. Empirical comparisons using real world traffic flow data aggregated at 15-min interval showed that the adaptive Kalman filter approach can generate workable level forecasts and prediction intervals; in particular, the adaptive Kalman filter approach demonstrates improved adaptability when traffic is highly volatile. Sensitivity analyses show that the performance of the adaptive Kalman filter stabilizes with the increase of its memory size. Remarks are provided on improving the performance of short term traffic flow forecasting.

1. Introduction

Congestion is causing serious issues for surface transportation systems around the world. Due to the increasing constraints on new road construction or expansion, traffic management and control systems under the umbrella of intelligent transportation systems (ITS) have become increasingly vital for improving the efficiency and safety of traffic operations. In contrast to reactive management and control systems that respond to currently observed traffic conditions, the proactive systems rely on accurate prediction of near-term traffic conditions. Considering the importance of traffic flow rate, defined as the number of vehicles passing a specific road section over a predefined time interval (TRB, 2000), short-term traffic flow rate forecasting has been identified as one of the major challenges for developing proactive ITS applications.

Short term traffic flow rate forecasting includes traffic flow rate level prediction, i.e., point forecast, and uncertainty quantification associated with level prediction, i.e., prediction interval generation (Chatfield, 1993). Intuitively, short-term traffic flow rate forecasting should be informed by our understanding of the traffic flow rate dynamics that is of primary

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http://dx.doi.org/10.1016/j.trc.2014.02.006
0968-090X/

importance in forecasting algorithm development (Stephanedes et al., 1981). Recently, based on previous findings in Williams (1999), Williams and Hoel (2003), Shekhar and Williams (2008), etc., a stochastic structure of seasonal autoregressive integrated moving average plus generalized autoregressive conditional heteroscedasticity (SARIMA + GARCH) is utilized to model the first and second conditional moment of traffic flow rate series, and this structure has been shown to be able to generate desirable traffic flow rate level forecasts and prediction intervals (Guo et al., 2008).

Due to the requirement of real time processing for many ITS-related transportation applications, the SARIMA + GARCH structure needs to be handled in an online fashion. In this regard, Kalman filter, due to its recursive nature, is one of the most widely adopted tools of achieving this purpose. In doing so, the time series models are converted into state space models, including a state transition equation and an observation equation for the hidden state process and the observation process, respectively. In the conventional Kalman filter, the process variances are important seeding parameters calibrated usually using historical traffic flow rate series. However, as shown in Guo (2005) and Guo et al. (2012), traffic condition is heteroscedastic in nature, and adaptive Kalman filters with time-varying process variances adaptation are expected to be theoretically more appealing than the conventional Kalman filters. In this paper, the performance of the adaptive Kalman filter for short term traffic flow rate forecasting is investigated. Following a review of related literatures, the methodology is presented, including the definition of the stochastic structure, state space representation, and adaptive Kalman recursion. The paper then presents the empirical results from application of the adaptive Kalman filter to real world data. The paper concludes with summaries and remarks.

2. Literature review

Over the decades, there has been a variety of approaches published on short term traffic flow forecasting. In this section, we summarize the studies of level forecasting and uncertainty quantification, i.e., point forecast and prediction interval generation.

2.1. Traffic condition level forecasting

Traffic flow level forecasting, i.e., point prediction, has been widely investigated and many studies have been published in the literature. First, linear time series model has been widely applied, including exponential smoothing (Ross, 1982), autoregressive integrated moving average (ARIMA) model (Ahmed and Cook, 1979; Levin and Tsao, 1980; Nihan and Holersland, 1980; Hamed et al., 1995), SARIMA (Williams, 1999; Williams and Hoel, 2003; Guo, 2005; Guo et al., 2008), multivariate time series models (Williams, 2001; Kamarianakis and Prastacos, 2003; Min and Wynter, 2011), spectral analysis (Nicholson and Swann, 1974; Tchrakian et al., 2012). In these models, the traffic dynamics are inherently assumed to be linear. It is worthwhile to note that SARIMA has been shown to generate promising performances (Smith et al., 2003; Guo et al., 2008; Lippi et al., 2013).

Second, non-parametric approaches have been applied, including neural network and its variations (Clark et al., 1992; Smith and Demetsky, 1994; Park et al., 1998; Zhang, 2000; Dia, 2001; Chen and Grant-Muller, 2001; Yin et al., 2002; Jiang and Adeli, 2005; Vlahogianni et al., 2005; Dunne and Ghosh, 2012), *k*-nearest neighbor approach (Davis and Nihan, 1991; Smith and Demetsky, 1996, 1997), kernel smoothing (El Faouzi, 1996), and local linear regression (Sun et al., 2003). These methods are in general automatic and do not make strong assumptions on the underlying model form. They have a notable advantage of adaptive learning of the underlying traffic dynamics through a historical traffic condition database.

Hybrid methods have also been exploited to enhance the performances of single forecasting approaches, including combined Kohonen maps with ARIMA (KARIMA) model (Der Voort et al., 1996), ATHENA (Danech-Pajouh and Aron, 1991), Bayesian-neural network approach (Zheng et al., 2006), hybrid fuzzy rule-based approach (Dimitriou et al., 2008), hybrid EMD-BPN (empirical mode decomposition-back propagation neural networks) approach (Wei and Chen, 2012), chaos-wavelet analysis-support vector machine approach (Wang and Shi, 2013). Intuitively, the implementation characteristics of hybrid methods are generally complex, thereby discouraging their wide-scale implementations.

In addition, filtering approaches have been widely applied, including recursive least square (RLS) (Kang et al., 1998; Yang et al., 2004), Kalman filter (Gazis and Knapp, 1971; Okutani and Stephanedes, 1984; Stathopoulos and Karlaftis, 2003; Shekhar, 2004; Guo, 2005), generalized linear model (GLM) (Lan and Miaou, 1999; Lan, 2001), Bayesian dynamic linear model (Fei et al., 2011), and least mean square (LMS) filters (Lu, 1990). It is worthwhile to note that the RLS, Kalman filter, and GLM are closely related by assuming the random walk model for the forecasting algorithm state evolution (Yang et al., 2004; Lan and Miaou, 1999; Lan, 2001). These methods are promising in imparting a self-adjusting ability into the forecasting process and the Kalman filter approach is theoretically appealing for short term traffic condition forecasting. However, as pointed out previously, the heteroscedastic nature of traffic condition series demands a process variances adaptation mechanism in the Kalman filters.

2.2. Uncertainty quantification

Compared with traffic flow level forecasting, studies on traffic uncertainty quantification or prediction interval generation are initially limited to several studies with discouraging results (Yang et al., 2004; Hugosson, 2005; Pattanamekar et al.,