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Abstract

Active traffic management aims to dynamically manage congestion based on existing and predicted traffic conditions. A challenge in this is that it is not usually possible to process data in real-time and use the output in control algorithms or in traveler information systems. A solution to this is to predict the traffic state based on assessments of current and past measurements. The work described in this paper develops an adaptive forecasting method to predict traffic speeds using dynamic linear models with Bayesian inference from *a priori* distributions. This study incorporates speeds collected from radar based sensors and validates the results with data collected from Bluetooth traffic monitoring technology. The highly adaptive model is confirmed with estimated traffic speeds during inclement weather and multiple incidents.

Selection and Peer-review under responsibility of the Program Chairs.

Keywords: Dynamic linear models; State-space; Kalman filtering, Bluetooth traffic monitoring; Traffic forecasting

Nomenclature

x_t	State vector
y_t	Observation vector
G_t	Known state matrix
F_t	Design matrix of known values of independent variables
w_t, v_t	Independent white noise sequences

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a_t	Prediction mean of state vector
R_t	Prediction variance of state vector
f_t	One-step-ahead forecast mean
Q_t	One-step-ahead forecast variance
m_t	Filter mean
C_t	Filter variance
K_t	Kalman gain

1. Introduction

Intelligent Transportation Systems (ITS) make possible the collection of large amounts of data but methodological gaps exist in its processing and deployment in the context of driver information or control measures. Many solutions have been proposed to predict the traffic state and can be broadly categorized as non-parametric, parametric, and hybrid methods.[1,10] In general, parametric methods require the parameters of traffic flow models to be estimated off-line and assume the underlying model process is fixed. Variations in traffic due to incidents, weather, and fluctuating traffic dynamics can adversely affect the performance of such models. The proposed model is capable of forecasting speeds online and is adaptive to sudden changes in traffic due to traffic variations. Forecasting of traffic speeds was achieved with Kalman recursions that were employed in a dynamic state-space model framework where parameters of the state are permitted to change with time. The work reported here on adaptive speed estimation is a part of a bigger project, which will use the forecasts in a ramp metering control scheme.

1.1. Outline of the paper

The remainder of this paper is organized as follows. The next section presents the problem statement. Section 3 explains dynamic linear models in the state-space framework, Kalman recursions, and a description of the data collection. Section 4 contains the results for speed forecasts for the radar collected time-mean speeds, validation results from Bluetooth based space-mean speeds, and a demonstration of the adaptive capabilities. Section 5 contains concluding remarks and suggestions for further work.

2. Problem statement

The need to forecast traffic speeds with an adaptive tuner arose from a challenge in processing real-time traffic data for a ramp metering application. Many ramp metering schemes attempt to maximize throughput by metering to a predetermined optimal occupancy or maximum capacity level. This suffers from the fact that capacity is known to not be a fixed value and the optimal measure of it may change under a wide range of conditions. An ongoing area of research is investigating the stochastic nature of freeway capacity and breakdowns.[3,4] This type of research have been applied to ramp metering algorithms (Stratified Zone Metering; Minnesota and COMPASS Ontario, Canada) by modifying them to incorporate the breakdown probability in the control scheme. Modifications have included adjusting the metering rates based on the maximum capacity prior to the onset of breakdown. However, this does not yield a system that is adaptive to the random fluctuations observed in traffic.

Because capacity is a random quantity that is difficult for practitioners to determine and apply in real-world settings, speeds is used as a measure for the quality of flow. Thus, a solution to the ramp metering problem is to minimize the disturbance of the traffic stream observed through the variance of speeds. The method proposed in this study is a stochastic modeling approach that is adaptive to conditions (e.g. driver behaviors, adverse weather, incidents, etc.) and is applied in an on-line manner, yielding real-time forecasts.

In this study, speeds collected from radar based sensors are forecasted and compared to Bluetooth collected speeds. The adaptive capabilities of the model was verified during inclement weather in which multiple accidents occurred. The modeling approach is an improvement of previous work[10] by introducing time-varying parameters in a polynomial structure.

3. Methodology

The state-space framework considers a time series as the output of a dynamic system perturbed by random disturbances and ones in which parameters are allowed to vary over time.[2] For this reason, state-space models are also called dynamic linear models. A Kalman filter is an optimal recursive data processing algorithm, meaning that predictions are based on only the previous time-step's prediction and the filter does not require all previous data to be stored and reprocessed with new measurements. The filter is optimal in the sense that it minimizes the variance of the estimation error at each iteration process. When the next measurement is taken, the algorithm calculates a correction of the state prediction using the new measurement along with the error covariance. The recursive algorithm uses only the current measurement and error covariance allowing for low computational cost and on-line forecasting.

3.1. State-space framework

State-space models can be used for modelling univariate non-stationary time series that allow for natural interpretation as a result of trend and seasonal (periodic) components.[5,6,8] The state-space local level model is a time series where observations can be modelled as random fluctuations around a stochastic level (described by a random walk). Traffic speeds were modeled with a stochastic local level model with seasonal components in the 'R' language and environment for statistical computing.[9]

The main tasks for the given state-space model were to make inferences on the unobserved traffic state and predict future observations based on part of the observation sequence. The main advantage of Bayesian inference is the prediction result is *a posteriori* distribution rather than a single-value, thus allowing one to quantify the reliability of the results.[10] Estimation and forecasting are solved by computing conditional distributions of the traffic state, given the available information. In dynamic state-space models, the Kalman filter provides the formulas for updating our current inference on the state vector x_t as new data y_t become available; that is for passing from the filtering density[5,6,7] $p(x_t/y_1,\dots,y_t)$ to $p(x_{t+1}/y_1,\dots,y_t)$.

3.2. Bayesian inference

Formulating reasonable assumptions about the dependence structure of time series can be made based on explicit use of prior information from data. It is common practice to use conjugate priors where a family of densities is said to be conjugate to the model if, whenever the prior belongs to that family, so does the posterior.[8] Bayes formula, in the framework of dynamic linear models, allows for the recursive one-step-ahead forecast of the *posteriori* distributions of the state vector solved by the Kalman filter.

3.3. Kalman recursions for the dynamic linear model

Let us denote D_t as the information provided by the first t observations, $y_1,\dots,y_t$ and it is assumed $x_0 \sim N(m_0, C_0)$. The Kalman filter allows us to compute the predictive and filtering densities recursively as new information becomes available starting from $x_0|D_0 \sim \mathrm{N}(m_0, C_0)$ given the state equation[7,11]:

$$x_t = G_t x_{t-1} + w_t \tag{1}$$

based on measurements y_t, according to the observation equation:

$$y_t = F_t x_t + v_t \tag{2}$$

Where, G_t and F_t are known matrices and w_t and v_t are independent white noise sequences with $Cov(w_t) = W_t$ and $Cov(v_t) = V_t$.

The state predictive density $x_t|D_{t-1} \sim N(a_t, R_t)$ (*a priori*):

where

$$a_t = G_t m_{t-1} \tag{3}$$

and

$$R_t = G_t C_{t-1} G_t^T + W_t \tag{4}$$

One-step-ahead predictive density of $y_t|D_{t-1} \sim N(f_t, Q_t)$:
where

$$f_t = F_t a_t \tag{5}$$

and

$$Q_t = F_t R_t F_t^T + V_t \tag{6}$$

Filtering density of $x_t|D_t \sim N(m_t, C_t)$ (*a posteriori*):
where

$$m_t = a_t + K_t(y_t - F_t a_t) \tag{7}$$

and

$$C_t = R_t - K_t F_t R_t \tag{8}$$

The predicted state estimate is also known as the *a priori* state estimate because it does not include information from the current time step. In the measurement update stage, the prediction is combined with the current observation information to refine the state estimate and is known as the *a posteriori* state estimate. The expression for m_t is intuitively the estimation-correction where the filter mean is equal to the prediction mean a_t plus a correction based on how much the new observation differs from its prediction. The weight of the correction term is given by the Kalman filter gain:

$$K_t = R_t F_t^T \mathrm{Q}_t^{-1} \tag{9}$$

which is the adaptive coefficient and can be regarded as an information tuner.[1,4]

3.4. Data collection

High-resolution (5-minute aggregate) data: volume, occupancy, vehicle classification, and average lane speed were collected on Interstate-84 (I-84) near the Meridian Road interchange in Meridian, Idaho. Radar based (SmartSensor105™ from Wavetronix) sensing devices were chosen to capture the data from November 11 through November 14 in 2013. Permanent installations of traffic monitoring equipment based on Bluetooth technology are in place throughout sections of I-84 and were used for validation. The Bluetooth devices collects and time-stamps media access control (MAC) addresses from Bluetooth devices in vehicles traveling on a road and, by matching these addresses collected at the two end points, can yield travel times and speeds between those points.

The radar based sensors, which collected time-mean speeds, were placed at the midpoint of a 4-mile route between two Bluetooth devices that captured the space-mean speeds.

4. Results

The present model is based on the idea that the observations y_t of the traffic are incomplete and a noisy function of the unobservable state process x_t, which we can only observe through noisy measurements. According to equations (1) and (2), a polynomial dynamic linear model with stochastic level and seasonal components was constructed for speed predictions. The speeds collected from the radar and Bluetooth devices can be seen in Figure 1.

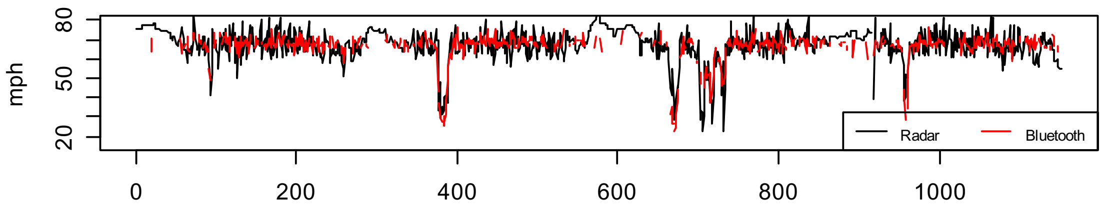

Figure 1. Radar and Bluetooth measured speeds.

The proposed model was calibrated using five-minute average speeds collected from the radar based equipment located at the Meridian interchange. The computed five-minute one-step-ahead forecasts are shown in Figure 2.

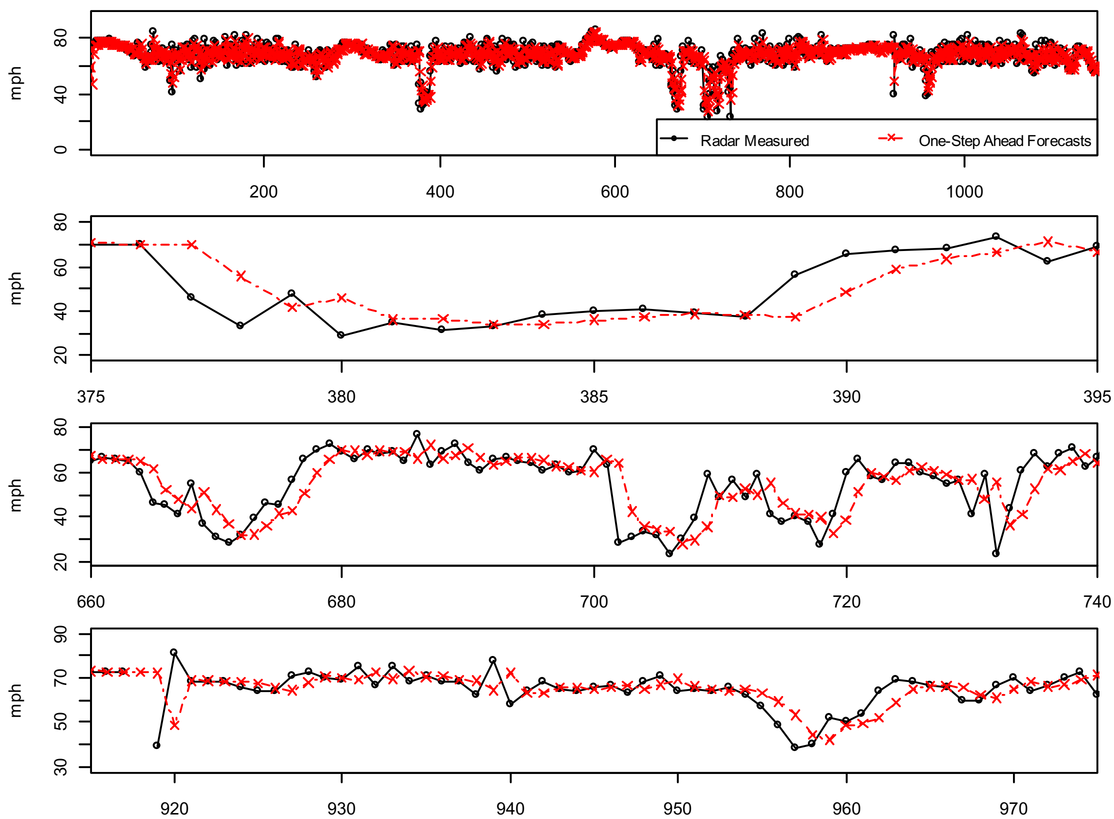

Figure 2. Radar measured five-minute one-step-ahead forecasts.

The radar dataset was used to train the model due to its high resolution and a matching rate[12] of 99% compared to that of Bluetooth's reported 5-7% average.[13] Plots of the one-step-ahead forecasts reveal that the model tuned early and had good performance. As seen in the second plot in Figure 2, the first recurrent congestion conditions occur between 7:25 AM and end at approximately 8:30 AM (from time index 377 and 389). The third plot of Figure 2, time index (TI) 665 – 680, corresponds to a peak hour AM congestion period from 7:00 to 8:40, the following day. Another period of congestion appears at TI 702 and continues intermittently through TI 737. The final plot shows a shorter phase for the AM congestion period occurring from 7:35 to 8:10 (TI 955 – 962) on Thursday November 14th.

4.1. Case study

To validate the model, speeds recorded from the Bluetooth devices between 12:00 AM, November 11 through November 12:00 AM, 14 were forecasted. Two Bluetooth devices were used to record the "driver perceived" actual travel times which were used to find the space-mean speeds. The observations recorded from the Bluetooth sensors have many time periods with missing observations. As seen in the five-minute observations in Figure 3, the model performed exceptionally well in spite of the missing observations. The second plot in Figure 3 displays the first recurrent congestion conditions beginning at 7:25 AM and ending at 8:30 AM (TI 375 – 390).

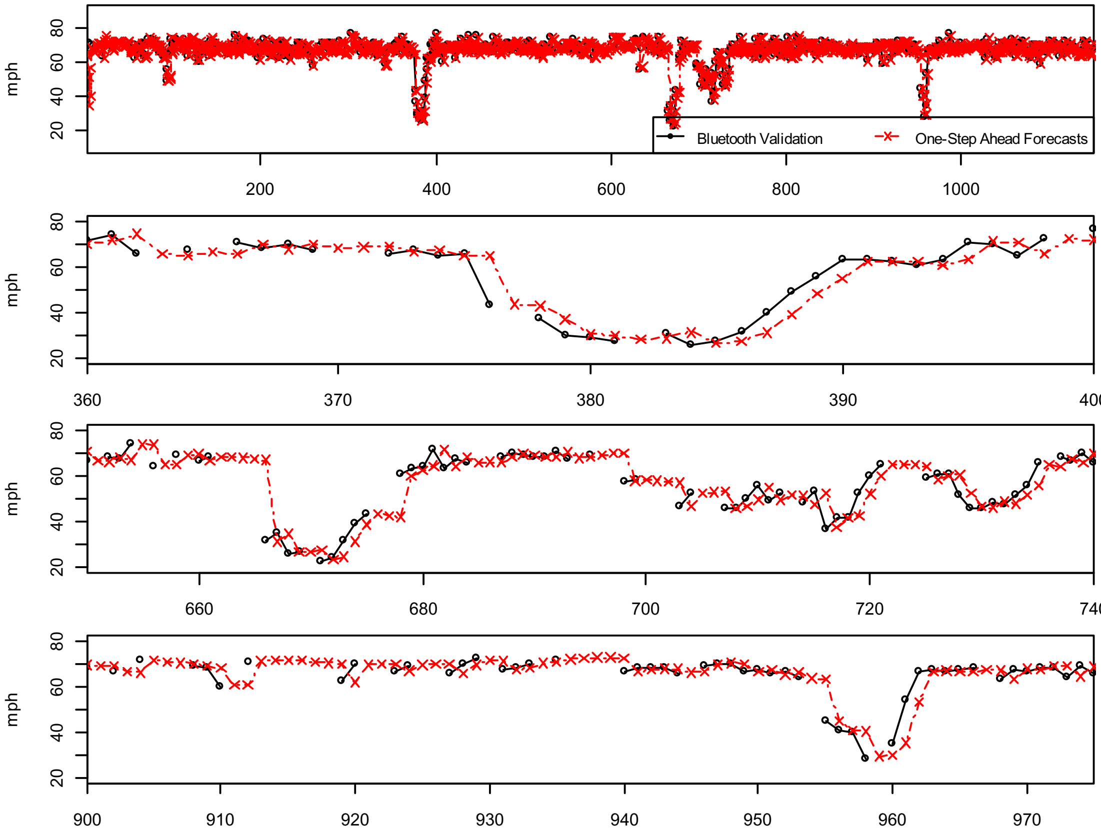

Figure 3. Bluetooth validation one-step-ahead forecasts.

The third plot of Figure 3, TI from approximately 665 – 680, corresponds to a peak hour AM congestion period from 7:00 to 8:40, the following day. The final plot shows a shorter phase for the AM congestion period occurring from 7:35 to 8:10 on Thursday, November 14th. This plot demonstrates the models ability to perform well in spite of 30 missing observations in the period between TI's 900 and 980.

4.2. Adaptive capabilities

A series of crashes due to inclement weather caused a 44 vehicle crash on January 9, 2014 along a one-mile stretch of westbound I-84 in the study area. Bluetooth sensors captured data during this time and five-minute average speeds collected from 6 AM to 4 PM were used to demonstrate the adaptive capabilities of the model. The 120 observation period is particularly incomplete with 42 missing observations. As seen in Figure 4, over one-third of the missing observations were estimated reasonably well and the model was able to adapt to speed variations greater than 45 miles per hour occurring in two time-steps as seen in the third plot of Figure 4 between TI 96 – 97. Fluctuations in the one-step ahead forecasts in the absence of measured data, for example as seen between TI 3 – 8, 27 – 39, and 27 – 30, reflect the daily seasonal trends captured by the model.

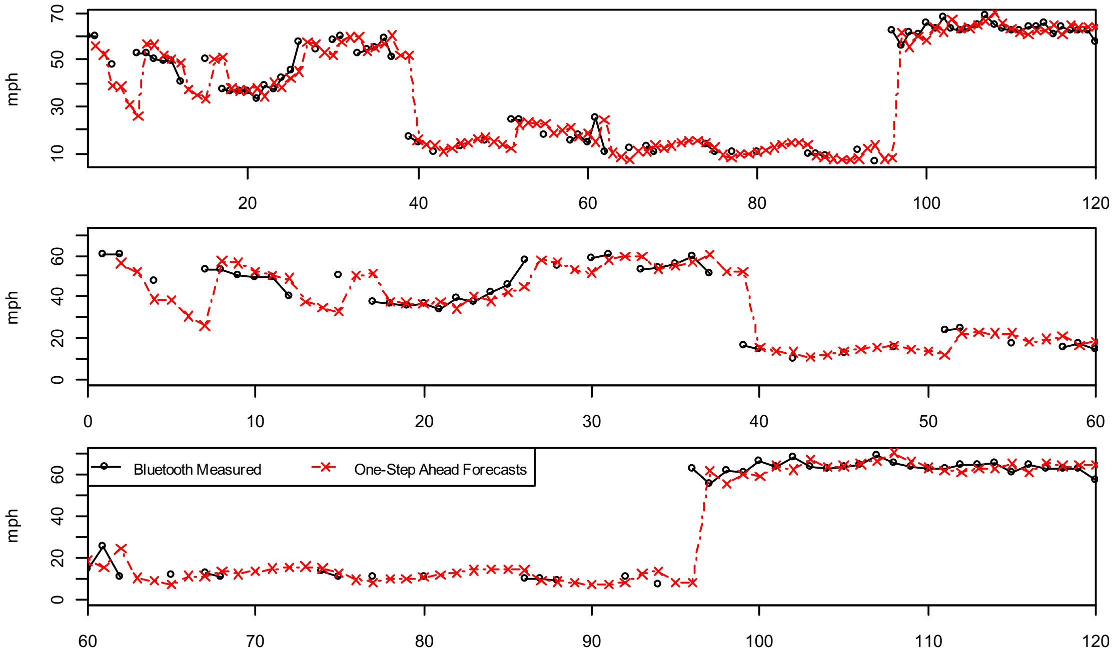

Figure 4. Bluetooth measured one-step-ahead forecasts during incident.

5. Conclusion

This paper developed a model for online adaptive speed estimation. To capture the dynamics of traffic, the traffic state was modeled using a dynamic linear model with its predictions performed by Kalman recursions. Plots of the models output show that it tuned relatively early and had good performance despite fluctuating levels of traffic. The third and fourth plot of Figure 3 demonstrate this with 25 and 30 missing observations, respectively. In addition, forecasted speeds are compared from radar and Bluetooth based sensors.

The methodology presented has been shown to adapt to abrupt changes in speeds due to incidents and weather as demonstrated in Figure 4. Speed variability greater than 45 miles per hour occurring between two time-periods, TI 96 – 97, was processed by the model in the absence of measurements. This recursive estimation scheme uses only the previous time step error covariance and current measurement in an on-line application that is capable of operating in the absence of missing data.

The Bayesian dynamic linear model presented in this paper is suitable for online speed and travel-time predictions. It has been shown that the model is capable of adapting to recurrent and non-recurrent traffic conditions and is able to cope with noisy and incomplete observations often measured by roadway sensors. This work can be expanded by incorporating an offline smoother for robust assessments of the behavior of the system. The highly adaptive capability of this model will in future work be incorporated into a ramp metering control scheme.

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References

1. Comert G, & Bezuglov, A. An Online Change-Point-Based Model for Traffic Parameter Prediction. *IEEE Transactions on Intelligent Transportation Systems*, *14*(3), 1360-1369. 2013.
2. Casdagli M. A dynamical systems approach to modeling input-output systems. *Santa Fe Institute Studies in the Sciences of Complexity-Proceedings Volume-* (Vol. 12, pp. 265-265). Addison-Wesley Publishing Co. 1992.
3. Elefteriadou L, Kondyli A, Washburn S, Brilon W, Lohoff J, Jacobson L Persaud, B. Proactive Ramp Management under the Threat of Freeway-Flow Breakdown. *Procedia - Social and Behavioral Sciences*, *16*, 4–14. 2009.
4. Geistefeldt J, & Brilon W. A Comparative Assessment of Stochastic Capacity. In *Transportation and Traffic Theory 2009*. Springer. 2009.
5. Durbin J, & Koopman S. J. *Time series analysis by state space methods*. Oxford: Oxford University Press. 2012.
6. Petris G, Campagnoli, P., & Petrone, S. *Dynamic linear models with R*. Springer. 2009.
7. West M, Harrison J. Bayesian forecasting and dynamic models, second edition, New York, Springer, 1999.
8. Petris G, Petrone, S. State Space Models in R, *Journal of Statistical Software*, 2011.
9. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria, 2013.
10. Fei X, Lu, C-C, Liu, K. A bayesian dynamic linear model approach for real-time short-term freeway travel time prediction. *Transportation Research Part C: Emerging Technologies*, *19*(6), 1306–1318. 2011.
11. Gibbs, Bruce P. *Advanced Kalman Filtering, Least-Squares and Modeling: A Practical Handbook*. Hoboken: Wiley, 2011.
12. SmartSensor 105 Performance Test. Wavetonix, Provo UT, 2011.
13. Tarnoff J, JS Wasson, SE Young, N Ganig, DM Bullock, JR Sturdevant. The Continuing Evolution of Travel Time Data Information Collection and Processing. Paper submitted for presentation at the Transportation Research Board Annual Meeting, January 2009.