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Prediction of arterial travel time considering delay in vehicle re-identification

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Abstract

Travel time is important information for management and planning of road traffic. In the past decades, automated vehicle identification (AVI) systems have been deployed in many cities for collecting reliable travel time data. The fast technology advance has made the budget cost of such data collection system much cheaper than before. For example, bluetooth and WiFi-based systems have become economically a more feasible way for collecting interval travel time information in urban area. Due to increasing availability of such type of data, this paper aims to develop a travel time prediction approach that may take into account both online and historical measurements. Indeed, a statistical prediction approach for real-time application is proposed, modeling the deviation of live travel time from historical distribution estimated per time interval. An extended Kalman Filter (EKF) based algorithm is implemented to combine online travel time with historical patterns. In particular, the system delay due to vehicle re-identification is considered in the algorithm development. The methods are evaluated using Automated Number Plate Recognition (ANPR) data collected in Stockholm. The results show that the prediction performance is good and reliable in capturing major trends during congestion buildup and dissipation.

1. Introduction

Being a key part of modern Intelligent Transportation System (ITS) technologies, traffic information systems can benefit travelers in planning their trip and making pre-trip and en-route decisions. Meanwhile, traffic planers require accurate and live information to make appropriate decisions in their planning and management projects. Moreover, with the fast development in information and communication technologies, the impacts of real-time information on traffic are expected to increase dramatically in many operational applications.

Travel time, defined as the time necessary to traverse a route between any two points within a road transportation network, is a fundamental performance measure to describe traffic states on road network and to evaluate facilities and systems. In reality, travel times between any pair of origin and destination are subject to fluctuations resulted from

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the stochastic nature of traffic flows and interactions between demand and supply on road networks. Travel times on roads can be estimated from data collected from different sources using various technologies. For instance, spot measurement using conventional loop detectors or other fixed sensors is one of the most widely used methods in traffic data collection. Travel times can be derived from pure spot measurements using analytical models that model traffic flow on road networks (e.g. Nam and Drew, 1996; Holt et al., 2003). Whilst the fixed sensors in the studies were shown to be applicable for travel time application, prediction accuracy under congested traffic conditions is indeed limited. In addition, the method is mainly applicable to motorways where traffic dynamics are relatively easier to describe.

In the past decade, the transport field has seen a skyrocket in the types of smart sensors capable to facilitate traffic data collection. Emerging data technologies, such as floating vehicle (FV) sensors, provide capability to measure real-time travel times on road network. Specially, taxi or other commercial fleets equipped with GPS transmitters have the capacity to supply large amount of online FV data in the urban area. In addition, cellular data has also been used to ob-serve path flows for long distance trips (Bahoken and Raimond, 2013). Similarly, TomTom, Google etc. are collecting anonymously position information from millions of mobile phone users on the road and more than one million TomTom devices. In Sweden, the low frequency FV data has been collected by the Taxi fleet in Stockholm, and shows capacity to facilitate traffic estimation both on highways and city arterials. For instance, using the Taxi GPS data a systematic approach has been developed from map matching and path inference to travel time estimation (Rahmani et al., 2015). Simultaneously, low frequency GPS data from Scania truck was also used to infer traffic information on highways for fleet management application (Yang et al., 2016). While the opportunistic FV data creates new chances in dynamic traffic prediction and applications, the use of FV data for traffic control and management still requires further development and validation using other more dedicated traffic data sources.

Automatic Vehicle Identification (AVI) has recently become widely adopted technology in traffic surveillance and ITS applications, and vehicle (or in-vehicle device) identity and passage times can be registered at different sensor locations. By identity matching, travel time becomes the main traffic performance index that can be directly obtained through the AVI system. The emergence of AVI systems can be traced back to the 1990s when electronic devices (e.g. electronic tags) were equipped to vehicles for applications. For example, AVI travel time data has been collected through a commercial traffic management system called TransGuide (S.R.I., 2000), deployed at San Antonio, Texas. An average filtering algorithm is applied to estimate online travel time every certain minutes based on previous measurements in a defined time window. Tam and Lam (2008) developed a travel time estimation approach for area-wide network using real-time AVI data and offline correlation analysis between links with data and without observations. Nowadays, AVI technologies based on automatic number plate recognition (ANPR) have been applied in many cities in the world. While deployment and maintenance of AVI system are often expensive, they provide reliable travel time information of the traversed network than indirect approaches. In addition, with latest technologies, vehicles on roads can be identified by using opportunistic communication signals from smart devices in vehicle (e.g. cellular or bluetooth signals). The reduction in infrastructure costs indicates a bright future of the AVI-based traffic information technology. For example, Araghi et al. (2015) proposed a method to estimate travel times using Bluetooth sensors on a bridge in Aalborg, Denmark.

In Sweden, ANPR system has been deployed for travel time observation on arterials of two major cities, Stockholm and Göteborg. In Stockholm, infra-red cameras are mounted at 85 sites and are measuring traffic on around 110 important routes. In addition, bluetooth devices are also installed along a section of the E4 motorway near the central Stockholm area. The previous study on AVI travel time estimation by Ma and Koutsopoulos (2010) focused on algorithm development for offline travel time estimation. Although the method can be used as a prediction approach, a system delay exists and it will be explained in the next section. In addition, due to the limited available data, historical information was not established for supporting real-time prediction. So this study intends to integrate live travel time data with historical patterns, and develop an effective prediction approach that can be easily implemented in real application. The next section elaborates the methodological approaches concerning the prediction models. Section 3 evaluates the methods using travel time data collected by ANPR system. Section 4 concludes the paper and points out future research potentials.
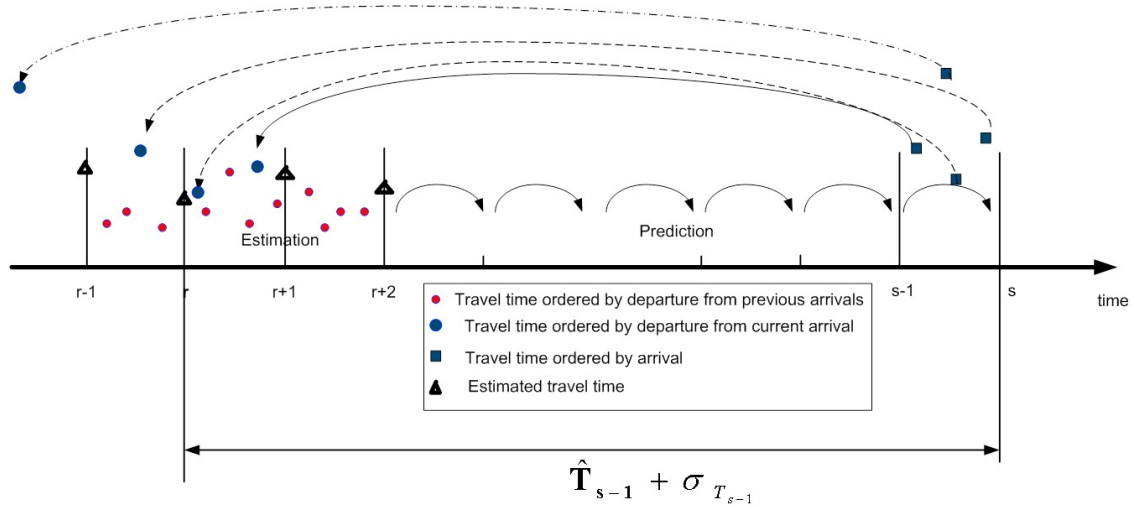
Fig. 1: An illustration of delayed measurement issues in real-time travel time system

2. Travel time prediction

2.1. Basic problem

Travel times between any pair of origin A and destination B are measured based on vehicle identification at the two stations. For example, the ANPR camera-based system are capable of recording timestamps that a vehicle is passing observing stations of the route. In Fig 1, we simply illustrate the basic travel time estimation problem. If a vehicle travels from the station A to B with the arrival (or entry) time t_A and the exit time t_B, the travel time is thus derived as the elapsed time between them, i.e.

$$TT(t_A) = t_B - t_A \tag{1}$$

where TT(t) is the travel time from the arrival point A to exit point B. Since one objective of the information system is to reflect real-time traffic conditions and inform other travelers with a proper route or departure time, the Eq. 1 represents, therefore, the travel time information at the entry time i.e. $t = t_A$. However, as it is obviously not possible to know the exact travel time unless a vehicle exits, the system in the previous studies (e.g. S.R.I., 2000) normally publishes the travel time estimated according to exits, i.e. $t = t_B$. This indicates a system delay depending on the route length between the two stations. In order to develop a truly real-time travel time information system, such delay should be considered in the principle formulation.

The delayed measurement problem can be illustrated by considering a real-time implementation where measurements are aggregated at fixed time interval, and prediction is then made for the next intervals in the future. This recalls the state space model formulation that we indeed apply in the later part of the paper. Fig. 1 shows a real-time scenario, and considers also delay in making measurements available to a real-time algorithm. The nth vehicle measurement has the measured arrival time $t_a[n]$ and the exit time stamp $t_e[n]$.

To address this problem, upon receiving the delayed measurement one must go back to previous time intervals and update the estimates accordingly. This approach is described in Algorithm 1. When real-time observations come to the system at time interval s, the observations $1...m_s$ are relocated backwards according to their arrival time t_a. The previous interval r, which receives new information, includes the new observation in the dataset for the correspond interval i.e. $TT_{set}[r]$. Thus, new measurements are aggregated for prediction and incoming measurements are added to TT_{set}. In the algorithm, the look-back window is bounded by a maximum value W. After all data in the interval are relocated, the prediction will be performed for the updated dataset. Indeed, the prediction algorithm we used in this study is based on Kalman Filter (KF), described in the next section.

```
1  TT_set = [] ;
2  for s=1 to N do
3  |    w_max = 0 ;
4  |    for i=1 to m_s do
5  |    |    n = dataind(i) ;                              /* The data index at arrival */
6  |    |    w_back = t_e[n] − t_a[n] ;
7  |    |    if w_back < W then
8  |    |    |    r = tind(t_s − w_back) ;
9  |    |    |    w_max = max(w_max, w_back) ;
10 |    |    |    TT_set[r] = TT_set[r] ∪ TT[n] ;
11 |    |    end
12 |    end
13 |    run one-step estimation and prediction from t_s − w_max to t_s ;
14 end
```

Algorithm 1: Implementation of the prediction algorithm considering delay in vehicle re-identification.

2.2. Kalman filter-based prediction models

Kalman filters have been a popular approach applied in the previous studies for travel time predictions (e.g. Nanthawichit et al., 2003; Chen and Chien, 2001). For AVI data, our previous study also tried to estimate travel time using only daily data (Ma and Koutsopoulos, 2008). Linear KF was applied to carry out estimation based on a state-space model of the deviation of travel times between two neighboring time intervals. This section starts with introduction of the KF algorithm and then proposes two models using historical travel time information.

2.2.1. Extended Kalman Filter

Given the properties of online travel time measurement, state-space model is a natural framework to estimate and predict travel time time series. As known, Kalman filter provides sequential procedures that solve the state-space model in an optimal way. This section briefly reviews the Kalman filtering theory. In engineering, there is a common problem to obtain an optimal state estimator for a linear state-space model as follows:

$$
\begin{aligned}
\mathbf{x}(t+1) &= \mathbf{F}(t) \cdot \mathbf{x}(t) + \mathbf{D}(t) \cdot \mathbf{u}(t) + \mathbf{G}(t) \cdot \mathbf{e}(t) \\
\mathbf{y}(t) &= \mathbf{H}(t) \cdot \mathbf{x}(t) + \mathbf{v}(t) + \mathbf{m}(t),
\end{aligned}
\tag{2}
$$

where $\mathbf{x}(t)$ is the real state at time t; $\mathbf{y}(t)$ is the measurement; $\mathbf{u}(t)$ and $\mathbf{v}(t)$ are the control and measurement inputs; $\mathbf{e}(t)$ and $\mathbf{m}(t)$ are white noise for state and observation equations, respectively. The conventional Kalman filter (Kalman, 1960) has been a standard approach for linear system estimation. The estimator at time t is defined by $\hat{\mathbf{x}}(t|t) = \mathbb{E}[\mathbf{x}(t)|\mathbf{y}(0) \cdots \mathbf{y}(t)]$. In linear Kalman filter, $\mathbf{P}(t|t-1)$ and $\mathbf{P}(t|t)$ are the covariance matrices of a prior and posterior error on $\mathbf{x}(t)$ respectively, and $\mathbf{R}_e(t)$ and $\mathbf{R}_m(t)$ are the covariance matrices of the white noise processes in the plant and measurement model respectively.

However, nonlinear dynamics is often involved in reality in the form as follows:

$$
\begin{aligned}
\mathbf{x}(t+1) &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t) + \mathbf{e}(t) \\
\mathbf{y}(t) &= \mathbf{h}(\mathbf{x}(t), \mathbf{v}(t), t) + \mathbf{m}(t).
\end{aligned}
\tag{3}
$$

where $\mathbf{f}(\cdot)$ and $\mathbf{h}(\cdot)$ are nonlinear state (or plant) and observation functions. To develop an algorithm for this case, Taylor expansion can be used to approximate the nonlinear system equation (3). Let us introduce the following Jacobian matrices for the nonlinear state and measurement equations respectively, i.e.,

$$
\begin{aligned}
\mathbf{F}(t) &= \nabla_{\mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{u}(t), t)|_{\mathbf{x}=\hat{\mathbf{x}}(t|t)} \\
\mathbf{H}(t) &= \nabla_{\mathbf{x}} \mathbf{h}(\mathbf{x}, \mathbf{v}(t), t)|_{\mathbf{x}=\hat{\mathbf{x}}(t|t-1)}.
\end{aligned}
\tag{4}
$$

State update (prediction):

$$\hat{\mathbf{x}}(t|t-1) = \mathbf{f}(\hat{\mathbf{x}}(t-1|t-1), \mathbf{u}(t-1), t-1)$$
$$\mathbf{F}(t-1) = \nabla_{\mathbf{x}}\mathbf{f}(\mathbf{x}, \mathbf{u}(t-1), t-1)|_{\mathbf{x}=\hat{\mathbf{x}}(t-1|t-1)}$$
$$\mathbf{P}(t|t-1) = \mathbf{F}(t-1)\mathbf{P}(t-1|t-1)\mathbf{F}(t-1)^T + \mathbf{R}_e(t)$$

Measurement update (correction):

$$\mathbf{H}(t) = \nabla_{\mathbf{x}}\mathbf{h}(\mathbf{x}, \mathbf{v}(t), t)|_{\mathbf{x}=\hat{\mathbf{x}}(t|t-1)}$$
$$\Gamma(t) = \mathbf{P}(t|t-1)\mathbf{H}(t)^T[\mathbf{H}(t)\mathbf{P}(t|t-1)\mathbf{H}(t)^T + \mathbf{R}_m(t)]^{-1}$$
$$\hat{\mathbf{x}}(t|t) = \hat{\mathbf{x}}(t|t-1) + \Gamma(t)(\mathbf{y}(t) - \mathbf{h}(\hat{\mathbf{x}}(t|t-1), \mathbf{v}(t), t))$$
$$\mathbf{P}(t|t) = (I - \Gamma(t)\mathbf{H}(t))\mathbf{P}(t|t-1)$$

Table 1: The Discrete-Time Extended Kalman Filter Algorithm

The approximation leads to the extended Kalman filter (EKF) algorithm in Table 1. In practice, EKF often performs well in solving state estimation problems with nonlinear state-space models. In particular, it fits for systems with relatively smooth nonlinearities or high measurement frequency.

2.2.2. Basic formulation based on historical median

In this application, state-space formulations are introduced to model AVI travel time data. In comparison to the previous effort on AVI travel time estimation (Ma and Koutsopoulos, 2010), a large amount of historical data are accumulated and applied in this study. The idea is to introduce models that integrate both historical and lively observed data for real-time prediction purpose. Let $ttn_m(k)$ denotes the median of all travel-time measurements available at time interval k and $ttn(k)$ is the corresponding state of travel time while $tth(k)$ represents the historical median for k. The new state $dT(k)$ is introduced as the difference (or innovation) of log-transform of the two state variables:

$$dT(k) = \log(ttn(k)) - \log(tth(k)). \tag{5}$$

The essential idea is to model the process $dT(k)$ using a random walk approach, but with adaptive parameters representing the non-stationary property in the innovation data sequence. Hence, the prediction model (Model 1) is formulated as follows:

$$dT(k+1) = \theta(k)dT(k) + m_1(k) \tag{6}$$
$$\theta(k+1) = \theta(k) + m_2(k) \tag{7}$$
$$dT_m(k) = dT(k) + n_1(k) \tag{8}$$

where $m_1(k)$, $m_2(k)$ and $n_1(k)$ are all white noise. The coupling of $\theta(k)$ and $dT(k)$ in the first equation makes the state transition model a nonlinear form. So EKF should be applied for state estimation and prediction. If the state vector is represented by $\mathbf{x}(\mathbf{k}) = \begin{bmatrix} dT(k) & \theta(k) \end{bmatrix}^T$, the Jacobian is represented by

$$\mathbf{F}(k) = \nabla_{\mathbf{x}}\mathbf{f}(k) = \begin{pmatrix} \theta(k) \\ dT(k) \end{pmatrix}. \tag{9}$$

The noise covariance matrices $\mathbf{R_1}$ and $\mathbf{R_2}$ are for model and measurement respectively.

2.2.3. Advanced model based on historical percentiles

While the inclusion of historical median makes real-time prediction model less sensitive to corrupted noise, the information on historical travel time distribution is not even used. The second model we proposed is to include historical travel time percentiles at aggregated intervals. The hypothesis is that more distribution information will enhance the

quality and robustness of travel time prediction. When calculating historical percentiles, empirical analysis promotes us to apply log-normal distribution for interval travel time data. Based on this idea, three innovation sequences are introduced as follows:

$$dT(k) = log(ttn(k)) - log(tth_{50}(k)) \tag{10}$$

$$dT_{low}(k) = log(ttn(k)) - log(tth_{25}(k)) \tag{11}$$

$$dT_{high}(k) = log(ttn(k)) - log(tth_{75}(k)) \tag{12}$$

where $ttn(k)$ is the state variable for time interval k, and $tth_p(k)$ is the pth percentile of historical data at interval k. The state transition model is:

$$dT(k + 1) = \theta(k)dT(k) + m_1(k) \tag{13}$$

$$dT_{low}(k + 1) = \theta_{low}(k)dT_{low}(k) + m_2(k) \tag{14}$$

$$dT_{high}(k + 1) = \theta_{high}(k)dT_{high}(k) + m_3(k) \tag{15}$$

$$\theta(k + 1) = \theta(k) + m_4(k) \tag{16}$$

$$\theta_{low}(k + 1) = \theta_{low}(k) + m_5(k) \tag{17}$$

$$\theta_{high}(k + 1) = \theta_{high}(k) + m_6(k) \tag{18}$$

and the measurement model is:

$$dTm(k) = dT(k) + n_1(k) \tag{19}$$

$$dTm_{low}(k) = dT_{low}(k) + n_2(k) \tag{20}$$

$$dTm_{high}(k) = dT_{high}(k) + n_3(k). \tag{21}$$

This indicates that travel time can be derived by:

$$tt = \sqrt[3]{tth_{50} \, tth_{25} \, tth_{75} \, exp(dT + dT_{low} + dT_{high})} \tag{22}$$

The measurement noise covariance matrix can be assumed to be diagonal. But it was not apparent how to treat the process noise. Empirical experiments show that good results could obtained using also a diagonal process covariance. Similar to Model 1, the coupling of θ and dT in Model 2 makes the transition model nonlinear. If we define $\mathbf{x}(k) = \left[dT(k) \, dT_{low}(k) \, dT_{high}(k) \, \theta(k) \, \theta_{low}(k) \, \theta_{high}(k) \right]^T$ with noise covariance matrices $\mathbf{R_1}$ and $\mathbf{R_2}$. EKF algorithm in Table 1 can be applied to predict real-time travel time with Jacobian calculated by:

$$\mathbf{F}(k) = \left[\theta(k)dT(k) \, \theta_{low}(k)dT_{low}(k) \, \theta_{high}(k)dT_{high}(k) \, \theta(k) \, \theta_{low}(k) \, \theta_{high}(k) \right]^T. \tag{23}$$

The measurement matrix is described by $\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$

3. Evaluation results and discussion

The study has applied the models proposed in the last section in travel time prediction algorithm considering system delay. Several months of ANPR data mentioned early are applied in model evaluation. The major part of the data are used as historical information for estimating percentiles by interval. Implementing the models requires setting values for the noise covariance matrices $\mathbf{R_1}$ and $\mathbf{R_2}$, as well as initializing the state estimate $\hat{\mathbf{x}}_{1|1}$ and estimation covariance $\mathbf{P}_{1|1}$. One common problem in observing the state is that for some time steps, no measurements or too few measurements may be available. Therefore, initializing the state to a measurement requires carefully selecting the starting time in which the filter runs. One solution to this problem that we favor is to initialize the state to the historical median measurement of the starting time step, which in our implementation is time 00:00. This approach overcomes the problem of a lack of measurements and is found to provide suitable initialization since time 00:00
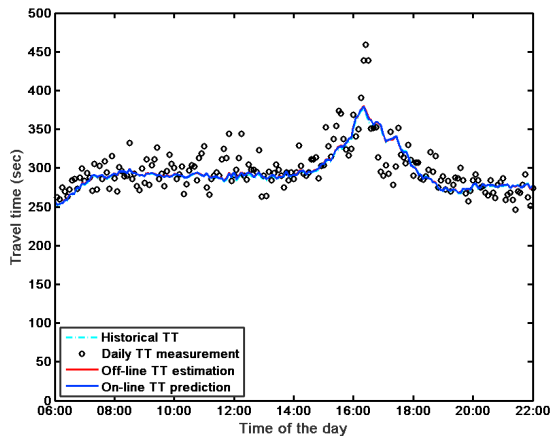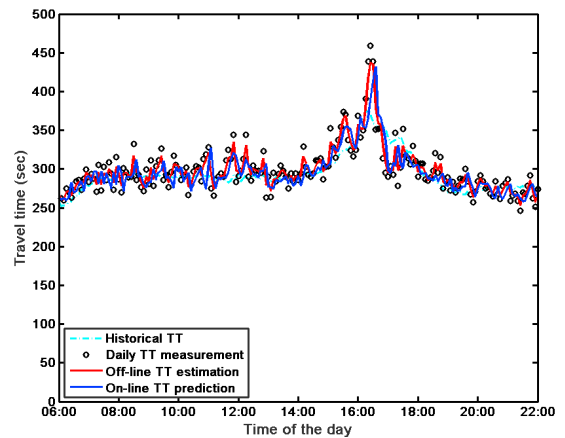
(a) Route 2 with noise ratio 0.001
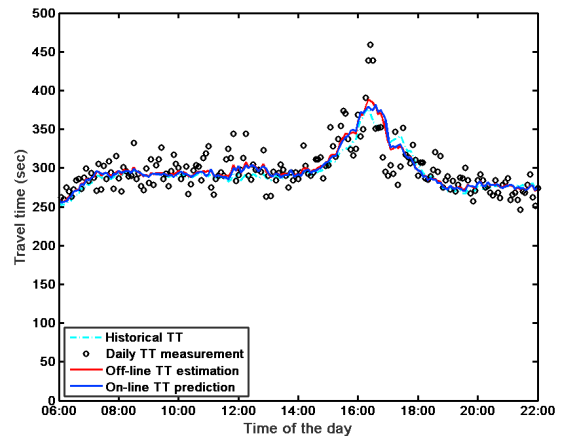
(b) Route 2 with noise ratio 0.01
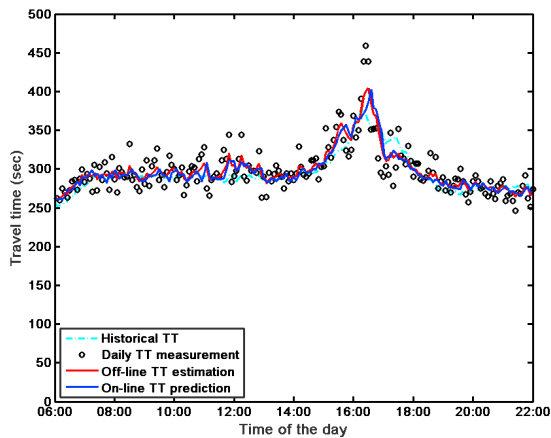
(c) Route 2 with noise ratio 0.1

(d) Route 2 with noise ratio 1

Fig. 2: Sensitivity analysis for different noise ratios (TT refers to travel time)

in historical data offers the lowest noise for many routes. We use the historical median also when fewer than two real-time measurements are available at any other time step in the day when the filter is running. As for the estimation covariance, $\mathbf{P}_{1|1}$ is initialized to $100\,\bar{\mathbf{I}}$, where $\bar{\mathbf{I}}$ is the 2×2 identity in the case of Model 1, or the 6×6 identity in the case of Model 2. The factor of 100 is sufficiently high to prevent the filter from prematurely converging, and with time evolving, the elements of $\mathbf{P}_{k|k}$ are seen to become converging.

Sensitivity analysis was performed to find suitable values of process and measurement noise covariances. It was assumed that the noise on the states and measurements are independent, and scalar multiples of identity matrices for simplicity. For Model 1, $\mathbf{R}_1 = \sigma_1^2 \mathbf{I}_{2\times2}$ and $\mathbf{R}_2 = \sigma_2^2$. For Model 2, $\mathbf{R}_1 = \sigma_1^2 \mathbf{I}_{6\times6}$ and $\mathbf{R}_2 = \sigma_2^2 \mathbf{I}_{3\times3}$. Fig. 2 compares the performance of EKF of Model 1 for different σ_1^2/σ_2^2 noise ratios. For the noise ratio of 0.001, we find that the filter closely follows historical data, and does not respond to measurements. This is because the model is viewed as much more reliable than measurements. On the other hand, for a noise ratio of 1, we see that the filter is highly influenced by measurements, with estimation and prediction curves no longer smooth. The noise ratio of 0.01 achieves a good balance and is able to follow the measurements smoothly. Noise ratios in the order of 0.01 and 0.1 were therefore seen to give best performance for most cases.
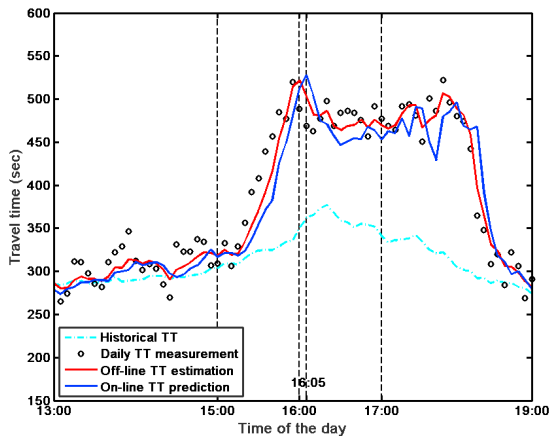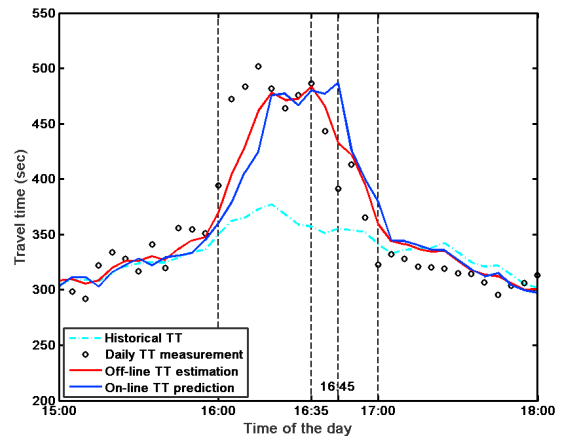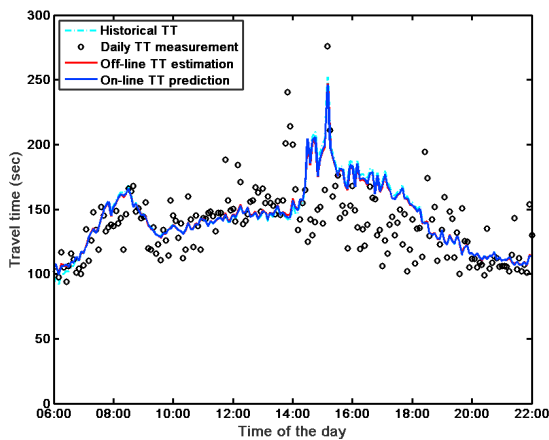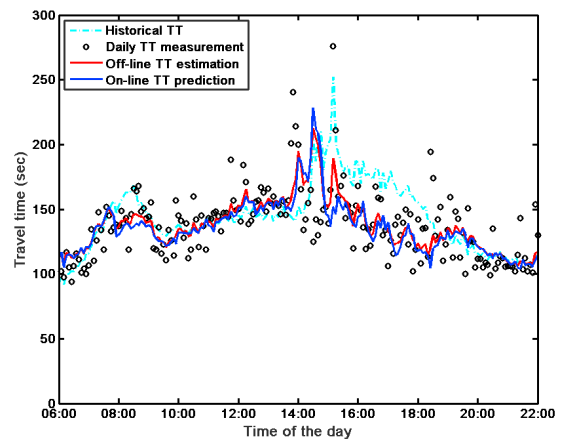
(a) 2012-10-11   (b) 2012-10-18

Fig. 3: Demonstrations of delayed travel time prediction for route 2 (TT refers to travel time)

(a) Model 1   (b) Model 2

Fig. 4: Comparison results between model 1 and model 2 for route 34 (TT refers to travel time)

The delay problem in real-time prediction can now be examined for cases where unexpected congestion occurs. Fig. 3 shows two examples of such cases, where the online prediction curve based on only measurements from completed journeys is compared to the offline estimation curve obtained with all measurements available. In both cases, the congestion behaviors deviates from historical travel-time. Fig. 3a shows the congestion build-up in the 11th of October, a delay of about 5 minutes is marked. A similar but shorter-lived congestion occurs on the 18th and is seen in Fig. 3b, with a delay also observed. In this case, a 10-minute delay in congestion dissipation is marked. When the travel times are in the range of 5 to 6 minutes, delays of 5 to 10 minutes are quite significant.

Having found good noise ratios for the filter, we proceed to compare the performance of models 1 and 2 for different scenarios. For the same noise ratio setting of 0.01, Fig. 4 illustrates the benefit of incorporating upper and lower percentiles into the filter. As can be seen, the noise in this test case is significant, and outliers are present. Fig. 4a shows the behavior of model 1, where the filter almost completely disregards the measurements in favor of the model, indicating that the measurement noise is more than it can tolerate. On the other hand, much better trend following ability is demonstrated for model 2, as seen in Fig. 4a. In particular, the filter is able to find the trend from 14:00 till
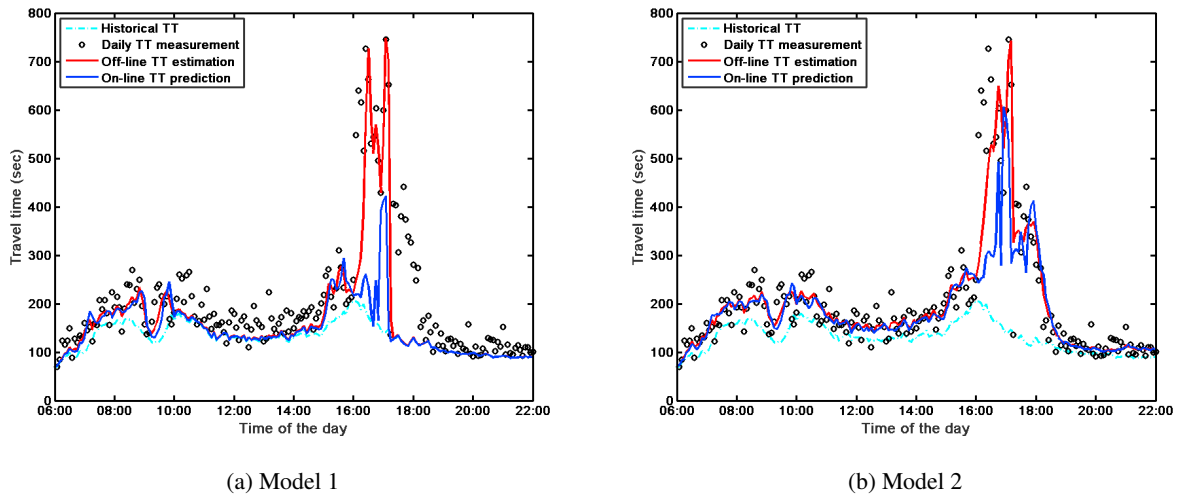
(a) Model 1   (b) Model 2

Fig. 5: The capability of incident detection for model 1 and model 2 (TT refers to travel time).

18:00, which deviates from the historical estimate, and better handle the noisy data. In model 2, less reliance is placed on the historical median. The model becomes sensitive also to the deviation of median measurement from historical upper and lower percentiles, when the percentiles are used in the model, which helps capture the trend.

The trend following benefit in model 2 can also be seen in Fig. 5. Fig. 5a shows the performance of model 1, while Fig. 5b shows the performance of model 2 for the same test case. During the period from 10:00 to 14:00, we see that model 1 favors the historical median and does not respond adequately to the data. Model 2, on the other hand, is more sensitive to the measurements. The period between 16:00 to 20:00 contains an incident and is a challenge for the filters. The delay of around 40 minutes in responding to the congestion build-up is much more severe in model 1, while model 2 was able to respond much better, with a delay of around 15 minutes. During the dissipation, model 2 was also able to follow the trend nicely starting at around 18:00.

4. Conclusions and future work

This paper has proposed a statistical approach to carry out real-time travel time prediction using both historical interval information and online data. Two parametric models in terms of state-space form are presented. The first state-space model is formulated based on the idea of modeling the difference of log-transform of current interval travel time and its corresponding historical interval median. The second model extends the idea by involving two historical interval percentiles. Both models assume non-stationary property in travel time sequence that has to be modeled by time-varying parameters. EKF has been applied as the major estimation algorithm. In the algorithm formulation, system delay due to the requirement of vehicle re-identification is considered. This means the EKF-based algorithm has to be running in a recursive way while responding to the measurements received in real-time.

Travel time data of ten selected routes in Stockholm collected by ANPR system are analyzed in our case study. The results show that the prediction algorithm can capture the live trends even when congestion builds up or dissolves in a rather fast pace, although certain delay still exists in the estimates. Model 2 considering historical percentiles shows advantages over Model 1 in capturing the fluctuation of travel time, therefore leading to more robust results.

In the future, the multiple-step prediction results should be further compared with other approaches. Some performance indexes can be applied to evaluate different algorithms. One limitation of the approach lies in the determination of the noise ratio σ_1^2/σ_2^2, which requires efforts on sensitivity tests. It should be possible to include it in the future model so that the most appropriate parameter can be identified from optimization. In addition, the current work has not consider correlation between different roads. A natural extension is to include spatial relation in the model formulation.

Acknowledgements

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