TRAFFIC STATE ESTIMATION USING TRAFFIC DATA FROM FIXED DETECTORS AND PROBE VEHICLES*

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1. Introduction

As availability and reliability of observed traffic data significantly affect the accuracy of traffic state estimation, traffic data from probe vehicle technique, which has a potential of network coverage, might be useful to improve the traffic state estimation. The applications of probe vehicle data are still limited as they mostly concentrated on travel time detection, such as in Chen[1), while some authors has used probe data to estimate O-D data, and detect incidents[2). As knowledge of the authors, so far, no work has applied the probe data with the macroscopic model to estimate traffic states. In fact, fundamental traffic state variables (traffic volume, space mean speed, and traffic density) have some advantages over travel time, such as, they are better to reflect traff conditions; they have a capability to convert to other variables. The objective of this study is to propose a method for integrating probe vehicle data into fixed detector data for estimating traffic states on a freeway. The Kalman filtering technique (KFT) is applied to update the state variables estimated by a macroscopic model. Firstly, the formulation of the proposed method, which considers how to treat the observation variables for the KFT in order to overcome the inconsistency of observation data, will be presented. Then, the methodology will be examined using several sets of hypothetical data under different traffic conditions

2. Probe Vehicle Technique

The probe vehicle concept is the monitoring technique that uses the vehicles as the moving sensors traveling in traffic, in contrast to the fixed detectors such as inductive loops, which exist only limited locations. The probe vehicle is a vehicle that measures and reports traffic flow conditions to roadside devices as real-time manner. A sufficient large number of probe vehicles should reasonably represent the traffic conditions that they experienced. With such mechanism, data from the links that no detector installed can be obtained.

Generally, there are three possible approaches by which probe vehicles can transmit traffic information.

1) Space-based probe data: probe vehicles transmit traffic information to roadside devices as they pass observation points.
2) Time-based probe data: probe data are reported at every specific time instant regardless of the probe vehicle position.
3) Event based probe data: traffic information is reported when a particular event occurs, for example, traffic accident or incident reports from drivers by cellular phone.

In this study, the second approach was adopted. Compared to the first approach, the second has a higher potential for covering the entire network. The anecdotal report as the third method is not applicable for our estimation problem.

3. Traffic State Estimation

Traffic state information is essential for the development of efficient control strategies and management schemes for traffic systems. Unfortunately, by mean of field observation, it is impossible to obtain such traffic data for a large network. Therefore, traffic state estimation is necessary. The common way to estimate traffic states is to use mathematical models.

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However, the results from static mathematical models seem to be not sufficient for real time applications. As a result, several strategies were introduced to apply with the models for real-time traffic prediction, such as artificial neural network, and KFT.

(1) Macroscopic Traffic Flow Model

The Payne's[3] macroscopic traffic flow model was selected to apply in this study due to its simplicity to integrate with other techniques, including the KFT. It is composed of three relationships as the followings.

$$\frac{\partial \rho}{\partial t}+\frac{\partial q}{\partial x}=g(x,t) \tag{1}$$

$$q=\rho v \tag{2}$$

$$\frac{\partial v}{\partial t}+v\frac{\partial v}{\partial x}=\frac{1}{\tau}\left[v-v_e(\rho)\right]-\frac{\nu}{\tau\rho}\frac{\partial \rho}{\partial x} \tag{3}$$

where t indicates time increment, whereas x indicates space increment. ρ, v, and q are the fundamental traffic state variables, which are density, space mean speed, and traffic volume, respectively. v_e is the speed at equilibrium state, which can be obtained from density-speed curve. τ, and ν are model parameters.

(2) Formulation of State Estimation Model

To estimate the traffic state variables in real-time, we apply the KFT with the macroscopic traffic flow model. Traffic state is first estimated by the macroscopic model. Then, as the system receives the observation variables, the estimated state variables are adjusted using the KFT. The adjustment of state variables is proportional to the difference between observed values and model predicted values of observation variables. This method has been used by Cremer[4], and Suzuki[5]. In their study, the state variables are traffic density and space mean speed, $\mathrm{x}(t)=(\rho,v)_{(t)}$, whereas traffic volumes and spot speeds are treated as obsevation variables, $\mathrm{y}(t)=(q,w)_{(t)}$; where w is the time mean speed measured from detectors. According to the macroscopic model system equations, the continuity equation (Eq.1) and the momentum equation (Eq.3) are treated as state equations, while observation equations consist of Eq. 2 and the relationship between spot speed and state variables. The linearized model of KFT has the form of:

$$\tilde{\mathrm{x}}(t+1)\cong \mathrm{f}\left[\hat{\mathrm{x}}(t)\right]+\frac{\partial \mathrm{f}}{\partial \mathrm{x}}\left(\mathrm{x}(t)-\hat{\mathrm{x}}(t)\right)+\xi(t)\cong A(t)\cdot x(t)+b(x)+\xi(t) \tag{4}$$

$$\tilde{\mathrm{y}}(t)\cong \mathrm{g}\left[\mathrm{x}(t)\right]+\frac{\partial \mathrm{g}}{\partial \mathrm{x}}\left(\mathrm{x}(t)-\tilde{\mathrm{x}}(t)\right)+\zeta(t)\cong C(t)\cdot x(t)+d(t)+\zeta(t) \tag{5}$$

$\tilde{\mathrm{x}}(t)$ and $\hat{\mathrm{x}}(t)$ are the estimated state vector before and after obtaining actaul measurement data, $\mathrm{y}(t)$, respectively. where $\xi(t)$ and $\zeta(t)$ are noises vectors representing the modeling errors and measurement errors. The state variables can be adjusted according to the correction steps of the KFT as described in **Fig.1**.

(3) Integration of the probe data into the state estimation problem

We modeled a road section as shown in **Fig. 2.** The road section was discretized so that fixed detectors, if any, were located at approximately the middle of a certain segment (except for the detectors at the entrance and exit points of the road

step 1: estimate state variables for the current step, *t;* $\tilde{\mathrm{x}}(t)=\mathrm{f}\left[\hat{\mathrm{x}}(t-1)\right]$

step 2: calculate error matrix of $\tilde{x}(t)$ at time *t;*

$\mathrm{M}(t)=\mathrm{A}(t-1)\mathrm{P}(t-1)\mathrm{A}^T(t-1)+\Phi$

step 3: calculate Kalman gain matrix at time *t;*

$\mathrm{K}(t)=\mathrm{M}(t)\mathrm{C}^T(t)\left[\mathrm{C}(t)\mathrm{M}(t)\mathrm{C}^T(t)+\mathrm{Z}\right]^{-1}$

step 4: estimate observation variables at time *t;* $\tilde{\mathrm{y}}(t)=\mathrm{g}\left[\tilde{\mathrm{x}}(t)\right]$

step 5: update estimated state variables; $\hat{\mathrm{x}}(t)=\tilde{\mathrm{x}}(t)+\mathrm{K}(t)\left[\mathrm{y}(t)-\tilde{\mathrm{y}}(t)\right]$

step 6: update error matrix of $\hat{\mathrm{x}}(t)$; $\mathrm{P}(t)=\mathrm{M}(t)-\mathrm{K}(t)\mathrm{C}(t)\mathrm{M}(t)$

set $t=t+1$, go to step 1 and repeat all steps

note: Φ and Z are covariance matrices of $\xi(t)$ and $\zeta(t)$.

Figure 1 Kalman filtering updating algorithm

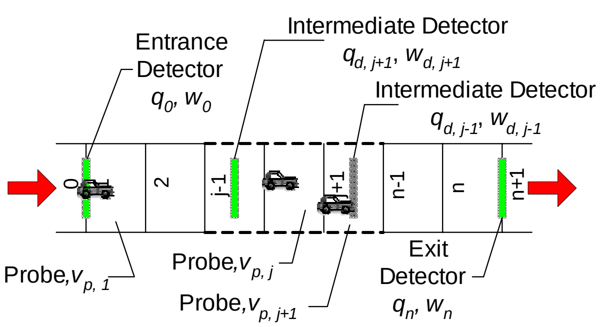

Figure 2 Road section with probe vehicles and fixed detectors

section) to avoid influence from neighboring segments in the calculation of the observation variables. This is what differs from the conventional approach, which models so that detectors are locate at segment boundaries. Here, we could assume that the observed speed from the fixed detector, $w_{d,j}$, is the observation variable of space mean speed of the segment, and the observed volume from the fixed detector, $q_{d,j}$, is the observation variable of the segment flow.

It is assumed that probe vehicles could submit their speed along with their current position, regardless of where they are. At every time step, the probe data are sorted by their location determined from which segment the data transmitted. Generally, probe data may not be available for all segments for every time step. As a result, the number of observation variables from probes is varying with time. For the segments where both detector and probe data are available, a data fusion technique is required for combining the data from different sources. In this study, for simplicity's sake, a weighted average of speed from both data sources was used.

The observation equations for the proposed method are composed of:

a) The observation equations at the entrance and exit detectors

$$q_0 = \rho_1 v_1 \quad , \quad w_0 = v_1 \tag{6),(7}$$

$$q_n = \rho_n v_n \quad , \quad w_n = v_n \tag{8),(9}$$

b) The observation equation for the segment that has fixed detector

$$q_{d,j} = \rho_j v_j \quad , \quad v_{d,j} = v_j \tag{10),(11}$$

where j identifies the number of segments with a fixed detector. v_{dj} is the observed speed from detector, in case that no probe data is available, while it is equal to the integrated speed from both fixed detector and probe vehicle data at a certain time step when probe data are available.

c) The observation equation for the segments where only probe data are available

$$v_{p,h} = v_h \tag{12}$$

where $v_{p,h}$ is the observed speed from the probe vehicles; and h identifies the segment that has only probe data.

The method proposed features the ability to deal with inconsistencies in observation data. According to the considerations above, the total number of observation variables is changeable with time. At a certain time step t, the number of observation variables is equal to $4+2m+p_0(t)$, where $p_0(t)$ is the number of segments where only probe data are available; m is the number of segments with fixed detector.

4. Numerical Experiments

(1) Traffic Data

A 5,550m road section was modeled as shown in **Fig. 3**. The road section is divided into nine segments ranging from 400m to 800m with two on-ramps and one off-ramp. The road section has three fixed detectors located at the entrance and exit boundaries and at the middle of segment 5. As the availability of probe data is still limited, the INTEGRATION[6)] software, which has various features suitable for ITS applications including the capability to generate fixed detector data and probe vehicle data, after careful calibration and validation with real traffic data, was used to generate traffic data..

Six sets of 3-hour generated data were used to test the proposed method.

Cases A to C: Low density

Cases D to F: Wide range density

(2) Experimental Results

For each data case, four different estimation scenarios were compared.

Scenario 1 (S1): the macroscopic model only;

Scenario 2 (S2): the macroscopic model with the KFT using the data from a supplementary detector;

Scenario 3 (S3): the macroscopic model with the KFT using the probe data;

Scenario 4 (S4): the macroscopic model with the KFT using both the probe vehicle data and the supplementary fixed detector data

Table 1 summarizes the experimental results. It shows that, in all cases, the estimation error of average speed, in term of root mean square of error (RMSEv), is smallest when the estimates are updated using the traffic data from both fixed detectors and probe vehicles (S4). The largest error occurs in the scenario that the macroscopic model was used without integrating with KFT (S1). That is the macroscopic model sometimes fails to capture the real traffic flow condition, as shown

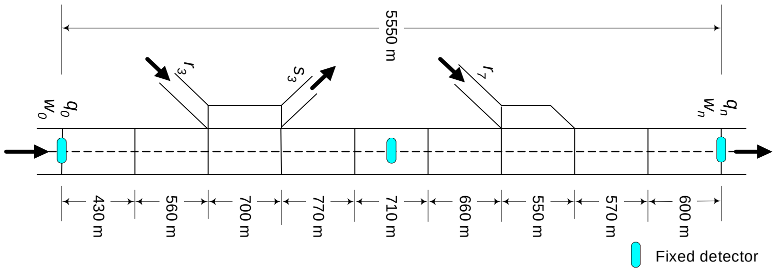

Figure 3 Geometry of the studied road section

Table 1 Error of the estimation

case	RMSEv			
	S1	S2	S3	S4
A	10.28	4.64	3.16	3.10
B	15.27	6.24	2.40	2.37
C	15.23	6.28	2.74	2.69
D	18.42	11.32	4.73	4.53
E	16.46	11.87	4.72	4.59
F	21.23	17.42	6.17	5.97

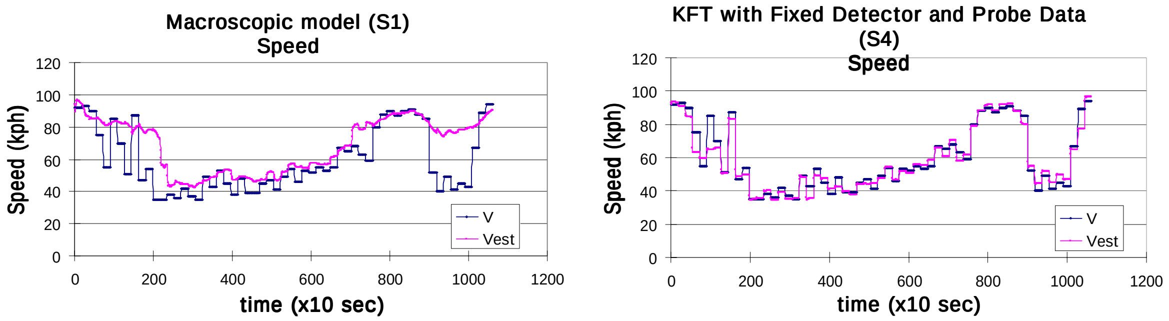

Fig. 4 Comparison of hypothetical data and its estimated values from different scenarios for link 6 of Case F (wide range)

in the speed from S1 of **Fig 4**. On the contrary, the profile of the estimated speed from S4 accurately follow the correct one, even in the abrupt change regions as shown around the time step of 900 to 1100 seconds in **Fig. 4**. Quantitatively, S4 could reduce the RMSEv by 70-85% compared with S1. Comparing among the scenarios which use the data from only one source, S2, which utilizes fixed detector data, provides poorer estimation results than S3, which uses probe data. The distance between detectors might affect this result. In other words, to provide the estimation accuracy on the same level as S3 and S4, larger number of detecting points from fixed detector is required in S2.

5. Conclusion

A method for treating probe vehicle data together with fixed detector data in order to estimate the traffic state variables of traffic volume, space mean speed and density was proposed. The method used a macroscopic model along with the Kalman filtering technique (KFT). The method can treat both conventional fixed detector data and probe vehicle data in a unified manner, regardless of the observation conditions, due to its ability to deal with the inconsistencies in the probe vehicle data (i.e. the probe data may not be available for the whole simulation period in a certain segment).

The method was verified with several traffic data sets generated by the INTEGRATION simulation program. Experimental results indicate that traffic state estimates could be improved using the combination of observation data from several sources (i.e. fixed detector and probe vehicle).

References

1) Chen, M., *et al.*: Dynamic freeway travel time prediction using probe vehicle data: link-based vs. path-based, Transportation Research Board 80th Annual Meeting (Preprint CD-ROM, paper no.01-2887), 2001.
2) Sethi, V., *et al.*: Arterial incident detection using fixed detector and probe vehicle data, Transportation Research-C, Vol. 3C(2), pp. 99-112, 1995.
3) Payne, H.J.: Models of freeway traffic and control, Simulation Councils Proceedings Series: Mathematical Models of Public Systems, Vol. 1, No.1, pp. 51-61, 1971.
4) Cremer, M.: Der Verkehrsfluβ auf Schnellstraβen, Springer Verlag, New York, 1979.
5) Suzuki, H., and Nakatsuji, T.: A new approach to estimate freeway OD travel time based on dynamic traffic states estimation using feedback estimator, J. Infrastructure Planning and Management, No. 695/IV-54, pp. 137-148, 2002.
6) Van Aerde, M., *et al.*: INTEGRATION Release 2.30 for Windows: User's Guide, M. Van Aerde & Assoc., Ltd., Ontario, 2001.