【土木計画学研究・講演集 No.21 (2) 1998年11月】

SIMULTANEOUS ESTIMATION OF DYNAMIC O-D TRAVEL TIME AND FLOW USING A NEURAL-KALMAN FILTER WITH MACROSCOPIC TRAFFIC MODEL*

by Hironori SUZUKI**, Takashi NAKATSUJI*** and Yordphol TANABORIBOON ****

1. Introduction

So far, two types of approaches have been directed to estimate dynamic origin-destination (O-D) travel time and flow. One is the approach that estimates O-D travel time and flow based on drivers' behavior models. When the information on current O-D travel time, traffic states and accident points are known, the model estimates how many vehicles diverge at intersections and how long it takes for them to get to destinations. Travel simulators are used to collect data on drivers' response to the traffic information in order to describe drivers' behavior [1]. In spite of extensive efforts, the drivers' behavior models may not be reliable because they are not successful in expressing actual drivers' behavior.

The other is the measurement data oriented approach which estimates dynamic O-D travel time and flow indirectly from measurable detector outputs such as link traffic volume and time mean speed. Cremer and Keller [2] first tackled dynamic O-D flow estimation problem for a large complicated intersection. By counting entering and exiting traffic volumes at the intersection, dynamic O-D flows were estimated recursively. Later Cremer and Keller [3] modified this method as a Kalman filter problem. Bell [4] developed time-dependent O-D flow estimation model based on the approach by Cremer and Keller [2]. This model has taken the platoon dispersion phenomenon into consideration as it is applied to a road network. The approaches by Cremer and Keller [2,3] and Bell [4] are applicable only for an intersection or for a small road network. Studies by Ashok and Ben-Akiva [5], Chang and Wu [6] attempted to estimate either dynamic O-D travel time or flow for a long distance freeway corridor by Kalman filter technique. Ashok and Ben-Akiva [6] estimated dynamic O-D flows from link traffic counts alone, while Chang and Wu [7] used link traffic counts as well as exit volume for estimating O-D flows.

Only a few studies have been reported for estimating dynamic O-D travel time. Cremer [8] estimated space mean speed by a macroscopic traffic model and calculated link travel time by dividing link length by the speed. O-D travel time is then given by summing up the link travel times along an O-D pair. Fu and Rilett [9] formulated an artificial neural network (ANN) model for estimating dynamic O-D travel time on urban road networks. The O-D travel time is estimated from variables such as coordinates and distance of O-D pair and departure time of vehicles. Wakao et al. [10] proposed a method for estimating dynamic O-D travel time based on a Kalman filter technique with a macroscopic traffic simulation model.

The measurement data oriented approach can be applied to estimate dynamic O-D travel time and flow, but there are some problems associated with this approach. These problems are: (1) No model is applicable for estimating O-D travel time and flow simultaneously within one process, (2) The Kalman filter technique cannot give accurate estimation of O-D travel times if traffic states on road section of O-D pairs are not predicted in advance [10], (3) It is sometimes difficult to define state and measurement equations of Kalman filter in analytical equations, (4) Summing up link travel times with discrete time steps results in inaccurate approximation of O-D travel time because the boundary between consecutive links does not always provide continuous travel time.

This study aims to develop a new model for estimating dynamic O-D travel time and flow on freeway corridors. The objectives of this study are: (1) To establish a method of estimating both dynamic O-D travel time and flow simultaneously, (2) To introduce a macroscopic traffic model for predicting traffic states in advance and investigate how the macroscopic model affects the estimation of O-D travel time and flow, (3) To employ ANNs for defining coefficient matrices in state and measurement equations of Kalman filter and analyze the effect of ANNs on the estimation of O-D travel time and flow.

Basic concept of the new model is presented in this paper. Chapter 2 briefly describes the model formulation including the definition of O-D travel time and flow, theory of Kalman filter, macroscopic model and ANNs. Chapter 3 discusses experimental analysis required for evaluating the proposed model. Concluding remarks and further recommendation are shown in the final chapter.

2. Model description

(1) O-D flow and travel time

a) O-D flow

Consider a freeway corridor (Figure 1) which consists of N road segments. For simplicity, only one way traffic is modeled. Each segment can have a pair of on and off-ramps. Note that:

$r_i(k)$ = the number of vehicles entering the freeway from on-ramp at segment i during time interval k ,

* Keywords : Traffic flow, Traffic management and Traffic information.

** Student Member of JSCE, Transportation Engineering Program, School of Civil Engineering, Asian Institute of Technology.
(Mailbox 661, AIT, P. O. Box 4, Klongluang, Pathumthani 12120, Thailand, TEL: +66-2-524-5515, FAX: +66-2-524-5509)
*** Member of JSCE, D. Eng., Associate Professor of Transportation Engineering Program, School of Civil Engineering, Asian Institute of Technology.
(P. O. Box 4, Klongluang, Pathumthani 12120, Thailand, TEL: +66-2-524-5511, FAX: +66-2-524-5509)
**** Non member, Ph. D., Associate Professor of Transportation Engineering Program, School of Civil Engineering, Asian Institute of Technology.
(P. O. Box 4, Klongluang, Pathumthani 12120, Thailand, TEL: +66-2-524-5517, FAX: +66-2-524-5509)

$s_l(k)$ = the number of vehicles leaving the freeway from off-ramp at segment l during time interval k,
$q_l(k)$ = the number of vehicles leaving the segment l during time interval k,
$w_l(k)$ = time mean speed of vehicles in the segment l at the beginning of time interval k,

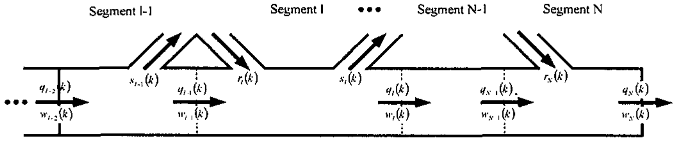

Figure 1 A freeway corridor

$x_{ij}(k)$ denotes an O-D flow between an O-D pair $i-j$ during time interval k. Then $r_l(k)$, $s_l(k)$ and $q_l(k)$ are respectively given by:

$$r_l(k)=\sum_{j=l}^{N} x_{lj}(k),\quad s_l(k)=\sum_{h=k-n}^{k}\sum_{i=1}^{l} b_{il}^{h}(k)x_{il}(h) \text{ and } q_l(k)=\sum_{h=k-n}^{k}\sum_{i=1}^{l} b_{il}^{h}(k)\left[\sum_{j=l+1}^{N} x_{ij}(h)\right], \tag{1}$$

with the constraints:

$$0\le b_{ij}^{h}(k)\le 1(1\le i\le j\le N, h=1,2,\ldots,k) \text{ and } \sum_{e=k}^{k+h} b_{ij}^{h}(e)=1(1\le i\le j\le N), \tag{2}$$

where n is the maximum number of time intervals required to travel between an O-D pair; $b_{ij}^{h}(k)$ denotes the fraction of the O-D flow that departed its origin i during time interval h and arrived at j during time interval k.

b) O-D travel time

If an O-D pair consists of several consecutive road segments, the O-D travel time can be calculated as sum of link travel times. Given space mean speed, the link travel time $T_l(k)$ on segment l can be written as: $T_l(k)=\Delta_l/v_l(k)$. If t_0 is time length of unit time interval and $t_{ij}(k)$ is defined as O-D travel time for O-D pair $i-j$, then

$$t_{ij}(k)=t_{i,j-1}\left(k-T_j(k)/t_0\right)+T_j(k), \tag{3}$$

(2) Kalman filter [11)]

a) State equation

State equation describes the relationship between current state variable and those of previous time intervals. O-D travel time and flow are selected as the state variables to be estimated. In this case, the state equation can be written as:

$$\mathbf{z}(k+1)=\mathbf{A}_k(k)\mathbf{z}(k)+\mathbf{A}_{k-1}(k)\mathbf{z}(k-1)+\cdots+\mathbf{A}_{k-m}(k)\mathbf{z}(k-m)+\mathbf{b}(k)+\mathbf{p}(k), \tag{4}$$

where
$\mathbf{z}(k)$ = $[\mathbf{x}^T(k),\mathbf{t}^T(k)]^T$ ($N(N+1)\times 1$ column vector), $\mathbf{x}(k)=[x_{11}(k),x_{12}(k),\ldots,x_{NN}(k)]^T$, $\mathbf{t}(k)=[t_{11}(k),t_{12}(k),\ldots,t_{NN}(k)]^T$,
$\mathbf{b}(k)$ = constant term of state equation (4) ($N(N+1)\times 1$ column vector),
$\mathbf{p}(k)$ = $N(N+1)\times 1$ system error vector,
$\mathbf{A}_k(k),\mathbf{A}_{k-1}(k),\ldots,\mathbf{A}_{k-m}(k)$ = coefficient matrices,

b) Measurement equation

Measurement equation defines the relationship between state and measurement variables. This study employs spot speed, link traffic and off-ramp volumes as measurement variables. As shown in Equations (1), O-D flow has explicit relationships with some measurement variables, whereas no analytical equation can be defined for the relationship between O-D travel time and measurement variables. Therefore, the measurement equation is assumed given by Equation (5) with $3M\times N(N+1)$ coefficient matrices $\mathbf{C}_k(k),\mathbf{C}_{k-1}(k),\ldots,\mathbf{C}_{k-n}(k)$:

$$\mathbf{y}(k)=\mathbf{C}_k(k)\mathbf{z}(k)+\mathbf{C}_{k-1}(k)\mathbf{z}(k-1)+\cdots+\mathbf{C}_{k-n}(k)\mathbf{z}(k-n)+\mathbf{d}(k)+\mathbf{u}(k), \tag{5}$$

where
M = the number of measurement points,
$\mathbf{y}(k)$ = $[s_1(k),q_1(k),w_1(k),\ldots,s_M(k),q_M(k),w_M(k)]^T$ ($3M*1$ column vector),
$\mathbf{d}(k)$ = $3M\times 1$ column vector which denotes intercept of measurement equation (5),
$\mathbf{u}(k)$ = $3M\times 1$ measurement error vector.

c) Estimation algorithm through the filtering process of Kalman filter

The algorithm for estimating dynamic O-D travel time and flow is illustrated in Figure 2. At first, coefficient matrices $\mathbf{A}_k(k),\mathbf{A}_{k-1}(k),\ldots,\mathbf{A}_{k-m}(k)$ and $\mathbf{C}_k(k),\mathbf{C}_{k-1}(k),\ldots,\mathbf{C}_{k-n}(k)$, intercepts $\mathbf{b}(k)$ and $\mathbf{d}(k)$ are estimated in advance by regression analysis. Next, initial values of state variables $\mathbf{z}(0),\mathbf{z}(-1),\ldots,\mathbf{z}(-m)$ and error covariance matrix $P[\max(m,n)]$ are given to the estimation system. Then, state and measurement variables are estimated using equations (6) and (7):

$$\tilde{\mathbf{z}}(k)=\mathbf{A}_{k-1}(k)\hat{\mathbf{z}}(k-1)+\mathbf{A}_{k-2}(k)\hat{\mathbf{z}}(k-2)+\cdots+\mathbf{A}_{k-m-1}(k)\hat{\mathbf{z}}(k-m-1)+\mathbf{b}(k-1), \tag{6}$$

$$\tilde{\mathbf{y}}(k)=\mathbf{C}_k(k)\tilde{\mathbf{z}}(k)+\mathbf{C}_{k-1}(k)\hat{\mathbf{z}}(k-1)+\cdots+\mathbf{C}_{k-n}(k)\hat{\mathbf{z}}(k-n)+\mathbf{d}(k). \tag{7}$$

When actual measurement variables $\mathbf{y}(k)$ and Kalman gain $\mathbf{K}(k)$ are given, estimated state variables $\tilde{\mathbf{z}}(k)$ are updated in the final step through the following equation:

$$\hat{\mathbf{z}}(k)=\tilde{\mathbf{z}}(k)+\mathbf{K}(k)[\mathbf{y}(k)-\tilde{\mathbf{y}}(k)]. \tag{8}$$

(3) Macroscopic traffic flow model [11)]

Wakao et al. [10)] have shown that the Kalman filter technique gives inaccurate estimation of O-D travel time on a freeway corridor if traffic states along O-D pairs are not predicted in advance. This is because measurement variables do not include the information on traffic states before vehicles enter the freeway. To overcome this difficulty, traffic states are predicted in advance by a macroscopic traffic model and used for estimating coefficient matrices of state and measurement equations. The traffic variables to be predicted are spot speeds, link traffic volumes at measurement points, off-ramp volumes and O-D travel times. Spot speeds and link traffic volumes are given by the following macroscopic model:

$$q_l(k)=\alpha\cdot\rho_l(k)\cdot v_l(k)+(1-\alpha)\cdot\rho_{l+1}(k)\cdot v_{l+1}(k) \quad (9)$$

$$w_l(k)=\alpha\cdot v_l(k)+(1-\alpha)\cdot v_{l+1}(k), \quad (10)$$

where, $\rho_l(k+1)=\rho_l(k)+{}^{t_0}\!/_{\Delta_l}\left[q_{l-1}(k)-q_l(k)+r_l(k)-s_l(k)\right]$,

$$v_l(k+1)=v_l(k)+{}^{t_0}\!/_{\tau}\left[v_f\left(1-\left(\rho(k)/\rho_{jam}\right)^l\right)^m-v_l(k)\right]+{}^{t_0\cdot\xi}\!/_{\tau}\left[v_{l-1}(k)-v_l(k)\right] -{}^{\nu\cdot t_0}\!/_{\tau\cdot\Delta_l}\left[{}^{\rho_{l+1}(k)-\rho_l(k)}\!/_{\rho_l(k)+\kappa}\right] \quad (11)$$

Here, v_f and ρ_{jam} denotes free flow speed and jam density respectively. α, τ, ξ, ν, l, m and κ are all macroscopic parameters to be optimized. Off-ramp volumes can be calculated from link traffic volume and diverging rate at the off-ramps. Also, approximate O-D travel times are determined by summing up link travel times using Equation (3). Substituting the value of predicted variables into state and measurement equations (4) and (5), the information on future traffic states can be included in the coefficient matrices of state and measurement equations.

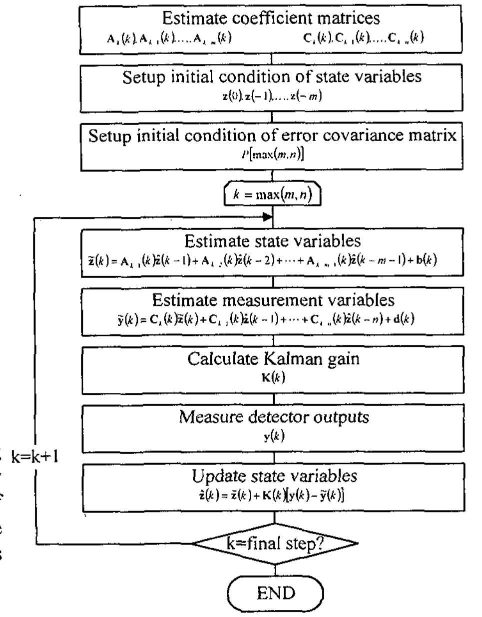

Figure 2 Algorithm

(4) ANNs [12]

Both state and measurement equations play important roles in the estimation process by Kalman filter technique, but there are some cases which have difficulties in defining analytical functions for state and measurement equations. Also in this study, no explicit analytical functions can be found for state and measurement equations (4) and (5). ANNs enable to estimate coefficient matrices $\mathbf{A}_k(k),\mathbf{A}_{k-1}(k),\ldots,\mathbf{A}_{k-m}(k)$ and $\mathbf{C}_k(k),\mathbf{C}_{k-1}(k),\ldots,\mathbf{C}_{k-n}(k)$ without defining any analytical functions. Furthermore, some measurable factors which affect O-D travel time and flow can be taken into account by the use of ANNs.

An ANN model has two or more layers of neurons. Each neurons in one layer is connected to all the neurons in the adjacent layers. This study will employ ANN models with three layers (Figures 3 and 4). Supervised learning scheme will optimize the connection weights between each pair of neuron. In this scheme, outputs are computed by:

$$Y_o=f\left(\sum_h W_{oh}\cdot f\left(\sum_i W_{hi}\cdot f(X_i)\right)\right), \quad (12)$$

where X_i are input variables, W_{hi} denotes connection weights between input and middle layers, W_{oh} defines the weights for middle and output layers. Then, the outputs Y_o are compared with the desired outputs Z_o for their inputs. The error information, difference between Y_o and Z_o, are propagated backward from the output layer to the hidden layer. Each entry of the coefficient matrices can be computed by the following equation:

$$\partial Y_o/\partial X_i=Y_o(1-Y_o)\cdot\sum_i W_{ho}\cdot Y_h(1-Y_h)W_{ih}. \quad (13)$$

The Kalman filter technique which state and measurement equations are formulated as ANNs is called Neural-Kalman filter. Figures 3 and 4 depict ANN models for state and measurement equations, respectively. For state equation, previous state variables are presented to the model and the supervised learning scheme optimizes the connection weights to find out appropriate function $\mathbf{F}$. The same scheme is applied to find function $\mathbf{G}$ in measurement equation.

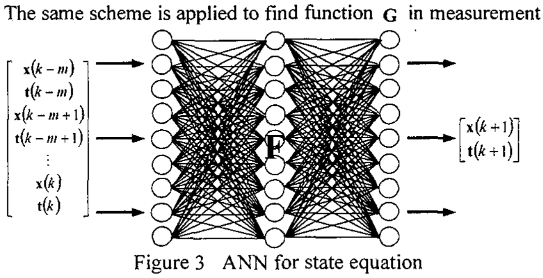

Figure 3 ANN for state equation

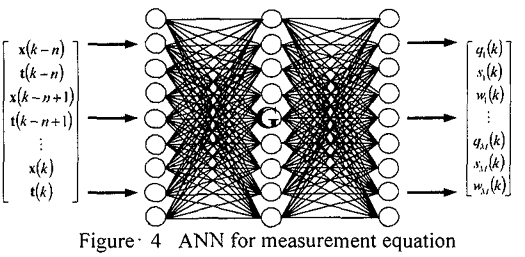

Figure 4 ANN for measurement equation

(5) Procedure of the development

Figure 5 illustrates the procedure of the development. In the first stage, dynamic O-D travel time and flow are estimated without using a macroscopic model as well as ANNs. State and measurement equations of the Kalman filter are formulated as regression models. In the second stage, a macroscopic model is introduced before the estimation of coefficient matrices of state and measurement equations. ANNs are used for formulating state and measurement equations instead of regression models in the final stage.

3. Required experimental analyses

(1) Impact analysis

It has been shown that O-D travel time is strongly affected by various factors such as the number of lanes, drivers' characteristics and visibility of road conditions [13]. This study investigates which factors affect O-D travel time and flow and takes into account these factors for estimating dynamic O-D travel time and flow.

The factors to be investigated are the number of lanes, width of each lane, road alignment and road gradient. These factors are assumed to have linear relationship with state variables such as O-D travel time and flow. Then, t-statistics in regression analysis evaluate how the factors contribute to the estimation of O-D travel time and flow.

(2) Observability condition

Observability condition defines the ability of the system to determine state variables from measurement variables. If this condition is not met, optimal estimation cannot be obtained. However, it is a difficult task to find out how many measurement variables or measurement points are required to fully satisfy the observability condition. Therefore, this study employs the observability index proposed by Schutt and Cremer [14]. This index does not give any absolute criteria to determine the number of measurement variables or points, but gives the relative quantity for comparison with different number of measurement variables or points.

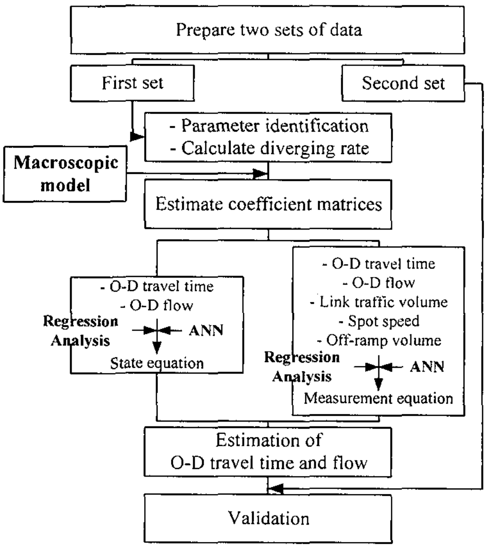

Figure 5 Flowchart of the Procedure

(3) Model calibration and verification

The proposed estimation system consists of three different models; a macroscopic model, ANNs models and Kalman filter model. Only the Kalman filter model gives the final outputs. Each model should be verified and validated. Also, all parameters of the macroscopic model will be optimized for a specific condition so as to minimize the difference between estimates and actual detector outputs. These parameters will be calculated for each road segment.

(4) Application

The proposed model will be applied for the first and second stage expressways in Bangkok, Thailand. Because of the insufficient traffic volumes, it may be difficult to obtain satisfactory O-D travel time and flow from field data collection. Therefore, artificial data will be created by a traffic simulation software. Artificial data is better than actual field data when it is used for investigating the influence of factors which affect O-D travel time and flow. Later, empirical field data also will be collected and used for evaluating the proposed system.

4. Concluding remarks

The concept of a new approach for estimating dynamic O-D travel time and flow on freeway networks is presented in this paper. In the new model, the Kalman filter technique is extended to cover state variables of several previous time steps. The extension is necessary especially when the model is applied for long distance freeway corridors. More accurate estimates of O-D travel time and flow are expected by the use of a macroscopic model and ANNs models. Further research will focus on numerical analyses for evaluating the proposed system.

References

1) Koutsuopoulos H. N. et al.: Travel simulators for data collection on driver behavior in the presence of information, Transpn. Res. 3C (3), pp. 143-159, 1995.
2) Cremer M., Keller H.: Dynamic identification of flows from traffic counts at complex intersections, 8th ISTTT, pp. 121-142, 1981.
3) Cremer M., Keller H.: A new class of dynamic methods for the identification of origin-destination flows, Transpn. Res 21B (2), pp. 117-132, 1987.
4) Bell M.G.H.: The real time estimation of origin-destination flows in the presence of platoon dispersion, Transpn. Res. 25B (2/3), pp. 115-125, 1989.
5) Ashok K., Ben-Akiva M. E.: Dynamic origin-destination matrix estimation and prediction for real-time traffic management system, 12th ISTTT, pp. 465-484, 1993.
6) Chang G. L., Wu J.: Recursive estimation of time-varying origin-destination flows from trafficcounts in freeway corridors, Transpn. Res 28B (2), pp. 141-160, 1994.
7) Cremer M.: On the calculation of individual travel times by macroscopic models, 6th VNIS Conference, pp. 187-193, 1995.
8) Fu L., Rilett R.: Dynamic O-D travel time estimation using an artificial neural network, 6th VNIS Conference, pp. 236-242, 1995.
9) Wakao M. et al.: A study on the travel time prediction for expressway, Proc. of Infrastructure Planning 20 (1), JSCE, pp. 477-480, 1997.
10) Arimoto S.: System Science Series: Kalman filter, Sangyo-Tosho, Tokyo, Japan, 1977.
11) Papageorgiou M. et al.: Modelling and real-time control of traffic flow on the southern part of boulevard peripherique in Paris: Part I: modelling, Transpn. Res. 24A (5), pp, 345-359, 1990.
12) Doughty M.: A review of neural networks applied to transport, Transpn. Res. 3C (4), pp. 247-260, 1993.
13) Hua J., Faghri A.: Applications of artificial neural networks to intelligent vehicle-highway systems, Transpn. Res. Rec. 1453, pp. 83-90, 1994.
14) Cremer M., Shutt H.: A comprehensive concept for simultaneous state observation parameter estimation and incident detection, 11th ISTTT, pp. 95-111, 1990.