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A Generalized Estimation Method of Traffic States on a Freeway using Traffic Detector Data

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Abstract: This paper presents a real-time traffic flow model for a freeway. The approach proposed here allows us to improve the Cremer method for determining the estimated traffic states and reducing the difference between the estimated and the actual situation. First, we established a generalization in the Cremer method which treats a road with several observation points. Finally, this method was evaluated by estimating of traffic states and stability for variation of model parameters. And also, the results were compared with the Cremer method. Test results are also presented.

Key Words; Cremer method ,Kalman filter, Multiple method, estimate of traffic states, model parameters

1. INTRODUCTION

This paper aims to present a method how we relate traffic states estimated by a dynamic traffic macroscopic simulation model with actually observed ones. Cremer[1] presented a dynamic estimation method, in which a Payne-type macroscopic simulation model was combined with the Kalman filter[2]. It is assumed in the model that traffic detectors are installed only at the end of road sections and no traffic data is observed in the middle of the section. In other word, it is necessary to divide it into several sections for a road with some intermediate observation points. Moreover, traffic states at boundaries would be estimated by an extrapolating technique, which decreased the estimation precision. To cope with this problem, we established a method, that treats a road with some observation points as a system without dividing it into subsections. This improvement increased the estimation precision and stability for variations of the model parameters.

2. THEORETICAL BACKGROUND

(1) Macroscopic Simulation Model

We divide a road on a freeway into several sections and divide each section into several segments. We defined the Payne-type macroscopic traffic flow model for each segment.

$$c_{i,j}(k+1) = c_{i,j}(k) + \frac{\Delta t}{\Delta_{i,j}}\left[q_{i,j-1} - q_{i,j} + r_{i,j} - s_{i,j}\right]_{(k)} \tag{1}$$

$$v_{i,j}(k+1) = v_{i,j}(k) + \frac{\Delta t}{\tau}\left[v\left(c_{i,j}\right) - v_{i,j}\right]_{(k)} + \frac{\Delta t}{\Delta_{i,j}}\left[v_{i,j}\left(v_{i,j-1} - v_{i,j}\right)\right]_{(k)} + \frac{\Delta t}{\Delta_{i,j}}\frac{\upsilon}{\tau}\left[\frac{c_{i,j} - c_{i,j+1}}{c_{i,j} + k}\right]_{(k)} \tag{2}$$

$$q_{i,j}(k) = \left[(\alpha c v)_{i,j} + ((1-\alpha)cv)_{i,j}\right]_{(k)} \tag{3}$$

$$w_{i,j}(k) = \left[(\alpha v)_{i,j} + ((1-\alpha)v)_{i,j}\right]_{(k)} \tag{4}$$

Where $c_{i,j}(k)$ is density at segment j in section i at time k. $v_{i,j}(k)$ is space mean sped. $q_{i,j}(k)$ is flow rate. $w_{i,j}(k)$ time mean speed. $r_{i,j}(k)$ and $s_{i,j}(k)$ are possible entrance and exit ramp flow rates. τ, κ, ν and $\alpha_{i,j}$ are model parameters. $\Delta_{i,j}$ is segment length and Δt is time interval of simulation. $v(c_{i,j})$ in Eq. (2) is the steady-state speed, which is defined by a density-speed characteristic (k-v) curve[3];

$$v\left(c_{i,j}\right) = v_{f_i}\left[1 - \left(\frac{c_{i,j}}{c_{max_i}}\right)^{l_i}\right]^{m_i} \tag{5}$$

where v_{fi} is the free speed, c_{maxi} is jam density, l_i and m_i are sensitivity factors.

(2) Filter Estimates

Choosing $c_{i,j}(k)$ and $v_{i,j}(k)$ as the state vector X_k, $q_{i,j}(k)$ and $w_{i,j}(k)$ as the measurement vector Y_k, we can define the following Kalman filter[2];

$$X_{k+1} = f(X_k) + \xi_k \tag{6}$$

$$Y_k = g(X_k) + \zeta_k \tag{7}$$

The linearized equation can be written as follows;

$$X_{k+1} = \Phi_k X_k + \xi_k \tag{8}$$

$$Y_k = \Psi_k X_k + \zeta_k \tag{9}$$

where $\Phi_k = \frac{\partial f}{\partial X}$ and $\Psi_k = \frac{\partial f}{\partial X}$.

3. GENERALIZATION

We extended the method which was first proposed by Cremer method, so that we were able to treat a road section where there are any numbers of observation points.

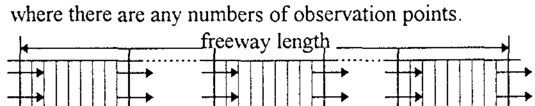

Fig.1 A road with several observation points

Fig. 1 shows a road which includes several observation points . The arrows in Fig. 1 denote the points. We divide it into several sections at every observation point.
There are several segments in each section. In general, for the flow rates $q_{i,j}(k)$ in Eq (1), we use the observed ones at observation points. Therefore, we have to redefine the dynamic equations so as to correspond to the observation condition. This inevitably requires the redefinition of the matrices of Φ_k and Ψ_k. We call this generalized model the multiple method.

4. NUMERICAL EXPERIMENT

To examine the effectiveness of the multiple model we applied it to a freeway in the Metropolitan Expressway Kanagwa Rout, Yokohane Line. There are 4 observation points, including both the ends of the road, where the flow rate , time occupancy, and time mean speed are measured every 1 minute. In this case, we divide it into 3 sections. Each section includes 3 to 4 segments. The segment length was raged from 400 to 600 meters. We used the data observed in October of 1993.
We identified the simulation model parameters using a set of the observation data on a day. Then we estimated traffic states using the data on another day. First, we examined the estimation precision by the proposed model and compared it with the one by the Cremer method.
Fig. 2 shows the RMS (Root Mean Square) errors of flow rates at check points, which are located in the middle of each section. We compared the estimated flow rates with the observed ones. White circles in Fig. 2 represent the errors by simulation before the filtering operation. Black circles represent the errors only corrected by the filtering operation. We can see that the introduction of the multiple method decreased the RMS errors of flow rates great deal, 8% to 68%. The reduction of the RMS errors of time mean speed was 58% to 90%.
Next, we examined the stability for the variations of the parameters of the (k-v) curve. Supposing that all the parameters of l_i, m_i, c_{maxi} and v_{fi} in Eq. (5) are biased from the optimum ones, we evaluated the RMS errors.
Fig 3 shows the RMS errors of flow rates for three cases; optimum-σ_{n-1}, optimum and optimum+σ_{n-1}, where σ_{n-1} is the standard deviation of each parameter.
We can see that the gradients by the multiple method is smaller than the one by the Cremer model. This means that the multiple method is more stable to the variations.

5. CONCLUSION;

Major findings are summarized as follows:
(1) We generalized the Cremer model in order to treat a road with several observation points in it.
(2) The proposed method improved the estimation precision a great deal.
(3) The method was stable for the variations of the model parameters.

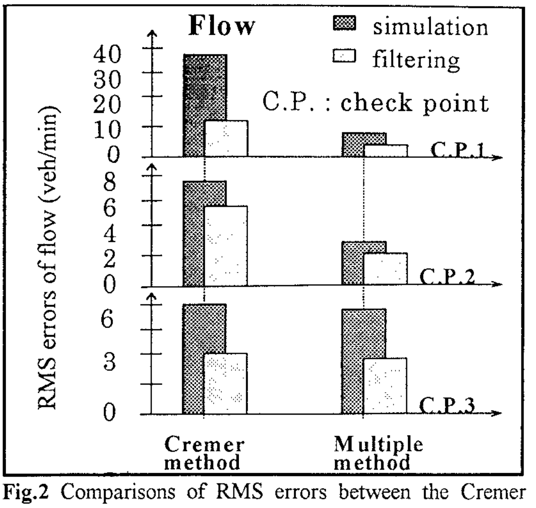

Fig.2 Comparisons of RMS errors between the Cremer method and the Multiple method.

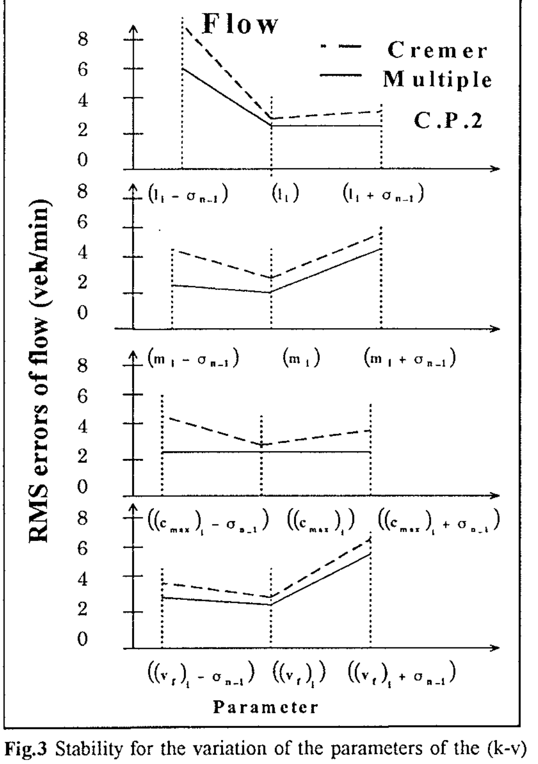

Fig.3 Stability for the variation of the parameters of the (k-v) curve.

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