

DYNAMIC ESTIMATION OF TRAFFIC STATES ON A FREEWAY USING PROBE VEHICLE DATA

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Traffic information from probe vehicles has great potential for improving the estimation accuracy of traffic situations, especially where no traffic detector is installed. A method for dealing with probe data along with conventional detector data is proposed in this paper. The probe data was integrated into the observation equation of the Kalman filter, in which state equations are represented by a macroscopic traffic flow model. The method was tested under several types of traffic conditions based on hypothetical data, giving considerably improved estimation results compared to those estimated without probe data. The effect of the percentage of probe vehicle deployment in a road network was also quantitatively assessed.

Key Words: probe vehicle, macroscopic traffic flow model, feedback estimation, Kalman filter

1. INTRODUCTION

Reliable traffic information is necessary for the development of efficient traffic network control strategies and management schemes. On-line traffic information can be utilized for various purposes, such as dynamic route guidance, incident detection, freeway ramp metering control, and the operation of variable message signs. Traffic information can be obtained by several traffic detection devices installed on a road network. However, it is very difficult to be aware of the traffic situation throughout an entire network using only fixed sensors. A traffic flow simulation model for describing the traffic phenomena is a key element in overcoming this difficulty. In general, a traffic management scheme or a route guidance system deals with a large-scale network. Among the various mathematical models for traffic flow, a macroscopic model describing the traffic states in an aggregate manner is one of the tools for real-time applications due to its simplicity of traffic flow description and its computational efficiency. Although every macroscopic model has its own deficiencies as discussed in, for example,

Daganzo¹⁾, Michalopoulos et al.²⁾, and Lebacque and Lesort³⁾, several techniques were introduced to compensate for these deficiencies. One such technique, the Kalman filtering technique (KFT), has been integrated into macroscopic models for the real-time estimation of traffic states. Cremer⁴⁾, Payne et al.⁵⁾, Pourmoallem et al.⁶⁾, and Suzuki and Nakatsuji⁷⁾ applied the KFT as a feedback method to estimate traffic states on a freeway. In these studies, observed traffic data were taken from fixed vehicle detectors, but with long separation between successive detectors, estimation results will probably deteriorate. In order to estimate traffic states more accurately, traffic information from additional sources is required, and with its ability to cover a road network, probe vehicle data has great potential in this respect.

Uplink data transmitted by probe vehicles has recently been receiving considerable interest within the modern surveillance system. Many projects, such as the ADVANCE^{8),9)10)} project in Chicago, the PATH¹¹⁾ program in California, the RTA project in the U.K.¹²⁾, the EURO-SCOUT¹³⁾ program in Germany, and the Internet ITS¹⁴⁾ project in Japan,

were launched to investigate the feasibility of using probe vehicles in obtaining real-time traffic data. In these systems, probe vehicles are taken as moving sensors traveling in a traffic flow, whereas conventional detectors, such as inductive loops, are treated as fixed sensors installed only at a limited number of locations. Under such circumstances, probe data from links where no conventional detectors are installed would be effective in telling us what is occurring there. A sufficiently large number of probe vehicles should reasonably represent the traffic conditions that they experienced. Various kinds of information can be collected with this technique, such as position, speed, time, lane used, link travel time, congested time/distance etc., however, so far, the applications for probe vehicle data are still limited. Most studies, such as Hellinga and Gudapati¹⁵⁾, Chen and Chien¹⁶⁾, and Sanwal and Walrand¹¹⁾, have concentrated on travel time detection, while some authors, such as Ivan et al.⁸⁾, Sethi et al.⁹⁾, and Sanwal and Walrand¹¹⁾, have used probe data to estimate O-D flows and to detect incidents. In the Nagoya area of Japan, the pilot program of the Internet ITS¹⁴⁾ project was launched in January 2002: more than 1500 taxis are taking part as probe vehicles to collect traffic data and weather conditions both for enhancing the taxi service as well as providing real-time information.

So far, very few studies have dealt with speed data for estimating traffic states and probe data has never been integrated into a macroscopic traffic flow model with the KFT. Recently, Dailey and Elango¹⁷⁾ and Cathey and Dailey¹⁸⁾ have studied the use of transit vehicles as probes for estimating the time series of vehicle locations and speeds. They updated the state variables of vehicle position, speed, and acceleration using the KFT. The system equations they used were taken from individual vehicle motion. Their method can be considered as an alternative for acquiring traffic data (other than fixed detector data), but a combination of both sources of data was not considered. In addition, apart from average speed, no interest has been paid to the estimation of the other fundamental traffic flow variables of traffic density and traffic volume. As far as the authors are aware, up until now no formulation for the estimation of traffic states (i.e. density, space mean speed and traffic volume) using a macroscopic traffic flow model with probe data has been developed. Moreover, an algorithm for combining probe data with conventional detector data to estimate traffic states is still lacking.

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

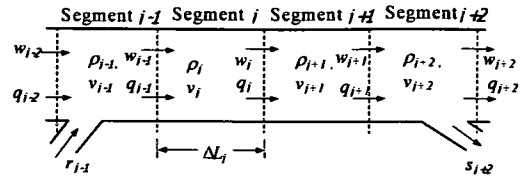


Fig. 1 Discrete Model of a Road Section

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. Finally, the effect of the percentage of probe vehicles in traffic flow, as well as that of the sampling interval of probe data on the reliability of the traffic state estimation, will be examined.

2. TRAFFIC STATE ESTIMATION

(1) The macroscopic traffic flow model

Payne's macroscopic traffic flow model¹⁹⁾ was selected to apply in this study due to its simplicity to integrate with other techniques, including the KFT. The accuracy of Payne's model has been investigated and discussed in many researches^{1),2),3)}. Fig. 1 shows the space-time discrete model of a freeway section, where each segment is ΔL_j long. It is divided on the assumption that traffic state is homogeneous within each segment. Eq. (1) to Eq. (3) describe the discretized form using the explicit finite difference approximation of a Payne-type model⁴⁾. The first relationship is the continuity of vehicles that describes how density varies with time. The second relationship, which is so called the momentum equation, defines the variation of space mean speed over time. The third relationship is derived from the fundamental relationship in traffic flow, volume, speed, and density.

$$\rho_j(t+1) = \rho_j(t) + \frac{\Delta t}{\Delta L_j} (q_{j-1} - q_j + r_j - s_j) \quad (1)$$

$$v_j(t+1) = v_j(t) + \frac{\Delta t}{\tau} \{v_e[\rho_j(t)] - v_j(t)\} + \frac{\Delta t}{\Delta L_j} v_j(t) [v_{j-1}(t) - v_j(t)] \quad (2)$$

$$\frac{v_e \cdot \Delta t}{\tau \Delta L_j} \frac{\rho_{j+1}(t) \cdot \lambda_j / \lambda_{j+1} - \rho_j(t)}{\rho_j(t) + \kappa}$$

$$q_j(t) = \alpha(v_j(t)\rho_j(t)) + (1 - \alpha)(v_{j+1}(t)\rho_{j+1}(t)) \quad (3)$$

The macroscopic traffic variables in the model were defined as follows:

$\rho_j(t)$: density of segment j at time t

$v_j(t)$: space mean speed of segment j at time t

$q_j(t)$: flow rate at the boundary point between segments j and $j+1$ at time t

$w_j(t)$: time mean speed at the boundary point between segments j and $j+1$ at time t

$r_j(t)$: entry flow rate at ramp of segment j at time t

$s_j(t)$: exit flow rate at ramp of segment j at time t

t indicates time, whereas x represents position; Δt is the time increment; λ_j is the number of lanes for segment j ; v_e is the speed at equilibrium state, which is obtained from the density-speed relationship; and τ , ν , and κ are model parameters. Eq. (3) reflects the fact that the states of both neighboring segments may affect the volumes determined at the edge of each segment, as suggested by Cremer⁴. α is a weighting parameter ranging from 0 to 1. Some literatures, including Pourmoallem et al.⁶, have discussed the effect of the parameter α depending on traffic density.

(2) The Kalman filtering technique (KFT)

The KFT is a method for adjusting the state variables by the available measurement data, has been widely used in various engineering fields and has also been applied to traffic flow problems in several studies^{4,5,6,7}. Traffic states are described by a macroscopic model and then adjusted according to the KFT algorithm, this adjustment of the state variables in proportion to the difference between the observed and predicted values for the observation variables being the core of the KFT.

The state variables, $x(t)$, are determined by the system equations, while the observation variables, $y(t)$, are measured in the system process. In a traffic state estimation problem where measurement data can be obtained from fixed detectors only, traffic density and space mean speed are treated as the state variables, $x(t) = (\rho, v)_{(t)}$, whereas traffic volumes, q , and spot speeds, w , are treated as the observation variables, $y(t) = (q, w)_{(t)}$. The continuity equation, Eq. (1), and the momentum equation, Eq.(2), are treated as state equations, while observation equations consist of a relationship between traffic volume and state variables, as in Eq.(3), and a relationship between spot speed and state variables which might be set as the following equation:

$$w_j(t) = \alpha v_j(t) + (1 - \alpha)v_{j+1}(t) \quad (4)$$

where α is the same weighting parameter as used in

Eq.(3).

To formulate the KFT, white noise errors were induced in both state and observation equations as follows:

$$x(t+1) = f[x(t)] + \xi(t) \quad (5)$$

$$y(t) = g[x(t)] + \zeta(t) \quad (6)$$

where $\xi(t)$ and $\zeta(t)$ are noises representing the modeling errors and measurement errors respectively. Next, the state and observation equations are linearized around the nominal solution $\tilde{x}(t)$, using Taylor's expansion. The system equations become:

$$\tilde{x}(t+1) \cong f[\tilde{x}(t)] + \frac{\partial f}{\partial x}(x(t) - \tilde{x}(t)) + \xi(t) \quad (7)$$

$$\cong A(t) \cdot x(t) + b(t) + \xi(t)$$

$$\tilde{y}(t) \cong g[x(t)] + \frac{\partial g}{\partial x}(x(t) - \tilde{x}(t)) + \zeta(t) \quad (8)$$

$$\cong C(t) \cdot x(t) + d(t) + \zeta(t)$$

where $A(t) = \frac{\partial f}{\partial x}$, $b(t) = f[\tilde{x}(t)] - \frac{\partial f}{\partial x} \tilde{x}(t)$

$C(t) = \frac{\partial g}{\partial x}$, $d(t) = g[\tilde{x}(t)] - \frac{\partial g}{\partial x} \tilde{x}(t)$

The linearization matrices A and C are used for deriving the Kalman gain. The dimension of matrix A is $2n \times 2n$, while that of matrix C is $2m \times 2n$, where n is the total number of road segments, and m the total number of observation points. $\tilde{x}(t)$ and $\hat{x}(t)$ are the estimated state vectors before and after obtaining the actual measurement data, $y(t)$, respectively. Before processing the KFT, the initial values of the state variables and error covariance matrices have to be set, after which the state variables can be adjusted according to the correction steps of the KFT as follows:

step 1: estimate state variables for the current step, t

$$\tilde{x}(t) = f[\tilde{x}(t-1)]$$

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

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

step 3: calculate Kalman gain matrix at time t

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

step 4: estimate observation variables at time t

$$\tilde{y}(t) = g[\tilde{x}(t)]$$

step 5: update estimated state variables

$$\hat{x}(t) = \tilde{x}(t) + K(t)[y(t) - \tilde{y}(t)]$$

step 6: update error matrix of $\hat{x}(t)$

$$P(t) = M(t) - K(t)C(t)M(t)$$

then set $t = t+1$ and repeat all the steps for the next

time interval until the required simulation time step is reached. Φ and Z are covariance matrices of $\xi(t)$ and $\zeta(t)$, respectively.

3. INTEGRATION OF THE PROBE DATA INTO THE OBSERVATION VARIABLE

(1) Probe data

In this study, we assumed that the probe vehicle could transmit the data to the control center at every specific time instant regardless of the position of the probe vehicle. This type of data can be obtained from a GPS-based system or a beacon-based system.

There are several types of information on the current status of the probe vehicle that could be available on a real-time basis, including position and speed. The probe information that we attempted to apply as the observation variable for the KFT is the probe speed, since speed is included in the macroscopic model that we adopted. In addition, it gives us definite traffic conditions.

(2) Integration of the probe data into the KFT

Here, a method for applying both the fixed detector data and the probe vehicle data into the KFT for the traffic state estimation problem will be presented. Fig. 2 presents the concept of the process. At every time step, traffic states are estimated by the macroscopic model with input conditions at the boundaries, while the probe data are sorted by their location determined from which segment the data came. Then, the probe data at each segment are averaged in a required aggregated data format. Together with the fixed detector data, the probe data are used as observation variables in the KFT to update the estimated states. The probe speed is applied as one of the observation data for the space mean speed. In case of both probe data and fixed detector data are available in the same segment, to combine the data from different sources, a data fusion technique is required.

We modeled a road section as shown in Fig. 3. The road section was divided so that fixed detectors, if any, were located at approximately the middle of a certain segment, not at the segment boundary (except for the detectors at the entrance and exit points of the road section), to avoid influence from neighboring segments in the calculation of the observation variables. This is what differs from the conventional approach mentioned in Chapter 2. That is, if a fixed detector is located in the middle zone of a segment instead of the segment boundary, $w_j(t)$ in Eq.(4) will reduce to $v_j(t)$. Therefore, here, we could assume that the observed speed from the fixed detector, $w_{d,j}$ is

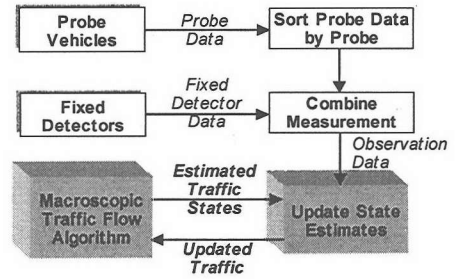


Fig. 2 Traffic States Estimating and Updating framework

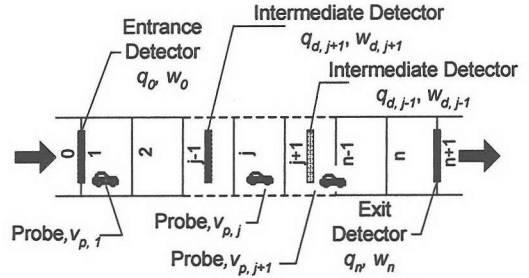


Fig. 3 Road section with probe vehicles and fixed detectors

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. In fact, the assumption of $w_j(t) = v_j(t)$ deriving from Eq.(4) contradicts with the fundamental of traffic flow theory. This is due to the hypothesis of Eq.(4), which is requisite to derive the Kalman gain. However, since the observation equation contains the additional noise term that could reflect the discrepancy between both speeds, the influence of the above assumption is expected to be very limited.

It was assumed that the fixed detectors must be available, at least, at both the entrance and exit of the road section as well as at every on-/off-ramp. On-and off-ramp volumes are used as the source and sink terms in the continuity equation. The traffic volume and spot speed at the entrance and exit are used as observation variables for the KFT, and as boundary conditions for the macroscopic traffic flow model.

To obtain observation data, four different monitoring patterns are possible in accordance with the condition of data sources:

- 1) only fixed detector data at the entrance and exit are available;
- 2) supplementary fixed detector data are available, together with entrance and exit detector data;
- 3) probe vehicle data are available, together with

entrance and exit detector data;

4) both supplementary fixed detector and probe vehicle data are available, together with entrance and exit detector data.

The observation equations for the entrance and exit detectors used for all patterns can be assumed as:

$$q_0 = \rho_1 \cdot v_1 \quad (9)$$

$$w_0 = v_1 \quad (10)$$

$$q_n = \rho_n \cdot v_n \quad (11)$$

$$w_n = v_n \quad (12)$$

For patterns 2 and 4, additional fixed detectors (or supplementary detectors) may be available between the entrance and exit detectors. Traffic volume and speed data from those detectors can be used as additional observation variables. Thus, the number of observation variables from these detectors is equal to $2m$, where m is the number of supplementary detectors. As detectors are located in about the middle of certain segments, we might assume that the average speed measured at the detectors is equal to the space mean speed of the segments, $w_{d,j} = v_{d,j}$. The observation equations for the supplementary detectors are:

$$q_{d,j} = \rho_j \cdot v_j \quad (13)$$

$$v_{d,j} = v_j \quad (14)$$

where j identifies the number of segments with a fixed detector.

In cases where probe vehicles are deployed (patterns 3 and 4), it is assumed that probe vehicles could submit their instantaneous speed along with their current position, regardless of where they are. The average of instantaneous speed of the probe vehicles in each segment at a certain instant is considered to be an observation variable for the space mean speed. For the segments where both detector and probe data are available in pattern 4, the speed data from the probe vehicles was to be integrated with the speed data from the fixed detectors (i.e. the observation speed, $v_{d,j}$, in Eq.(14) was to be replaced with the speed integrated from both sources). In this study, for simplicity's sake, a weighted average of speed from both data sources was used to combine the data from different sources. Other data fusion techniques could, however, be used for this purpose.

Generally, probe data may not be available for all segments for every time step. As a result, the number of observation variables from probes, $p(t)$, varies with time. The observation equation for the segments where only probe data are available at time step t reduces to:

$$v_{p,h} = v_h \quad (15)$$

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 can vary with time. At a certain time step t , it is equal to $4+2m+p(t)-m$. Accordingly, the dimension of matrix C reduces to $(4+2m+p(t)-m) \times (2n)$ and that of the covariance matrix of the observation variable noises, Z , becomes $(4+2m+p(t)-m) \times (4+2m+p(t)-m)$.

The initial value of the error matrix, P , was assumed to be equal to the covariance of the noises of the state variables, Φ . The statistics of noises were determined on a trial-and-error basis bearing in mind the possible ranges suggested by Cremer⁹. The state variable noises were set to be about 2-10% of their values. For the observation variable noises, a value of 200 vph was selected for noises in the observed volume, and one of 3-7 vph for noises in the observed speed. A smaller noise value was used for the links where data from both sources were available.

4. TRAFFIC DATA

(1) Simulation field

In this study, a 5,550m road section was modeled emulating the road section of the Yokohane Line of the Metropolitan Expressway in Tokyo, Japan, in an inbound direction between Namamugi Junction and the Taishi Ramp. The road section is divided into nine segments ranging from 400m to 800m with two on-ramps and one off-ramp. The number of lanes varies from two to three. Fig. 4 depicts the geometry of the study road section.

(2) Simulation data

The availability of probe data is still limited in Japan. At present, as the number of vehicles equipped with monitoring and communicating devices is still small in real traffic, it is almost impossible to obtain probe data that covers extensive traffic situations. In this study, the traffic data was generated by a traffic flow simulation program, after careful calibration and validation with real traffic data. The calibration was done on a trial-and-error basis. The simulation was repeated several times with different set of model parameters. By determining the deviation of the simulation from the real data, the possible range of each model parameter

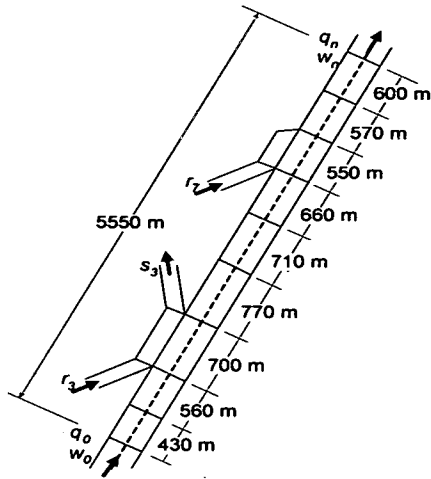


Fig. 4 Geometry of the studied road section.

Table 1 Description of simulated data.

Case	Traffic Condition	Description
A	Low-density	low main inflow
B	Low-density	wide range inflow with peak around the middle of simulation
C	Low-density	high inflow
D	Wide range	high inflow and on-ramp r7
E	Wide range	rising main inflow from moderate to high with moderate ramp inflows
F	Wide range	high inflow with high on-ramps in the first half of simulation

can be defined. The calibrated model produced the root mean square error in speed of 9.9 kph, and in volume of 362 vph for the calibrating data. A simulation program offers the opportunity to generate a variety of traffic data under various scenarios for extensive analytical purposes, and numerous researchers have used hypothetical data in their studies. What is important here is to adopt a simulation program whose concept is different from that used in the current analysis. In this study, the INTEGRATION²⁰⁾ software, a trip-based microscopic traffic simulation, was used to generate traffic data. It has various features suitable for Intelligent Transportation Systems applications, including the capability to generate fixed detector data and probe vehicle data, and has been used in several studies^{15),21)} to generate hypothetical data.

A variety of traffic data conditions can be obtained by varying inflow volumes at the entrance of the road section, and the inflow/outflow at the on/off ramps (i.e. by changing the O-D demands in INTEGRATION). Table 1 lists the six cases of 3-hour traffic condition simulated in this study. Fig. 5 presents the variation in space mean speed in each segment for the simulated data. Cases A, B and C

represent low-density and smooth traffic conditions, while cases D, E and F contain a wide range of traffic conditions from low- to high-density. Among all the simulated data, case A has the smoothest conditions, while in cases B and C the variation in speed is slightly larger and more obvious. In case D, traffic speed continues to drop from the beginning of simulation right through to its end. In case E, the speed drops around the middle of the simulation, then returns to low-density conditions at the end. In case F, around the middle of simulation there are speed drops in some segments, while there are some segments where speed remains high and some segments where speed remains low for the whole simulation period.

It was assumed that, if available, probe data could be obtained from anywhere in the study network at any specific interval. Both probe data and fixed detector data can be transmitted to the traffic control center in real-time. The space mean speed from INTEGRATION was defined as the average speed of the vehicles that are in a specific segment at that instantaneous time step. To reduce fluctuation, the data were aggregated into 3-minute for both the fixed detectors and probe vehicles. Therefore, the observation variables in this study are the 3-min aggregated detector data (volume, speed, and occupancy) at certain points and the 3-min aggregated probe (speed) data from certain segments. The later are the average speeds transmitted from probe vehicles in each segment in each 3-min interval.

5. PERFORMANCE INDICES

In order to evaluate the performance of the estimations, error indices based on the deviations of the estimated results from the references were calculated. Three types of indices are adopted, including a root mean square error of volume, $RMSEq$, a root mean square error of speed, $RMSEv$, and a normalized variance, J . These indices present the model deviation in the same unit as the interested variables. $RMSEq$ and $RMSEv$ are defined as:

$$RMSEq = \sqrt{\frac{1}{N-1} \sum_{i=1}^N [q_i - q_{mi}]^2} \quad (16)$$

$$RMSEv = \sqrt{\frac{1}{N-1} \sum_{i=1}^N [v_i - v_{mi}]^2} \quad (17)$$

The normalized variance, J , is set as the error between the reference variables and the model outputs:

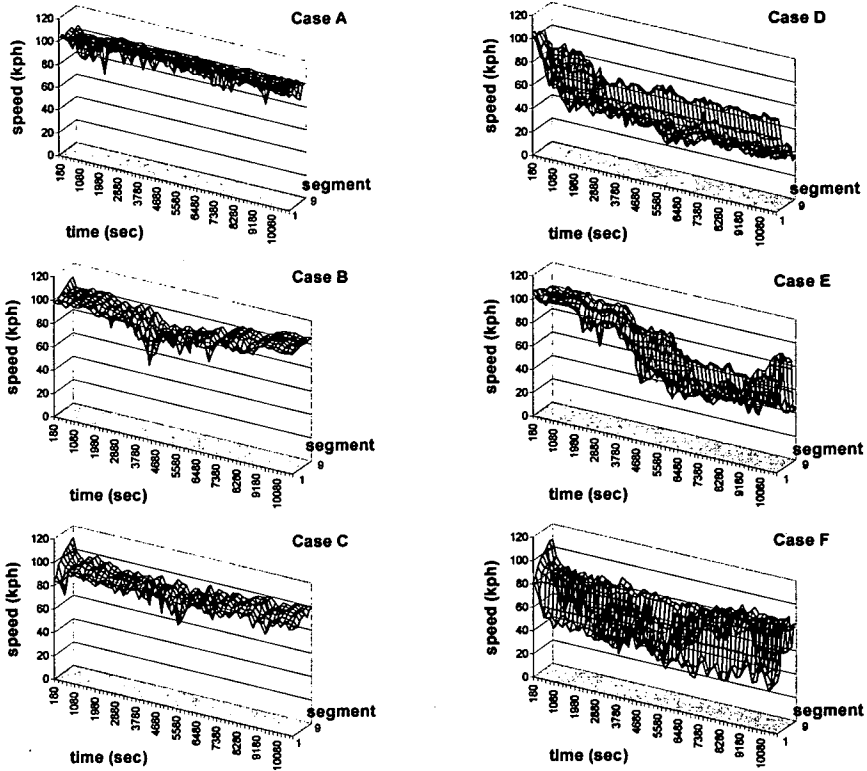


Fig. 5 Simulated data

$$J = \sum_{i=1}^N (\gamma_q \cdot (q_i - q_{mi})^2 + \gamma_v \cdot (v_i - v_{mi})^2) \quad (18)$$

where N is the total number of reference outputs used for comparison. Here, N is equal to the number of segments multiplied by the number of time steps; q_i and v_i are the real values of the reference outputs; q_{mi} and v_{mi} are the corresponding module outputs; γ_q and γ_v are the weighting factors for balancing the volume and speed errors ranging within the possible values of the reciprocal of the variance of volume and speed respectively. Cremer and Papageorgiou²²⁾ have suggested the values of γ_q/γ_v should be 10^{-3} , therefore, considering the variance of observed data in this study, values of 10^{-5} and 10^{-2} were selected for γ_q and γ_v , respectively.

6. NUMERICAL EXPERIMENTS

(1) Efficiency of the probe data

For each data case in Table 1, four estimation scenarios, differing in their estimation technique and the level of traffic information, were compared.

Scenario 1 (S1): the macroscopic model only;

Scenario 2 (S2): the macroscopic model with the

KFT using the data from a supplementary fixed 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

In this numerical experiment, it was assumed that detector data at the entrance and exit of the road section were available for all scenarios. One supplementary detector was inserted at segment 5 for scenarios 2 and 4. In scenarios 3 and 4, we adopted 5% of probe vehicles in the total amount of traffic in the network with a transmitting frequency of 1 report/second. Prior to the estimation processes, the parameters in the macroscopic model were calibrated for each case using traffic data measured at the Yokohane Line of the Metropolitan Expressway²³⁾.

Table 2 summarizes the overall estimation results. They show that the KFT contributes to the improvement of estimation accuracy. Compared to the scenario that uses the macroscopic model only (S1), estimation errors decrease in almost all cases, except for the $RMSEq$ in case D of scenarios 2 and 3. The combination error, J , is reduced by 30%-87% compared to that estimated by the macroscopic

Table 2 Effect of observation information

case	Scenario	RMSE _q		RMSE _v		J	
		% Improve		% Improve		% Improve	
A	S1: Macro Only	274.5		10.28		16,816	
	S2: Macro+KFT(D)	123.0	55.2	4.64	54.9	3,404	79.8
	S3: Macro+KFT(P)	168.7	38.5	3.16	69.3	3,567	78.8
	S4: Macro+KFT(P+D)	128.0	53.4	3.10	69.9	2,413	85.7
B	S1: Macro Only	239.4		15.27		26,983	
	S2: Macro+KFT(D)	166.5	30.5	6.24	59.1	6,195	77.0
	S3: Macro+KFT(P)	223.0	6.8	2.40	84.3	5,156	80.9
	S4: Macro+KFT(P+D)	179.9	24.9	2.37	84.5	3,527	86.9
C	S1: Macro Only	237.8		15.23		26,780	
	S2: Macro+KFT(D)	171.7	27.8	6.28	58.8	6,394	76.1
	S3: Macro+KFT(P)	234.1	1.5	2.74	82.0	5,790	78.4
	S4: Macro+KFT(P+D)	184.7	22.3	2.69	82.3	3,841	85.7
D	S1: Macro Only	264.3		18.42		37,986	
	S2: Macro+KFT(D)	296.5	-12.2	11.32	38.5	20,057	47.2
	S3: Macro+KFT(P)	295.9	-11.9	4.73	74.3	10,206	73.1
	S4: Macro+KFT(P+D)	231.4	12.5	4.53	75.4	6,880	81.9
E	S1: Macro Only	308.4		16.46		34,003	
	S2: Macro+KFT(D)	268.2	13.0	11.87	27.9	19,769	41.9
	S3: Macro+KFT(P)	275.4	10.7	4.72	71.3	9,113	73.2
	S4: Macro+KFT(P+D)	217.3	29.5	4.59	72.1	6,339	81.4
F	S1: Macro Only	324.8		21.23		51,668	
	S2: Macro+KFT(D)	290.9	10.4	17.42	18.0	36,046	30.2
	S3: Macro+KFT(P)	272.4	16.1	6.17	70.9	10,426	79.8
	S4: Macro+KFT(P+D)	242.2	25.4	5.97	71.9	8,756	83.1

% Improve: the percentage of the error reduction by each scenario compared to the error of S1
D: detector data, P: probe data

model only.

Scenario 2 provides less error in the volume, *RMSE_q*, than scenario 3, while scenario 3 gives less error in the speed, *RMSE_v*, than scenario 2. This implies that fixed detector data contributed greatly to the improvement in volume, whereas the improvement in speed stems mainly from probe vehicle data. In case D for scenarios 2 and 3, the estimation errors in volume are larger than those of scenario 1, the main reason for this being that the deterioration from the output fluctuation outweighs the improvement from the KFT correcting process. However, if fixed detector and probe data were used in tandem as in scenario 4, the estimation results were improved.

Scenario 4 provides the best results for all cases, except some cases in *RMSE_q*, in low-density conditions of cases A to C, in which the *RMSE_q* of scenario 4 is a little larger than that of scenario 2. The estimation method used in scenario 4 reduced the combination errors, *J*, by 81%-87% compared with those of scenario 1. The volume errors, *RMSE_q*, and the speed errors, *RMSE_v*, reduced by 12%-53% and 70%-85%, respectively. In this way, the usage of both detector and probe data was very effective in improving estimation accuracy.

The estimation results of scenario 4 are very accurate, since all of the error indices are sufficiently small: the errors in volume range from 128 to 185

vph in the low-density cases (A to C), and from 217 to 242 vph in the wide range density cases (D to F). Errors in speed are about 2 to 3 kph in low-density cases, and about 4-6 kph in wide range density cases.

Fig. 6 shows the variation in both volume and speed at segment 7 of case B for scenarios 1 and 4, while Fig. 7 shows the one at segment 6 of case F. The fluctuation of the volume for scenario 4 is large in the volume data, especially under wide range density conditions, as can be seen in Fig. 6 and Fig. 7. This is why there are some large errors of volume estimation in scenarios 3 and 4, as stated above. That is, the use of speed data from probe vehicles made the estimation results fluctuate more. The fluctuation might stem from the length of the aggregation period for observation data. The fluctuation is large when the aggregating period is short, although if a long aggregation period were adopted, the estimation would fail to capture the dynamic of the traffic, especially when the traffic situation changes abruptly. Another reason for the fluctuation may come from the statistics of noises assigned in the KFT, something which needs to be investigated further.

Although the volumes estimated by scenario 4 fluctuate, their means still follow the correct profiles, while the profiles of the estimated speeds accurately follow the correct ones, even in the abrupt change regions as shown around the time step of 900 to 1100 seconds in Fig. 7. On the other hand, the macroscopic model sometimes fails to capture the real traffic flow, as shown in the speed from scenario 1 of Figs 6 and 7. This suggests that a macroscopic model itself cannot capture uncertainty in a traffic flow, such as traffic incidents. It is worth seeing that scenario 4 significantly improved the estimation accuracy in both cases.

Scenario 2, which used only fixed detector data, did not yield good results, especially in speed under high-density and fluctuating conditions. The distance between adjacent detectors may have influenced on the estimation errors of *RMSE_v* and *J*. That is a larger number of fixed detectors are required to be installed densely to gain the estimation accuracy on the same level as scenarios 3 and 4.

It was to be expected that the large amount of probe data obtained from a 5% level of probe vehicles contributed greatly to the estimation results of scenarios 3 and 4 being better than those of scenario 2. The effect of the number of probes deployed in the network are discussed in the next section.

(2) Effect of the number of probe vehicles and the sampling interval of probe data

To investigate the feasibility of the probe vehicle

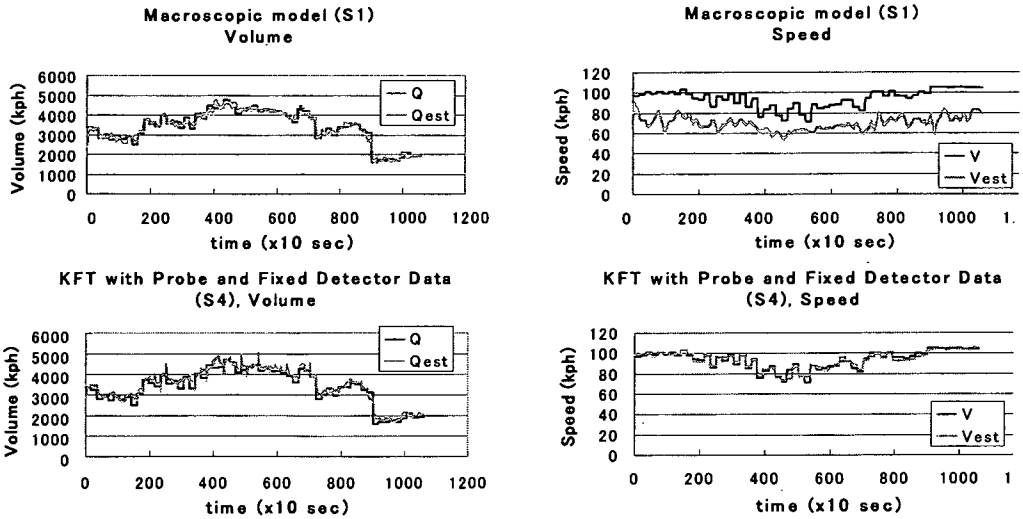


Fig. 6 Comparison of hypothetical data and its estimated values from different scenarios for link 7 of Case B (low-density)

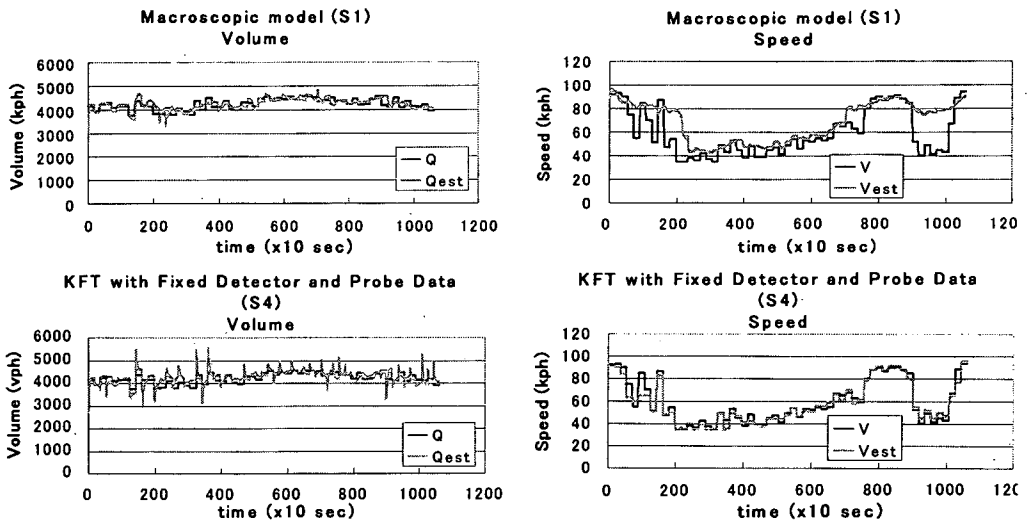


Fig. 7 Comparison of hypothetical data and its estimated values from different scenarios for link 6 of Case F (wide range)

technique from an economic viewpoint, it is worth examining how many probe vehicles are required in a road network and how often they should report traffic data in order to obtain continuous traffic information from a variety of locations for reliable traffic state estimation.

Many researchers^{10),11),24)} have evaluated the accuracy of population estimates based on probe vehicle reports. They have quantified the proportion of the number of probe vehicles to the total number of vehicles in the network (or the level of market penetration) required to achieve the desired level of reliability in the estimated variables. However, the variables considered are limited only to link travel time and O-D demand. As far as the authors are

aware, no work on the relationship between the proportion of probe vehicles in the network and the estimation accuracy of traffic state variables, including volume, speed, and density, has been performed thus far.

a) The number of probes in a network

For this analysis, scenario 4 was adopted by varying the percentage of probe vehicles in the network at 1%, 2%, 3%, 4%, 5%, 8%, and 10%. Each probe vehicle was supposed to transmit a report once per second. Fig. 8 shows the average number of probe reports per segment per time step in which only segments where probe vehicles exist were taken into account for the different level of market penetration for each study case. This index indicates

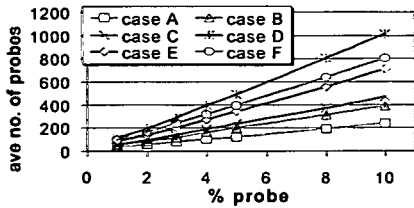


Fig. 8 Average number of probes per segment per time step for different levels of probe vehicle market penetration

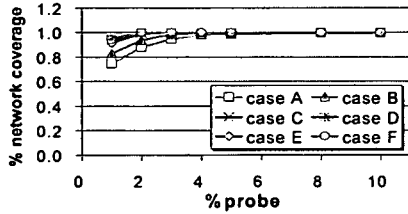


Fig. 9 Network coverage for different levels of probe vehicle market penetration

how large the probe sampling is for representing the traffic population. Fig. 9 depicts the percentage of network coverage, which is defined as the ratio of the number of segments where probe data are available for a certain time step to the total number of segments, for a different level of market penetration for each study case. These two indices depend on the traffic conditions, the network configuration and the level of probe deployment.

In this analysis, the average number of probe reports per segment per time step was quite high in every case. Even in the lowest case, there were, on average, more than 30 probe reports per segment-step for 1% of market penetration. The number of reports per segment-step increases more or less linearly with the level of market penetration. The rate of increase is sharper in high-density cases because most vehicles stay in the network longer. The percentages of network coverage for the simulation runs are also very high, because the freeway section studied had only one off-ramp. Probe vehicles can cover more than 70% of the study network with only 1% of market penetration.

Fig. 10 shows the effect of the number of probe vehicles in the network on the estimation precision of the traffic states. As the percentage of probes in the network increases, the estimation errors should reduce, however the figure indicates that the estimation of traffic state variables does not significantly improve beyond a certain level of probe information. This result is similar to that of the travel time estimation problem, as pointed out by Sen et

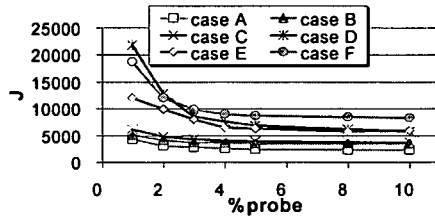
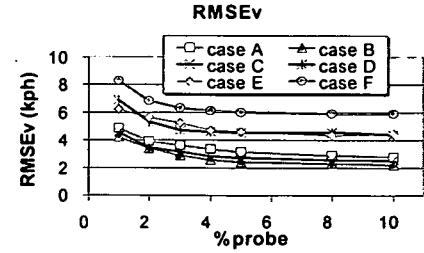
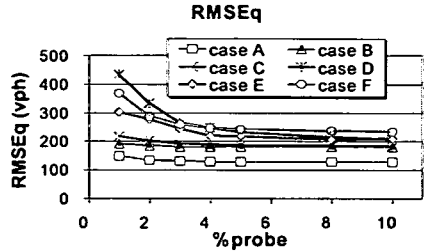


Fig. 10 Effect of the level of market penetration of probe vehicles on the traffic states estimation

al.²⁴). For the study freeway network, the estimation errors are not notably reduced above 4-5% of market penetration.

b) Probe data sampling intervals

Scenario 4 was adopted again with changes in the frequency of the probe report to one report per 1 sec, 10 secs, 30 secs, 60 secs and 180 secs. Fig. 11 shows the effect of the sampling interval for case F. As the sampling interval increases, so does the number of probe vehicles required for covering the network. The overall results indicate that, at a certain level of market penetration, the shorter the sampling interval of probe data is, the better the estimation result becomes. However, the results of the 1-sec sampling interval are almost the same as those of the 10-sec interval. The 30-sec sampling interval gives moderate results, which are slightly different from those of the 1-sec interval. The 60-sec and 180-sec sampling intervals produce considerably high estimation errors due to their small network coverage and the small number of reports per segment per time step. Far more than 10 % of probe vehicles in the network is required for the 180-sec sampling interval. Hence a 10-sec or 30-sec sampling interval is

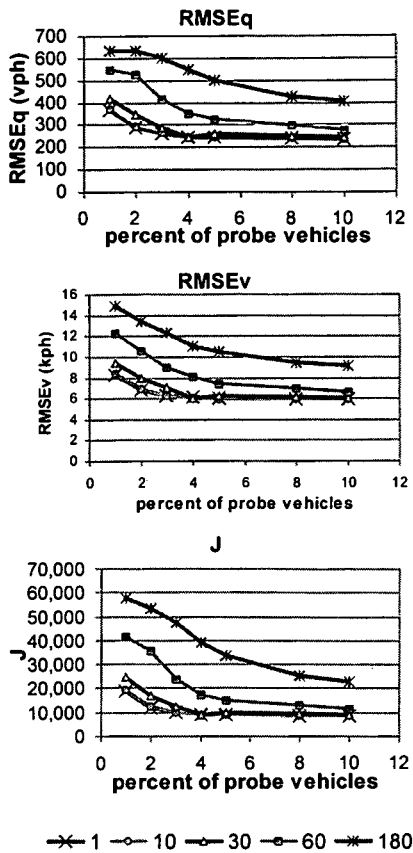


Fig. 11 Effect of the report interval of probe data (Case F)

necessary to maintain estimation accuracy with 5% of probe vehicles for the study network.

7. CONCLUSIONS

In this paper, 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 traffic states described by the macroscopic model are adjusted according to the KFT algorithm. The special features of the proposed method are:

- 1) It can treat both conventional fixed detector data and probe vehicle data in a unified manner, regardless of the observation conditions.
- 2) It can 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. Four different scenarios according to the estimation method and available traffic data were examined for a single freeway section. The major findings can be summarized as follows:

- 1) The KFT contributes to improving the state estimation accuracy. For the road section studied, the normalized variance, J , was reduced by 30%-87% compared to that estimated using the macroscopic model only.
- 2) The method using both fixed detector and probe data shows the smallest errors. It reduced the normalized variance, J , by 81%-87%, the root mean square of error in volume by 12%-53%, and the root mean square of speed by 70%-85% compared to those estimated using only the macroscopic model.
- 3) With the high network covering data obtained from probe vehicles, the proposed method can capture the traffic dynamic without any incident information, even when the traffic conditions change abruptly.
- 4) Although fluctuation could occur when the probe data were applied as observation variables, the method can trace the overall profile of the variation in terms of its mean values. However, a procedure to reduce the fluctuation remains unresolved.
- 5) A high percentage of probe deployment might not be necessary for effective state estimation. Probe vehicles of 4% to 5% with a sampling interval of 10 to 30 seconds is enough to produce the highly accurate estimation results for the studied section.

What has been found in this study is encouraging for dynamic traffic state estimation. Both the macroscopic model and the numerical technique adopted in this study were very simple. Thus, a highly complex model might not be necessary if available traffic data were able to cover most parts of a network. However, the findings are validated only for a small single road section. For further analysis, the proposed method should be applied to diverse road configurations, particularly to a large network. The mutual interaction between detector data and probe vehicle data should be investigated more in detail. As the results of this study are based on the simulation program, a validation of the proposed method with the real traffic data should be performed. Additionally, this approach should be examined with the more complicated macroscopic models with more careful calibration of model parameters before applying it into practice. Finally, the proposed method should be extended to the estimation of real-time travel time and traffic assignment volume.

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プローブカーデータを用いた高速道路における動的交通状態推定について

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プローブカーデータと従来型地点感知器データを統合的に組み合わせて高速道路の交通密度や空間平均速度の動的推定を試みた。まず、マクロ交通流モデルをシステム方程式としたカルマンフィルターによる定式化を行った。プローブカーデータや感知器データの有無による数値計算を自由流、渋滞流の6つの交通パターンに対して行い、プローブカーデータが推定精度の向上に極めて有効であることを定量的に検証した。さらに、プローブカーの混入率やサンプリング率に関しても数値解析を行い、混入率が4~5%までは推定誤差は減少するが、それ以上では推定誤差に改善はあまり見られないこと、あるいは所要の推定精度を保つためには10ないし30秒ごとのサンプリングが必要であることなどを明らかにした。