Adaptive Kalman Filter Based Freeway Travel time Estimation

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ABSTRACT

Recent advances in vehicle-based surveillance technologies using Global Positioning Systems (GPS) promise high accuracy traffic information; however, their performance in field is insufficient yet mostly due to the lack of the number of probe vehicles. Meantime, the most prevailing traffic surveillance system in the world is the conventional inductive loop detector system although this system often fails to provide accurate measures. This paper discusses how to improve travel time estimates by incorporating data from a small sample of probe vehicles, and proposes an Adaptive Kalman Filter (AKF) based method that can dynamically estimate noise statistics of the system model by adapting to the real-time data. The proposed algorithm is evaluated under both recurrent and non-recurrent congestion using a microscopic simulation model, PARAMICS. The evaluation results show that the proposed algorithm significantly improves section travel time estimates compared to the cases when a single data source was used. Some sensitivity analyses show the robustness and applicability of the method by showing its capability working with the erratic point detector data at different freeway sections, and under different probe rates.

1. INTRODUCTION

Most traffic control and management systems depend on traffic surveillance systems. Among them, inductance loop detectors are the most widely used. However, loop detectors do not directly provide travel times and have limitations in capturing area-wide traffic dynamics although travel time data are preferable for some Advanced Transportation Management and Information Systems (ATMIS) applications, such as the traffic information and route guidance systems. Furthermore, in many cases, loop detectors collect data from single loop, which does not measures speed but volume and occupancy. Two methods have been used to estimate link travel times from single loop data. The first method estimates point speeds, and then convert them to travel times based on the assumption of a common vehicle length and a constant speed over the link. Several researchers have attempted to develop better algorithms for accurate speed estimation (1, 2, 3, 4), rather than the conventional method assuming a common vehicle length. However, this method suffers from errors in both speed estimation and travel time conversion. The other method estimates travel times directly from loop detector data (5, 6, 7, 8). The basis of these works was stochastic models of traffic flow and estimated travel times by investigating traffic flows. Most of these studies have focused on overcoming the problems in speed estimation from single-loop data, assuming that the travel times estimated from double loop data are accurate. However, the travel times estimated from double loop speeds may also be flawed under congested traffic conditions, perhaps when the accurate travel time estimation is most important.

Because of the inaccuracy of the travel time estimation from point detectors, traffic data from other sources can be incorporated to improve the estimation. Due to the recent advances in probe vehicle technologies, such as Global Positioning Systems (GPS) (9), Automatic Vehicle Identification (AVI) (10), cellular phone positioning (11), and vehicle re-identification technology (12,13), probe vehicle has shown its potential to be another valuable real-time traffic data source. Such vehicle-based systems are expected to provide high-fidelity traffic information when there are enough probe vehicles. Studies on the accuracy of travel time estimation with repect to the market penetration has shown that a low probe rate causes a biased travel time estimate with a higher variance (14,15,16,17). Considering the low probe rate at the beginning phase, it is necessary to incorporate this data with other data sources for better travel time estimation.

The main interest of this paper is to develop an improved travel time estimation method by applying Adaptive Kalman Filtering (AKF) that fuses both point detection data and probe vehicle data. Kalman fitering has been applied to many traffic studies, such as the dynamic estimation of traffic density (18,19), freeway OD demand matrices (20), the prediction of traffic volume and travel time (21, 22, 23). However, these papers did not describe how to estimate the covariance matrices of the state and observation noise sequences although it is a key issue in the Kalman filtering technique. Nanthawichit et al. (24) has considered the application of probe vehicle data for traffic state estimation and short-term travel time prediction. However, their model depends on basic traffic flow diagram, and ignores detector errors and effects of different probe rates. The solution for the noise covariance matrix has not been addressed either. The study addresses statistics on system model noises derived from both model errors and detector errors, and develops an algorithm to estimate section travel times with on-line estimation of such error statistics.

This paper is organized as follows. Section 2 discusses the definition of section travel time and the exiting methods to estimate section travel times from loop detectors and probe vehicle data. In Section 3, we propose a section travel estimation algorithm based on AKF. The algorithm is evaluated under both recurrent and non-recurrent scenarios in a microscopic simulation environment in Section 4. Finally the concluding remarks are given in Section 5.

2. BACKGROUND

2.1 Definition of Section Travel Time

The representative section travel time can be defined as a mean travel time within the closed area defined by the time (t and t+1) and space (x_u and x_d), as shown in Figure 1. The true space-mean speed for vehicles within the closed area is equal to the total travel distance divided by the total travel time of all vehicles in the closed area (25). An unbiased estimate of the space-mean speed is:

$$\bar{v} = \frac{\sum_{n=1}^{N} \left\{ \min\left(x_{t+1}^{n}, x_d\right) - \max\left(x_t^{n}, x_u\right) \right\}}{\sum_{n=1}^{N} \left\{ \min\left(t+1, t_d^{n}\right) - \max\left(t, t_u^{n}\right) \right\}} \qquad (1)$$

where,

N = number of vehicles traversing the section during the time interval

x_t^n = position of vehicle n at time t

x_u = position of the upstream boundary

x_d = position of the downstream boundary

t_d^n = time when vehicle n passes the downstream boundary

t_u^n = time when vehicle n passes the upstream boundary

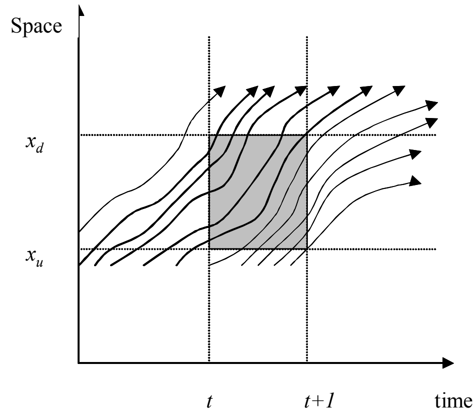


Figure 1 A temporal and spatial illustration of section travel time

The average section travel time (tt_s) can then be estimated from on the unbiased estimate of the space-mean speed as

$$tt_S = \frac{x_d - x_u}{\bar{v}} = \frac{\Delta x}{\bar{v}} \quad (2)$$

Such an average section travel time can be considered as a "true" mean travel time of the temporal and spatial section. In this study, we will investigate how to estimate this section travel time.

2.2 Section Travel Time Estimate from Loop Detector Data

A typical method to estimate section travel time from loop detector data is based on average speed estimates at the boundary detector stations. The average speed by lane can be obtained directly from double loops or estimated from single loops (26,27). Based on these lane-based speeds, the station speed is generally defined as the weighted average of lane speeds.

$$v = \frac{\sum_{i=1}^{L}(q_i * v_i)}{\sum_{j=1}^{L} q_j} \quad (3)$$

where L is number of lanes. $q_i(t)$ and $v_i(t)$ are traffic count and speed at lane i of a detector station, respectively.

Then the section travel time can be estimated (28):

$$tt_l = \frac{1}{2}\left(\frac{\Delta x}{v_u} + \frac{\Delta x}{v_d}\right) \quad (4)$$

where $v_u(t)$ and $v_d(t)$ are spot speeds at upstream and downstream detector stations.

The method based on loop detector data includes two kinds of estimation errors: (1) speed estimation from loop data and (2) travel time conversion from speed as in Equation 4.

2.3 Section Travel Time Estimate from Probes

Section travel time can also be estimated from probe vehicle reports. The section travel time of a time interval (t-1, t) can be calculated by averaging travel times of individual vehicles arriving at the downstream boundary within (t-1, t) (29).

$$tt_p = \frac{\sum_{n=1}^{N}(t_d^n - t_u^n)}{N} \tag{5}$$

where t_d^n and t_u^n are times when vehicle n passes the downstream and upstream boundaries of the section. N is the number of sample vehicles arriving the downstream boundary within (t-1, t).

The travel time estimated from probes is regarded as arrival-based travel time. Vehicles arrived at x_d during (t-1, t) in Figure 1 do not truly reflect the shaded temporal spatial section, which leads to a biased estimate of the mean travel time of the section.

3. METHODOLOGY

Both methods described in previous section do not truly reflect accurate section travel time especially under recurrent or non-recurrent traffic congestion condition. This study proposes a method to estimate section travel time by fusing both loop detector and probe vehicle data. The method consists of two parts. First,

3.1 Travel Time Estimation based on Section Density

The model we are proposing here is based on the conservation or continuity equation. This equation shows the same form as in fluid flow, and the solution of the conservation equation in traffic flow was first proposed by Lighthill and Whitham (30) and Richards (31). The fluid conservation equation characterizes compressible flow, that is,

$$\frac{\partial q}{\partial \mathrm{x}} + \frac{\partial \mathrm{k}}{\partial \mathrm{t}} = 0 \text{ (or traffic generation rate)} \tag{6}$$

where q is flow (vehicles/hour), k is density (vehicles/mile), x is location, and t is time.

If the speed of such traffic fluids is v, we have the following basic identity:

$$q = k \cdot v \tag{7}$$

For a typical urban freeway section including one on-ramp and one off-ramp, as shown in Figure 2, the traffic flow passing the section during time period (t-1, t) can be estimated as:

$$q(t) = \alpha \cdot [q_u(t) + q_{on}(t)] + (1-\alpha) \cdot [q_d(t) + q_{off}(t)] \quad (8)$$

where α is a smoothing parameter that is set to 0.5 in this paper. $q_u(t)$ and $q_d(t)$ are traffic flows of the upstream and downstream boundaries within (t-1, t). $q_{on}(t)$ and $q_{off}(t)$ are total on-ramp and off-ramp traffic flows within (t-1, t).

Assuming that the traffic inside of the section is homogeneous, an intuitive estimation of the section travel time is:

$$tt(t) = \frac{\Delta x}{v(t)} = \frac{\Delta x}{q(t)} \cdot k(t) \quad (9)$$

where Δx is length of the section between upstream and downstream detectors.

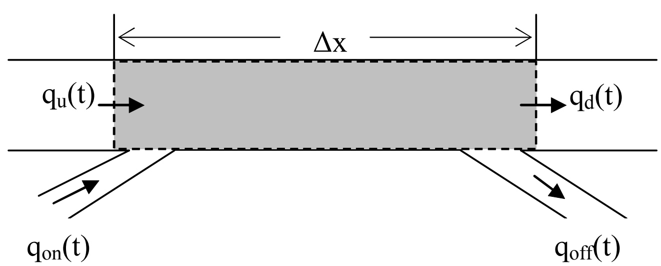


Figure 2 A typical freeway section

Based on the traffic flow conservation equation, the estimation of section travel time depends on a non-observable state variable, section density, k(t), which can be represented as a time series:

$$k(t) = k(t-1) + \frac{1}{L * \Delta x} \cdot \{q_u(t) + q_{on}(t) - [q_d(t) + q_{off}(t)]\} \quad (10)$$

where L is the number of lanes on the mainline freeway.

3.2 Kalman Filter for Data Fusion

The aforementioned method may incorrectly estimate travel times if detectors have errors in measuring traffic counts. In real applications, loop detectors' malfunctioning happen quite often. In study, Kalman filtering technique is employed as a way of correcting the section density estimates in equation (10) and the corresponding travel time in equation (9) using another source of data.

When there are two set of data from loop detectors and probe vehicles, the Kalman filter associates two data in order to correct the section density (and thus section travel time). Equations 9 and 10 are rewritten as follows:

State equation: $k(t) = k(t-1) + u(t) + w(t-1)$ (11)

Measurement equation: $tt(t) = H(t) * k(t) + v(t)$ (12)

u(t) and H(t) can be estimated by:

$$u(t) = \frac{1}{L * \Delta x} \cdot \{q_u(t) + q_{on}(t) - [q_d(t) + q_{off}(t)]\} \quad (13)$$

$$H(t) = \frac{\Delta x}{\alpha \cdot [q_u(t) + q_{on}(t)] + (1-\alpha) \cdot [q_d(t) + q_{off}(t)]} \quad (14)$$

In the Kalman filter, the section density is treated as a state variable and the section travel time is treated as a measurement variable. Because of model errors and detector errors, both systematic error and random error may apply to both state and measurement equations. Consequently, the state noise, w(t), is assumed a Gaussian noise with the mean of q(t) and variance of Q(t). The observation noise, v(t), is assumed a Gaussian noise with the mean of r(t) and variance of R(t).

The solution to this Kalman filter problem is:

$$\bar{k}(t) = \hat{k}(t-1) + u(t) + q(t-1) \quad (15)$$

$$\bar{P}(t) = \hat{P}(t-1) + Q(t-1) \quad (16)$$

$$G(t) = \bar{P}(t) H(t)^T [H(t) \bar{P}(t) H(t)^T + R(t)]^{-1} \quad (17)$$

$$\hat{k}(t) = \bar{k}(t) + G(t)[tt(t) - H(t)\bar{k}(t) - r(t)] \quad (18)$$

$$\hat{P}(t) = \bar{P}(t) - G(t) H(t) \bar{P}(t) \quad (19)$$

where $\bar{k}(t)$ and $\bar{P}(t)$ are propagated state (i.e section density) estimation and its estimated covariance prior to time t. $\hat{k}(t)$ and $\hat{P}(t)$ are defined as a posteriori state estimate and its estimated covariance after the incorporation of the section travel time observation. G(t) is defined as Kalman gain at time t.

3.3 On-line Estimate of Noise Statistics

A well-known limitation in applying Kalman Filter to real-world problems is that priori statistics of the stochastic errors in both state and observation processes are assumed to be known. In this application, the noise statistics may change with time due to the nature of the traffic system and detection errors. As a result, the set of unknown time-varying statistical parameters of noises, {q, Q, r, R}, needs be simultaneously estimated with the system state and the error covariance. This is the so-called Adaptive Kalman Filter (AKF) problem. Methods for the problem are classified into four categories: Bayesian, maximum likelihood, correlation, and covariance matching (32).

This study applies an empirical estimation method proposed by Myers K.A. and Tapley B.D. (33) to noise statistics estimations because of its simplicity and ability to handle both systematic errors and random errors in noise sequences. This method is based on a limited memory algorithm developed to adaptively correct the priori statistics by compensating time-varying model errors.

3.3.1 Estimation of Observation Noise

In Equation 12, the observation noise sequence, v(t), cannot be determined if the true state vector k(t) is unknown. An intuitive approximation of the observation noise is given by:

$$r_j = tt_j - H_j \bar{k}_j \tag{20}$$

where r_j is defined as the observation noise sample at time t_j. If the noise samples are assumed representatives of v, r_j and v_j should be independently identically distributed. An unbiased estimator for r, is taken as the sample mean:

$$\hat{r} = \frac{1}{N}\sum_{j=1}^{N} r_j \tag{21}$$

The actual covariance of v_j can be approximated by the unbiased estimate of its sample covariance:

$$\hat{C}_r = \frac{1}{N-1}\sum_{j=1}^{N}(r_j - \hat{r})\cdot(r_j - \hat{r})^T \tag{22}$$

where N is the number of observation noise samples, which is selected empirically in order to provide a reasonable noise statistics based on the latest data. Based on Equations 20 to 22, the expected value of $\hat{C}_r$ is:

$$E(\hat{C}_r) = \frac{1}{N}\sum_{j=1}^{N} H_j \bar{P}_j H_j^T + R \tag{23}$$

The unbiased estimation of R becomes:

$$\hat{R} = \frac{1}{N-1}\sum_{j=1}^{N}[(r_j - \hat{r})\cdot(r_j - \hat{r})^T - (\frac{N-1}{N}) H_j \bar{P}_j H_j^T] \tag{24}$$

3.3.2 Estimation of Q

In Equation 11, the state noise sequence, w(t), cannot be determined if the true state vectors k(t) and k(t-1) are unknown. The intuitive approximation of the state noise at time step j is given by:

$$q_j = \hat{k}_j - \Phi_{j,j-1}\hat{k}_{j-1} - u_j \tag{25}$$

where q_j is defined as the state noise sample at time t_j. Assuming that the noise sample sequence q_j are representatives of the state noise sequence w_j, q_j and w_j should be independently identically distributed. An unbiased estimator for q, is taken as the sample mean:

$$\hat{q} = \frac{1}{N}\sum_{j=1}^{N} q_j \tag{26}$$

Then the actual covariance of w_j can be approximated by the unbiased estimate of its sample covariance:

$$\hat{C}_q = \frac{1}{N-1}\sum_{j=1}^{N}(q_j - \hat{q})\cdot(q_j - \hat{q})^T \tag{27}$$

where N is the number of state noise samples, which is selected empirically in order to provide a reasonable noise statistics based on the latest data. Following the same procedure in estimating R, the unbiased estimation of Q is:

$$\hat{Q} = \frac{1}{N-1}\sum_{j=1}^{N}[(q_j - \hat{q})\cdot(q_j - \hat{q})^T - (\frac{N-1}{N})\Phi_{j,j-1}\hat{P}_{j-1}\Phi_{j,j-1}^T - \hat{P}_j] \tag{28}$$

3.4 Summary of the proposed algorithm

The proposed algorithm for section travel time estimation based on AKF can be summarized as follows. At each time step,

(1) Calculating u(t) and H(t) based on the data of last time interval from point detector using Equations 13 and 14.
(2) State propagation: calculating a priori estimate of k(t) and estimation covariance using Equations 11 and 12.
(3) Estimating R using Equation 24 based on last N observation noise samples
(4) Updating Kalman gain using Equation 17.
(5) State estimation: calculating a posteriori estimate of k(t) and estimation covariance using Equations 18 and 19.
(6) Estimating Q using Equation 28 based on last N state noise samples.
(7) Calculating the section travel time based on Equation 9.

4. EVALUATION

This study evaluates the proposed algorithm by comparing with other travel time estimation methods. The evaluation is performed in a stretch of freeway using a microscopic traffic simulation model, PARAMICS mainly because of the unavailability of probe data.

4.1 Study Site

The study site is a six-mile stretch of northbound freeway I-405, between junctions of freeway I-5 and Culver Drive, in Orange County, California. The schematic representation of the study site is illustrated in Figure 3. The lines across the freeway lanes represent locations of loop detectors whose exact locations are represented by their post-miles on the bottom of the figure. In this study, we test the section from Sand Canyon Drive to Jeffery Drive which includes one on-ramp and one off-ramp.

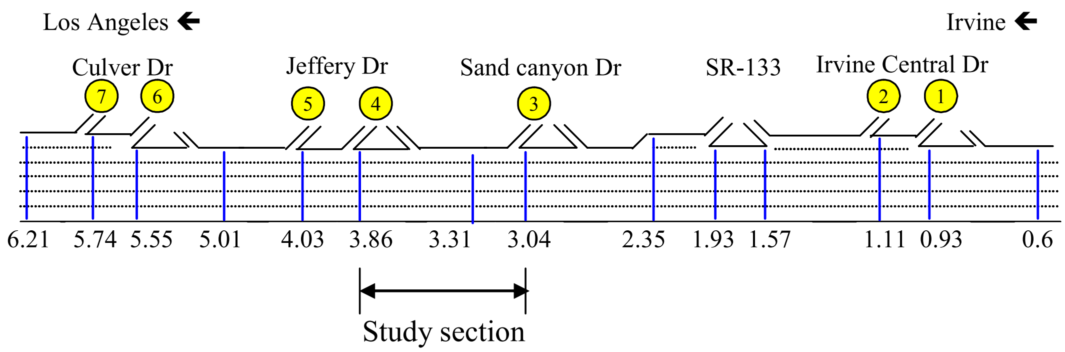


Figure 3 Schematic figure of the study site

This network used in PARAMIC simulation has been calibrated based on previous simulation studies (34). The time-dependent origin and destination demands, estimated based on the real world traffic data of May 22, 2001, were used for this simulation experiment.

4.2 Performance Index

Mean Absolute Percentage Error (MAPE) is employed for the performance evaluation of section travel time methods. It is defined as:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{|z_i - \hat{z}_i|}{z_i} \tag{29}$$

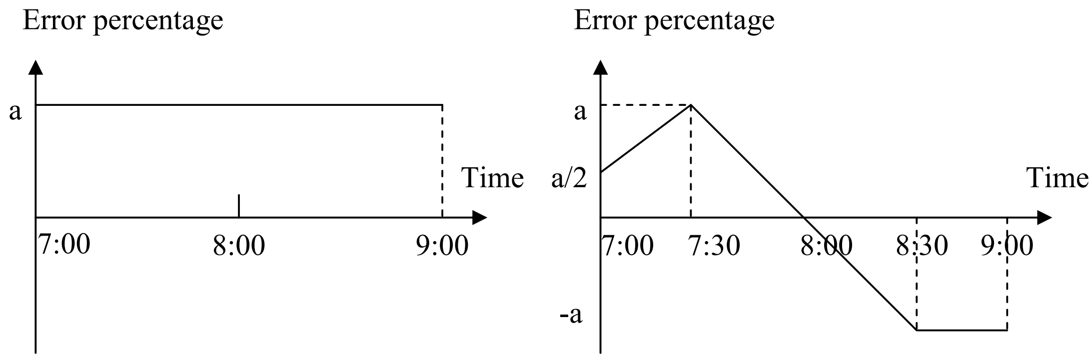
where
z_i = the true value of variable z at sampling point i
$\hat{z}_i$ = the estimated value of variable z at sampling point i
N = total number of samples of variable z

4.3 Modeling Detector Errors

Loop detector data includes detection errors. The inductance may change with temperature, moisture, corrosion, and mechanical deformation. Traffic controllers and communication devices may also malfunction. Such mechanical problems are sources of errors in loop detector systems. This study considers such errors and intentionally includes errors in traffic measures as follows:

$$q(t) = q_0(t) \cdot [1 + \alpha(t) + \beta(t)] \tag{30}$$

where $q_0(t)$ is the true count. $\alpha(t)$ represents the systematic or locally systematic error percentage, which is a constant or a time-dependent value. Examples of $\alpha(t)$ are shown in Figure 4. $\beta(t)$ represents random error, which varies randomly between measurements. $\beta(t)$ is assumed to be a Gaussian white noise sequence with zero mean and standard deviation of δ. Because 95% of the population of normal distribution is within (-2*δ, 2*δ), δ can be estimated as half of the maximum random error percentage.



(a) constant error pattern (b) time-varying error pattern

Figure 4 Systematic error function: alpha(t)

4.4 Evaluation scenarios

We have two scenarios to evaluate the proposed AKF algorithm:

(1) Recurrent congestion scenario
(2) Incident scenario

In the incident scenario, an incident was injected to a location between Sand Canyon Dr junctions and the off-ramp at Jeffery Dr. The incident was assumed to block the rightmost lane of freeway for 10 minutes (i.e. from 8:20 to 8:30 AM).

For the study section, there are four detectors placed on boundaries of the section. We assume all of them have both systematic and random errors, as shown in Table 1. Random errors were drawn from a standard Normal distribution with the mean of 0 and different standard deviations (δ) by detector.

Loop detector data in the California freeway system are aggregated with 30 seconds interval. Considering 30-sec section travel time can be further used for various ATMIS applications, this paper chose 30 seconds as the section travel time estimation interval.

Table 1 Detector error pattern in the evaluation scenario

	Systematic detector error	Standard deviation for random error(δ)
Upstream detector	a = -5%; error pattern: Figure 4(b)	1.0
Downstream detector	a = 8%; error pattern: Figure 4(a)	1.5
On-ramp detector	a = -5%; error pattern: Figure 4(a)	0.5
Off-ramp detector	a = 10%; error pattern: Figure 4(a)	2.0

4.5 Evaluation results

We implemented the proposed AKF algorithm and other two estimation methods (one based on double-loop speed and the other based on probe vehicles) within the PARAMICS simulation model. The true mean section travel time described in section 2.1 was treated as the benchmark travel time. We applied detector errors only to the proposed AKF algorithm while assuming that there were no error in double loop speed and probe vehicle data for the other two methods.

All simulations started from 6:30 AM and ended at 9:00 AM. The first 15 minutes of each simulation run were treated as a warming up period. Since the proposed algorithm needs some time to initialize and fine-tune parameters, performances were compared during 7:00 A.M. to 9:00 AM.

Section travel times from each method were compared with the benchmark travel time in terms of MAPE. As shown in Table 2, the proposed AKF algorithm outperforms the other two methods. Figure 5 and 6 compare the estimation of section travel time over time using three evaluated algorithms under two scenarios. Compared to the probe-based method and the point-detection-based method, the proposed algorithm provides better estimates throughout the whole study period. Especially, during the congestion period, the AKF algorithm effectively estimates section travel times.

Table 2 Comparison of various estimation algorithms under different scenarios

	Scenario 1	Scenario 2
Point-detector-based Algorithm	10.6%	16.0%
Probe-based Algorithm (5% probe rate)	10.8%	14.3%
AKF Algorithm (5% probe rate)	7.6%	9.8%

As shown in Figure 5 and 5, the probe based algorithm trends to over-estimate section travel time during a certain time period after traffic congestion occurs. This is because the probe-based method estimates travel times based vehicles arrived at the downstream. The point-detector-based algorithm is not robust, showing strong fluctuations during the congestion period. It seems because of the bottleneck caused by vehicle weaving and road curvature or the incident in Scenario 2. This implies that the point detector data often fails accurately capturing the area-wide traffic condition.

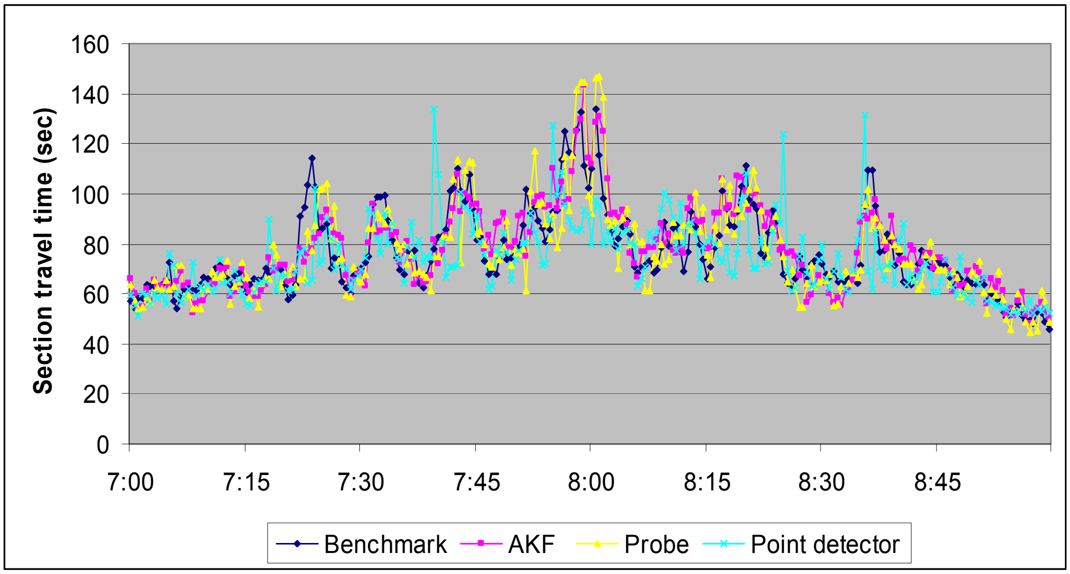


Figure 5 Performance comparisons under the recurrent traffic congestion (Scenario 1)

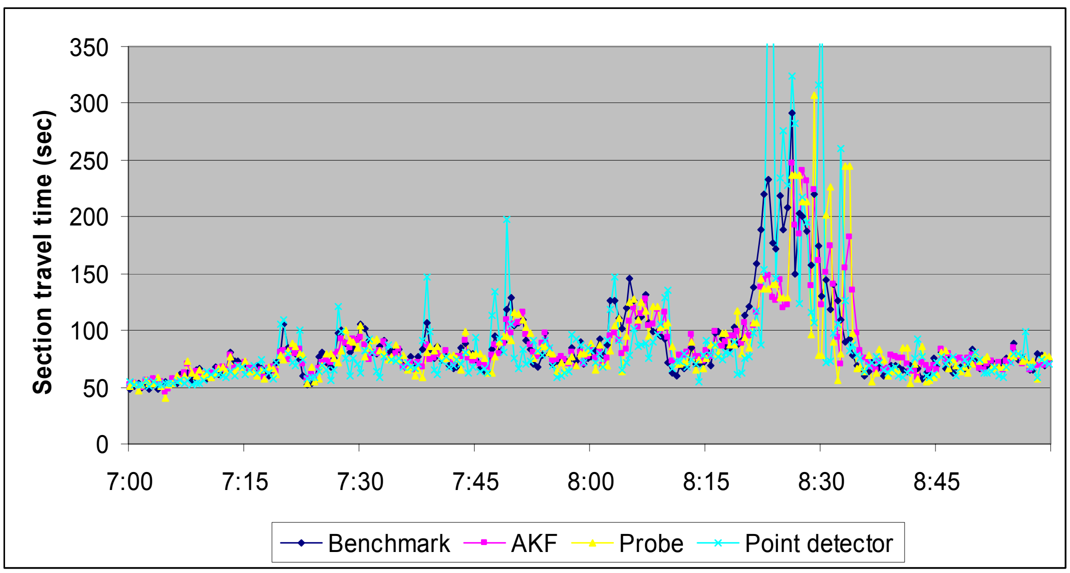


Figure 6 Performance comparisons under incident scenario (Scenario 2)

The proposed algorithm effectively captures the variation of section travel time using the adaptive Kalman filter technique that associates both count data from single loops and travel time data from probe vehicles. The key point of the algorithm is its on-line capability estimating statistics of the state noise and the observation noise. Under Scenario 1, the estimated means of state, r(t), and observation noises, q(t), are shown in Figure 7 and their estimated variances, R and Q, are shown in Figure 8. Since R has high values, we used ln(R) instead of R in order to show it together with Q in the figure.

q(t) is used to capture the systematic error in the state equation mainly from systematic detector errors. r(t) is used to capture the systematic error in the observation equation. Q and R are used to capture random errors in the state equation and observation equation. Thanks to the capability effectively capturing the variation of noises in the state equation and observation equation, the proposed algorithm provides accurate estimates of the section density and the travel time.

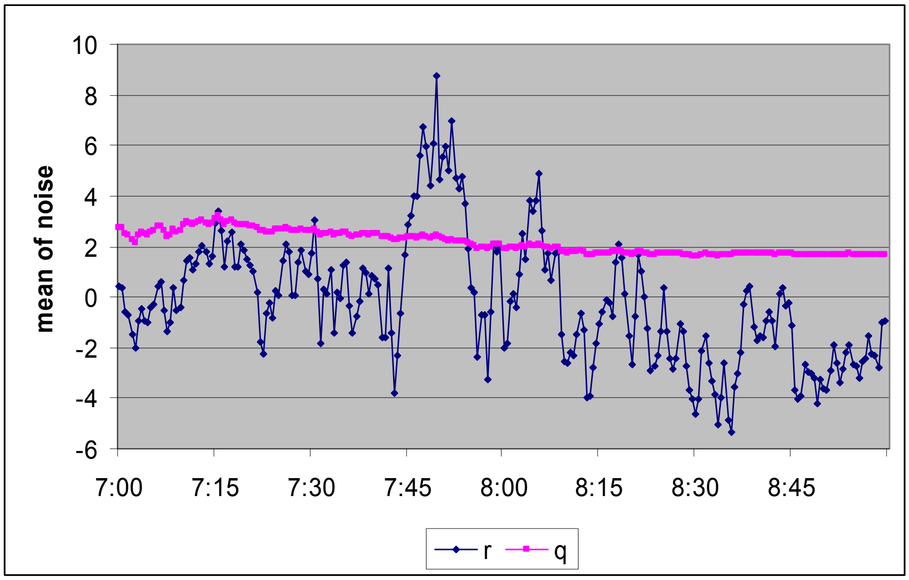


Figure 7 On-line estimation of noise mean under scenario 1

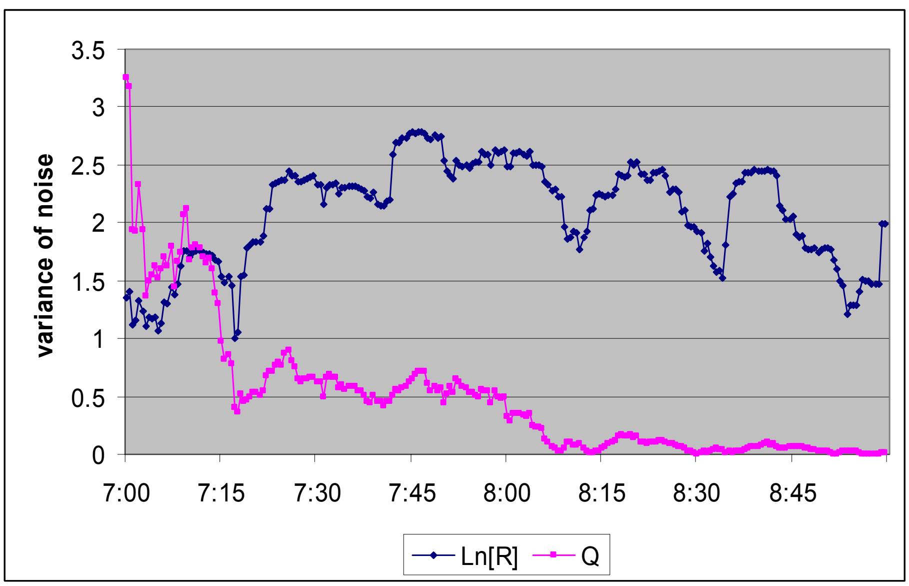


Figure 8 On-line estimation of noise variances under scenario 1

4.6 Sensitivity Analysis

In this section, we conduct sensitivity analyses in order to discover how the proposed algorithm performs under different errors and settings.

4.6.1 Systematic Detector Errors

Because the mean of observation noises, r(t), mainly comes from detector errors, we performed a sensitivity analysis in order to further discover that q corresponds to systematic error of state equation. In this study, we assumed that only upstream detector had systematic errors and the probe rate was 5%.

Firstly, the error pattern shown in Figure 4(a) is applied to the upstream detector data. Figure 9 shows that the proposed algorithm is not sensitive to this type of detector errors. It is because the mean of state noises is successfully captured by the algorithm, as shown in Figure 10.

As shown in Figure 11, the algorithm can also handle time-dependent systematic errors as in Figure 4(b). The algorithm provides better estimates than the probe-based method as long as the maximum detector error (a in Figure 4(b)) is smaller than 25%. The mean of state noises is also successfully captured as shown in Figure 12.

Each detector station includes multiple lane detectors. The last case is when some of lane detectors are malfunctioning. The proposed algorithm was tested under the condition that some parts of detector data are missing. Figure 13 shows that the algorithm outperforms the probe-based method even when data are missing from two lanes among all four lanes.

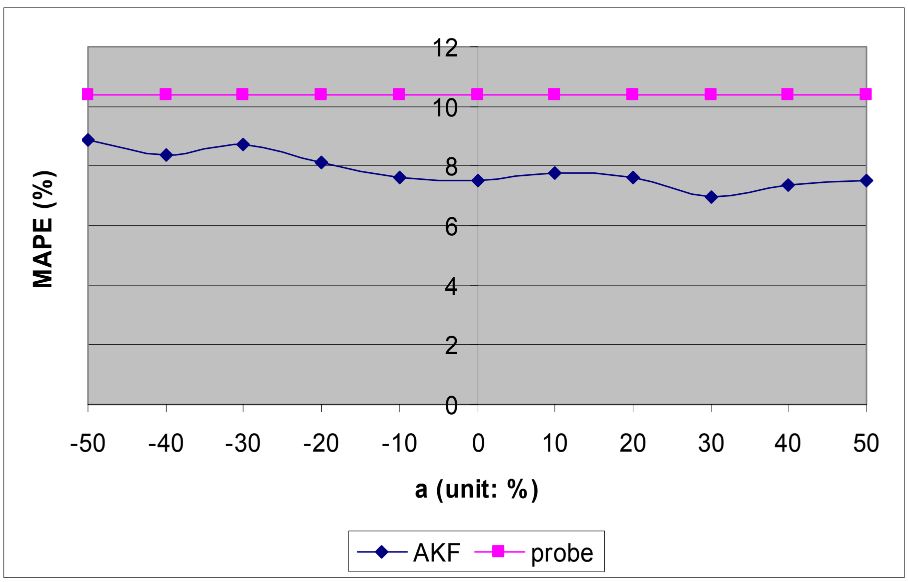


Figure 9 Performance under constant system errors

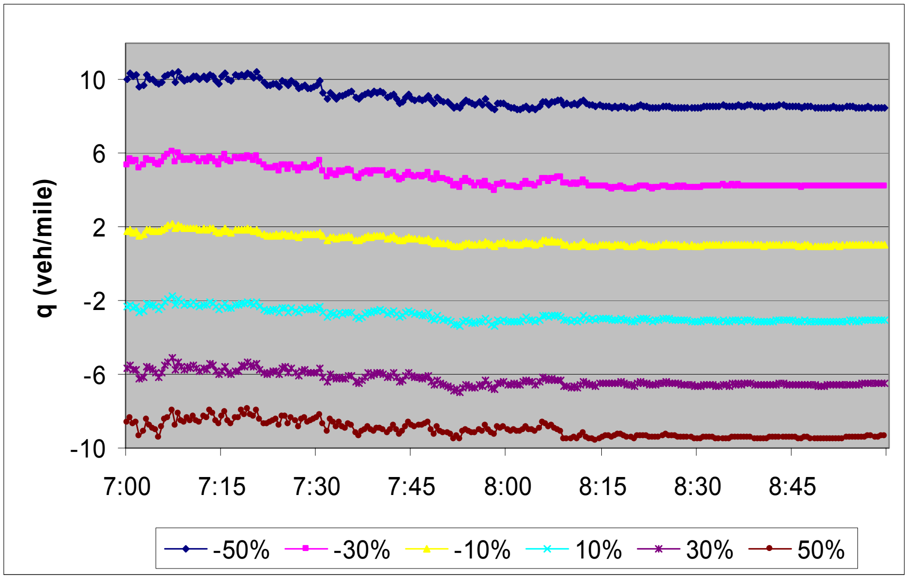


Figure 10 Mean of state noises under different systematic errors

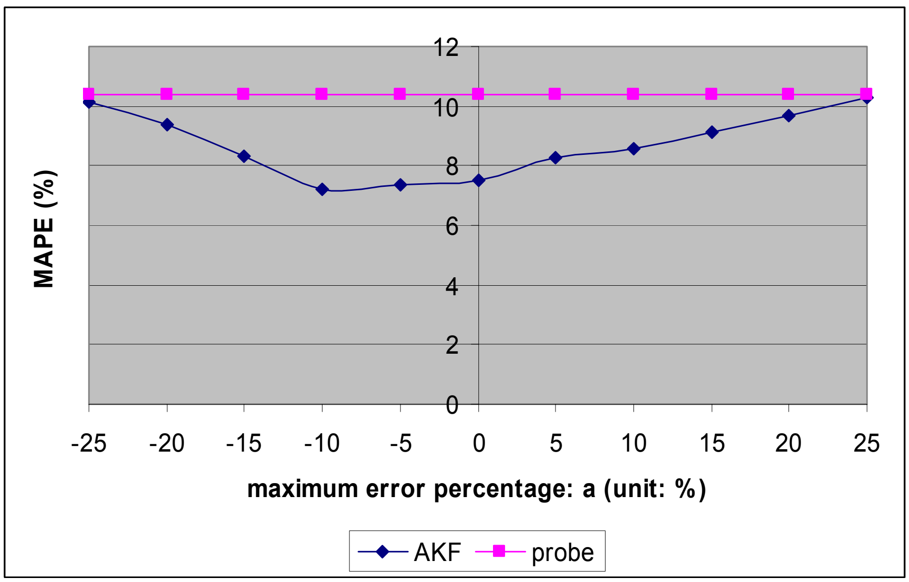


Figure 11 Performance under time-dependent systematic errors

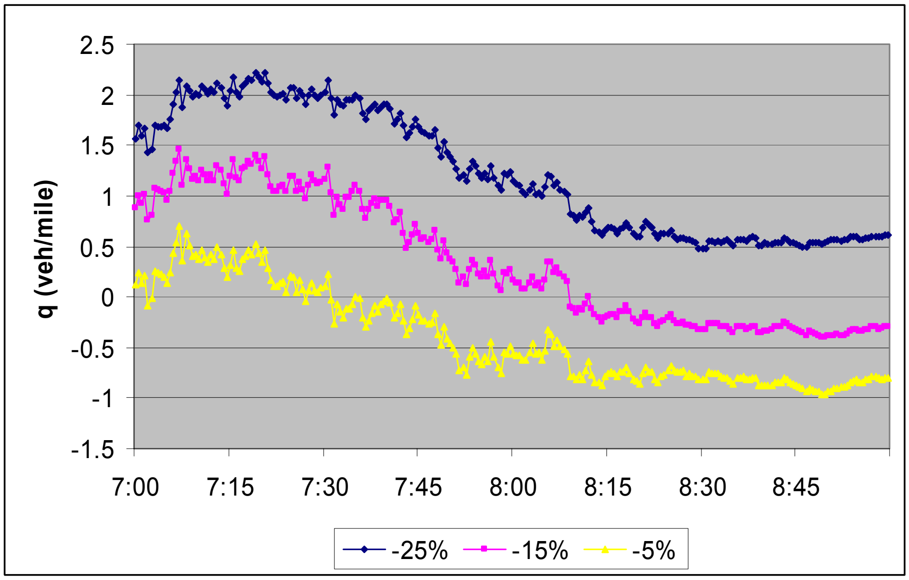


Figure 12 Mean of state noises under time-dependent systematic errors

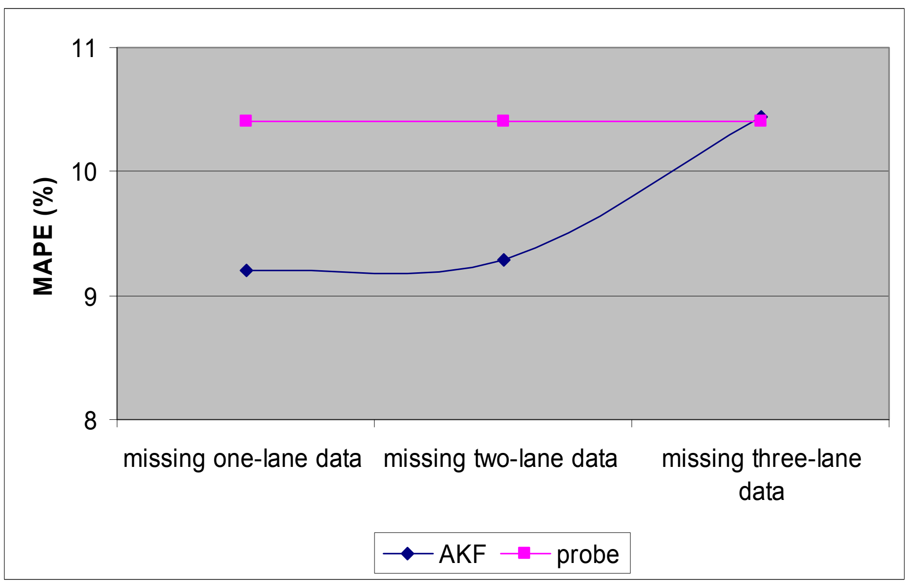


Figure 13 Performance under partial data missing

4.6.2 Random Errors from Detectors

In this section, we investigate how the algorithm works with different random errors. In this experiment, we consider different random error rates with a probe rate of 5%, but no systematic errors. As shown in Figure 14, the algorithm is not sensitive to random errors from detector data.

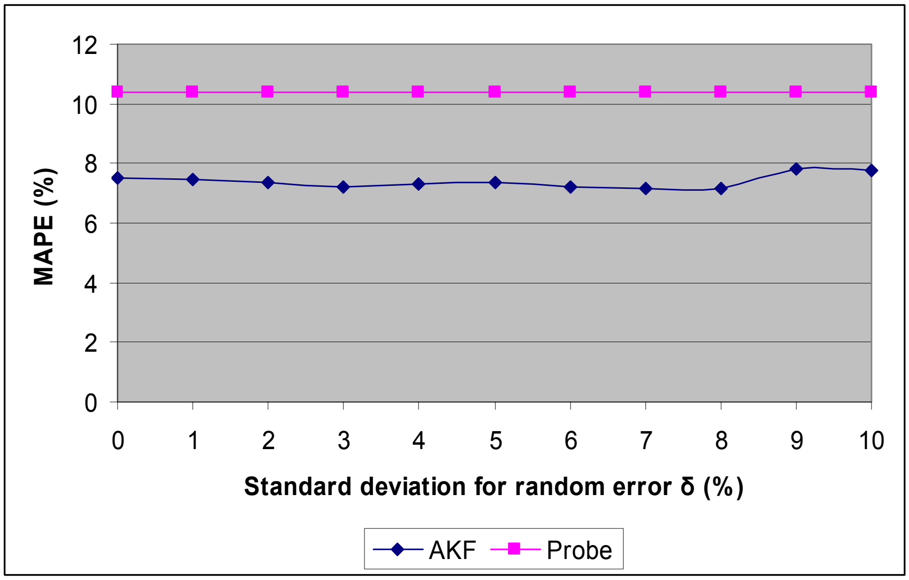


Figure 14 Algorithm's performance under random errors from detectors

4.6.3 Different sections

We examine if the performance of the algorithm varies by location. We applied the proposed algorithm to other two sections in our study network using the same configuration as described in Section 4.5. The performance of the proposed algorithm under the recurrent traffic congestion is shown in Table 3. The table shows that the proposed algorithm provides consistent performance in different sections of freeways.

Table 3 Performance in different sections

	Section between post-mile 2.35 and 2.99	Section between post-mile 3.86 and 5.55
Point detector based Method	16.6%	14.0%
Probe-based Method (5% probe rate)	13.8%	12.3%
AKF Algorithm (5% probe rate)	9.7%	8.8%

4.6.4 Probe vehicle rate

We have assumed the same rate of probe vehicles in previous experiments. However, as more probe vehicles are available, the performance of probe-based method becomes better. So does the AKF algorithm as shown in Figure 15. However, when the probe rate is higher than 20%, no more improvement is observed. This means that a probe rate of 20% is enough to provide accurate averages by removing the randomness of probe vehicles.

While the probe-based travel time does not well represent the benchmark travel time because this method is based on vehicles arrived at downstream, the proposed algorithm improves the accuracy by integrating two data sources. However, the benefit of the proposed algorithm decreases as the probe rate increases. For example, the proposed algorithm improves the performance by 15.8% with a probe rate of 1%, but only 10.4% with a probe rate of 5%.

Figure 15 also shows that the proposed algorithm does not require more than 10% of probe vehicles. In other word, a probe rate of 10% is enough to remedy the errors in loop detectors. With higher than 10% probe size, there are still some errors that the algorithm cannot reduce perhaps because of the randomness of the traffic system.

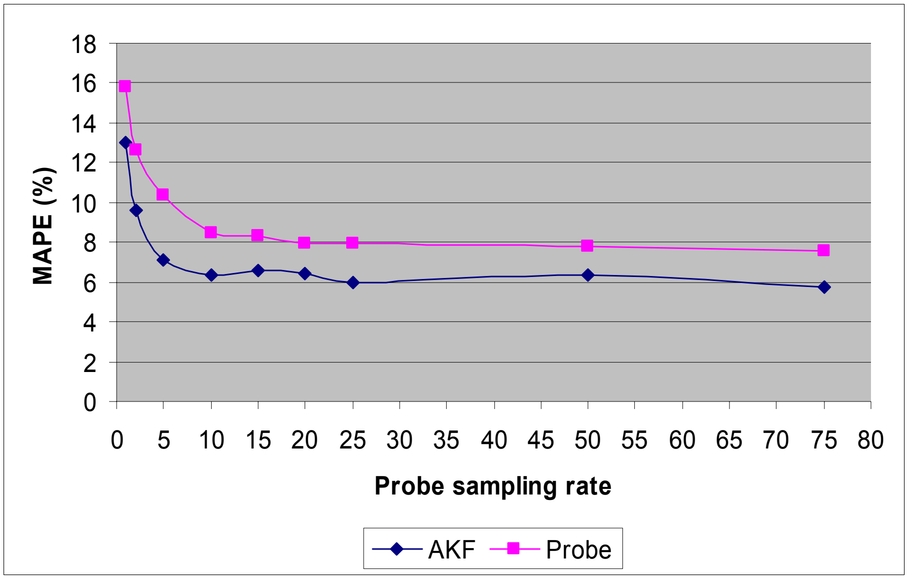


Figure 15 Performance comparison between the AKF algorithm and the probed-based method with respect to probe rate

5. CONCLUDING REMARKS

This paper develops a method for section travel time estimation by applying the Adaptive Kalman filter technique that incorporates two data sources, i.e. point detector data and area-wide probe data. In the proposed method, the traffic system is regarded as a discrete-time dynamic system. The system model is described with a state equation and an observation equation based on the traditional traffic flow theory. An advantage of the proposed method is its capability working with the erratic detector data and model errors.

The proposed algorithm was tested in a stretch of freeway using a microscopic simulation model. Compared to the probe-based method and the double-detector-based method, the proposed algorithm outperformed under both recurrent and non-recurrent traffic conditions despite the errors in loop detector. Some sensitivity analyses further proved the robustness of the method by showing its capability working with the erratic point detector data at different freeway sections under different probe rates. The benefit of the proposed algorithm decreased as the probe rate increases, but always shows better performance than probe data only.

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