Travel Time Prediction Using Dedicated Short-Range Communications Probe Data

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ABSTRACT: This paper proposes algorithms for dynamic travel time prediction to provide reliable real-time travel time information using probe travel time data collected by a dedicated short range communication (DSRC) system. The travel time predictions were performed using arrival-time-based travel time; subsequently, the accuracy of these predictions was evaluated using the concurrent departure-time-based travel time data, which were also collected by the DSRC system. The prediction methodologies proposed in this research include the Kalman filter and a newly developed algorithm that uses weighting factors according to probe sample size. An evaluation of the performance of the two algorithms showed their errors ranged from 5 to 7%, thereby showing satisfactory results. Considering the fact that the Kalman filter requires historical travel time for prediction, the similarity between the historical and current data is core factor for reliable travel time prediction. On the other hand, the newly developed algorithm does not need historical data, thereby the benefit could be enhanced especially when historical travel time data analogous to current ones are not easily available.

Keywords: ATIS, Travel Time Prediction, DSRC, Kalman Filter

I. INTRODUCTION

Advanced traveler information system (ATIS), one service area of intelligent transportation systems (ITS), has been widely deployed in many developed countries to efficiently mitigate traffic congestion (1-5). In addition to the conventional point detector-based real-time traffic information system, a probe-based system using dedicated short range communication (DSRC) is being popularized all over Korea. DSRC (5.8GHz) was originally introduced in Korea in 2002 for electronic toll collection system (ETCS). Consequently, the probe vehicles used in DSRC traffic information systems have been designated as vehicles with ETCS (or Hi-Pass) tags. As of 2011, the market penetration of the Hi-Pass tags (or on-board units, OBUs) was nearly 40% for all the cars in Korea. This high penetration rate has led to the widespread deployment of DSRC-based real-time traffic information systems in the country.

In the DSRC traffic information system shown in Figure 1, passage time of probe vehicle is recorded in roadside equipment (RSE). The time-stamp data are then transmitted to the traffic information center (TIC). At the TIC, the transmitted probe data are processed (matching, filtering, etc.) to generate real-time traffic information that is supposed to be disseminated to OBUs of the upstream vehicles as well as conventional media such as variable message sign (VMS), automated response system (ARS), and the Internet.

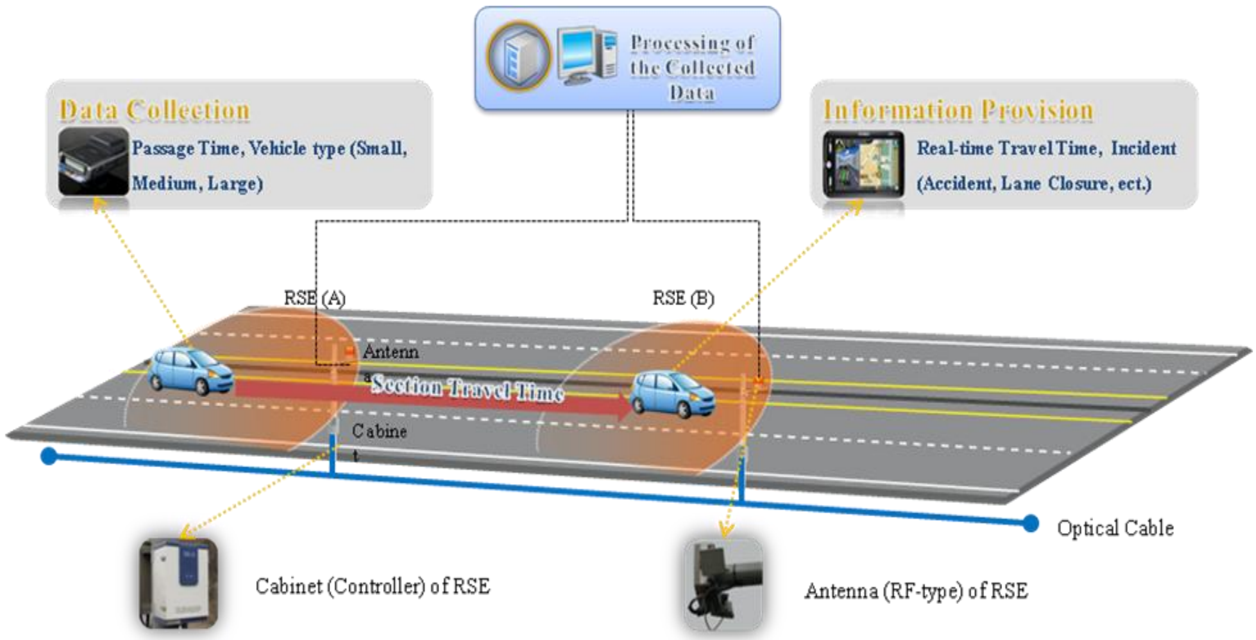

Figure 1 Schematic of DSRC Traffic Information System

Conventionally, in Korea, automatic number plate recognition (ANPR) was used to collect section travel time (TT). However, ANPR needs to be installed on each lane; further, it requires a strobe to recognize vehicle number plates at night. As a result, the cost of their deployment and maintenance is considerably higher than that of DSRC RSE (approximately six times more for a four-lane roadway). This aspect expedites the deployment of DSRC traffic information systems in Korea. However, despite its efficiency, a DSRC RSE can collect TT only from vehicles with OBUs; this implies that the accuracy of collected TT depends on the vehicle sample rate (i.e., accuracy may decrease with low probe rates). Moreover, given that the section TT obtained via DSRC includes time lag, TT prediction is considered to be essential to provide reliable real-time travel time information.

In our study, we propose and implement dynamic TT prediction algorithms for reliable real-time TT information for DSRC traffic information systems. The proposed algorithms consist of the Kalman filter and a new algorithm. The new algorithm considers the characteristics of the DSRC traffic information system that generates TT information with low vehicle sample rates. The two algorithms predict future TT using arrival-time-based TT that includes time lags. Subsequently, the predicted TT is evaluated by the concurrent departure- time-based TT as baseline data. The data used in this study were collected on a multilane highway near Seoul, Korea.

II. LITERATURE REVIEW

The ATIS was introduced to mitigate traffic congestion problems through real-time traffic information, thereby enabling drivers to choose less congested routes or to delay their schedules to less congested times; consequently, TT prediction has become a very important issue. In particular, TT prediction is of paramount importance in probe-based traffic information systems such as the DSRC that collects probe vehicle TT with time lags.

Thus far, several studies have focused on predicting TT using various approaches. Mei Chen et al. (6) predicted TT collected by probe cars on a freeway using the Kalman filtering algorithm; further, they evaluated the predicted TT by means of the TT generated by Corridor Simulation (CORSIM), which is one of the widely used microscopic traffic simulation programs. Chien et al. (7) applied the Kalman filter to predict TT calculated by traffic detector data in New Jersey, and they compared the predicted TT against the TT generated by the CORSIM. Kuchipudi et al. (8) developed link- and path-based TT prediction techniques using the Kalman filter. They utilized TT gathered by probe vehicles with EZ tags on the New York State Thruway (NYST). Huisken et al. (9) used a neural network algorithm to predict TT using detector data obtained on a freeway in Rotterdam, and they demonstrated the superiority of their proposed algorithm over traditional ones. Chien et al. (10) predicted TT using real-time and historical data from a freeway and evaluated the predicted TT.

Since the widely recognized prediction models (such as time series models using autoregressive integrated moving average (ARIMA), regression analysis, fuzzy models, and neural networks) predict TT using historical data, certain drawbacks exist when these models are used in predicting dynamic short-term TT (e.g., 5-min intervals) that contains severe fluctuations. In general, if the current data pattern is analogous to historical ones, the well-known prediction models are considered to be appropriate. However, for the data without similarity in a time series context due to extreme fluctuation (such as short-term TT), the well-known models might not perform satisfactorily.

On the other hand, the Kalman filter predicts TT with continuously updated parameters according to dynamically changing short-term TT (11); therefore, it can be regarded as an appropriate technique for short-term TT prediction. However, because the Kalman filter also uses historical data (e.g., data obtained at the same time of the day over a period of days) for a parameter calculation, the similarity between current and historical data plays a crucial role in its prediction performance (11). As stated above, the current pattern of short-term real-time TT (5 min) can widely deviate from historical patterns on certain days such as national holidays (this study was carried out on Children's Day of Korea).

In the light of the above discussion, our study proposes a new algorithm for short-term TT prediction that can surmount the disadvantages of the methods using the Kalman filter. Our method requires past TT for only three previous intervals (15 min) in order to predict real-time TT. This feature implies that the new algorithm can be effectively applied for situations where historical TT analogous to the current TT pattern cannot be easily obtained.

III. ALGORITHMS FOR TRAVEL TIME PREDICTION

Kalman Filtering Algorithm

Vehicle TT is affected by traffic volume, geometric condition, speed limit, traffic incidents (such as accidents or lane closures), vehicle type and composition, and the driver. Thus, modeling components to estimate vehicle TT is a challenge, especially when traffic approaches capacity. As mentioned earlier, the Kalman filtering algorithm constantly updates its parameters to predict the required state variables (e.g., TT) as new state variables are obtained (11); therefore, in our study, we used the Kalman filtering algorithm to predict TT. The prediction was obtained using arrival-time-based TT; subsequently, the predicted TT was evaluated by the concurrent departure-time-based TT that is the TT experienced by the drivers who received the TT information.

The Kalman filter operates in the following manner to predict TT: Let x(t) denote the TT which is required to be predicted at the time interval t. Let the parameter Φ(t) denote the transition parameter at time interval t, which is calculated from current and historical TT, and let w(t) represent a noise term that is normally distributed with a mean of zero and variance of Q(t). The state equation (or system model) can be written as follows:

$$x(t) = \phi(t-1)x(t-1) + w(t-1) \tag{1}$$

Let z(t) denote the observed TT at time interval t and v(t) denote the measurement error at time interval t; v(t) is normally distributed with a mean of zero and variance of R(t). Since no parameter except TT is considered, the observation equation related to the state variable x(t) can be written as follows:

$$z(t) = x(t) + v(t) \tag{2}$$

In this study, z(t), the average TT between two successive RSEs at time interval t, is collected from the DSRC traffic information system. The data in the previous time interval is used to calculate the transition parameter Φ(t); this parameter indicates the relationship between the state variables (TT in this study) between two time intervals. Let us suppose that for every i and j, E[w(i)v(j)] = 0, and let P(t) represent the covariance of estimation errors at time step t; consequently, the Kalman filtering algorithm can be applied using the procedure listed below. Generally, in a linear system, the value of I is set to 1 (5-9). Thus, we assigned the value of I as 1 in our study. Moreover, since our study was carried out on Children's Day, the current departure-time-based probe TT at previous intervals were used to calculate the transition parameter Φ(t). The Kalman filtering algorithm is applied as follows:

Step 1 Initialization

Let $t = 0$ and let $E[x(0)] = \hat{x}(0)$ and $E[(x(0) - \hat{x}(0))^2] = P(0)$

Here, $\hat{x}(0)$ equals predicted travel time at time 0.

Step 2 Extrapolation

Extrapolation of state estimate: $\hat{x}(t)_- = \phi(t-1)\hat{x}(t-1)_+$

Extrapolation of error covariance: $P(t)_- = \phi(t-1)P(t-1)_+ + \phi(t-1) + Q(t-1)$

Step 3 Calculation of Kalman gain

$$K(t) = P(t)_-[P(t)_- + R(t)]^{-1}$$

Step 4 Parameter update

Updating of state estimate: $\hat{x}(t)_+ = \hat{x}(t)_- + K(t)[z(t) - \hat{x}(t)_-]$

Updating of error covariance: $P(t)_+ = [I - K(t)]P(t)_-$

Step 5 Next iteration

Let $t = t + 1$. The next iteration begins from step 2.

New Algorithm

As stated above, the Kalman filter requires historical data similar to current observations for reliable predictions. Hence, the similarity between historical and current TT is regarded as an important factor for the prediction accuracy. However, the TT pattern on Children's Day (on which this study was based on) did not follow the historical TT pattern. Consequently, the day provided an ideal situation for the implementation of our new TT prediction algorithm that predicts future TT in the absence of historical TT.

Our developed algorithm predicts short-term TT (e.g., 5 min) using the observed TT ($x_{t\ to\ t\text{-}2}$). One issue of the DSRC-based traffic information system when compared with the traditional ANPR-based system is the possibility of low sampling rate because the DSRC system only uses the cars that have DSRC OBUs as probes (12). In actuality, the number of probes varied from 14 to 72veh/5min under similar traffic volume conditions at the test section. In order to address this problem, the developed algorithm includes weighting factors according to the number of samples obtained at each collection interval, thereby minimizing the prediction errors induced by low sampling rates. In addition, if the predicted TT (average of 5 min) by the developed algorithm is lower than the TT that occurs when cars travel 1.5 times over the speed limit, the predicted TT is considered as an outlier, and consequently, this value is substituted by present TT. The equations involved in our developed algorithm are as follows:

$$\hat{x}_{t+1} = x_t + w_t + w_{t-1} + w_{t-2}, \text{ If } \hat{x}_{x+1} \le \frac{l_i}{s_{\max} \times 1.5}, \text{ then } \hat{x}_{t+1} = x_t \tag{3}$$

Where, l_i = the length of link i,

$$w_t = \left[(x_t - x_{t-1}) \times (n_t / \sum_{t=t-2}^{t} n_i) \right], \quad w_{t-1} = \left[(x_{t-1} - x_{t-2}) \times (n_{t-1} / \sum_{t=t-2}^{t} n_i) \right]$$

$$w_{t-2} = \left[(x_{t-2} - x_{t-3}) \times (n_{t-2} / \sum_{t=t-2}^{t} n_i) \right]$$

IV. EVALUATION OF THE PROPOSED ALGORITHMS

In order to evaluate our algorithm and the Kalman filter algorithm, we used the probe TT collected by three consecutive DSRC RSEs (see Figure 2) that have been deployed between Seongdong IC and Jayuro service area on the national highway (NH) 77 in Korea. The data were gathered on May 5 (Children's day), 2011. Usually, traffic congestion does not occur in this roadway section; however, severe traffic congestion occurred on this day due to the traffic demand created by special events held at several locations along the route. In order to evaluate the proposed algorithms under different traffic conditions (e.g., congestion and non-congested), the data were obtained from 1 h before to1 h after the congestion period.

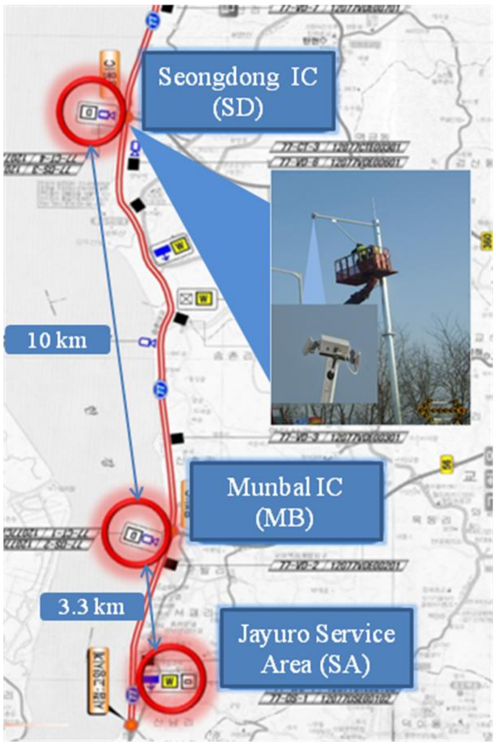

Figure 2 DSRC Data Collection Site

In order to measure to the magnitude of the prediction errors of both algorithms, we used two indices—mean absolute error (MAE, which measures the quantity of the error), and mean absolute percent error (MAPE, which measures the ratio of the error). In particular, MAPE has been officially adopted as an evaluation index for traffic detector evaluation in Korea. The equations for these two indices are shown below.

$$MAE = \frac{\sum |e_t|}{n} \tag{3}$$

$$MAPE = \frac{\sum |PE_t|}{n} \tag{4}$$

Where, $PE_t = \frac{e_t}{V_t} \times 100\%$, e_t = (baseline value at time t) – (observed value at time t)

The evaluation results (shown in Table 1) were relatively satisfactory upon considering the criterion that judges real-time TT information as "good" when TT error is lower than 10% (13, 14). The error obtained from the application of the Kalman filter is relatively small; however, the difference test (conducted using a T-test) on the average errors of the two algorithms shows that the difference is statistically insignificant as shown in Table 2 showing the p-values being considerably higher than the significance level of 0.05 for the two sections.

Table 1 Evaluation of the prediction algorithms

Algorithm	Section	MAE (s)	MAPE (%)	Std. of MAPE (%)
Kalman filter	SD-MB	33	5.9	4.3
	MB-SA	24	7.2	7.9
New	SD-MB	41	6.8	5.3
	MB-SA	27	7.0	6.5

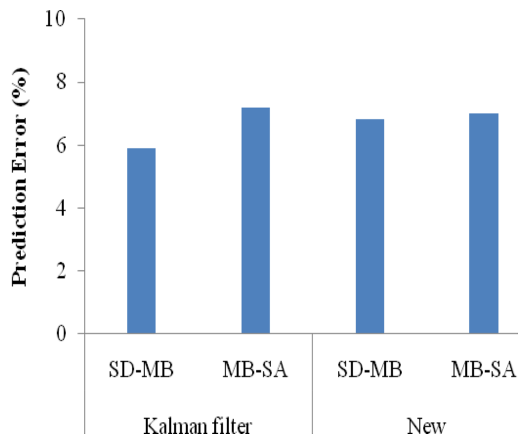

Table 2 T-test for the prediction errors

Section	Algorithm	Mean	Std. Dev.	Sample	T value	P value (Two tail)
SD-MB	Kalman filter	5.9	4.3	70	-1.03	0.30
	New	6.8	5.3			
MB-SA	Kalman filter	7.2	7.9		0.23	0.82
	New	7.0	6.5			

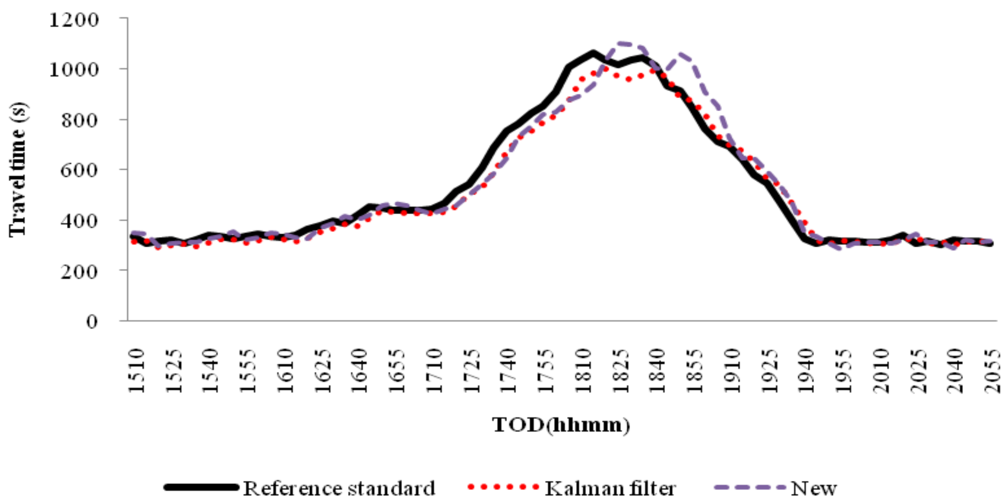

Figure 3 Travel Time Predictions for Seongdong (SD) IC to Munbal (MB) IC

From Figures 3 and 4, it can be observed that our new algorithm performs relatively better than the Kalman filter for sections of sudden change (both positive and negative) in the TT. This phenomenon presumably results from the fact that the new algorithm uses only the previous 3- interval (15 min) TT instead of historical TT. However, for wildly fluctuating TT, such as in Figure 4, the Kalman filter that uses the historical TT—actually, due to the significant different pattern between current and historical TT, the current TT was substituted for historical TT in the Kalman filter for this study. Inversely, this implies that if the similarity between current and historical data reduces, the prediction performance of the Kalman filter could deteriorate. Therefore, despite its simpler logic, the new algorithm has high applicability particularly when present and past data have low correlation.

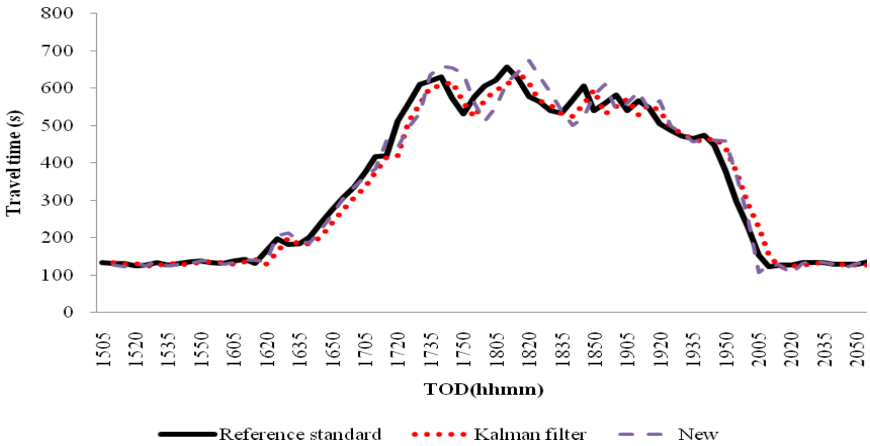

Figure 4 Travel Time Predictions for Munbal (MB) IC to Jayuro Service Area (SA)

V. CONCLUSIONS AND FUTURE STUDIES

This research proposed and implemented two dynamic travel time (TT) prediction algorithms to disseminate accurate real-time TT information in DSRC traffic information systems; the DSRC system uses the TT obtained by probe vehicles with DSRC (or Hi-Pass) OBUs. The suggested algorithms consist of the Kalman filter (which has been widely used for probe-based traffic information systems), and our newly developed algorithm.

We evaluated the proposed algorithms using the probe data collected from three consecutive DSRC RSEs installed on NH 77. On the date of data collection (May 5, Children's Day in Korea), NH 77 was subject to extreme traffic congestion due to special events organized for the day. The TT predictions were conducted using arrival-time-based TT, and the TT data were aggregated at 5-min intervals; these intervals were identical to the information provision intervals. As a consequence of the evaluation using the concurrent departure-time-based TT, the prediction errors ranged from 5 to 7% on an average, thereby showing a relatively satisfactory algorithm performance. The T-test on the errors of the two algorithms exhibits that the differences were statistically meaningless at 5% significance level.

Because traffic congestions rarely occur in the test sections, long-term data with various traffic conditions could not be used for evaluating the proposed algorithms. However, given that DSRC-based traffic information systems are being actively deployed in Korea, we intend to evaluate the proposed algorithms with more data under various traffic conditions in the near future, thereby leading to further improvement in the accuracy of TT predictions obtained by our algorithm.

VI. ACKNOWLEDGEMENT

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