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A Travel Time Fusion Algorithm Based on Point and Interval Detector Data

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Abstract

Up to now studies on the fusion of travel time from various detectors have been conducted based on the variance ratio of the intermittent data mainly collected by GPS or probe vehicles. The fusion model based on the variance ratio of intermittent data is not suitable for the license plate recognition AVIs that can deal with vast amount of data. This study was carried out to develop the fusion model based on travel time acquired from the license plate recognition AVIs and the point detectors. In order to fuse travel time acquired from the point detectors and the license plate recognition AVIs, the optimized fusion model and the proportional fusion model were developed in this study. As a result of verification, the optimized fusion model showed the superior estimation performance. The optimized fusion model is the dynamic fusion ratio estimation model on real time base, which calculates fusion weights based on real time historic data and applies them to the current time period. The results of this study are expected to be used effectively for National Highway Traffic Management System to provide traffic information in the future. However, there should be further studies on the proper distance for the establishment of the AVIs and the license plate matching rate according to the lanes for AVIs to be established.

Keyword*: Real-time travel time estimation, Point & Interval detector, AVI (Automatic Vehicle Identification), Fusion model, Fusion ratio.*

1. Introduction

1.1 Necessity and purposes

The fusion of travel time from various detectors is the key to improve the reliability and accuracy of real time data. Up to now, there are a variety of detectors developed to provide real time traffic data. In addition, they can be divided into point detector and section detector, depending on data collection method. In case of the former one, it collects point data such as traffic, speed and occupancy rate. On the other hand, interval detector such as GPS, AVL and AVI directly calculates traffic time for a specific section.

However, it is not necessarily true that when collecting data from a variety of detectors, one data collection system is superior to another one, in view of accuracy. Furthermore, a data collection system may not offer all types of traffic data (incidents, controlling signals, vehicle type and etc) necessary for various applications. On this account, it needs data fusion that collects data from a variety of data collection systems and derives organized information from the collected data.

Regarding data fusion model of detector system, the previous fusion models based on variance ratio were developed, based on intermittent data. A variance ratio model allows a high fusion weight if a detector has a low data variation typically despite of the low estimation, resulting in error and furthermore, it may cause higher error due to absence of real time filtering by true values. On the other hand, a neural network model disadvantageously costs a lot for model settlement and may not perform parameter settlement although it determines fusion weight by historic data. Therefore, the previous variance ratio models or neural network models are not suitable for travel time fusion based on license plate recognition AVI data, not on intermittent data. Therefore, it would be recommended to develop a fusion model suitable for characteristics of collected data depending on detector. Unlike Prove vehicle data or GPS (global positioning systems) data, license plate recognition AVI data can be collected plentifully in real time and it is possible to develop a real time filtering model or a dynamic fusion ratio estimation model on real time base by using the above-mentioned real time collection characteristics of AVI data, which is, however, simply and easily apply in real time.

Therefore, this study is intended to develop a real time fusion model for travel time, which is calculated respectively, based on point detector and license plate recognition AVI.

1.2. Content and scope

This study was performed for a section of the National Highway No.3, Gonjiam IC ~ Jangji IC. The extension of the section is 10.7km long and consists of a subsection of urban and suburban road and a subsection of multiple-lane road. The temporal range of data is for three days between July 20 ~ 22, 2004, which are also subdivided into forenoon, afternoon and the transitional period.

This study was to consider the previous studies about fusion models suggest the limitation of study and propose methods to overcome the limitation and directions to develop an ideal model. Regarding settlement of travel time fusion model, this study proposes the optimized fusion model and the proportional fusion model. The proposed models are evaluated by comparing to a previous model, the proportional fusion model by Chi-Hyun Shin and Seong-Ho Kim.

2. Consideration of the previous studies

Data fusion is referred as a technology of how to integrate data collected from a variety of collection systems. The previous data fusion was applied by Bayesian theory, Dempster-Shafter theory, Fussy theory and neural network theory while the following studies have been performed for the data fusion related to travel time estimation.

Rouphil[1], Tarko [2] fused data of link travel time using regression analysis and Bayesian theory, where the regression analysis was used to calculate travel time from detector data and Bayesian theory was used when fusing probe vehicle data and detector data, and real time data and historic data. As a model similar to a virtual sampling technique, probe vehicle data fusion model and point detector data fusion model use the weighted average method using variances of individual detector systems. Chi-Hyun Shin and Seong-Ho Kim [3] suggested the data fusion model of ultra-short wave AVI data and image detector data, which is similar to the model by Rouphil and Tarko [4]. The fusion model is a type of weighted average using both ultra-short wave AVI data and image detector data together. Yeon-Sik Jeong, Gi-Ju Choi [5] used, as a method to fuse loop detector data and GPS probe vehicle data, a fussy linear regression model and reliability ratio. In case a GPS prove vehicle passes over a link where a loop detector is installed and travel time data is calculated from two data collection systems, it estimated reliability (inclusion degree) for the fusion by each data collection system by applying the fussy linear regression technique during data integration process to derive organized information of link. For organized travel time estimation by links, the inclusion degree calculated by each detection system was fused to simplified travel time, based on Bayesian theory. As mentioned previously, the weight determination models by variance ratio or reliability use, as the fusion weight, variance ratio or reliance ratio between both data collection systems with the variance or reliability of travel time calculated from each data collection system taken as the factor.

Ivan [6], however, developed the fusion model of probe vehicle travel time and point detector travel time, based on the neural network model in order to detect incidents in arterial. Chi Xie [7] suggested a multi-layer neural network model and a multiple regression model. The point detector travel time estimation model consists of moving time and delay time while probe vehicle travel time was used only when the number of samples is more than 10 or the minimum number of samples calculated is more than that. As a result of building and analyzing a multi-layer neural network model and a multiple regression model, the former one (multi-layer neural network model) was superior to the latter one. The multi-layer neural network model consisted of fixed detector travel time, probe travel time and the number of probe samples as its input pattern.

In addition, Klein and et al. suggested a fusion model to support advanced traffic management by using Dempster-Shafer theory. The Dempster-Shafter inference is a kind of statistical data classification to detect and confirm traffic status affecting normal traffic stream. It, however, needs more studies so to estimate parameters and/or traffic parameters. Helinga [8] fused loop detector data in order to reduce error of estimated travel time in probe-based arterial, especially caused by signal control around intersection by using stratified random sampling.

Regarding data fusion models of each detector system, the previous variance ratio models and neural network models were based on intermittent data, which means they are lack of real time dynamic filtering function. The variance ratio models generate errors due to higher fusion weight if the variance of data collected is typically low even though a detector system has poor estimation and they may have more error due to absence of real time filtering function from true values. On the other hand, the neural network models determine, based on historic data, fusion weights but they need a lot of cost to settle a model and it’s difficult to calculate real time parameters. Therefore, they are not suitable for data fusion based on license plate recognition AVI data, not on intermittent data. It is necessary to develop, by using the characteristics of obtaining real time AVI data, a real time filtering or dynamic fusion ratio estimation model, which should be simple and easily applicable.

3. Model establishment

Figure 1 shows the general schematic view presenting data provision sections and locations of detectors dealt in this study. The data provision sections have high recognition of geographical destinations and become the basic unit offering data. Point detectors collects data of traffic, speed and occupancy rate of a link where detection in question is located in a specific interval while AVI also collects travel time data of individual vehicles passing between nodes 1 to node 6, which is data provision sections.

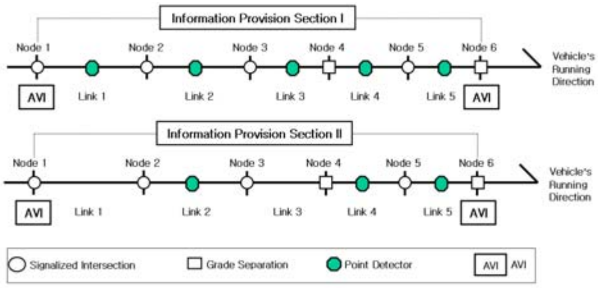

Figure 1. Schematic view of data provision section and detector

3.1 Optimized Fusion Model (Proposed Model 1)

3.1.1 Point detector model: The point detector model estimated travel time of individual links by using the arterial link travel time estimation model of KHCM [9] seen in Figure 2 while section travel time was estimated with multi-periodic estimation model using Kalman Filtering Algorithm.

In the KHCM model, the link travel time is calculated from the sum of moving time and delay time in a link. Therefore, in order to calculate of travel time of data provision sections comprising multiple links, it is necessary to sum up travel time of individual links. At the time, calculating travel time of data provision sections in this KHCM model has a problem, so-called, time lag. To overcome the time-lag problem, the multi-periodical estimation model was applied, based on Kalman filtering algorithm.

The average travel speed of arterial in KHCM can be expressed as Formula 1. Section travel time is obtained by dividing section length by the average travel speed. That is, the relation between section travel time and average travel speed of section is inverse proportional.

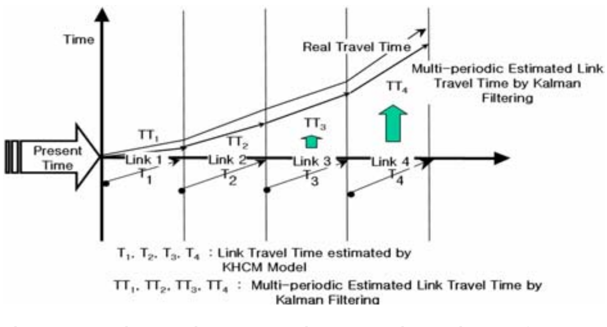

Figure 2. Point detector-based travel time estimation of proposed model 1

The principle of the multi-periodic estimation model is to calculate travel time of a vehicle from the current period up to just before the next link and estimate the future time period corresponding to the travel time. The entire section travel time is calculated if summing up the travel time of individual links estimated by the above method. The multi-periodic estimation model assumes that the past travel time has a uniform pattern(s). That is, the multi-periodic estimation is effective unless the past travel time pattern is significantly different with the current. Especially, the multi-periodic estimation is effective in recurrent traffic jamming because the transition matrix (or transitional value), which is used to calculate estimation when predicting multi-period by Kalman filtering algorithm, is calculated by the past patterns.

The transition equation and observation equation for multi-periodic travel time estimation is as same as the single periodic travel time, and the multi-periodic estimation value is calculated in the transition equation of Kalman filter model formed in Formula 2 by the transitional value, Φ_{nk}. At the moment, if the past travel time patterns of k time period and $k+n$ time period are TP_k and TP_{k+n} respectively. Φ_{nk} is given by:

$$\frac{(TP_{k+n})}{(TP_k)} \tag{1}$$

$$x_{k+1} = \Phi_{nk} x_k + Q_k \tag{2}$$

Where, x_{k+1} is the travel time state vector of $k+1$ time, Φ_{nk} is the transition matrix to $k+1$ time when estimating travel time of k time after n periods, Q_k is the covariance matrix of state error in k time, n is the number of estimation periods.

3.1.2 Section detector model: The section detector model was applied with AVI travel time Kalman filter 2 periodic estimation model. As seen in Figure 3, there is certain interval (time-lag) in true value of travel time and AVI travel time. Therefore, if the collected raw AVI data is used without process, it may produce error due to time lag. In this study, the estimation of real travel time was calculated by using Kalman filter.

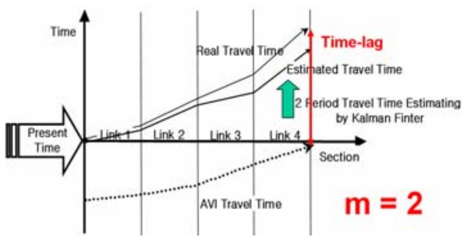

Figure 3. Section detector model of proposed model 1

That is to say, it applied the 4-step Kalman filter period estimation procedure to estimate the current time period, k based on AVI travel time before the past m period. The following procedure shows it when $m = 2$

1) Step 0 (initialize)

$$\hat{x}_{k-1}(-), P_{k-1}(-) \tag{3}$$

2) Step 1 (Kalman gain calculation)

$$R_{k-1} = (Z_{k-2} - H \cdot \hat{x}_{k-1}(-))^2 \quad (4)$$

$$\overline{K}_{k-1} = \frac{(P_{k-1}(-) \cdot H_{k-1}^T)}{(H_{k-1}P_{k-1}(-)H_{k-1}^T + R_{k-1})} \quad (5)$$

3) Step 2 (update)

- Updating transition estimation

$$\hat{x}_{k-1}(+) = \hat{x}_{k-1}(-) + \overline{K}_{k-1}[Z_{k-2} - H_{k-1}\hat{x}_{k-1}(-)] \quad (6)$$

- Updating covariance of error

$$P_{k-1}(+) = [I_{k-1} - \overline{K}_{k-1}H_{k-1}]P_{k-1}(-) \quad (7)$$

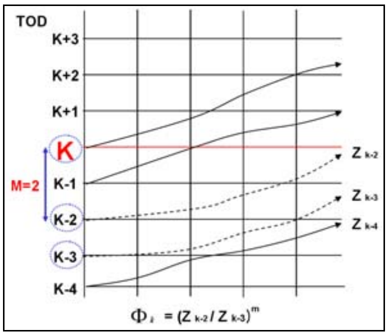

Figure 4. Calculating the transition matrix Φ_k

4) Step 3 (estimating traffic time of the current time period, k)

$$\Phi_{k-1} = Z_{k-2} / Z_{k-3}$$

$$\Phi_k = (Z_{k-2} / Z_{k-3})^m$$

$$\hat{x}_k(-) = \Phi_{k-1}\hat{x}_{k-1}(+) \quad (8)$$

$$Q_{k-1} = [\hat{x}_k(-) - \Phi_{k-1} \cdot \hat{x}_{k-1}(-)]^2$$

$$P_{k-1}(-) = \Phi_{k-1}P_{k-1}(+)\Phi_{k-1}^T + Q_{k-1}$$

3.1.3 Fusion model: 1) Model establishment: Fusing travel time data collected from two and more data collection systems is as same as determining the fusion weights of such systems. This study proposed the optimized fusion model to determine the fusion weights of point detector and section detector in order to minimize the errors of travel time, which is fused as the first fusion model and the true values.

The previous fusion models based on variance ratio or reliability ratio are not based on estimation accuracy but depend on variance ratio, from which they disadvantageously assign high fusion weight to detector systems of which estimation and variance are low. In addition, as estimation of detector systems is significantly different, the error of fusion estimation would be relatively larger. Therefore, the model features determination of fusion ratio considering variation of real time error pattern in order to overcome the above problem and increase accurate estimation.

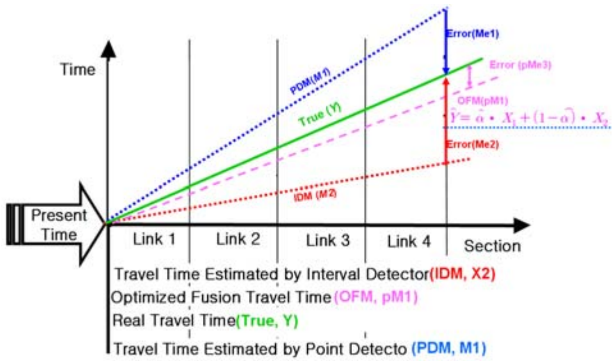

Figure 5. Conceptual view of the optimized fusion of the proposed model 1

This model consists of two steps largely. The first step determines the true values during the past time collected real time by AVI and the optimized fusion ratio depending on estimated travel time of each detector and error pattern. The second step calculates the estimated real travel time of the present time by fusing the estimated travel time of each detector.

The model determines dynamic real time fusion ratio using the true values(based on start from starting point), which are collected real time by AVI, AVI travel time(based on arrival at end point) and real time data collected by point detector.

Assuming that the travel time data of point detector is X_1 and AVI travel time data is X_2, the optimized model determining α to minimize the error between the travel time fusing both data collection systems and true values is as follows.

$$MIN.\sqrt{\frac{\sum(Y-\hat{Y})^2}{N}} = MIN.\sum(Y-\hat{Y})^2 \tag{9}$$

Where, $\hat{Y} = \alpha \cdot X_1 + (1-\alpha)\cdot X_2$, $0 \le \alpha \le 1$

The objective function α can be expressed and summarized as follows;

$$\begin{aligned} f(\alpha) &= \sum(X_1 - X_2)^2 \cdot \alpha^2 \\ &+ \sum[-2\cdot\{Y\cdot(X_1 - X_2) - X_2(X_1 - X_2)\}]\cdot\alpha \\ &+ \sum\{Y^2 + X_2^2 - 2\cdot Y\cdot X_2\} \end{aligned} \tag{10}$$

That is, $f(\alpha)$ is expressed as the second order quadratic equation for α. It can be also arranged as follows;

$$
\begin{aligned}
& f(\alpha) = A \cdot \alpha^2 + B \cdot \alpha + C \\
& A = \sum (X_1 - X_2)^2 \\
& B = \sum [-2 \cdot \{Y \cdot (X_1 - X_2) - X_2 (X_1 - X_2)\}] \\
& C = \sum \{Y^2 + X_2^2 - 2 \cdot Y \cdot X_2\}
\end{aligned}
\tag{11}
$$

The question is to find α to minimize $f(\alpha)$, so α^* satisfying ' $f'(\alpha) = 0$ ' is as follows;

$$
\begin{aligned}
& f'(\alpha) = 2 \cdot A \cdot \alpha + B = 0 \\
& \alpha^* = -\frac{B}{2 \cdot A}
\end{aligned}
\tag{12}
$$

The result can be also expressed as follows:

$$
\alpha^* = -\frac{\sum [-2 \cdot \{Y \cdot (X_1 - X_2) - X_2 (X_1 - X_2)\}]}{2 \cdot \sum (X_1 - X_2)^2}
\tag{13}
$$

At this moment, since, $A \geq 0$, $f(\alpha)$ is a convex quadratic equation and has the following three types depending on α^*.

That is, interpreting it regarding data fusion, it is determined that $\alpha = 0$ if $\alpha^* < 0$, $\alpha = \alpha^*$ if $0 < \alpha^* < 1$ and $\alpha = 1$ if $\alpha > 1$. So to speak, it is possible to choose the best estimation depending on a case. When data characteristics fall under case 1 or case 2, the previous estimated weighted average exist between X1 and X2. However, the proposed model would have $\alpha = 0$ or, $\alpha = 1$ from which the best estimation is selected. If variance ratio is as same as error ratio even in case of CASE 3, it can calculate accurate estimation. Since variance ratio is, however, rarely same with error ratio, it is difficult to calculate accurate estimation. On the other hand, the optimized model can select the closest estimation.

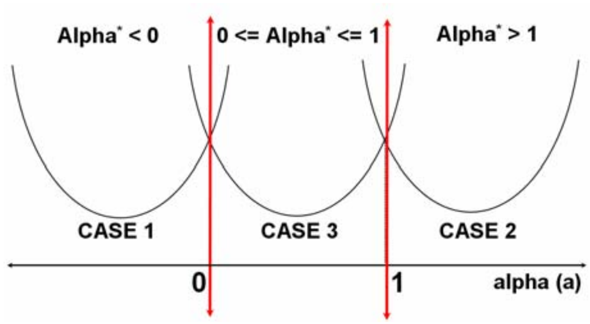

Figure 6. Alpha (α) and the quadratic equation

2) Generalization of the proposed model: The generalized proposed model is as follows; it is an n order quadratic equation for α.

$$
f(\alpha_1, \alpha_2, \cdots, \alpha_n) = (\sum_{i=1}^{n} \alpha_i \cdot X_i)^2 - 2 \cdot Y \cdot (\sum_{i=1}^{n} \alpha_i \cdot X_i) + Y^2
$$

(14)

Therefore, if partially differentiating $f(\alpha_1, \alpha_2, \cdots, \alpha_n)$ with α_i and solving the following n order linear simultaneous equations, the solution set, $A(\alpha_1^*, \alpha_2^*, \cdots, \alpha_n^*)$ is obtained.

$$\frac{\partial f}{\partial \alpha_i} = 0 \quad i = 1, 2, \cdots, n \tag{15}$$

3) Real time application of the proposed model: The fusion ratio estimation to apply the optimized fusion model in real time $\hat{\alpha}$ is calculated by the following formula.

$$\hat{\alpha}_i = \frac{\sum_{k=i-m-n}^{i-m} [-2 \cdot \{Y_k \cdot (X_{1k} - X_{2k}) - X_{2k} \cdot (X_{1k} - X_{2k})\}]}{2 \cdot \sum_{k=i-m-n}^{i-m} (X_{1k} - X_{2k})^2} \tag{16}$$

Where m is the time-lag interval of true value, n is the range of past data used to determine fusion ratio, X_{1k} is the travel time estimation in k time period of data collection system 1, X_{2k} is the travel time estimation in k time periods of data collection system

3. 2 Proportional fusion model (proposed model 2)

Unlike the optimized fusion model proposed in the previous paragraph, the proportional fusion model fuses data in individual links and estimates the final travel time by multi-periodic estimation procedure. KHCM model was selected as the point detector model in this proportional fusion model, and the sectional detector model uses AVI travel time (based on arrival time). The proportional fusion is by the following formula.

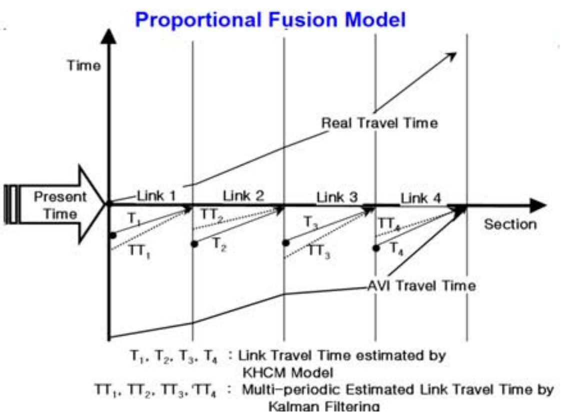

Figure 7. Schematic view of proportional model fusion

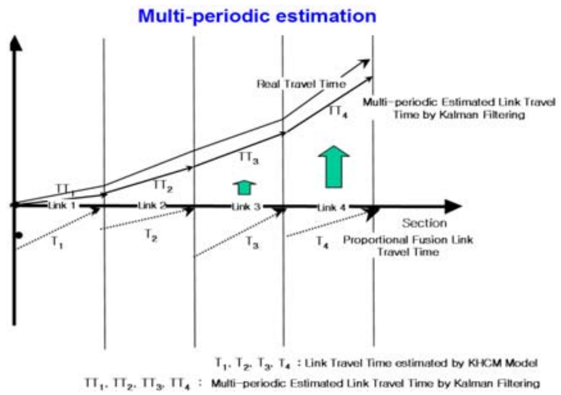

Figure 8. Schematic view of proportional model fusion

$$FTT_i^{VDS} = \frac{TT_i^{VDS}}{\sum_{i=1}^{n} TT_i^{VDS}} \times TT^{AVI} \quad (17)$$

Where, TT^{AVI} the section travel time by AVI is, TT_i^{VDS} is the travel time of the link i by the point detector, FTT_i^{VDS} is the travel time of individual link i after proportional fusion.

Figure 7 shows a procedure fusing travel time (T1, T2, T3 and T4) of individual links (section 1 ~ section 4) proportionally by point detectors and updating the travel time (TT1, TT2, TT3 and TT4). Figure 8 shows a procedure calculating the section travel time from the travel time of individual travel time updated by proportional fusion by using multi-periodic estimation.

4. Application and evaluation

4.1 Status of Sections

This study was performed for a section of the National Highway No.3, Gonjiam IC ~ Jangji IC (10.72km). The section consists of 12 individual links. The section meets Jungbu Expressway at Gonjiam IC and it forms a grade separation with the National Highway No.43 at Gyeongan IC and Jangji IC. The provincial highway No.337 meets the section at Siniri and Chowol police station.

The section is divided into two data provision sections; one sub-section (I) between Gonjiam IC ~ Chowol police station and the other subsection (II) between Chowol police station ~ Jangji IC. Data provision section I (Gonjiam IC ~ Chowol police station) is a section of interrupted flow entirely. All other links but Link 7(Lotte Apt ~ Chowol police station) were 0.55 km and shorter long and the signal density was 1.36(each/km). On the other hand, data provision section II (Chowol police station ~ Jangji IC) has 0.78(each/km) of signalized intersection density, showing continuous flow typically.

Table 1. Status of sections

Sec.	**Start**	**→**	**End**	**Conn-ected road**	**Section length (km)**	**Data provision section.**
1	GonjiamIC	→	Samri 2 ri		0.50	
2	Samri 2 ri	→	Sini-ri	No.337	0.46	
3	Sini-ri	→	Byucksan APT		0.24	
4	Byucksan APT	→	Koryeo Ind.		0.40	
5	Koryeo Ind.	→	Ssangdong 1 ri		0.55	□
6	Ssangdong 1 ri	→	Front of Lotte APT		0.40	
7	Front of Lotte APT	→	Chowol police sta.	No.337	1.83	
8	Chowol police sta.	→	Sobang police station		0.51	
9	Sobang Police station	→	Namchon Swimming Pool		0.40	
10	Namchon Swimming Pool	→	Ssangryeong 2 ri		1.49	□
11	Ssangryeong 2 ri	→	Gyeongan IC	No. 43	1.54	
12	Gyeongan IC	→	Jangji IC		2.40	

Table 2. Data and time surveyed

Date	**Time period**	**Weather**
July 10(Tue.)	17:30~9:00(Afternoon peak)	Cloudy
July 21(Wed.)	07:30~09:00(Forenoon peak)	Rainy
July 21(Wed.)	12:00~4:00(Afternoon non-peak)	Clean
July21(Wed.)	17:00~9:00(Afternoon peak)	〃
July 22(Thu.)	07:30~9:00(Forenoon peak)	〃
July 22(Thu.)	12:00~4:00(Afternoon non-peak)	〃
July 22(Thu.)	17:00~9:00(Forenoon peak)	〃

Note) Forenoon peak time and afternoon non-peak time on July 20 were surveyed but the data had to be excluded in this study because it was regarded abnormal due to rainy weather.

4.2 Collection method and contents

The field survey was performed for three days between July 20 ~ 22, 2004 and the data collected was traffic and speed for a minute by point detector and the travel time in the data provision section for 5 minutes interval by license plate survey. The time period of this survey were divided into forenoon peak time (07:00 ~ 09:00), afternoon non-peak time (12:00 ~ 14:00) and afternoon peak time (17:00 ~ 19:00). During the forenoon peak time, rush hour vehicles from Icheon, Gwangju and other cities to Seongnam and Seoul generate heavy traffic, resulting in partial peak traffic. The afternoon non-peak time does not have traffic jamming but during afternoon peak time, rush our vehicles returning to Seongnam and Seoul generates heavy traffic again, resulting in ordinary traffic congestion. That is, since typically, forenoon peak time has partially heavy traffic, afternoon non-peak time generates non-heavy traffic and afternoon peak time produces heavy traffic congestion, the three time periods were surveyed.

Table 3. Verification of fusion models

Section	Link	Time zone	MOE	Installing point detector at all links				
				PDM	IDM	VRFM	OFM	PFM
Sec. I	1-7	Fore-noon	MARE	0.11	0.14	0.10	0.07	0.10
			RMSE	43.69	73.21	41.22	33.39	42.08
			EC	0.93	0.90	0.94	0.95	0.94
		Transi-tional	MARE	0.20	0.07	0.18	0.05	0.05
			RMSE	78.26	32.66	70.44	21.62	24.08
			EC	0.88	0.95	0.90	0.97	0.97
		After-Noon	MARE	0.26	0.11	0.10	0.11	0.07
			RMSE	136.02	69.82	69.31	72.49	40.92
			EC	0.83	0.92	0.92	0.92	0.96
Sec. II	8-12	Fore-Noon	MARE	0.22	0.13	0.16	0.14	0.17
			RMSE	80.41	59.05	58.99	60.49	69.06
			EC	0.89	0.92	0.92	0.91	0.90
		Transi-tional	MARE	0.10	0.13	0.08	0.07	0.06
			RMSE	44.85	44.32	43.61	32.58	42.29
			EC	0.94	0.91	0.94	0.96	0.94
		After-noon	MARE	0.12	0.12	0.11	0.09	0.12
			RMSE	84.74	71.48	68.83	58.01	69.26
			EC	0.92	0.93	0.93	0.95	0.93

4.3. Evaluation

4.3.1 Comparison by evaluation scale: For verification of fusion model, estimations of point detector model (multi-periodic estimation after estimating individual links), section detector model (Kalman filter multi-periodic estimation for data provision section), variance ratio fusion model as a previous model, and the proposed model 1: optimized fusion model and the proposed model 2: proportional fusion model were compared one another. For the comparison, three evaluation scales such as MARE, RMSE and EC are used. The time periods were divided into forenoon(partial traffic jam), transitional time(non traffic jam) and afternoon(traffic congestion); the section consisted of two sub-sections; data provision section I of urban and suburban section(congestion section, 7 signalized intersections) and data provision section II of multiple lane section(non-congestion section, 3 signalized sections).

In case of the data provision section I, as seen in Table 3 and Figure 9, the proposed model 1 and 2 were superior to a previous model, the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim. For forenoon, the proposed model 1 was superior to the model and for afternoon, the model 2 was superior to it. During transitional time, the proposed model 1 and 2 had similar estimation.
First of all, comparing point detector and section detector models, the estimation of point detector was better for forenoon but the section detector was better for transitional time and afternoon. It demonstrates that a detector does not have always excellent estimation. In general, the error of point detector model consists of the sum of estimation error and time-lag error while that of the section detector model consists of filtering error and time-lag error. In addition, the estimation of each detector is affected by various conditions such as time period, that is, traffic status and arrangement of detector. Therefore, any detector may not always have the best estimation. This study also demonstrates it, which means data fusion is necessary.

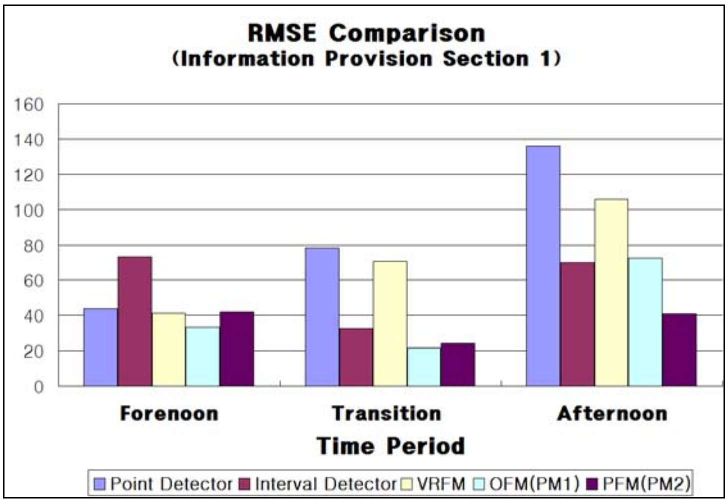

Figure 9. Data provision section I – RMSE Comparison

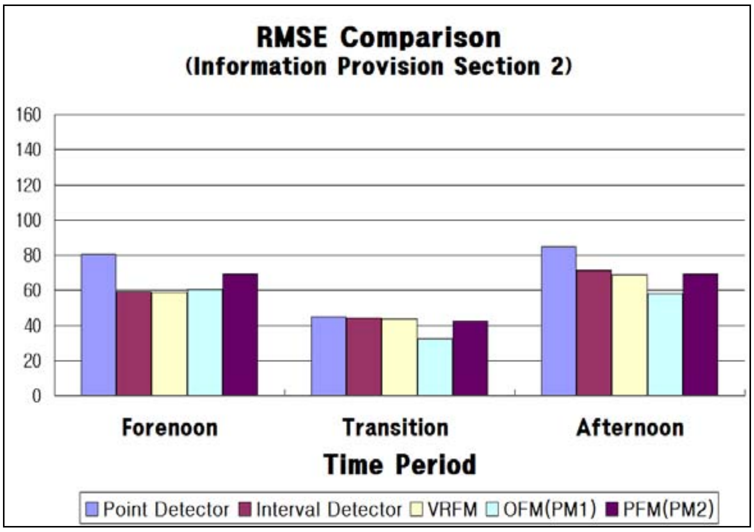

Figure 10. Data provision section II – RMSE Comparison

Consequently, the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim showed significantly different results as expected. That is, the estimation of point detector was excellent for forenoon and had low variance, but since section detector has low estimation and high variance, the variance ratio model allocate most weight to point detector, resulting in the fusion results similar to point detector. On the other hand, since the estimation of point detector for transitional time and afternoon had low estimation, it allocates high fusion weight to point detector estimation of which variance is low, resulting in low estimation accordingly. The proposed models may overcome the above problem because it basically contains filtering procedure, instead of determining fusion weight by variance ratio.

The proposed model 1 showed the excellent results superior to individual detectors and the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim for all time periods. That's because it continues to estimate fusion weights, based on fusion pattern from true values just before the time in real time, instead of determining fusion weights by variance ratio.

The proposed model 2 contains incomplete filtering procedure, so it is expected that this model does not have high estimation comparing to the proposed model 1. Indeed, it showed lower estimation results for forenoon and transitional time than the proposed model 1 as expected. However, it showed that the proposed model 2 had better results for afternoon. That's because the proposed model 1 is based on the very previous fusion patterns, but it may not have excellent estimation in suddenly changing traffic congestion. On the other hand, the proposed model 2 estimates it based on the past recurrent pattern, so it is concluded that the latter may have higher estimation than the proposed model 1.

In case of the data provision period II, as seen in Table 3 and Figure 10, the proposed model 1 showed the excellent results than the individual detectors and the previous models. On the other hand, the proposed model 2 showed lower estimation for forenoon than section detector, but its results for transitional time and afternoon were similar to AVI and the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim. It also showed better results than point detector. The proposed model 2, as a point detector model, uses the sum of travel time estimated by

KHCM and the section detector model fuses AVI travel time data (based on arrival time). However, in case of the data provision section II, the point detector model showed better estimation than section detector model. Therefore, it may result in increased error of fusion travel time in individual links when fusing data due to structure, showing low estimation as expected. That is resulted from the fact that the model may not designate a link of point detector model to a link when individual vehicles pass over.

Additionally, in case of point detector model, the estimation in the data provision section I (urban and suburban roads) is lower than that of multi-lane section. It must be that urban and suburban roads have heavier signalized intersection density, short link length and contain more friction than multi-lane road. On the other hand, the section detector showed similar results both in the data provision section I and II.

In conclusion, it is evaluated that the variance ratio model is not suitable for fusing data of point detector and AVI. Generally, AVI estimation was superior but had high variance, resulting in poor fusion estimation than AVI estimation. On the other hand, the proposed model 1 and the proposed model 2 showed better estimation than individual detectors. Especially, the proposed model 1 showed the best estimation. Owing to the advantage of selecting the best estimation depending on variation in estimation of each detector, the model, as a real time dynamic fusion ratio estimation model, showed better estimation than individual detectors and the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim. It demonstrates the excellence of fusion model with filtering procedure. In case of the proposed model 2, it is necessary to modify the model so to estimate multiple periods based on travel time of link when vehicles pass over as expected.

4.3.2 Comparison of the variance ratio model and the proposed model 1

This paragraph compares the variance ratio model by Chi-Hyun Shin and Seong-Ho Kim to the proposed model 1 in terms of variation pattern of real time fusion ratio. The fusion ratio is a key factor to determine the estimation of a model. Therefore, looking into the variation pattern of real time fusion ratio may show the key of estimation at a glance.

First of all, in case of the variance ratio model, the fusion ratio is inverse proportional to the variance ratio. Therefore, high fusion weight of a detector means that the detector has low variance, and vice versa. As seen in Figure 11 and Figure 12, the fusion ratio by variance ratio (fusion weight of a detector) is relatively high uniformly. For instance, in case of 12:40 in Figure 11, the previous model, that is, the fusion ratio by variance ratio(fusion weight of a point detector, the fusion weight of AVI is '1-fusoin weight of point detector') is 0./986, which is relatively high, which means that it allocates a weight of 0.986 to the estimated travel time based on point detector but it does 0.014 calculated by '1-0.986 to the estimated travel time based on AVI. For instance, assuming that the travel time of point detector is 100 seconds and the AVI travel time is 50 seconds, the fusion travel time is determined as 98.6+0.7 = 99.3(seconds) from (100 × 0.986) + (50 × 0.014). On the other hand, the fusion ratio of the proposed model 1 is calculated from the very past fusion ratio pattern, which is used as the estimation of the current fusion ratio, as a dynamic fusion ratio estimation model. Therefore, it is found that it follows the variation pattern of the true values of fusion ratio. For instance, in case of 12:40 time period in Figure 1, the proposed model 1 is 0.280 and the true value of the fusion ratio is 0.083, which means the model estimates the value very close to the fusion ratio of the previous model.

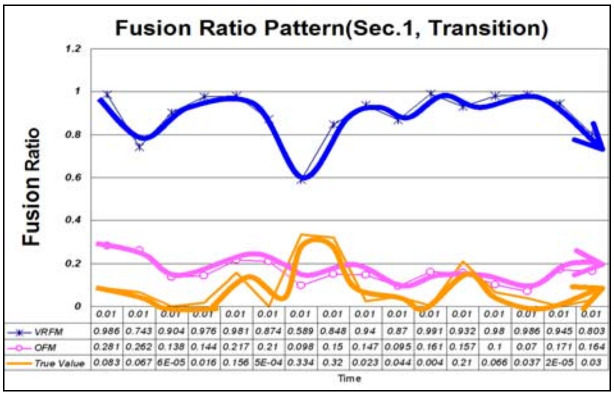

Figure 11. Data provision section I – Variation pattern of fusion ratio

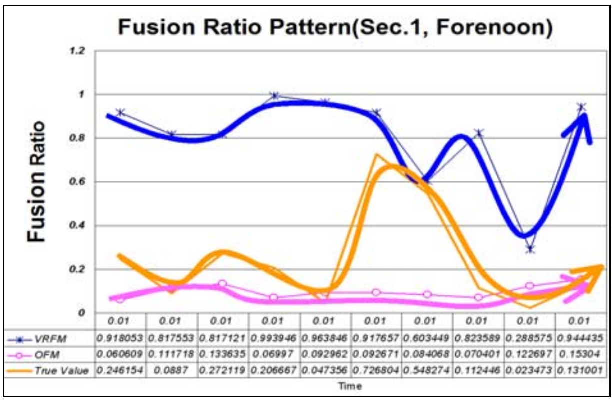

Figure 12. Data provision section I – Variation pattern of fusion ratio

However, due to the structural characteristics of the model, if it is converted to different status with the past pattern, it may have disadvantageously low estimation. That is, when the status fluctuates heavily such as changing from non-traffic jamming to heavy traffic congestion or changing from congestion to non-traffic jamming, the pattern may be different to the past fusion pattern, so in this case, the estimation may be relatively low. In detail, around the boundary where the pattern of highly accurate travel time based on AVI is changing to a pattern of highly accurate travel time based on point detector, that is, in the status where a pattern is changing, the proposed model 1 produces estimation error. However, the problem is a common problem that may happen even in individual detector. However, since the results show that the variance of point detector is lower than that of AVI, it may have better estimation than the variance ratio fusion model by Chi-Hyun Shin and Seong-Ho Kim if a pattern of which AVI variance is high is changed to a pattern of which detector accuracy is high. In any other situations, the proposed model 1 showed better estimation.

5. Conclusion

This study was carried out to develop the fusion model based on travel time acquired from the license plate recognition AVIs and the point detectors. Also, this study contains fusion model of travel time and considerations of the previous studies about grouping and suggests the model development directions. Therefore, in order to fuse travel time acquired from the point detectors and the license plate recognition AVIs, the optimized fusion model and the proportional fusion model were developed in this study. In developing fusion model, the optimized fusion model a real time dynamic fusion ratio estimation model to calculate fusion weights based on real time historic data in order to determine fusion weights of each detector currently collected and to apply them to the present time. That is, it would be the first multi-periodic estimation and after filtering (fusion) model. As a result of the verification, the proposed model 1 showed the most excellent estimation as expected. The limitation and research direction of this study are as follows.

Firstly, this study collected data for every lane by substituting AVI with license plate survey and the only installation intervals of 5km were included. However, it needs further studies about matching of appropriate AVI installation interval and installation lanes.

Secondly, the optimized fusion model (proposed model 1) in this study showed disadvantageously low estimation in case of traffic congestion. Therefore, it should be further studied that estimation is increased by an estimation model when applying the fusion ratio determined by historic data to the current time. In addition, the proposed model 2 –Proportional fusion model should be modified so to divide AVI travel time in proportion to travel time ratio of links where vehicles actually pass.

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