MULTI-STEP AHEAD PREDICTION OF LINK TRAVEL TIME USING KALMAN FILTER

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Abstract: In this research, a multi-step ahead prediction algorithm of link travel time was developed using Kalman filter technique. Control variables commonly used for freeway control are flow rate (volume), occupancy and density, and speed. Currently these traffic variables are collected by broadcasting reporters or CCTV, and by 17 image detectors on Olympic expressway. Various techniques such as time series analysis, neural network, and Kalman filter were investigated to estimate and to predict short-term link travel time. The algorithm performance were tested in terms of performance measures such as MARE(mean absolute relative error), MSE(mean square error), EC(equality coefficient). The performance of the proposed algorithm was superior to the current one-step ahead prediction algorithm.

1. INTRODUCTION

Control variables are measurement of certain variables that describe traffic conditions. They are used as a basis for evaluating traffic control strategies. Control variables commonly used for freeway control are flow rate(volume), occupancy and density, and speed. Currently these traffic variables are collected by broadcasting reporters or CCTV, and by 17 image detectors on Olympic expressway. The measured data include the stochastic nature of the variables themselves and the presence of measurement errors. If the data describe traffic conditions, an operator wants to know whether the situations are going better or worse. In addition, some traffic information providing strategies require predictions of what would be the values of traffic variables during the next time period. In such situations, it is necessary to use a prediction algorithm in order to extract the average trends in traffic data or make short-term predictions of the control variables. In this research, a multi-step ahead prediction algorithm using Kalman filter was developed to predict a short-term link travel time.

2. LITERATURE REVIEW

The emphasis of the state-of-the-art review is on the short-term prediction of link travel time. Okutani(1984) proposed a model employing Kalman Filter theory for predicting short-term traffic. Prediction parameters are improved using the most recent prediction error and better volume prediction on a link is achieved by taking into account data from a number of links. The new model performed substantially (up to 80%) better than UTCS-2.
Okutani(1987) presents some applications of the Kalman Filter algorithm in transportation and traffic problem. Two methods are developed for estimating and forecasting unobserved traffic volume on a link from volume data on other link. The methods are tested using data collected from a street network in Nagoya. And it is shown that one of the above methods can be easily altered into a method of predicting future traffic volume on a link from observed data on a number of links including the subject link. Sisiopiku and Rouphail(1993) investigated the correlation between traffic flow and occupancy obtained from detectors for predicting the link travel time. They showed that the correlation between travel time, and traffic flow or occupancy is independent in the low traffic demand, but is getting increasing as occupancy increases.
Dailey(1995) presented an algorithm for estimating mean traffic speed using volume and occupancy data from a single inductance loop. The algorithm is based on the statistics of the measurements obtained from management system. The algorithm produces reasonable

speed estimates in the reliability test. Iwasaki and Shirao(1996) showed that short-term prediction scheme of travel time on a long section of a motorway using the pseudo-traffic patterns. The auto-regressive method was introduced as a prediction model, and parameters of the model were identified adapting an extended Kalman Filter method. The predictions error(RME) were almost less than 10%, which was significantly smaller than the results of other studies. Chen and Dougherty(1997) suggested a process for finding suitable location of detector using Neural Network. Cohen(1997) tested the efficiency of on-line travel time information on urban arterials in Paris.
Most studies have been conducted based on the one-step ahead prediction of the link travel time. The multi-step ahead prediction of link travel time should consider the time-varying traffic conditions of the upstream links on the dynamic time interval basis. The multi-step ahead prediction of link travel time is on the early stage of the research.

3. ALGORITHM DESCRIPTION

3.1 Short-term Prediction Algorithms

Several techniques such as time series analysis and neural network have been employed to predict link travel time but its complexity seems to become increase. In this research, Kalman filter technique is employed for developing the prediction algorithm. The algorithm makes use of the time series of link travel time data on the test link. This chapter shows the algorithms of time series analysis, neural network, exponential smoothing and Kalman filter briefly as follows.
<u>ARIMA</u>: Box-Jenkins methodology is suitable for predicting time series variables. ARIMA model is fairly superior when time-series data is stationary. So this model is suitable for application to the stationary traffic pattern using historical information. To apply Box-Jenkins(ARIMA) model for short-term prediction, it needs the process of identification, parameter estimation, diagnostic checking. ARIMA model has limit to build prediction model by non-stationary traffic variables and doesn't react sensitively the change of the irregular (unsteady) speed or travel time to the future prediction. General ARIMA(p,d,q) model is described as the equation (1).

$$\phi(B)\,\Delta^d y(t) = \theta(B)a(t) \tag{1}$$

Where, $y(t)$: the series value at time t $\Delta y(t) = y(t) - y(t-1)$

$$\phi(B) = 1 - \phi_1 B^2 - \phi_1 B^2 - \ldots - \phi_p B^p$$
$$\theta(B) = 1 - \theta_1 B^2 - \theta_1 B^2 - \ldots - \theta_q B^q$$

<u>Artificial Neural Network</u>: Artificial Neural Network model on this study is Multi-Layer Feedforward model, as shown in Figure 1, which is generally used among Artificial Neural Network. In particular, the back-propagation method specifies what changes to make to the weights so that the difference of the actual and the desired network output is reduced. The transition function to generate output value from neuron is the sigmoid function that most generally used. The composition of networks using Artificial Neural Network theory, through testing various alternatives, determines the network. A mathematical program, MATLAB, was used to make the formation of this Neural Network. The architecture of Artificial Neural Network on this study is shown as the equation (2).

$$\Delta pW_{ji}(n+1) = \eta\ \delta_{pj} O_{pj} + \alpha\ \Delta pW_{ji}(n)$$
$$\delta_{pj} = f'_j(net_{pj})\ \Sigma_k (\delta_{pk} W_{kj}) \tag{2}$$

where, i, j, k= perceptrons of input, hidden, and output layers
$W_{ji}(n)$= weights of j and i
η = gain
O_{pj}= output value of perceptron j
α = momentum (constant)
$\alpha\ \Delta pW_{ji}(n)$= momentum

netpj= input value of perceptron *j*
f= sigmoid function

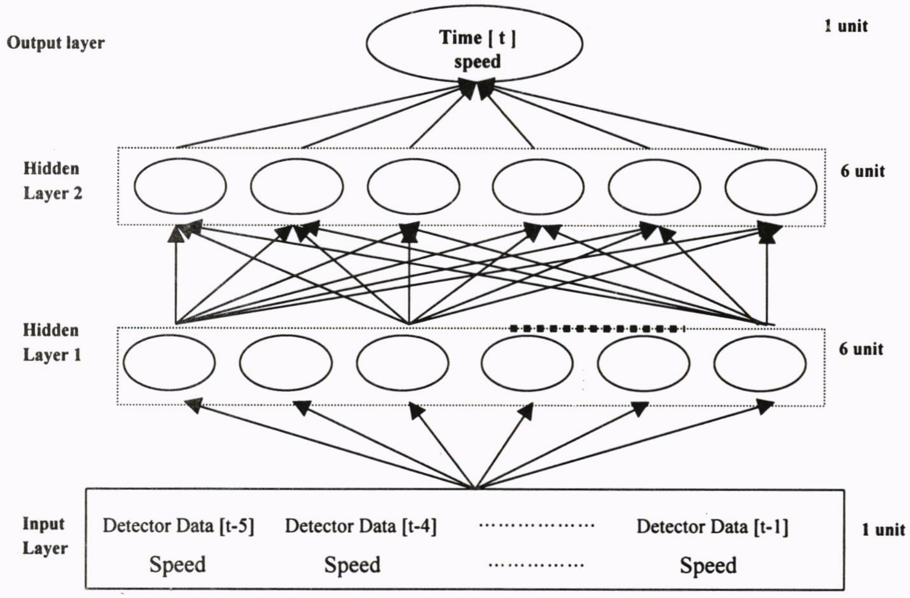

Figure 1. Architecture of Artificial Neural Network

Exponential Smoothing: The exponential smoothing technique uses the historical traffic data for predicting travel speeds. General exponential smoothing model is described as the equation (3).

$$x(t+1) = x(t) + a\ (X(t) - x(t)) \tag{3}$$

where, $X(t)$ = measurement at time t
$x(t)$ = prediction at time t
a = smoothing parameter

Kalman Filter: The Kalman filter estimates state variables using the state-space model for dynamic and random processes. The dynamic system and stochastic process (random process) associated with Kalman filter can be represented by a system of ordinary differential (or difference) equations describing the evolution over time of the state of a physical system. Figure 2 shows the sequence of Kalman filter variables in discrete time. Kalman filter model improves state variable relating to system of prediction. The linear discrete-time dynamic system can be represented as the equation (4).

$$\begin{aligned} xk+1 &= Ak\, xk + \omega\ k && \text{state equation} \\ zk &= Hk\, xk + vk && \text{observation equation} \end{aligned} \tag{4}$$

where, $xk+1$ = state vector(nx1) at tk
Ak = transition matrix(nxn) from tk to $t\ k+1$
$\omega\ k$ = white sequence(nx1)
zk = observation vector(mx1) at tk
Hk = connection vector(mxn) at tk
vk = observation error(mx1)

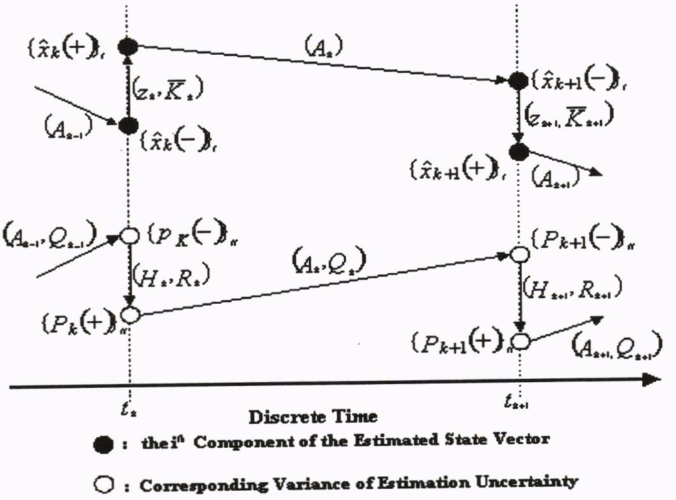

Figure 2. Representative Sequence of Kalman Filter Variables in Discrete Time (Mohinder S. Grewal, "Kalman Filter Theory and Practice", Prentice Hall, 1993. p.114)

3.2 Multi-Step Ahead Prediction Algorithm

A multi-step ahead prediction algorithm is developed using Kalman Filter technique that is described in the previous section. In the travel time prediction process, the travel time of each link is to be predicted at the time step when the individual vehicle passes through the respective link. The travel time from the origin to the destination, then, is predicted by adding travel times of downstream links those are predicted by respective-step ahead. The required time steps are varied depending on the travel speeds of upstream links of the respective link. The basic concept of the proposed algorithm is described in the figure 3.

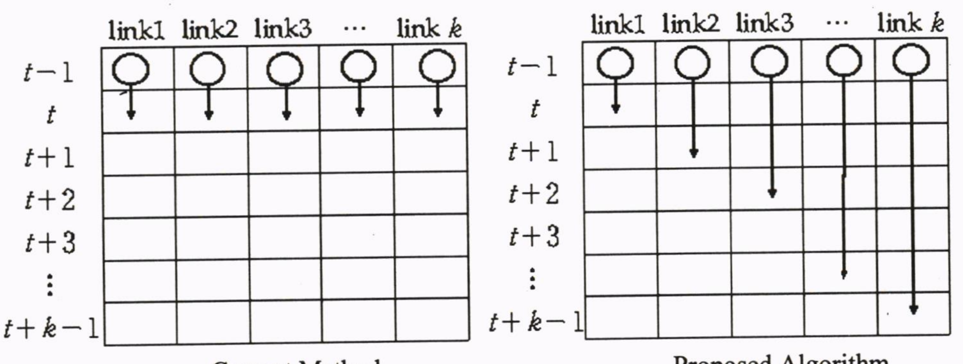

Figure 3. Description of Algorithm

The multi-step ahead prediction algorithm is as follows:
Step 0: Initialization. Estimate travel speeds of links at current time step t = 0.
Step 1: Set time step t = 0 and link number k =0.
Step 2: Update time step t = t + r(r: the time step required to traversing link k with the speed estimated). Predict the speed and the travel time of link k until total travel time from origin to link k reaches to the time step t +r using Kalman Filter.
Step 3: Update link number k = k + 1. Predict the travel time of link k until total travel time from origin to the link k reaches to the time step t +r using Kalman Filter.
Step 4: Continue step 2 and 3 for all k.

4. ALGORITHM DESCRIPTION

4.1 Data Collection

To test the feasibility of the algorithm, it is necessary to obtain link travel time data in the real world. In this study, the link travel time data for the test network were obtained by converting average spot speeds to the link travel times for the respective test sections. The proposed algorithm was applied to an actual network to investigate the performance. The test network in this research is a portion of the Olympic Expressway in Seoul that is composed of 7 sections divided by 8 bridges of Han river. The traffic flow, occupancy, and spot speed data of the test sections are collected by 17 image detectors on 30-second interval basis. The data are then aggregated on the one-minute interval. Figure 4 shows the fundamental method by which these variables are measured or estimated.

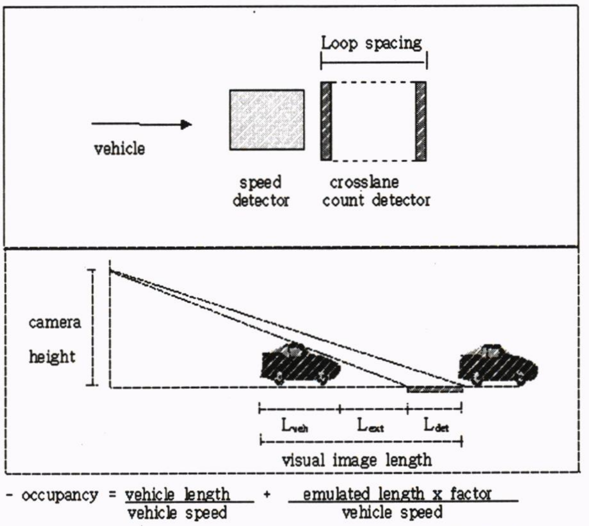

Figure 4. Measuring Method of Image Detector

The traffic flow, occupancy, and spot speed data of the test sections were collected by image detectors that were installed on the sections of the test network. Table 1 represents the image detector locations of the test network. The historical data for the test network were collected on 28 May 6, 10, 11 and 18 June 1998. The historical data were required to set up models tested in this research: (1) ARIMA model, and (2) Artificial Neural Network, (3) Exponential Smoothing (4) Kalman Filter model (5) the Proposed Multi-Step ahead Prediction model.

Table 1. Section Lengths and Detector Numbers of the Test Network

Section	Test Sections(from Youngdong to Seoul Bridge, 14.98km)						
	Youngdong To Sungsu	Sungsu to Dongho	Dongho To Hannam	Hannam to Banpo	Banpo to Dongjak	Dongjak to Hangang	Hangang to Seoul
Length	2.12km	1.03km	1.17km	2.20km	2.01km	2.55km	3.9km
Detector Number	#16, #15	#13	#11	#9	#6	#4	#2

4.2. Algorithm Evaluation

4.2.1 Performance Measures

In this study, the performances of the four techniques were compared. The algorithm performance were tested in terms of performance such as MARE (Mean Absolute Relative Error), MSE (Mean Square Error), and EC (Equality Coefficient). The performance measures are defined as equations (5-7).

$$MARE = \frac{1}{m}\sum \frac{|e(t)|}{x(t)} \tag{5}$$

$$MSE = \frac{1}{m}\sum e(t)^2 \tag{6}$$

$$EC = 1 - \frac{\sqrt{\sum |e(t)^2|}}{\sqrt{\sum x(t)^2} + \sqrt{\sum \hat{x}(t)^2}} \tag{7}$$

where is, $e(t) = x(t) - x(t)$
$x(t)$ = observed value
$x(t)$ = predicted value

4.2.2 Performance of Short-term Prediction Algorithms

Table 2 represents the performance of ARIMA(2,0,0), 4-layers artificial neural network, exponential smoothing, and Kalman filter for the data of the detector number 16. The orders of ARIMA and the numbers of layer of neural network were determined by several test runs, respectively. MAREs and MSEs of four techniques are lower than 0.1 and 32.0, respectively. ECs of four techniques are higher than 0.95. It means that four techniques could be suitable for predicting short-term travel speed.
At all levels of NARE, MSE, and EC the Kalman Filter technique is slightly superior to other techniques. The primary evaluation of this study, therefore, shows that Kalman Filter technique is more suitable for predicting short-term travel speeds than other techniques. The link travel time can be obtained by applying the predicted speed to the appropriate link. Thus, the speed estimates were used for updating time step and link number. Figures 5-8 represent the predicted values of travel speeds for four techniques.

Table 2. Result of Prediction Technique

Prediction Technique	MSE	MARE	EC
ARIMA(2,0,0)	28.85	0.086	0.954
Artificial Neural Network	31.48	0.091	0.952
Exponential Smoothing	29.12	0.085	0.955
Kalman Filter	25.38	0.078	0.958

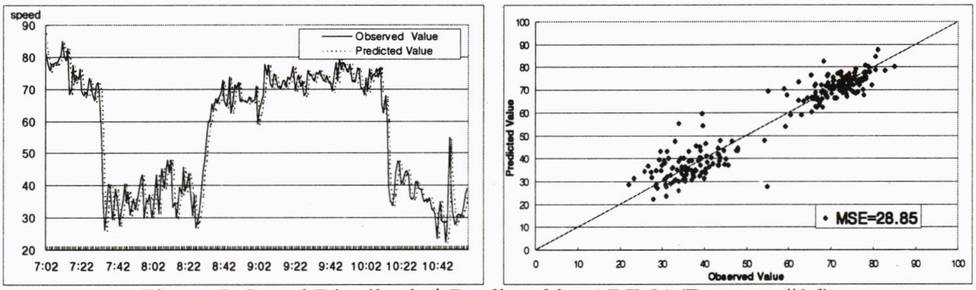

Figure 5. Speed Distribution Predicted by ARIMA(Detector #16)

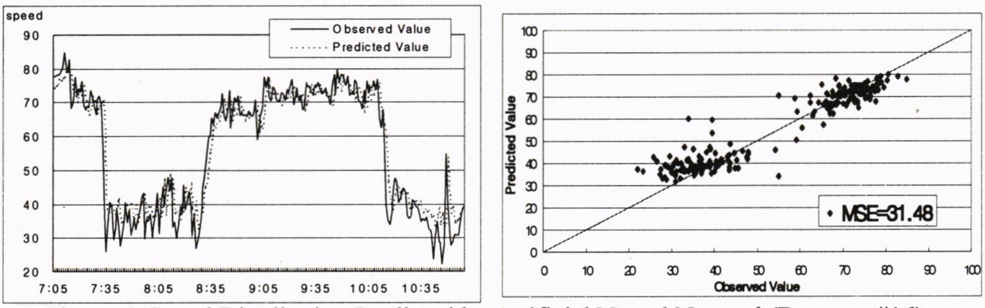

Figure 6. Speed Distribution Predicted by Artificial Neural Network(Detector #16)

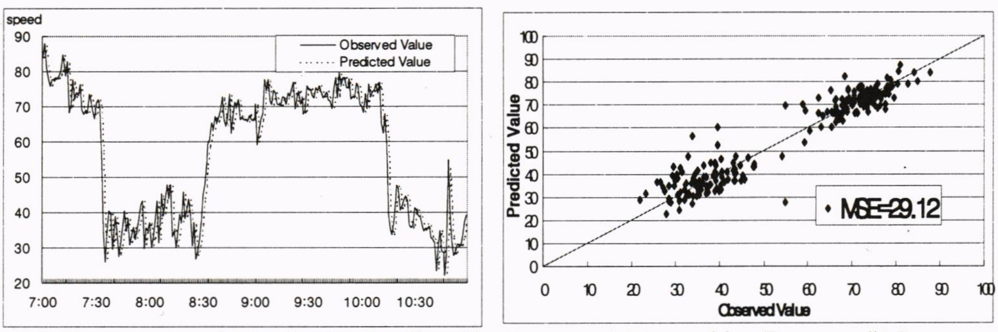

Figure 7. Speed Distribution Predicted by Exponential Smoothing(Detector #16)

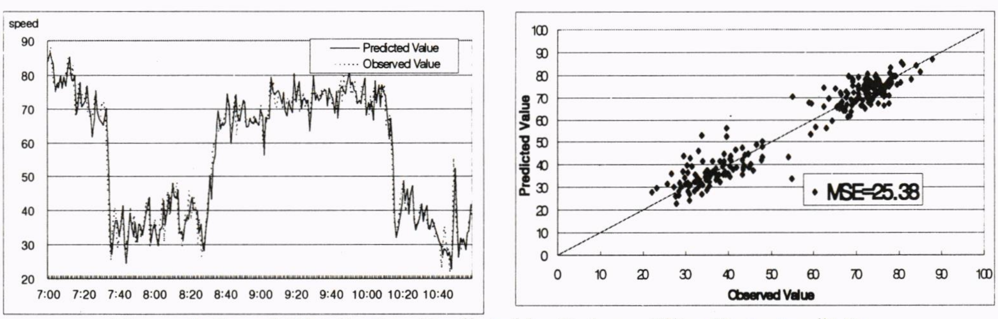

Figure 8. Speed Distribution Predicted by Kalman Filter(Detector #16)

4.2.3 Performance of the Proposed Multi-Step ahead Algorithm

The results of the current one-step ahead and the proposed multi-step ahead algorithms were compared against the observed speeds to determine whether the proposed algorithm result more consistent with the observed speeds than the current algorithm for the travel time prediction. In this section, the speed estimates of the one-step ahead and the proposed multi-step ahead algorithms were compared because the link travel times can be estimated by applying the predicted speeds to the appropriate links. Figures 9 and 10 represent the distributions of the predicted speeds and the observed speeds, respectively at the section between Banpo and Seoul bridge. It shows that the proposed algorithm produces more reasonable results than the current algorithm.

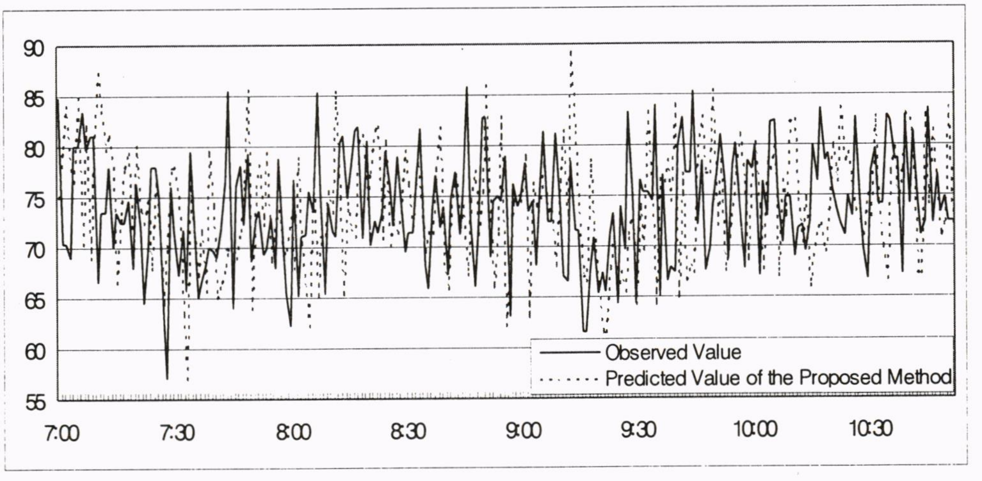

Figure 9. Comparison Observed Value with Current Method

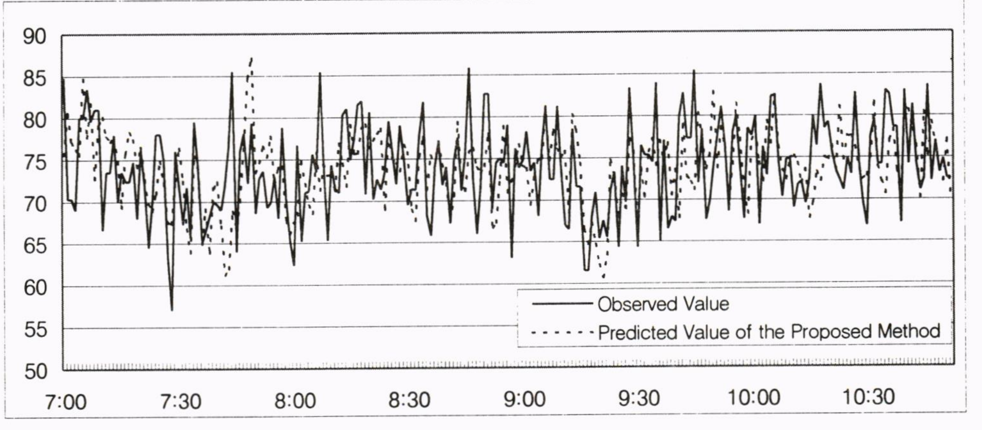

Figure 10. Comparison Observed Value with Proposed Method

The reliability of the multi-step ahead speed estimates was tested by t-test and F-test. Table 3. Demonstrates a part of the t-test and F-test results for 7 detectors, especially for the detector #2(Hangganf to Seoul bridge section). The multi-step ahead speed estimates using Kalman Filter were satisfied on significance level 0.05 for one to 15 minute step ahead predictions.

Table 3. t-test and F-test Results for the Multi-step ahead Speed Prediction(detector #2)

Speed Estimate	**Degree of Freedom**	**T Statistic**	**P(T<=t)**	**t value**
1-step ahead (t+1) Speed	476	-0.059	0.047	1.964
3-step ahead (t+3) Speed	472	-0.050	0.040	1.965
5-step ahead (t+5) Speed	468	-0.110	0.048	1.965
10-step ahead (t+10) Speed	458	-0.138	0.060	1.965
15-step ahead (t+15) Speed	448	-0.123	0.050	1.965
Speed Estimate	**Degree of Freedom**	**F Statistic**	**P(F<=f)**	**f value**
1-step ahead (t+1) Speed	238	0.737	0.009	0.807
3-step ahead (t+3) Speed	236	0.768	0.021	0.807
5-step ahead (t+5) Speed	234	0.774	0.025	0.806
10-step ahead (t+10) Speed	229	0.807	0.053	0.804
15-step ahead (t+15) Speed	224	0.755	0.017	0.802

Table 4 represents the performances of the current one-step ahead and the proposed multi-step ahead algorithms at the sections from Youngdong to Seoul bridge. In the MSE's value, the proposed multi-step ahead algorithm is superior to the current one-step ahead algorithm. The evaluation of this study, therefore, shows that the proposed algorithm is more suitable for predicting short-term travel speeds than the current algorithm. Figure 11. Represents the predicted values of travel speeds for two algorithms.

Table 4. MSE Comparison of the Current and the Proposed Algorithm

Section	Test Sections(from Youngdong to Seoul Bridge, 14.98km)						
	Youngdong to Sungsu	Sungsu to Dongho	Dongho To Hannam	Hannam to Banpo	Banpo to Dongjak	Dongjak to Hangang	Hangang To Seoul
Length	2.12km	1.03km	1.17km	2.20km	2.01km	2.55km	3.9km
Detector Number	#16, #15	#13	#11	#9	#6	#4	#2
MSE of Current Algorithm (step ahead)	21.85 (1)	23.29 (1)	43.41 (1)	43.70 (1)	59.65 (1)	60.63 (1)	67.11 (1)
MSE of Proposed Algorithm (step ahead)	16.01 (1)	18.20 (2)	28.73 (4)	31.51 (6)	29.63 (8)	36.61 (11)	27.61 (15)

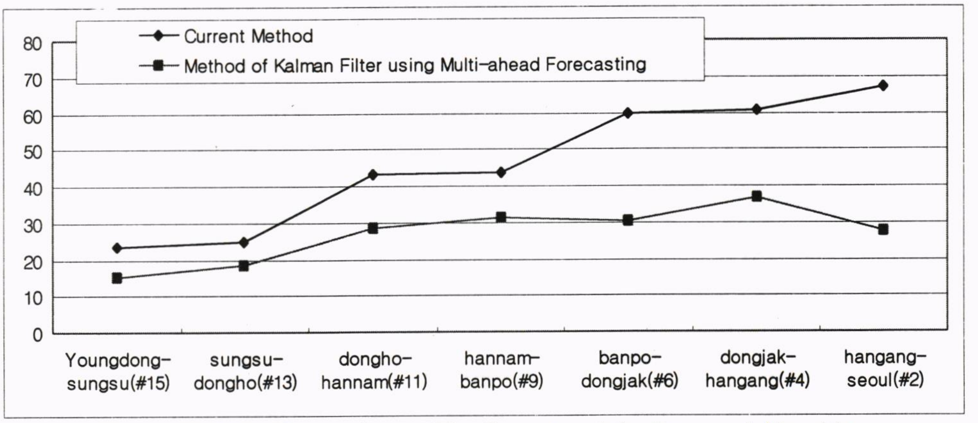

Figure 11. MSE Comparison of the Current and the Proposed Algorithm

5. CONCLUSIONS

In this study, the performance of the ARIMA, Artificial Neural Network, Exponential Smoothing, and Kalman Filter techniques were evaluated in terms of MARE, MSE and EC. The primary evaluation of study shows that Kalman Filter technique is more suitable for predicting short-term travel speeds than other techniques. A multi-step ahead prediction algorithm using Kalman Filter was developed to predict a short-term link travel time. The proposed algorithm was applied on a portion of the Olympic Expressway in Seoul. The evaluation of this study shows that the proposed algorithm is more suitable for predicting short-term collecting process and location transferability. To overcome these problems, further research will be continued by the authors.

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