IMPLEMENTING A TRAVEL TIME FORECASTING MODEL USING TRAFFIC PATTERN ANALYSES WITH GIS

Jinsoo You
Research Assistant
Dept. of Urban and Regional Planning
Univ. of Illinois at Urbana-Champaign
111 Temple Buell Hall
611 East Lorado Taft Drive
Champaign, IL 61820
U.S.A.
Fax: +1-217-244-1717
E-mail: j-you1@uiuc.edu

Tschangho John Kim
Professor
Dept. of Urban and Regional Planning
Univ. of Illinois at Urbana-Champaign
111 Temple Buell Hall
611 East Lorado Taft Drive
Champaign, IL 61820
U.S.A.
Fax: +1-217-244-1717
E-mail: t-kim7@uiuc.edu

Abstract: The main purpose of this paper is to explore a possible way of predicting link travel times for congested highway networks by implementing a hybrid forecasting model with geographic information systems (GIS) technologies. Upon reviewing various forecasting methods that include historical profile approaches, time series models, neural networks, nonparametric regression models, traffic simulation models, and dynamic traffic assignment (DTA) models, a nonparametric regression model with discrete wavelet transform (DWT) techniques has been developed to reduce computation time and to increase forecasting accuracy. GIS technologies have been utilized for storing, retrieving, and displaying traffic data to assist in the forecasting procedures. A pilot historical database has been developed using raw traffic data coming from dual loop detectors installed and managed by Korea Highway Corporation (KHC). The developed hybrid model has been tested using the pilot historical database, from which traffic patterns have been delineated.

1. INTRODUCTION

Travel time forecasting has been recognized as one of the most critical elements of intelligent transportation systems (ITS). For instance, traffic management systems require estimated future travel times so that traffic control centers could avoid delayed controls by making decisions before congestion problems occur. Traffic information systems also demand future travel times to disseminate timely traffic information to commercial vehicle operators and individual drivers. In fact, this noble idea is extremely cumbersome to accomplish due to the complex nature of traffic networks. Nevertheless, travel time forecasting systems have been studied intensively because they have strong impacts on various ITS applications such as advanced traffic management systems (ATMS), advanced traveler information systems (ATIS), and commercial vehicle operations (CVO) (Ben-Akiva et al., 1995; Smith and Demetsky, 1997; Dougherty et al., 1993).

In the field of ITS, many researchers have endeavored to develop reasonable and reliable travel time forecasting models, including historical profile approaches, time series models, neural networks, nonparametric regression models, traffic simulation models, and dynamic traffic assignment (DTA) models (Sen et al., 1997; Ben-Akiva et al., 1995; Gilmore and Abe, 1995; Peeta and Mahmassani, 1995; Ben-Akiva et al., 1994; Mahmassani et al., 1991; Davis et al., 1990). From these experimental efforts, it has been recognized that future travel times are difficult to calculate using a single forecasting method. In this manner, it is understood that a practical approach is to develop a hybrid forecasting model by combining available models and technologies wherever possible.

2. FOUNDATION OF A CORE FORECASTING ALGORITHM

In order to develop a reliable forecasting model, it is useful to construct and utilize a historical database. Moreover, a travel time forecasting model should be able to manage real-time traffic data, and should be easy to implement among traffic management centers that are equipped with various types of computer systems. Furthermore, such a model should be able to use as less amount of computer resource and computation time as possible, and should be able to respond to traffic incidents that usually cause rapid and abrupt speed changes.

To select a core forecasting algorithm of a hybrid forecasting model, a generalized comparison has been conducted, based on six evaluation categories: (1) Utilization of Historical Database, (2) Capability of Online Data Use, (3) Transferability of Forecasting Algorithm, (4) Effectiveness of Forecasting Algorithm, (5) Accuracy of Forecasting Algorithm, and (6) Capability of Forecasting with Traffic Incidents.

(1) *Utilization of Historical Database*: Historical profile approaches, nonparametric regression models, and time series models utilize historical databases relatively well. For instance, historical profile approaches compute historical averages of traffic data using historical databases. Nonparametric regression models search similar conditions in historical databases that occurred in the past. Time series models can perform autoregression (AR) and moving average (MA) analyses using time series data stored in historical databases.

(2) *Capability of Online Data Use*: A travel time forecasting model should be able to promptly produce outputs using real time data. In general, historical profile approaches are a static model that does not consider real time data. Time series models should persistently accomplish complicated parameter estimations, and neural networks have to learn input patterns continuously. Moreover, DTA models require complex dynamic origin-destination (O-D) estimations whenever input data are changed. Therefore, time series models, neural networks, and DTA models are difficult to utilize real time data with currently available computing technologies. On the other hand, nonparametric regression models, which are based on pattern recognition techniques that search similar conditions occurred in the past, do not require any assumption, and thus they can effectively utilize real time data. However, nonparametric regression models need a well-designed search algorithm for large size historical databases to reduce computing time.

(3) *Transferability of Forecasting Algorithm*: A forecasting model needs to be adopted easily among traffic management and information centers that are equipped with various types of computer systems. It is economical that a forecasting model is readily

customized among these centers. DTA models, time series models, traffic simulation models, and neural networks usually require intensive calibration processes for different road networks. On the other hand, historical profile approaches and nonparametric regression models do not require any assumption, and thus they can be applied with relatively simple calibration processes.

(4) *Effectiveness of Forecasting Algorithm*: Computation time strongly affects the success of a forecasting model development. For instance, forecasting results should be calculated at least within forecasting time horizon. Thus total computing time should not be more than 15 minutes to perform a 15-minute forecasting. Moreover, it is always necessary to minimize the computing time so that the forecasted results can be disseminated within traffic management and information centers and to general public. In real-time applications, high performance and parallel processing capable computer systems are often considered for neural networks that require continuous network learning processes with real time data inputs, and for DTA models that repeatedly calculate dynamic O-D tables. In traffic simulation models, the computing time grows quickly when road network sizes become larger. Nonparametric regression models require relatively simple calculations, but they have to optimize search processes to minimize computing time (Smith and Demetsky, 1997).

(5) *Accuracy of Forecasting Algorithm*: A forecasting algorithm should be able to produce accurate outputs. In general, neural networks are relatively accurate when they learn input networks sufficiently (Weigend and Gershenfeld, 1994). Nonetheless, computing time in neural networks grows rapidly when more accurate results are required, i.e., more network learning processes are required. Like neural networks, nonparametric regression models have showed relatively accurate forecasting results while their computing times are much shorter than neural networks' (Weigend and Gershenfeld, 1994).

(6) *Capability of Forecasting with Traffic Incidents*: A forecasting model should be able to deal with traffic incidents. In this category, none of existing models are satisfactory. Historical profile approaches and time series models are very difficult to deal with real-time traffic data with traffic incidents. Nonparametric regression models, neural networks, traffic simulation models and DTA models need to be modified and enhanced to deal with traffic incidents.

Table 1 shows a generalized comparison of existing forecasting models. Based on the comparison, a nonparametric regression model has been selected as a core forecasting algorithm in this study. Nonparametric regression models provide relatively simple forecasting mechanisms with reasonably high forecasting accuracy (Smith and Demetsky, 1997). However, in order to implement an effective nonparametric regression model with limited computer resources, it is necessary to optimize its complex search procedures. In addition, a supplementary algorithm should be developed to make nonparametric regression models capable of dealing with traffic incidents, which could cause conventional nonparametric regression models to generate inaccurate forecasting results.

Table 1. Comparison of Existing Forecasting Models

(O) Excellent; (Δ) Good; (×) Poor

Model \ Evaluation Category	Utilization of Historical Database	Capability of Online Data Use	Transferability of Forecasting Algorithm	Effectiveness of Forecasting Algorithm	Accuracy of Forecasting Algorithm	Capability of Forecasting with Traffic Incidents
Historical Profile Approaches	O	×	O	O	×	×
Time Series Models	O	Δ	×	Δ	Δ	×
Neural Networks	O	Δ	×	×	O	Δ
Nonparametric Regression	O	O	O	Δ	O	Δ
Traffic Simulation	Δ	O	Δ	Δ	Δ	Δ
Dynamic Traffic Assignment Models	Δ	O	×	×	Δ	Δ

3. OBJECTIVES OF THE STUDY

To implement a hybrid travel time forecasting model for congested highway networks, multiple methodologies are adopted in this study, including nonparametric regression models, wavelet transform techniques, and GIS for transportation (GIS-T). For a reliable travel time forecasting model, this study has focused on pursuing the following objectives:

- Designing and developing a historical database using GIS-T technologies and traffic data collected from dual loop detectors,
- Analyzing traffic patterns using discrete wavelet transform (DWT) techniques,
- Developing a hybrid travel time forecasting model, which uses nonparametric regression techniques as a core forecasting algorithm, and
- Simulating and evaluating the developed forecasting model.

4. DEVELOPING A HYBRID TRAVEL TIME FORECASTING MODEL

In this study, a hybrid travel time forecasting model has been developed and tested using nonparametric regression analyses after reviewing various types of existing travel time forecasting models. GIS-T technologies have been adopted to integrate related models and technologies and to construct a historical database using raw traffic data collected from loop detectors. This historical database has been analyzed to delineate traffic patterns using wavelet transform techniques by removing embedded noises. A nonparametric regression model has been applied to forecast future traffic conditions using de-noised traffic data. In this manner, Figure 1 shows a schematic system framework with data flow for the implementation of a hybrid travel time forecasting model.

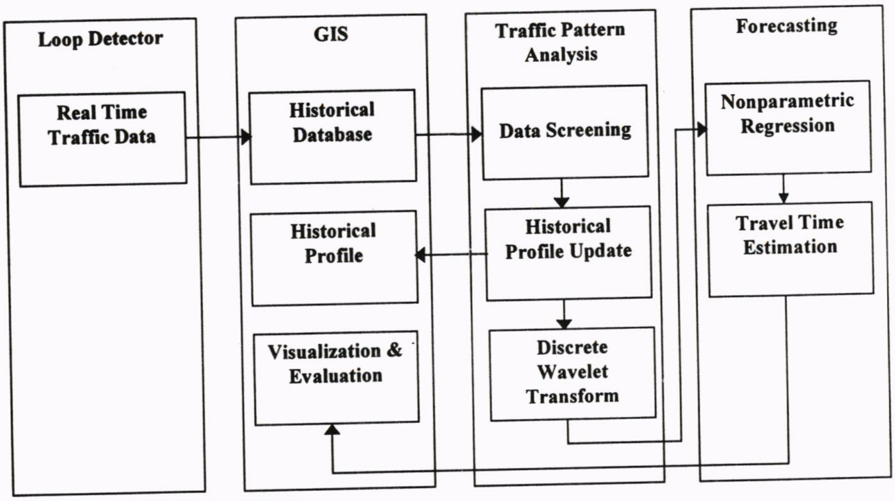

Figure 1. A Schematic System Framework with Data Flow

Particularly, GIS-T technologies have been utilized to construct a historical database as a relational database using raw traffic data, which collected from loop detectors. GIS-T technologies play the important roles in the development of hybrid forecasting model by providing the following functions:

- Creating and editing traffic networks with the topological data structure,
- Assisting in both managing and visualizing historical and real-time traffic data,
- Providing graphic user interfaces for user environments,
- Supporting application development tools for the integration of forecasting algorithms, and
- Providing flexible spatial data analysis tools, using search and query functions.

For the implementation of the proposed hybrid forecasting model, traffic data have been collected from dual loop detectors that are managed by Korea Highway Corporation (KHC). These detectors cover the total length of 114.3 km, and transmit traffic speed, traffic volume, and occupancy rate for every 30 seconds from a Korean highway.

4.1 The Scope of Prediction

Among a variety of traffic forecasting models, it is acknowledged that the majority of existing models predict future travel times for a very short-term period (typically within 15 minutes) to a short-term period (up to 60 minutes) (Ben-Akiva et al., 1995; Gilmore and Abe, 1995; Smith and Demetsky, 1997). When predictions occur every 15-minute, this problem can be formally stated as follows:

Predict: $X(t+15)$
Given: $X(t)$
$X(t-15)$

where,
$X(t)$: Current Condition

4.2 Traffic Pattern Analysis and Noise Reduction

In general, recurrent traffic patterns are existing on highway networks. However, these traffic patterns are difficult to delineate because they are influenced by various types of traffic characteristics such as location, time, speed, road condition, weather, and so forth. Nevertheless, it is advantageous to identify embedded traffic patterns in a systematic way despite of the complex and time-consuming process at the beginning of forecasting procedures. In this study, DWT techniques are utilized to analyze traffic patterns by decomposing and de-noising raw traffic data.

A wavelet transform is a relatively new method to analyze various types of signals, particularly, for data compressing and de-noising. Wavelet transform techniques have originated from the work of Fourier, which is the well-known Fourier analysis, in the nineteenth century although wavelet transform techniques have been acknowledged as a useful signal analysis tool during the late 1980s (Misiti, 1997; Kaiser, 1994). Basically, wavelet transform analyses are capable of identifying various aspects of signal including trends, breakdown points, and self-similarity. By using such effective capabilities, data de-noising techniques without appreciable degradation are often applied in various fields such as seismic tremors, human speech, medical images, financial data, and many other types of time series signals that have to be efficiently analyzed.

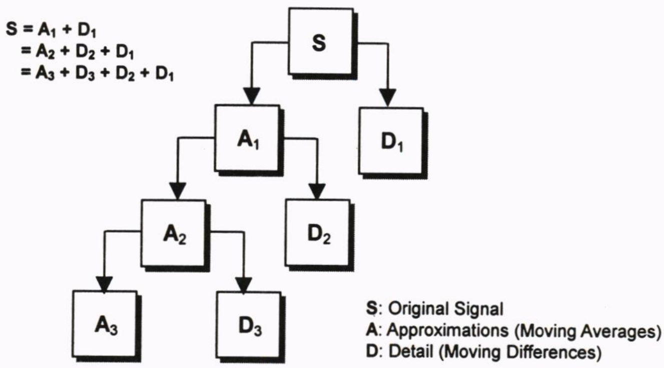

Figure 2. Multiple-Level Decomposition Tree (Adapted from Misiti et al., 1997)

In the DWT analysis, original signals are hierarchically decomposed, and it allows original signals to be described in terms of a coarse overall shape, plus details that range from broad to narrow. This recursive averaging and differencing method is called a filter bank and it is illustrated in Figure 2. In order to understand wavelets better, the following example demonstrates the simplest form of wavelets.

Suppose there is a signal (i.e., a vector) $S = [\ 9\ 7\ 3\ 5\ ]$. Averaging the elements together, pairwise, the new lower resolution signal with values [8 4] are calculated. Because some information has been lost in this averaging process, it is necessary to store some detail coefficients that captures missing information so that the original signal S can be reconstructed. In this example, "1" can be chosen for the first detail coefficient because the first average was 8 which is 1 less than 9 and 1 more than 7. This single number can be used to recover the first two elements of the original four-element signal. Similarly, the second detail coefficient is -1 because 4 + (-1) = 3 and 4 - (-1) = 5. Thus the original signal S has been decomposed into a lower resolution and a pair of detail coefficients. Repeating this process, the wavelet transform of the original signal becomes [6 2 1 -1] (Stollnitz et al., 1995). In this example, no information has been gained or lost, but it is possible to reconstruct the original signal in any level. More significantly, it is also possible to apply this process to de-noising the original signal by removing some of the detail coefficients when raw traffic data (i.e., signal) are decomposed.

Because traffic conditions change rapidly as time goes by, it is possible to consider traffic data as a time series signal. Thus the DWT analysis can be applied to analyze raw traffic data. In fact, a historical database stores a vast amount of traffic data that contain various types of noises. Therefore, it is profitable to remove embedded noises from the historical data for the enhancement of forecasting results. Figure 3 shows an example for 4-level DWT of vehicle speeds at the 30-second interval, 5-day speed data transmitted from a loop detector located at PanGyo Interchange (I/C). In this process, it is observed that high frequency signals are removed, but overall trends are remained. The upper graph shows the de-noised traffic data with the original data, and the middle and the lower graphs show all 4-level approximations and details of original data, respectively.

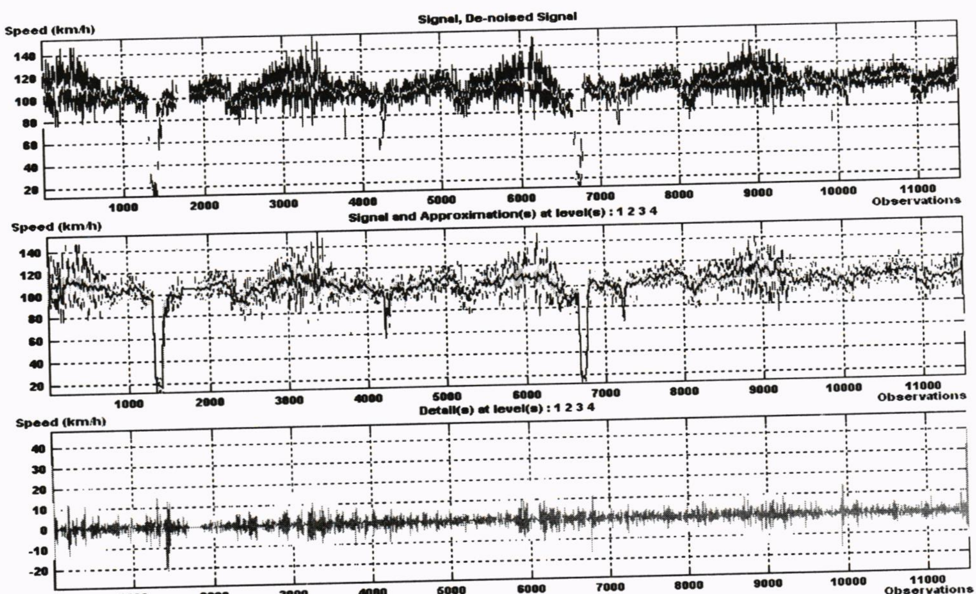

Figure 3. Noise Reduction using 4-level Discrete Wavelet Transform (DWT) of 30-second Interval Speed Data (From Detector No. KDV01131 of the sample Data)

Traffic patterns have been initially analyzed by loop detector's installed locations and data collection times. Figure 4 shows daily traffic patterns at PanGyo I/C, which are calculated after applying DWT to the original traffic data. By inspecting the de-noised traffic data, it is recognized that overall patterns are changing daily without considering some irregular patterns on March 12 and 14 due to traffic incidents. Thus it is advantageous to search a historical database by day of the week, date, and time for a nonparametric regression model, which searches similar conditions that occurred in the past.

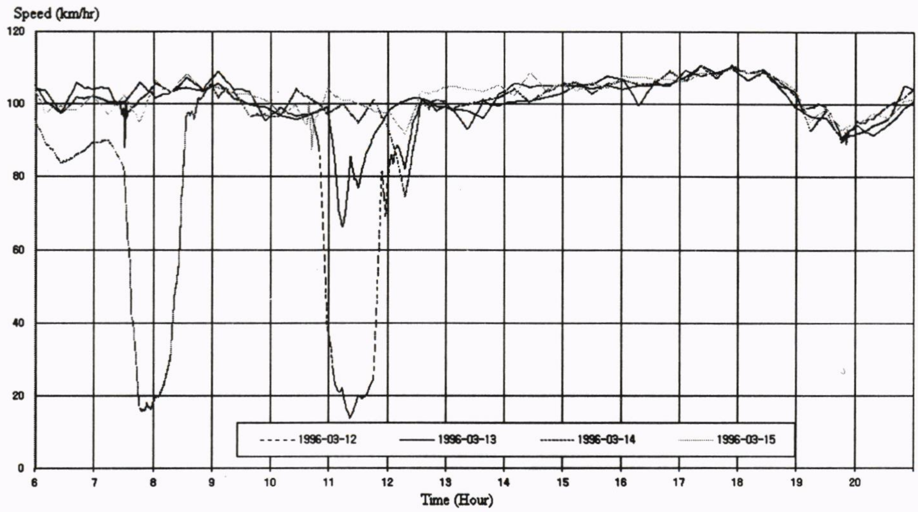

Figure 4. Wavelet Transformed Traffic Speed (Pangyo I/C)

4.3 Nonparametric Regression Analysis and Traffic Pattern Search

In general, a regression function explains a relationship between an explanatory (i.e., independent) variable X and a response (i.e., dependent) variable Y. Having observed X, the average value of Y is given by the regression function. If n data points $\{(X_i, Y_j)\}_{i=1}^{n}$ have been collected, the unknown regression function m with observation errors ε_i can be formally written as follows:

$$Y_i = m(X_i) + \varepsilon_i, \qquad (i = 1, \ldots, n) \tag{1}$$

In a regression analysis, the unknown function m is estimated using a reasonable approximation by minimizing the observational errors. This function approximation procedure is commonly called "smoothing," and there are two ways of regression function approximation: parametric and nonparametric smoothing approaches.

The frequently used *parametric* smoothing approach assumes that the regression function m has some prespecified functional form, for example, a line with unknown slope and intercept. This approach is called parametric because the functional form is fully described by a finite set of parameters, for example, a polynomial regression equation. On the other hand, the nonparametric smoothing approach estimates the unknown regression function m *nonparametrically* without reference to a specific form. Thus it provides a flexible tool in analyzing unknown regression relationships, whereas a preselected parametric model might be too restricted or too low-dimensional to fit unexpected features (Härdle, 1990).

Among frequently used smoothing methods such as kernel, k-nearest neighbor (k-NN), orthogonal series, and spline smoothing, the k-NN smoothing has been applied to formulate a nonparametric regression model in this study. Basically, the k-NN smoother is a weighted average in a varying neighborhood. This neighborhood is defined through those X-variables which are among the k-nearest neighbors of x in Euclidean distance. The k-NN smoother $m_k(x)$ is formally defined as

$$m_k(x) = n^{-1}\sum_{i=1}^{n} W_{ki}(x)Y_i \tag{2}$$

where $\{W_{ki}(x)\}_{i=1}^{n}$ is a weight sequence defined through the set of indexes $J_X = \{i$: X_i is one of the k nearest observations to $x\}$. With the set of indexes of neighboring observations the k-NN weight sequence is constructed as

$$W_{ki}(x) = \begin{cases} n/k, & \text{if } i \in J_x; \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

For instance, in order to obtain the k-NN weight sequence $\{W_{ki}(x)\}_{i=1}^{n}$ for $x = 4$ and $k = 3$ when $\{(X_i, Y_j)\}_{i=1}^{5}$ is {(1,5), (7,12), (3,1), (2,0), (5,4)}, the set of indexes J_x becomes $J_4 = \{3, 4, 5\}$ because the k observations closest to x are the last three data points. Thus $W_{k1}(4) = 0$, $W_{k2}(4) = 0$, $W_{k3}(4) = 5/3$, $W_{k4}(4) = 5/3$, and $W_{k5}(4) = 5/3$ (Härdle, 1990).

The following example demonstrates the nonparametric formulation using the k-NN smoother. Consider a bivariate relationship, $f(x) = y$, for which estimates of y are desired for $x_a = 4$ and $x_b = 9$ as shown in Figure 5. A database of 13 previously observed x, y pairs is available. Assuming a neighborhood size of $k = 3$, neighborhoods A and B are identified. Both A and B include the three cases with x-values closest to x_a and x_b, respectively. Estimates for y are then calculated by averaging the y-values of the cases in the neighborhood. For x_a, y is estimated as 5.6, the average of the observed y values of 6.5, 4.3, and 5.9. For x_b, y is estimated as 8.2 (Smith and Demetsky, 1997).

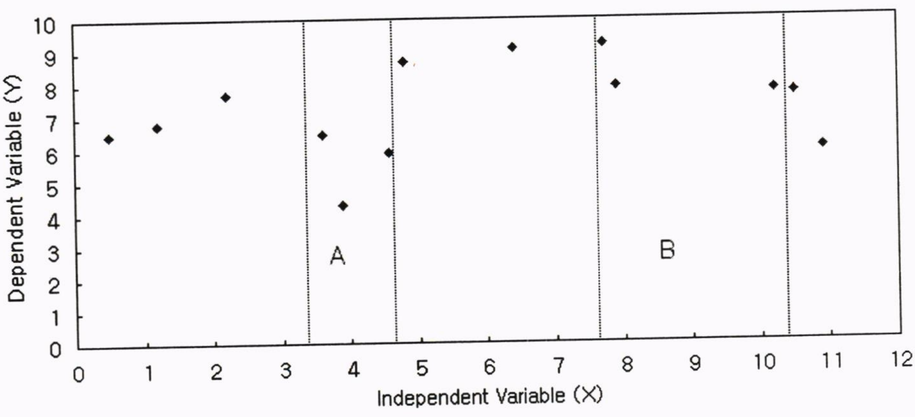

Figure 5. k-Nearest Neighbor Example (Smith and Demetsky, 1997)

In this study, the nearest neighbor formulation is implemented with a two-step traffic pattern search algorithm with the standard deviation of the differences between matched pairs, which is often calculated to perform the paired t-test, as shown in Figure 6. Using a historical database, the first search process attempts to locate the most similar K (a predetermined parameter) sets of data values to the current traffic data in order of traffic speed, traffic volume, and occupancy rate. A predefined search range can be given for the first search process. For instance, in order to predict a 15-minute ahead traffic condition at 7:00 AM, the first search process locates similar conditions occurred in previous days between 6:00 to 8:00 AM from a historical database when the search range is set to ± 1 hour. The second search process applies the standard deviation of the differences to refine the intermediate search results, which are *K* sets of traffic data obtained from the first search process. By analyzing the standard deviations of the differences, the most similar *k* (a predetermined parameter) sets are selected among *K* sets of traffic data. Finally, the *k-NN* smoother is calculated using the next 15-minute traffic data of the selected *k* data sets.

In this study, it is important to consider each value in each set of traffic data to identify the similarity between two sets of traffic data. Thus calculating the standard deviation of the differences is useful. This procedure is shown as follows (Burt and Barber, 1996):

$$d_j = x_j^o - x_j^c \qquad (j = 1,2,\ldots n) \tag{4}$$

$$\bar{d} = \frac{\sum_{j=1}^{n} d_j}{n} \tag{5}$$

$$s_d = \sqrt{\frac{\sum_{j=1}^{n} \left(d_j - \bar{d}\right)^2}{n-1}} \tag{6}$$

where d_j: the Difference between Members, x_j^o: Observed Value, x_j^c: Coressponding Value, $\bar{d}$: Average Difference, *n*: the Number of Observations, s_d: Standard Deviation of the differences.

For instance, consider a historical database that is constructed using 30-second interval traffic data collected from highway loop detectors. Because a *k* value could be smaller than or equal to a *K* value, let *K* be 10 and *k* be 3. The first process then searches 10 sets of similar traffic data sets, which observed in the past. For a 15-minute ahead forecasting, each set of traffic data consists of 30 data values (i.e., each data value represents a 30-second period). By calculating the standard deviations of the differences in the second search process, the most similar 3 sets of traffic data are selected and their next 15-minute data values are obtained from the historical database. Finally, the *k-NN* smoother (*k*=3) is calculated using these next 15-minute data.

In general, there are two trade-off problems regarding the determination of reasonable *K* and *k* values. The first trade-off problem exists between the size of *K* value and the search processing time. The probability of finding similar conditions becomes higher when the *K* value becomes larger (i.e., when the sample size becomes larger), but the larger *K* values result longer search processing times. The second trade-off problem exists between the size of *k* value and the reduction of noisy data (i.e., the larger the *k* value, the greater the noise). In the second search process as described previously, the *K* sets of traffic data are ranked from the most similar case to the least similar one using the standard deviation of the differences. By excluding dissimilar cases, the *k-NN* smoother is further refined. In an ideal situation, the best prediction could be performed when a traffic condition in the past is exactly same as the current one (i.e., same traffic speed, traffic volume, and occupancy rate). If this situation occurs, the best results can be obtained when the k value is 1. Nevertheless, it is nearly impossible to observe search an ideal situation in a highway network, and thus the k value needs to be greater than 1, but much smaller than the K value. By excluding dissimilar cases, future travel times can be estimated more accurately.

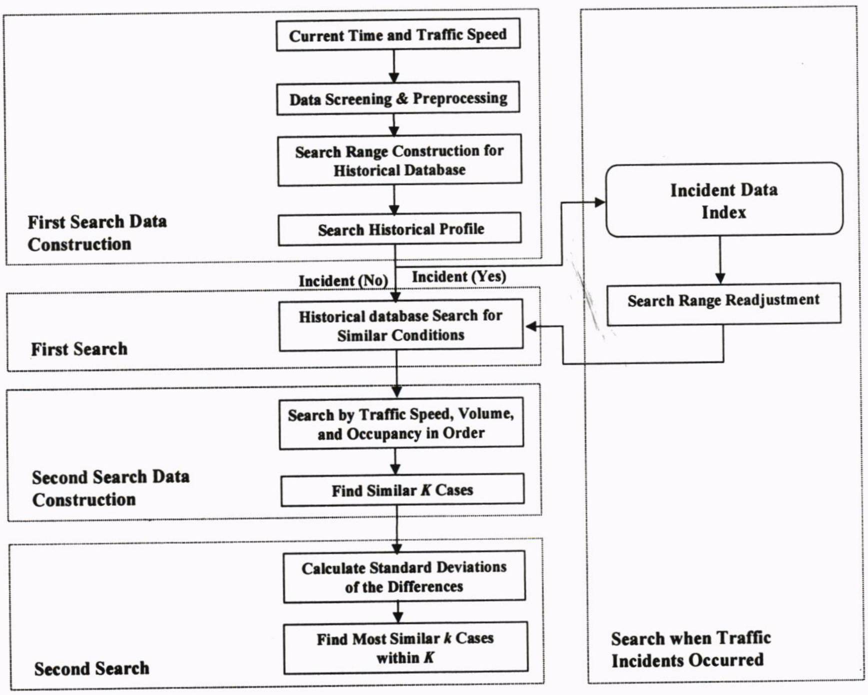

Figure 6. A Schematic Traffic Pattern Search Algorithm

4.4 Forecasting with Traffic Incidents

For traffic incidents that usually cause rapid and abrupt speed changes, a supplementary search process is considered in addition to the previously explained search algorithm. In this study, the following algorithm has been devised to form search ranges when traffic incidents are occurred.

1) Identify sets of traffic data with traffic incidents by searching the historical database before initiating the proposed forecasting system. The standard deviation of the differences between matched pairs is used to identify the difference between two sets of traffic data. Traffic data sets are compared each other for same time ranges but different days.
2) After excluding sets of traffic data with traffic incidents, calculate weighted averages and update historical profiles.

3) Index the time ranges that include traffic incidents in the historical database.

The first and the second steps need to be fulfilled as a system initialization task, and thus they do not affect the system performance. The third step is performed every time when predictions are performed. This procedure is illustrated in Figure 6 with the traffic pattern search algorithm.

5. PROTOTYPE DEVELOPMENT AND EVALUATION

To evaluate the proposed forecasting model, a prototype forecasting system has been implemented using a Windows NT-based workstation. For the development of historical database, ARC/INFO GIS software package has been utilized. To program the proposed nonparametric regression model, both C++ language and AML, which is a macro language available in ARC/INFO, have been used.

In order to evaluate the accuracy of forecasting results, the root mean square error (RMSE) and the root mean percent error (RMPE) have been calculated. Basically, RMSE and RMPE are used to understand the deviation between actual and forecasted values as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{x}_i - x_i)^2} \tag{7}$$

$$RMPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{\hat{x}_i - x_i}{x_i}\right)^2} \tag{8}$$

where x_i: Actual Data, $\hat{x}_i$: Forecasted Data, and n: the Number of Observations.

A number of predictions have been performed to evaluate the prototype forecasting system with the parameter $K = 10$ and $k = 3$. Both parameters have been obtained empirically after applying different parameter settings to the prototype forecasting system. A sample traffic data set, which transmitted from a loop detector, has been decomposed using the 4-level DWT. Figure 7 and 8 shows the difference of forecasting results between actual and wavelet transformed data for three possible forecasting results. By a brief inspection, it is understood that the forecasted results with actual data tend to be very chaotic. On the other side, the forecasted results with wavelet transformed data tend to follow the general trend relatively well.

It is more evident when root mean square errors (RMSE) are calculated as shown in Figure 9. It also shows a chaotic behavior of the forecasting results with actual data, and a relatively consistent behavior of forecasting results with wavelet transformed data. Moreover, it is also observed that the RMSE values for the forecasting results with actual data are almost 10 times greater than the forecasting results with wavelet transformed data. It explains that the proposed nonparametric model with wavelet transformed data performs better than the proposed model with the original raw traffic data does.

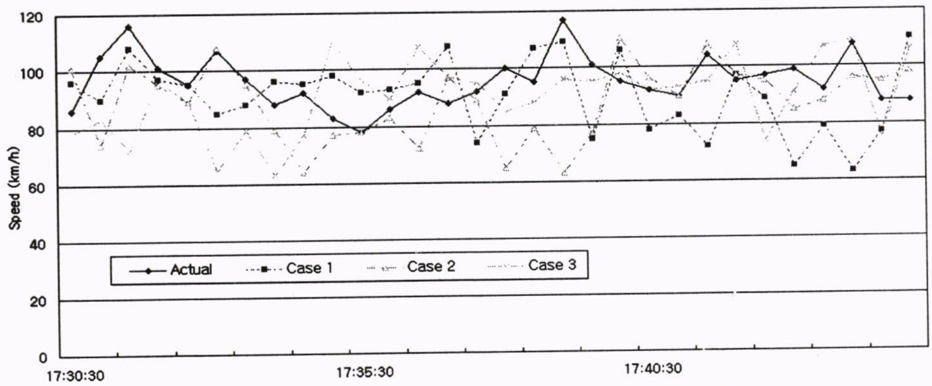

Figure 7. Sample Forecasting Results using Actual Data

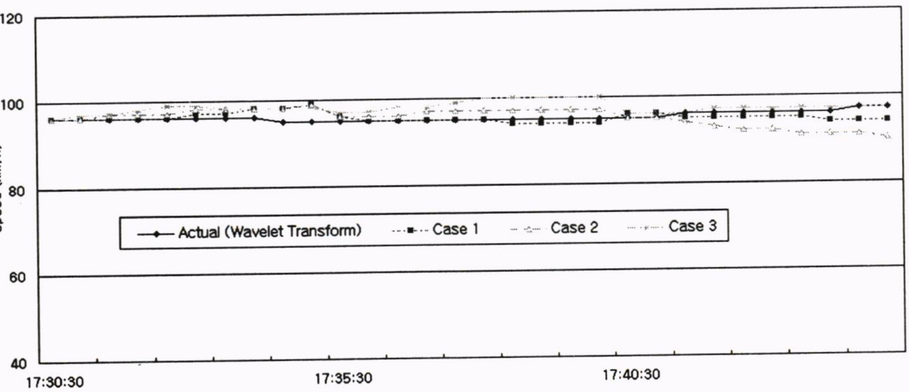

Figure 8. Sample Forecasting Results using Wavelet Transformed Data

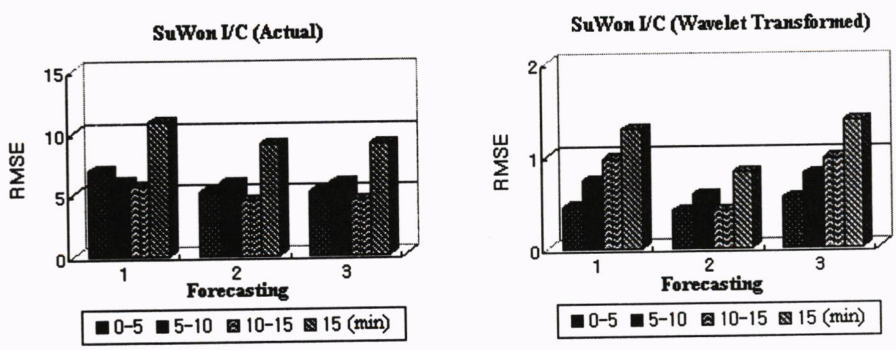

Figure 9. 15-Minute Forecasting Results: Actual vs. Wavelet Transformed Data

Table 2 and 3 show average RMSE and RMPE values for actual and wavelet transformed data of 8 locations after forecasting traffic speeds 30 times for each location. These tables also show that the proposed model with wavelet transformed data predicts better than the model with raw data does. Using wavelet transformed data, predicted results are slightly different between locations, but three cases show nearly similar results for each location. Nonetheless, these tables show relatively reasonable predicted results despite of using relatively small amounts of traffic data (for one week).

Table 2. RMSE: Actual vs. Wavelet Transformed Data

	Actual			Wavelet Transformed		
	Prediction 1	Prediction 2	Prediction 3	Prediction 1	Prediction 2	Prediction 3
PanGyo I/C	9.191	8.702	8.151	2.082	2.082	2.082
SinGal J/C	6.804	6.804	6.804	4.450	4.502	4.502
SuWon I/C	10.773	9.018	9.018	1.291	0.816	1.366
KDV05211	10.942	10.515	12.220	3.773	2.677	2.436
KDV07211	11.939	11.606	11.473	6.611	6.411	6.611
MokChun I/C	9.861	9.978	9.978	3.044	1.983	3.044
NamYi J/C	16.955	16.933	17.531	1.472	2.893	2.733
ChungWon I/C	16.519	12.462	15.662	5.820	5.896	5.896

Table 3. RMPE: Actual vs. Wavelet Transformed Data

	Actual			Wavelet Transformed		
	Prediction 1	Prediction 2	Prediction 3	Prediction 1	Prediction 2	Prediction 3
PanGyo I/C	0.094	0.088	0.085	0.022	0.022	0.022
SinGal J/C	0.064	0.064	0.064	0.041	0.042	0.042
SuWon I/C	0.106	0.087	0.087	0.012	0.008	0.013
KDV05211	0.102	0.095	0.113	0.035	0.025	0.023
KDV07211	0.110	0.113	0.115	0.062	0.060	0.062
MokChun I/C	0.103	0.109	0.109	0.033	0.021	0.033
NamYi J/C	0.172	0.164	0.178	0.015	0.030	0.029
ChungWon I/C	0.221	0.173	0.219	0.069	0.070	0.070

In addition, a heuristic approach has been adopted to estimate travel times, based on the forecasted future traffic conditions as shown in Figure 10. Average speeds of μ_{i-1}, μ_i, and μ_{i+1} are calculated for detectors D_{i-1}, D_i, and D_{i+1}. For a 15-minute prediction, the average speed up to M_{i-1} point (μ_{i-1}) is the average speed at the detector D_{i-1}, and the average speed between M_{i-1} and M_{i+1} (μ_i) is the average speed at the detector D_i. Therefore, S_{i-1} becomes the travel time between D_{i-1} and D_i. However, for the travel time between D_i and D_{i+1}, it is not a 15-minite prediction, but should be a $15+S_{i-1}$ prediction to consider the traveling time between D_{i-1} and D_i.

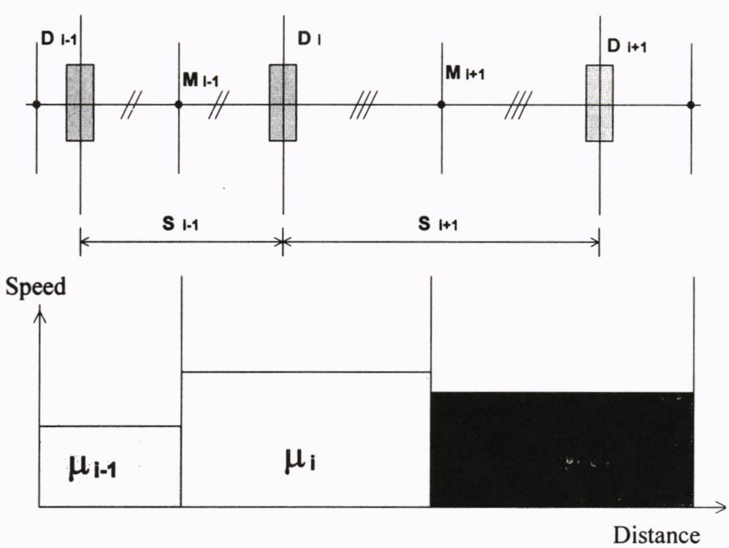

Figure 10. Travel Time Estimation. Adapted from Sisiopiku et al. (1994)

6. CONCLUSION

In order to perform reliable travel time predictions, a hybrid forecasting model has been proposed and tested using traffic data transmitted from loop detectors. A nonparametric regression model with wavelet transform techniques has been developed to reduce computation time and to increase forecasting accuracy. GIS-T technologies have been utilized for storing, retrieving, and displaying analyzed traffic patterns to assist in the forecasting procedures. A pilot historical database has been developed using raw traffic data coming from loop detectors installed and managed by Korea Highway Corporation.

In the implementation and evaluation of the prototype forecasting system, this study shows that the developed hybrid model could be utilized as a core function in various ITS applications such as ATMS and ATIS. Nonetheless, the following tasks need to be fulfilled in the future for more accurate predictions:

- Devising a way of defining the reasonable size of K and k values,
- Improving the developed forecasting model using other data sources such as probe vehicle data,
- Developing a real time data simulator that uses a part of historical database as real time data for further evaluation of the prototype forecasting system, using both GIS-T and server-client network technologies, and
- Validating the prototype forecasting system empirically by comparing actual driving times with forecasted travel times.

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