Dynamic Travel Time Prediction using Pattern Recognition

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ABSTRACT

Travel-time information is an essential part of Advanced Traveler Information Systems (ATISs) and Advanced Traffic Management Systems (ATMSs). A key component of these systems is the prediction of travel times. From the perspective of travelers such information may assist in making better route choice and departure time decisions. For transportation agencies these data provide criteria with which to better manage and control traffic to reduce congestion. This study proposes a dynamic travel time prediction algorithm that matches current traffic patterns to historical data. Unlike previous approaches that use travel time as the control variable, the approach uses the temporal-spatial traffic state evolution to match traffic states and predict travel times. The approach first identifies candidate historical time intervals by matching real-time traffic state data against historical data for use in prediction purposes. Subsequently, the selected candidates are used to predict the temporal-spatial evolution of traffic. Lastly, dynamic travel times are constructed using the identified candidate historical data. The proposed algorithm is tested on a 37-mile freeway segment from Newport News to Virginia Beach along the I-64 and I-264 freeways using historical INRIX data. The prediction results indicate that the proposed method produces predictions that are more accurate than the state-of-the-art K-Nearest Neighbor methods reducing the prediction error by 15 percent to less than 3 minutes on a 50-minute trip.

INTRODUCTION

Congestion has proven to be a serious problem across urban areas in the United States. In 2007, it cost highway users 4.2 billion extra hours of sitting in traffic and an extra 2.8 billion gallons of fuel. This all translated into an additional $87.2 billion in congestion costs for road users in 2007, which showed a 50% increase in cost compared to data from the previous decade. Even though the recent economic downturn is said to have marginally eased the congestion problem nationwide, new evidence shows an uptrend in traffic and consequently congestion [1].

Tackling congestion (both recurrent and non-recurrent) has proven to be a challenge for highway agencies. Adding capacity in response to congestion is becoming less of an option for these agencies due to a combination of financial, environmental, and social issues. Therefore, the main focus has been on improving the performance of existing facilities through continuous monitoring and dissemination of traffic information. The minimum that can be accomplished is to inform the public or, specifically, the potential users of what they should expect on the roadways before and during their trips. Additionally, this information can be applied to provide alternatives to users so that they may make informed decisions about their trips. This is the essence of Advanced Traveler Information System (ATIS) applications such as 511 that have been implemented nationwide. In many states relevant traffic information is also posted on variable message signs (VMSs) that are strategically positioned along highways. Consequently, there is a need to provide predicted travel times to road users for better planning their trips and choosing their route of travel, further reducing congestion.

Various traffic sensing technologies have been used to collect traffic data for use in computing travel times, including point to point travel time collection (license plate recognition systems, automatic vehicle identification systems, mobile, Bluetooth, probe vehicle, etc.) and station based traffic state measuring devices (loop detector, video camera, remote traffic microwave sensor, etc.). Private companies such as INRIX integrate different sources of measured data to provide section-based traffic state data (speed, average travel time), which is used in our study to develop algorithms for predicting travel times. The benefit of using section-based traffic state data is that travel time can be easily calculated from traffic state data. More importantly, the section-based data provides the flexibility for scalable applications on traffic networks.

By providing section-based traffic state data, there are two approaches to compute travel time depending on the trip experience [2, 3]. Dynamic travel time is the actual, realized travel time that a vehicle could experience during a trip. If a vehicle leaves it's origin at the current time, the roadway speed will not only change across space but also across time during the entire trip. Consequently, dynamic travel time can be obtained by using a prediction algorithm to compute the speed evolution in future time steps. Instantaneous travel time is the other approach available to compute travel times without the consideration of speed evolution across time. It is usually computed using the current speed along the entire roadway; in other words the speed field is assumed to remain constant in time. The instantaneous travel time is close to the dynamic travel time when the roadway speed does not change significantly across time space during the trip. However, this approach may deviate substantially from the actual, experienced travel time under transient states during which congestion is forming or dissipating during a trip [4].

Some attempts have been conducted using macroscopic traffic modeling to predict short-term traffic states, however the accuracy degrades rapidly with the increase in the prediction time span [5, 6]. It should be noted that traffic state in the near future usually cannot provide enough information to cover the entire trip, especially for long trips. For instance, in the case of a 100-

mile trip, departures at the current time would still be traveling one hour in the future even under free-flow traffic conditions. For this case, the traffic state for the following one hour or more should be predicted in order to compute dynamic travel times. An alternative to solving this problem is to use historical data. The historical dataset provides a pool of past experienced traffic patterns which can be used to predict future traffic states. The key issue is determining the similar historical traffic patterns to match with the changeable real-time traffic information.

The purpose of this study is to develop an algorithm to predict dynamic travel times for departures at the current time or in the future (look ahead time duration). The proposed method seeks historical candidates with similar traffic patterns to the current conditions. Afterward, the future traffic state can be predicted by the subsequent traffic state of each candidate. Dynamic travel times for each candidate are aggregated with associated weights to compute future travel times. A freeway stretch from Newport News to Virginia Beach is selected to test the proposed algorithm using five-minute aggregated traffic data for 2010 provided by INRIX. The travel time prediction results during the summer season demonstrate that the proposed method produce higher prediction accuracies compared to state-of-the-art K-Nearest Neighbor methods, especially during highly congested weekdays.

The remainder of this paper is organized as follows. A literature review of previous travel time prediction methods is provided. Subsequently, the proposed methodology of using current and historical traffic state data to predict dynamic travel times is presented. This is followed by a description of the test data for the case study and the comparison results of using proposed approach and the traditional *k*-NN algorithm for prediction. The last section provides the summary conclusions of the research and some research recommendations for future research.

LITERATURE REVIW

During the past decades, many studies have been conducted to predict travel times. Some of the reviews of different methods can be found in earlier publications [7-10]. According to the manner of modeling, those methods can be classified into time series models including Kalman filter [11, 12], Auto-Regressive Integrated Moving Average (ARIMA) models [12-14] and data-driven methods, such as neural networks [9, 15], support vector regression (SVR) [16, 17] and K-Nearest Neighbor (*k*-NN) [8, 18, 19] models. These techniques are implemented through direct and indirect procedures to predict travel times using different types of state variables. Travel time is directly used as the state variable in model-based or data-driven methods to predict travel times. Indirect procedures are performed by using other variables (such as traffic speed, density, flow, occupancy , etc.) as the state variable to predict traffic status, and then future travel time can be calculated based on the transition to predicted traffic status.

Time series models construct the time series relationship of travel time or traffic state, and then current and/or past traffic data are used in the constructed models to predict travel times in the next time interval [20]. A Kalman filter (KF) is a popular method for data estimation and tracking, in which time update and measurement update processes are included. A time series equation is used to predict state variables and then state values are corrected according to the new measurement data. The main advantage of a KF is that the recursive framework ensures traffic data is efficiently updated only using data from previous states and not the entire history [5]. Kalman filters were proposed to predict travel times using Global Positioning System (GPS) information and probe vehicle data [12, 21]. The state transient parameter in the time series equation is defined from average historical data to calculate future travel times. The similar idea was used in the Bayesian dynamic linear model for real-time short-term travel time prediction [11]. The system noise can be adjusted for unforeseen events (incidents, accidents or bad weather) and integrated into the recursive Bayesian filter framework to quantify random variations on travel times. The experiment results based on loop detector data from a segment of I-66 demonstrates the proposed method produces higher prediction accuracy under both recurrent and non-recurrent traffic conditions. However, in these methods a problem exists in that the travel time in the previous time interval is needed to calculate the future travel time. For real-time applications, the travel time is usually greater than the time interval step size. Hence, the actual travel time from the previous time interval is not available to apply in the algorithms used to predict travel times for the next time interval.

A seasonal ARIMA model was proposed to quantify the seasonal recurrent pattern of traffic conditions (occupancy) [13, 14]. Moreover, an embedded adaptive Kalman filter was developed in order to update the occupancy estimate in real-time using new traffic volume measurements. Consequently, multi-step look ahead occupancy information are estimated to obtain a data matrix representing the temporal-spatial traffic condition for the future trip. Since travel time cannot be directly computed through traffic conditions (occupancy), future traffic speed can be calculated using occupancy data by assuming an average vehicle length and using a constant conversion factor known as the g-factor in the literature. Consequently, dynamic freeway corridor travel times are predicted with the consideration of traffic state evolution along the corridor. However, this approach may be difficult to implement since the described recurrent pattern of traffic conditions may not be found everywhere.

Data-driven methods usually predict travel times using a large amount of historical traffic data. Time series models are not specified in the data-driven methods, considering the complex stochasticity of traffic systems. Neural networks can be trained from historical data to discover hidden dependencies which can be used for predicting future states. A space neural network (SSNN) method was proposed to predict freeway travel times for missing data [9]. The missing data problem was tackled by simple imputation schemes, such as exponential forecasts and spatial interpolation. Travel time was the direct state variable used for the training process and the experiment results demonstrated the SSNN methods produced accurate travel time predictions on inductive loop detector data. Supported vector machine (SVM) is a successor to ANNs, which has greater generalization ability and is superior to the empirical risk minimization principle as adopted in ANNs [17]. The application of SVM to time series forecasting is called SVR. The SVR predictor was demonstrated to perform well for travel time prediction. The point to point travel time is usually used as the input to ANNs and SVRs. However, both methods require long training processes and are nontransferable to other sites [8].

The *k*-NN method can be used to find several candidate sequences from historical data, by matching with current to short past data sequences. Travel time and occupancy sequences were used to predict dynamic travel times using the *k*-NN method with combined data from vehicle detectors and automatic toll collection systems [8]. The occupancy was used since travel time sequence was collected for the recent past time intervals. The results from the case study demonstrated the improvement of prediction accuracy by combining two types of sequences for the matching process. Moreover, a *k*-NN method was proposed by selecting candidates through the Euclidean distance and data trend measures to predict freeway travel times under different weather conditions [18]. Unlike ANNs and SVRs, *k*-NN methods are easy to implement at different sites without data training required.

In summary, existing methods are either insufficient or have limitations for predicting dynamic travel times for departures at the current time or future times. The proposed approach used in this study is a data-driven method, yet outperforms the previous methods by fully utilizing the relationship between traffic states and travel times. Moreover, other than previous studies using travel time sequences as input, the proposed method uses temporal-spatial traffic data to match traffic patterns between real-time and historical data. The temporal-spatial traffic matrix can be further applied with advanced pattern matching techniques to extract candidates more efficiently and accurately to obtain better travel time prediction results.

METHODOLOGY

The Dynamic Travel Time Prediction Framework

The proposed algorithm comprises three stages: identify current traffic status, obtain similar traffic patterns from historical data, and predict travel times. The framework of the three stages is demonstrated in Figure 1. The current traffic status is initially selected to represent the traffic status of all freeway sections from short-past to the current time interval. The traffic status in this case is a matrix across temporal and spatial axes. Thereafter, the historical traffic speed data with the same dimension to current traffic status is selected as a candidate. Based on the dissimilarity to the current speed matrix, several candidates are extracted to represent the historical recurrent traffic patterns that are similar to the current status. Finally, the subsequence dynamic travel times of those candidates are aggregated to represent the travel time distributions in the future.

The proposed algorithm fully utilizes the relationship between traffic state and travel time, and the selected candidate traffic state maps are used to predict future travel times. Consequently, the full coverage of historical traffic state data is required in the proposed approach. However, the problem of missing data is common in the field and thus must be addressed. Many traffic state estimation methods were proposed in order to obtain full coverage traffic state data by solving the mentioned problems [22, 23]. In the following sections, the traffic status is the full coverage traffic data after the process of state estimation. A detailed description of state estimation methods is beyond the scope of this paper and thus is not discussed further in this paper.

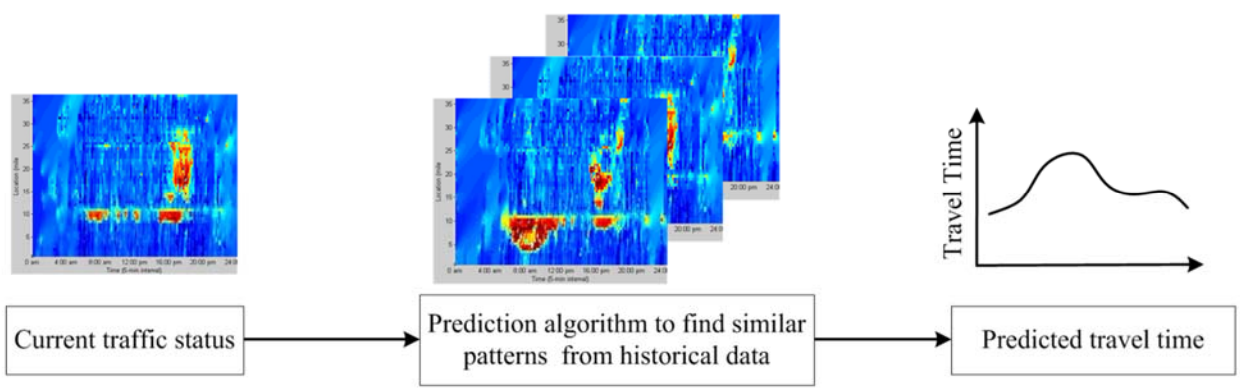


Figure 1: Framework of Proposed Dynamic Travel Time Prediction Algorithm.

Matching Traffic Patterns

A candidate selection scheme is proposed to select temporal-spatial traffic state candidates from a historical dataset by matching with the real-time traffic state. Suppose c denotes the current time; the current traffic state $[c-L+1, c-L+2, \ldots, c]$ and the matching temporal-spatial traffic data $[t-L+1, t-L+2, \ldots, t]$ from a historical dataset are denoted by tail time c and t, respectively. Here, L is the data length across time intervals to be matched. It should be noted that the traffic data of each time interval is a vector that covers all spatial sections (N sections) of the freeway stretch, therefore the traffic data for L time intervals is a matrix with dimension L by N. Various pattern-matching methods can be used to define the dissimilarity between the current traffic status and historical data, such as the Euclidean distance [24-27], data trends [18, 28], image pattern recognition [29, 30], neural networks [15, 31], etc. In this study, the average Euclidean distance between the current temporal-spatial traffic data and each data matrix with the same dimension from the historical dataset is calculated using Equation (1) to represent a dissimilarity measure. Other advanced methods can be adopted to increase the matching speed and accuracy and are being considered as part of future research efforts.

$$d(c,h) = \left| M(c,L) - M(h,L) \right| / (L \times N). \tag{1}$$

where $M(c,L)$ and $M(h,L)$ represent the traffic data of the current and historical time intervals, respectively; $d(c,h)$ is the average Euclidean distance between the traffic speed matrix data of different time intervals.

A small dissimilarity measure indicates the matching historical data is similar to the current traffic pattern. Consequently, several candidates are selected according to the ascending order of the dissimilarity measure. Here, the maximum number of candidates is denoted by K, and the minimum acceptable dissimilarity is defined by d_{MIN}. The set of candidates H_c is selected as

$$\begin{aligned} H_c &= \{h_1, h_2, \cdots, h_{K'},\} \\ \textit{where} \quad & h_1 = \arg\min d(c,h) \\ & d(c,h_i) \le d(c,h_{i+1}) \\ & K' = \max\{i \mid i \le K, d(c,h_i) \le d_{MIN}\} \\ & \left| h_i - h_j \right| \le e, \quad i \ne j \end{aligned} \tag{2}$$

where h_i is the selected candidate from historical dataset; K' denotes the resulting number of the selected candidates; ε is used to avoid selecting adjacent candidates from the same day in the history data. The selected candidates represent the best matching to the current traffic status and will be used to calculate future travel times.

Dynamic Travel Time Prediction

The future dynamic travel times on the current day can be calculated based on the selected historical candidates. Considering the stochastic nature of a traffic system, the travel time prediction problem can be recognized as a time series prediction for nonlinear dynamic (chaotic) systems [32, 33]. The future traffic state for the current day can be predicted by the subsequent traffic state of each candidate from the historical dataset. The linear combination of each candidate's subsequent traffic state is used to predict the future traffic status, and the corresponding weight is defined as the inverse of the dissimilarity measure of each candidate. The prediction traffic state starting from time interval $c+p$ is obtained as

$$M(c+p) = \sum_{i=1}^{K'} w(h_i) \cdot M(h_i + p). \tag{3}$$

$$w(h_i) = \frac{d(c,h_i)^{-1}}{\sum_{i=1}^{K'} d(c,h_i)^{-1}}. \tag{4}$$

where $M(h_i+p)$ represents the p steps ahead subsequent traffic state for i^{th} candidate; and $w(h_i)$ denotes the weight of i^{th} candidate data.

The next step is to calculate the dynamic travel time based on the subsequent traffic state of each candidate. Dynamic travel time is the actual, realized travel time that a vehicle could experience during a trip. If a vehicle leaves a trip origin at the current time, the roadway speed will not only change across space but also across time during the entire trip. Therefore, the traffic state evolution over space and time is considered in our approach as shown in Figure 2 in the computation of dynamic travel times. The speed values of shaded cells are used to compute dynamic travel times. In this paper, the traffic state is assumed to be homogenous within each cell. Therefore the trajectory slope, which represents the traffic speed, is a constant value in each cell. Assume the trip starts from time interval t_n. In this way, once the vehicle enters a new cell, the trajectory within this cell can be drawn as the straight dotted line in Figure 2 with the slope value equal to the traffic stream speed. Finally, the dynamic travel time can be calculated when the trajectory reaches the downstream boundary of the last freeway section (destination).

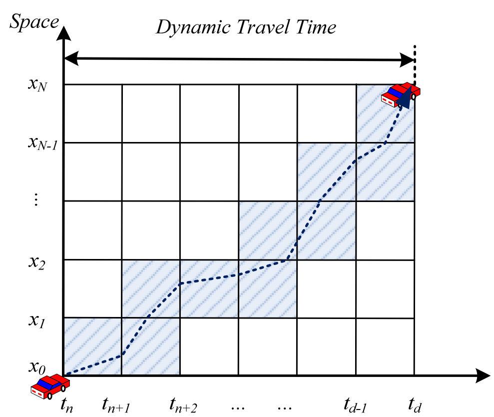


Figure 2: Illustration of Dynamic Travel Time.

The procedure for estimating dynamic travel times is shown in Figure 3. The dynamic travel time of each subsequent candidate can be obtained and the corresponding weight (recurrent probability) is defined by the dissimilarity measure of Equation (4). Finally, the travel time distribution of the future trip can be represented as

$$TT(c+p) = \{TT(h_i+p), w(h_i) \mid i = 1, \ldots, K'\}. \tag{5}$$

where $TT(c+p)$ represents the dynamic travel time starting from time interval $c+p$; and $TT(h_i+p)$ denotes the subsequent travel time of i^{th} candidate according to the calculation of Figure 3. The travel time prediction result can also be calculated as the average value using Equation (6).

$$\overline{TT}(c+p) = \sum_{i=1}^{K'} w(h_i) \cdot TT(h_i+p). \tag{6}$$

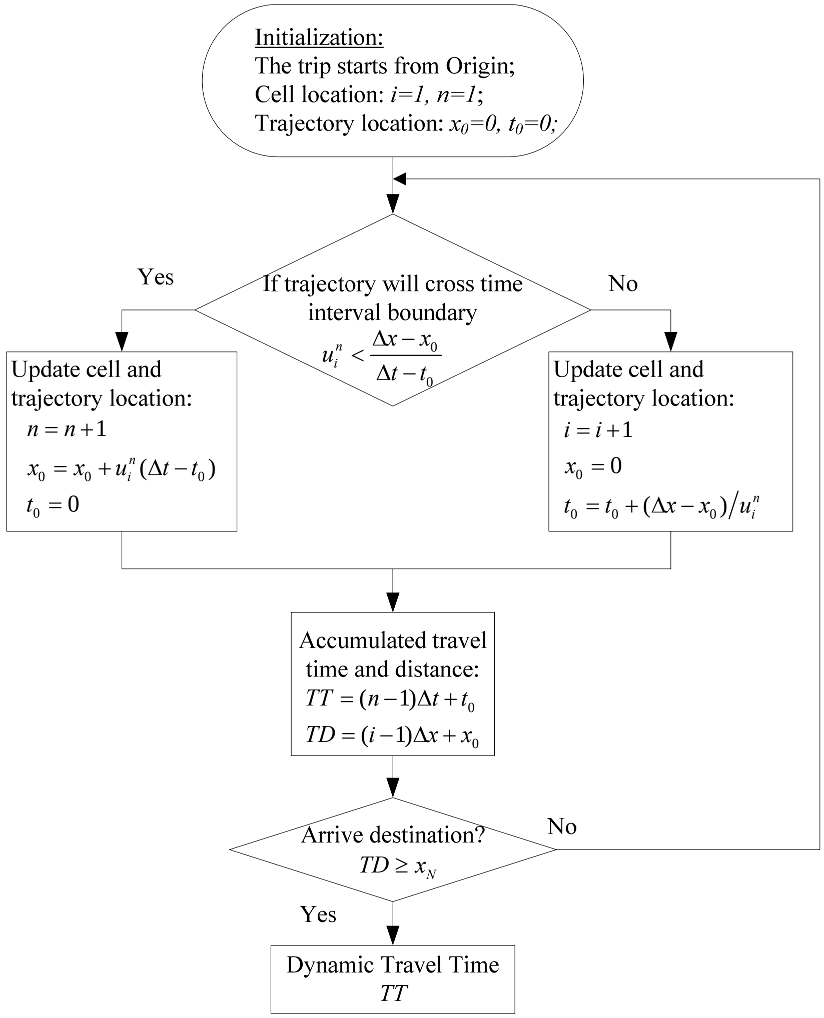


Figure 3: The Flow Chart of Dynamic Travel Time Calculation.

CASE STUDY

The performance of the proposed dynamic travel time prediction approach is tested on a study section. The description of the test data is first introduced and followed by the comparison between the proposed approach and traditional *k*-NN methods for travel time prediction.

Data Description

The case study is conducted based on privately developed INRIX traffic data collected during 2010, which is mainly collected by GPS equipped vehicles. The collected probe data is supplemented by traditional road sensors, as well as mobile devices and other sources [34]. As a result, the traffic data is the average speed of a roadway segment and aggregated at 5-minute intervals. The INRIX data on the main segments along I-64 and I-264 are used to construct the travel database in our study. Since heavy traffic volumes are usually observed along I-64 and I-264 heading to Virginia Beach during summer seasons and weekends, efficient and accurate travel time prediction can be helpful to travelers in planning their trips and reducing traffic congestion around the area. A 37-mile freeway stretch is selected to test the prediction algorithm, which includes most of the congested areas heading towards Virginia Beach from Richmond. The selected freeway stretch is located from Newport News to Virginia Beach along I-64 and I-264 and includes 59 sections as shown in Figure 4. The average length of all the sections is 0.65 miles and the longest section is the 3.7 miles segment located at Hampton Roads Bridge-Tunnel (HRBT).

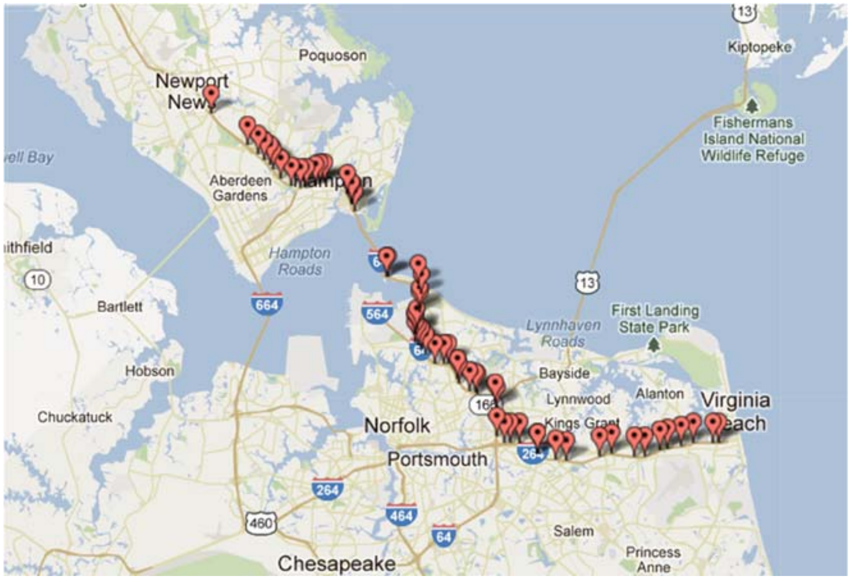


Figure 4: Selected 37-mile Freeway Stretch for Algorithm Testing.

A procedure of data reduction is conducted on the raw data to obtain daily traffic data, which is a speed matrix along time and space. The data samples for typical weekday and weekend traffic occurring in June 2010 are presented in Figure 5. The figure illustrates a significant amount of missing data, especially for June 5 and 6, 2010 (Saturday and Sunday). It appears from inspection of the data that the weekends involve more missing data than weekdays, which may pose a problem especially when making travel time predictions for weekends. According to the speed map of Figure 5 (a), most missing data (white areas) for a typical weekday occur between 21:00 p.m. and 5:00 a.m. (i.e., during the night and early morning hours). Normally there are few traffic volumes during this time period and free-flow speed could be assumed. However, sometimes the missing data also occur around a congested area (e.g., Figure 5 (c) and (e)). Consequently, free-flow speed cannot be simply assumed for all missing data.

As demonstrated earlier, various traffic data estimation algorithms have been developed for different data sources. Since ramp traffic data are not available, large errors will be introduced if macroscopic traffic models are used to estimate missing data. Alternatively, a statistical approach of data imputation is employed here that utilizes neighboring speed data over temporal and spatial conditions to estimate missing data. Here, the average value of eight neighboring cells is used to estimate the missing speed data in our dataset. Advanced approaches such as using kernel regression over temporal and spatial coordinates can be considered in the future. The samples of estimated speed maps for typical weekday and weekend traffic in June 2010 are presented in the right-hand column of Figure 5. Consequently, the full coverage daily temporal-spatial traffic data on the selected freeway stretch is estimated and can be used in the proposed travel time prediction algorithm.

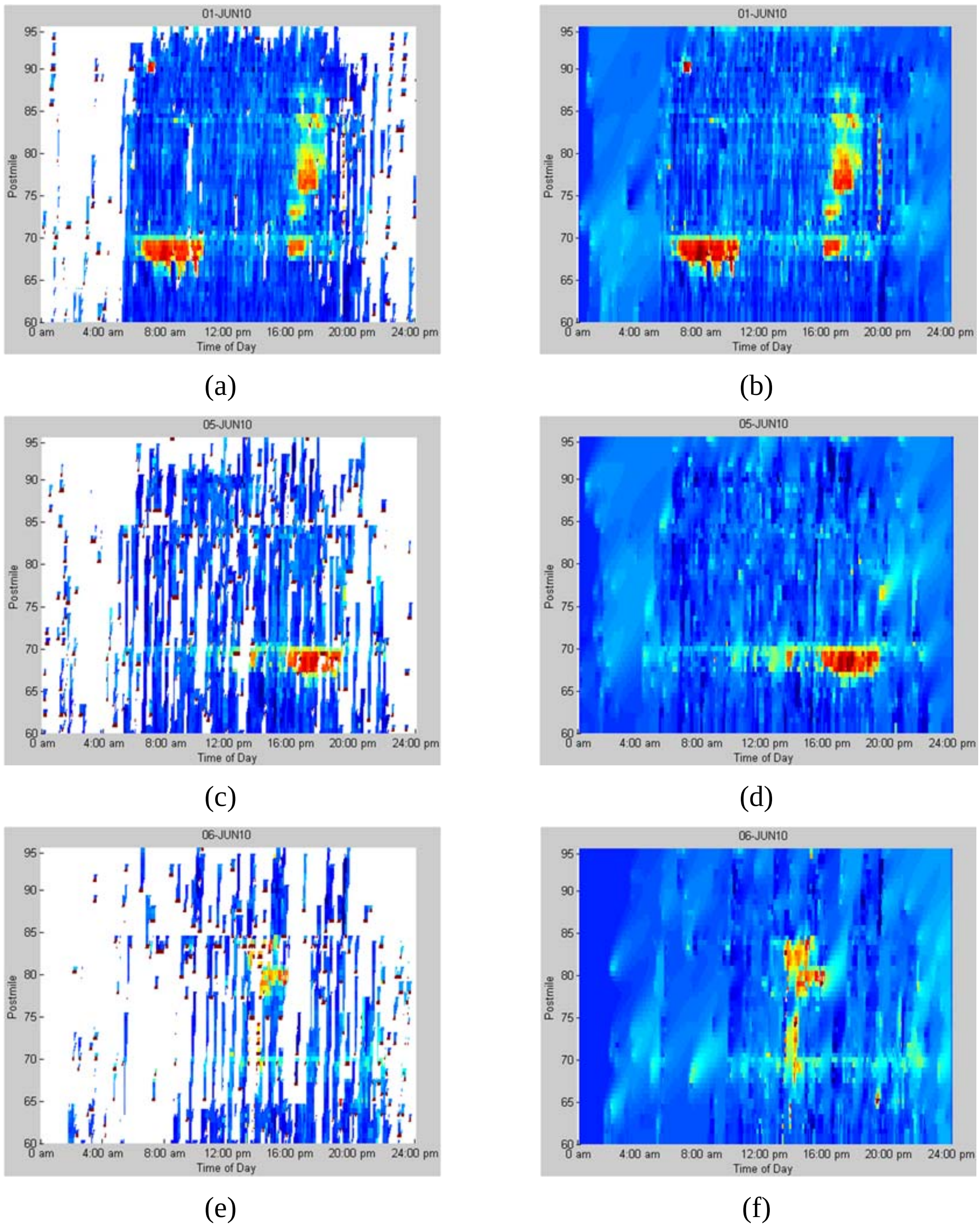


Figure 5: Samples of Daily Temporal-spatial Traffic State Variation.

As heavy congestion for the selected freeway stretch usually happens during the summer holiday season and weekends, the evaluation of the travel-time prediction algorithm focuses on traffic data from June to August of 2010. Here, traffic data from June and July are used as the historical data set; the data from August are used for the testing data set. The dynamic travel time of August 2010, which serves as the ground truth data, is calculated every five minutes using the daily temporal-spatial traffic data as demonstrated on Figure 2. The prediction span p equals zero for this test, which indicates that predictions are made from the current time. Different values of p

will be used for the future research to evaluate the prediction performance considering different look ahead times. Finally, the average travel time is predicted using Equation (6).

Test Results

Different parameters are tested to identify the best combination to minimize the prediction error. The *L* parameter, which represents the data length across the time axis (look ahead time duration), is varied between 10 to 60 minutes at 10-minute intervals. *H* is another parameter representing the shift distance across the time axis when searching for a traffic data slice from the historical data set. The size of *H* should not be too small otherwise, many overlapping candidates may be extracted by matching to the real-time traffic pattern, and the computation time would be significant. Conversely, detailed information may be ignored if the value of *H* is too large. Therefore, the domain of the *H* value is also tested from 10 to 60 minutes at 10-minute increments. The value of ε is chosen as 12 to avoid selecting adjacent candidates from the same day in the history dataset. The maximum number of candidates *K* is 20 and the minimum acceptable dissimilarity d_{MIN} is set at 0.3.

Both relative and absolute prediction errors are calculated to evaluate the proposed algorithm. The relative error is computed as the Mean Absolute Percentage Error (MAPE) using Equation (7). This error is the average absolute percentage change between the predicted and the true values. The corresponding absolute error is presented by the Mean Absolute Deviation (MAD) of Equation (8). This error is the absolute difference between the predicted and the true values.

$$MAPE = \frac{100}{I \times J} \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\left| y_i^j - \hat{y}_i^j \right|}{y_i^j}. \tag{7}$$

$$MAD = \frac{1}{J \times I} \sum_{j=1}^{J} \sum_{i=1}^{I} \left| y_i^j - \hat{y}_i^j \right|. \tag{8}$$

Here *J* is the total number of days in the testing data set (i.e., 30 days); *I* is the total number of time intervals in one day (i.e., 204 intervals occurring every five minutes between 5:00 a.m. and 22:00 p.m.); and y_i^j and $\hat{y}_i^j$ denote the ground truth and the predicted value, respectively, of the dynamic travel time for the i^{th} time interval on the j^{th} day in August 2010.

The relative and absolute errors calculated by the proposed method across various parameters are presented in Table 1. Both the minimum relative error of 5.96 percent and the minimum absolute error of 2.96 minutes are obtained assuming that *L* = 20 minutes and *H* = 40 minutes. According to the tables, prediction errors are comparatively stable values of 6 and 3 minutes when *L* is less than 40 minutes. The change of the *H* value seems to have little impact on the average prediction accuracy. The optimum values of parameters can be used as a reference for applications on different sites.

Table 1: Relative (MAPE) and Absolute (MAE) Errors by Proposed Travel Time Prediction Method

MAPE (%)		Time Interval of H (min.)					
		10	20	30	40	50	60
Time Interval of L (min)	10	6.09	5.98	6.13	5.98	6.00	6.03
	20	6.07	6.01	6.14	5.96	5.99	6.05
	30	6.17	6.05	6.14	5.99	5.97	5.98
	40	6.24	6.12	6.14	6.10	6.06	6.02
	50	6.27	6.15	6.20	6.15	6.21	6.12
	60	6.37	6.32	6.31	6.25	6.33	6.20

MAD (min.)		Time Interval of H (min.)					
		10	20	30	40	50	60
Time Interval of L (min)	10	3.02	2.98	3.05	2.99	2.99	3.00
	20	3.05	3.00	3.06	2.96	3.00	3.02
	30	3.11	3.04	3.08	3.01	3.00	3.00
	40	3.15	3.08	3.08	3.07	3.04	3.03
	50	3.17	3.09	3.11	3.10	3.12	3.09
	60	3.22	3.19	3.18	3.14	3.19	3.14

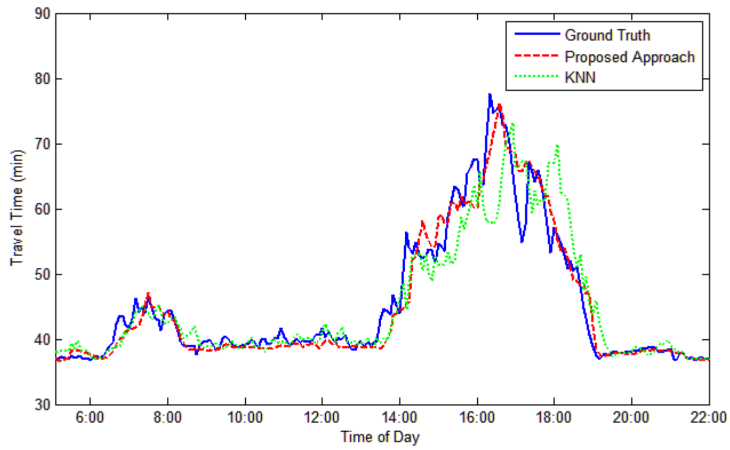
To better evaluate the proposed method used during this study, a traditional *k*-NN algorithm [18, 19] is tested to predict travel time using the same historical and testing data sets. However, instantaneous travel time is used in the *k*-NN method instead of dynamic travel times as is used in the literature. Assuming the purpose is to predict, the travel time starts from time interval *t*, the traditional *k*-NN method uses the travel time sequence between recent past *t-L* and time interval *t-1* to find a similar data sequence in the historical dataset. However, the dynamic travel time for the recent past travel time sequence may not be available since the trip has not been completed (the travel time is around 38 minutes for free-flow conditions for the selected 37-mile freeway stretch). Therefore, instantaneous travel times between time interval *t-L* and *t-1* are used in the K-NN method to predict travel times in the next time interval *t*.

Table 2: Relative (MAPE) and Absolute (MAE) Errors by K-NN Method

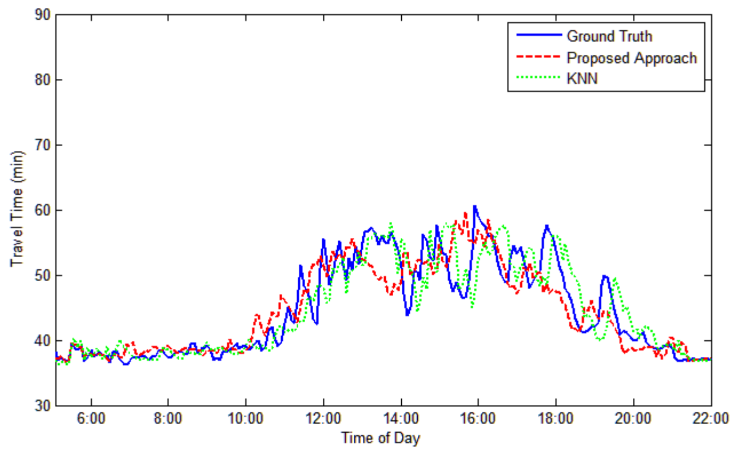
MAPE (%)		Time Interval of H (min.)					
		10	20	30	40	50	60
Time Interval of L (min)	10	6.80	6.68	6.85	6.68	6.70	6.74
	20	6.78	6.71	6.86	6.85	6.69	6.76
	30	6.61	6.59	6.61	6.69	6.66	6.68
	40	6.97	6.84	6.86	6.81	6.77	6.73
	50	7.01	6.87	6.93	6.87	6.94	6.83
	60	7.11	7.06	7.05	6.98	7.07	6.92
MAD (min.)		Time Interval of H (min.)					
		10	20	30	40	50	60
Time Interval of L (min)	10	3.51	3.53	3.55	3.51	3.53	3.52
	20	3.52	3.49	3.51	3.50	3.53	3.56
	30	3.52	3.48	3.47	3.51	3.56	3.54
	40	3.56	3.58	3.54	3.60	3.59	3.64
	50	3.59	3.61	3.58	3.67	3.64	3.68
	60	3.67	3.64	3.64	3.68	3.71	3.73

The same parameter of 20 candidates is used to select the historical travel time sequence using the average Euclidean distance. The weight of each sequence is also calculated using the inverse of dissimilarity measure estimated in Equation (4) and then the weighted average travel time for the future trip is computed. The relative and absolute errors calculated by the traditional *k*-NN method across various parameters are presented in Table 2. The optimum parameter of *L*, which represents the domain of continuous time included in the traffic map slice, is 30 minutes; the corresponding minimum relative and absolute prediction errors are 6.59 and 3.47 minutes, respectively. Therefore, the average performance of the proposed method includes fewer errors compared to the traditional K-NN method. The main difference between the two methods is that the travel time sequence is used to obtain similar traffic patterns from historical data in the *k*-NN method, while the traffic status across the temporal and spatial axes are used in the proposed method. The temporal-spatial traffic status provides more dynamic information given that it accounts for the spatial variation in the information. Consequently, such information serves a better pattern-matching result from the historical data and results in a more accurate travel time prediction performance. Moreover, the instantaneous travel time predicted by the *k*-NN method may deviate substantially from the dynamic travel time under transient states during the trip. Based on the testing results, we observed that the predicted travel time using the *k*-NN method is usually underestimated when congestion is forming and is overestimated when congestion is dissipating.

A comparison of the two methods for a typical weekday (i.e., August 2, 2010) is presented in Figure 6 (a). The typical weekday traffic occurring on the selected 37-mile freeway stretch usually includes two peak hours during the morning and afternoon peak. The heavy traffic jam occurred during the afternoon peak hours. The ground truth curve in Figure 6 indicates that the travel time during this period could be more than two times (78 minutes) the travel time occurring during a free-flow period (38 minutes). The red curve obtained from the proposed method is a better fit to the ground truth data for congested and uncongested time periods. However, the blue curve obtained by the *k*-NN method underestimates the actual travel time during congested afternoon periods and overestimates the actual travel time as the peak ends around 18:00 pm. Consequently, the proposed method produces more accurate travel time prediction results compared to the *k*-NN method for the subject day. Specifically, the proposed approach offers a 15 percent reduction in the prediction error compared to state-of-the-art *k*-NN method.



(a)



(b)

Figure 6: Comparison of Prediction Results for Typical Weekday (August 2, 2010) and Weekend (August 7, 2010)

Another comparison of the two methods for typical weekend traffic occurring on August 7, 2010, is presented in Figure 6 (b). Unlike typical weekday traffic, light traffic congestion occurs during the weekend that lasts for an extended time as many travelers go to Virginia Beach during that time period. Although the prediction accuracy is almost the same during this day when using the two methods, the green curve calculated by traditional *k*-NN approach also indicates that the deviation from ground truth data happens under transient states during which congestion is forming or dissipating. The red curve from the proposed method seems to be a smooth result from the ground truth curve, because the current matching method by average Euclidean distance may not work well to reflect the dynamic change in traffic patterns. It is expected that the prediction results under this situation will be improved by using more advanced data matching algorithms as part of future research efforts.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

This study develops a travel time prediction algorithm by matching traffic patterns from historical data to current real-time conditions. The real-time and historical temporal-spatial traffic data is used as the input of proposed approach to predict future traffic patterns based on past experience. The average Euclidean distance is used as the criterion to calculate a dissimilarity measure in the matching process to select candidate similar traffic patterns. The selected similar traffic patterns are then used to predict dynamic travel times for departures from the current time or from future time intervals. A freeway stretch from Newport News to Virginia Beach is selected as the test site to evaluate the prediction accuracy of the proposed algorithm. The section-based INRIX data along the selected freeway is used to obtain daily temporal-spatial traffic data. The proposed method is demonstrated to enhance predictions relative to state-of-the-art *k*-NN methods by reducing the prediction error by 15 percent to within 3 minutes on a 50-minute trip.

The proposed algorithm employed during this study provides a framework to use traffic data across temporal and spatial axes to predict dynamic travel times. It is proposed that other popular pattern recognition techniques and data-mining areas be incorporated within the proposed algorithm to more efficiently and accurately obtain similar traffic patterns from historical data. On the other hand, since the historical dataset only included two months of previous traffic state data, more extensive testing will be performed to further test the proposed method. Moreover, the performance to predict travel time reliability based on the proposed algorithm, as well as weather and incident impacts on traffic prediction should be examined in future studies.

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