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Travel time estimation using speed predictions

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Abstract— **Adanced traveler information systems (ATIS) use sensing, communication and data processing technologies to collect and disseminate real time road traffic information. Route guidance systems utilize this data to estimate and optimize travel times. Paths with the shortest travel times are then computed to suggest to the users, an optimal path to reach their destination. In this study, we examine the accuracy of popular travel time calculation techniques, that use historical, instantaneous and predictive data to compute travel time. A dynamic time calculation technique that accounts for time varying road speeds is used and the driver is considered to experience changes in the traffic pattern as the journey progresses. We base our study on real world traffic data collected from Singapore. We calculate the travel times for trips on major routes based on these techniques and compare them with the true average travel time on the particular route. We also analyze the variablity in travel time that can be experienced by the user when guided by different route guidance system. The results show that dynamic predictive routing using multiple prediction horizons provides a better estimate of actual travel times as opposed to routing algorithms that only utilize real-time data about current traffic conditions.**

I. INTRODUCTION

Metropolitans today are expanding at an ever growing rate and one of the major challenges faced by expanding cities is the efficient utilization of transportation resources. With the increase in urban population and greater preference towards automobiles, traffic congestion is a serious problem these days and is a major cause of productivity loss and a constraint to economic growth. In most large cities, it is very difficult to augment the existing road infrastructure by adding new roads due to space constraints. Advanced traveler information systems (ATIS) are one of the critical elements of Intelligent Transport Systems (ITS) that aim to efficiently utilize the existing road infrastructure by monitoring and controlling vehicular flow in a road network, thereby reducing the impact of traffic congestion. In ATIS, advanced sensing technologies are used to gather real time traffic data which is sent to a central server where it is then processed to obtain meaningful travel information. This can be passed on to the user in the form of route guidance, network visualization or travel time estimation [1], [2]. For commercial vehicles, ATIS can directly contribute to increased profits by efficient fleet management and increased reliability of timely deliveries. In most instances of ATIS, information is provided to the traveler using smartphone applications, GPS devices or as a website. It has been shown that ATIS through conventional routing algorithms can offer reduction in travel time (up to 14%) and fuel consumption (up to 7.8%) [3], [4].

Route guidance is one of the most popular methods of dissemination of traffic information in ATIS, and has been used by many experimental as well as commercial applications. Guidance aims to provide improved information to the users, which they can use to make better route choices. Route guidance can be offered in the form of prescriptions, such as suggesting optimal routes, or in the form of descriptive information. These may include estimates of travel time on the user's selected route or updates of the traffic conditions in the road ahead [1]. Many ATIS applications aim to optimize the travel time in one way or the other to make route prescriptions. These applications mostly estimate the travel time along a particular route, given the user's start time by either considering historical travel time estimates or the current traffic conditions. They then compare the travel time for various possible routes between source and destination in order to select the optimal route [5]. This estimate of travel time provided by ATIS is difficult to validate since it may be different for different vehicles travelling on the same route. Various methods of travel time calculation have been used by researchers, but most of the previous work about analyzing these methods has been limited to field tests or modelling techniques. Field tests do not present a comprehensive evaluation since they are limited by the specific experiment setup, ATIS limitations and driver mentality. Modelling is also not accurate as it involves several assumptions regarding the driver's route choices and the reliability of the ATIS systems [6].

The commonly used travel time calculation techniques include: (1) calculation on the basis of historical data of average speeds or travel times; (2) calculation using the real time road speed information; and (3) calculation based on predicted traffic speeds; [5], [7], [8]. In this paper, we analyze the different methods of travel time estimation, by studying the real ATIS data from the highway network of Singapore. The Singapore highway network contains 2156 links, divided

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into 8 highways. Land Traffic Authority of Singapore (LTA) provided as speed data for the highway traffic network and period of three months, August - October 2011. We use this dataset to calculate the travel time for different routes and trips beginning at different times in a week. We calculate the travel time using various techniques and then compare these travel times with an estimate of the correct indicative travel time for the given route and start time. The performance of the different techniques is compared for different route lengths with different traffic patterns to reduce the effect of any selection bias. This analysis validates the use of prediction algorithms for estimating traffic and gives a more practical estimate of the accuracy and limitations of the traffic predictions. We also perform a temporal analysis of travel time errors for different starting times of the day using the above techniques and study the variations in performances of the different methods.

The rest of the paper is organized as follows: In Section II, we present an account of the previous research related to travel time calculation. Section III explains the methodology used to calculate the different travel times, and to estimate the travel time experienced by the driver. The prediction technique used to predict the future traffic states is also described here. Section IV presents the results of the comparison of travel time calculated by the different techniques and an analysis of the possible reasons for the same. We discuss the results, their implications and the future course of work in Section V.

II. RELATED WORK

This paper deals with various techniques of travel time calculation and compares them. These travel time calculation techniques are generally used in route guidance systems of ATIS. Validation for these techniques are usually being carried out using field tests, where the chosen model for travel time calculation has been compared with actual travel times experienced by driving on the particular route. However, tests for only limited starting times have been conducted and there has been no discussion regarding the style of driving, traffic conditions, or the variance in travel time between vehicles travelling on the same route [9], [10]. In many studies, a network model has been created to simulate a road network and some of the travel time calculation techniques have been adopted to these models, to analyze the accuracy [5], [11], [12]. Ben-Akiva et. al [1], have compared the performance of real time and predictive route guidance schemes and concluded that predictive routing schemes achieve greater accuracy and provide more travel time savings. In Toledo et. al. [6], traffic information for a real network is obtained, and different methods of travel time calculation are compared for the ideal case. That is, the errors in predictions are assumed to be zero and the real time information is assumed to be available to the users with no delay. Also, only selected routes are studied, which are selected as being the optimal route suggested by the guidance systems based on the different travel time calculation methods. In the aforementioned work, the general consensus is that using predictive time calculation techniques are more accurate but there has been no discussion about multiple horizon prediction or errors in the prediction algorithms.

III. METHODOLOGY

In this section, we discuss historical, instantaneous and predictive approaches for the travel time estimation along the particular route for given past speed information and trip starting time. For this purpose, we consider the traffic data in the form of a matrix $\mathbf{A} \in \quad ^{m\times n}$ where $a_{i,j}$ contains the average speed of all vehicles that traverse the road $\{s_j\}_{j=1}^{n}$ during the sampling interval $(t_i - \Delta t, t_i)$. The rows of the matrix represents the various time instants at which the speeds are recorded/predicted.

For travel time calculation, we use a dynamic algorithm considering time dependent traffic speeds. The algorithm assumes that: (i) the initial start time is zero; (ii) all vehicle which enter a segment s_j during the interval of time $(t_i - \Delta t, t_i)$ have speed $a_{i,j}$; where Δt is the sampling period (e.g., 5 or 15 minutes) [13]. The latter assumption allows us to make a travel time matrix $\mathbf{B} \in \quad ^{m\times n}$ where $b_{i,j} = d_j/a_{i,j}$ and d_j is the length of the s_j.

A. Historical method

This method estimates the total travel time (T_l^i) along the ℓ-segment route, starting at time instant i by adding up the time required to travel each link. We write that as follows:

$$T_l^i = \sum_{j=1}^{\ell} b_{i+k_j,j}, \tag{1}$$

where k_j is the number of time instants (after the start time), when the driver is expected to enter j^{th} link of the tested route. Hence, $b_{i+k_j,j}$ refers to the time it takes to travel the j^{th} link when starting the journey at time instant i. We compute k_j in a recursive fashion by dividing the total travelled time before reaching the j^{th} link, by the sampling time (Δt). We write that as follows:

$$k_j = \lfloor \frac{1}{\Delta t} T_{j-1}^i \rfloor + 1, \quad k_j \in \{1, 2 \ldots n\}. \tag{2}$$

The historical travel time for link j, starting at time i is computed as the mean value of the N past travel times for the same link j that started at the same time of the day i. We write that as follows:

$$b_{i,j} = \frac{1}{N} \sum_{n=1}^{N} b_{i-nT_0,j} \tag{3}$$

where T_0 is a constant that shows repetitiveness in traffic behavior (e.g., one day or one week).

This approach relies on fact that traffic tends to follow distinctive patterns which are repetitive on regular (e.g., weekly) basis. This method is easy to implement and provides estimates for larger horizons (up to one week). However, this method does not provide for localised variations in traffic patterns caused due to accidents, bad weather etc. Thus the accuracy of such estimates is often lower than approaches that we will describe in the following.

B. Instantaneous method

This approach assesses travel time (T_l^i) along the ℓ-th segment route at time i as follows:

$$T_l^i = \sum_{j=1}^{\ell} b_{i-1,j}, \qquad (4)$$

where $b_{i-1,j}$ is the most recent traffic data available for link j at time i.

Underlying assumption of the instantaneous method says that traffic conditions will not (significantly) change during the duration of the trip (see (4)). Such an assumption might be reasonable for the short trips and stable traffic conditions during the entire time of the trip. However, for longer trips and those trips that start and/or end during the peak hours such an approach might not be suitable.

C. Predictive method

Historical and instantaneous methods use past and current traffic data, respectively to estimate route travel time. Unlike these two approaches, predictive method takes in consideration assessed future conditions along the route as follows:

$$T_l^i = \sum_{j=1}^{\ell} \hat{b}_{i+k_j,j}, \qquad (5)$$

where $\hat{b}_{i+k_j,j}$ is the predicted travel time for the link j and k^{th} prediction horizon, inferred from the predicted traffic speed for the identical link and prediction horizon. The prediction horizon (k_j) is computed using the same recursive method described in (2).

This method accounts for time varying travel times as well as localized variation due to weather or accidents. It efficiently uses current and past values of traffic parameter at a particular location in order to predict future value.

Traffic prediction involves computing the nonlinear relationship between the past traffic states and the future traffic states. To predict average speed on each link, we apply Support Vector Regression (SVR), which is a commonly used prediction method in the field of transportation studies [14]–[19]. It efficiently uses current and past values of a traffic parameter at a particular location in order to predict future value. SVR has been shown to perform well in large scale networks and for multiple prediction horizons [14]–[19]. Hence we use the SVR method for computing real time traffic predictions.

IV. EXPERIMENTAL SETUP

This section describes the setup we have used to calculate the travel times using the historical, instantaneous and predictive methods and the true travel time estimate. We considered the Singapore highways road networks for our analysis. It contains 2156 links divided into 8 highways (see Fig. 1). The average length of the highway segment is 138 meters. The variable of interest is the average link speed, i.e., the mean speed of all vehicles which traverse a highway link during the given time. The sampling interval Δt is 5 minutes. We use data provided by Land Transportation

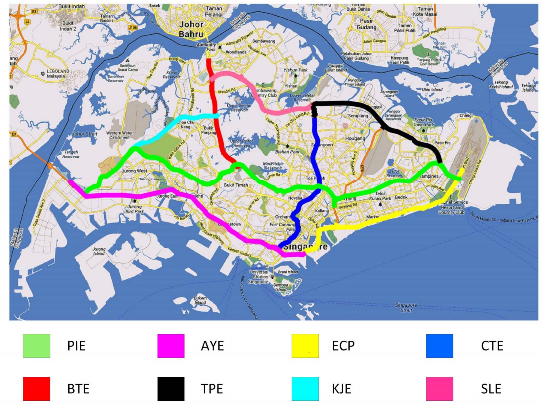


Fig. 1: Singapore Highway Network; with 8 routes highlighted

Authority for the months of August, September and October 2011. This data set is used to predict the average link speeds using the SVR algorithm. The data is split into training and testing data. The speed data of the months August and September is used to train the predictors. The speed data of the months October is used as the testing subset. We select the 8 major highways (end to end) as the routes for the travel time calculation. Each direction of the highway is considered as a separate route. The start times for the journeys are assumed to be at the start of every 5 minute interval, leading to the 288 start times for one day. This encompasses morning and evening peak and night lean hours, leading to an unbiased estimate. It is also assumed that real time information from only the previous 5 minute interval is available to the user because of the system delay. This can also be thought of as a pre-trip travel time calculation where a user uses the route guidance system before the trip actually starts.

A. Historical method

For the historical travel time calculation, we calculate the average of the past link speeds for the same time and day over the previous 4 weeks (see Eq. 3 for $N = 4$). The dynamic time calculation algorithm (described in Section III) is then used to calculate the travel time.

B. Instantaneous method

For the instantaneous time calculation, the real time speeds are used. Since there is always a certain delay associated with collection and availability of speeds of the entire network, it is assumed that the vehicle has real time access to only the speed reported for the previous time instant ($i-1$). The instantaneous travel times for each link can be described as $b_{i,j}^{inst}$=$b_{i-1,j}$ as the speed is assumed to be constant throughout the length of the journey. The travel time for each trip (consisting of j links) is calculated using the Eq. 5.

C. Predictive method

For the predictive time calculation, the SVR algorithm is used to predict future traffic states for multiple prediction

TABLE I: PRD error for different travel time techniques and various route lengths.

Name of Road	Number of Links (Length)	Direction	Historical	Instantaneous	Predictive
PIE	301 (42.8 km)	East - West	8.44	7.71	4.78
		West - East	8.15	8.78	6.42
AYE	171 (26.5 km)	East- West	6.80	4.52	3.11
		West - East	5.19	3.13	2.34
CTE	133 (15.8 km)	North - South	6.76	4.91	2.91
		South - North	6.80	3.99	2.55
SLE	84 (10.8 km)	East - West	6.74	3.53	1.46
		West - East	5.74	4.01	2.22
ECP	138 (20 km)	East - West	6.70	5.71	3.24
		West - East	6.21	4.13	2.62
KJE	56 (8.4 km)	East - West	5.58	3.57	0.93
		West - East	6.65	3.71	1.34
BKE	76 (10 km)	North - South	6.42	3.52	0.71
		South - North	5.85	3.71	1.44
TPE	88 (14 km)	East - West	5.59	4.02	2.22
		West - East	5.97	3.63	1.53

horizons starting at 5 mins, 10 mins, and so on. For the first 5 minute horizon, the instantaneous travel time vector $b_{i_1,j}$ as described above, is used. The calculation assumes that 5 minutes into the journey, the driver experiences the speeds denoted by the first prediction horizon (t+5 mins.) and 10 minutes into the journey, the driver experiences the speed denoted by the second prediction horizon (t+10 mins.). Thus, $\hat{b}_{i+1,j}$ is the prediction for 5 minute horizon, $\hat{b}_{i+2,j}$ is the prediction for the 10 minute horizon and so on. Based on the dynamic travel time calculation algorithm described in Section II, the total travel time is estimated as cumulative sum of the travel time for each segment along the route.

D. True travel time

We compute the true travel time along the route by applying the average link travel times in Eq. 5. We write that as follows:

$$T_l^i = \sum_{j=1}^{\ell} b_{i+k_j,j}, \tag{6}$$

where $b_{i+k_j,j}$ is the average travel time of all vehicles that traverse the link j at time instant $i+k_j$. This method assures that the true travel time is an average value for all the travellers on the particular route and does not depend on any experimental bias.

E. Error calculation

We use percent root mean distortion (PRD) to evaluate the performance of the three travel time calculation techniques. The PRD quantifies the error as:

$$\mathbf{PRD}(\%) = (\frac{||\mathbf{T} - \hat{\mathbf{T}}||}{||\mathbf{T}||}) \tag{7}$$

where T and $\hat{T}$ are true and assessed values, respectively. The travel times are calculated for journeys starting at 5 minute intervals for one week (2016 journeys), thereby

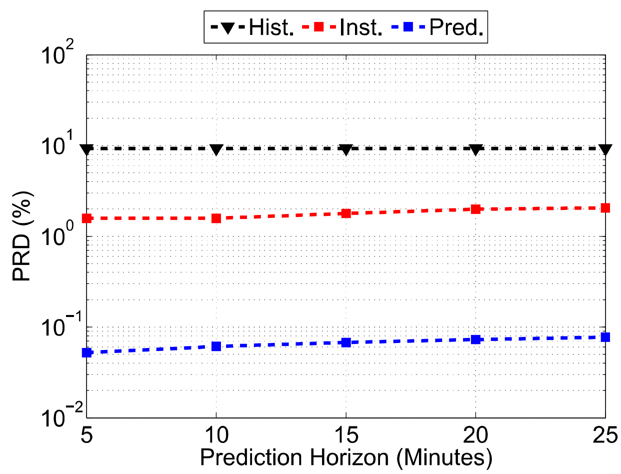


Fig. 2: Accuracy of travel time techniques across the entire network.

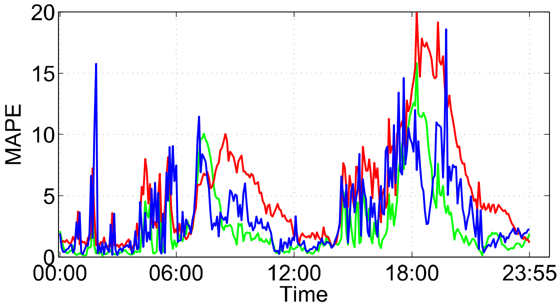
ensuring that patterns for all days are captured. PRD gives a measure of the variability of the travel time estimates from the true value for a period of one week. For analysing temporal variations of travel time estimates, we use mean absolute percentage error (MAPE). The MAPE quantifies the error as follows:

$$\mathbf{MAPE}(\%) = \frac{\mathbf{1}}{\mathbf{n}} \sum_{\mathbf{i=1}}^{\mathbf{n}} (\frac{|\mathbf{a_i} - \hat{\mathbf{a}}_\mathbf{i}|}{|\mathbf{a_i}|}) \tag{8}$$

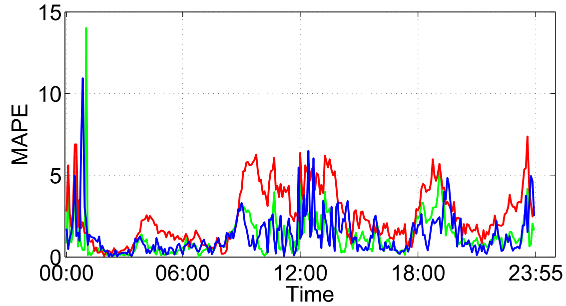
where a_i and $\hat{a}_i$ are the true and assessed values, respectively for a particular time instance i.

V. RESULTS

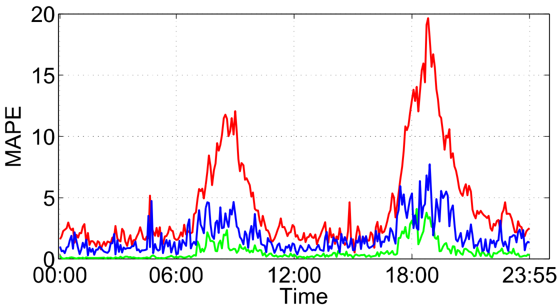
This section describes the results of the analysis of the various travel time calculation techniques. Table I illustrates the PRD for the historical, instantaneous and predictive travel time calculation techniques for the different routes. The



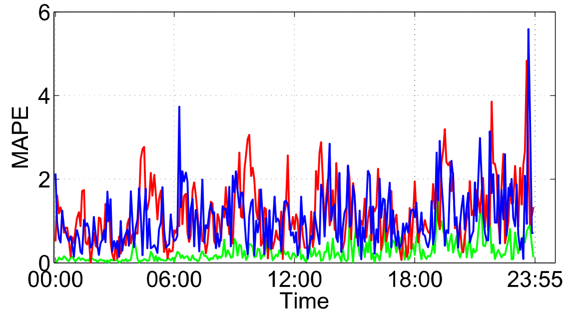
(a) PIE (Weekdays)



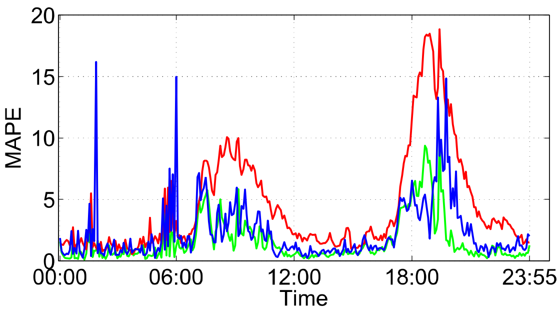
(b) PIE (Weekends)



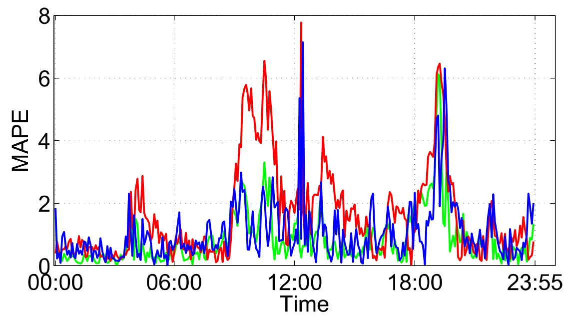
(c) KJE (Weekdays)



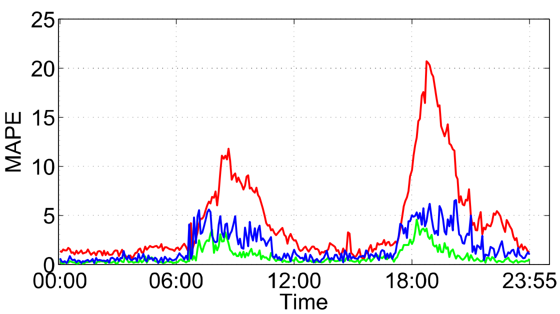
(d) KJE (Weekends)



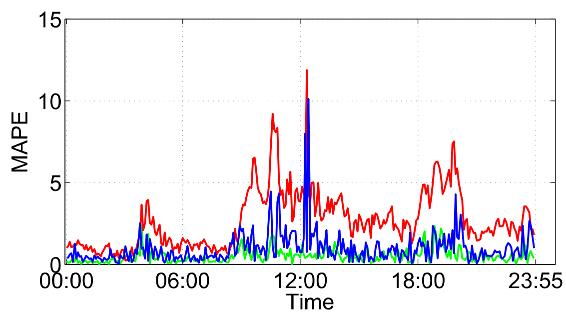
(e) ECP (Weekdays)



(f) ECP (Weekends)



(g) SLE (Weekdays)



(h) SLE (Weekends)

Fig. 3: Temporal distribution of MAPE along selected routes for Historical (Red), Instantaneous (Blue) and Predictive (Green) techniques.

PRD error is consistently lowest for the predictive travel time technique, indicating that it is the more accurate than the instantaneous and historical travel time estimates. Also, it can be observed that PRD errors are higher for longer trip lengths as the route with the maximum length (42.8 km (301 links), Pan Island Expressway) is found to have the maximum error for all three calculation techniques. It is interesting to note that for shorter trips, the predictive and instantaneous techniques result in smaller errors but the historical technique still results in a comparatively large error. Further, the performance of the instantaneous technique is consistently better than the performance of the historical technique but worse than the predictive technique. Fig. 2 shows the prediction accuracy, when the entire network is considered. As it can be seen from Fig. 2 , the instantaneous and predictive estimates are much lower than the historical estimates.

Fig. 3 illustrates the temporal variation of average error for weekdays and weekends. There is no appreciable variation in travel time patterns for different directions for the same route, and hence only one direction is shown. We illustrated results only for four routes since the travel time patterns are similar for the remaining routes. As expected, weekdays show higher errors due to higher traffic and the effect of morning and evening peak hour is clearly seen. In almost all the chosen roads, the predictive technique is found to have a lower average error than the instantaneous technique or the historical technique, which is found to have the worst performance of the three. Particularly, it is also notable that the performance of the predictive technique is superior when compared to the other methods even during the morning and evening peak hours, when the traffic patterns are volatile and traffic prediction is less accurate. It is interesting to note that the MAPE for the instantaneous and predictive techniques has a lot of peaks during the peak hours but the MAPE for the historical technique has a smoother pattern, albeit with a worse performance.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we identify the advantage of using the predictive travel time calculation technique over the instantaneous and historical techniques in ATIS applications using real world data. We show that incorporating multi horizon predictions in travel time calculations results in better travel time estimates even during the volatile peak hour conditions. In our future work, we aim to improve the travel time estimates by including field trips and considering driving patterns. We will also perform route guidance on smartphones based on the predictive travel time technique and improve the quality of predictions by considering weather and accident information.

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