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Multi-step prediction of experienced travel times using agent-based modeling ☆

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ABSTRACT

This paper develops an agent-based modeling approach to predict multi-step ahead experienced travel times using real-time and historical spatiotemporal traffic data. At the microscopic level, each agent represents an expert in a decision-making system. Each expert predicts the travel time for each time interval according to experiences from a historical dataset. A set of agent interactions is developed to preserve agents that correspond to traffic patterns similar to the real-time measurements and replace invalid agents or agents associated with negligible weights with new agents. Consequently, the aggregation of each agent's recommendation (predicted travel time with associated weight) provides a macroscopic level of output, namely the predicted travel time distribution. Probe vehicle data from a 95-mile freeway stretch along I-64 and I-264 are used to test different predictors. The results show that the agent-based modeling approach produces the least prediction error compared to other state-of-the-practice and state-of-the-art methods (instantaneous travel time, historical average and k-nearest neighbor), and maintains less than a 9% prediction error for trip departures up to 60 min into the future for a two-hour trip. Moreover, the confidence boundaries of the predicted travel times demonstrate that the proposed approach also provides high accuracy in predicting travel time confidence intervals. Finally, the proposed approach does not require offline training thus making it easily transferable to other locations and the fast algorithm computation allows the proposed approach to be implemented in real-time applications in Traffic Management Centers.

1. Introduction

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

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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 (e.g. license plate recognition systems, automatic vehicle identification systems, mobile, Bluetooth, probe vehicle, etc.) and station based traffic state measuring devices (e.g. 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 speed or travel time, which can be used to construct traffic speed matrix over spatial and temporal and thus is used in this paper. The benefit of using temporal-spatial speed data is that travel time can be easily estimated afterward (van Lint and van der Zijpp, 2003). More importantly, such data provides the flexibility for scalable applications on traffic networks. By providing section-based traffic state data, generally there are two approaches to compute travel time depending on the trip experience, which are instantaneous and experienced travel time (Mazaré et al., 2012; Tu, 2008).

Previous research has demonstrated that prediction accuracy typically deteriorates quickly with the increase in prediction horizon (Chen et al., 2012). In order to demonstrate the discrepancy between instantaneous and experienced travel times, especially the errors of using instantaneous information for multi-step prediction of experienced travel time, a spatiotemporal traffic speed data provided by INRIX is presented in Fig. 1. The traffic data was collected along I-64 from Richmond to Norfolk during afternoon peak hours on June 22, 2013. The trip trajectories are plotted on the contour speed map. According to the black trajectory, the instantaneous travel time is calculated as 40 min for time interval at 4 p.m. Although the traffic on the selected route is uncongested at 4 p.m., two bottlenecks rapidly form afterward. Consequently, the instantaneous travel time at 4 p.m. underestimates the experienced travel time by 28 min, 50 min and 60 min for the prediction horizon of 0 min, 30 min and 60 min, respectively. These results demonstrate that the instantaneous travel time may not be a good predictor of experienced travel time, especially for multi-step prediction.

During the past decades, many studies have been conducted attempting to predict travel times. According to the manner of modeling, these methods can be classified into parametric methods (e.g. linear regression models (Rice and Van Zwet, 2004; Zhang and Rice, 2003), Kalman filter methods (Chen and Chien, 2001; Chien and Kuchipudi, 2003; Nanthawichit et al., 2003), Auto-Regressive Integrated Moving Average (ARIMA) models (Billings and Yang, 2006; Guin, 2006; Xia et al., 2011)) and non-parametric methods (e.g. *k*-Nearest Neighbor (*k*-NN) (Bustillos and Chiu, 2011; Myung et al., 2011; Qiao et al., 2012), artificial neural network (ANN) models (Lint et al., 2005; Park and Rilett, 1998; van Lint, 2006) and support vector regression (SVR) methods (Vanajakshi and Rilett, 2007; Wu et al., 2004)). These techniques are implemented through direct or indirect procedures to predict travel times using different types of state variables (Chen and Rakha, 2013). Travel time is directly used as the state variable in parametric or non-parametric methods to predict travel times. Indirect procedures are performed using other variables (such as traffic speed, density, flow, and occupancy) as the state variable to predict

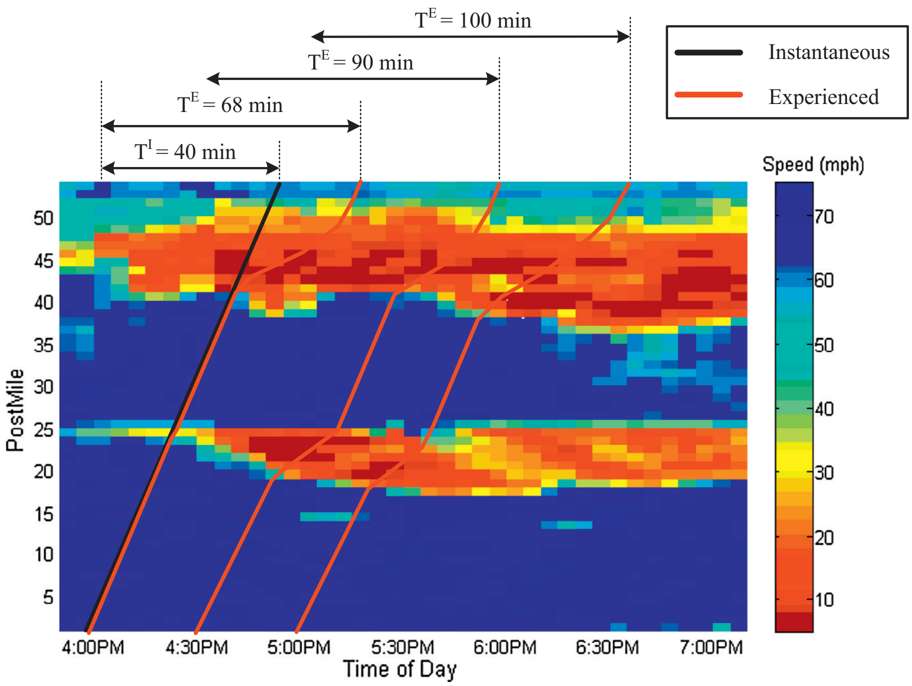

Fig. 1. Spatiotemporal traffic speed map and trip trajectories on I-66 (June 22, 2013).