Transportation Research Part C 42 (2014) 82–98

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Dynamic travel time prediction using data clustering and genetic programming

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ARTICLE INFO

Article history:
Received 28 March 2013
Received in revised form 9 February 2014
Accepted 13 February 2014

Keywords:
Travel time prediction
Clustering
Genetic programming
Sampling with replacement
Probe data

ABSTRACT

The current state-of-practice for predicting travel times assumes that the speeds along the various roadway segments remain constant over the duration of the trip. This approach produces large prediction errors, especially when the segment speeds vary temporally. In this paper, we develop a data clustering and genetic programming approach for modeling and predicting the expected, lower, and upper bounds of dynamic travel times along freeways. The models obtained from the genetic programming approach are algebraic expressions that provide insights into the spatiotemporal interactions. The use of an algebraic equation also means that the approach is computationally efficient and suitable for real-time applications. Our algorithm is tested on a 37-mile freeway section encompassing several bottlenecks. The prediction error is demonstrated to be significantly lower than that produced by the instantaneous algorithm and the historical average averaged over seven weekdays (p-value <0.0001). Specifically, the proposed algorithm achieves more than a 25% and 76% reduction in the prediction error over the instantaneous and historical average, respectively on congested days. When bagging is used in addition to the genetic programming, the results show that the mean width of the travel time interval is less than 5 min for the 60–80 min trip.

1. Introduction

Congestion has proven to be a serious problem in most urban areas in the United States. In 2011, it caused urban Americans to spend 5.5 billion hours more in traveling and cost them an extra 2.9 billion gallons of fuel, for a congestion cost of $121 billion. Congestion has also environmental side effects because of the CO_2 produced during congested periods, which was estimated to be as much as 56 billion pounds in 2011 (Schrank et al., 2012). Adding capacity has been the traditional solution to the congestion problem, but this has become impractical given the financial, environmental, and social constraints. Consequently, highway agencies are seeking new solutions to overcome recurrent and non-recurrent congestion.

Thanks to advanced new technologies that enable continuous monitoring and dissemination of traffic information, it is possible to manage the transportation system more efficiently. The minimum that can be accomplished is to inform the potential users of a road what they can expect during their trip. Such information helps travelers compare alternative routes

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http://dx.doi.org/10.1016/j.trc.2014.02.016
0968-090X/

and make better routing and departure time decisions. This is the essence of Advanced Traveler Information Systems (ATISs), such as the 511 systems 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. Because the infrastructure is already available, we can assist travelers in making better decisions by providing accurate travel time predictions. In case of congestion, many road users may change their routes of travel based on displayed travel time information.

Recently, various traffic-sensing technologies, such as point-to-point travel time measurement systems (e.g., license plate recognition systems, automatic vehicle identification systems, mobile devices, Bluetooth tracking systems, and probe vehicles, etc.) and station-based traffic-state-measuring devices (e.g., loop detectors, video cameras, remote traffic microwave sensors, etc.), have been used to collect traffic data. The data collected using these technologies are used in several applications, including computing travel times. Private companies such as INRIX integrate different sources of measured data to provide section-based traffic state data (speed, average travel time), which are used in our study to develop algorithms for predicting travel times. The benefit of using section-based traffic state data is that travel times can be easily calculated. More importantly, the section-based data provide the flexibility for scalable applications on traffic networks.

Travel time prediction algorithms that use section-based traffic state data can be categorized into two broad categories depending on the trip experience: dynamic and instantaneous travel time (Mazare et al., 2012; Tu, 2008). Dynamic travel time reflects the actual, realized travel time that a vehicle experiences during a trip. Dynamic travel time algorithms account for speed changes over both space and time. Consequently, some algorithms predict future speed patterns and use them to predict travel times. Instantaneous travel time usually computes travel time using the current speed along the entire roadway; in other words, the speed distribution is assumed to remain constant for the duration of the trip. As long as the change of speed with time is not significant, both approaches provide comparable travel time estimates. However, instantaneous approaches may deviate substantially from the actual, experienced travel time under transient states during which congestion is forming or dissipating during a trip (Chen et al., 2012).

Some attempts have been conducted using macroscopic traffic modeling to predict short-term traffic states; however, this approach is computationally expensive and the accuracy degrades rapidly with the increase in the prediction temporal horizon (Chen et al., 2011, 2012). For long trips, traffic states may change significantly, and the traffic state in the near future usually cannot provide enough information to cover the entire trip. For example, in the case of a 100-mile trip, if the driver departs at the time t_d, and the trip would take 1 h or more depending on traffic conditions, then the traffic state for the following 1 h or more would need to be predicted in order to compute dynamic travel times.

An alternative approach to solving this problem is to assume that these states are hidden variables and are function of the current and previous traffic states. This function can be derived from historical data. The historical dataset provides a pool of past experienced traffic conditions and shows how traffic status changes over time and space. The key issue is how to develop this function (model) and its parameters and then use it to predict travel times. The purpose of this study is to develop a simple and fast algorithm to predict dynamic travel times. The proposed method searches the model space guided by the historical data set to construct a model that best describes the relationship between traffic states along time. A freeway stretch from Newport News to Virginia Beach is selected to test the proposed algorithm using 5-min aggregated traffic data for 2010 provided by INRIX. The travel time prediction results from April to August demonstrate that the proposed method produces higher prediction accuracies compared to the state-of-practice instantaneous algorithm.

The remainder of this paper is organized as follows. A literature review of previous travel time prediction methods is provided. Subsequently, the proposed genetic programming-based approach is presented. This is followed by a description of the test data used for the case study and the results of a comparison of the proposed approach to traditional instantaneous algorithms. The last section provides the conclusions of the research and some recommendations for future research.

2. Literature review

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 (Du et al., 2012; Lint et al., 2005; Myung et al., 2011; Vlahogianni et al., 2004). According to the manner of modeling, these methods can be classified into time series models or data-driven methods. Time series models include the Kalman filter (Yang, 2005; Fei et al., 2011) and Auto-Regressive Integrated Moving Average (ARIMA) models (Chen and Chien, 2001; Xia et al., 2011; Yang, 2005). Data-driven methods include neural networks (Fei et al., 2011; Hinsbergen et al., 2011; Lint et al., 2005; Vlahogianni et al., 2004; Xia and Chen, 2009; Xia et al., 2011; Yang, 2005); support vector regression (SVR) (Vanajakshi and Rilett, 2007; Wu et al., 2004), and *k*-nearest-neighbor (*k*-NN) (Bustillos and Chiu, 2011; Myung et al., 2011; Qiao et al., 2012) 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 using other variables (such as traffic speed, density, flow and occupancy) as the state variable to predict the traffic status from which future travel times can be calculated based on some transition function.

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 (Yang et al., 2010). Kalman filters were proposed to predict travel times using Global Positioning System (GPS) information and probe vehicle data (Yang, 2005; Nanthawichit et al., 2003). A Kalman filter (KF) is a popular method for data estimation and tracking, in which the time