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Probe data-driven travel time forecasting for urban expressways by matching similar spatiotemporal traffic patterns

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ABSTRACT

Travel time is an effective measure of roadway traffic conditions. The provision of accurate travel time information enables travelers to make smart decisions about departure time, route choice and congestion avoidance. Based on a vast amount of probe vehicle data, this study proposes a simple but efficient pattern-matching method for travel time forecasting. Unlike previous approaches that directly employ travel time as the input variable, the proposed approach resorts to matching large-scale spatiotemporal traffic patterns for multi-step travel time forecasting. Specifically, the Gray-Level Co-occurrence Matrix (GLCM) is first employed to extract spatiotemporal traffic features. The Normalized Squared Differences (NSD) between the GLCMs of current and historical datasets serve as a basis for distance measurements of similar traffic patterns. Then, a screening process with a time constraint window is implemented for the selection of the best-matched candidates. Finally, future travel times are forecasted as a negative exponential weighted combination of each candidate's experienced travel time for a given departure. The proposed approach is tested on Ring 2, which is a 32km urban expressway in Beijing, China. The intermediate procedures of the methodology are visualized by providing an in-depth quantitative analysis on the speed pattern matching and examples of matched speed contour plots. The prediction results confirm the desirable performance of the proposed approach and its robustness and effectiveness in various traffic conditions.

1. Introduction

Traffic congestion has become a critical problem. Advanced Traveler Information Systems (ATISs) and Advanced Traffic Management Systems (ATMSs) provide a practicable solution for both traffic managers and travelers, which can improve the efficiency and service standard of existing transportation systems and mitigate road congestion problems. Numerous studies (Tu et al., 2008; Liu, 2008; Khosravi et al., 2011; Cai et al., 2016; Chen et al., 2017a, 2017b) have shown that travel time, as an important measure of roadway performance in ATIS and ATMS, can be easily perceived and is applicable to the perspectives of both road operators and users. Consequently, accurate travel time information is urgently needed for better travel planning, route choice, and congestion alleviation.

Due to the highly dynamic and nonlinear nature of traffic states over time and space, travel time forecasting remains a difficult yet important challenge. Thanks to advanced traffic sensing technologies (Zhu et al., 2013), various travel time-related information can

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be conveniently collected, which offers a new solution to congestion by monitoring and disseminating traffic information to road users. These technologies include direct measurement and estimation (Yeon et al., 2008). Direct measurement can be obtained by point-to-point travel time collection, e.g., license plate recognition systems, automatic vehicle identification (AVI), and Bluetooth technologies. Estimation is derived from station-based traffic state measuring devices, e.g., loop detector, global positioning system (GPS) devices and probe vehicle techniques. Because direct measurement usually cannot guarantee sufficient statistics for low sampling rates, estimation approaches are pursued. Currently, a surge of studies has focused on the development of data-driven travel time estimation/prediction approaches. For an extensive review, one can refer to the study by Karlaftis and Vlahogianni (2011), Oh et al. (2015), Mori et al. (2015). The existing data-driven methods can be classified into two major categories, i.e., parametric approaches and non-parametric approaches.

Parametric approaches rely on established theories, including linear regressive models (Zhang and Rice, 2003), time series models such as the Kalman filter (Lint, 2008) and the Auto-Regressive Integrated Moving Average (ARIMA) (Xia and Huang, 2011). Non-parametric approaches consist of neural networks (NN) (Zeng and Zhang, 2013), support vector regression (SVR) (Lam and Toan, 2008), and k-nearest-neighbor (KNN) (Kobrin, 2011), hybrid or ensemble techniques (Zhang and Haghani, 2015). These methods are implemented by direct or indirect procedures to predict travel times using different types of state variables. Direct procedures utilize the travel time in past periods as the state variable to predict future travel time. Indirect procedures are performed using other variables (such as traffic speed, density, flow, and occupancy) as the state variable to predict state condition, and future travel time can be calculated based on the transition.

Parametric approaches, which establish the theoretical framework with straightforward model structures, have been utilized to predict short-term travel time with various degrees of success. For example, time series models were employed to construct the time series relationship of travel time or traffic state, and current and/or past traffic data were employed in the constructed models to predict travel times in the next time interval (Chen et al., 2016). A vast amount of freeway traffic prediction literature addresses these models (Kamarianakis and Prastacos, 2005; Billings and Yang, 2006; Chen et al., 2012; Xiong et al., 2014). Among these types of models, ARIMA is extensively recognized as an accepted framework to construct a freeway traffic prediction model due to its well-defined theoretical foundations and effectiveness in prediction (Karlaftis and Vlahogianni, 2009). Fei et al. (2011) developed the Bayesian dynamic linear model for real-time, short-time travel time prediction in two traffic conditions of recurrent and non-recurrent congestion. Some parametric approaches have been combined with macroscopic traffic models (Celikoglu, 2013a, 2013b) to predict travel time. These estimation models, which are based on flow conservation and propagation principles, enhance the adaptiveness to the actual measurement. Wang et al. (2008) utilized macroscopic traffic flow models and the Kalman filtering technique to predict freeway travel time with synthetic detector and probe vehicle data. However, the accuracy rapidly degrades with an increase in the prediction temporal horizon. Parametric approaches can produce desirable forecasts in traffic conditions that show regular variations. However, they may be computationally extensive and produce larger deviations when highly dynamic and nonlinear traffic states are present over time and space.

Conversely, alternative approaches include building the function of the current and previous traffic states by assuming hidden variables. These approaches are essentially non-parametric and are capable of capturing the underlying structure of data and excavating the intrinsic spatiotemporal traffic features without strong assumptions about its temporal evolution. Support vector regression (SVR) techniques (Lam and Toan, 2008) have been commonly employed to predict travel time. This approach maps the data into a higher dimensional space using a kernel function to find the flattest linear function that relates these modified input vectors with the target variable. Then, the linear function is mapped into the initial space to obtain a final nonlinear function and predict travel time. In addition, neural network (NN) models have gained increasing attention and are frequently applied in traffic state prediction. An NN can be trained using historical data to identify hidden dependencies that can be employed for predicting future states. Lint et al. (2005) proposed a state space neural network (SSNN) method to predicted freeway travel time. Recently, a novel recurrent neural network method that considers temporal-spatial input dynamics for freeway travel time modeling was developed (Zeng and Zhang, 2013). However, NN-based methods employ black-box procedures to predict traffic conditions and lack a suitable interpretation of the dependency relationship. The applications of the methods require long training processes and are usually nontransferable to other sites.

As another representative non-parametric approach, the pattern-matching method is easy to implement at different sites without data training, as required by the NN and SVR. The basic assumption of the pattern-matching method is that traffic patterns are recurrent in nature and the historical database, which provides a variety of previously experienced traffic patterns, can be employed to predict future "experienced" traffic states, e.g., travel times by matching current data to historical data. Candidates were selected by the Euclidean distance or other data trend measures and utilized to predict travel times in different conditions. The pattern-matching method has greater flexibility than the parametric approach. The predictions are based on huge amounts of data which are presumed to contain a variety of traffic state patterns. Several studies have applied the pattern-matching method to predict traffic flow rates (Zheng and Su, 2014; Habtemichael and Cetin, 2015). Similarly, other studies have applied this method for travel time prediction (Bajwa and Kuwahara, 2003; Bajwa et al., 2005). The main shortcomings of these studies are that only the simplest forms of KNN were employed with the consideration of high-dimensional spatiotemporal traffic states in a limited manner, which prevents the implementation of the method in large-scale traffic networks. Due to the short spacing of merging and diverging traffic flows, the traffic states on urban expressways are considerably more unstable than freeways. Compared with the extensive application of the pattern-matching method for traffic states or travel time prediction on freeways (Zou et al., 2014), less attention has been given to urban expressways.

In principle, the performance of any data-driven approach is dependent on the representativeness and extensiveness of the data. An accurate forecast of dynamic travel time requires the availability of high-resolution data. In the past few years, interval detectors