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Experienced travel time prediction for congested freeways

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Travel time is an important performance measure for transportation systems, and dissemination of travel time information can help travelers make reliable travel decisions such as route choice or departure time. Since the traffic data collected in real time reflects the past or current conditions on the roadway, a predictive travel time methodology should be used to obtain the information to be disseminated. However, an important part of the literature either uses instantaneous travel time assumption, and sums the travel time of roadway segments at the starting time of the trip, or uses statistical forecasting algorithms to predict the future travel time. This study benefits from the available traffic flow fundamentals (e.g. shockwave analysis and bottleneck identification), and makes use of both historical and real time traffic information to provide travel time prediction. The methodological framework of this approach sequentially includes a bottleneck identification algorithm, clustering of traffic data in traffic regimes with similar characteristics, development of stochastic congestion maps for clustered data and an online congestion search algorithm, which combines historical data analysis and real-time data to predict experienced travel times at the starting time of the trip. The experimental results based on the loop detector data on Californian freeways indicate that the proposed method provides promising travel time predictions under varying traffic conditions.

1. Introduction

Predictive travel time is valuable information required by drivers and transportation managers to improve the quality of travel and to make control decisions. The provision of travel time information through Advanced Traveler Information Systems (ATISs) enables drivers to make decisions, such as route choice and departure time. In addition, besides the fundamental relation with traffic flow modeling, travel time can be used by transportation agencies to deploy efficient control measures and to prevent potential traffic congestion. Apart from its direct implementation for users and practitioners, travel time experiences strong fluctuations and stochastic traffic phenomena that make its reliable estimation and prediction a challenging physical and mathematical task. Thus, its modeling and estimation requires a combination of correct physics and strong statistical tools.

There are two general methods for obtaining travel time; direct measurement and estimation (Yeon et al., 2008). Direct measurement of travel time can be obtained through test vehicles, license plate matching techniques (automatic vehicle identification, AVI) and ITS probe vehicle techniques. Direct measurement techniques may be misleading in the case of low sampling rates and existence of outlier travel time observations. In order to suppress noise signals, Dion and Rakha (2006) developed an adaptive filtering algorithm, which adjusts its validity window by tracking average travel times. On the other hand, travel time estimation is conducted using the data taken from loop detectors, smart phones or global

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positioning system (GPS) devices. As numerous freeways around the world are equipped with loop detectors that collect flow, speed and occupancy information, a vast literature of travel time estimation in freeways relies on them. Travel time estimation can be either based on local velocity measurements, or more sophisticated models that attempt to correlate vehicle observations at multiple locations (Coifman, 2002; Coifman and Krishnamurthy, 2007). In addition, estimation models tend to underestimate travel times under congested conditions because of the queue dynamics which cannot be adequately represented in the model. To address this problem, Yeon et al. (2008) made use of discrete time Markov Chains, where the states correspond to whether or not a link is congested, and computed the expected route travel time for several adjacent short links. Furthermore, GPS data provide new opportunities for traffic state estimation and they can be incorporated in estimation algorithms for travel time (Herrera and Bayen, 2010). Mazaré et al. (2012), using the experimental probe data from a field experiment and loop detector data from California Performance Measurement System (PeMS), evaluated the trade-offs between the two types of data. To produce an improved estimate of velocity field, speed measurements from GPS or loop detectors are combined using a mathematical traffic model equivalent to Cell Transmission Model and a traffic state estimation algorithm, the ensemble Kalman filtering. Resulting velocity fields are used to compute travel time, assuming that a vehicle travels at the mean speed reported in each cell. However, the essential problem with travel time information is that it always has to refer to future conditions in the roadway. On the contrary, traffic data collected in real time reflect past or current conditions in the roadway.

Using traffic speed information, there are two ways to compute travel time; instantaneous and experienced. Instantaneous travel time is calculated combining the speed measurements in different locations at the departure time of a trip. On the other hand, experienced travel time is calculated by traveling a trajectory through the velocity field. The time it takes to traverse each segment is calculated, and the speed measurement at the time when the trajectory reaches the next segment is used to compute its travel time. Mathematically speaking, if a freeway is divided into $i = 1,\ldots,I$ sections (I is the most downstream section), and $\tau_i(t_d)$ is the travel time of section i for starting time t_d, then the instantaneous $T^{in}_{S,i}(t_d)$ and experienced, $T^{ex}_{S,I}(t_d)$ travel times to traverse all sections between S and I for departure time t_d are estimated as follows ($T^{ex}_{S,I} = 0,\ \text{for } S \geq I$):

$$T^{in}_{S,I}(t_d) = \sum_{i=S}^{I-1} \tau_i(t_d) \tag{1a}$$

$$T^{ex}_{S,I}(t_d) = \sum_{i=S}^{I-1} \tau_i\left(t_d + T^{ex}_{S,i}(t_d)\right) \tag{1b}$$

To further motivate this research direction, a speed contour plot is presented for a section in freeway I-5S in California in Fig. 1. This plot is constructed with loop detector data for a congested *Friday* of 2011. A few active bottlenecks can be seen in the site that start at different times and propagate upstream. Travel trajectories for instantaneous and experienced travel time approaches are constructed using the speed measurements at the fixed detectors. Space–time (x,t) points on the trajectories are calculated using Eq. (1) and replacing I and S with the corresponding section numbers. Fig. 1 clearly shows

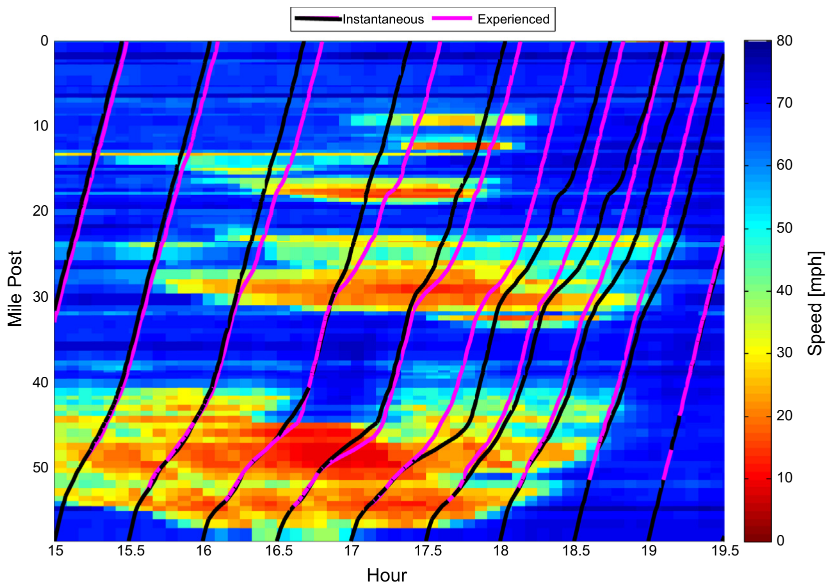

Fig. 1. Speed contour plot and trajectories for a congested day (15:00–19:30) on I5-S freeway.