Transportation Research Part C 17 (2009) 586–606

Contents lists available at ScienceDirect

Transportation Research Part C

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

Arterial travel time estimation based on vehicle re-identification using wireless magnetic sensors

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ARTICLE INFO

Article history:
Received 24 July 2008
Received in revised form 1 April 2009
Accepted 2 April 2009

Keywords:
Real-time travel time estimation
Vehicle re-identification
Arterial performance measures
Queue length
Discharge rate
Magnetic signature

ABSTRACT

A practical system is described for the real-time estimation of travel time across an arterial segment with multiple intersections. The system relies on matching vehicle signatures from wireless sensors. The sensors provide a noisy magnetic signature of a vehicle and the precise time when it crosses the sensors. A match (re-identification) of signatures at two locations gives the corresponding travel time of the vehicle. The travel times for all matched vehicles yield the travel time *distribution*. Matching results can be processed to provide other important arterial performance measures including capacity, volume/capacity ratio, queue lengths, and number of vehicles in the link. The matching algorithm is based on a statistical model of the signatures. The statistical model itself is estimated from the data, and does not require measurement of 'ground truth'. The procedure does *not* require measurements of signal settings; in fact, signal settings can be inferred from the matched vehicle results. The procedure is tested on a 1.5 km (0.9 mile)-long segment of San Pablo Avenue in Albany, CA, under different traffic conditions. The segment is divided into three links: one link spans four intersections, and two links each span one intersection.

1. Introduction and previous work

Estimating arterial travel time is difficult. Since the movement of vehicles is interrupted by signals, estimates based on speeds measured by loop detectors or radar are inaccurate.

Approaches for estimating travel times on arterial links include speed vs. volume to capacity ratio relationships or procedures based on the Highway Capacity Manual. The latter calculates average travel time as the sum of the running time, based on arterial design characteristics, and the intersection delay, based on a deterministic point delay model. These approaches are not suited for real-time applications with variable traffic conditions.

Statistical models have been proposed for estimating travel times from surveillance data. For example, Zhang (1999) estimates link-speed as a function of volume to capacity ratio and volume and occupancy measured by loop detectors. Since the estimation itself requires collection of travel times, the model is site-specific and impractical to implement.

By contrast, Skabardonis and Geroliminis (2005) develop a generally applicable kinematic wave model to construct a link travel time estimate from 30-s flow and occupancy data collected at an upstream loop detector, together with the exact

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0968-090X/$ - see front matter
doi:10.1016/j.trc.2009.04.003

times of the red and green phases. Their procedure can be explained as follows: The upstream detector counts the number n of vehicles that arrive in a 30-s interval, say during $[s, s+30]$. These n vehicles are assumed to cross the detector at uniformly spaced times $s + 30i/n,\ i = 1, \ldots, n$. From the assumed or estimated free flow travel time T_f, these vehicles will arrive at the intersection at times $T_f + s + 30i/n$. Knowing the signal phase at these arrival times and the previously calculated queue at the intersection, and using the kinematic wave model (with assumed or estimated congestion wave speed and jam density), one can calculate the delay faced by each of the n vehicles, and the queue remaining at the end of the 30 s. The procedure is then repeated, to yield the average travel time across the link and the average delay.

Liu and Ma (2009) use a similar model. However, by measuring individual vehicle detector actuations they know the exact times that the vehicles crossed the upstream detector, instead of assuming that these are uniformly spaced times. The rest of their procedure is similar. The models of individual vehicle trajectories in both Skabardonis and Geroliminis (2005) and Liu and Ma (2009) are more elaborate than the uniform free flow speed assumed above, as they take into account the vehicle's deceleration as it approaches a queue and its acceleration as it departs from the signal. However, this elaboration does not measurably affect the average travel time and delay estimates (Liu and Ma, 2009, Fig. 10).

The two approaches outlined above have limitations. They require precise signal phase times, and these must be synchronized with the detector times. Moreover, for a link with multiple intersections, each intersection must be instrumented. Such instrumentation is expensive. Second, both approaches require knowledge of parameters such as free flow travel time, which may not be constant across the entire range of traffic conditions, and lead to bias in the estimates. Third, *average* travel time and delay are insufficient to calculate interesting arterial performance measures provided by the scheme proposed here, as seen in Section 3.

In principle, vehicle re-identification schemes overcome these limitations. These schemes work as follows: Sensors placed at the two ends of a link record the times when a vehicle crosses them and measure its signature. When a vehicle's signature is matched at the two sensors, its travel time is obtained. Signal phase information is not needed. If sufficiently many vehicles are re-identified, the travel time distribution can be estimated. Vehicles can be easily re-identified by matching unique tags or license plates; but besides raising privacy concerns, these schemes are too expensive to deploy over an arterial network.

Re-identification schemes for *freeway* travel times have been demonstrated. Sun et al. (1999) match waveforms from inductive loops produced by the passage of a vehicle. The waveforms are first normalized using independently measured speeds. Features from the normalized waveform pairs are extracted and compared in a multi-criterion optimization framework to obtain the best match. Coifman (1999) compares lengths of vehicle platoons at the two detector locations. The length estimate too requires independent speed measurements.

Ndoye et al. (2008) and Oh and Ritchie (2002) report experiments using inductive loop signatures. Again, vehicle speed is used to normalize the raw waveform and produce a speed-independent signature. The speed normalization procedure assumes that vehicle speed is constant. If a vehicle is accelerating or decelerating, this assumption is invalid: as Ndoye et al. (2008) report, the rate of correct matching then drops drastically. Oh and Ritchie (2002) only report results for a non-peak period. Neither scheme would perform well in a link with significant acceleration and deceleration, caused by traffic signals on an arterial or by vehicles arriving at a queue behind a freeway bottleneck. Platoon lengths used in Coifman (1999) would not work well for the additional reason that signalized intersections would break platoons up.

Sun et al. (2004) use vehicle color (extracted from video images) in addition to the loop-based signature and speed in a data 'fusion' algorithm that achieves a high matching rate for vehicle platoons in a link without an intersection. The selection of the parameters of the fusion algorithm requires an extensive and expensive collection of 'ground truth' measurements. The fusion algorithm weights loop signature, speed, vehicle color and platoon traversal time. In the best fusion scheme, color receives a weight of 95%. The scheme is impractical and would not work in a link with an intersection that breaks platoons up.

This paper presents a system to estimate the travel time *distribution* of a single arterial link, spanning several signalized intersections. The system is based on matching individual vehicle signatures obtained from wireless magnetic sensors placed at the two ends of the link. The signature consists of the sequence of peak values of the 'raw' magnetic signal. The peak values are independent of the vehicle speed, so speed measurements are not needed. The matching scheme is anonymous, whereas approaches that rely on reading licence plates or RFID tags or tracking cell phones risk violating privacy.

Unlike Skabardonis and Geroliminis (2005) and Liu and Ma (2009) the scheme requires *no* signal phase measurements. Indeed, signal phases, queue lengths, delay distributions and other performance measures can all be evaluated from the matched vehicles. The scheme is tested on a 1.5 km (0.9 mile)-long segment of San Pablo Avenue in Albany, CA, spanning six intersections. The segment is divided into three links: one link spans four intersections, and two links each span one intersection. The peak hour per lane flow over the segment is 500–600 vph.

The paper is organized as follows: The test site and measurement system are described in Section 2. Test results are presented in Section 3. The matching problem and the statistical signature model used to evaluate matching algorithms occupy Section 4. The optimal unconstrained matching algorithm and the optimal constrained matching algorithm are described in Sections 5 and 6, respectively. (The results of Section 3 are based on optimal constrained matching.) A real-time version of the optimal constrained algorithm is presented in Section 7. Estimation of the statistical signature model without measurement of ground truth is described in Section 8. Major conclusions and some suggestions for future work are collected in Section 9. Some of the more technical material is presented in Appendix.