Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors

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ABSTRACT

Recent research has investigated various means of measuring link travel times on freeways. This search has been motivated in part by the fact that travel time is considered to be more informative to users than local velocity measurements at a detector station. But direct travel time measurement requires the correlation of vehicle observations at multiple locations, which in turn requires new communications infrastructure and/or new detector hardware.

This paper presents a method for estimating link travel time using data from an individual dual loop detector, without requiring any new hardware. The estimation technique exploits basic traffic flow theory to extrapolate local conditions to an extended link. In the process of estimating travel times, the algorithm also estimates vehicle trajectories. The work demonstrates that the travel time estimates are very good provided there are no sources of delay, such as an incident, within a link.

Keywords:

traffic surveillance, loop detectors, travel time estimation, vehicle trajectories

INTRODUCTION

A recent report from the California Department of Transportation noted that, "rapid changes in link travel time represent perhaps the most robust and deterministic indicator of an incident [and] link travel time ... is perhaps the most important parameter for ATIS functions such as congestion routing." (Palen, 1997) Similar views have lead the Federal Highway Administration and several states to develop and deploy new detector technologies capable of collecting true travel time data over extended freeway links, e.g., Balke et al., 1995, Coifman, 1998, Huang and Russell, 1997, Sun et al., 1999.

The emphasis on new technology to measure travel time is partially due to a misunderstanding of how to interpret vehicle travel times. For example, Sun et al. used conventional average velocity sampled at a detector station over fixed time periods as a base case in their analysis. The authors found that link travel times differed significantly from the quotient of local velocity and the link distance. But this result is not surprising, since the link travel time for a vehicle reflects traffic conditions averaged over a fixed distance and a variable amount of time, while the detector data only reflects traffic conditions averaged over a fixed time period at a single point in space.

In contrast to the naive approach of generalizing point measurements over an entire link, this paper will show that judicious application of traffic flow theory can yield accurate link travel time estimates from point data. In particular, Lighthill and Whitham (1955) postulated that signals propagate through the traffic stream in a predictable manner and that a single curve in the flow versus density plane defines the set of stationary traffic states. When the state transitions from one point on the curve to another, the resulting signal should propagate through the traffic stream at a velocity equal to the slope of the line between the two points. Building off of this earlier work, Newell (1993) proposed a simplified flow density relationship, as shown in Figure 1. Provided the traffic state remains on one leg of the *triangle*, all signals should propagate at the same velocity: u_F for free flow or u_C for congested conditions. Windover and Cassidy (2000) have verified empirically that this simplification is reasonably accurate. If a freeway link does not contain a source of delay, such as a recurring bottleneck or an incident, then all of the signals that influence a vehicle's travel time must pass at least one end of the link at a known velocity.

If we postulate that traffic velocity, v, over time, t, and space, x, has the functional form

$$v(x,t) = f(x + u \cdot t) \tag{1}$$

where u is either u_F or u_C. Then, the level sets of function f are straight lines and thus, v is completely determined by observing this parameter over time at a single point in space, i.e., at a detector station. The evolution of vehicle trajectories in the time-space plane are defined by the differential equation

$$\frac{dx}{dt} = v(x,t) \tag{2}$$

and vehicle's link travel time is simply the time it takes the corresponding trajectory to propagate across the link, i.e., from one detector station to the next.

Using this postulate, the remainder of this paper develops a methodology to estimate link travel times by integrating the signals that pass a dual loop detector, without deploying new hardware or combining data from multiple locations. The estimation method should be beneficial for traveler information applications, where travel time is considered more informative to users than average velocity. One could also view the estimation method as providing "expected travel times" without an incident. Used in conjunction with one of the new technologies capable of measuring the true vehicle travel times, a significant deviation between the expected and measured travel times would be indicative of congestion. Then, historical trends could be used to differentiate between recurring congestion and an incident. If a travel time estimation system is deployed for real time traffic control, the system could also prove beneficial for planning applications such as quantifying congestion or model calibration. This last point is an important task for the traditional four-step planning process as well as the on-going Travel Model Improvement Program, which seeks to replace the process with microsimulation models. For example, the TRANSIMS designers at Los Alamos National Labs note that "The most important result of a transportation microsimulation in [the planning] context should be the delays..." (Nagel et al., 1998). Finally, in the process of developing the estimation method, the paper will also show how it can be used to estimate vehicle trajectories over a freeway link, which in turn could be useful for quantifying vehicle emissions and other applications.

TRAVEL TIME ESTIMATION

A dual loop detector station is capable of recording vehicle velocities and arrival times at a single point in space. We use this information to define a *chord* in the time-space plane, where a chord is simply a straight line with a slope equal to a vehicle's measured velocity and passes the location of the detector at the instant the vehicle passes. Figure 2A shows a single chord for a detector at zero distance and Figure 2B adds the next 13 chords recorded at the detector. Empirically, the chords provide a rough approximation of vehicle trajectories for a short distance downstream of the detector, but the approximation quickly breaks down, as evidenced by the intersection of several cords in Figure 2B. Assuming that individual vehicle measurements represent discrete observations from a slowly varying traffic state at the detector location, the changing state can be approximated by discrete samples equal to the vehicle headways. During congested conditions, i.e., the right hand leg of the curve in Figure 1, the transition between one discrete state and another should propagate at u_C. In other words, a vehicle passage represents an observed signal. These signals are shown with dashed lines in Figure 2C, where each chord is truncated as soon as it reaches the next observed signal. Figure 3 shows the relationships

between u_C, vehicle velocity, v_j, headway, h_j, travel time, τ_j, and distance traveled, x_j, for j-th truncated chord. It is a simple exercise to show that,

$$\tau_j = \frac{h_j}{1 + v_j / u_C} \tag{3}$$

$$x_j = v_j \cdot \tau_j \tag{4}$$

Because all signals are assumed to travel at the same speed, the parameters from Figure 3 are the same for any vehicle passing through a given *band* between two signals. Connecting the truncated cords end-to-end yields an estimated trajectory, shown in Figure 2D, for the vehicle from part A. In practice, one need only add up successive x_j's until the total exceeds the link distance. The sum of the corresponding τ_j's yields a travel time estimate. To enumerate the steps in this estimation, first, measure h_j and v_j then calculate x_j and τ_j using Equations 3 and 4. For the k-th vehicle, find the largest N_k such that,

$$d \geq \sum_{j=k}^{k+N_k} x_j \tag{5}$$

where d is the length of the link and N_k+1 represents an estimate of the number of vehicles that pass the detector while the k-th vehicle traverses the link. Typically the link distance will exceed the sum of x_j's by some percentage of the next x_j, so a better estimate of travel time will include the corresponding τ_j, weighted by the same percentage. More formally, calculate a weight, p, as follows,

$$p = \frac{\left(x_{k+N_k+1} + \sum_{j=k}^{k+N_k} x_j \right) - d}{x_{k+N_k+1}} \tag{6}$$

Finally, calculate the estimated travel time, T_k,

$$T_k = p \cdot \tau_{k+N_k+1} + \sum_{j=k}^{k+N_k} \tau_j \tag{7}$$

Another improvement comes by recognizing that h_j occurs between vehicle observations. So the harmonic mean of two successive velocity measurements, v_j and v_{j+1}, should be more representative of conditions during the j-th band than either velocity measurement taken alone. The remainder of this paper uses this improvement. It is a simple extension to show that rotating Figures 2-3 by 180 degrees, the methodology can also be applied to traffic upstream of a detector. Lastly, to estimate the k-th vehicle trajectory, one only need calculate the cumulative sum at each j from Equations 5 and 7.

A Short Example

This example applies the travel time estimation methodology during congested conditions, over an 1,800 foot long freeway link that does not contain any ramps. Dual loop detector stations bound the link on either end (see Coifman et al., 2000 for more information). In this configuration, each detector station can be used to generate an independent estimate of travel time over the link. Before making this estimate, one must settle on a value of u_C. Examining a different freeway, Windover, 1998 found u_C had a small variance from signal to signal and most signals during congested conditions traveled between 12 mph and 16 mph. The velocity range was manually verified at the subject link by comparing extrema points in time series flow and occupancy at either end of the link. A constant value of 14 mph is assumed for u_C throughout the rest of the paper.

Examining a single lane, the solid line in Figure 4A shows the estimated travel times from the upstream detector. Using concurrent video to visually match every vehicle that stayed in the lane between the two stations, the points show the corresponding ground truth travel times. This process is repeated in Figure 4B at the downstream station. For the sake of comparison throughout this paper, all plots of travel time are shown relative to vehicle arrival times at downstream station. The performance of each detector station is summarized on the left-hand side of Table 1. Both estimates were, on average, within 10 percent of the true value while the corresponding naive link travel time estimates, presented in the center of the table, have an average error on the order of 25 percent.

Although the travel time estimation is not perfect, it is still quite good considering the fact that it is based on data from a single point in space. Looking closer at the data, Figure 5 shows a detail of the estimated trajectories implicit in the upstream travel time estimation. In this plot, the upstream detector is at zero feet and the downstream detector is at 1,800 feet. A total of 137 trajectories are shown, of which, 106 pass the downstream detector during the five minute period. The trajectories are not exact, e.g., no effort has been made to account for potential variance in u_C or the presence of lane change maneuvers, but the simple fact that they provide a good estimate of true travel time over an extended distance suggests that they are a good approximation. As further motivation, consider Figure 6. The methodology was used to estimate vehicle trajectories one half mile upstream and one half mile downstream of a detector station using data from the I-880 Field Experiment (Skabardonis et al., 1996), while the bold lines show actual probe vehicle trajectories over the same segment.

The trajectory approximations could be useful for planning applications or emissions modeling. For example, emissions are typically estimated using vehicle miles traveled, average velocity, average flow, or more recently, using point detectors capable of measuring instantaneous emissions from individual vehicles. But none of these methods are capable of capturing the effects of vehicle dynamics. As a result, significant factors contributing to vehicle emissions,

such as acceleration, often go unmeasured (Holemen and Neimeier, 1998). On the other hand, a vehicle's dynamics are implicit in its trajectory and when used in conjunction with calibrated vehicle emissions (e.g., West et al., 1999), this work could allow for real time estimates of emissions along an entire freeway. Future research will examine the accuracy of the trajectory estimates in terms of such applications.

Extending to Free Flow Conditions - a Long Example

During free flow traffic conditions, signals travel downstream with the vehicles and the transitions shown in Figure 2C should correspond to individual chords. Or, if we continue the assumption of constant signal velocities, they should now travel downstream at u_F. By erroneously assuming that free flow signals travel against the direction of travel with velocity u_C and treating the data the same way as congested periods, the travel time estimate will be based on the wrong set of vehicle observations. But, free flow traffic is characterized by approximately constant velocity over time and space. So the vehicles selected with u_C should have similar velocities to the correct set of vehicles and any resulting errors in the travel time estimate should be negligible.

Putting this hypothesis to the test, consider 24 hours of data between the same detector stations used in the previous example. This time, however, we arbitrarily present one of the lanes in the opposite direction. The two parts of Figure 7 show the estimated travel times from each detector station with a solid line. Manually generating ground truth matches for this long data set would be prohibitively time consuming. Instead, two vehicle reidentification algorithms are employed. For a given downstream measurement, each algorithm searches the upstream observations for the measurement that corresponds to the same vehicle (Coifman and Cassidy, 2000, Coifman, 1999). The resulting travel times for the matched vehicles are shown with points in each plot. As predicted, the estimation methodology performed quite well during free flow conditions, when the true travel time was on the order of 20 seconds.

Figure 8A shows a detail of the congested measurements. Again, the estimation method appears to follow the measured values while Figures 8B-C show the corresponding naive link travel time estimate using the local average velocity sampled every 30 seconds. As expected, the fixed time samples do not provide a good estimator of link travel time, with some samples being over eight times too large.

Applying the methodology to conventional traffic data

The large errors from the naive estimate are due to the simple fact that a single 30 second sample at one point in space can not capture the travel time experienced by a vehicle traversing a link. Although the proposed methodology promises greater accuracy, most operating agencies would have to upgrade their hardware and/or software in the field to estimate travel time based on

individual vehicle measurements. But the use of vehicle headways was chosen out of convenience. If a surveillance system only reports samples over fixed time periods and care is taken to measure space mean speed accurately, then the preceding theory is still valid and one can apply the estimation methodology to these data using a constant h, equal to the sampling period. In this scenario, the estimation methodology combines data from several fixed time samples rather than from individual vehicle measurements. The results for the short example using a 30 second sampling period are reported on the right hand side of Table 1. Note that the error is still less than half of that from the naive estimate.

Limitations

The estimation methodology assumes that *all* signals travel through the *entire* freeway link. This assumption fails when a queue partially covers a link. Unfortunately, the end of a queue can not be tracked using data from a single detector station.[1] Figure 9 shows two examples of this failure. In each case, traffic over the downstream station is congested while vehicles at the upstream station are free flowing. Comparing the top and bottom halves of this figure, we see the upstream detector underestimates the travel time and the downstream overestimates it during these periods. Of course these errors would be reversed when the upstream end of the segment is queued while the downstream is free flowing. In any event, the periods where the method breaks down typically represent a small percentage of the day and as illustrated in this figure, they can be identified by differing estimates from either end of the link. Provided the estimates are transmitted to a central location, such as a Traffic Management Center, such comparisons would be easy to conduct.

Finally, one may have to assume a different flow-density relationship to apply this method at other locations. This modification could be as easy as calibrating the value of u_C, but if need be, one could extend the work to any flow density relationship in which flow is a strictly decreasing function of density in the congested regime.

CONCLUSIONS

Link travel time is considered to be more informative to users than flow, velocity, or occupancy measured at a point detector. This paper has employed basic traffic flow theory to estimate link travel time using point detector data. Rather than simply measuring local velocity over fixed sample periods, the approach presented herein could be used to increase the "information"

[1] Daganzo (1997) presents a method to estimate the end of a queue between two detector stations using data from both stations. Used in conjunction with the present work, it could lead to better travel time and trajectory estimates; however, such work is beyond the scope of this paper, which focuses on extracting information from a single detector station.

available from dual loop detectors and other vehicle detectors. The accuracy of the method lends further evidence that the linear approximation of flow density relationship is reasonable during congestion, supporting the work of Newell, Cassidy and others.

Since the method uses observations from a single point in space, changes in the traffic stream may be overrepresented or underrepresented, as illustrated in Figure 9. Because it is possible to estimate link travel time from either end of the link, the periods when the method breaks down can be identified easily. In contrast, vehicle reidentification techniques using data from more than one detector station actually measure conditions over the link. Combining measured and estimated travel times, it should be possible to produce a robust incident detection system by looking for periods where the two approaches differ; perhaps even enabling incident detection during congested conditions. Naturally, such a system would have to account for recurring bottlenecks as well as normal queue growth and decay. To this end, future research will seek to extend the estimation methodology to inhomogeneous freeway links and improve performance during periods when a queue partially covers a link.

Although the estimation method is not perfect, it is surprisingly accurate for an approach that uses data from a single point in space. The estimated vehicle trajectories constructed en route, e.g., Figure 5, could be useful for applications such as quantifying vehicle emissions due to start/stop cycles on congested freeways.

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Figure 1, Triangular flow density relationship showing the signal velocity during free flow, u_F, and congestion, u_C.

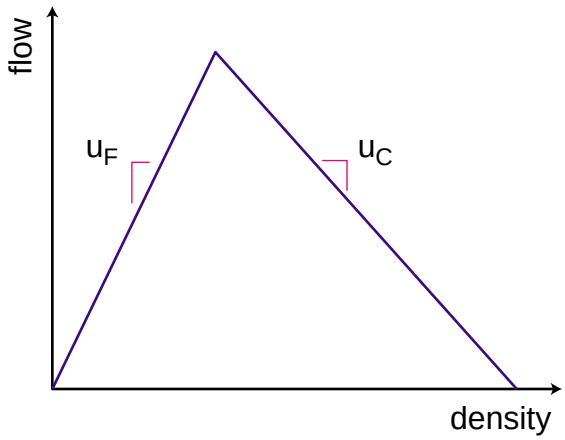

Figure 2, Time space diagram showing, (A) the chord for a vehicle passing the origin at 748 sec, (B) chords for subsequent vehicles, (C) truncated chords, (D) estimated trajectory and travel time for the vehicle in part A.

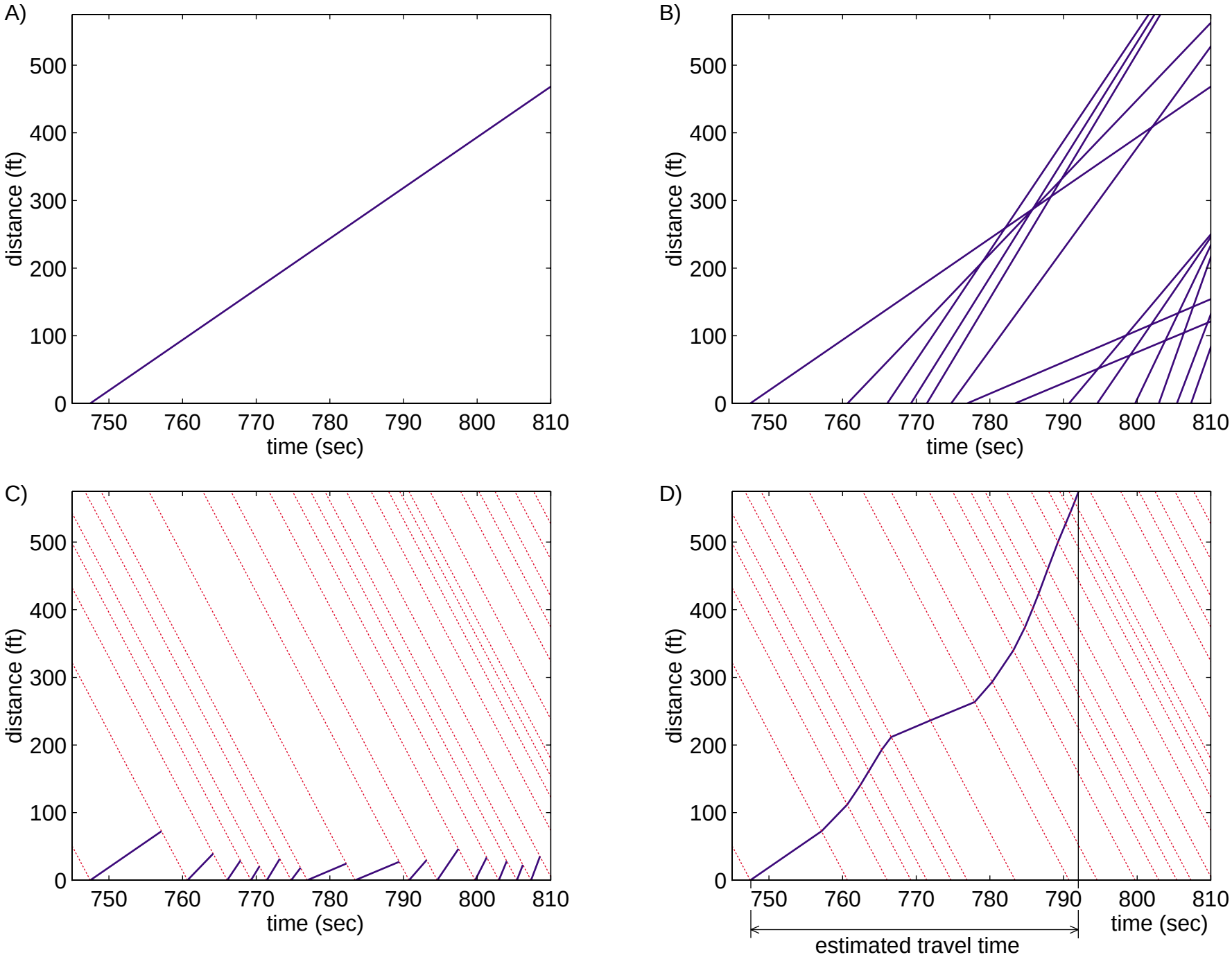

Figure 3, Schematic showing the relationships between signal velocity, u_C, vehicle velocity, v_j, headway, h_j, travel time, τ_j, and distance traveled, x_j, for a vehicle passing through band j.

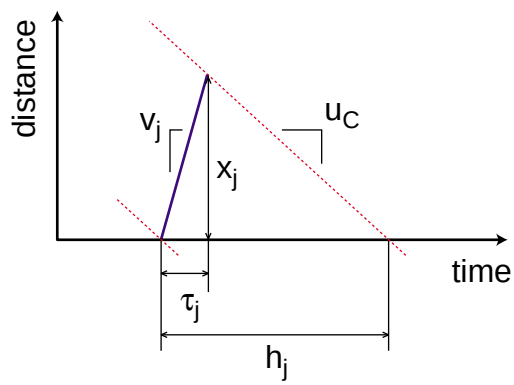

Figure 4, (A) Measured travel times (dots) and estimated from the upstream detector data (line), (B) repeated for the downstream detector data.

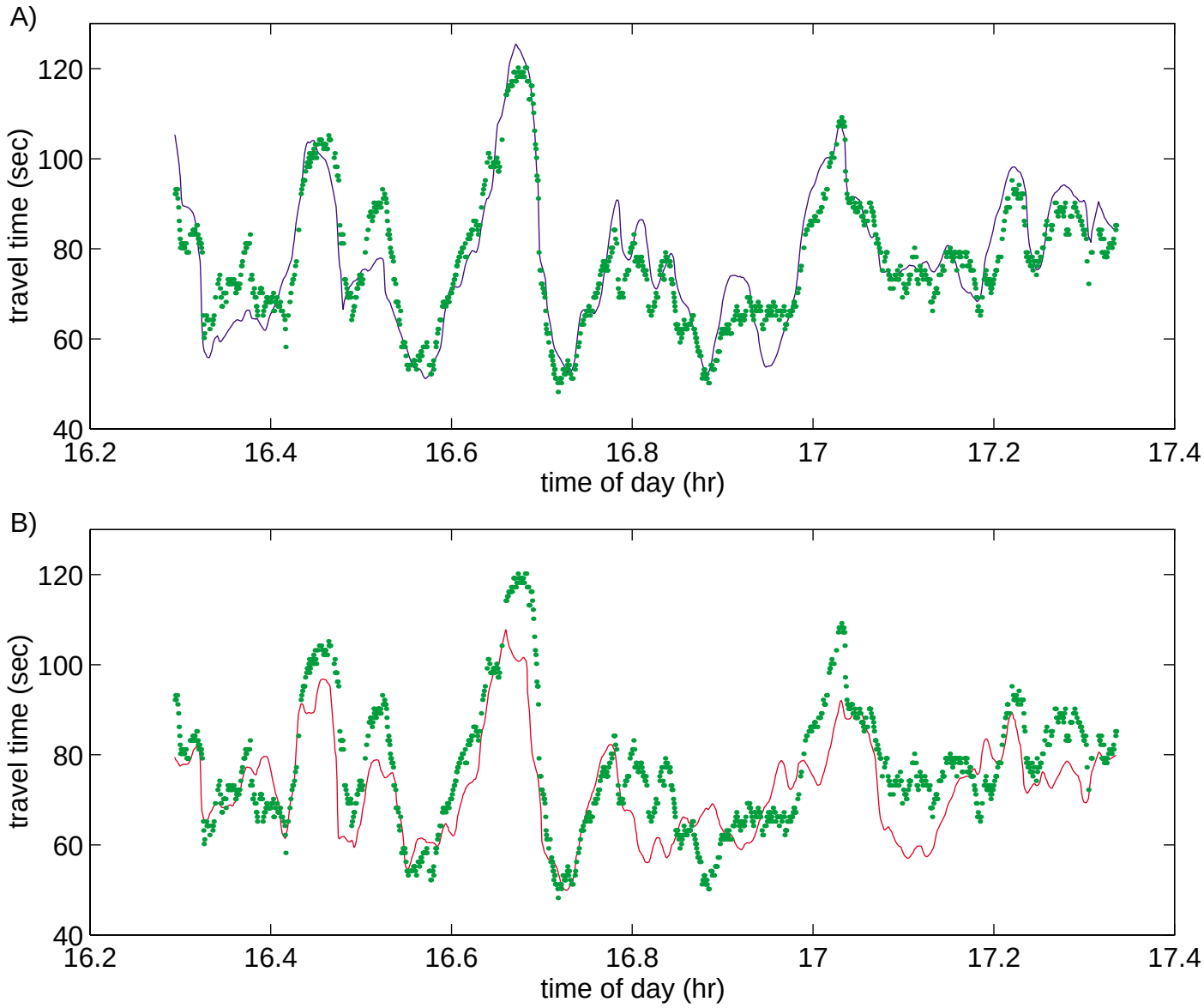

Figure 5, Detail from the estimated vehicle trajectories implicit in the travel time estimates of Figure 4A

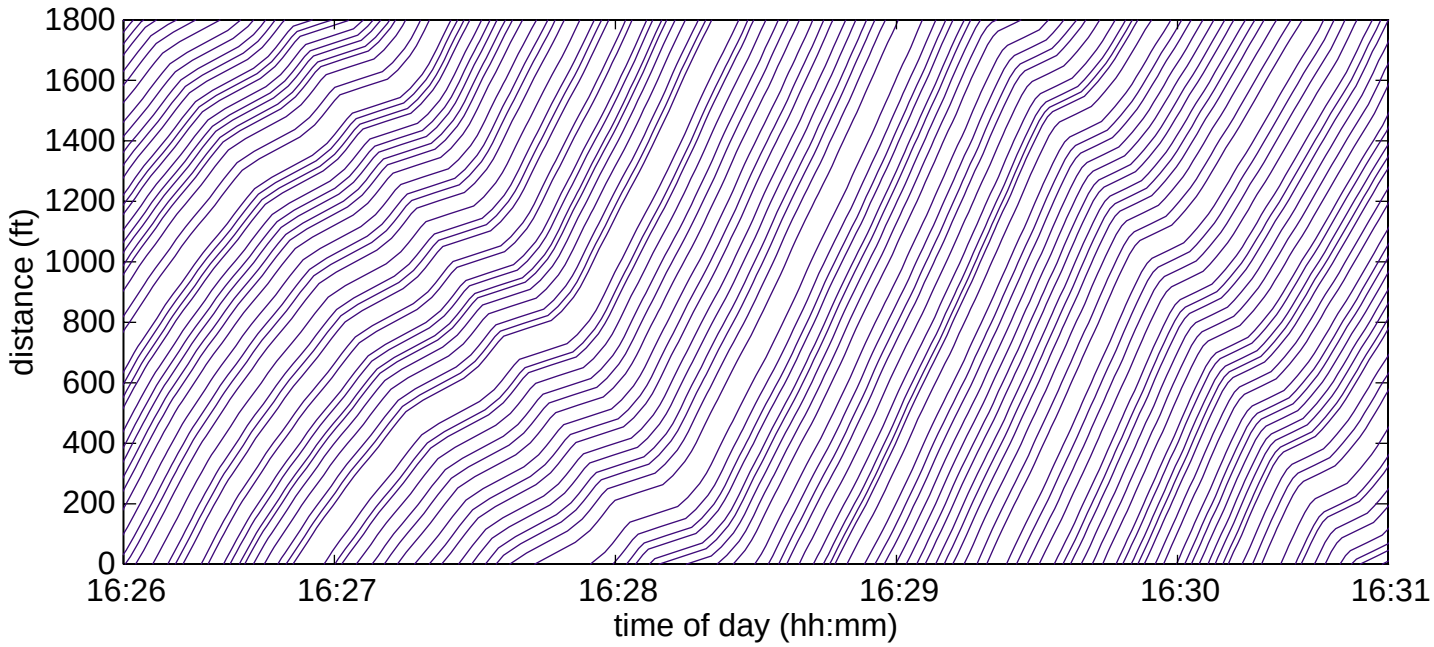

Figure 6, Estimated trajectories over one mile using data from a single detector station (at zero distance) and measured probe vehicle trajectories (shown with bold lines) for the same period.

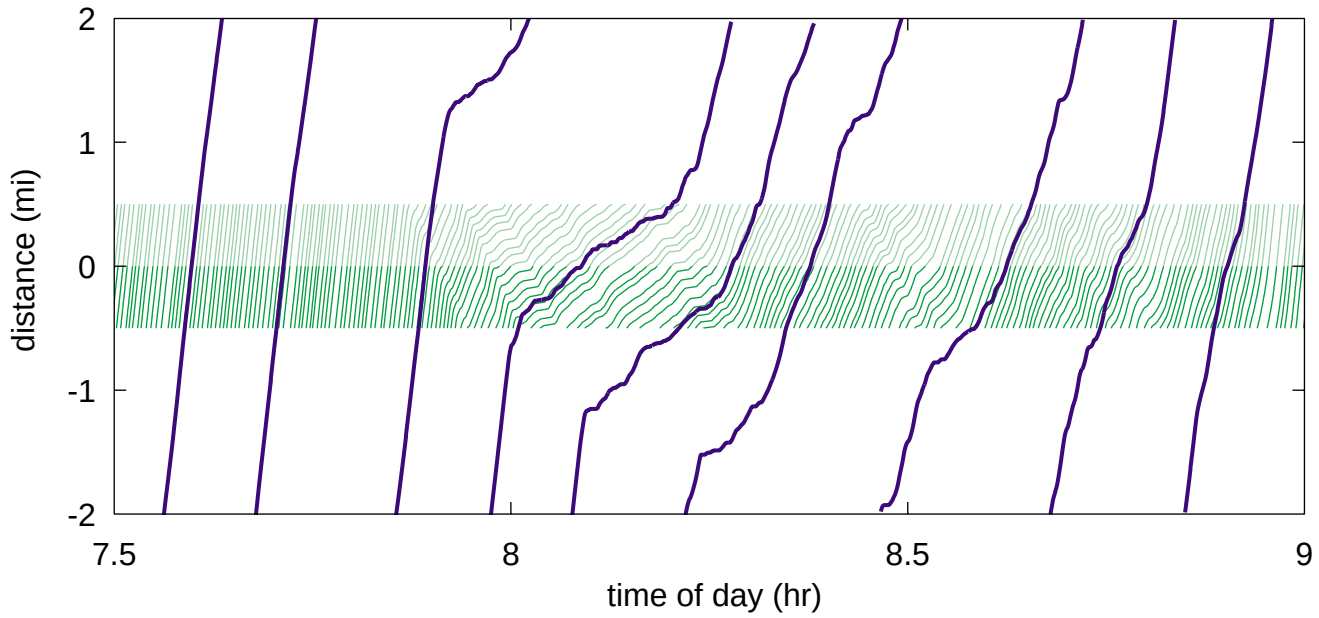

Figure 7, Measured travel times (dots) and estimated (line) from detector data over 24 hours, (A) upstream estimate (B) downstream estimate.

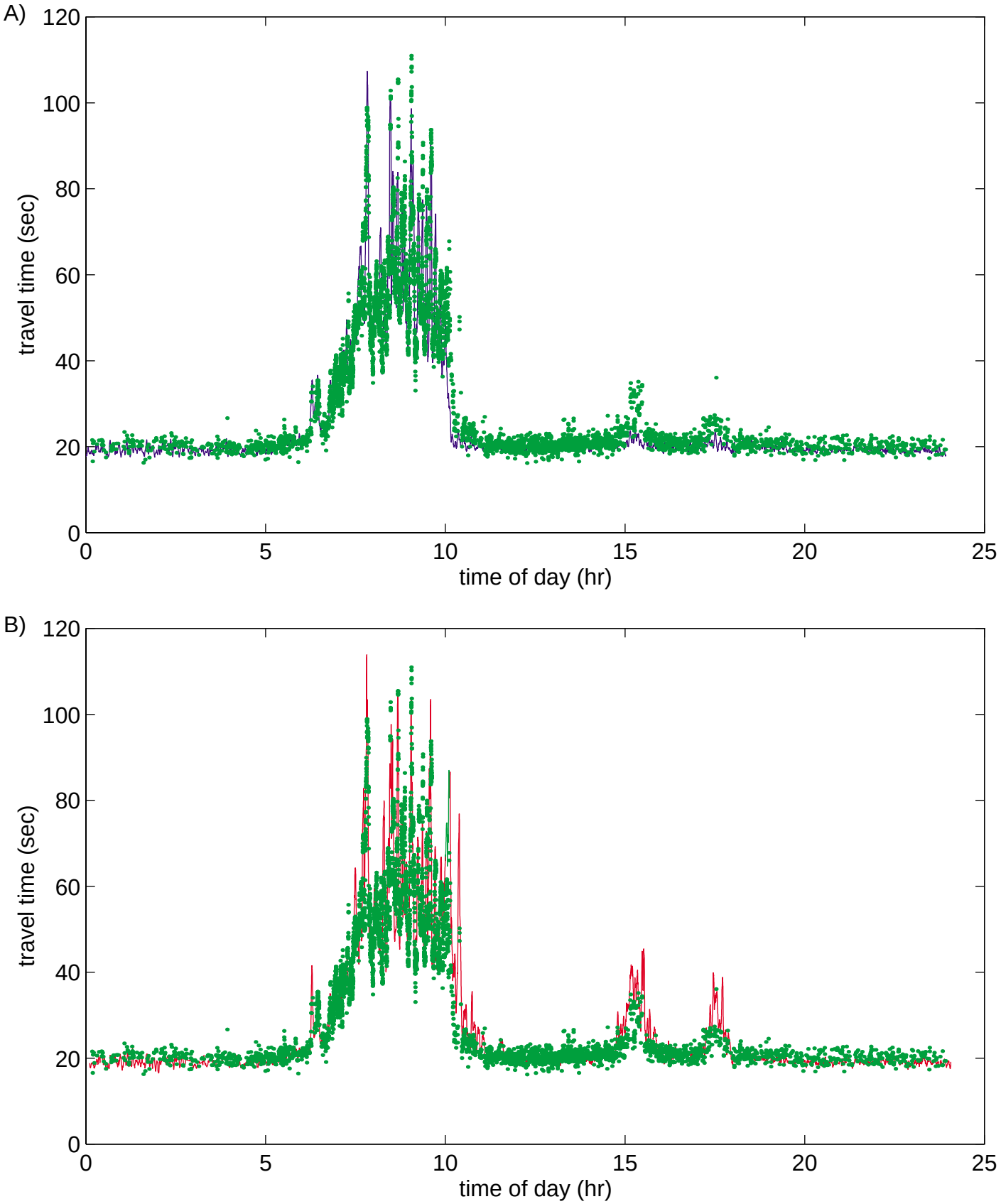

Figure 8, (A) Detail from Figure 7B, (B) the corresponding naive estimates taking the distance between detectors divided by 30 second average velocity downstream, (C) part B repeated with a larger vertical scale.

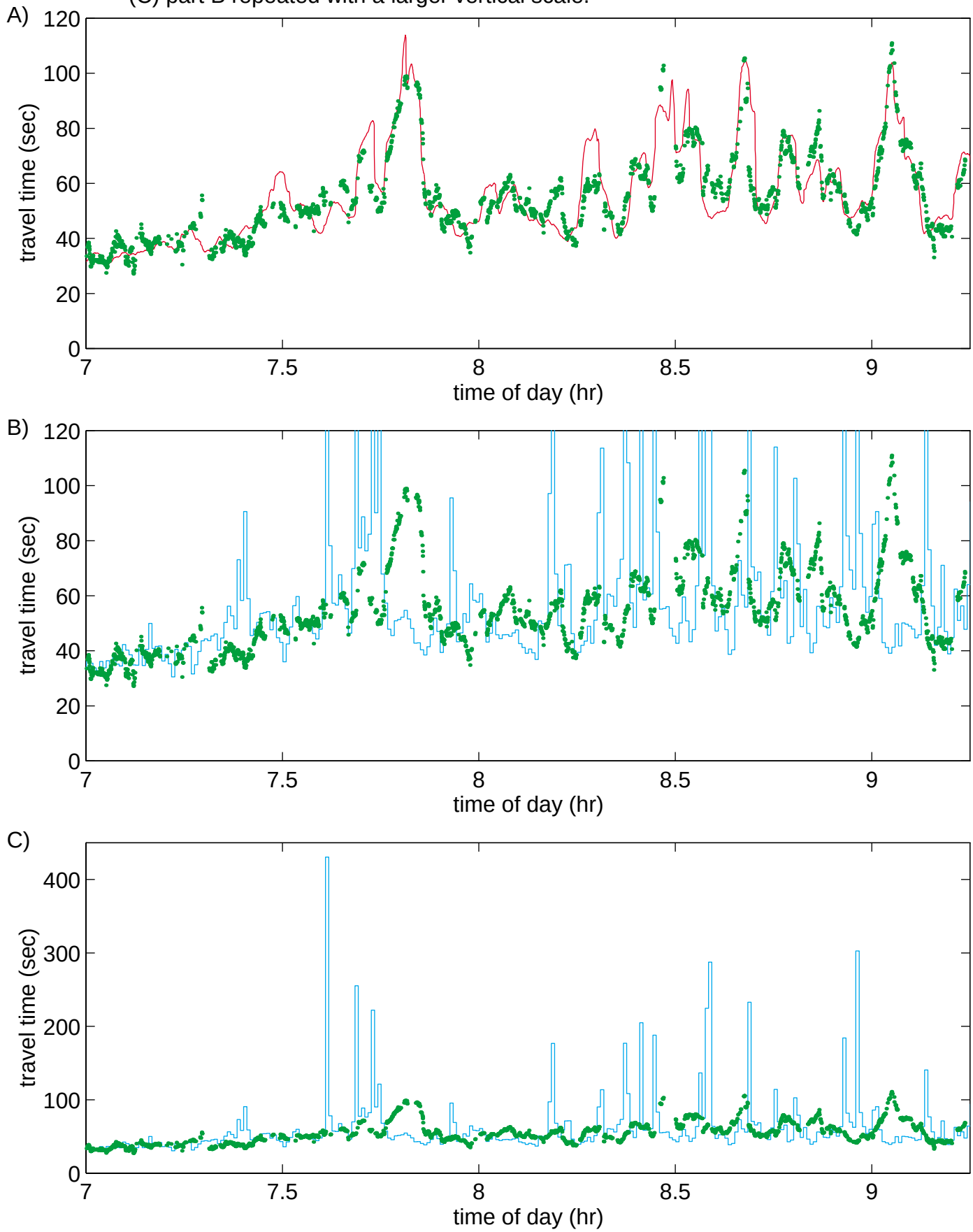

Figure 9, Examples where the estimation technique fails, (A)-(B) Details from Figure 7A and (C)-(D) corresponding details from Figure 7B.

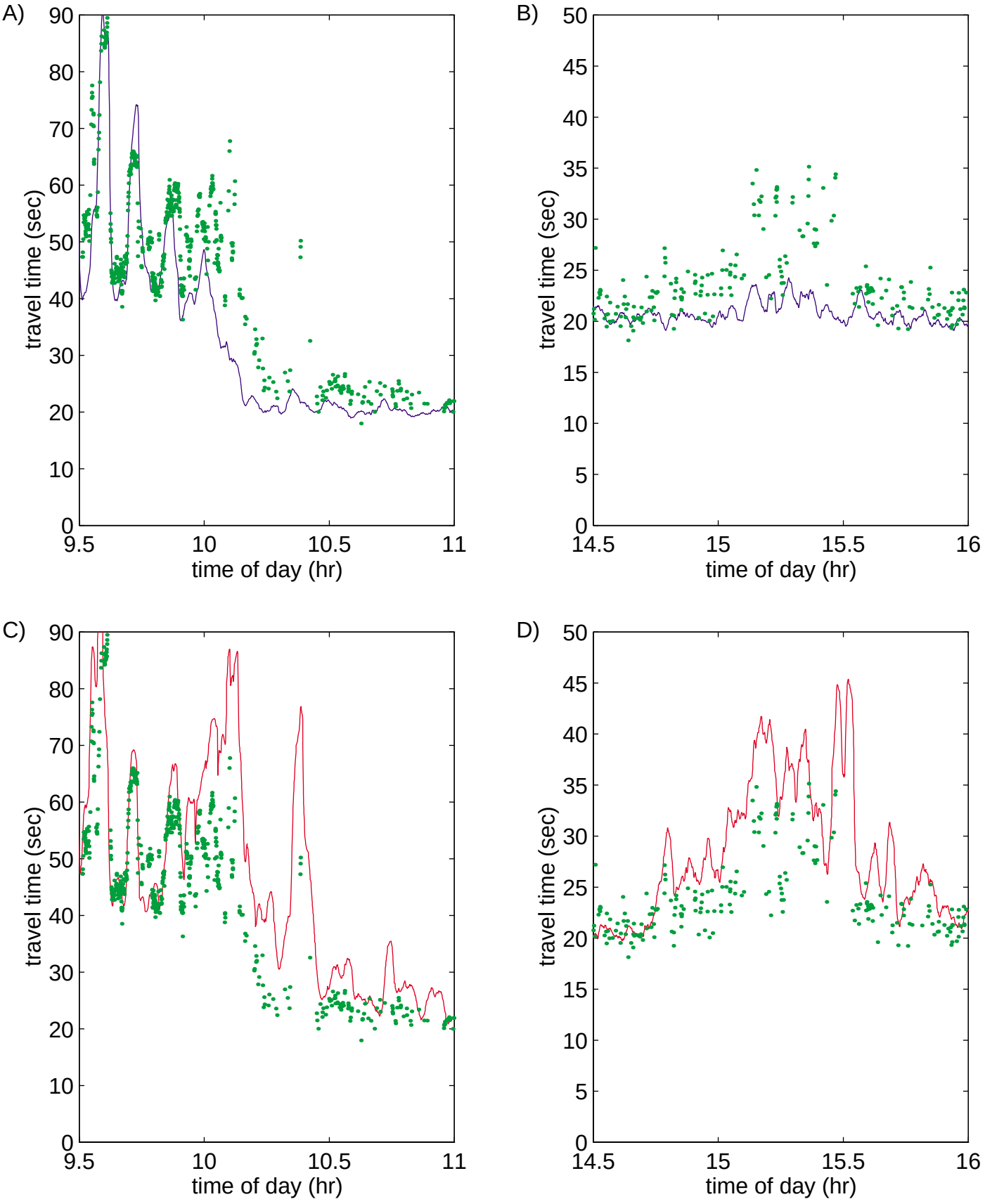

Table 1, Travel time estimation accuracy for the *short example* [a]

	Proposed estimate using measured headways		naive estimate		Proposed estimate using 30 second samples	
	upstream	downstream	upstream	downstream	upstream	downstream
average error (percent)	7	9.8	26.4	27.9	11.5	10.1
bias (sec)	0.6	-4.4	-0.2	-0.1	-2.8	-4.2

[a] Mean ground truth travel time is 77 seconds for this data set